workspace

March 20, 2023

1 Bella & Bona Data Analysis Case Study

1.1 Challenge 2

[1]:
```
# Importing libraries

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

[2]:
```
# Reading the data sets

order_data = pd.read_excel('Data Analyst Case Study - Datasets.xlsx',␣
 ↪sheet_name='order data')
company_data = pd.read_excel('Data Analyst Case Study - Datasets.xlsx',␣
 ↪sheet_name='company data')
user_data = pd.read_excel('Data Analyst Case Study - Datasets.xlsx',␣
 ↪sheet_name='user data')
```

1.1.1 Part I: Capture Rate Calculation

[3]:
```
company_data.head()
```

[3]:
```
  Company Name                                Contractual Weekdays  \
0     company1  ["Monday", "Tuesday", "Wednesday", "Thursday",…
1     company2  ["Monday", "Tuesday", "Wednesday", "Thursday",…
2     company3  ["Monday", "Tuesday", "Thursday", "Friday", "W…
3     company4                      ["Monday", "Wednesday"]
4     company5  ["Monday", "Tuesday", "Wednesday", "Thursday",…

   Main Dish Price  Employer Contribution  Employee Paid Main Dish Price
0              7.5                    7.5                            0.0
1              8.5                    3.8                            4.7
2              7.5                    3.1                            4.4
3              7.5                    0.0                            7.5
4              7.5                    0.0                            7.5
```

The company sheet includes a list of contractual weekdays for each company, whose "lenth" should be extracted to be used to calculate capture rate.

[4]:
```
# Removing the special characters from the column "Contractual Weekdays"

company_data["Contractual Weekdays"] = company_data["Contractual Weekdays"].
 ↪replace({'\[': '', '\]': '','\,': '', '\"': ''}, regex = True)
```

[5]:
```
# Converting the elements of the column to indexible lists

company_data["Contractual Weekdays"] = company_data["Contractual Weekdays"].str.
 ↪split(" ", expand = False)
```

[6]:
```
# Testing the column's structure (The very first day of the very first row,␣
 ↪should yield Monday)

company_data["Contractual Weekdays"][0][0]
```

[6]:
```
'Monday'
```

Well, now that we converted strings to lists, we can get their length as well and append it to the table as a new column.

[7]:
```
# New column: Number of contractual weekdays

company_data["Num. of Cont. Days"] = company_data["Contractual Weekdays"].
 ↪apply(len)
company_data.head()
```

[7]:
```
  Company Name                              Contractual Weekdays  \
0     company1  [Monday, Tuesday, Wednesday, Thursday, Friday]
1     company2  [Monday, Tuesday, Wednesday, Thursday, Friday]
2     company3  [Monday, Tuesday, Thursday, Friday, Wednesday]
3     company4                                [Monday, Wednesday]
4     company5  [Monday, Tuesday, Wednesday, Thursday, Friday]

   Main Dish Price  Employer Contribution  Employee Paid Main Dish Price  \
0              7.5                    7.5                            0.0
1              8.5                    3.8                            4.7
2              7.5                    3.1                            4.4
3              7.5                    0.0                            7.5
4              7.5                    0.0                            7.5

   Num. of Cont. Days
0                   5
1                   5
2                   5
3                   2
```

```
4                    5
```

[8]:
```
# Subsetting the data (keeping the relevant columns only)

table_1 = order_data[["Company Name", "Email", "Week of deliveryDate␣
↪(deliverydata)", "Day of deliveryDate (deliverydata)"]]
```

[9]:
```
# New column: Number of weekdays that an order is delivered by each customer,␣
↪weekly

table_1 = table_1.groupby(["Company Name",
                           "Email",
                           "Week of deliveryDate (deliverydata)"])["Day of␣
↪deliveryDate (deliverydata)"].nunique().reset_index(name="Num. of Orders")
table_1.head()
```

[9]:
```
  Company Name                      Email Week of deliveryDate (deliverydata)  \
0     company1  g.gumugwaukw@company1.com                                Week 5
1     company1  g.gumugwaukw@company1.com                                Week 6
2     company1  g.gumugwaukw@company1.com                                Week 7
3     company1  g.gumugwaukw@company1.com                                Week 8
4     company1  g.gumugwaukw@company1.com                                Week 9

   Num. of Orders
0               1
1               3
2               3
3               4
4               1
```

[10]:
```
# Merging the companies' number of contractual weekdays to the table

table_1 = table_1.merge(company_data[["Company Name", "Num. of Cont. Days",␣
↪"Employee Paid Main Dish Price"]], on="Company Name", how="left")
table_1.head()
```

[10]:
```
  Company Name                      Email Week of deliveryDate (deliverydata)  \
0     company1  g.gumugwaukw@company1.com                                Week 5
1     company1  g.gumugwaukw@company1.com                                Week 6
2     company1  g.gumugwaukw@company1.com                                Week 7
3     company1  g.gumugwaukw@company1.com                                Week 8
4     company1  g.gumugwaukw@company1.com                                Week 9

   Num. of Orders  Num. of Cont. Days  Employee Paid Main Dish Price
0               1                   5                            0.0
1               3                   5                            0.0
2               3                   5                            0.0
```

```
3                4                    5                                0.0
4                1                    5                                0.0
```

Since we are finished with gathering the ingredients, it is time to calculate capture rate as follows:

$$\frac{\text{Number of Orders}}{\text{Number of Contractual Days}} \times 100$$

[11]:
```
# New column: Capture Rate (user level, weekly)

table_1["Capture Rate"] = table_1["Num. of Orders"] / table_1["Num. of Cont.␣
 ↪Days"] * 100

table_1.head()
```

[11]:
```
  Company Name                      Email Week of deliveryDate (deliverydata)  \
0     company1  g.gumugwaukw@company1.com                                Week 5
1     company1  g.gumugwaukw@company1.com                                Week 6
2     company1  g.gumugwaukw@company1.com                                Week 7
3     company1  g.gumugwaukw@company1.com                                Week 8
4     company1  g.gumugwaukw@company1.com                                Week 9

   Num. of Orders  Num. of Cont. Days  Employee Paid Main Dish Price  \
0               1                   5                            0.0
1               3                   5                            0.0
2               3                   5                            0.0
3               4                   5                            0.0
4               1                   5                            0.0

   Capture Rate
0          20.0
1          60.0
2          60.0
3          80.0
4          20.0
```

[12]:
```
# Capture Rate (user level, monthly)

cr_user_m = table_1.groupby('Email')['Capture Rate'].mean()
cr_user_m.head()
```

[12]:
```
Email
Ggwwmawa.utwwtt@company10.com    33.333333
Guautaw.wggu@company37.com       50.000000
Gumwwguma.wgma@company6.com      20.000000
Guwwuu.wawwmguu@company10.com    33.333333
J.kwuww@company4.com             50.000000
```

```
Name: Capture Rate, dtype: float64
```

[13]:
```
# Capture Rate (company level, weekly)

cr_company_w = table_1.groupby(['Company Name', "Week of deliveryDate␣
 ↪(deliverydata)"])['Capture Rate'].mean()
cr_company_w.head()
```

[13]:
```
Company Name  Week of deliveryDate (deliverydata)
company1      Week 5                                40.000000
              Week 6                                38.000000
              Week 7                                40.000000
              Week 8                                48.000000
              Week 9                                26.666667
Name: Capture Rate, dtype: float64
```

[14]:
```
# Capture Rate (company level, monthly)

cr_company_m = table_1.groupby('Company Name')['Capture Rate'].mean()
cr_company_m.head()
```

[14]:
```
Company Name
company1     39.523810
company10    51.540616
company11    34.883721
company12    58.461538
company13    69.117647
Name: Capture Rate, dtype: float64
```

1.1.2 Part II: Correlation Analysis

[15]:
```
table_2 = company_data[["Company Name", "Employee Paid Main Dish Price"]].
 ↪merge(cr_company_m, on="Company Name")
table_2 = table_2.sort_values(by=['Employee Paid Main Dish Price'])
```

[16]:
```
# Correlation matrix of the weekly capture rates

table_1.corr().style.background_gradient(cmap='coolwarm').set_precision(3)
```

```
C:\Users\ayigi\AppData\Local\Temp\ipykernel_13608\2848919669.py:3:
FutureWarning: The default value of numeric_only in DataFrame.corr is
deprecated. In a future version, it will default to False. Select only valid
columns or specify the value of numeric_only to silence this warning.
  table_1.corr().style.background_gradient(cmap='coolwarm').set_precision(3)
C:\Users\ayigi\AppData\Local\Temp\ipykernel_13608\2848919669.py:3:
FutureWarning: this method is deprecated in favour of
```

```
`Styler.format(precision=..)`
  table_1.corr().style.background_gradient(cmap='coolwarm').set_precision(3)
```

[16]:
```
<pandas.io.formats.style.Styler at 0x2aafffda9d0>
```

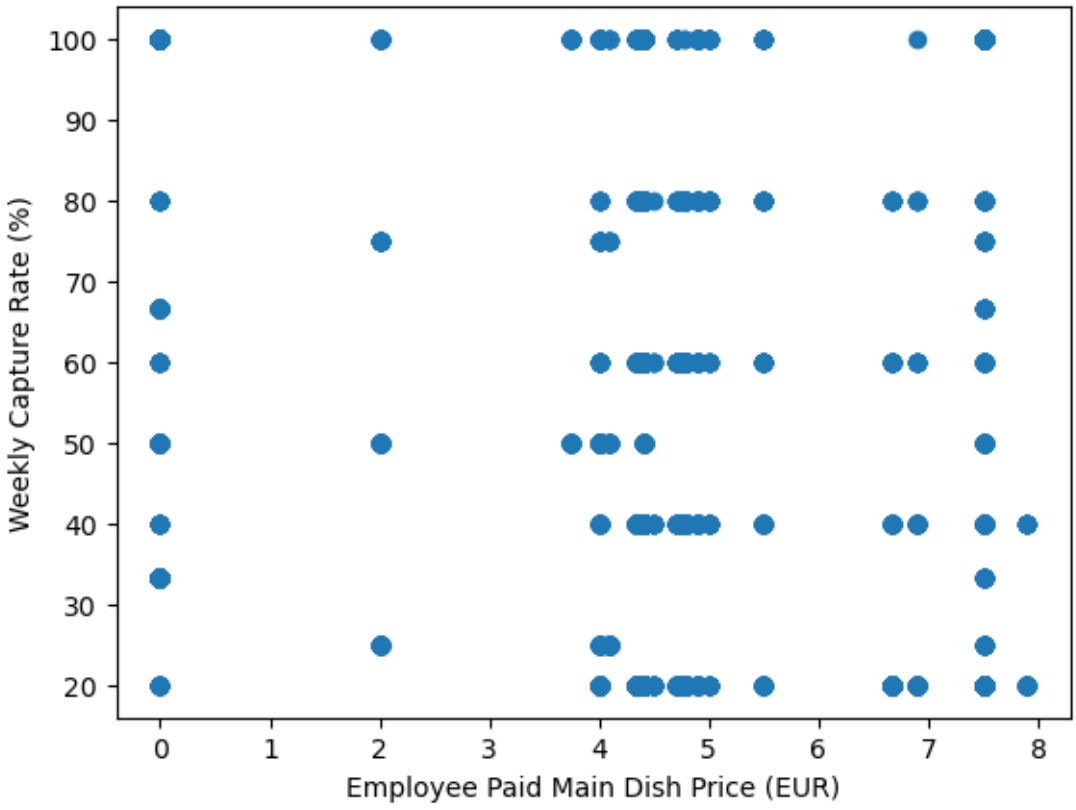
[17]:
```
# Correlation matrix of the monthly capture rates
# (Calculated with Pearson correlation coefficient)

table_2.corr(method='pearson').style.background_gradient(cmap='coolwarm').
  ↪set_precision(3)
```

```
C:\Users\ayigi\AppData\Local\Temp\ipykernel_13608\3497911579.py:4:
FutureWarning: The default value of numeric_only in DataFrame.corr is
deprecated. In a future version, it will default to False. Select only valid
columns or specify the value of numeric_only to silence this warning.
  table_2.corr(method='pearson').style.background_gradient(cmap='coolwarm').set_
precision(3)
C:\Users\ayigi\AppData\Local\Temp\ipykernel_13608\3497911579.py:4:
FutureWarning: this method is deprecated in favour of
`Styler.format(precision=..)`
  table_2.corr(method='pearson').style.background_gradient(cmap='coolwarm').set_
precision(3)
```

[17]:
```
<pandas.io.formats.style.Styler at 0x2aa81c1d640>
```

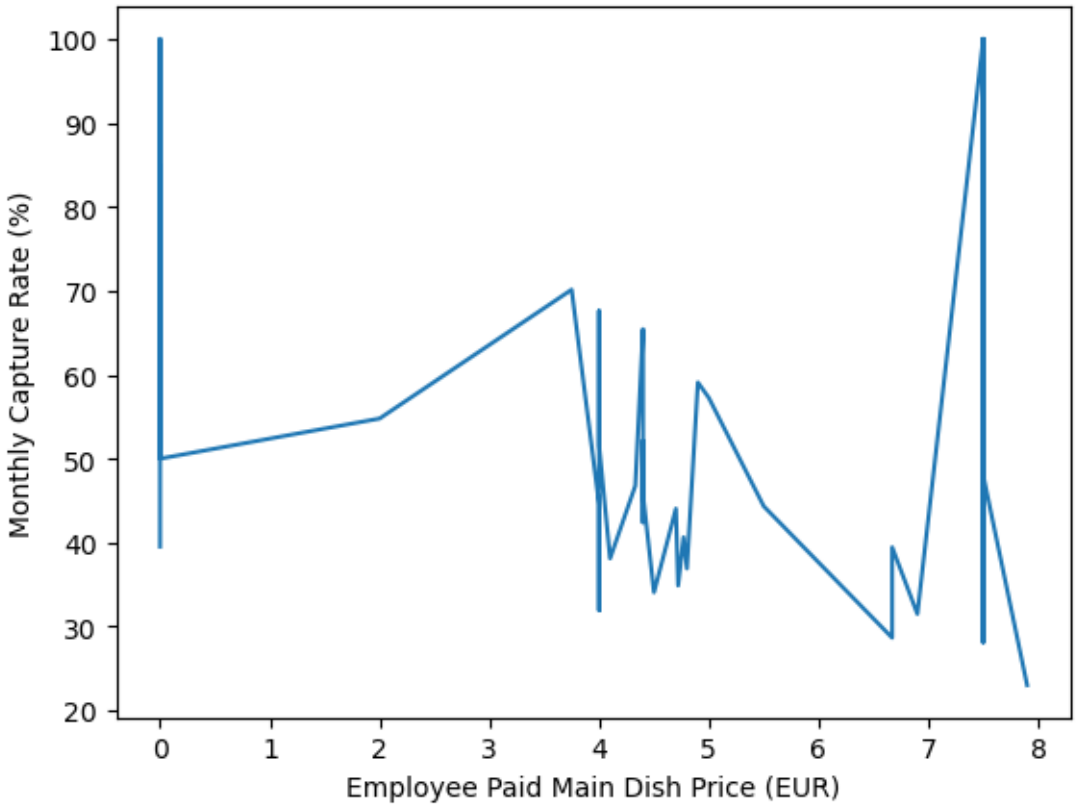
The correlation coefficient takes a value between 0.1 and 0.3 in both cases, which indicates that there is a correlation between end-user price and capture rate, yet it is not that strong. Notice that the value is negative since end-user price and capture rate are inversely proportional, as can be expected.

[18]:
```
# Scatter plot of the weekly capture rates

plt.scatter(table_1["Employee Paid Main Dish Price"], table_1["Capture Rate"])
plt.xlabel("Employee Paid Main Dish Price (EUR)")
plt.ylabel("Weekly Capture Rate (%)")
plt.show()
```



The scatter plot clearly shows some segments of the end-user price range: no payments, 2 EUR, 4-5.5 EUR, and more than 6.5 EUR. In each group, there is no significantly dominating capture rate percentage and observations are balanced, taking values between 20% and 100%.

[19]:
```
# Line chart of the monthly capture rates

plt.plot(table_2["Employee Paid Main Dish Price"], table_2["Capture Rate"])
plt.xlabel("Employee Paid Main Dish Price (EUR)")
plt.ylabel("Monthly Capture Rate (%)")
plt.show()
```



When it comes to the line chart of the monthly averages, again, there is no significant trend. Interestingly, there is a peak in 7.5 EUR, which is one of the highest prices an employee can pay. Finally, we can take a look at the monthly capture rates table:

[20]:
```
table_2
```

[20]:

	Company Name	Employee Paid Main Dish Price	Capture Rate
0	company1	0.00	39.523810
28	company29	0.00	84.848485
41	company42	0.00	64.000000
9	company10	0.00	51.540616
6	company7	0.00	100.000000
13	company14	0.00	100.000000
26	company27	0.00	50.000000
8	company9	2.00	54.777070
20	company21	3.75	70.129870
40	company41	4.00	44.571429
22	company23	4.00	31.932773
18	company19	4.00	67.582418
29	company30	4.00	51.578947
23	company24	4.10	38.106796

35	company36	4.33	46.784452
7	company8	4.40	65.432099
11	company12	4.40	58.461538
2	company3	4.40	42.416107
34	company35	4.40	52.093023
5	company6	4.40	45.732484
38	company39	4.50	34.074074
1	company2	4.70	44.044944
10	company11	4.72	34.883721
30	company31	4.77	40.641026
27	company28	4.80	36.914286
17	company18	4.90	59.086758
36	company37	5.00	57.241379
21	company22	5.50	44.333333
19	company20	6.67	28.671329
39	company40	6.67	39.459459
14	company15	6.90	31.500000
24	company25	7.50	100.000000
31	company32	7.50	100.000000
32	company33	7.50	45.000000
33	company34	7.50	28.133971
15	company16	7.50	100.000000
12	company13	7.50	69.117647
37	company38	7.50	72.131148
4	company5	7.50	38.333333
3	company4	7.50	63.559322
25	company26	7.50	54.629630
42	company43	7.50	48.000000
16	company17	7.90	23.018868

Since there is only one company whose monthly capture rate is lower than 50%, we can conclude that free meals contribute significantly to capture rate. On the other side, price is not that significant when the meal is paid, as there are good capture rates at high prices as well. However, this claim must be investigated further since this study is held considering only one-month data.

With the data we have, we can put forward one final argument by adding a new binary feature that indicates whether the meal is free.

[21]:
```
# New column: Is the meal free for the end-customer?

table_2["Free Meal"] = np.where(table_2['Employee Paid Main Dish Price'] == 0,␣
↪1, 0)
table_2.corr(method='pearson').style.background_gradient(cmap='coolwarm').
↪set_precision(3)
```

```
C:\Users\ayigi\AppData\Local\Temp\ipykernel_13608\621796198.py:4: FutureWarning:
The default value of numeric_only in DataFrame.corr is deprecated. In a future
version, it will default to False. Select only valid columns or specify the
```

```
value of numeric_only to silence this warning.
  table_2.corr(method='pearson').style.background_gradient(cmap='coolwarm').set_
precision(3)
C:\Users\ayigi\AppData\Local\Temp\ipykernel_13608\621796198.py:4: FutureWarning:
this method is deprecated in favour of `Styler.format(precision=..)`
  table_2.corr(method='pearson').style.background_gradient(cmap='coolwarm').set_
precision(3)
```

[21]: `<pandas.io.formats.style.Styler at 0x2aa817b7610>`

This time, the correlation coefficient takes a larger value (Pearson correlation coefficient values between 0.3 and 0.5 are considered as medium-level correlation), which is a considerable evidence that offering free meals is more important than discounts.

1.1.3 Part III: Assessing Other Factors

[22]:
```
table_1
```

[22]:

	Company Name	Email	\
0	company1	g.gumugwaukw@company1.com	
1	company1	g.gumugwaukw@company1.com	
2	company1	g.gumugwaukw@company1.com	
3	company1	g.gumugwaukw@company1.com	
4	company1	g.gumugwaukw@company1.com	
…	…	…	
5046	company9	wwwwwmguazkugawwaw@company9.com	
5047	company9	wwwwwmguazkugawwaw@company9.com	
5048	company9	wzwmawwmu@company9.com	
5049	company9	wzwmawwmu@company9.com	
5050	company9	wzwmawwmu@company9.com	

	Week of deliveryDate (deliverydata)	Num. of Orders	Num. of Cont. Days	\
0	Week 5	1	5	
1	Week 6	3	5	
2	Week 7	3	5	
3	Week 8	4	5	
4	Week 9	1	5	
…	…	…	…	
5046	Week 8	4	4	
5047	Week 9	2	4	
5048	Week 5	1	4	
5049	Week 6	2	4	
5050	Week 9	1	4	

	Employee Paid Main Dish Price	Capture Rate
0	0.0	20.0
1	0.0	60.0
2	0.0	60.0

```
3                                0.0          80.0
4                                0.0          20.0
…                                …            …
5046                             2.0         100.0
5047                             2.0          50.0
5048                             2.0          25.0
5049                             2.0          50.0
5050                             2.0          25.0

[5051 rows x 7 columns]
```

[23]:
```
order_data.head()
```

[23]:
```
                               Order Id                       Email  \
0  9f315c01-f7bc-46b6-9cbb-6fac0644e27f  g.gumugwaukw@company1.com
1  55d6f8db-c994-43a3-88da-ccaaeb14c448  g.gumugwaukw@company1.com
2  82e0163f-35ce-4f56-8d50-f4a9fe2ab168  g.gumugwaukw@company1.com
3  084cf85e-f703-43f8-bec5-54d985d38eb1  g.gumugwaukw@company1.com
4  20846cc2-415f-4ff1-a6dd-b83e2b85c613  g.gumugwaukw@company1.com

  Company Name   DishType               orderId (deliverydata)  \
0     company1  Main Dish  9f315c01-f7bc-46b6-9cbb-6fac0644e27f
1     company1  Main Dish  55d6f8db-c994-43a3-88da-ccaaeb14c448
2     company1  Main Dish  82e0163f-35ce-4f56-8d50-f4a9fe2ab168
3     company1  Main Dish  084cf85e-f703-43f8-bec5-54d985d38eb1
4     company1  Main Dish  20846cc2-415f-4ff1-a6dd-b83e2b85c613

                                  Dish Name Type (Recipe Variants)  \
0                            Lasagna Ligure                    hot
1   Roasted chicken with Potatoes and Speck                    hot
2               Herakleio's Vegan Pita Gyros                   cold
3                          Vegan Currywurst                    hot
4  Chicken with Leipziger Allerlei and rösti                   hot

         diet  Quantity  Year of placedAt (orders)  …  \
0  vegetarian         1                       2023  …
1        meat         1                       2023  …
2       vegan         1                       2023  …
3       vegan         1                       2023  …
4        meat         1                       2023  …

   Week of placedAt (orders)  Year of deliveryDate (deliverydata)  \
0                     Week 5                                2023
1                     Week 7                                2023
2                     Week 8                                2023
3                     Week 8                                2023
4                     Week 6                                2023
```

```
  Month of deliveryDate (deliverydata) Day of deliveryDate (deliverydata)  \
0                                    2                                   3
1                                    2                                  14
2                                    2                                  23
3                                    2                                  27
4                                    2                                   9

   deliveryDate (deliverydata)  Week of deliveryDate (deliverydata)  Rating  \
0                   2023-02-03                                Week 5     NaN
1                   2023-02-14                                Week 7     NaN
2                   2023-02-23                                Week 8     NaN
3                   2023-02-27                                Week 9     NaN
4                   2023-02-09                                Week 6     NaN

  Satisfaction Taste  Delivery
0          NaN   NaN       NaN
1          NaN   NaN       NaN
2          NaN   NaN       NaN
3          NaN   NaN       NaN
4          NaN   NaN       NaN

[5 rows x 23 columns]
```

[24]:
```
# New columns: Monthly user feedback averages

table_3 = table_1.merge(order_data.groupby('Email')['Rating'].mean(),␣
 ↪on="Email", how="left")
table_3 = table_3.merge(order_data.groupby('Email')['Satisfaction'].mean(),␣
 ↪on="Email", how="left")
table_3 = table_3.merge(order_data.groupby('Email')['Taste'].mean(),␣
 ↪on="Email", how="left")
table_3 = table_3.merge(order_data.groupby('Email')['Delivery'].mean(),␣
 ↪on="Email", how="left")
table_3.head()
```

[24]:
```
  Company Name                      Email Week of deliveryDate (deliverydata)  \
0     company1  g.gumugwaukw@company1.com                                Week 5
1     company1  g.gumugwaukw@company1.com                                Week 6
2     company1  g.gumugwaukw@company1.com                                Week 7
3     company1  g.gumugwaukw@company1.com                                Week 8
4     company1  g.gumugwaukw@company1.com                                Week 9

   Num. of Orders  Num. of Cont. Days  Employee Paid Main Dish Price  \
0               1                   5                            0.0
1               3                   5                            0.0
2               3                   5                            0.0
```

```
3                4                    5                              0.0
4                1                    5                              0.0

   Capture Rate    Rating  Satisfaction     Taste  Delivery
0          20.0  8.285714      8.428571  8.285714      10.0
1          60.0  8.285714      8.428571  8.285714      10.0
2          60.0  8.285714      8.428571  8.285714      10.0
3          80.0  8.285714      8.428571  8.285714      10.0
4          20.0  8.285714      8.428571  8.285714      10.0
```

[25]:
```
# New column: Company size (Probably ignoring non-B&B user employees, but still␣
 ↪might give an insight about company sizes)

table_3 = table_3.merge(user_data.groupby(["Company Name"])["Email"].nunique().
 ↪reset_index(name="Num. of Employees"), on="Company Name", how="left")
table_3.head()
```

[25]:
```
  Company Name                     Email Week of deliveryDate (deliverydata)  \
0     company1  g.gumugwaukw@company1.com                                Week 5
1     company1  g.gumugwaukw@company1.com                                Week 6
2     company1  g.gumugwaukw@company1.com                                Week 7
3     company1  g.gumugwaukw@company1.com                                Week 8
4     company1  g.gumugwaukw@company1.com                                Week 9

   Num. of Orders  Num. of Cont. Days  Employee Paid Main Dish Price  \
0               1                    5                              0.0
1               3                    5                              0.0
2               3                    5                              0.0
3               4                    5                              0.0
4               1                    5                              0.0

   Capture Rate    Rating  Satisfaction     Taste  Delivery  Num. of Employees
0          20.0  8.285714      8.428571  8.285714      10.0                 20
1          60.0  8.285714      8.428571  8.285714      10.0                 20
2          60.0  8.285714      8.428571  8.285714      10.0                 20
3          80.0  8.285714      8.428571  8.285714      10.0                 20
4          20.0  8.285714      8.428571  8.285714      10.0                 20
```

[26]:
```
# Checking the correlation matrix

table_3.corr(method='pearson').style.background_gradient(cmap='coolwarm').
 ↪set_precision(3)
```

```
C:\Users\ayigi\AppData\Local\Temp\ipykernel_13608\236254570.py:3: FutureWarning:
The default value of numeric_only in DataFrame.corr is deprecated. In a future
version, it will default to False. Select only valid columns or specify the
value of numeric_only to silence this warning.
```

```
  table_3.corr(method='pearson').style.background_gradient(cmap='coolwarm').set_
precision(3)
C:\Users\ayigi\AppData\Local\Temp\ipykernel_13608\236254570.py:3: FutureWarning:
this method is deprecated in favour of `Styler.format(precision=..)`
  table_3.corr(method='pearson').style.background_gradient(cmap='coolwarm').set_
precision(3)
```

[26]: <pandas.io.formats.style.Styler at 0x2aa81d1ed60>

According to the above results, user feedbacks seem like irrelevant, all of which have a magnitude near zero. This probably stems from the fact that many users do not take their times to give ratings, and consequently one-month data becomes inadequate. A possibly useful modification can be narrowing down the scale from 1-20 to 1-5, which would reflect the users' satisfaction better in small sample sizes.

On the other hand, company size's coefficient has a higher magnitude compared to the feedbacks, yet its correlation (-0.127) is still weak.

The feature with the highest correlation with capture rate is the number of contractual days, which has a negative coefficient equal to almost 0.6. It is inversely proportional with the capture rate, which can be interpreted as follows: End-users who have fewer opportunities per week to eat B&B meals have a higher tendency to benefit from these opportunities.

At the first glance, offering the most frequent deliveries possible to the businesses might seem like a good idea to maximize profits. Considering the last outcome (the inverse proportionality of capture rate and frequency), reassessing the negotiation strategy might be helpful. For example, an optimum number of weekly deliveries can be determined (such as 2 or 3 days a week), and this number can be used as a first offer.

This would decrease the total profit in the short-term for sure. But as a long-term strategy it can be helpful when supported with a second strategy: Working with more companies. Focusing on increasing the number of businesses served instead of number of days served would probably yield better results. To exemplify, serving 5 companies 3 days a week would probably be better than serving 3 companies for 5 days a week, in terms of capture rate, of course.

The below table supports this idea.

[27]:
```
# Table: Capture rate averages for each frequency

table_3.groupby("Num. of Cont. Days")["Capture Rate"].mean()
```

[27]:
```
Num. of Cont. Days
1    100.000000
2     68.763557
3     51.823579
4     49.626866
5     42.561670
Name: Capture Rate, dtype: float64
```

1.1.4 Part IV: Modeling

[28]:
```
import seaborn as sns
from sklearn import linear_model
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from sklearn import metrics
```

[31]:
```
# Preparing a clean table before train-test split with the columns to be␣
 ↪assessed and the target column

# Company Name, End-user Price, Frequency
table_4 = company_data[["Company Name", "Employee Paid Main Dish Price", "Num.␣
 ↪of Cont. Days"]]
# Company Size
table_4 = table_4.merge(user_data.groupby("Company Name")["Email"].nunique().
 ↪reset_index(name="Num. of Employees"), on="Company Name", how="left")
# Rating
table_4 = table_4.merge(order_data.groupby('Company Name')['Rating'].mean(),␣
 ↪on="Company Name", how="left")
# Satisfaction
table_4 = table_4.merge(order_data.groupby('Company Name')['Satisfaction'].
 ↪mean(), on="Company Name", how="left")
# Taste
table_4 = table_4.merge(order_data.groupby('Company Name')['Taste'].mean(),␣
 ↪on="Company Name", how="left")
# Delivery
table_4 = table_4.merge(order_data.groupby('Company Name')['Delivery'].mean(),␣
 ↪on="Company Name", how="left")
# Is Free?
table_4["Free Meal"] = np.where(table_4['Employee Paid Main Dish Price'] == 0,␣
 ↪1, 0)
# Weekly capture rate
week_9_dropped = table_1.drop(table_1[table_1['Week of deliveryDate␣
 ↪(deliverydata)'] == 'Week 9'].index)
week_9_dropped = week_9_dropped.groupby(["Company Name", "Week of deliveryDate␣
 ↪(deliverydata)"])["Capture Rate"].mean()
table_4 = table_4.merge(week_9_dropped, on="Company Name", how="right")
# Company name is not required from this line on
table_4 = table_4.drop(['Company Name'], axis=1)

table_4.head()
```

[31]:

	Employee Paid Main Dish Price	Num. of Cont. Days	Num. of Employees	\
0	0.0	5	20	
1	0.0	5	20	
2	0.0	5	20	

```
3                          0.0                  5                 20
4                          0.0                  3                133
```

	Rating	Satisfaction	Taste	Delivery	Free Meal	Capture Rate
0	8.222222	8.625000	8.500000	9.625000	1	40.000000
1	8.222222	8.625000	8.500000	9.625000	1	38.000000
2	8.222222	8.625000	8.500000	9.625000	1	40.000000
3	8.222222	8.625000	8.500000	9.625000	1	48.000000
4	7.717647	8.231884	7.521739	10.264706	1	54.222222

Note that we have dropped the rows that belong to Week 9, since this week consists of only two days (27 and 28th of February), causing a bias in the averages. The following table shows how capture rate average is inconsistent in these rows.

[29]:
```
table_1.groupby('Week of deliveryDate (deliverydata)')['Capture Rate'].mean()
```

[29]:
```
Week of deliveryDate (deliverydata)
Week 5    54.470272
Week 6    56.429207
Week 7    56.186957
Week 8    55.957854
Week 9    38.352941
Name: Capture Rate, dtype: float64
```

[32]:
```
table_4.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 170 entries, 0 to 169
Data columns (total 9 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   Employee Paid Main Dish Price   170 non-null    float64
 1   Num. of Cont. Days              170 non-null    int64
 2   Num. of Employees               170 non-null    int64
 3   Rating                          166 non-null    float64
 4   Satisfaction                    162 non-null    float64
 5   Taste                           162 non-null    float64
 6   Delivery                        162 non-null    float64
 7   Free Meal                       170 non-null    int32
 8   Capture Rate                    170 non-null    float64
dtypes: float64(6), int32(1), int64(2)
memory usage: 12.6 KB
```

[33]:
```
table_4.describe()
```

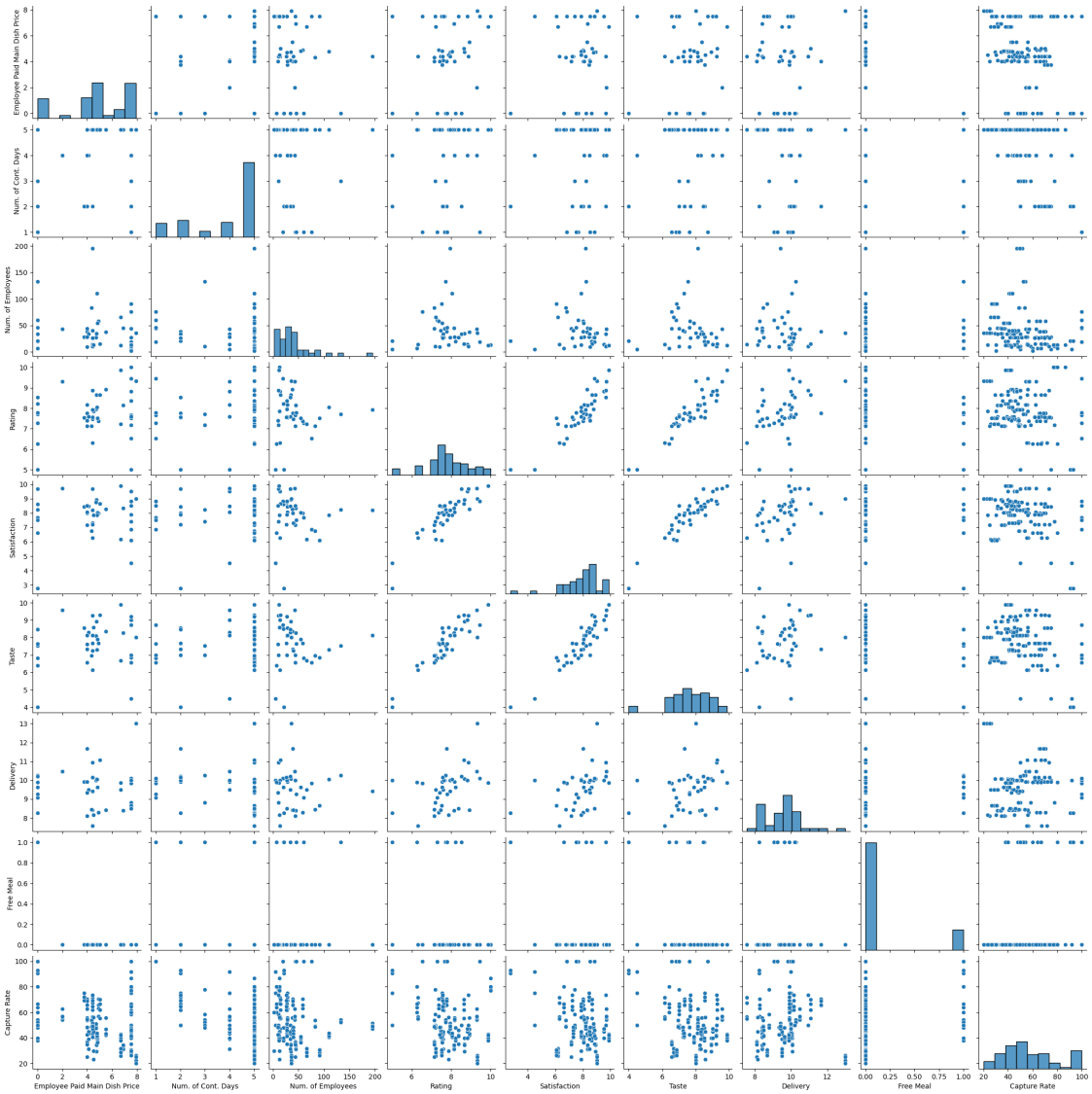
[33]:

	Employee Paid Main Dish Price	Num. of Cont. Days	Num. of Employees	\
count	170.000000	170.000000	170.000000	

```
mean                    4.702000          3.935294         40.958824
std                     2.519293          1.480221         36.964617
min                     0.000000          1.000000          2.000000
25%                     4.000000          3.000000         14.000000
50%                     4.700000          5.000000         34.000000
75%                     7.500000          5.000000         46.000000
max                     7.900000          5.000000        195.000000

           Rating  Satisfaction       Taste    Delivery   Free Meal  \
count  166.000000    162.000000  162.000000  162.000000  170.000000
mean     7.811812      7.859977    7.683819    9.572922    0.158824
std      1.063717      1.370835    1.215639    1.048268    0.366591
min      5.000000      2.750000    4.000000    7.571429    0.000000
25%      7.371212      7.291667    7.000000    8.666667    0.000000
50%      7.717647      8.071429    7.678571    9.833333    0.000000
75%      8.490809      8.657895    8.500000   10.050000    0.000000
max     10.000000      9.875000    9.875000   13.000000    1.000000

       Capture Rate
count    170.000000
mean      56.971689
std       21.786017
min       20.000000
25%       41.615385
50%       50.555556
75%       69.270833
max      100.000000
```

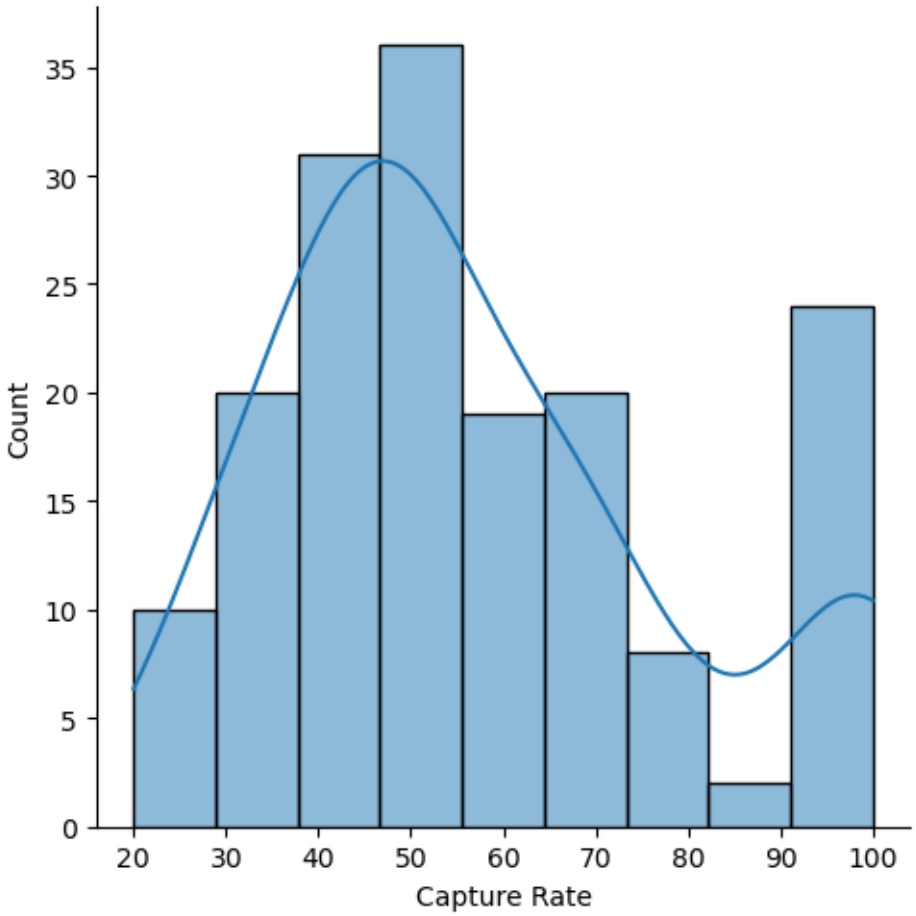
[34]:
```
sns.pairplot(table_4)
```

[34]:
```
<seaborn.axisgrid.PairGrid at 0x2aa85290bb0>
```



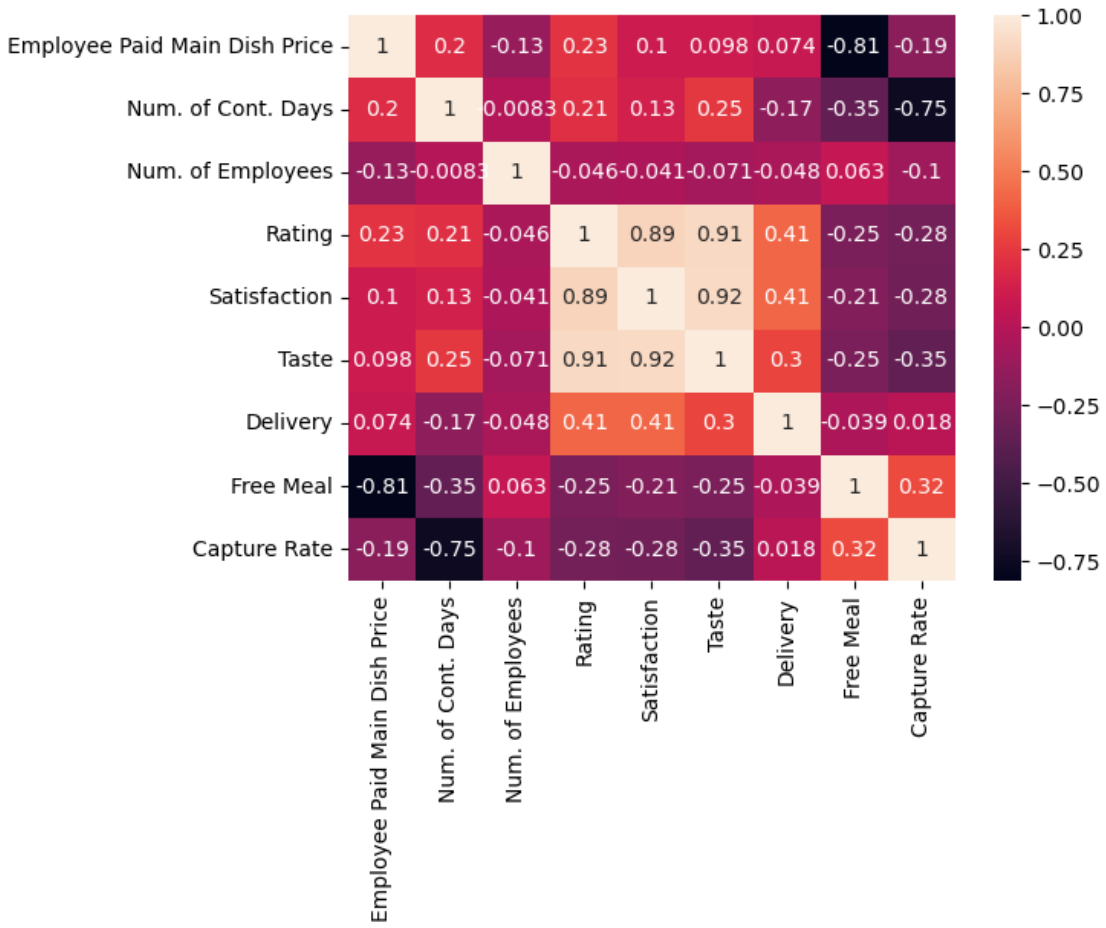
[35]:
```
sns.displot(table_4["Capture Rate"], kde=True)
```

[35]: <seaborn.axisgrid.FacetGrid at 0x2aa8176f220>



[36]:
```
sns.heatmap(table_4.corr(), annot=True)
```

[36]: <AxesSubplot: >



Model I: Linear Regression

[37]:
```
table_5 = table_4[['Employee Paid Main Dish Price', 'Num. of Cont. Days', 'Free␣
↪Meal', 'Rating', 'Satisfaction', 'Taste', 'Capture Rate']].dropna()
X = table_5.drop(['Capture Rate'], axis=1)
y = table_5['Capture Rate']
```

[38]:
```
# Train-test split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=100)
```

[39]:
```
lm = linear_model.LinearRegression()
lm.fit(X_train, y_train)
```

[39]:
```
LinearRegression()
```

[40]:
```
print(lm.intercept_)
```

143.94340466054786

[41]:
```
pd.DataFrame(lm.coef_, X.columns, columns=["Coefficient"])
```

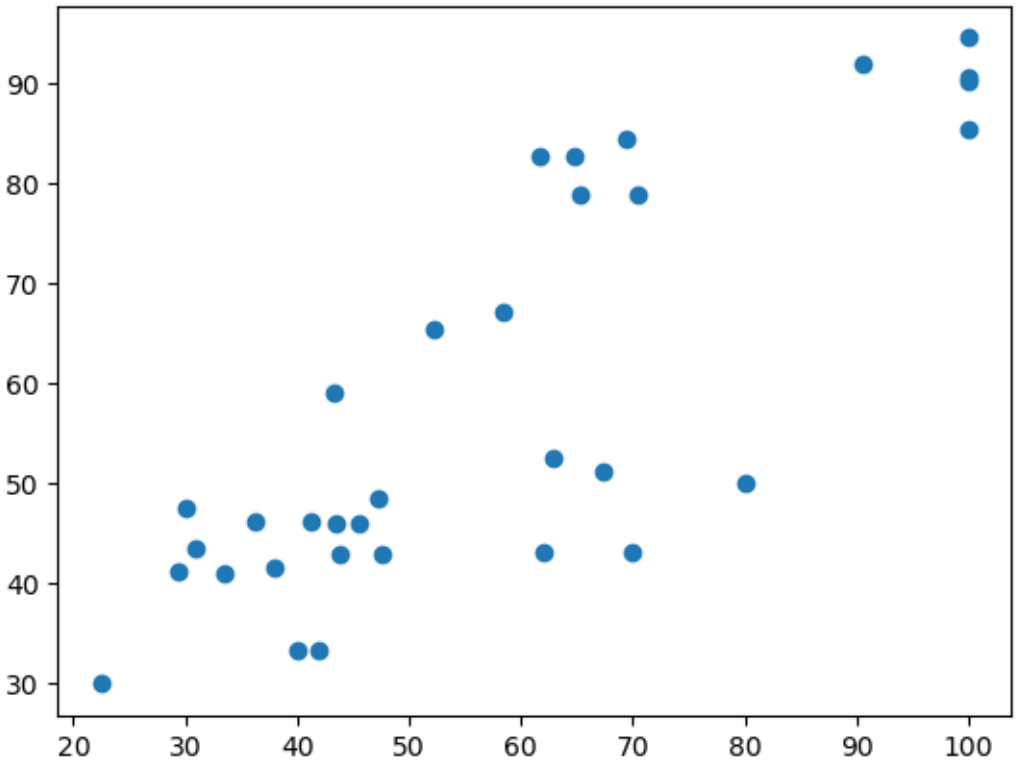
[41]:

	Coefficient
Employee Paid Main Dish Price	-0.987318
Num. of Cont. Days	-11.854722
Free Meal	-6.167521
Rating	-6.474924
Satisfaction	-2.080462
Taste	4.022314

[42]:
```
predictions_1 = lm.predict(X_test)
```

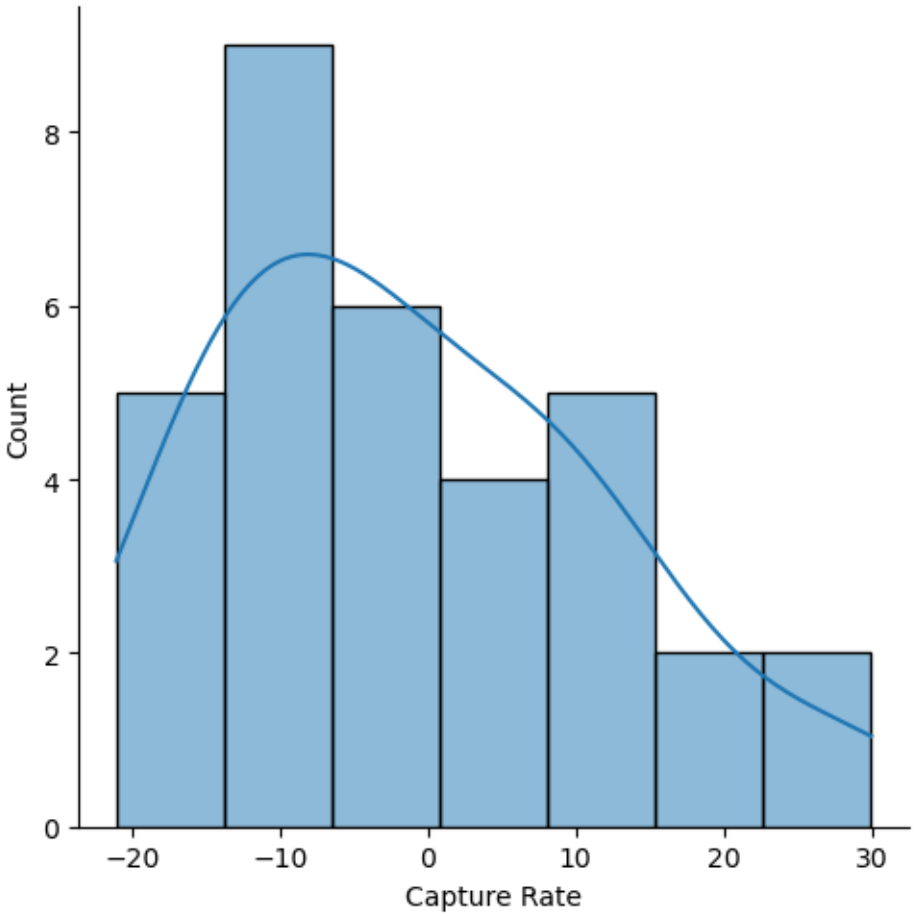
[43]:
```
plt.scatter(y_test, predictions_1)
```

[43]: <matplotlib.collections.PathCollection at 0x2aa8e0e74f0>



[44]:
```
sns.displot(y_test - predictions_1, kde=True)
```

[44]: <seaborn.axisgrid.FacetGrid at 0x2aa8e102dc0>



[45]:
```
# MAE

metrics.mean_absolute_error(y_test, predictions_1)
```

[45]: 10.827508939350276

[46]:
```
# RMSE

np.sqrt(metrics.mean_squared_error(y_test, predictions_1))
```

[46]: 12.943877812889221

[47]:
```
metrics.mean_absolute_percentage_error(y_test, predictions_1)
```

[47]: 0.20691885964843956

Model II: Random Forest

[48]:
```
from sklearn.ensemble import RandomForestRegressor
```

[49]:
```
rf = RandomForestRegressor(n_estimators = 100, random_state = 100)
```

[50]:
```
rf.fit(X_train, y_train)
```

[50]:
```
RandomForestRegressor(random_state=100)
```

[51]:
```
predictions_2 = rf.predict(X_test)
```

[52]:
```
metrics.mean_absolute_error(y_test, predictions_2)
```

[52]:
```
3.703734670812414
```

[53]:
```
np.sqrt(metrics.mean_squared_error(y_test, predictions_2))
```

[53]:
```
5.4366629988575585
```

[54]:
```
metrics.mean_absolute_percentage_error(y_test, predictions_2)
```

[54]:
```
0.07669321459652612
```

[62]:
```
# Feature Importance (More feature engineering needed for this to be useful)

#sorted_idx = rf.feature_importances_.argsort()
#plt.barh(rf.feature_names_in_[sorted_idx], rf.feature_importances_[sorted_idx])
#plt.xlabel("Random Forest Feature Importance")
```

1.1.5 Part V:

- "Is Free?" column contributes well. More custom features can be engineered.
- Holidays in Germany and other special days can be introduced as a column. (For exemple Ramadan, during which Muslims fast.)
- In addition, separate analysis for each diet type can be held.

1.1.6 Part VI:

[207]:
```
company_a = pd.read_excel('test_data.xlsx', sheet_name='company_a')
company_b = pd.read_excel('test_data.xlsx', sheet_name='company_b')
company_c = pd.read_excel('test_data.xlsx', sheet_name='company_c')
```

[208]:
```
table_6 = table_4[['Employee Paid Main Dish Price', 'Num. of Cont. Days', 'Free␣
↪Meal', 'Capture Rate']].dropna()
X = table_6.drop(['Capture Rate'], axis=1)
y = table_6['Capture Rate']
```

[209]:
```
X_train = X
y_train = y
```

[210]:
```
rf = RandomForestRegressor(n_estimators = 100, random_state = 100)
```

[211]:
```
rf.fit(X_train, y_train)
```

[211]:
```
RandomForestRegressor(random_state=100)
```

[212]:
```
def modify_test_set(company_data):

    company_data = company_data.transpose()
    company_data = company_data.iloc[1:]
    company_data.columns = ["Company Size", "Num. of Cont. Days", "Nominal␣
 ↪Price", "Employer Contribution", "Employee Paid Main Dish Price"]
    company_data["Free Meal"] = np.where(company_data['Employee Paid Main Dish␣
 ↪Price'] == 0, 1, 0)
    return(company_data)
```

[213]:
```
company_a = modify_test_set(company_a)
company_b = modify_test_set(company_b)
company_c = modify_test_set(company_c)
```

[214]:
```
company_a_test = company_a.iloc[:, [4, 1, 5]]
company_b_test = company_b.iloc[:, [4, 1, 5]]
company_c_test = company_c.iloc[:, [4, 1, 5]]
```

[215]:
```
predictions_a = rf.predict(company_a_test)
company_a["Prediction (Weekly CR)"] = predictions_a
company_a["Prediction (Monthly Revenue)"] = 4.2*company_a["Nominal␣
 ↪Price"]*company_a["Company Size"]*company_a["Num. of Cont.␣
 ↪Days"]*company_a["Prediction (Weekly CR)"]/100
company_a
```

[215]:

	Company Size	Num. of Cont. Days	Nominal Price	Employer Contribution	Employee Paid Main Dish Price	Free Meal	Prediction (Weekly CR)	Prediction (Monthly Revenue)
Scenario 1	30.0	4.0	7.9	0.0	7.9	0	1.0	1.0
Scenario 2	30.0	4.0	7.9	2.0	5.9	0	1.0	1.0
Scenario 3	30.0	4.0	7.9	4.0	3.9	0	1.0	1.0
Scenario 4	30.0	4.0	7.9	6.0	1.9	0	1.0	1.0
Scenario 5	30.0	4.0	7.9	7.9	0.0	1	1.0	1.0

```
            Prediction (Weekly CR) Prediction (Monthly Revenue)
Scenario 1               42.125683                   1677.276207
Scenario 2               57.709531                   2297.762705
Scenario 3               55.619439                   2214.543603
Scenario 4               57.549393                   2291.386617
Scenario 5               55.312690                   2202.330059
```

[216]:
```
predictions_b = rf.predict(company_b_test)
company_b["Prediction (Weekly CR)"] = predictions_b
company_b["Prediction (Monthly Revenue)"] = 4.2*company_b["Nominal␣
 ↪Price"]*company_b["Company Size"]*company_b["Num. of Cont.␣
 ↪Days"]*company_b["Prediction (Weekly CR)"]/100
company_b
```

[216]:
```
            Company Size Num. of Cont. Days Nominal Price  \
Scenario 1         40.0                2.0           7.9
Scenario 2         40.0                2.0           7.9
Scenario 3         40.0                2.0           7.9
Scenario 4         40.0                2.0           7.9
Scenario 5         40.0                2.0           7.9

            Employer Contribution Employee Paid Main Dish Price  Free Meal  \
Scenario 1                    0.0                           7.9          0
Scenario 2                    2.0                           5.9          0
Scenario 3                    4.0                           3.9          0
Scenario 4                    6.0                           1.9          0
Scenario 5                    7.9                           0.0          1

            Prediction (Weekly CR) Prediction (Monthly Revenue)
Scenario 1               64.127605                   1702.203148
Scenario 2               67.435241                   1790.001042
Scenario 3               67.498056                   1791.668387
Scenario 4               72.174755                   1915.806709
Scenario 5               73.790737                   1958.701313
```

[217]:
```
predictions_c = rf.predict(company_c_test)
company_c["Prediction (Weekly CR)"] = predictions_c
company_c["Prediction (Monthly Revenue)"] = 4.2*company_c["Nominal␣
 ↪Price"]*company_c["Company Size"]*company_c["Num. of Cont.␣
 ↪Days"]*company_c["Prediction (Weekly CR)"]/100
company_c
```

[217]:
```
            Company Size Num. of Cont. Days Nominal Price  \
Scenario 1        100.0                5.0           7.9
Scenario 2        100.0                5.0           7.9
Scenario 3        401.0                5.0           7.9
```

```
Scenario 4         40.0                5.0           7.9
Scenario 5         40.0                5.0           7.9

           Employer Contribution Employee Paid Main Dish Price  Free Meal  \
Scenario 1                   0.0                           7.9          0
Scenario 2                   2.0                           5.9          0
Scenario 3                   4.0                           3.9          0
Scenario 4                   6.0                           1.9          0
Scenario 5                   7.9                           0.0          1

            Prediction (Weekly CR) Prediction (Monthly Revenue)
Scenario 1               23.929712                  3969.939208
Scenario 2               46.544270                  7721.694439
Scenario 3               39.944251                 26573.272731
Scenario 4               52.062459                  3454.864792
Scenario 5               55.217127                   3664.20852
```

1.2 Challenge 3

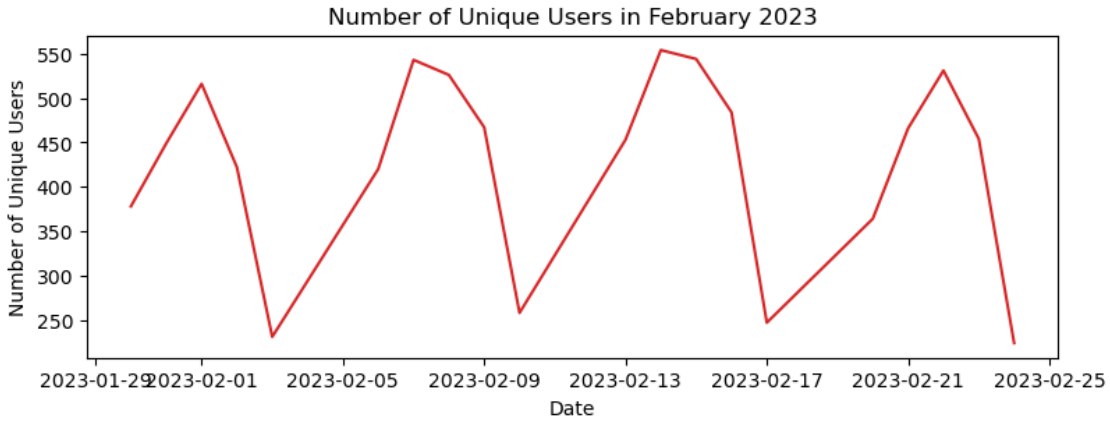
[218]:
```
df = order_data.drop(order_data[order_data['Week of deliveryDate␣
↪(deliverydata)'] == 'Week 9'].index)
```

[219]:
```
df = df.groupby(["deliveryDate (deliverydata)"])["Email"].nunique().
↪reset_index(name="Unique Users")
df.columns = ['Date','Unique Users']
```

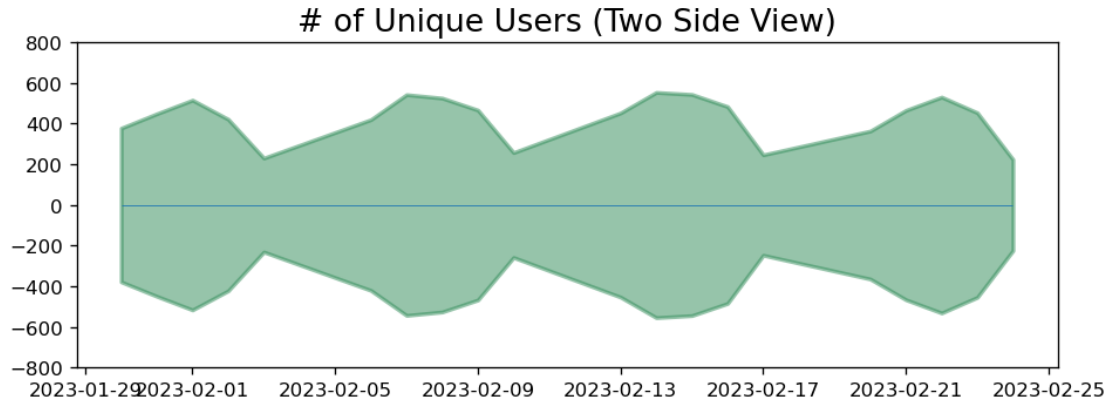
[220]:
```
df.head()
```

[220]:
```
        Date  Unique Users
0 2023-01-30           378
1 2023-01-31           449
2 2023-02-01           516
3 2023-02-02           422
4 2023-02-03           231
```

[221]:
```
def plot_df(df, x, y, title="", xlabel='Date', ylabel='Number of Unique Users',␣
↪dpi=100):
    plt.figure(figsize=(9,3), dpi=dpi)
    plt.plot(x, y, color='tab:red')
    plt.gca().set(title=title, xlabel=xlabel, ylabel=ylabel)
    plt.show()


plot_df(df, x=df['Date'], y=df['Unique Users'], title='Number of Unique Users␣
↪in February 2023')
```

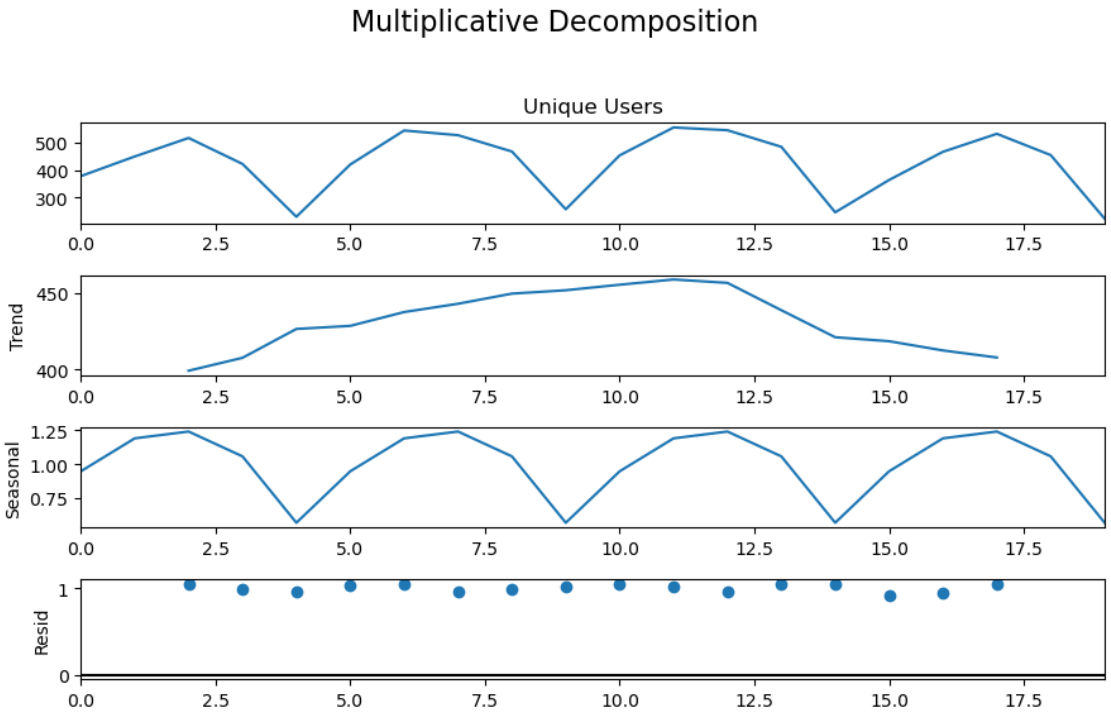


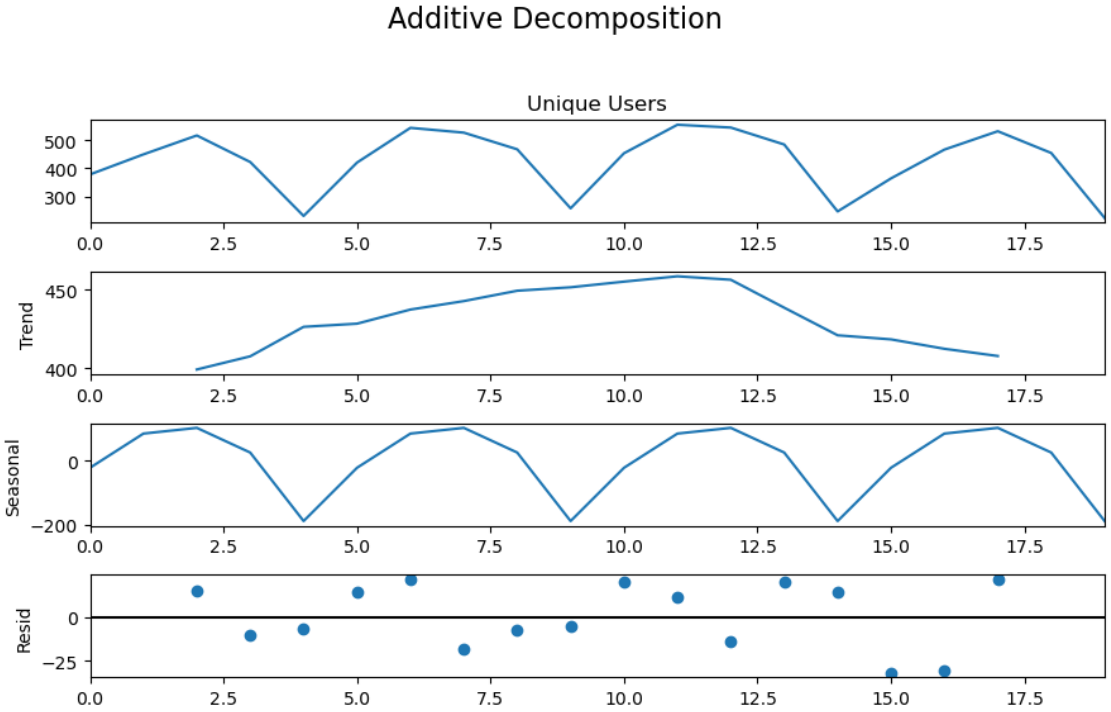
[222]:
```
x = df['Date'].values
y1 = df['Unique Users'].values

# Plot
fig, ax = plt.subplots(1, 1, figsize=(9,3), dpi= 120)
plt.fill_between(x, y1=y1, y2=-y1, alpha=0.5, linewidth=2, color='seagreen')
plt.ylim(-800, 800)
plt.title('# of Unique Users (Two Side View)', fontsize=16)
plt.hlines(y=0, xmin=np.min(df['Date']), xmax=np.max(df['Date']), linewidth=.5)
plt.show()
```



[223]:
```
from statsmodels.tsa.seasonal import seasonal_decompose
from dateutil.parser import parse


# Multiplicative Decomposition
```

```
multiplicative_decomposition = seasonal_decompose(df['Unique Users'],␣
 ↪model='multiplicative', period=5)

# Additive Decomposition
additive_decomposition = seasonal_decompose(df['Unique Users'],␣
 ↪model='additive', period=5)

# Plot
plt.rcParams.update({'figure.figsize': (9,6)})
multiplicative_decomposition.plot().suptitle('Multiplicative Decomposition',␣
 ↪fontsize=16)
plt.tight_layout(rect=[0, 0.03, 1, 0.95])

additive_decomposition.plot().suptitle('Additive Decomposition', fontsize=16)
plt.tight_layout(rect=[0, 0.03, 1, 0.95])

plt.show()
```



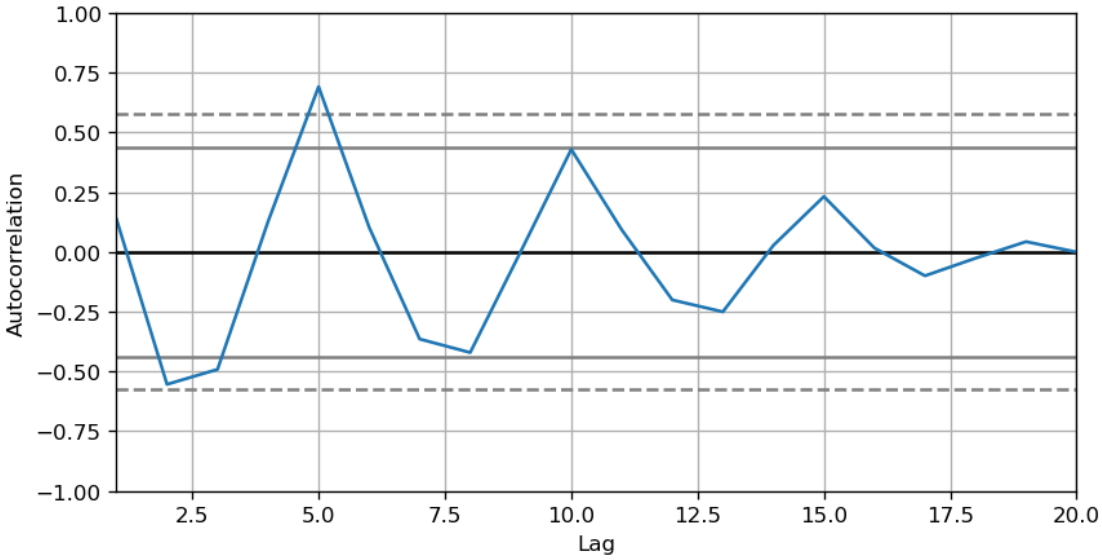


1.3 Seasonality Test

[224]:
```
from pandas.plotting import autocorrelation_plot
from statsmodels.tsa.stattools import acf, pacf
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
```

[225]:
```
plt.rcParams.update({'figure.figsize':(8,4), 'figure.dpi':120})
autocorrelation_plot(df['Unique Users'].tolist())
```

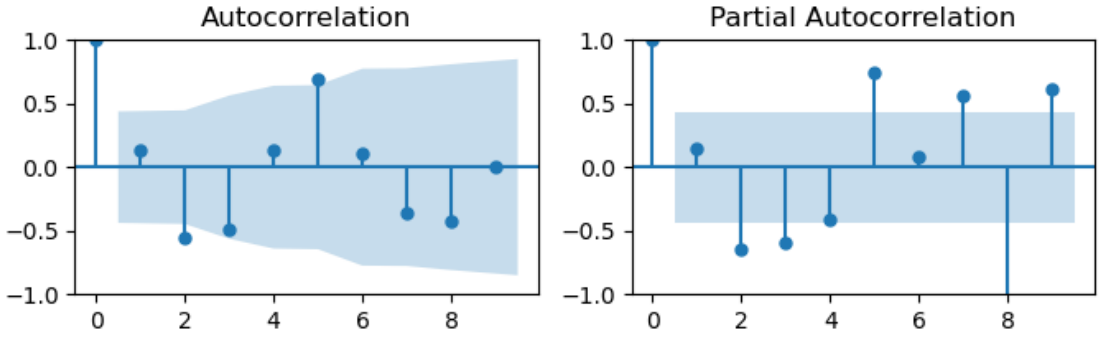
[225]:
```
<AxesSubplot: xlabel='Lag', ylabel='Autocorrelation'>
```

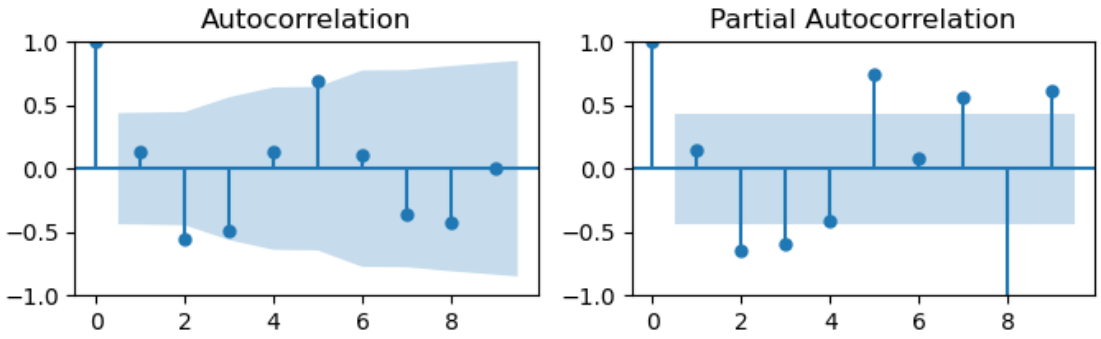


[226]:
```
fig, axes = plt.subplots(1,2,figsize=(8,2), dpi= 100)
plot_acf(df['Unique Users'].tolist(), lags=9, ax=axes[0])
plot_pacf(df['Unique Users'].tolist(), lags=9, ax=axes[1])
```

```
c:\ProgramData\Anaconda3\lib\site-packages\statsmodels\graphics\tsaplots.py:348:
FutureWarning: The default method 'yw' can produce PACF values outside of the
[-1,1] interval. After 0.13, the default will change tounadjusted Yule-Walker
('ywm'). You can use this method now by setting method='ywm'.
  warnings.warn(
```

[226]:





[227]:
```
import xgboost as xgb
from sklearn.metrics import mean_squared_error
```

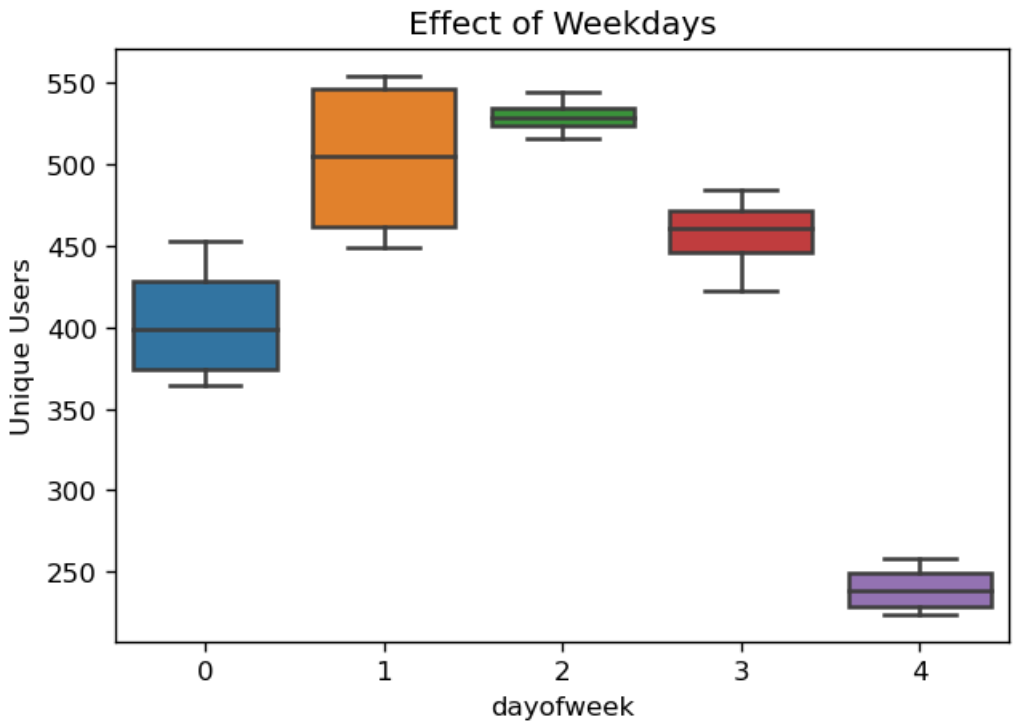
[228]:
```
ts = df.set_index("Date")
ts = ts["Unique Users"]
ts.info()
```

```
<class 'pandas.core.series.Series'>
DatetimeIndex: 20 entries, 2023-01-30 to 2023-02-24
Series name: Unique Users
Non-Null Count  Dtype
--------------  -----
20 non-null     int64
dtypes: int64(1)
memory usage: 320.0 bytes
```

[229]:
```
ts = ts.to_frame()
ts.index = pd.to_datetime(ts.index)
```

[230]:
```
ts["dayofweek"] = ts.index.dayofweek
# ts['dayofyear'] = ts.index.dayofyear
# ts['dayofmonth'] = ts.index.day
# ts['weekofyear'] = ts.index.isocalendar().week
```

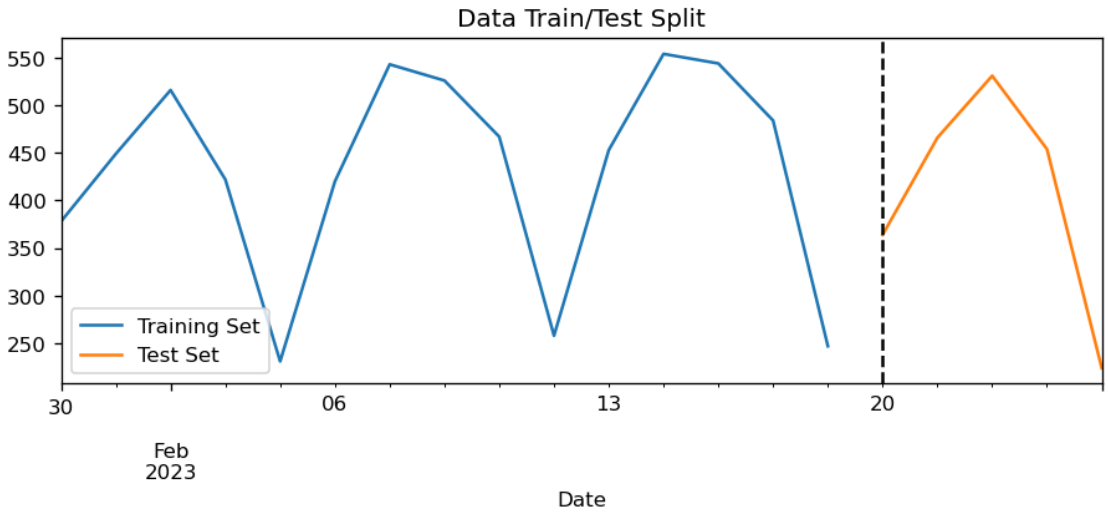
[231]:
```
fig, ax = plt.subplots(figsize=(6, 4))
sns.boxplot(data=ts, x='dayofweek', y='Unique Users')
ax.set_title('Effect of Weekdays')
plt.show()
```



1.4 Model

[232]:
```
# Train test split

train = ts.loc[ts.index < '2023-02-20']
test = ts.loc[ts.index >= '2023-02-20']

FEATURES = ['dayofweek']
TARGET = 'Unique Users'

X_train = train[FEATURES]
y_train = train[TARGET]

X_test = test[FEATURES]
y_test = test[TARGET]
```

[233]:
```
fig, ax = plt.subplots(figsize=(9, 3))
y_train.plot(ax=ax, label='Training Set', title='Data Train/Test Split')
y_test.plot(ax=ax, label='Test Set')
ax.axvline('2023-02-20', color='black', ls='--')
ax.legend(['Training Set', 'Test Set'])
plt.show()
```



[234]:
```
reg = xgb.XGBRegressor(n_estimators=400, learning_rate=0.01)
```

[235]:
```
reg.fit(X_train, y_train,
        eval_set=[(X_train, y_train), (X_test, y_test)],
        verbose=100)
```

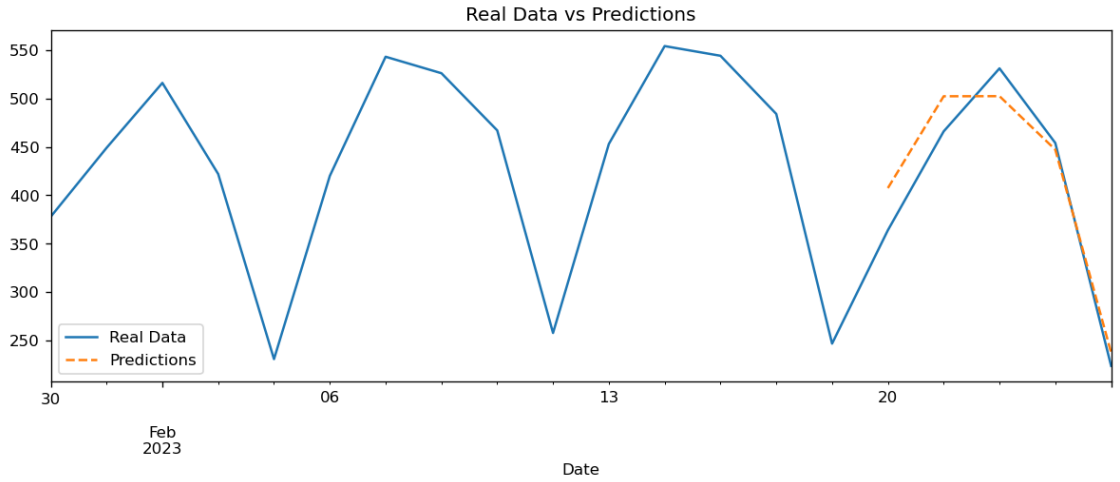
```
[0]     validation_0-rmse:441.08078     validation_1-rmse:416.91486
[100]   validation_0-rmse:182.40433     validation_1-rmse:159.81275
[200]   validation_0-rmse:82.20001      validation_1-rmse:60.94927
[300]   validation_0-rmse:43.91413      validation_1-rmse:29.86778
[399]   validation_0-rmse:32.33737      validation_1-rmse:29.19967
```

[235]:
```
XGBRegressor(base_score=None, booster=None, callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=None, early_stopping_rounds=None,
             enable_categorical=False, eval_metric=None, feature_types=None,
             gamma=None, gpu_id=None, grow_policy=None, importance_type=None,
             interaction_constraints=None, learning_rate=0.01, max_bin=None,
             max_cat_threshold=None, max_cat_to_onehot=None,
             max_delta_step=None, max_depth=None, max_leaves=None,
             min_child_weight=None, missing=nan, monotone_constraints=None,
             n_estimators=400, n_jobs=None, num_parallel_tree=None,
             predictor=None, random_state=None, …)
```

[236]:
```
# Forecast on test

test['prediction'] = reg.predict(X_test)
ts = ts.merge(test[['prediction']], how='left', left_index=True,␣
 ↪right_index=True)
```

```
C:\Users\ayigi\AppData\Local\Temp\ipykernel_13608\1376732270.py:3:
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
  test['prediction'] = reg.predict(X_test)
```

[237]:
```
ax = ts[['Unique Users']].plot(figsize=(12, 4))
ts['prediction'].dropna().plot(ax=ax, style='--')
plt.legend(['Real Data', 'Predictions'])
ax.set_title('Real Data vs Predictions')
plt.show()
```



[238]:
```
# Training with all data and predicting the next week

range_date = pd.date_range(start='27/2/2023', end ='3/3/2023',
                                              freq ='D')

next_week = pd.DataFrame(range_date, columns=['date'])
next_week['Unique Users'] = np.NaN

print(next_week.head())
```

```
        date  Unique Users
0 2023-02-27           NaN
1 2023-02-28           NaN
2 2023-03-01           NaN
3 2023-03-02           NaN
4 2023-03-03           NaN
```

```
C:\Users\ayigi\AppData\Local\Temp\ipykernel_13608\405317220.py:3: UserWarning:
Parsing dates in DD/MM/YYYY format when dayfirst=False (the default) was
specified. This may lead to inconsistently parsed dates! Specify a format to
ensure consistent parsing.
  range_date = pd.date_range(start='27/2/2023', end ='3/3/2023',
```

[239]:
```
next_week = next_week.set_index("date")
next_week.index = pd.to_datetime(next_week.index)
next_week["dayofweek"] = next_week.index.dayofweek
X_next_week = next_week[FEATURES]
```

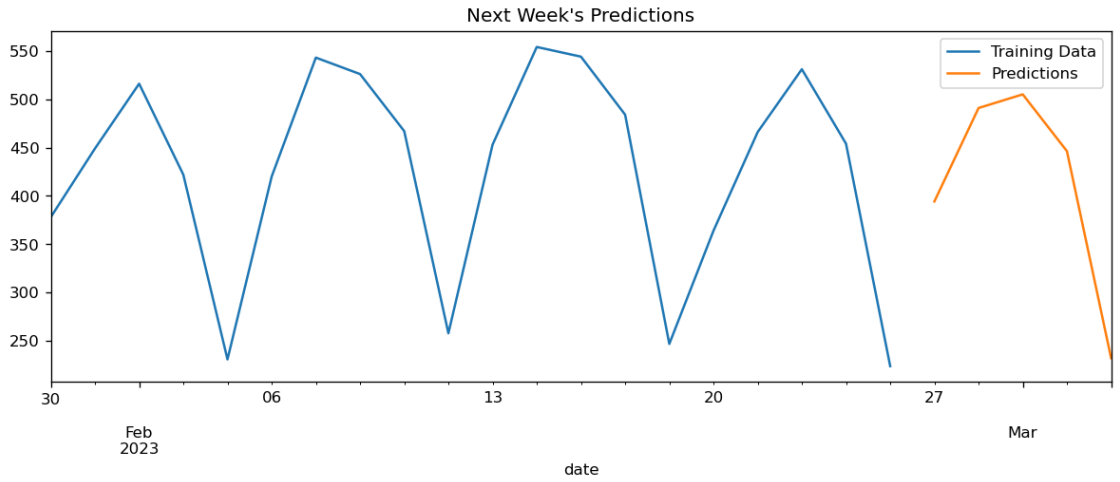
[240]:
```
X_ts = ts[FEATURES]
y_ts = ts[TARGET]
```

[241]:
```
reg.fit(X_ts, y_ts)
```

[241]:
```
XGBRegressor(base_score=None, booster=None, callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=None, early_stopping_rounds=None,
             enable_categorical=False, eval_metric=None, feature_types=None,
             gamma=None, gpu_id=None, grow_policy=None, importance_type=None,
             interaction_constraints=None, learning_rate=0.01, max_bin=None,
             max_cat_threshold=None, max_cat_to_onehot=None,
             max_delta_step=None, max_depth=None, max_leaves=None,
             min_child_weight=None, missing=nan, monotone_constraints=None,
             n_estimators=400, n_jobs=None, num_parallel_tree=None,
             predictor=None, random_state=None, …)
```

[242]:
```
next_week['prediction'] = reg.predict(X_next_week)
ts = ts.merge(test[['prediction']], how='left', left_index=True,␣
 ↪right_index=True)
```

[243]:
```
ax = ts[['Unique Users']].plot(figsize=(12, 4))
next_week['prediction'].plot(ax=ax, style='-')
plt.legend(['Training Data', 'Predictions'])
ax.set_title("Next Week's Predictions")
plt.show()
```



[244]:
```
next_week
```

[244]:

date	Unique Users	dayofweek	prediction
2023-02-27	NaN	0	394.273010
2023-02-28	NaN	1	490.891113
2023-03-01	NaN	2	505.008423
2023-03-02	NaN	3	446.290070
2023-03-03	NaN	4	232.288803