Certification-Project1

November 22, 2024

1 Certification Project 1

1.1 Data Science & ML Intership

1.2 Travel Aggregator Analysis

[80]:
```
# Date: 22-11-2024
# Programmer: Mr A. M.
```

[2]:
```
import pandas as pd
import matplotlib.pyplot as plt

# Load the data
booking_data = pd.read_csv("Bookings.csv")
sessions_data = pd.read_csv("Sessions.csv")

booking_data.info()
booking_data.head(10)

sessions_data.info()
sessions_data.head(10)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 339 entries, 0 to 338
Data columns (total 13 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   customer_id        339 non-null    object
 1   booking_id         339 non-null    object
 2   from_city          339 non-null    object
 3   from_country       339 non-null    object
 4   to_city            339 non-null    object
 5   to_country         339 non-null    object
 6   booking_time       339 non-null    object
 7   device_type_used   339 non-null    object
 8   INR_Amount         339 non-null    float64
 9   service_name       339 non-null    object
 10  no_of_passengers   339 non-null    float64
 11  days_to_departure  339 non-null    float64
```

```
 12  distance_km        339 non-null    float64
dtypes: float64(4), object(9)
memory usage: 34.6+ KB
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1497 entries, 0 to 1496
Data columns (total 5 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   session_id             1497 non-null   object
 1   search_id              1497 non-null   object
 2   search_time            1497 non-null   object
 3   session_starting_time  1497 non-null   object
 4   booking_id             366 non-null    object
dtypes: object(5)
memory usage: 58.6+ KB
```

[2]:

```
     session_id    search_id               search_time  \
0   session_322   search_784  2020-01-21T21:35:38.910Z
1   session_322   search_776  2020-01-21T21:37:37.697Z
2   session_322   search_623  2020-01-21T21:36:11.392Z
3   session_322   search_270  2020-01-21T21:16:07.685Z
4   session_322   search_905  2020-01-21T21:34:55.673Z
5   session_322   search_506  2020-01-21T21:10:58.482Z
6   session_283   search_880  2020-01-21T05:33:48.061Z
7   session_194   search_312  2019-09-05T09:04:40.423Z
8    session_52  search_1227  2020-01-20T16:54:07.232Z
9    session_52  search_1110  2020-01-20T17:03:52.145Z

       session_starting_time   booking_id
0       2020-01-21T21:10:12Z          NaN
1       2020-01-21T21:10:12Z          NaN
2       2020-01-21T21:10:12Z          NaN
3       2020-01-21T21:10:12Z          NaN
4       2020-01-21T21:10:12Z          NaN
5       2020-01-21T21:10:12Z   booking_54
6   2020-01-21T05:33:33.559Z  booking_106
7       2019-09-05T09:04:32Z    booking_1
8   2020-01-20T16:53:47.477Z          NaN
9   2020-01-20T16:53:47.477Z  booking_282
```

[11]:

```python
# 1. Find the number of distinct bookings, sessions, and searches
distinct_bookings = booking_data['booking_id'].nunique()
distinct_sessions = sessions_data['session_id'].nunique()
distinct_searches = sessions_data['search_id'].nunique()

# Displaying the distinct counts
print(f"Distinct Bookings: {distinct_bookings}")
```

```
print(f"Distinct Sessions: {distinct_sessions}")
print(f"Distinct Searches: {distinct_searches}")
```

```
Distinct Bookings: 339
Distinct Sessions: 331
Distinct Searches: 1360
```

[38]:

```
# 2. Sessions with more than one booking
sessions_with_bookings = sessions_data.dropna(subset=['booking_id'])
#print(sessions_with_bookings)
sessions_with_multiple_bookings = sessions_with_bookings.
 ↪groupby('session_id')['booking_id'].nunique()
#print(sessions_with_bookings.groupby('session_id').groups)
# .nunique()        Counts distinct values (ensures uniqueness).

sessions_with_multiple_bookings_count = (sessions_with_multiple_bookings > 1).
 ↪sum()

# Displaying the distinct counts and session analysis results
print(f"Sessions with More than One Booking:␣
 ↪{sessions_with_multiple_bookings_count}")
print(sessions_with_multiple_bookings[sessions_with_multiple_bookings > 1])
```

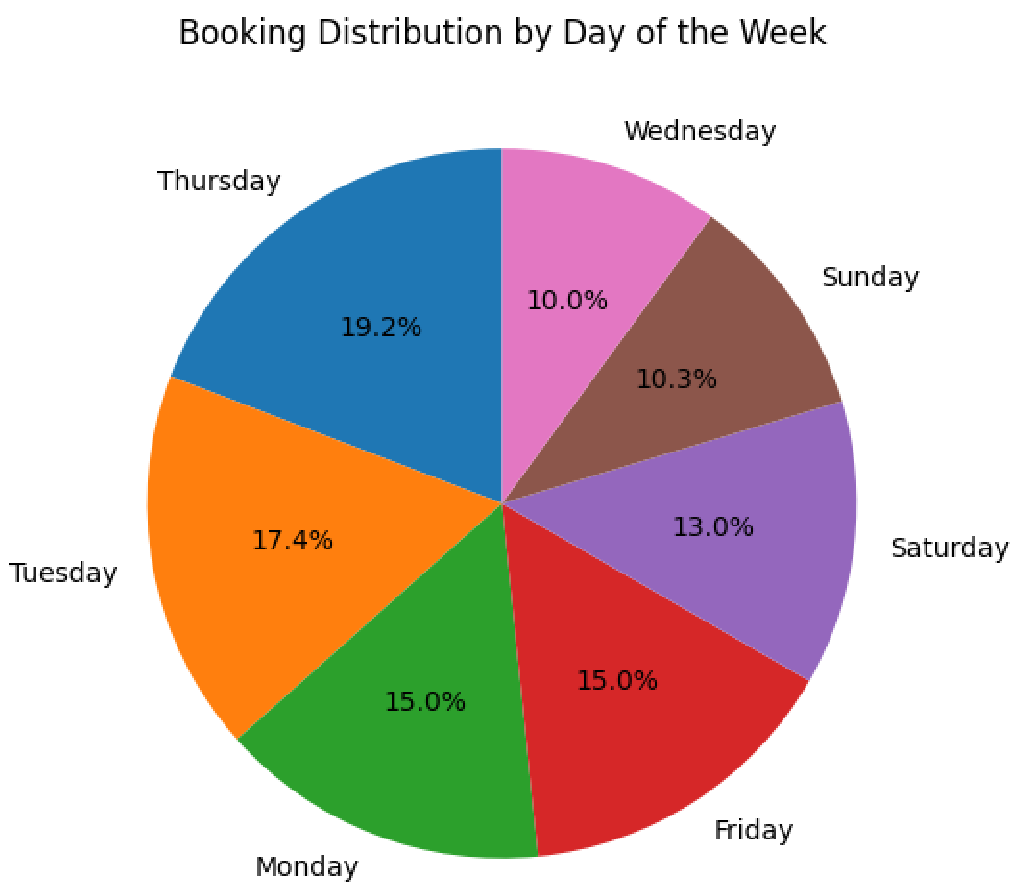
```
Sessions with More than One Booking: 10
session_id
session_134    2
session_154    2
session_196    2
session_231    2
session_27     2
session_290    2
session_298    2
session_324    2
session_50     2
session_76     2
Name: booking_id, dtype: int64
```

[46]:

```
# 3. Days of the week with the highest bookings
booking_data['booking_time'] = pd.to_datetime(booking_data['booking_time'])
booking_data['day_of_week'] = booking_data['booking_time'].dt.day_name()
print(booking_data[['booking_time' , 'day_of_week']].head())
bookings_per_day = booking_data['day_of_week'].value_counts()
print(bookings_per_day)

# Plot a pie chart for the distribution
plt.figure(figsize=(8, 6))
bookings_per_day.plot.pie(autopct='%1.1f%%', startangle=90, ylabel='',␣
 ↪title='Booking Distribution by Day of the Week')
```

```
plt.show()
```

```
                booking_time day_of_week
0 2020-02-05 16:12:08+00:00   Wednesday
1 2018-11-21 08:21:47+00:00   Wednesday
2 2019-12-16 22:54:58+00:00      Monday
3 2021-10-29 12:25:38+00:00      Friday
4 2020-08-11 16:09:10+00:00     Tuesday
day_of_week
Thursday     65
Tuesday      59
Monday       51
Friday       51
Saturday     44
Sunday       35
Wednesday    34
Name: count, dtype: int64
```



[56]:
```python
# 4. Total number of bookings and total Gross Booking Value in INR per service␣
 ↪name
print(booking_data['service_name'].unique())

print(booking_data.groupby('service_name').groups) # All rows with the same␣
 ↪service_name are grouped together.
#Keys are the unique values in service_name (the groups).
#Values are lists of row indices in the DataFrame that belong to each group.


service_bookings = booking_data.groupby('service_name').agg(
    total_bookings=('booking_id', 'count'), # Counts the number of non-null␣
 ↪entries in the booking_id column. total number of bookings for each service.
    total_gross_value=('INR_Amount', 'sum') # Sums up all the values in the␣
 ↪INR_Amount column. total gross booking value for each service.
).reset_index()  # Adding .reset_index() makes service_name a regular column,␣
 ↪making the data easier to work with.

# Displaying the Service Booking Summary
print(service_bookings)
```

```
['MMT' 'YATRA' 'GOIBIBO']
{'GOIBIBO': [3, 4, 5, 6, 7, 11, 13, 14, 18, 21, 24, 25, 28, 29, 32, 34, 35, 36,
38, 43, 44, 45, 46, 47, 48, 49, 50, 51, 59, 60, 61, 63, 65, 66, 68, 69, 70, 77,
78, 79, 80, 81, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 97, 98, 100, 101,
102, 103, 104, 105, 106, 107, 111, 113, 114, 115, 119, 120, 121, 122, 123, 124,
125, 128, 129, 130, 132, 133, 137, 138, 139, 140, 141, 145, 146, 147, 152, 153,
154, 155, 158, 162, 163, 165, 166, 167, 169, 172, 173, …], 'MMT': [0, 8, 16,
17, 54, 55, 56, 57, 71, 72, 73, 74, 82, 94, 116, 126, 142, 150, 160, 161, 174,
182, 183, 190, 199, 200, 212, 218, 219, 230, 231, 235, 261, 269, 282, 287, 288,
289, 290, 300, 301, 302, 303, 314, 323, 331, 332, 333], 'YATRA': [1, 2, 9, 10,
12, 15, 19, 20, 22, 23, 26, 27, 30, 31, 33, 37, 39, 40, 41, 42, 52, 53, 58, 62,
64, 67, 75, 76, 95, 96, 99, 108, 109, 110, 112, 117, 118, 127, 131, 134, 135,
136, 143, 144, 148, 149, 151, 156, 157, 159, 164, 168, 170, 171, 175, 176, 185,
187, 188, 191, 195, 196, 198, 201, 202, 204, 205, 206, 210, 213, 220, 221, 224,
233, 234, 236, 237, 240, 242, 243, 244, 250, 251, 252, 256, 257, 258, 259, 262,
263, 264, 265, 273, 274, 280, 285, 286, 296, 311, 312, …]}
  service_name  total_bookings  total_gross_value
0      GOIBIBO             186         5897637.97
1          MMT              48          665669.08
2        YATRA             105         3378702.13
```

[72]:
```python
# 5. Most booked route for customers with more than 1 booking

# Step 1: Group by customer_id
# This groups the data by unique customer IDs and organizes rows belonging to␣
 ↪each customer.
```

```python
group_by_customer_id = booking_data.groupby('customer_id')
print("# Step 1: Grouping the data by customer_id")
print(group_by_customer_id.groups)  # View the grouped indices for each customer
print("-" * 50)

# Step 2: Count unique booking_id values for each customer
# For each customer, we calculate the number of unique booking IDs to find out how many bookings they made.
customer_booking_counts = booking_data.groupby('customer_id')['booking_id'].nunique()
print("# Step 2: Count unique booking IDs for each customer")
print(customer_booking_counts.head())  # Display the first few results
print("-" * 50)

# Step 3: Create a boolean series for customers with more than 1 booking
# This creates a filter to identify customers who made more than one booking.
customers_with_more_than_one_booking = customer_booking_counts > 1
print("# Step 3: Boolean filter for customers with more than 1 booking")
print(customers_with_more_than_one_booking)  # View the boolean values
print("-" * 50)

# Step 4: Filter the customer IDs with more than one booking
# We extract the indices (customer IDs) where the filter is True.
customers_with_multiple_bookings = customer_booking_counts[customers_with_more_than_one_booking].index
print("# Step 4: Extract customer IDs with more than one booking")
print(customers_with_multiple_bookings)  # Display the filtered customer IDs
print("-" * 50)

# Step 5: Filter the original data for these customers
# Use the filtered customer IDs to subset the original data.
multiple_bookings_data = booking_data[booking_data['customer_id'].isin(customers_with_multiple_bookings)]
print("# Step 5: Filtered data for customers with more than one booking")
print(multiple_bookings_data.head())  # Display the first few rows of the filtered data
print("-" * 50)

# Step 6: Group by route (from_city to to_city) and count occurrences
# Count the frequency of each route (combination of from_city and to_city) for customers with multiple bookings.
route_counts = multiple_bookings_data.groupby(['from_city', 'to_city']).size() # Number of rows in each group
print("# Step 6: Count the frequency of each route")
print(route_counts.head())  # Display the first few route counts
print("-" * 50)
```

```python
# Step 7: Identify the most booked route
# Find the route with the highest count.
most_booked_route = route_counts.idxmax()  # This returns the route (from_city, to_city) with the maximum count
most_booked_route_count = route_counts.max()  # This returns the count of that route
print("# Step 7: Most booked route for customers with more than one booking")
print(f"The most booked route is {most_booked_route} with {most_booked_route_count} bookings.")
print("-" * 50)

# Step 8: Sort the route counts in descending order
sorted_routes = route_counts.sort_values(ascending=False)

# Step 9: Extract the top 5 destinations
top_5_routes = sorted_routes.head(5)

# Step 10: Print the results
print("# Step 8: Top 5 destinations for customers with more than one booking")
print(top_5_routes)
```

```
# Step 1: Grouping the data by customer_id
{'customer_0': [155], 'customer_1': [195], 'customer_10': [252], 'customer_100':
[138], 'customer_101': [84], 'customer_102': [247], 'customer_103': [212],
'customer_104': [144], 'customer_105': [232], 'customer_106': [327],
'customer_107': [302], 'customer_108': [324], 'customer_109': [47],
'customer_11': [107], 'customer_110': [221], 'customer_111': [10],
'customer_112': [103], 'customer_113': [179], 'customer_114': [20],
'customer_115': [141], 'customer_116': [79], 'customer_117': [71],
'customer_118': [112], 'customer_119': [56], 'customer_12': [197],
'customer_120': [190, 191], 'customer_121': [99], 'customer_122': [95],
'customer_123': [210], 'customer_124': [124], 'customer_125': [219],
'customer_126': [311], 'customer_127': [234], 'customer_128': [49],
'customer_129': [77], 'customer_13': [204], 'customer_130': [117],
'customer_131': [61], 'customer_132': [58], 'customer_133': [334],
'customer_134': [265], 'customer_135': [180], 'customer_136': [315],
'customer_137': [42, 163], 'customer_138': [59], 'customer_139': [230],
'customer_14': [330], 'customer_140': [102], 'customer_141': [51],
'customer_142': [97], 'customer_143': [158], 'customer_144': [111, 227],
'customer_145': [240], 'customer_146': [75], 'customer_147': [37],
'customer_148': [168], 'customer_149': [233], 'customer_15': [122],
'customer_150': [9], 'customer_151': [270], 'customer_152': [292],
'customer_153': [306], 'customer_154': [136], 'customer_155': [85, 274],
'customer_156': [209], 'customer_157': [239], 'customer_158': [278],
'customer_159': [143], 'customer_16': [161], 'customer_160': [116, 200, 323],
'customer_161': [8], 'customer_162': [189], 'customer_163': [308],
```

```
'customer_164': [167], 'customer_165': [93], 'customer_166': [215],
'customer_167': [220], 'customer_168': [249], 'customer_169': [304],
'customer_17': [258], 'customer_170': [235], 'customer_171': [134],
'customer_172': [246], 'customer_173': [322], 'customer_174': [38],
'customer_175': [147], 'customer_176': [81, 173, 305], 'customer_177': [92],
'customer_178': [11], 'customer_179': [16, 24], 'customer_18': [54],
'customer_180': [236], 'customer_181': [288], 'customer_182': [275],
'customer_183': [36], 'customer_184': [64], 'customer_185': [170],
'customer_186': [132], 'customer_187': [137], 'customer_188': [25], …}
--------------------------------------------------
# Step 2: Count unique booking IDs for each customer
customer_id
customer_0      1
customer_1      1
customer_10     1
customer_100    1
customer_101    1
Name: booking_id, dtype: int64
--------------------------------------------------
# Step 3: Boolean filter for customers with more than 1 booking
customer_id
customer_0      False
customer_1      False
customer_10     False
customer_100    False
customer_101    False
                …
customer_95     False
customer_96     False
customer_97      True
customer_98     False
customer_99     False
Name: booking_id, Length: 306, dtype: bool
--------------------------------------------------
# Step 4: Extract customer IDs with more than one booking
Index(['customer_120', 'customer_137', 'customer_144', 'customer_155',
       'customer_160', 'customer_176', 'customer_179', 'customer_200',
       'customer_217', 'customer_230', 'customer_235', 'customer_237',
       'customer_245', 'customer_246', 'customer_247', 'customer_255',
       'customer_265', 'customer_28', 'customer_282', 'customer_297',
       'customer_33', 'customer_44', 'customer_49', 'customer_67',
       'customer_93', 'customer_97'],
      dtype='object', name='customer_id')
--------------------------------------------------
# Step 5: Filtered data for customers with more than one booking
     customer_id   booking_id    from_city from_country     to_city  \
6    customer_28  booking_129      Kolkata        India     Gurgaon
7   customer_217   booking_18  Bhubaneswar        India     Durlaga
```

```
13  customer_282  booking_212       Indore        India      Mumbai
16  customer_179  booking_218      Gurgaon        India  Port Blair
24  customer_179  booking_157       Mumbai        India      Jaipur

   to_country              booking_time device_type_used  INR_Amount  \
6       India 2022-02-16 15:50:27+00:00          Desktop     13442.4
7       India 2021-09-10 19:09:12+00:00          Desktop      4352.0
13      India 2021-10-16 07:56:59+00:00              IOS      4725.6
16      India 2020-01-12 17:34:59+00:00          Desktop     17804.8
24      India 2020-01-23 13:58:39+00:00          Desktop      6953.6

   service_name  no_of_passengers  days_to_departure  distance_km day_of_week  \
6       GOIBIBO               1.0               13.0       1310.7   Wednesday
7       GOIBIBO               2.0               47.0        260.5      Friday
13      GOIBIBO               1.0                0.0        506.2    Saturday
16          MMT               2.0               35.0       2486.8      Sunday
24      GOIBIBO               1.0               15.0        921.8    Thursday

   quarter
6   2022Q1
7   2021Q3
13  2021Q4
16  2020Q1
24  2020Q1
--------------------------------------------------
# Step 6: Count the frequency of each route
from_city    to_city
Ahmedabad    Gwalior       1
Barelā       Gurgaon       1
Bhubaneswar  Durlaga       1
Bikaner      Gurgaon       1
Bālāpur      Düsseldorf    2
dtype: int64
--------------------------------------------------
# Step 7: Most booked route for customers with more than one booking
The most booked route is ('Gurgaon', 'Roissy-en-France') with 5 bookings.
--------------------------------------------------
# Step 8: Top 5 destinations for customers with more than one booking
from_city  to_city
Gurgaon    Roissy-en-France    5
           Rāja Sānsi          3
Durlaga    Bhubaneswar         2
Gurgaon    Bagdogra            2
Bālāpur    Düsseldorf          2
dtype: int64
```

[79]:
```python
# 6. Top 3 departure cities for advance bookings (min 5 departures)

# Step 1: Group by 'from_city'
# Group the data by 'from_city' to calculate statistics for each departure city.
group_by_city = booking_data.groupby('from_city')

# Step 2: Calculate Aggregations
# For each city, calculate:
# 1. Average days to departure ('days_to_departure', 'mean') -> Indicates how␣
↪far in advance bookings are made.
# 2. Total number of departures ('from_city', 'size') -> Total bookings␣
↪departing from each city.
booking_advance = group_by_city.agg(
    avg_days_to_departure=('days_to_departure', 'mean'),
    total_departures=('from_city', 'size')
)
print("# Step 2: Aggregated data for each city")
print(booking_advance.head())  # Display the first few rows of the aggregated␣
↪data
print("-" * 50)

# Step 3: Filter Cities with At Least 5 Departures
# Retain only the cities with 5 or more departures to ensure the analysis is␣
↪meaningful.
eligible_cities = booking_advance[booking_advance['total_departures'] >= 5]
print("# Step 3: Cities with at least 5 departures")
print(eligible_cities.head())  # Display the first few rows of the filtered data
print("-" * 50)

# Step 4: Identify Top 3 Cities with Highest Average Days to Departure
# Sort cities by 'avg_days_to_departure' in descending order and select the top␣
↪3.
top_3_advance_cities = eligible_cities.nlargest(3, 'avg_days_to_departure')
print("# Step 4: Top 3 Departure Cities for Advance Bookings")
print(top_3_advance_cities)  # Display the top 3 cities
```

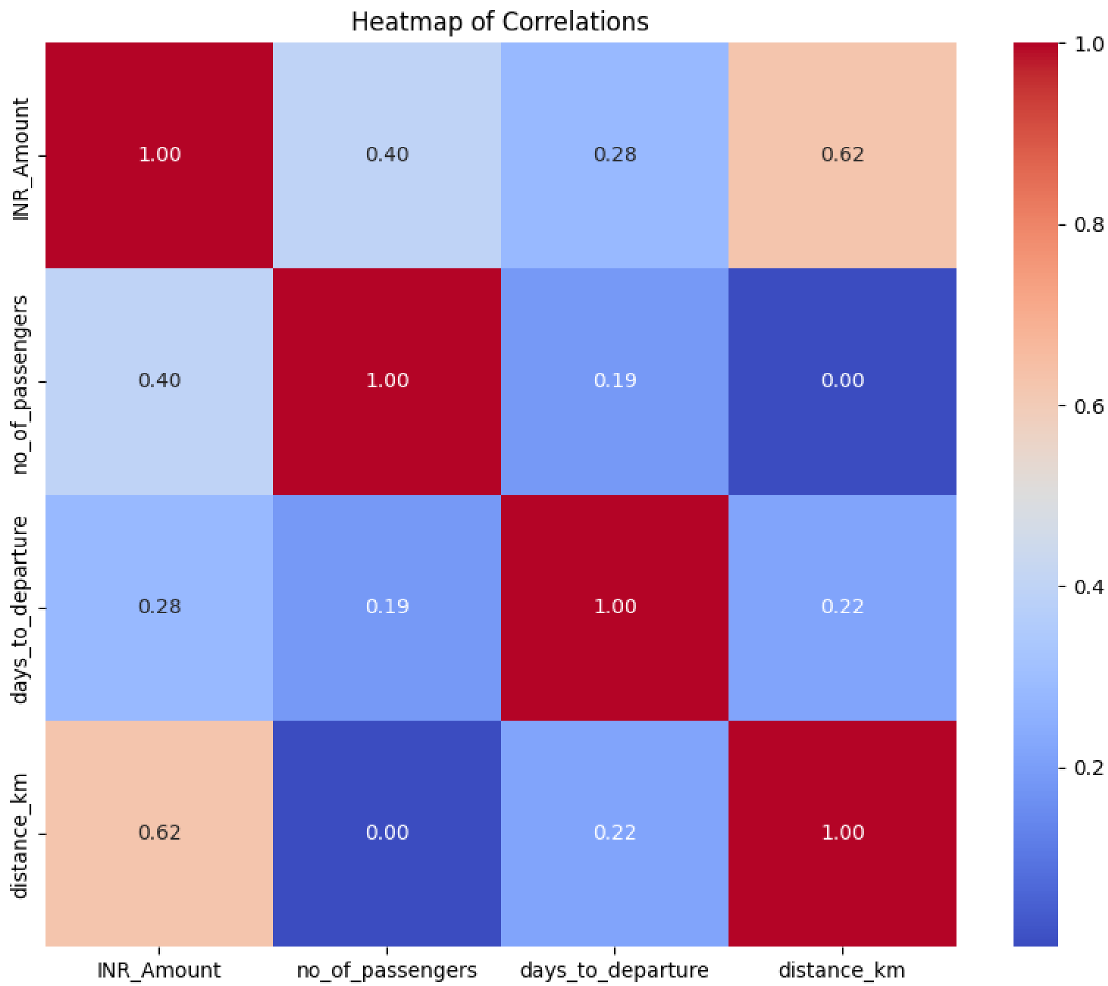
```
# Step 2: Aggregated data for each city
           avg_days_to_departure  total_departures
from_city
Agartala                    1.00                 1
Ahmedabad                  11.75                 8
Angamāli                   29.50                 2
Bangalore                  37.50                 2
Barelā                      3.00                 1
--------------------------------------------------
# Step 3: Cities with at least 5 departures
            avg_days_to_departure  total_departures
```

```
from_city
Ahmedabad              11.750000                 8
Bālāpur                46.166667                 6
Chennai                26.187500                16
Delhi                  12.758621                29
Devanhalli             29.583333                24
--------------------------------------------------
# Step 4: Top 3 Departure Cities for Advance Bookings
            avg_days_to_departure  total_departures
from_city
Bālāpur                46.166667                 6
Devanhalli             29.583333                24
Chennai                26.187500                16
```

[84]:
```
# 7. Heatmap for correlations and most correlated pair
import seaborn as sns

# Step 1: Select Numerical Columns
# Use pandas to filter the columns with numerical data types from the␣
↪booking_data DataFrame.
numerical_columns = booking_data.select_dtypes(include='number')

print("# Step 1: Numerical columns selected for correlation analysis")
print(numerical_columns.columns)  # Display the numerical columns being analyzed
print("-" * 50)

# Step 2: Compute the Correlation Matrix
# Calculate the correlation matrix for the numerical columns. This shows how␣
↪strongly each pair of columns is related.
correlation_matrix = numerical_columns.corr()

print("# Step 2: Correlation matrix of numerical columns")
print(correlation_matrix)  # Display the correlation matrix
print("-" * 50)

# Step 3: Plot the Correlation Heatmap
# Visualize the correlation matrix using a heatmap. Correlation values closer␣
↪to 1 or -1 indicate stronger relationships.
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f')
plt.title("Heatmap of Correlations")
plt.show()

# Step 4: Identify the Most Correlated Pair
# Flatten the correlation matrix, sort it, and find the most correlated pair␣
↪(ignoring self-correlations).
```

```python
correlation_flat = correlation_matrix.abs().unstack()  # Flatten the matrix and take absolute values
sorted_correlation = correlation_flat.sort_values(ascending=False)  # Sort values in descending order

# Ignore self-correlation (diagonal values = 1)
most_correlated_pair = sorted_correlation[sorted_correlation < 1].idxmax()  # Get the pair with the highest correlation
most_correlation_value = sorted_correlation[sorted_correlation < 1].max()  # Get the corresponding correlation value

# Step 5: Display the Most Correlated Pair
print("# Step 4: Most correlated pair of numerical columns")
print(f"The most correlated pair is {most_correlated_pair} with a correlation value of {most_correlation_value:.2f}")
print(f"The correlation analysis indicates that the longer the distance traveled, the higher the price of the booking tends to be, with a correlation of {most_correlation_value:.2f}.")
```

```
# Step 1: Numerical columns selected for correlation analysis
Index(['INR_Amount', 'no_of_passengers', 'days_to_departure', 'distance_km'],
dtype='object')
--------------------------------------------------
# Step 2: Correlation matrix of numerical columns
                   INR_Amount  no_of_passengers  days_to_departure  \
INR_Amount           1.000000          0.397229           0.284534
no_of_passengers     0.397229          1.000000           0.187128
days_to_departure    0.284534          0.187128           1.000000
distance_km          0.623565          0.001698           0.216972

                   distance_km
INR_Amount            0.623565
no_of_passengers      0.001698
days_to_departure     0.216972
distance_km           1.000000
--------------------------------------------------
```




```
# Step 4: Most correlated pair of numerical columns
The most correlated pair is ('INR_Amount', 'distance_km') with a correlation
value of 0.62
The correlation analysis indicates that the longer the distance traveled, the
higher the price of the booking tends to be, with a correlation of 0.62.
```

[92]:
```python
# 8. Most used device type for each service

# Step 1: Group by 'service_name' and 'device_type_used'
# Count the number of bookings for each combination of service and device type.
device_usage_by_service = booking_data.groupby(['service_name',␣
↪'device_type_used']).size()

print("# Step 1: Count of device usage for each service")
print(device_usage_by_service)  # Display the counts for each combination
print("-" * 50)
```

```
# Step 2: Find the Most Used Device Type for Each Service
# Group the results by 'service_name' and identify the device type with the␣
↪highest count for each service.
# Find the index of the most used device type for each service
most_used_device_indices = device_usage_by_service.groupby(level=0).idxmax()
print(most_used_device_indices)
# Output: ('GOIBIBO', 'Desktop'), ('MMT', 'Android'), ('YATRA', 'Desktop')

# Extract only the device type (second element of the tuple)
most_used_device_by_service = most_used_device_indices.map(lambda x: x[1])
print(most_used_device_by_service)
# Output: GOIBIBO -> Desktop, MMT -> Android, YATRA -> Desktop
print("-" * 50)

print("# Step 2: Most used device type for each service")
print(most_used_device_by_service)  # Display the most used device type for␣
↪each service
print("-" * 50)

# Step 3: Generate a Summary Sentence for Each Service
# Iterate over the results and create a human-readable explanation.
print("# Step 3: Explanation for each service")
for service, device in most_used_device_by_service.items():
    print(f"For {service}, the most used device type is {device}.")
```

```
# Step 1: Count of device usage for each service
service_name  device_type_used
GOIBIBO       Android             44
              Desktop             61
              IOS                 70
              MobileWeb           11
MMT           Android              8
              Desktop             30
              IOS                  5
              MobileWeb            5
YATRA         Android             18
              Desktop             51
              IOS                 22
              MobileWeb           11
              Tablet               3
dtype: int64
--------------------------------------------------
service_name
GOIBIBO      (GOIBIBO, IOS)
MMT          (MMT, Desktop)
YATRA      (YATRA, Desktop)
```

```
dtype: object
<class 'pandas.core.series.Series'>
service_name
GOIBIBO        IOS
MMT        Desktop
YATRA      Desktop
dtype: object
--------------------------------------------------
# Step 2: Most used device type for each service
service_name
GOIBIBO        IOS
MMT        Desktop
YATRA      Desktop
dtype: object
--------------------------------------------------
# Step 3: Explanation for each service
For GOIBIBO, the most used device type is IOS.
For MMT, the most used device type is Desktop.
For YATRA, the most used device type is Desktop.
```

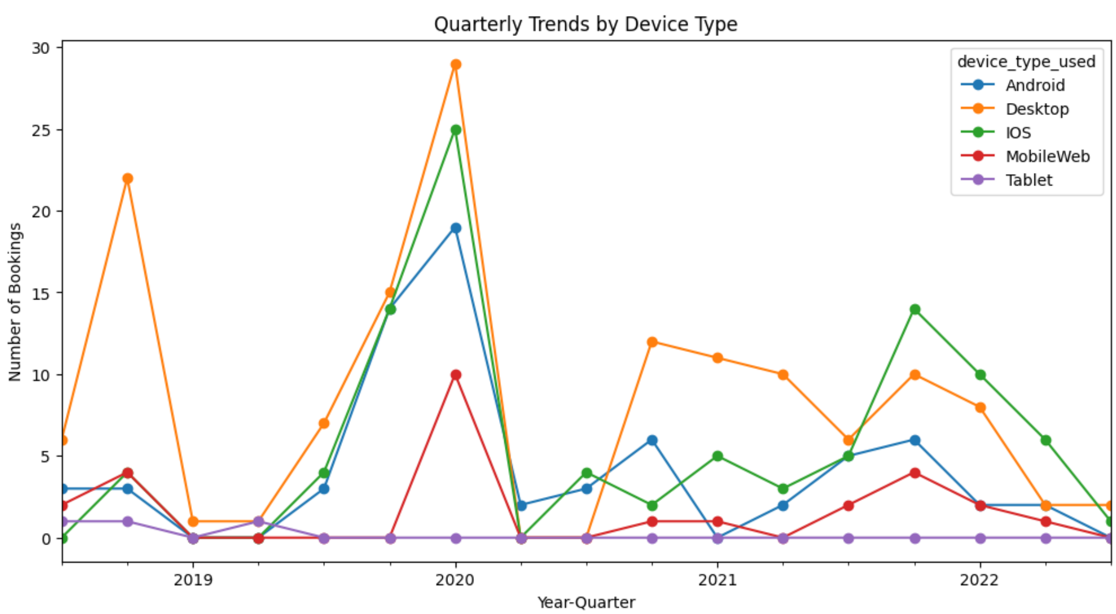
[98]:

```
# 9. Quarterly trends for bookings by device type

# Step 1: Convert 'booking_time' to Quarterly Period
# Extract the quarter (Year-Quarter) from the 'booking_time' column.
# The 'dt.to_period("Q")' method converts timestamps to quarterly periods.
booking_data['quarter'] = booking_data['booking_time'].dt.to_period('Q')

print("# Step 1: Add a 'quarter' column based on 'booking_time'")
#print(booking_data[['booking_time', 'quarter']].head())  # Display the first␣
↪few rows with the new column
print(booking_data.head())
print("-" * 50)

# Step 2: Group by 'quarter' and 'device_type_used'
# Count the number of bookings for each combination of 'quarter' and␣
↪'device_type_used'.
quarterly_trends = booking_data.groupby(['quarter', 'device_type_used']).size()

print("# Step 2: Grouped data (counts by quarter and device type)")
print(quarterly_trends.head())  # Display the first few results
print("-" * 50)

# Step 3: Reshape the Data to Wide Format
# Use '.unstack()' to pivot the 'device_type_used' column into separate␣
↪columns, filling missing values with 0.
# .unstack() pivots one of the levels in a MultiIndex (by default, the last␣
↪level of the index) into columns. --> Each device_type_used becomes a column.
```

```
# The .unstack() method pivots only one level of the index at a time, and by␣
↪default, it pivots the innermost level (in this case, device_type_used).
quarterly_trends_wide = quarterly_trends.unstack(fill_value=0)

print("# Step 3: Reshaped data (wide format with device types as columns)")
print(quarterly_trends_wide.head())  # Display the first few rows of the␣
↪reshaped data
print("-" * 50)

# Step 4: Plot the Trends
# Create a line plot showing the number of bookings by device type over time␣
↪(quarters).
quarterly_trends_wide.plot(kind='line', figsize=(12, 6), marker='o',␣
↪title="Quarterly Trends by Device Type")
plt.xlabel("Year-Quarter")
plt.ylabel("Number of Bookings")
plt.show()
```

```
# Step 1: Add a 'quarter' column based on 'booking_time'
    customer_id   booking_id   from_city from_country            to_city  \
0  customer_259   booking_82     Gurgaon        India          Ahmedabad
1  customer_303  booking_156       Delhi        India           Brussels
2  customer_203   booking_99  Devanhalli        India  Frankfurt am Main
3  customer_211  booking_319     Gurgaon        India  Frankfurt am Main
4  customer_287  booking_222     Gurgaon        India   Roissy-en-France

  to_country              booking_time device_type_used  INR_Amount  \
0      India 2020-02-05 16:12:08+00:00          Desktop     2565.28
1    Belgium 2018-11-21 08:21:47+00:00          Android    23120.00
2    Germany 2019-12-16 22:54:58+00:00          Android    25717.60
3    Germany 2021-10-29 12:25:38+00:00          Desktop   135969.60
4     France 2020-08-11 16:09:10+00:00          Android    31791.20

  service_name  no_of_passengers  days_to_departure  distance_km day_of_week  \
0          MMT               1.0               10.0        747.8   Wednesday
1        YATRA               1.0                1.0       6701.5   Wednesday
2        YATRA               1.0               32.0       7712.0      Monday
3      GOIBIBO               2.0               69.0       6112.5      Friday
4      GOIBIBO               1.0                3.0       6570.4     Tuesday

  quarter
0  2020Q1
1  2018Q4
2  2019Q4
3  2021Q4
4  2020Q3
--------------------------------------------------
```

```
# Step 2: Grouped data (counts by quarter and device type)
quarter  device_type_used
2018Q3   Android             3
         Desktop             6
         MobileWeb           2
         Tablet              1
2018Q4   Android             3
dtype: int64
--------------------------------------------------
# Step 3: Reshaped data (wide format with device types as columns)
device_type_used  Android  Desktop  IOS  MobileWeb  Tablet
quarter
2018Q3                  3        6    0          2       1
2018Q4                  3       22    4          4       1
2019Q1                  0        1    0          0       0
2019Q2                  0        1    0          0       1
2019Q3                  3        7    4          0       0
--------------------------------------------------

C:\Users\akram\AppData\Local\Temp\ipykernel_13904\3811917305.py:6: UserWarning:
Converting to PeriodArray/Index representation will drop timezone information.
  booking_data['quarter'] = booking_data['booking_time'].dt.to_period('Q')
```



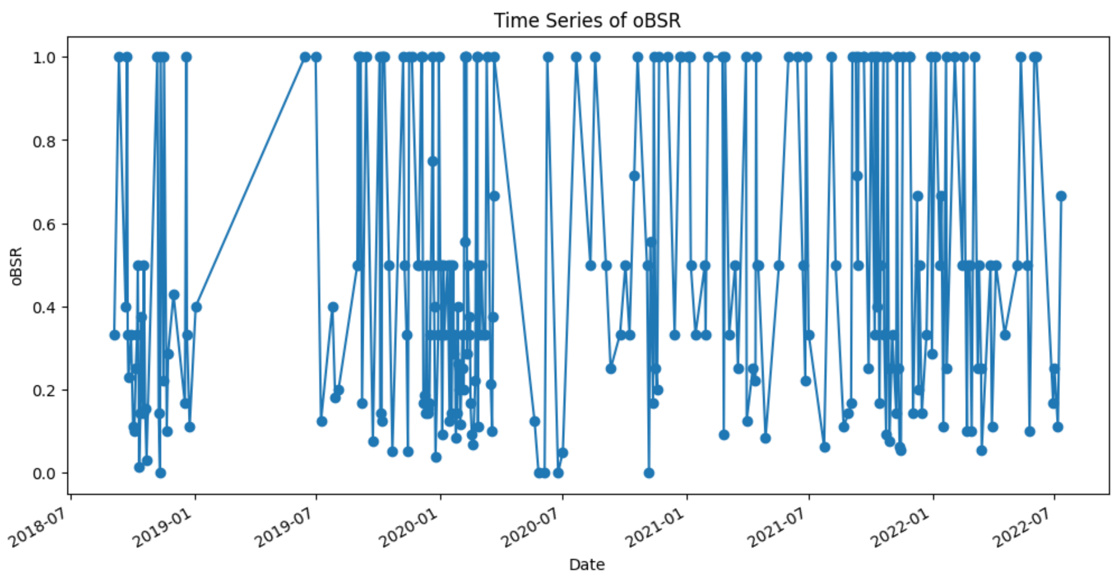
[101]:
```
# 10. oBSR (Overall Booking to Search Ratio) Analysis

# Step 1: Add a Booking Flag
```

```python
# Create a new column 'booking_flag' where 1 indicates a booking exists, and 0␣
↪indicates no booking.
sessions_data['booking_flag'] = sessions_data['booking_id'].notnull().
↪astype(int)

print("# Step 1: Added 'booking_flag' column")
print(sessions_data[['session_starting_time', 'booking_id', 'booking_flag']].
↪head(10))  # Display the first few rows
print("-" * 50)

# Step 2: Group by Date and Aggregate Metrics
# Group the data by date (extracted from 'session_starting_time') to calculate:
# - Total searches (`count` of search_id).
# - Total bookings (`sum` of booking_flag).
obsr_data = sessions_data.groupby(sessions_data['session_starting_time'].str[:
↪10]).agg(
    total_searches=('search_id', 'count'),
    total_bookings=('booking_flag', 'sum')
)

print("# Step 2: Aggregated data by date")
print(obsr_data.head())  # Display the first few rows of aggregated data
print("-" * 50)

# Step 3: Calculate oBSR (Overall Booking to Search Ratio)
# oBSR is the ratio of total bookings to total searches for each date.
obsr_data['oBSR'] = obsr_data['total_bookings'] / obsr_data['total_searches']

print("# Step 3: Calculated oBSR")
print(obsr_data.head())  # Display the first few rows with oBSR
print("-" * 50)

# Step 4: Add Temporal Information
# Convert the index to datetime format and extract month and day of the week.
obsr_data.index = pd.to_datetime(obsr_data.index)
obsr_data['month'] = obsr_data.index.month_name()
obsr_data['day_of_week'] = obsr_data.index.day_name()

print("# Step 4: Added month and day of the week")
print(obsr_data[['month', 'day_of_week', 'oBSR']].head())  # Display the first␣
↪few rows with temporal information
print("-" * 50)

# Step 5: Calculate Average oBSR by Month and Day of the Week
# Group by month and day of the week to calculate the average oBSR.
avg_obsr_by_month = obsr_data.groupby('month')['oBSR'].mean()
avg_obsr_by_day = obsr_data.groupby('day_of_week')['oBSR'].mean()
```

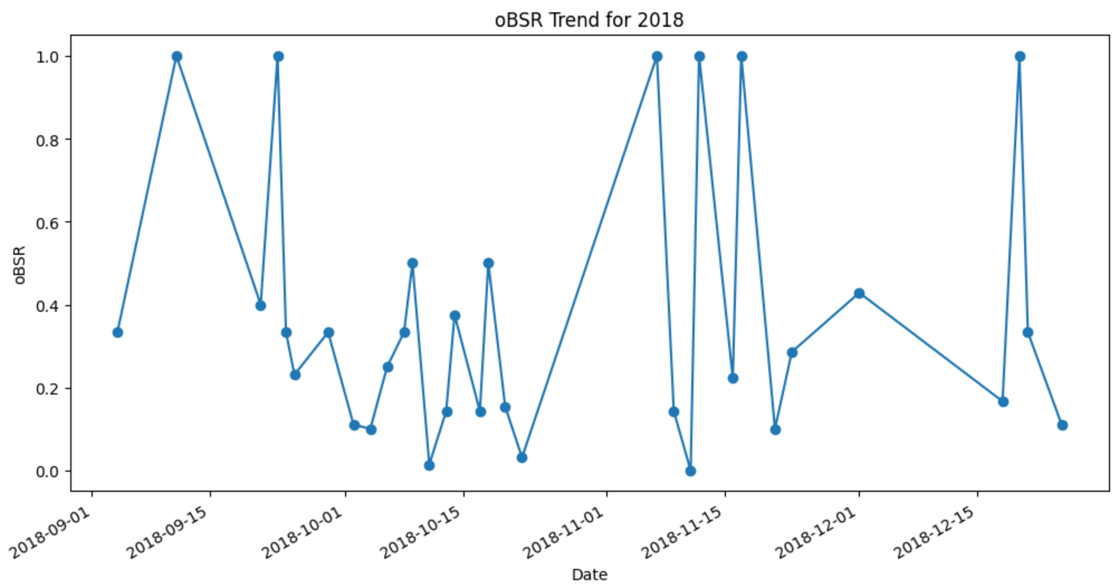
```python
print("# Step 5: Average oBSR by Month")
print(avg_obsr_by_month)
print("-" * 50)

print("# Step 5: Average oBSR by Day of the Week")
print(avg_obsr_by_day)
print("-" * 50)

# Step 6: Plot oBSR Time Series
# Plot the oBSR values over time to visualize trends.
obsr_data['oBSR'].plot(figsize=(12, 6), title="Time Series of oBSR", marker='o')
plt.xlabel("Date")
plt.ylabel("oBSR")
plt.show()
```

```
# Step 1: Added 'booking_flag' column
      session_starting_time   booking_id  booking_flag
0       2020-01-21T21:10:12Z          NaN             0
1       2020-01-21T21:10:12Z          NaN             0
2       2020-01-21T21:10:12Z          NaN             0
3       2020-01-21T21:10:12Z          NaN             0
4       2020-01-21T21:10:12Z          NaN             0
5       2020-01-21T21:10:12Z   booking_54             1
6   2020-01-21T05:33:33.559Z  booking_106             1
7       2019-09-05T09:04:32Z    booking_1             1
8   2020-01-20T16:53:47.477Z          NaN             0
9   2020-01-20T16:53:47.477Z  booking_282             1
--------------------------------------------------
# Step 2: Aggregated data by date
                       total_searches  total_bookings
session_starting_time
2018-09-04                          3               1
2018-09-11                          2               2
2018-09-21                          5               2
2018-09-23                          1               1
2018-09-24                          3               1
--------------------------------------------------
# Step 3: Calculated oBSR
                       total_searches  total_bookings      oBSR
session_starting_time
2018-09-04                          3               1  0.333333
2018-09-11                          2               2  1.000000
2018-09-21                          5               2  0.400000
2018-09-23                          1               1  1.000000
2018-09-24                          3               1  0.333333
--------------------------------------------------
# Step 4: Added month and day of the week
```

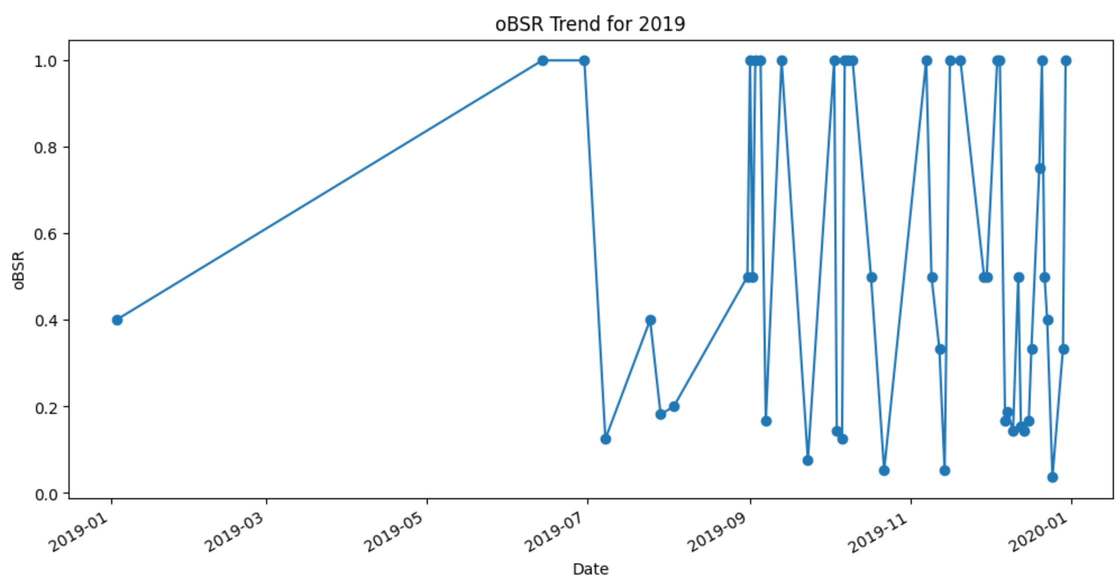
```
                           month day_of_week      oBSR
session_starting_time
2018-09-04             September     Tuesday  0.333333
2018-09-11             September     Tuesday  1.000000
2018-09-21             September      Friday  0.400000
2018-09-23             September      Sunday  1.000000
2018-09-24             September      Monday  0.333333
--------------------------------------------------
# Step 5: Average oBSR by Month
month
April        0.423611
August       0.494246
December     0.484075
February     0.519831
January      0.432166
July         0.318043
June         0.683761
March        0.447506
May          0.389286
November     0.519795
October      0.464157
September    0.618794
Name: oBSR, dtype: float64
--------------------------------------------------
# Step 5: Average oBSR by Day of the Week
day_of_week
Friday       0.463095
Monday       0.469626
Saturday     0.492722
Sunday       0.505030
Thursday     0.499807
Tuesday      0.575140
Wednesday    0.420465
Name: oBSR, dtype: float64
--------------------------------------------------
```



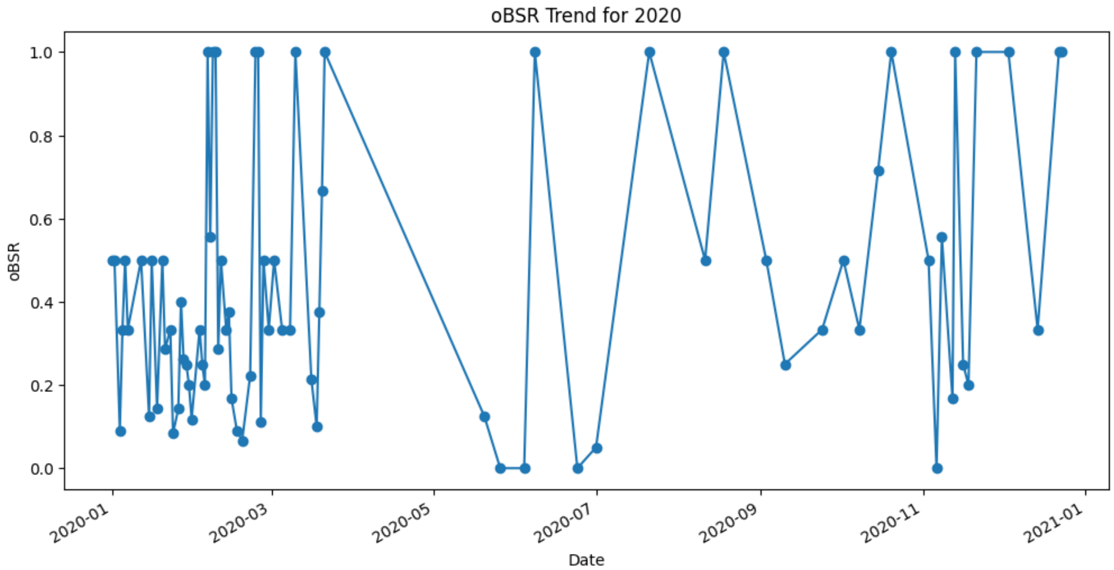
[102]:
```
#  Yearly oBSR Plots

# Step 1: Add Year Column
# Extract the year from the index to facilitate yearly grouping.
obsr_data['year'] = obsr_data.index.year

# Step 2: Group and Plot oBSR for Each Year
# Iterate through the unique years and create separate plots for each.
unique_years = obsr_data['year'].unique()
for year in unique_years:
    yearly_data = obsr_data[obsr_data['year'] == year]

    # Plot the oBSR for the current year
    plt.figure(figsize=(12, 6))
    yearly_data['oBSR'].plot(marker='o', title=f"oBSR Trend for {year}")
    plt.xlabel("Date")
    plt.ylabel("oBSR")
    plt.show()
```

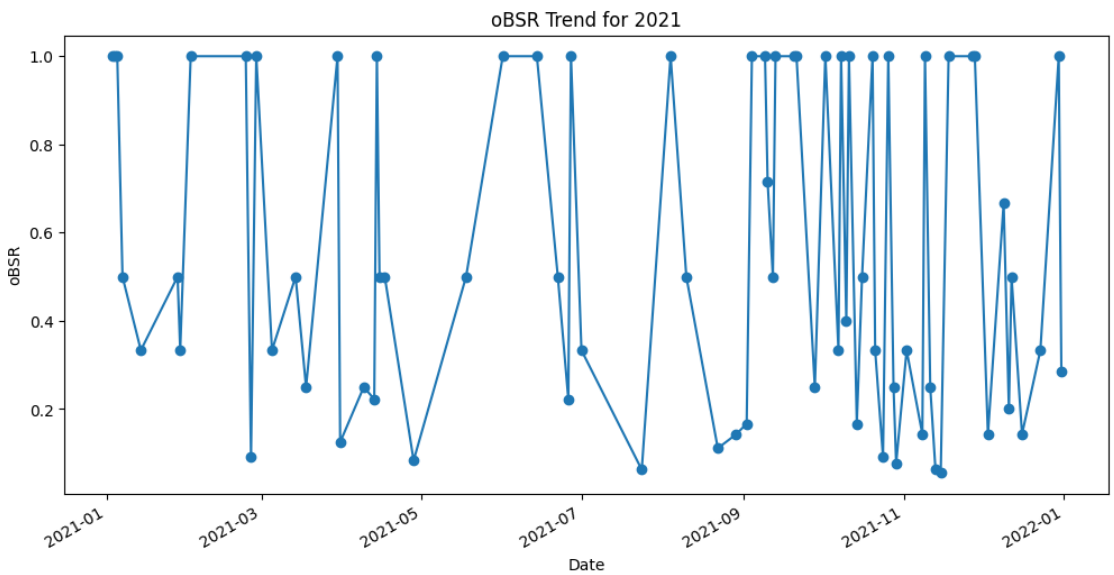


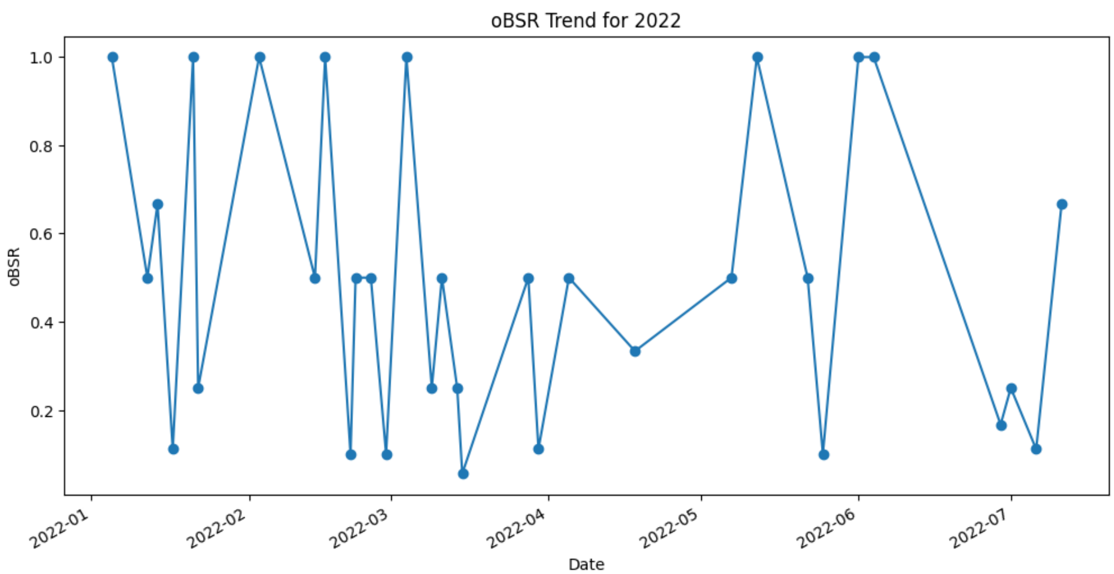
oBSR Trend for 2018
oBSR
Date
1.0
0.8
0.6
0.4
0.2
0.0
2018-09-01
2018-09-15
2018-10-01
2018-10-15
2018-11-01
2018-11-15
2018-12-01
2018-12-15



oBSR Trend for 2019
oBSR
Date
1.0
0.8
0.6
0.4
0.2
0.0
2019-01
2019-03
2019-05
2019-07
2019-09
2019-11
2020-01


oBSR Trend for 2020
oBSR
1.0
0.8
0.6
0.4
0.2
0.0
2020-01
2020-03
2020-05
2020-07
2020-09
2020-11
2021-01
Date


oBSR Trend for 2021
oBSR
1.0
0.8
0.6
0.4
0.2
2021-01
2021-03
2021-05
2021-07
2021-09
2021-11
2022-01
Date


oBSR Trend for 2022
1.0
0.8
0.6
0.4
0.2
oBSR
2022-01
2022-02
2022-03
2022-04
2022-05
2022-06
2022-07
Date