```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as stats
from datetime import datetime
import numpy as np
```

```
df=pd.read_csv("/content/Customer_Order.csv",sep=';')
```

```
df['creationDate'] = pd.to_datetime(df['creationDate'], format="%d/%m/%Y %H:%M")
df
```

	codCustomer	orderNumber	orderToCollect	Reference	Size (US)	quantity (units)	creationDate	waveNumber	operator
0	C0000016	124438	8	8N10W9	9.0	6	2023-10-19 07:18:00	43175	Operator_1
1	C0000016	124438	7	2T1DJM	13.0	1	2023-10-19 07:18:00	43175	Operator_1
2	C0000016	124438	6	QVFB0Q	105.0	1	2023-10-19 07:18:00	43175	Operator_1
3	C0000016	124438	5	W25EZN	13.0	1	2023-10-19 07:18:00	43175	Operator_1
4	C0000016	124438	4	W25EZN	11.0	1	2023-10-19 07:18:00	43175	Operator_1
...	...	...	...	...	...	...	...	...	...
122365	C0000747	89481	1	5HQR89	105.0	1	2023-01-05 07:42:00	33168	Operator_2
122366	C0000747	89480	1	8E9F1P	105.0	1	2023-01-05 07:42:00	33169	Operator_8
122367	C0000747	89479	1	56TC1Z	6.0	1	2023-01-05 07:42:00	33168	Operator_2
122368	C0000747	89478	1	6M2FJM	12.0	1	2023-01-05 07:42:00	33168	Operator_2
122369	C0000747	89477	1	6M2FJM	12.0	1	2023-01-05 07:42:00	33168	Operator_2

122370 rows × 9 columns

```
for i in df['Reference'].value_counts():
  print(i)
```

```
5
4
3
3
3
3
3
2
1
1
1
1
1
1
1
1
1
```

```
import pandas as pd

freq = df['Reference'].value_counts()
selected_refs = freq[freq >= 2500].index  # or ABC selection logic
df_filtered = df[df['Reference'].isin(selected_refs)]
```

```
# Assuming 'filtered_df' is your top 50 products dataframe
# and 'creationDate' is a datetime column

jan_filtered_df = df_filtered[df_filtered['creationDate'].dt.month == 6]
```

```
jan_filtered_df['Reference'].value_counts()
```

Reference	count
PY5UPB	1144
8N10W9	925
WRRW1W	551
SMMRK3	422
I1KDJ0	391
KTDZY0	359
8D9SAW	339
KUFVRI	325
2T1DJM	307
XUZJ74	238
6M2FJM	213

dtype: int64

```
import pandas as pd

# Step 1: Value counts on 'Reference' in Jan data
jan_filtered_freq = jan_filtered_df['Reference'].value_counts()

# Step 2: Select references with count >= 30
selected_refs = jan_filtered_freq[jan_filtered_freq >= 30].index

# Step 3: Filter the original jan_filtered_df to keep only selected references
jan_data = jan_filtered_df[jan_filtered_df['Reference'].isin(selected_refs)]
```

```
jan_data['Reference'].value_counts()
```

Reference	count
PY5UPB	1144
8N10W9	925
WRRW1W	551
SMMRK3	422
I1KDJ0	391
KTDZY0	359
8D9SAW	339
KUFVRI	325
2T1DJM	307
XUZJ74	238
6M2FJM	213

dtype: int64

```
jan_data
```

	codCustomer	orderNumber	orderToCollect	Reference	Size (US)	quantity (units)	creationDate	waveNumber	operator
44015	C0000555	111476	31	PY5UPB	290.0	5	2023-06-30 11:33:00	39737	Operator_4
44016	C0000555	111476	31	PY5UPB	290.0	5	2023-06-30 11:33:00	39737	Operator_4
44017	C0000555	111476	31	PY5UPB	290.0	5	2023-06-30 11:33:00	39737	Operator_4
44018	C0000555	111476	30	PY5UPB	280.0	5	2023-06-30 11:33:00	39737	Operator_4
44019	C0000555	111476	30	PY5UPB	280.0	5	2023-06-30 11:33:00	39736	Operator_1
...	...	...	...	...	...	...	...	...	...
55871	C0000010	108395	3	8D9SAW	105.0	1	2023-06-01 11:29:00	38574	Operator_17
55873	C0000010	108395	1	I1KDJ0	9.0	1	2023-06-01 11:29:00	38574	Operator_17
55876	C0000008	108392	1	6M2FJM	9.0	2	2023-06-01 11:29:00	38574	Operator_17
55887	C0000747	108381	1	8N10W9	6.0	1	2023-06-01 11:29:00	38573	Operator_2
55888	C0000747	108380	2	8N10W9	10.0	1	2023-06-01 11:29:00	38573	Operator_2

5214 rows × 9 columns

Next steps: Generate code with `jan_data` View recommended plots New interactive sheet

Double-click (or enter) to edit

```
# jan_data_p1 = jan_data.loc[jan_data['Reference'] == 'PY5UPB']#Constant orders on Monday Friday Wedne
# jan_data_p1 = jan_data.loc[jan_data['Reference'] == 'KUFVRI']#Constant orders on Monday Tuesday Wedn
jan_data_p1 = jan_data.loc[jan_data['Reference'] == '6M2FJM']#Rest need to model some distribution tak
```

Double-click (or enter) to edit

```
df=jan_data_p1
```

```
jan_data_p1
```

	codCustomer	orderNumber	orderToCollect	Reference	Size (US)	quantity (units)	creationDate	waveNumber	operator
44400	C0000721	111474	1	6M2FJM	11.0	1	2023-06-29 11:11:00	39660	Operator_3
44405	C0000640	111469	1	6M2FJM	105.0	3	2023-06-29 11:11:00	39660	Operator_3
44408	C0000621	111466	1	6M2FJM	11.0	4	2023-06-29 11:11:00	39660	Operator_3
44410	C0000552	111464	1	6M2FJM	105.0	1	2023-06-29 11:11:00	39660	Operator_3
44411	C0000552	111463	2	6M2FJM	11.0	1	2023-06-29 11:11:00	39660	Operator_3
...	...	...	...	...	...	...	...	...	...
55563	C0000487	108494	1	6M2FJM	10.0	1	2023-06-01 16:28:00	38662	Operator_1
55608	C0000223	108470	1	6M2FJM	9.0	2	2023-06-01 16:28:00	38660	Operator_1
55756	C0000008	108443	1	6M2FJM	9.0	2	2023-06-01 16:25:00	38651	Operator_6
55837	C0000223	108403	1	6M2FJM	9.0	2	2023-06-01 11:30:00	38576	Operator_1
55876	C0000008	108392	1	6M2FJM	9.0	2	2023-06-01 11:29:00	38574	Operator_17

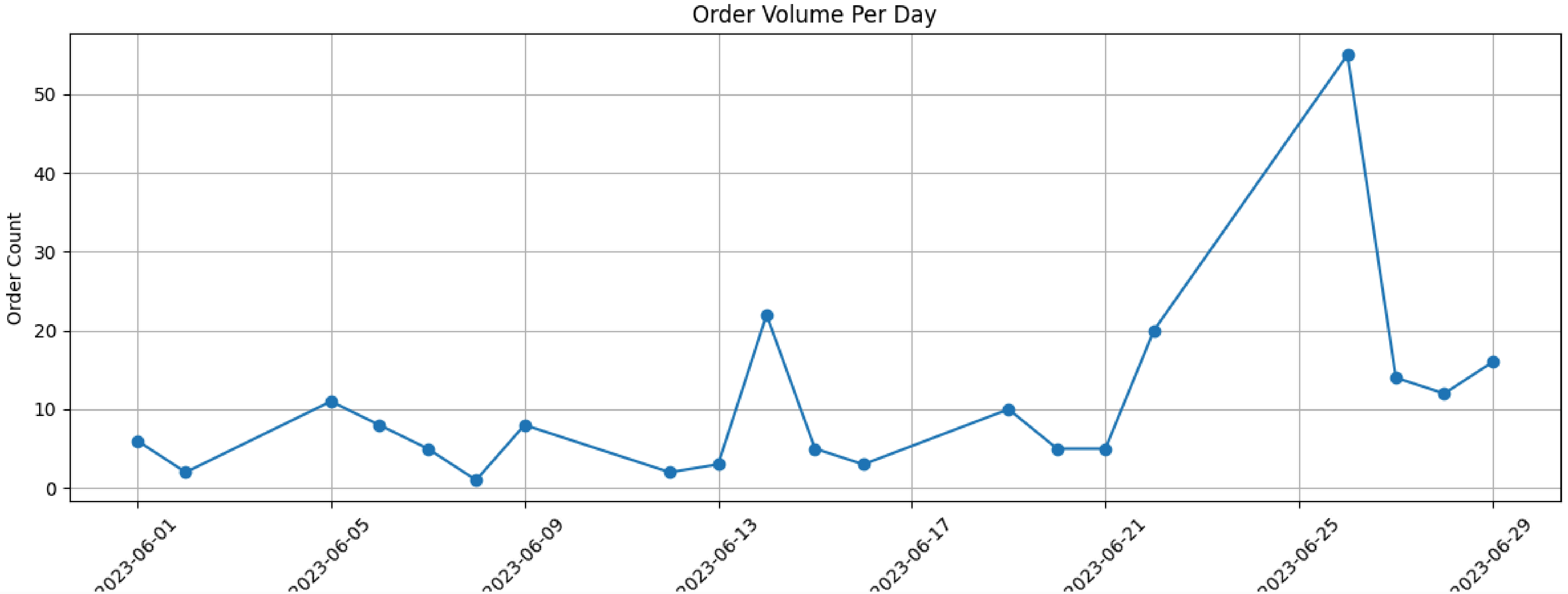
213 rows × 9 columns

Next steps: Generate code with df View recommended plots New interactive sheet

Start coding or generate with AI.

```
df['date'] = df['creationDate'].dt.date
daily_counts = df.groupby('date').size()

plt.figure(figsize=(12, 5))
daily_counts.plot(marker='o')
plt.title("Order Volume Per Day")
plt.xlabel("Date")
plt.ylabel("Order Count")
plt.grid(True)
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

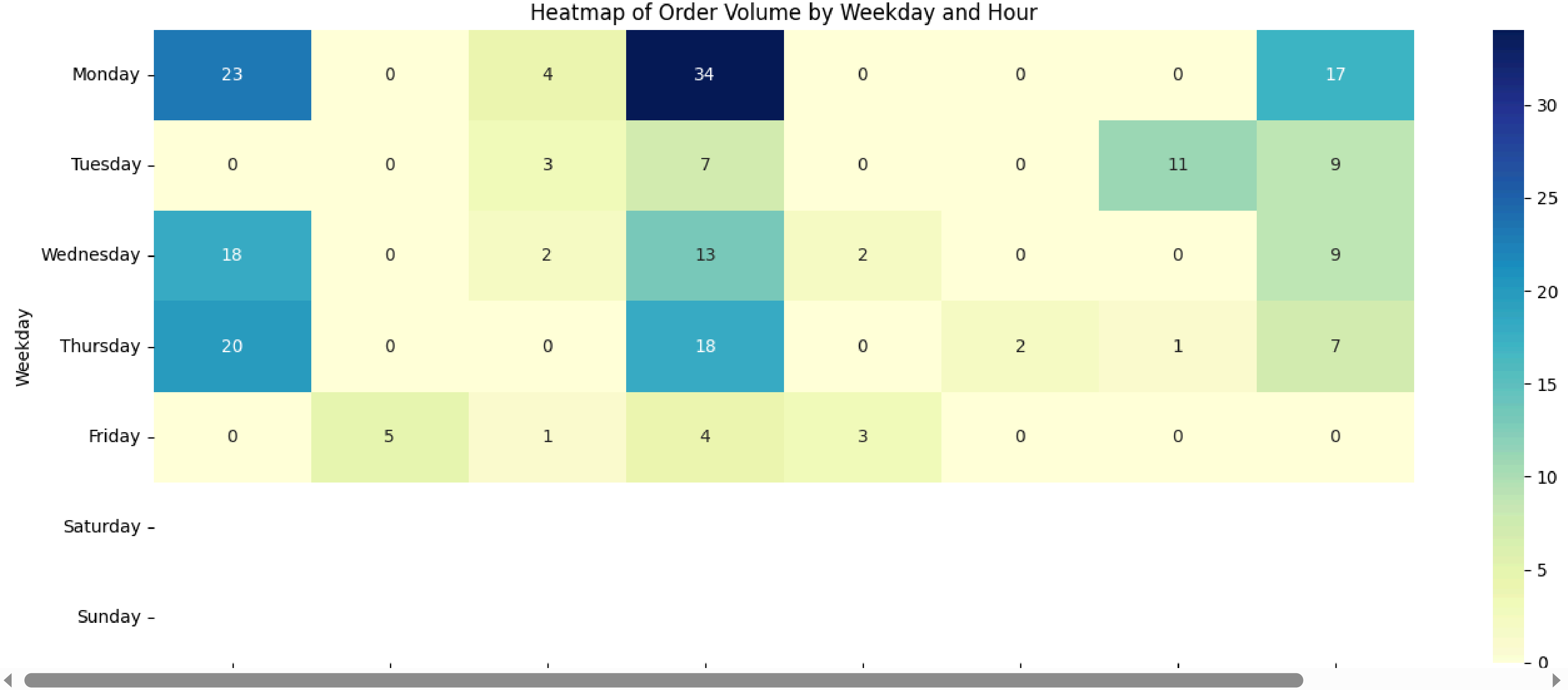
```
<ipython-input-32-dfc58bea87c9>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returnin
  df['date'] = df['creationDate'].dt.date
```




```
 df['weekday'] = df['creationDate'].dt.day_name()
df['hour'] = df['creationDate'].dt.hour
heatmap_data = df.groupby(['weekday', 'hour']).size().unstack().fillna(0)

# Reorder weekdays
ordered_days = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday', 'Sunday']
heatmap_data = heatmap_data.reindex(ordered_days)

plt.figure(figsize=(14, 6))
sns.heatmap(heatmap_data, cmap='YlGnBu', annot=True, fmt=".0f")
```

```
    plt.title("Heatmap of Order Volume by Weekday and Hour")
    plt.xlabel("Hour of Day")
    plt.ylabel("Weekday")
    plt.tight_layout()
    plt.show()
```

```
<ipython-input-15-a867efbda7f4>:1: 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#returnin
  df['weekday'] = df['creationDate'].dt.day_name()
<ipython-input-15-a867efbda7f4>:2: 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#returnin
  df['hour'] = df['creationDate'].dt.hour
```



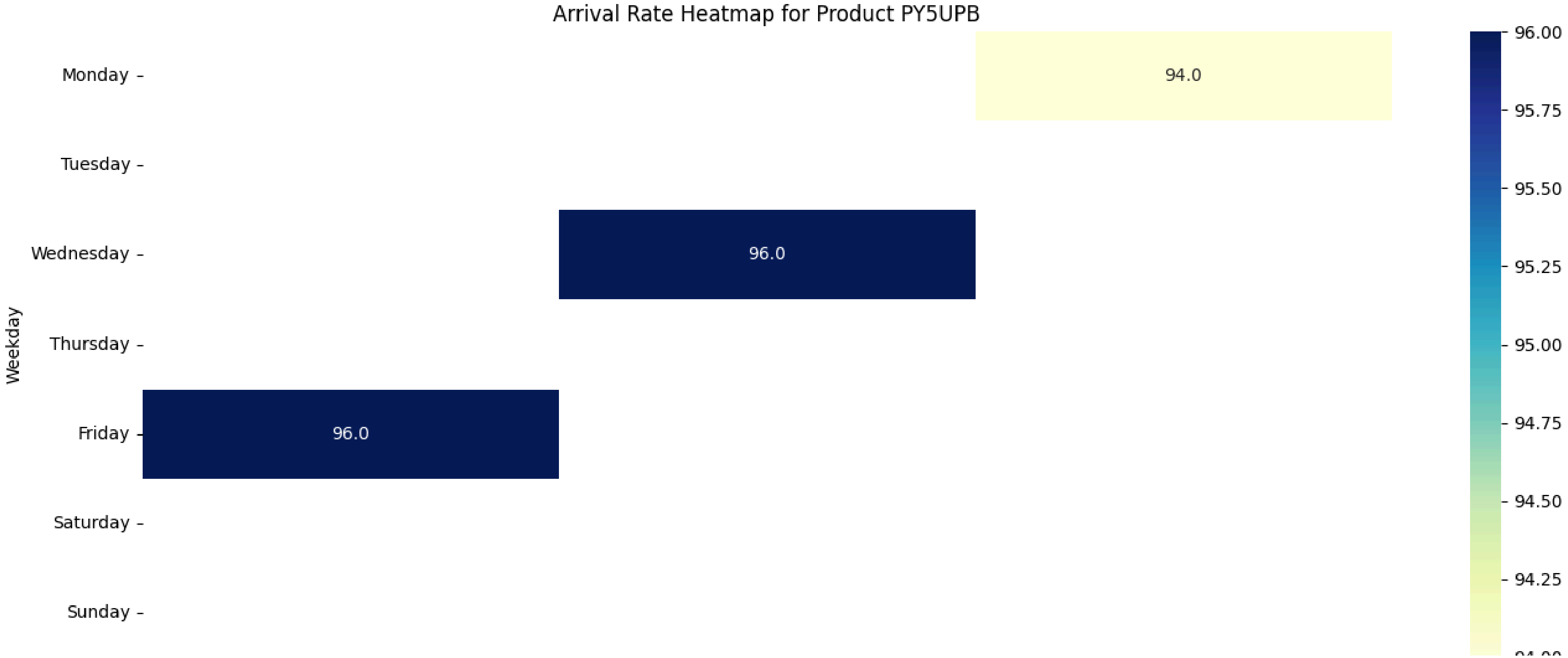

```
import pandas as pd
import numpy as np
```

```
import matplotlib.pyplot as plt
import seaborn as sns

# Assuming jan_data is already loaded with creationDate and product columns
# Ensure creationDate is in datetime format
jan_data['creationDate'] = pd.to_datetime(jan_data['creationDate'])

# Extract weekday and hour information
jan_data['weekday'] = jan_data['creationDate'].dt.day_name()
jan_data['hour'] = jan_data['creationDate'].dt.hour

# Calculate number of unique days for each weekday to use as denominator
weekday_counts = jan_data.groupby('weekday')['creationDate'].apply(
    lambda x: len(x.dt.date.unique())
).to_dict()

# Calculate arrival rates for each product by weekday and hour
product_hourly_rates = []

# Process each product in the reference list
products = ['PY5UPB', '8N10W9', 'WRRW1W', 'SMMRK3', 'I1KDJ0',
            'KTDZY0', '8D9SAW', 'KUFVRI', '2T1DJM', 'XUZJ74', '6M2FJM']

for product_id in products:
    # Filter data for this product
    product_data = jan_data[jan_data['Reference'] == product_id]

    # Group by weekday and hour
    arrival_counts = product_data.groupby(['weekday', 'hour']).size().reset_index(name='arrivals')

    # Calculate arrival rate (arrivals per hour)
    arrival_counts['arrival_rate'] = arrival_counts.apply(
        lambda row: row['arrivals'] / weekday_counts.get(row['weekday'], 1), axis=1
    )

    # Add product info
    arrival_counts['Reference'] = product_id
```

```
        product_hourly_rates.append(arrival_counts)

    # Combine all products
    all_product_rates = pd.concat(product_hourly_rates)

    # Create half-hour intervals if needed (similar to the table in images)
    def create_half_hour_rates(df):
        half_hour_rates = []

        for product_id in products:
            product_df = df[df['Reference'] == product_id]

            for weekday in product_df['weekday'].unique():
                weekday_df = product_df[product_df['weekday'] == weekday]

                for hour in weekday_df['hour'].unique():
                    rate = weekday_df[weekday_df['hour'] == hour]['arrival_rate'].values[0]

                    # Split the hourly rate into two half-hour periods
                    # This is a simple approach - could be refined with actual half-hour data
                    half_hour_rates.append({
                        'product': product_id,
                        'weekday': weekday,
                        'time_period': f"{hour:02d}:00-{hour:02d}:30",
                        'arrival_rate': rate / 2  # Assuming even distribution
                    })

                    half_hour_rates.append({
                        'product': product_id,
                        'weekday': weekday,
                        'time_period': f"{hour:02d}:30-{(hour+1):02d}:00",
                        'arrival_rate': rate / 2  # Assuming even distribution
                    })

        return pd.DataFrame(half_hour_rates)
```

```
# Create half-hour rates (optional)
half_hour_product_rates = create_half_hour_rates(all_product_rates)

# Display results
print("Hourly arrival rates by product, weekday, and hour:")
print(all_product_rates.head(10))

# Example: Create a heatmap for a specific product
def plot_product_heatmap(product_id):
    product_data = all_product_rates[all_product_rates['Reference'] == product_id]

    # Prepare data for heatmap
    heatmap_data = product_data.pivot(index='weekday', columns='hour', values='arrival_rate')

    # Reorder weekdays
    ordered_days = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday', 'Sunday']
    heatmap_data = heatmap_data.reindex(ordered_days)

    # Plot heatmap
    plt.figure(figsize=(14, 6))
    sns.heatmap(heatmap_data, cmap='YlGnBu', annot=True, fmt=".1f")
    plt.title(f"Arrival Rate Heatmap for Product {product_id}")
    plt.xlabel("Hour of Day")
    plt.ylabel("Weekday")
    plt.tight_layout()
    plt.show()

# Example usage: Plot heatmap for first product
plot_product_heatmap(products[0])
```

```
Hourly arrival rates by product, weekday, and hour:
     weekday  hour  arrivals  arrival_rate Reference
0     Friday    11       384         96.00    PY5UPB
1     Monday    19       376         94.00    PY5UPB
2  Wednesday    16       384         96.00    PY5UPB
0     Friday     8        37          9.25    8N10W9
1     Friday    10         3          0.75    8N10W9
2     Friday    11        18          4.50    8N10W9
3     Friday    12        10          2.50    8N10W9
4     Monday     7        33          8.25    8N10W9
5     Monday    10        99         24.75    8N10W9
6     Monday    11        81         20.25    8N10W9
```




```
# First, ensure you've combined the list into a single DataFrame
```

```
all_product_rates = pd.concat(product_hourly_rates)

# Then save the combined DataFrame to CSV
all_product_rates.to_csv("product_hourly_rates_June_Ten_Frequent.csv", index=False)
```

```
all_product_rates['Reference'].value_counts()
```

Reference	count
6M2FJM	22
WRRW1W	21
8N10W9	21
KTDZY0	21
I1KDJ0	21
2T1DJM	20
8D9SAW	19
SMMRK3	19
XUZJ74	18
KUFVRI	4
PY5UPB	3

dtype: int64

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

```
import seaborn as sns

# First, get all distributions that can be fitted
def get_fittable_distributions():
    """Get all continuous distributions from scipy.stats that have a .fit method"""
    all_objects = dir(scipy.stats)
    distributions = []
    for obj_name in all_objects:
        obj = getattr(scipy.stats, obj_name)
        # Check if it's a distribution with a fit method
        if hasattr(obj, 'fit') and callable(obj.fit):
            distributions.append(obj_name)
    return distributions

# Updated MyFit function with error handling
def MyFit(dataseries, distribution_name):
    try:
        # Get distribution details from scipy
        distribution = getattr(scipy.stats, distribution_name)

        # Check if this distribution has a fit method
        if not hasattr(distribution, 'fit'):
            print(f"{distribution_name} doesn't have a fit method. Skipping.")
            return None

        # Do MLE using the predefined .fit() function to find parameter values
        param = distribution.fit(dataseries)
        print('Fitted: ', distribution_name, ' with parameters ', param)

        # Do KS TEST using predefined kstest() function from scipy.stats package
        D, pval = scipy.stats.kstest(dataseries, distribution_name, args=param)

        print('\nKS Test')
        print('KS Test Statistics: ', D)
        if pval > 0.05:
            print('p-value is ', pval, '. Do not reject null hypothesis')
        else:
            print('p-value is ', pval, '. Reject null hypothesis')
```

```
        # Create dictionary to store results
        results = {
            'distribution': distribution_name,
            'parameters': param,
            'ks_statistic': D,
            'ks_pvalue': pval,
            'reject_null_ks': pval <= 0.05
        }

        # Do ANDERSONDARLING TEST using anderson() function from scipy.stats package.
        # Works only for a few distributions
        print('\n\nAnderson-Darling Test')
        possibledist = ['norm', 'expon', 'logistic', 'gumbel_l', 'gumbel_r']

        if distribution_name in possibledist:
            try:
                A, c_val, pvalA = scipy.stats.anderson(dataseries, distribution_name)
                print("Statistics", A, "; criticalValues: ", c_val, "; significanceLevel: ", pvalA)

                if all(i < A for i in c_val):
                    print('Test Statistics ', A, ' is more than all critical values. Reject H0')
                    ad_reject = True
                else:
                    print('Test Statistics ', A, ' is less than some critical values. Cannot Reject H0
                    ad_reject = False

                # Add Anderson-Darling results to results dictionary
                results['ad_statistic'] = A
                results['ad_critical_values'] = c_val
                results['ad_significance_levels'] = pvalA
                results['reject_null_ad'] = ad_reject
            except Exception as e:
                print(f"Error in Anderson-Darling test: {e}")
                results['ad_test_performed'] = False
        else:
            print('The given distribution cannot be tested with A-D test.')
            results['ad test performed'] = False
```

```
        # PLOT DATA AS HISTOGRAM along with the theoretical curve
        plt.figure(figsize=(10, 5))
        plt.hist(dataseries, bins=int(len(dataseries)/2), density=True, alpha=0.8, color='g')
        xmin, xmax = plt.xlim()

        x = np.linspace(xmin, xmax, 100)
        try:
            prob = distribution.pdf(x, *param[:-2], loc=param[-2], scale=param[-1])
            plt.plot(x, prob, label=distribution_name)
            plt.legend(loc='upper right')
            plt.grid(alpha=0.3)
            plt.xlabel('Inter-arrival Time (minutes)')
            plt.ylabel('Probability Density')
            plt.title(f'{distribution_name.capitalize()} Distribution Fit (KS p-value: {pval:.4f})')
            plt.show()
        except Exception as e:
            print(f"Error plotting PDF: {e}")

        return results
    except Exception as e:
        print(f"Error processing distribution {distribution_name}: {e}")
        return None
```

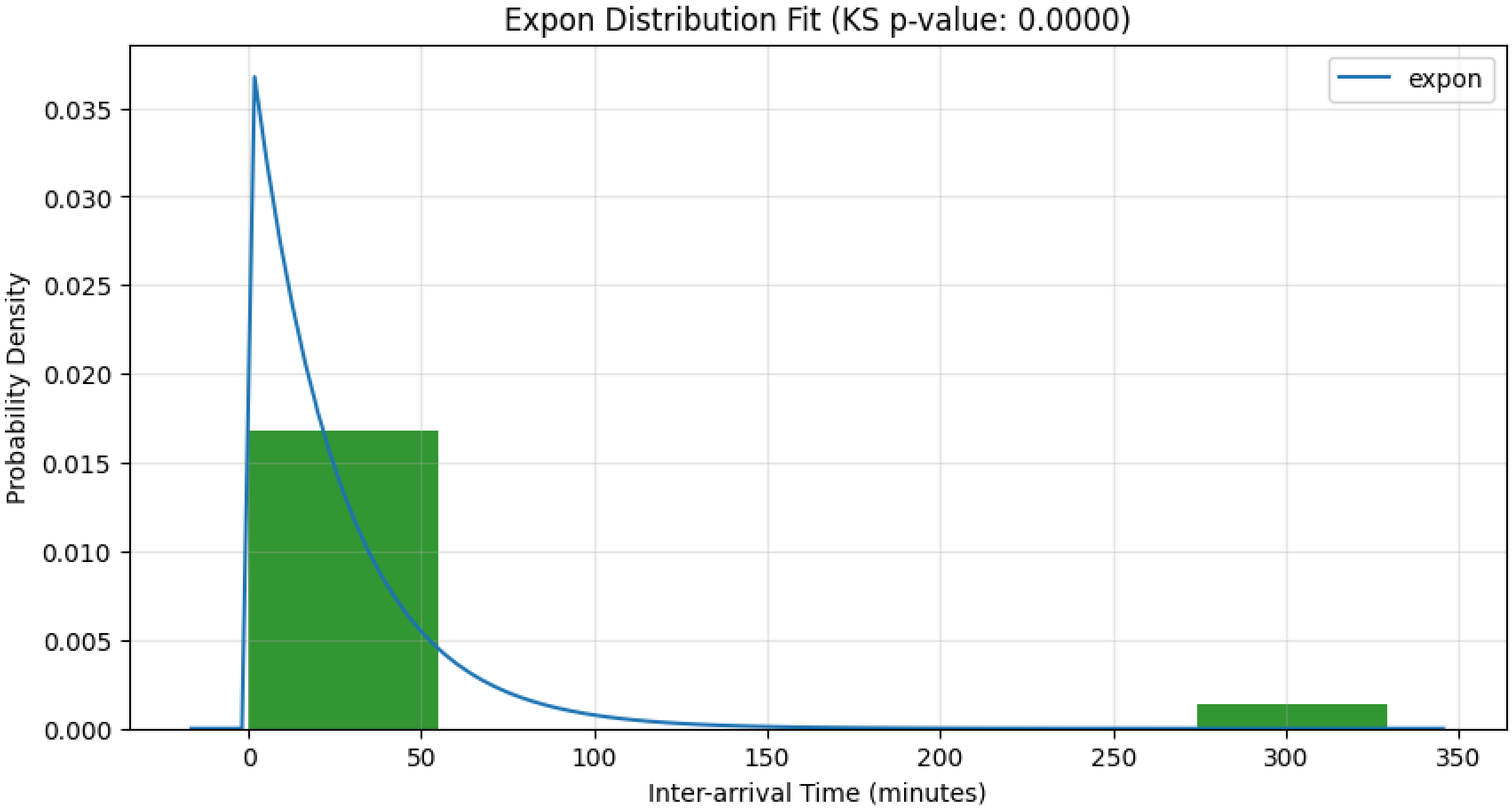
```
# prompt: df['creationDate'] filter on date 01-05 only

# Filter df['creationDate'] for the date 01-05 (May 1st)
df_d1 = df[df['creationDate'].dt.strftime('%m-%d') == '06-07']
df_d1
```

	codCustomer	orderNumber	orderToCollect	Reference	Size (US)	quantity (units)	creationDate	waveNumber	operator	date
53133	C0000418	109104	17	XUZJ74	85.0	1	2023-06-07 16:11:00	38832	Operator_19	2023-06-07
53256	C0000186	109084	33	XUZJ74	12.0	1	2023-06-07 16:11:00	38822	Operator_19	2023-06-07
53257	C0000186	109084	32	XUZJ74	10.0	1	2023-06-07 16:11:00	38822	Operator_19	2023-06-07
53258	C0000186	109084	31	XUZJ74	9.0	1	2023-06-07 16:11:00	38822	Operator_19	2023-06-07
53259	C0000186	109084	30	XUZJ74	85.0	1	2023-06-07 16:11:00	38822	Operator_19	2023-06-07
53290	C0000186	109083	18	XUZJ74	10.0	1	2023-06-07 16:11:00	38820	Operator_1	2023-06-07
53291	C0000186	109083	17	XUZJ74	95.0	1	2023-06-07 16:11:00	38820	Operator_1	2023-06-07
53292	C0000186	109083	16	XUZJ74	9.0	2	2023-06-07 16:11:00	38820	Operator_1	2023-06-07
53511	C0000016	109040	12	XUZJ74	11.0	1	2023-06-07 10:42:00	38803	Operator_5	2023-06-07
53512	C0000016	109040	11	XUZJ74	105.0	2	2023-06-07 10:42:00	38803	Operator_5	2023-06-07
53513	C0000016	109040	10	XUZJ74	85.0	1	2023-06-07 10:42:00	38803	Operator_5	2023-06-07
53538	C0000016	109036	17	XUZJ74	13.0	1	2023-06-07 10:42:00	38798	Operator_6	2023-06-07
53539	C0000016	109036	16	XUZJ74	12.0	2	2023-06-07 10:42:00	38798	Operator_6	2023-06-07
53540	C0000016	109036	15	XUZJ74	11.0	1	2023-06-07	38798	Operator_6	2023-

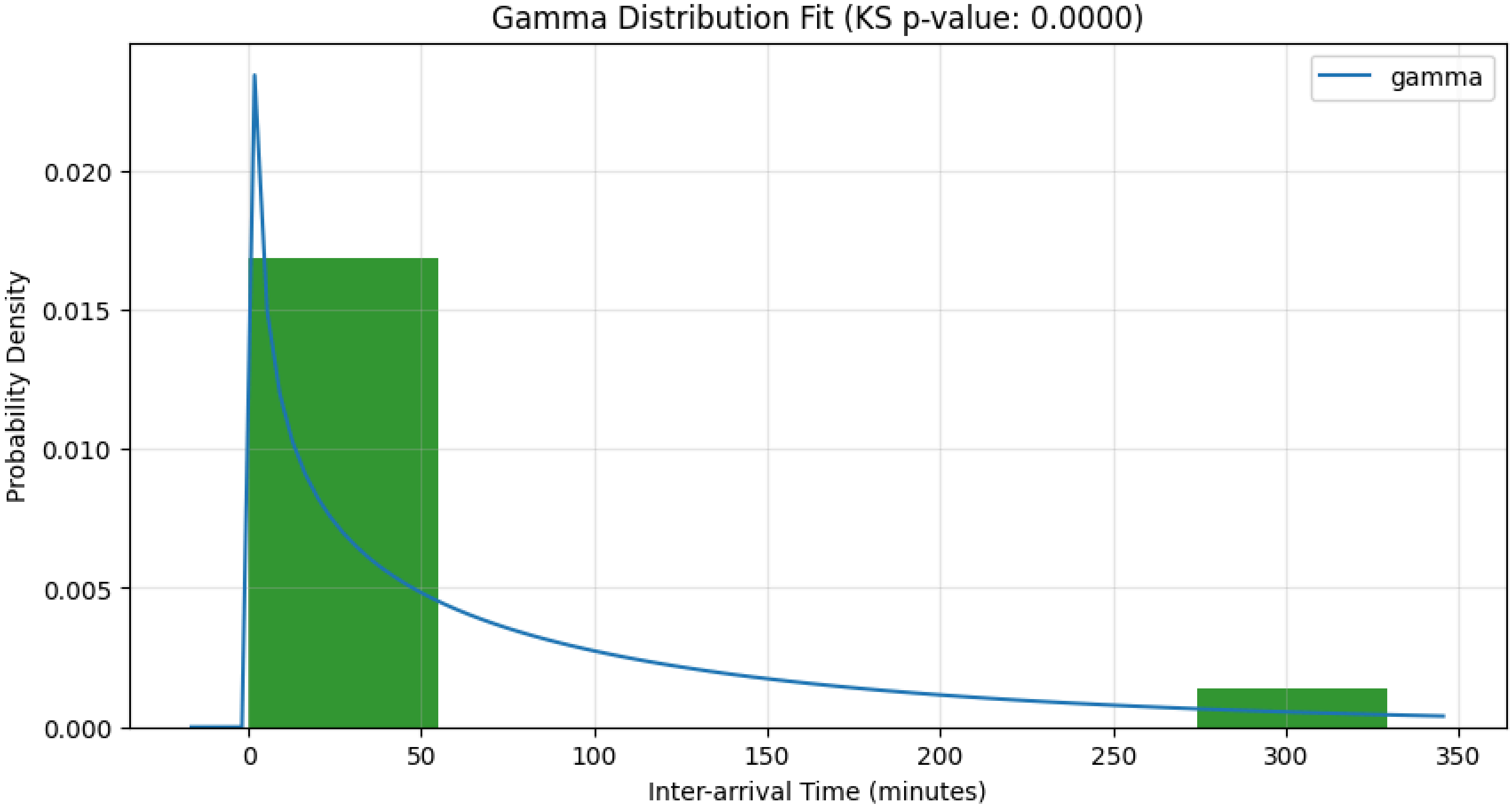
10:42:00 06-07

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import scipy.stats
import seaborn as sns

# Calculate inter-arrival times
df_d1 = df_d1.sort_values(by='creationDate')
df_d1['inter_arrival_time'] = df_d1['creationDate'].diff().dt.total_seconds() / 60
inter_arrival = df_d1['inter_arrival_time'].dropna()

# Test multiple distributions
distributions = ['expon', 'gamma', 'weibull_min', 'lognorm']
results = {}

for dist in distributions:
    print(f"\n\n======= Testing {dist} distribution =======")
    results[dist] = MyFit(inter_arrival, dist)

# Compare results
result_summary = pd.DataFrame({
    'Distribution': list(results.keys()),
    'KS Statistic': [results[d]['ks_statistic'] for d in results],
    'KS p-value': [results[d]['ks_pvalue'] for d in results],
    'Reject Null': [results[d]['reject_null_ks'] for d in results]
})

print("\nSummary of Distribution Tests:")
print(result_summary.sort_values('KS p-value', ascending=False))
```

```
======= Testing expon distribution =======
Fitted:  expon  with parameters  (0.0, 25.307692307692307)

KS Test
KS Test Statistics:  0.9230769230769231
p-value is  6.603381910460181e-15 . Reject null hypothesis


Anderson-Darling Test
Statistics inf ; criticalValues:  [0.881 1.03  1.282 1.535 1.871] ; significanceLevel:  [15.  10.   5.   2.5  1. ]
Test Statistics  inf  is more than all critical values. Reject H0
```

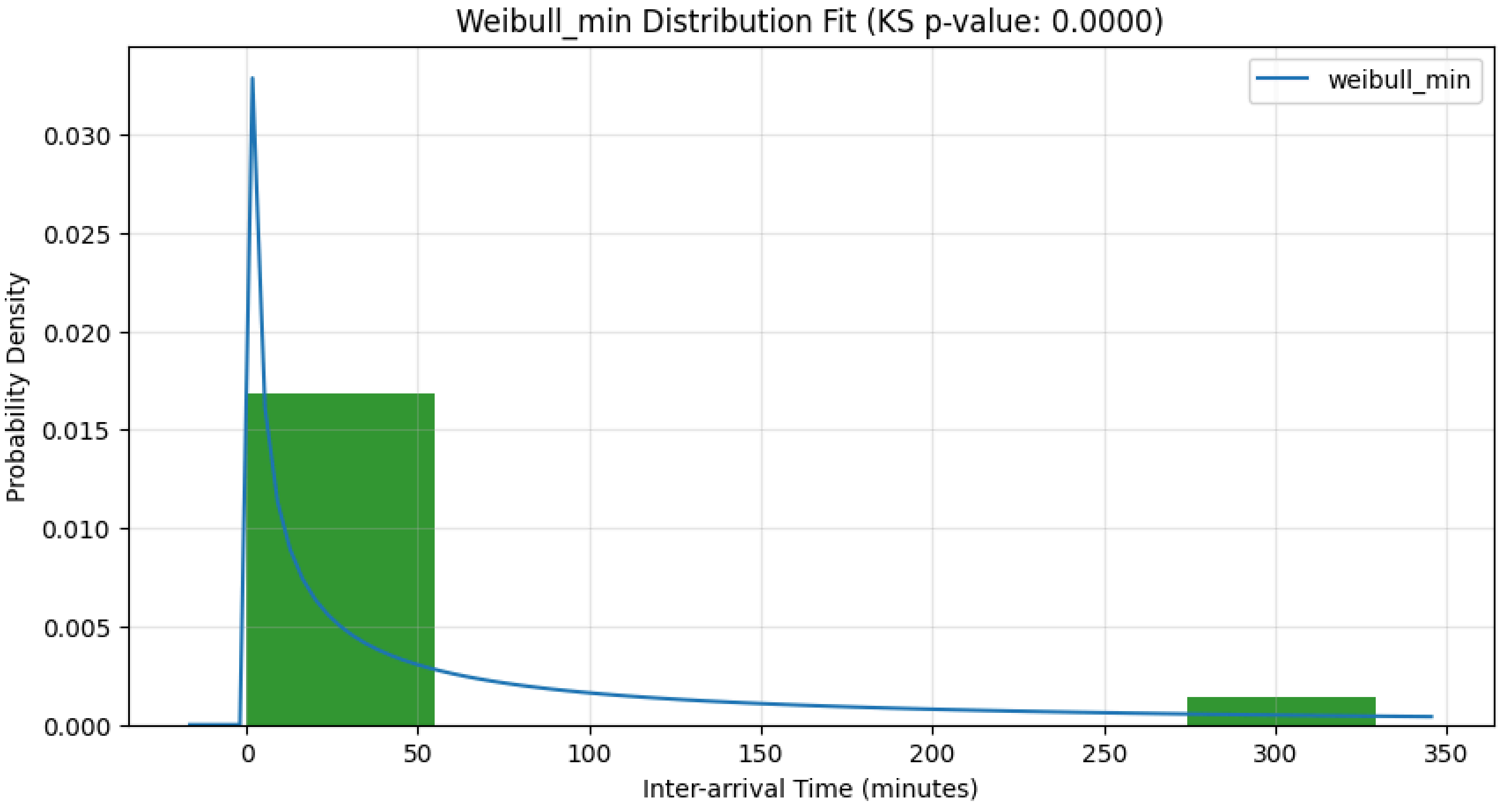


```
======= Testing gamma distribution =======
Fitted:  gamma  with parameters  (np.float64(0.6093862667865055), np.float64(-4.289896780244586e-27), np.float64(16

KS Test
KS Test Statistics:  0.9230769230769231
p-value is  6.603381910460181e-15 . Reject null hypothesis


Anderson-Darling Test
The given distribution cannot be tested with A-D test.
```



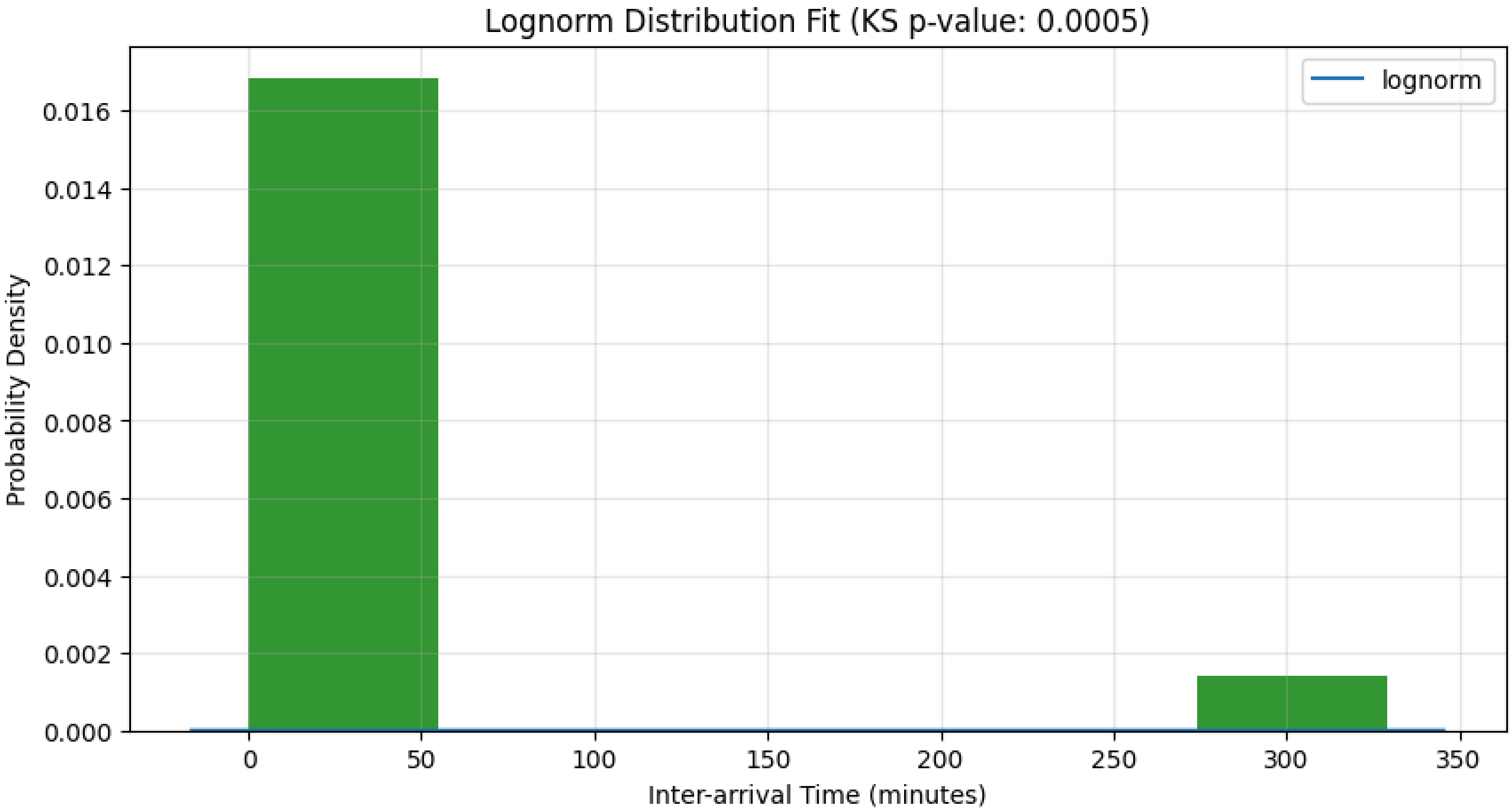

```
======= Testing weibull_min distribution =======
```

```
Fitted:  weibull_min  with parameters  (np.float64(0.4415472397596448), np.float64(-1.2349936888247217e-27), np.flo
KS Test
KS Test Statistics:  0.9230769230767624
p-value is  6.603381910639586e-15 . Reject null hypothesis


Anderson-Darling Test
The given distribution cannot be tested with A-D test.
```




```
======= Testing lognorm distribution =======
Fitted:  lognorm  with parameters  (np.float64(199.91493757938315), np.float64(-5e-324), np.float64(5.716418066453
KS Test
```

```
KS Test
KS Test Statistics:  0.5366619267346995
p-value is  0.0004995437014434428 . Reject null hypothesis


Anderson-Darling Test
The given distribution cannot be tested with A-D test.
/usr/local/lib/python3.11/dist-packages/scipy/stats/_continuous_distns.py:6626: RuntimeWarning: overflow encountere
  return np.sum((1 + np.log(shifted/scale)/shape**2)/shifted)
/usr/local/lib/python3.11/dist-packages/numpy/_core/fromnumeric.py:86: RuntimeWarning: overflow encountered in redu
  return ufunc.reduce(obj, axis, dtype, out, **passkwargs)
```




```
Summary of Distribution Tests:
  Distribution  KS Statistic    KS p-value  Reject Null
3      lognorm      0.536662  4.995437e-04        True
```

```
2  weibull_min      0.923077  6.603382e-15         True
1        gamma      0.923077  6.603382e-15         True
0        expon      0.923077  6.603382e-15         True
```

Start coding or generate with AI.

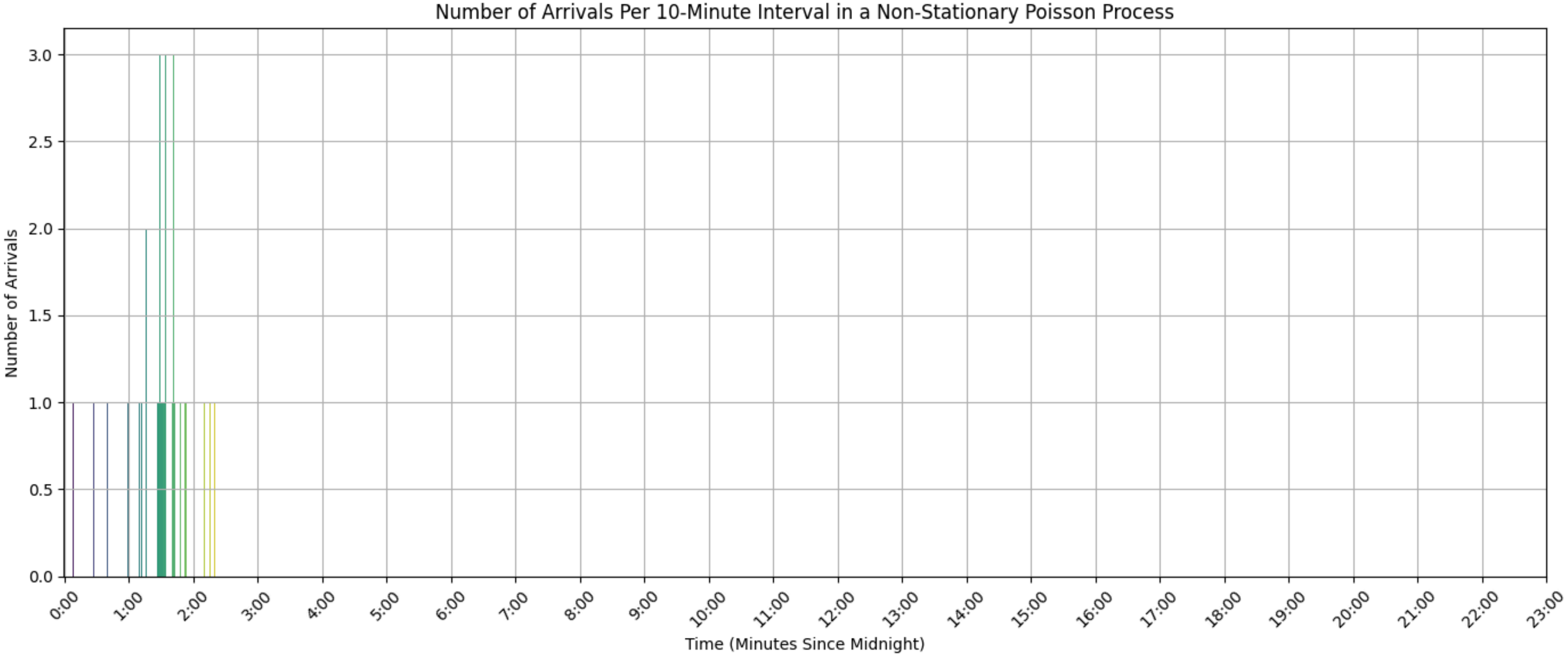
```
# Assuming df['creationDate'] already converted to datetime
df_d1['hour'] = df_d1['creationDate'].dt.hour

hourly_counts = df_d1.groupby('hour').size()

plt.figure(figsize=(10, 5))
sns.barplot(x=hourly_counts.index, y=hourly_counts.values, palette='viridis')
plt.title("Order Counts Per Hour of the Day")
plt.xlabel("Hour of Day")
plt.ylabel("Number of Orders")
plt.grid(True)
plt.xticks(range(0, 24))
plt.tight_layout()
plt.show()
```

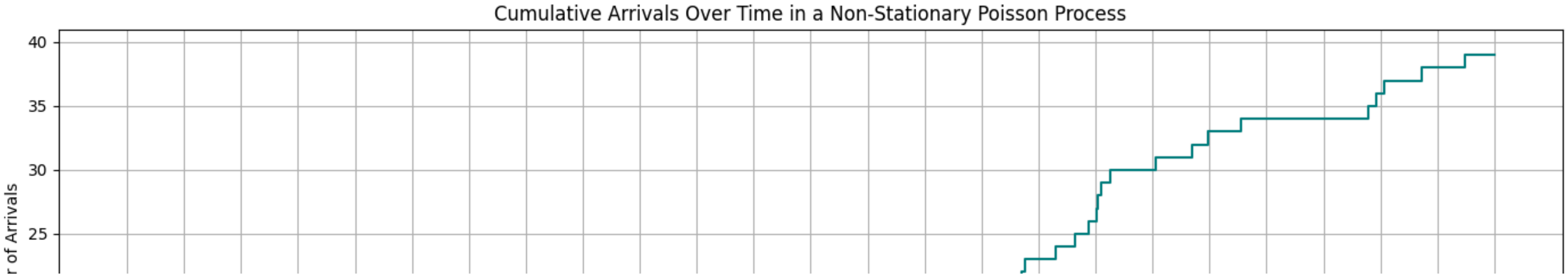
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Set random seed for reproducibility
np.random.seed(42)

# Define the time-varying rate function λ(t) for a 24-hour day (in minutes)
def lambda_t(t):
    # t is in minutes (0 to 1440 for a day)
    # Example: Higher rate in afternoon (e.g., around 16:00 = 960 minutes)
    base_rate = 0.01  # Baseline rate (arrivals per minute)
    peak_rate = 0.1   # Peak rate during busy hours
    # Gaussian-like peak around 16:00 (960 minutes)
    return base_rate + peak_rate * np.exp(-((t - 960)**2) / (2 * 120**2))
```

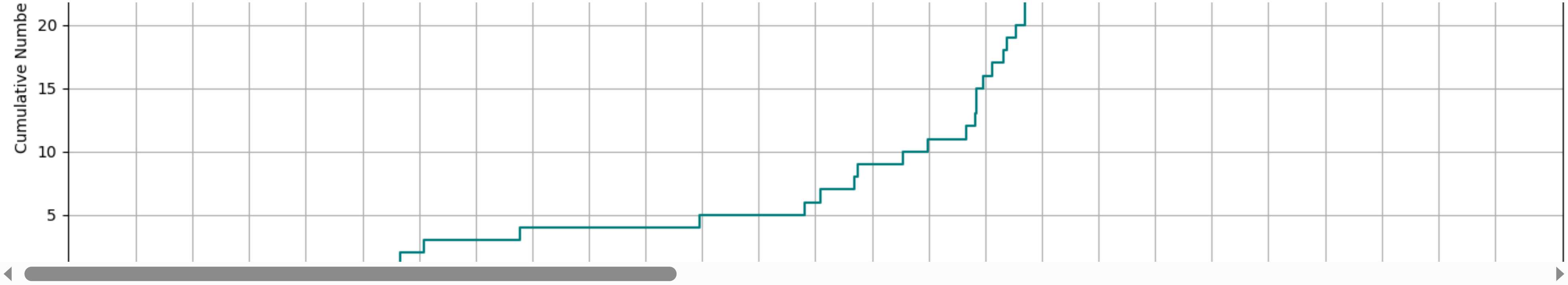
```
# Simulate non-stationary Poisson process using thinning algorithm
def simulate_nonstationary_poisson(lambda_func, T=1440):
    # T is total time in minutes (1440 = 24 hours)
    lambda_max = max(lambda_func(np.linspace(0, T, 1000)))  # Upper bound for λ(t)
    t = 0
    arrivals = []

    while t < T:
        # Generate candidate arrival time
        t += np.random.exponential(1 / lambda_max)
        if t >= T:
            break
        # Accept with probability λ(t)/λ_max
        if np.random.uniform(0, 1) < lambda_func(t) / lambda_max:
            arrivals.append(t)

    return np.array(arrivals)

# Simulate arrivals for one day
T = 1440  # 24 hours in minutes
arrival_times = simulate_nonstationary_poisson(lambda_t, T)

# Create a DataFrame with arrival times
df_arrivals = pd.DataFrame({'time_minutes': arrival_times})

# Bin arrivals into 10-minute intervals for plotting
bins = np.arange(0, T + 10, 10)  # 10-minute bins
df_arrivals['time_bin'] = pd.cut(df_arrivals['time_minutes'], bins=bins, labels=bins[:-1], include_lowest=True)
arrival_counts = df_arrivals.groupby('time_bin').size().reindex(bins[:-1], fill_value=0)

# Plot arrivals per 10-minute interval
plt.figure(figsize=(14, 6))
sns.barplot(x=arrival_counts.index, y=arrival_counts.values, palette='viridis')
plt.title("Number of Arrivals Per 10-Minute Interval in a Non-Stationary Poisson Process")
plt.xlabel("Time (Minutes Since Midnight)")
plt.ylabel("Number of Arrivals")
```

```
    plt.grid(True)
    plt.xticks(np.arange(0, T, 60), labels=[f"{int(t//60)}:00" for t in np.arange(0, T, 60)], rotation=45)
    plt.tight_layout()
    plt.show()

    # Optional: Plot cumulative arrivals
    plt.figure(figsize=(14, 6))
    plt.step(np.concatenate([[0], arrival_times, [T]]),
             np.concatenate([[0], np.arange(1, len(arrival_times) + 1), [len(arrival_times)]]),
             where='post', color='teal')
    plt.title("Cumulative Arrivals Over Time in a Non-Stationary Poisson Process")
    plt.xlabel("Time (Minutes Since Midnight)")
    plt.ylabel("Cumulative Number of Arrivals")
    plt.grid(True)
    plt.xticks(np.arange(0, T + 1, 60), labels=[f"{int(t//60)}:00" for t in np.arange(0, T + 1, 60)], rotation=45)
    plt.tight_layout()
    plt.show()
```

```
<ipython-input-121-59ed0f5db6ce>:46: FutureWarning: The default of observed=False is deprecated and will be changed
  arrival_counts = df_arrivals.groupby('time_bin').size().reindex(bins[:-1], fill_value=0)
<ipython-input-121-59ed0f5db6ce>:50: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `

  sns.barplot(x=arrival_counts.index, y=arrival_counts.values, palette='viridis')
```







These three plots give **excellent clarity** for understanding the dynamics of your warehouse's order arrivals and are great for informing your **Discrete Event Simulation (DES)** model in AnyLogic. Here's a breakdown of each with insights and how they can help structure your simulation:

📊 1. Order Counts Per Hour of the Day (Barplot)

Insight:

- Massive spike at **7 AM**, which likely corresponds to a **batch job or scheduled order upload**.
- Steady flow from **10 AM to 4 PM**, with smaller peaks around 11 AM and 3-4 PM.
- Minimal activity before 7 AM and after 5 PM.

Simulation Implication:

- You should **model a burst arrival** at 7 AM (possibly a bulk order drop).
- Between 10 AM to 4 PM, use a **time-varying Poisson process** or **non-homogeneous Poisson process** for arrivals.
- Outside active hours, arrival rates can be set close to zero or ignored.

📈 2. Order Volume Per Day (Line Plot)

Insight:

- Significant **fluctuations across days**, with some clear spikes.

- There's **weekly seasonality** visible — higher order counts on certain days.
- Possible data gaps or lower activity in mid-June and August.

Simulation Implication:

- **Use a date-dependent distribution** if you're modeling over long time periods.
- Consider **weekly cycles** with high volume days like Wednesday/Thursday and low volume on weekends.
- You may simulate a representative day (e.g., Wednesday vs. Sunday) if full-scale simulation is infeasible.

🔥 3. Heatmap of Order Volume by Weekday and Hour

Insight:

- **Wednesday and Thursday are peak days**, especially 7 AM and 10-11 AM.
- **Saturday is silent**. Sunday has sparse activity — aligns with a warehouse closed/low-staff schedule.
- Heatmap reveals **when operators are most loaded**, which can help in shift planning.

Simulation Implication:

- Your simulation model should:
  - Account for **day-of-week** and **hour-of-day** jointly.
  - Assign **higher arrival intensities for mid-week mornings**.
  - Possibly skip or modify the process for weekends.
- Use this to **parameterize arrival rates for each weekday-hour** combo.

✅ Recommendation for Next Step:

Since your goal is to **fit a distribution** for DES input:

1. **Bin creation timestamps by weekday & hour**.
2. **Estimate arrival rates** per bin (e.g., orders/hour).
3. Fit **Poisson or time-varying rate models**, possibly smoothed by kernel density or lowess.