Supply Chain Analytics

Objectives

- Conduct a clustering analysis of SKUs to identify distinct groups based on sales patterns and other relevant features.
- Determine the key factors influencing each SKU cluster.

In [ ]:
```
import warnings

import folium
import geopandas as gpd
import matplotlib.pyplot as plt
import pandas as pd
import squarify
from matplotlib.ticker import FuncFormatter, PercentFormatter
from shapely.geometry import Point

warnings.filterwarnings("ignore")

pd.set_option("display.max_rows", None)
pd.set_option("display.max_columns", None)
```

In [ ]:
```
df = pd.read_csv(
    filepath_or_buffer="data\DataCoSupplyChainDataset.csv", encoding="latin-1"
)
```

In [ ]:
```
df.shape
```

Out[ ]:
```
(180519, 53)
```

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

Out[ ]:

	Type	Days for shipping (real)	Days for shipment (scheduled)	Benefit per order	Sales per customer	Delivery Status	Late_delivery_risk	Category Id	Category Name	Customer City	Customer Country	Cu
0	DEBIT	3	4	91.250000	314.640015	Advance shipping	0	73	Sporting Goods	Caguas	Puerto Rico	XXXX
1	TRANSFER	5	4	-249.089996	311.359985	Late delivery	1	73	Sporting Goods	Caguas	Puerto Rico	XXXX
2	CASH	4	4	-247.779999	309.720001	Shipping on time	0	73	Sporting Goods	San Jose	EE. UU.	XXXX
3	DEBIT	3	4	22.860001	304.809998	Advance shipping	0	73	Sporting Goods	Los Angeles	EE. UU.	XXXX
4	PAYMENT	2	4	134.210007	298.250000	Advance shipping	0	73	Sporting Goods	Caguas	Puerto Rico	XXXX

In [ ]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 180519 entries, 0 to 180518
Data columns (total 53 columns):
 #   Column                         Non-Null Count   Dtype
---  ------                         --------------   -----
 0   Type                           180519 non-null  object
 1   Days for shipping (real)       180519 non-null  int64
```

```
2   Days for shipment (scheduled)  180519 non-null  int64
3   Benefit per order              180519 non-null  float64
4   Sales per customer             180519 non-null  float64
5   Delivery Status                180519 non-null  object
6   Late_delivery_risk             180519 non-null  int64
7   Category Id                    180519 non-null  int64
8   Category Name                  180519 non-null  object
9   Customer City                  180519 non-null  object
10  Customer Country               180519 non-null  object
11  Customer Email                 180519 non-null  object
12  Customer Fname                 180519 non-null  object
13  Customer Id                    180519 non-null  int64
14  Customer Lname                 180511 non-null  object
15  Customer Password              180519 non-null  object
16  Customer Segment               180519 non-null  object
17  Customer State                 180519 non-null  object
18  Customer Street                180519 non-null  object
19  Customer Zipcode               180516 non-null  float64
20  Department Id                  180519 non-null  int64
21  Department Name                180519 non-null  object
22  Latitude                       180519 non-null  float64
23  Longitude                      180519 non-null  float64
24  Market                         180519 non-null  object
25  Order City                     180519 non-null  object
26  Order Country                  180519 non-null  object
27  Order Customer Id              180519 non-null  int64
28  order date (DateOrders)        180519 non-null  object
29  Order Id                       180519 non-null  int64
30  Order Item Cardprod Id         180519 non-null  int64
31  Order Item Discount            180519 non-null  float64
32  Order Item Discount Rate       180519 non-null  float64
33  Order Item Id                  180519 non-null  int64
34  Order Item Product Price       180519 non-null  float64
35  Order Item Profit Ratio        180519 non-null  float64
36  Order Item Quantity            180519 non-null  int64
37  Sales                          180519 non-null  float64
38  Order Item Total               180519 non-null  float64
39  Order Profit Per Order         180519 non-null  float64
40  Order Region                   180519 non-null  object
41  Order State                    180519 non-null  object
42  Order Status                   180519 non-null  object
```

```
 43  Order Zipcode                  24840 non-null   float64
 44  Product Card Id                180519 non-null  int64
 45  Product Category Id            180519 non-null  int64
 46  Product Description            0 non-null       float64
 47  Product Image                  180519 non-null  object
 48  Product Name                   180519 non-null  object
 49  Product Price                  180519 non-null  float64
 50  Product Status                 180519 non-null  int64
 51  shipping date (DateOrders)     180519 non-null  object
 52  Shipping Mode                  180519 non-null  object
dtypes: float64(15), int64(14), object(24)
memory usage: 73.0+ MB
```

In [ ]:

```
# Drop unnecessary columns, containing missing data
df.drop(
    columns=[
        "Product Description",
        "Customer Fname",
        "Customer Lname",
        "Customer Zipcode",
        "Order Zipcode",
        "Customer Email",
        "Customer Password",
        "Product Image",
        "Category Id",
        "Customer Id",
        "Department Id",
        "Order Customer Id",
        "Order Id",
        "Order Item Cardprod Id",
        "Order Item Id",
        "Product Card Id",
        "Product Category Id",
    ],
    inplace=True,
)
# Change the date-columns to the appropriate format
df["order date (DateOrders)"] = pd.to_datetime(df["order date (DateOrders)"])
df["shipping date (DateOrders)"] = pd.to_datetime(df["shipping date (DateOrders)"])
df["Year"] = df["order date (DateOrders)"].dt.year
```

In [ ]:
```python
df.isnull().sum().any()
```

Out[ ]:
```
False
```

In [ ]:
```python
df.duplicated().any()
```

Out[ ]:
```
False
```

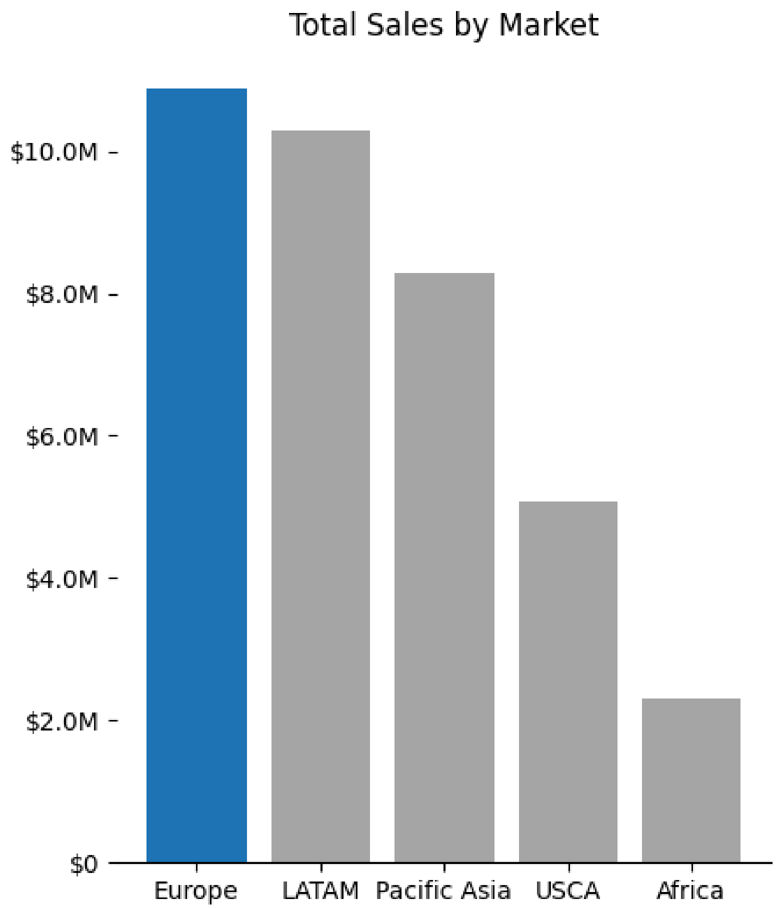
In [ ]:
```python
print(df["order date (DateOrders)"].min(), df["order date (DateOrders)"].max())
```

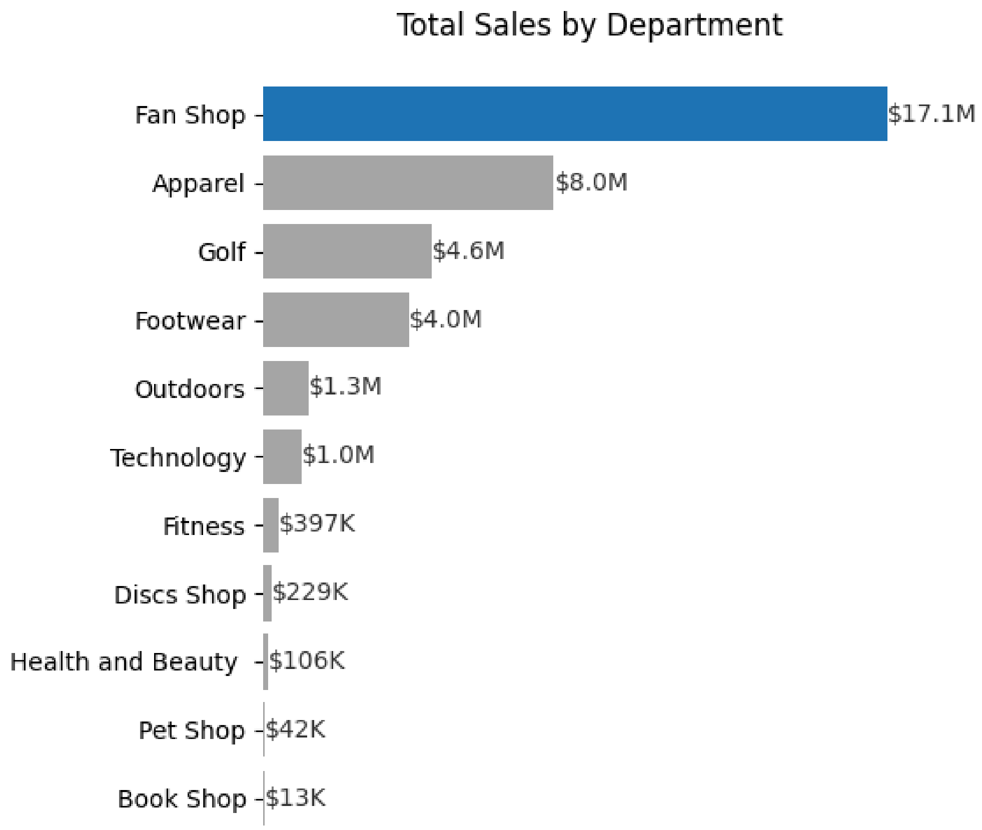
```
2015-01-01 00:00:00 2018-01-31 23:38:00
```

In [ ]:
```python
market_sales = df.groupby("Market")["Sales"].sum().sort_values(ascending=False)
department_sales = (
    df.groupby("Department Name", observed=False)["Sales"]
    .sum()
    .sort_values(ascending=True)
)
```

In [ ]:
```python
# Get the top markets and departments
top_markets = dict(
    sorted(market_sales.items(), key=lambda item: item[1], reverse=True)[:1]
)
top_department = "Fan Shop"


# Define a currency formatter function
def currency_formatter(x, pos):
    if x >= 1e9:
        return "${:,.1f}B".format(x / 1e9)
    elif x >= 1e6:
        return "${:,.1f}M".format(x / 1e6)
    elif x >= 1e3:
        return "${:,.0f}K".format(x / 1e3)
    else:
        return "${:,.0f}".format(x)


# Create the figure and subplots
fig, ax = plt.subplots(nrows=1, ncols=2, figsize=(12, 6))
```

```python
# Plot sales by market
for market, sales in market_sales.items():
    color = "tab:blue" if market in top_markets else "darkgrey"
    ax[0].bar(market, sales, color=color)

ax[0].set_title("Total Sales by Market")
ax[0].yaxis.set_major_formatter(FuncFormatter(currency_formatter))

# Plot sales by department
for department, sales in department_sales.items():
    color = "tab:blue" if department == top_department else "darkgrey"
    barh = ax[1].barh(department, sales, color=color)
    ax[1].text(
        sales,
        department,
        currency_formatter(sales, None),
        va="center",
        ha="left",
        color="black",
        alpha=0.8,
    )

ax[1].set_title("Total Sales by Department")
ax[1].xaxis.set_major_formatter(FuncFormatter(currency_formatter))
ax[1].spines["bottom"].set_visible(False)
ax[1].xaxis.set_visible(False)

for axes in ax:
    axes.spines[["top", "right", "left"]].set_visible(False)
    axes.set_axisbelow(True)

plt.subplots_adjust(wspace=0.5)
plt.show()
```





Europe and Latin America (LATAM) seem to be larger markets compared to all other regions combined. Let's look at it on an annual basis.

In [ ]:
```
df.pivot_table(index="Year", columns="Market", values="Sales", aggfunc="sum")
```

Out[ ]:

Market	Africa	Europe	LATAM	Pacific Asia	USCA
Year					
2015	NaN	4.913405e+06	5.072188e+06	2.355238e+06	NaN
2016	2.046623e+06	7.613233e+05	NaN	4.452406e+06	5.043466e+06

2017	2.478302e+05	5.197668e+06	5.205424e+06	1.134450e+06	2.306319e+04
2018	NaN	NaN	NaN	3.316501e+05	NaN

According to the table;

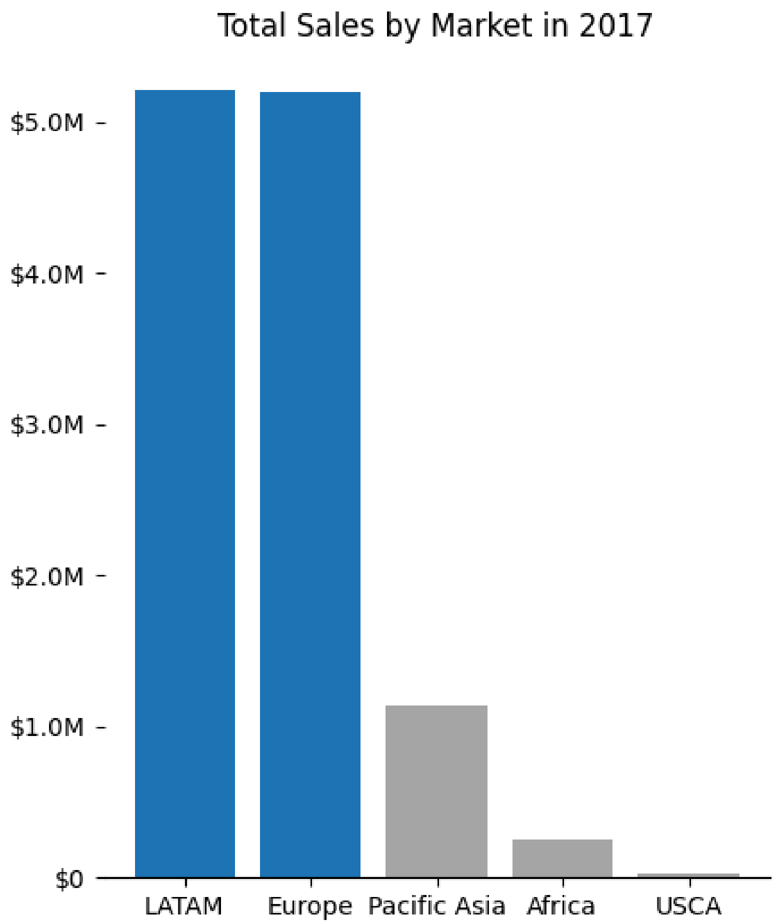
- The company entered the **African** market in 2016.
- The company stopped its operations in **LATAM** in 2016 and restarted them in 2017.
- The company entered the **USCA** market in 2016.

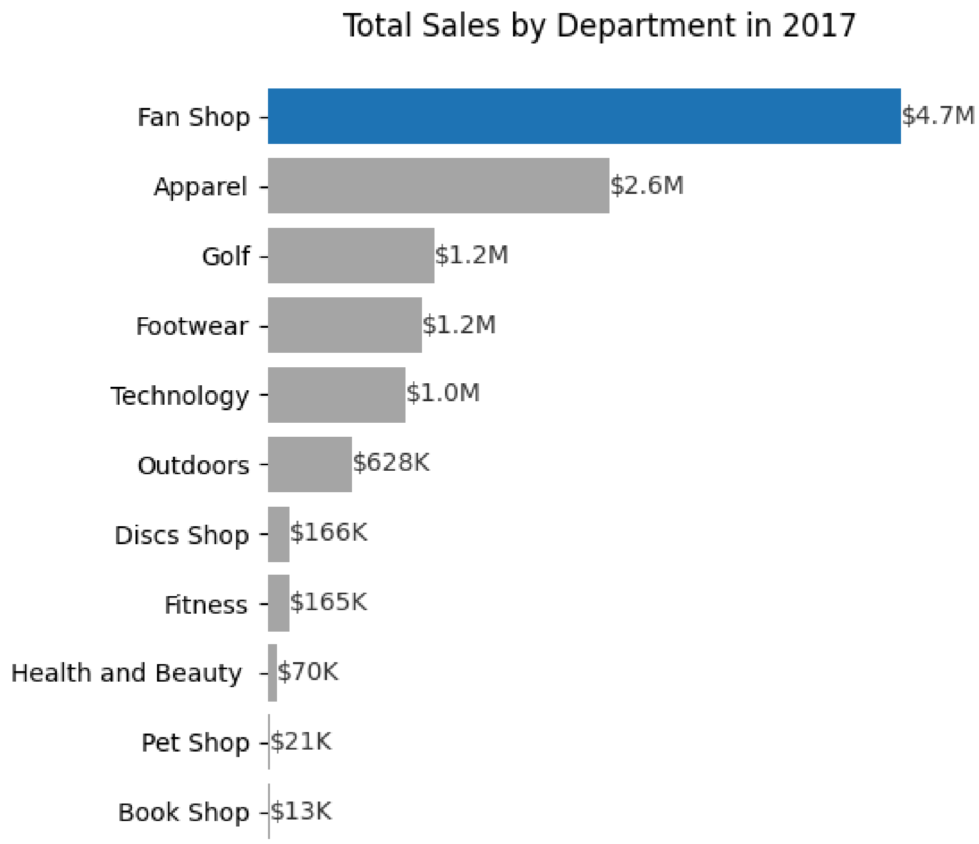
To maintain consistency, we can only consider **2017** for inventory management processes.

In [ ]:
```
df_ = df.query("Year == 2017")
```

In [ ]:
```
market_sales_2017 = df_.groupby("Market")["Sales"].sum().sort_values(ascending=False)
department_sales_2017 = (
    df_.groupby("Department Name", observed=False)["Sales"]
    .sum()
    .sort_values(ascending=True)
)

top_markets_2017 = dict(
    sorted(market_sales_2017.items(), key=lambda item: item[1], reverse=True)[:2]
)
top_department_2017 = "Fan Shop"

# Create the figure and subplots
fig, ax = plt.subplots(nrows=1, ncols=2, figsize=(12, 6))

# Plot sales by market
for market, sales in market_sales_2017.items():
    color = "tab:blue" if market in top_markets_2017 else "darkgrey"
    ax[0].bar(market, sales, color=color)

ax[0].set_title("Total Sales by Market in 2017")
ax[0].yaxis.set_major_formatter(FuncFormatter(currency_formatter))

# Plot sales by department
```

```python
for department, sales in department_sales_2017.items():
    color = "tab:blue" if department == top_department_2017 else "darkgrey"
    barh = ax[1].barh(department, sales, color=color)
    ax[1].text(
        sales,
        department,
        currency_formatter(sales, None),
        va="center",
        ha="left",
        color="black",
        alpha=0.8,
    )

ax[1].set_title("Total Sales by Department in 2017")
ax[1].xaxis.set_major_formatter(FuncFormatter(currency_formatter))
ax[1].spines["bottom"].set_visible(False)
ax[1].xaxis.set_visible(False)

for axes in ax:
    axes.spines[["top", "right", "left"]].set_visible(False)
    axes.set_axisbelow(True)

plt.subplots_adjust(wspace=0.5)
plt.show()
```

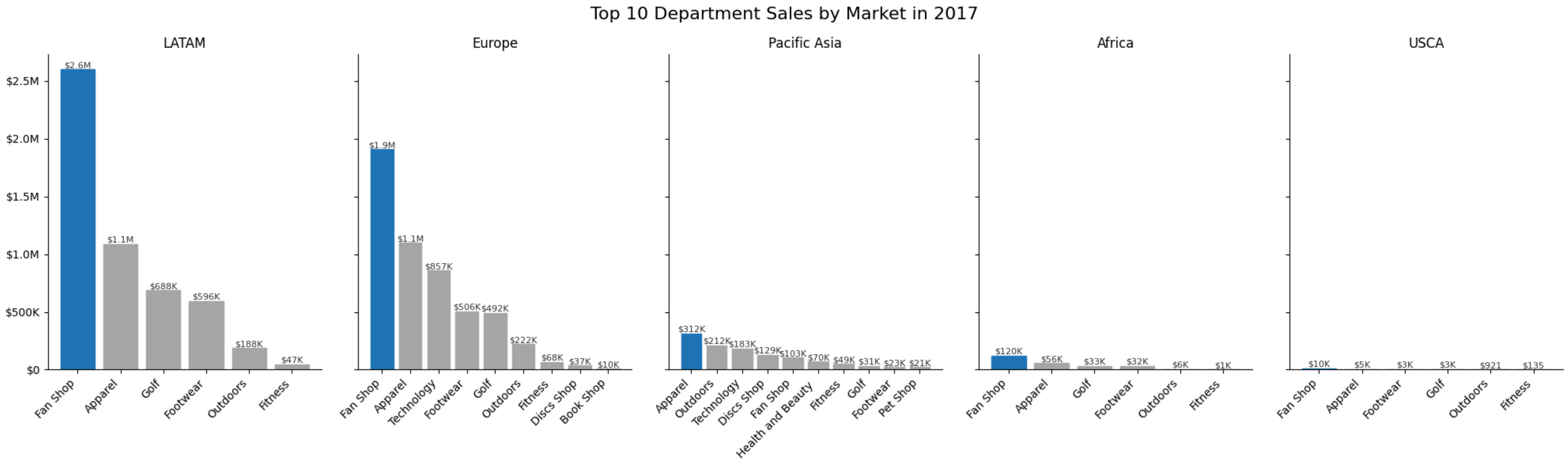




LATAM and Europe appear to be the largest markets in terms of sales, followed by Pacific Asia, Africa, and USCA.

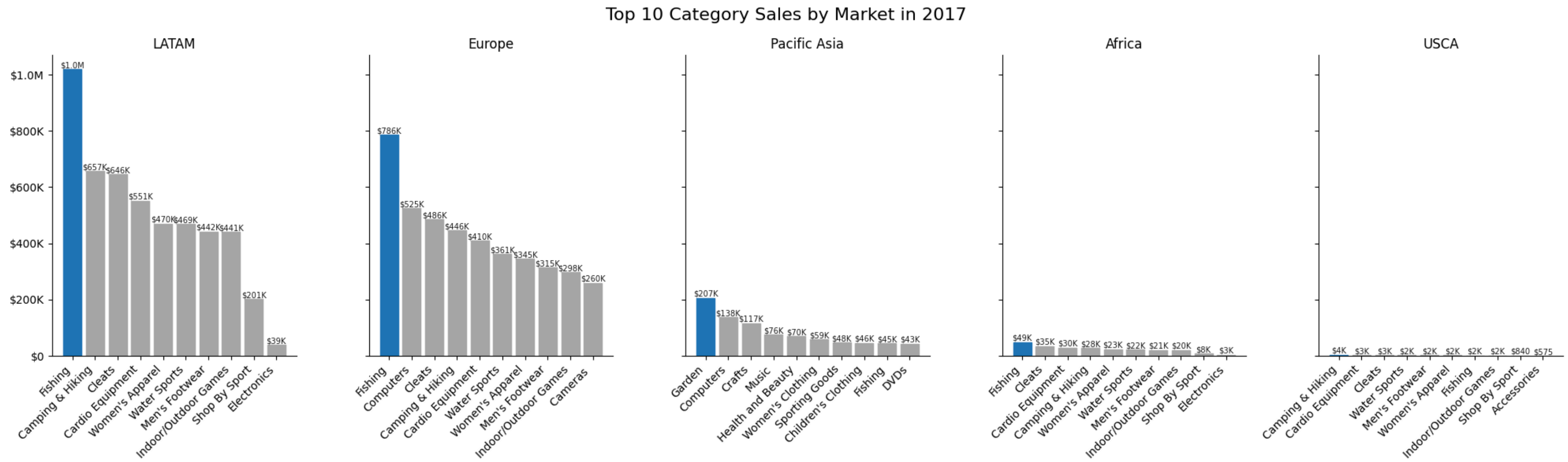
In [ ]:
```
market_sales_idx = (
    df_.groupby("Market")["Sales"].sum().sort_values(ascending=False).index
)
total_sales_by_market_department = (
    df_.groupby(["Market", "Department Name"])["Sales"].sum().reset_index()
)
top5_departments = (
    total_sales_by_market_department.groupby("Market")
    .apply(lambda x: x.nlargest(10, "Sales"))
```

```python
    .reset_index(drop=True)
)

fig, axs = plt.subplots(nrows=1, ncols=5, figsize=(20, 6), sharey=True)

for ax, market in zip(axs, market_sales_idx):
    data = top5_departments[top5_departments["Market"] == market]
    max_sales_department = data.loc[data["Sales"].idxmax()]
    bars = ax.bar(data["Department Name"], data["Sales"])
    for bar in bars:
        if bar.get_height() == max_sales_department["Sales"]:
            bar.set_color("tab:blue")
        else:
            bar.set_color("darkgray")

    ax.set_title(market)
    ax.yaxis.set_major_formatter(FuncFormatter(currency_formatter))
    ax.spines[["top", "right"]].set_visible(False)

    for i, (index, row) in enumerate(data.iterrows()):
        # Use the index of the bar as the x-coordinate
        ax.text(
            i,
            row["Sales"],
            currency_formatter(row["Sales"], None),
            va="bottom",
            ha="center",
            color="black",
            alpha=0.8,
            fontsize=8,
        )
    ax.set_axisbelow(False)
    ax.set_xticklabels(data["Department Name"], rotation=45, ha="right")
fig.suptitle("Top 10 Department Sales by Market in 2017", fontsize=16)
plt.tight_layout()
plt.show()
```



In [ ]:
```
total_sales_by_market_category = (
    df_.groupby(["Market", "Category Name"])["Sales"].sum().reset_index()
)

top5_departments = (
    total_sales_by_market_category.groupby("Market")
    .apply(lambda x: x.nlargest(10, "Sales"))
    .reset_index(drop=True)
)

fig, axs = plt.subplots(nrows=1, ncols=5, figsize=(20, 6), sharey=True)

for ax, market in zip(axs, market_sales_idx):
    data = top5_departments[top5_departments["Market"] == market]
    max_sales_category = data.loc[data["Sales"].idxmax()]
    bars = ax.bar(data["Category Name"], data["Sales"])
    for bar in bars:
        if bar.get_height() == max_sales_category["Sales"]:
            bar.set_color("tab:blue")
        else:
            bar.set_color("darkgray")

    ax.set_title(market)
```

```
    ax.yaxis.set_major_formatter(FuncFormatter(currency_formatter))
    ax.spines[["top", "right"]].set_visible(False)

    for i, (index, row) in enumerate(data.iterrows()):
        # Use the index of the bar as the x-coordinate
        ax.text(
            i,
            row["Sales"],
            currency_formatter(row["Sales"], None),
            va="bottom",
            ha="center",
            color="black",
            alpha=0.9,
            fontsize=7.1,
        )
    ax.set_axisbelow(False)
    ax.set_xticklabels(data["Category Name"], rotation=45, ha="right")
fig.suptitle("Top 10 Category Sales by Market in 2017", fontsize=16)
plt.tight_layout()
plt.show()
```



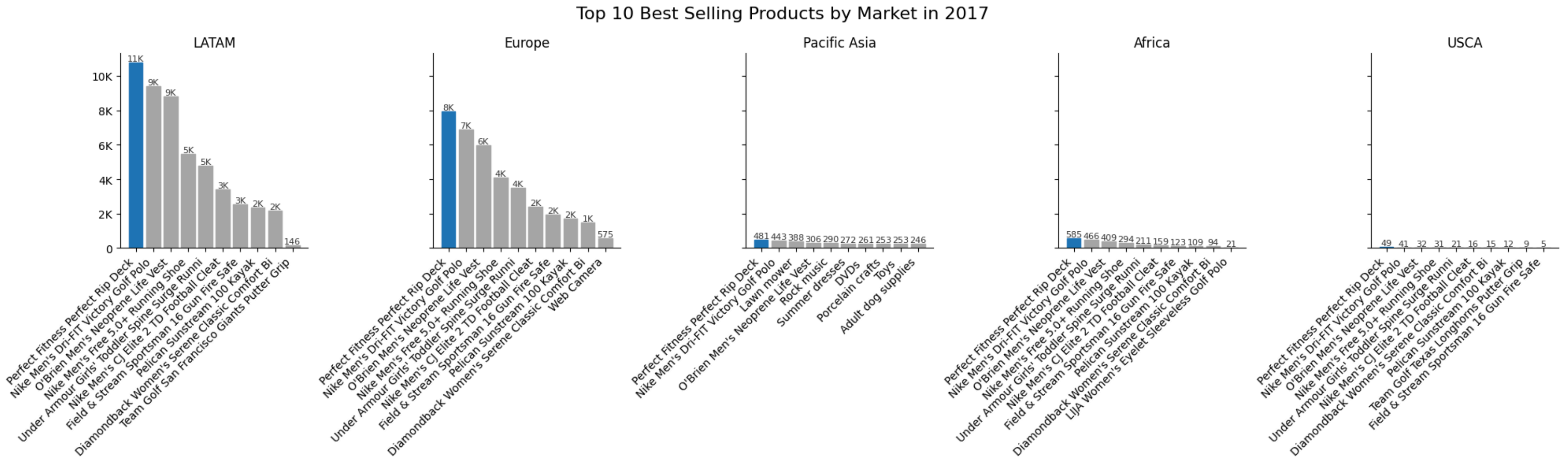
In [ ]:

```
def quantity_formatter(x, pos):
    if x >= 1e9:
        return "{:,.1f}B".format(x / 1e9)
```

```python
    elif x >= 1e6:
        return "{:,.1f}M".format(x / 1e6)
    elif x >= 1e3:
        return "{:,.0f}K".format(x / 1e3)
    else:
        return "{:,.0f}".format(x)
```

In [ ]:
```python
market_order_idx = (
    df_.groupby("Market")["Order Item Quantity"]
    .sum()
    .sort_values(ascending=False)
    .index
)
total_order_by_market_product = (
    df_.groupby(["Market", "Product Name"])["Order Item Quantity"].sum().reset_index()
)

top10_product = (
    total_order_by_market_product.groupby("Market")
    .apply(lambda x: x.nlargest(10, "Order Item Quantity"))
    .reset_index(drop=True)
)

fig, axs = plt.subplots(nrows=1, ncols=5, figsize=(20, 6), sharey=True)

for ax, market in zip(axs, market_order_idx):
    data = top10_product[top10_product["Market"] == market]
    max_order_product = data.loc[data["Order Item Quantity"].idxmax()]
    bars = ax.bar(data["Product Name"], data["Order Item Quantity"])
    for bar in bars:
        if bar.get_height() == max_order_product["Order Item Quantity"]:
            bar.set_color("tab:blue")
        else:
            bar.set_color("darkgray")

    ax.set_title(market)
    ax.yaxis.set_major_formatter(FuncFormatter(quantity_formatter))
    ax.spines[["top", "right"]].set_visible(False)

    for i, (index, row) in enumerate(data.iterrows()):
```

```
        # Use the index of the bar as the x-coordinate
        ax.text(
            i,
            row["Order Item Quantity"],
            quantity_formatter(row["Order Item Quantity"], None),
            va="bottom",
            ha="center",
            color="black",
            alpha=0.8,
            fontsize=8,
        )
    ax.set_axisbelow(False)
    ax.set_xticklabels(data["Product Name"], rotation=45, ha="right")
fig.suptitle("Top 10 Best Selling Products by Market in 2017", fontsize=16)
plt.tight_layout()
plt.show()
```



The 'Perfect Fitness Perfect Rip Deck' is the top-selling product in all markets. LATAM market shows higher performance in terms of order quantity compared to other markets.

In [ ]:

```
df_.columns
```

Out[ ]:
```
Index(['Type', 'Days for shipping (real)', 'Days for shipment (scheduled)',
       'Benefit per order', 'Sales per customer', 'Delivery Status',
       'Late_delivery_risk', 'Category Name', 'Customer City',
       'Customer Country', 'Customer Segment', 'Customer State',
       'Customer Street', 'Department Name', 'Latitude', 'Longitude', 'Market',
       'Order City', 'Order Country', 'order date (DateOrders)',
       'Order Item Discount', 'Order Item Discount Rate',
       'Order Item Product Price', 'Order Item Profit Ratio',
       'Order Item Quantity', 'Sales', 'Order Item Total',
       'Order Profit Per Order', 'Order Region', 'Order State', 'Order Status',
       'Product Name', 'Product Price', 'Product Status',
       'shipping date (DateOrders)', 'Shipping Mode', 'Year'],
      dtype='object')
```

Creating World Map with Geopandas

In [ ]:
```
all_countries_sales = df_.groupby(["Order Country"])["Sales"].sum().reset_index()
all_cities_sales = df_.groupby(["Order City"])["Sales"].sum().reset_index()
all_order_region_sales = df_.groupby(["Order Region"])["Sales"].sum().reset_index()
```

In [ ]:
```
brasil_sales_query = all_countries_sales.query("`Order Country` == 'Brasil'")
```

In [ ]:
```
all_countries_sales.shape
```

Out[ ]:
```
(129, 2)
```

In [ ]:
```
world = gpd.read_file(gpd.datasets.get_path("naturalearth_lowres"))
```

In [ ]:
```
world.query("name == 'Brazil'")
```

Out[ ]:

	pop_est	continent	name	iso_a3	gdp_md_est	geometry
29	211049527.0	South America	Brazil	BRA	1839758	POLYGON ((-53.37366 -33.76838, -53.65054 -33.2...

Country names do not match. Let's see which countries don't match.

In [ ]:
```
unmatched_countries = set(all_countries_sales["Order Country"]).difference(
    set(world["name"])
)
```

In [ ]:
```
unmatched_countries
```

Out[ ]:
```
{'Afganistán',
 'Alemania',
 'Arabia Saudí',
 'Argelia',
 'Azerbaiyán',
 'Bangladés',
 'Barbados',
 'Belice',
 'Benín',
 'Bielorrusia',
 'Bosnia y Herzegovina',
 'Brasil',
 'Bután',
 'Bélgica',
 'Camboya',
 'Camerún',
 'Chipre',
 'Corea del Sur',
 'Costa de Marfil',
 'Croacia',
 'Dinamarca',
 'Egipto',
 'Eslovaquia',
 'España',
 'Filipinas',
 'Finlandia',
 'Francia',
 'Gabón',
 'Grecia',
 'Guadalupe',
 'Guayana Francesa',
 'Haití',
 'Hong Kong',
 'Hungría',
```

```
'Irak',
'Irlanda',
'Irán',
'Italia',
'Japón',
'Jordania',
'Kazajistán',
'Kenia',
'Kirguistán',
'Lituania',
'Luxemburgo',
'Líbano',
'Macedonia',
'Malasia',
'Marruecos',
'Martinica',
'Moldavia',
'Myanmar (Birmania)',
'México',
'Noruega',
'Níger',
'Pakistán',
'Panamá',
'Papúa Nueva Guinea',
'Países Bajos',
'Perú',
'Polonia',
'Reino Unido',
'República Checa',
'República Democrática del Congo',
'República Dominicana',
'Ruanda',
'Rumania',
'Rusia',
'Singapur',
'SudAfrica',
'Suecia',
'Suiza',
'Surinam',
'Tailandia',
'Taiwán',
```

```
 'Trinidad y Tobago',
 'Turkmenistán',
 'Turquía',
 'Ucrania',
 'Uzbekistán',
 'Yibuti',
 'Zimbabue'}
```

In [ ]:

```python
mapping_dict = {
    "Afganistán": "Afghanistan",
    "Alemania": "Germany",
    "Arabia Saudí": "Saudi Arabia",
    "Argelia": "Algeria",
    "Azerbaiyán": "Azerbaijan",
    "Bangladés": "Bangladesh",
    "Barbados": "Barbados",
    "Baréin": "Bahrain",
    "Belice": "Belize",
    "Benín": "Benin",
    "Bielorrusia": "Belarus",
    "Bosnia y Herzegovina": "Bosnia and Herzegovina",
    "Botsuana": "Botswana",
    "Brasil": "Brazil",
    "Bután": "Bhutan",
    "Bélgica": "Belgium",
    "Camboya": "Cambodia",
    "Camerún": "Cameroon",
    "Chipre": "Cyprus",
    "Corea del Sur": "South Korea",
    "Costa de Marfil": "Ivory Coast",
    "Croacia": "Croatia",
    "Dinamarca": "Denmark",
    "Egipto": "Egypt",
    "Emiratos Árabes Unidos": "United Arab Emirates",
    "Eslovaquia": "Slovakia",
    "Eslovenia": "Slovenia",
    "España": "Spain",
    "Estados Unidos": "United States of America",
    "Etiopía": "Ethiopia",
    "Filipinas": "Philippines",
    "Finlandia": "Finland",
```

```
    "Francia": "France",
    "Gabón": "Gabon",
    "Grecia": "Greece",
    "Guadalupe": "Guadeloupe",
    "Guayana Francesa": "French Guiana",
    "Guinea Ecuatorial": "Equatorial Guinea",
    "Haití": "Haiti",
    "Hong Kong": "Hong Kong",
    "Hungría": "Hungary",
    "Irak": "Iraq",
    "Irlanda": "Ireland",
    "Irán": "Iran",
    "Italia": "Italy",
    "Japón": "Japan",
    "Jordania": "Jordan",
    "Kazajistán": "Kazakhstan",
    "Kenia": "Kenya",
    "Kirguistán": "Kyrgyzstan",
    "Lesoto": "Lesotho",
    "Libia": "Libya",
    "Lituania": "Lithuania",
    "Luxemburgo": "Luxembourg",
    "Líbano": "Lebanon",
    "Macedonia": "North Macedonia",
    "Malasia": "Malaysia",
    "Marruecos": "Morocco",
    "Martinica": "Martinique",
    "Moldavia": "Moldova",
    "Myanmar (Birmania)": "Myanmar",
    "México": "Mexico",
    "Noruega": "Norway",
    "Nueva Zelanda": "New Zealand",
    "Níger": "Niger",
    "Omán": "Oman",
    "Pakistán": "Pakistan",
    "Panamá": "Panama",
    "Papúa Nueva Guinea": "Papua New Guinea",
    "Países Bajos": "Netherlands",
    "Perú": "Peru",
    "Polonia": "Poland",
    "Reino Unido": "United Kingdom",
```

```
    "República Centroafricana": "Central African Republic",
    "República Checa": "Czech Republic",
    "República Democrática del Congo": "Democratic Republic of the Congo",
    "República Dominicana": "Dominican Republic",
    "República de Gambia": "The Gambia",
    "República del Congo": "Republic of the Congo",
    "Ruanda": "Rwanda",
    "Rumania": "Romania",
    "Rusia": "Russia",
    "Sierra Leona": "Sierra Leone",
    "Singapur": "Singapore",
    "Siria": "Syria",
    "Suazilandia": "Eswatini",
    "SudAfrica": "South Africa",
    "Sudán": "Sudan",
    "Sudán del Sur": "South Sudan",
    "Suecia": "Sweden",
    "Suiza": "Switzerland",
    "Surinam": "Suriname",
    "Sáhara Occidental": "Western Sahara",
    "Tailandia": "Thailand",
    "Taiwán": "Taiwan",
    "Tayikistán": "Tajikistan",
    "Trinidad y Tobago": "Trinidad and Tobago",
    "Turkmenistán": "Turkmenistan",
    "Turquía": "Turkey",
    "Túnez": "Tunisia",
    "Ucrania": "Ukraine",
    "Uzbekistán": "Uzbekistan",
    "Yibuti": "Djibouti",
    "Zimbabue": "Zimbabwe",
}
```

Let's replace them with their correct names.

In [ ]:

```
all_countries_sales["Order Country"] = all_countries_sales["Order Country"].replace(
    mapping_dict
)
```

Now we can merge the datasets.

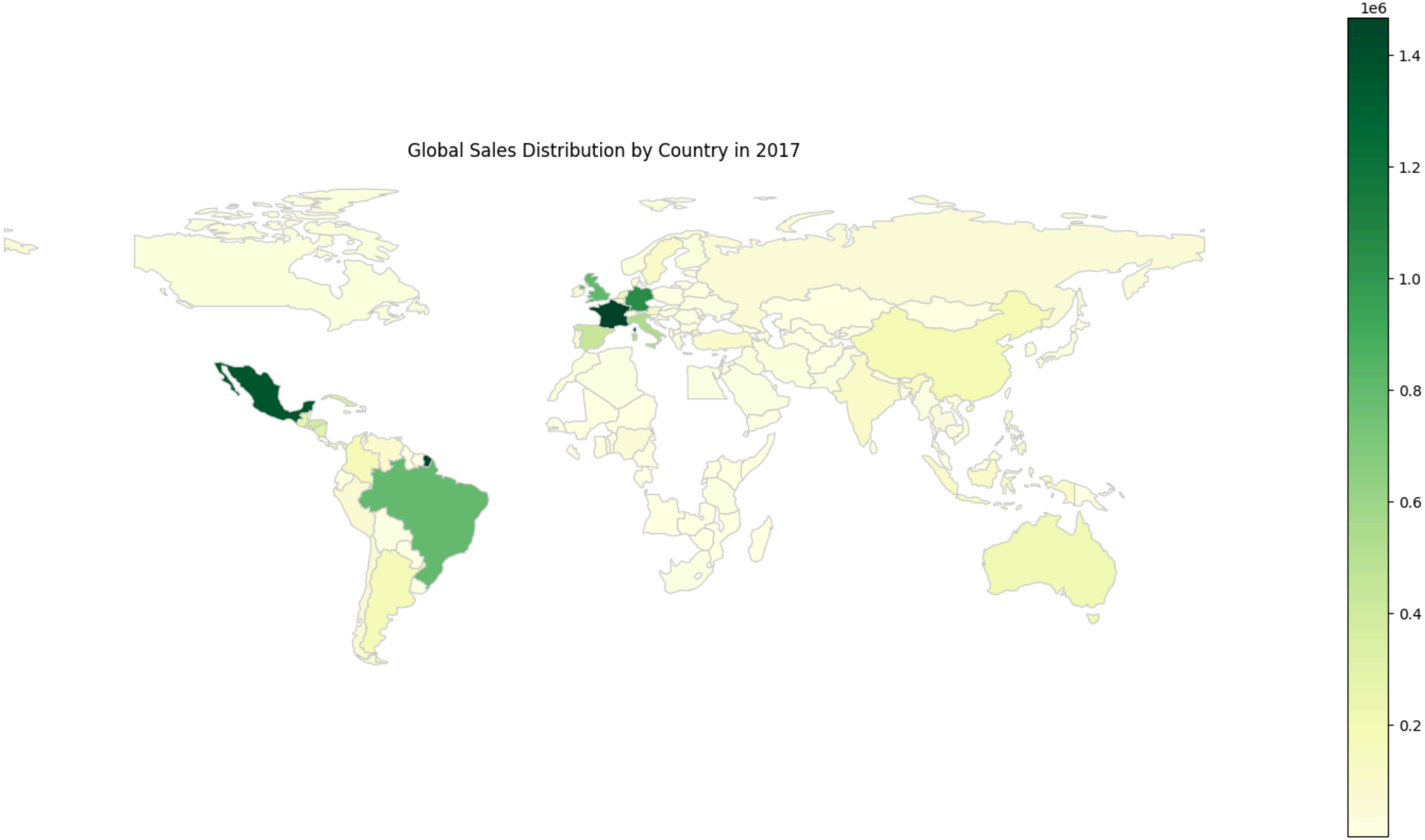
In [ ]:
```
world_sales = world.merge(all_countries_sales, left_on="name", right_on="Order Country")
```

In [ ]:
```
world_sales.head()
```

Out[ ]:

	pop_est	continent	name	iso_a3	gdp_md_est	geometry	Order Country	Sales
0	58005463.0	Africa	Tanzania	TZA	63177	POLYGON ((33.90371 -0.95000, 34.07262 -1.05982...	Tanzania	12913.420294
1	37589262.0	North America	Canada	CAN	1736425	MULTIPOLYGON (((-122.84000 49.00000, -122.9742...	Canada	23063.190499
2	18513930.0	Asia	Kazakhstan	KAZ	181665	POLYGON ((87.35997 49.21498, 86.59878 48.54918...	Kazakhstan	3589.650062
3	33580650.0	Asia	Uzbekistan	UZB	57921	POLYGON ((55.96819 41.30864, 55.92892 44.99586...	Uzbekistan	2642.630039
4	8776109.0	Oceania	Papua New Guinea	PNG	24829	MULTIPOLYGON (((141.00021 -2.60015, 142.73525 ...	Papua New Guinea	425.029999

In [ ]:
```
fig, ax = plt.subplots(figsize=(20, 10))
world_sales.plot(
    column="Sales",
    cmap="YlGn",
    linewidth=0.8,
    edgecolor="0.8",
    legend=True,
    ax=plt.gca(),
).set_axis_off()

# Set the title and show the plot
plt.title("Global Sales Distribution by Country in 2017")
plt.show()
```



In [ ]:

```
# Interactive version of the graph above.
# m = folium.Map(location=[0, 0], zoom_start=3,tiles="cartodb positron")

# folium.Choropleth(
#     geo_data=world_sales,
#     name="choropleth",
#     data=world_sales,
#     columns=["name", "Sales"],
#     key_on="feature.properties.name",
```

```python
#     fill_color="YlGn",
#     fill_opacity=0.7,
#     line_opacity=0.2,
#     nan_fill_color="white",

#     legend_name="Sales",
#      highlight=True,

# ).add_to(m)


# folium.GeoJson(
#     data=world_sales,
#     style_function=lambda feature: {
#         "color":"",
#         "weight": 0.2,
#     },
#     tooltip=folium.GeoJsonTooltip(
#         fields=["name", "Sales"],
#         aliases=["Country:", "Sales: "],
#         labels=True,
#         sticky=True,
#         style="background-color: white;"

#         )
#     ).add_to(m)

# m
```

In [ ]:

```python
world_sales.groupby("Order Country")["Sales"].sum().reset_index(
    name="Sales"
).sort_values(by="Sales", ascending=False)[:10]
```

Out[ ]:

	Order Country	Sales
34	France	1.466954e+06
65	Mexico	1.371471e+06
37	Germany	1.064684e+06

110	United Kingdom	8.170683e+05
15	Brazil	8.019948e+05
51	Italy	5.422939e+05
96	Spain	4.334722e+05
43	Honduras	3.942301e+05
31	El Salvador	3.758007e+05
25	Cuba	3.386557e+05

Let's check the store's location.

In [ ]:
```
# Load the shapefile containing the boundaries of US states
us_states = gpd.read_file("data\states.shp")
```

In [ ]:
```
# Group the data by longitude and latitude to count the number of stores at each location
stores_count = (
    df_.groupby(["Longitude", "Latitude"]).size().reset_index(name="Store_Counts")
)
```

In [ ]:
```
# We need to create Point(longitude,latitude) from Store_count.
# Create a list of Point geometries based on longitude and latitude coordinates
geometry = [
    Point(xy) for xy in zip(stores_count["Longitude"], stores_count["Latitude"])
]

# Add the Point geometries to the stores_count DataFrame as a new column named "point_geometry"
stores_count["point_geometry"] = geometry
```

In [ ]:
```
# Create a GeoDataFrame from the stores_count DataFrame with Point geometries and EPSG:4326 CRS
stores_gdf = gpd.GeoDataFrame(stores_count, geometry="point_geometry", crs="EPSG:4326")
```

Stores are mainly in the US, with some outliers.

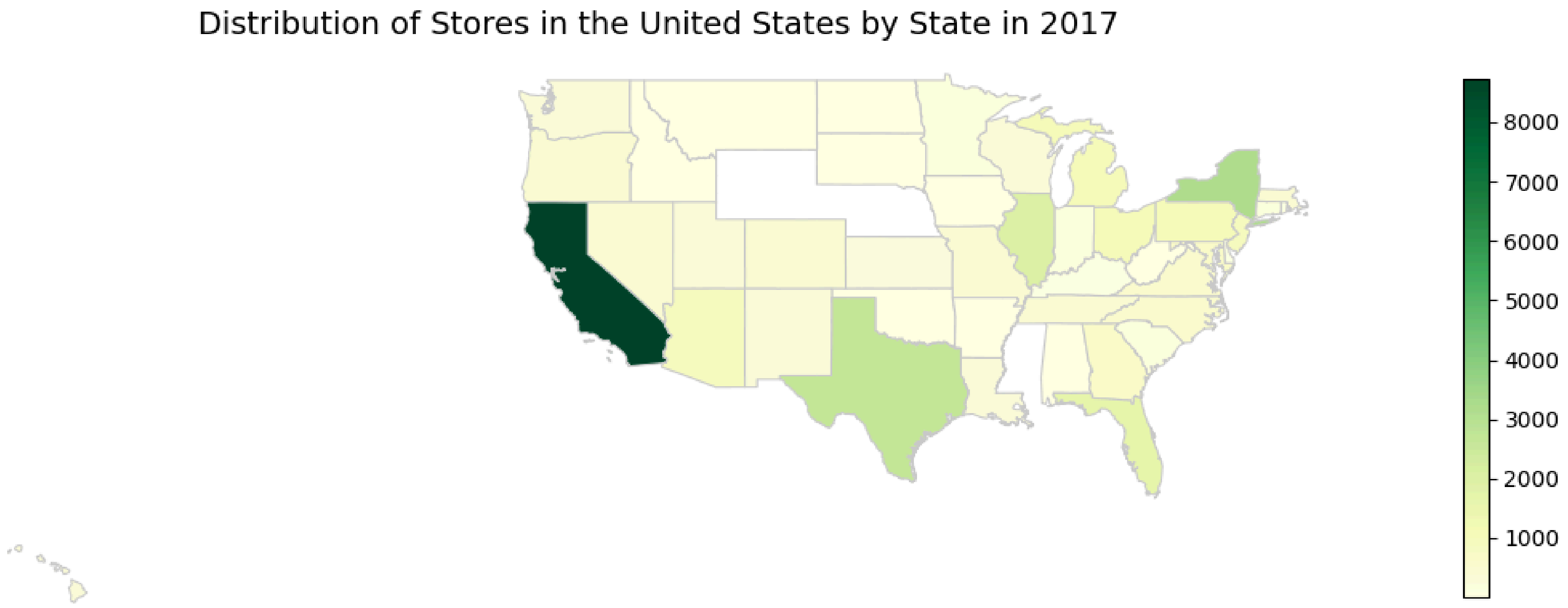
In [ ]:
```
# Create a GeoDataFrame containing only stores that are within the boundaries of the USA states
stores_gdf_usa = stores_gdf[stores_gdf.within(us_states.unary_union)]
```

In [ ]:
```
# Perform a spatial join between the GeoDataFrame of stores within the USA and the GeoDataFrame of USA states
gdf_with_states = gpd.sjoin(stores_gdf_usa, us_states, op="within")
```

In [ ]:
```
# Aggregate store counts by state
state_counts = gdf_with_states.groupby("STATE_NAME")["Store_Counts"].sum().reset_index()
```

In [ ]:
```
merged_states_counts = pd.merge(us_states, state_counts, on="STATE_NAME")
```

In [ ]:
```
fig, ax = plt.subplots(figsize=(18, 14))

merged_states_counts.plot(
    column="Store_Counts",
    cmap="YlGn",
    linewidth=0.8,
    edgecolor="0.8",
    legend=True,
    ax=ax,
).set_axis_off()
cbar = ax.get_figure().colorbar(ax.collections[0], shrink=0.3)
old_cbar = ax.get_figure().get_axes()[1]
old_cbar.remove()
# Set the title and show the plot
plt.title(
    "Distribution of Stores in the United States by State in 2017",
    fontdict={"fontsize": "14", "fontweight": "1"},
)
plt.show()
```



It seems that all the customers are located within the US, however, the orders are shipped worldwide. This indicates that the company might be an online shop, where stores across the US are selling their goods online to customers all over the world.

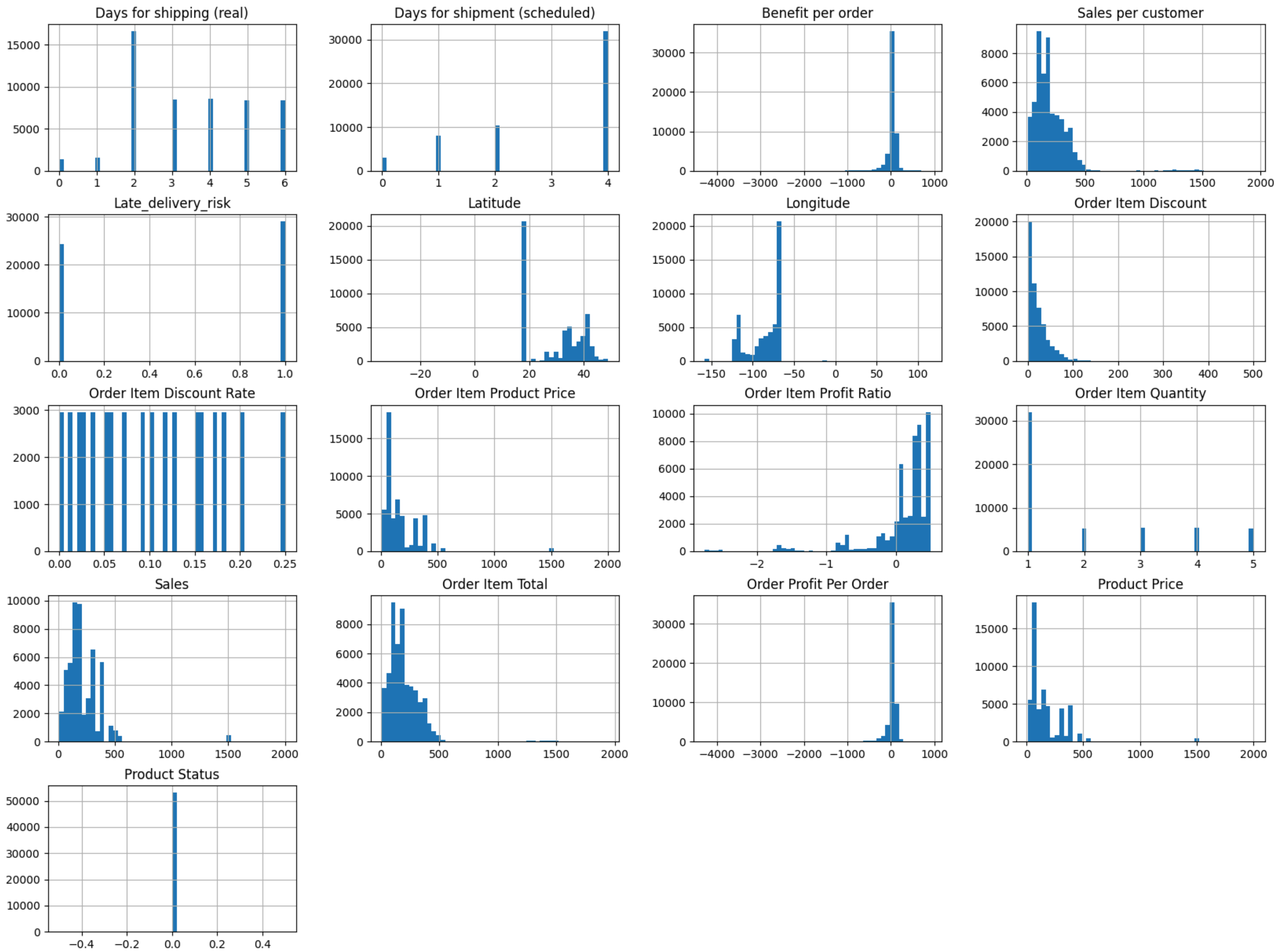
In [ ]:
```
# Interactive version of the graph above
# f = folium.Map(location=[37, -95], zoom_start=5,tiles="cartodb positron")

# folium.Choropleth(
#     geo_data=merged_states_counts,
#     name="choropleth",
#     data=merged_states_counts,
#     columns=["STATE_NAME", "Store_Counts"],
#     key_on="feature.properties.STATE_NAME",
#     fill_color="YlGn",
#     fill_opacity=0.7,
#     line_opacity=0.2,
#     nan_fill_color="white",
```

```
#     legend_name="Store_Counts",
#      highlight=True,

# ).add_to(f)
# f
```

Let's examine how numerical data is distributed

In [ ]:
```
numerical_df = df_.select_dtypes(include=["int64", "float64"])
```

In [ ]:
```
fig, ax = plt.subplots(figsize=(20, 15))
numerical_df.hist(ax=ax, bins=50)
plt.show()
```


Days for shipping (real)
Days for shipment (scheduled)
Benefit per order
Sales per customer
Late_delivery_risk
Latitude
Longitude
Order Item Discount
Order Item Discount Rate
Order Item Product Price
Order Item Profit Ratio
Order Item Quantity
Sales
Order Item Total
Order Profit Per Order
Product Price
Product Status

The delivery time for most orders was 4 days, but orders were delivered in 2 days. Most other distributions are skewed to the right.

In [ ]:
```
df_.columns
```

Out[ ]:
```
Index(['Type', 'Days for shipping (real)', 'Days for shipment (scheduled)',
       'Benefit per order', 'Sales per customer', 'Delivery Status',
       'Late_delivery_risk', 'Category Name', 'Customer City',
       'Customer Country', 'Customer Segment', 'Customer State',
       'Customer Street', 'Department Name', 'Latitude', 'Longitude', 'Market',
       'Order City', 'Order Country', 'order date (DateOrders)',
       'Order Item Discount', 'Order Item Discount Rate',
       'Order Item Product Price', 'Order Item Profit Ratio',
       'Order Item Quantity', 'Sales', 'Order Item Total',
       'Order Profit Per Order', 'Order Region', 'Order State', 'Order Status',
       'Product Name', 'Product Price', 'Product Status',
       'shipping date (DateOrders)', 'Shipping Mode', 'Year'],
      dtype='object')
```

Clustering the SKUs

First, to cluster the SKUs, the data needs to be aggregated so that only one row per SKU is obtained.

What is SKU?

"SKU" stands for Stock Keeping Unit. It's a term used as a stock tracking unit, commonly in retail sales. It serves as a unique identifier for a product. SKUs can include information about product specifications, supplier details, prices, and they are often readable via barcodes. Businesses such as stores and online sales platforms use SKUs for inventory management and sales tracking purposes.

There are different approaches and methods for segmentation. We will use the inventory management approach. Clustering groups similar SKUs, while ABC Classification emphasizes important SKUs for inventory management strategies.

In [ ]:
```
clustering_features = [
    "Product Name",
    "Order Item Discount",
    "Order Item Discount Rate",
    "Order Item Product Price",
    "Order Item Profit Ratio",
```

```python
    "Order Item Quantity",
    "Sales",
    "Order Item Total",
    "Order Profit Per Order",
    "Product Price",
    "order date (DateOrders)",
]

df_clustering = df_[clustering_features]

df_clustering_agg = (
    df_clustering.groupby("Product Name")
    .agg(
        {
            "Order Item Quantity": "sum",
            "Order Item Discount Rate": "mean",
            "Sales": "sum",
            "Order Item Profit Ratio": "mean",
        }
    )
    .reset_index()
)
```

In [ ]:
```python
df_clustering_agg.head()
```

Out[ ]:

	Product Name	Order Item Quantity	Order Item Discount Rate	Sales	Order Item Profit Ratio
0	Adult dog supplies	246	0.099634	20762.400376	0.094837
1	Baby sweater	207	0.104300	12229.560379	0.139420
2	Bag Boy Beverage Holder	98	0.109143	2449.019973	0.249429
3	Bag Boy M330 Push Cart	208	0.103623	16637.919929	0.184493
4	Bowflex SelectTech 1090 Dumbbells	10	0.138000	5999.899902	0.233000

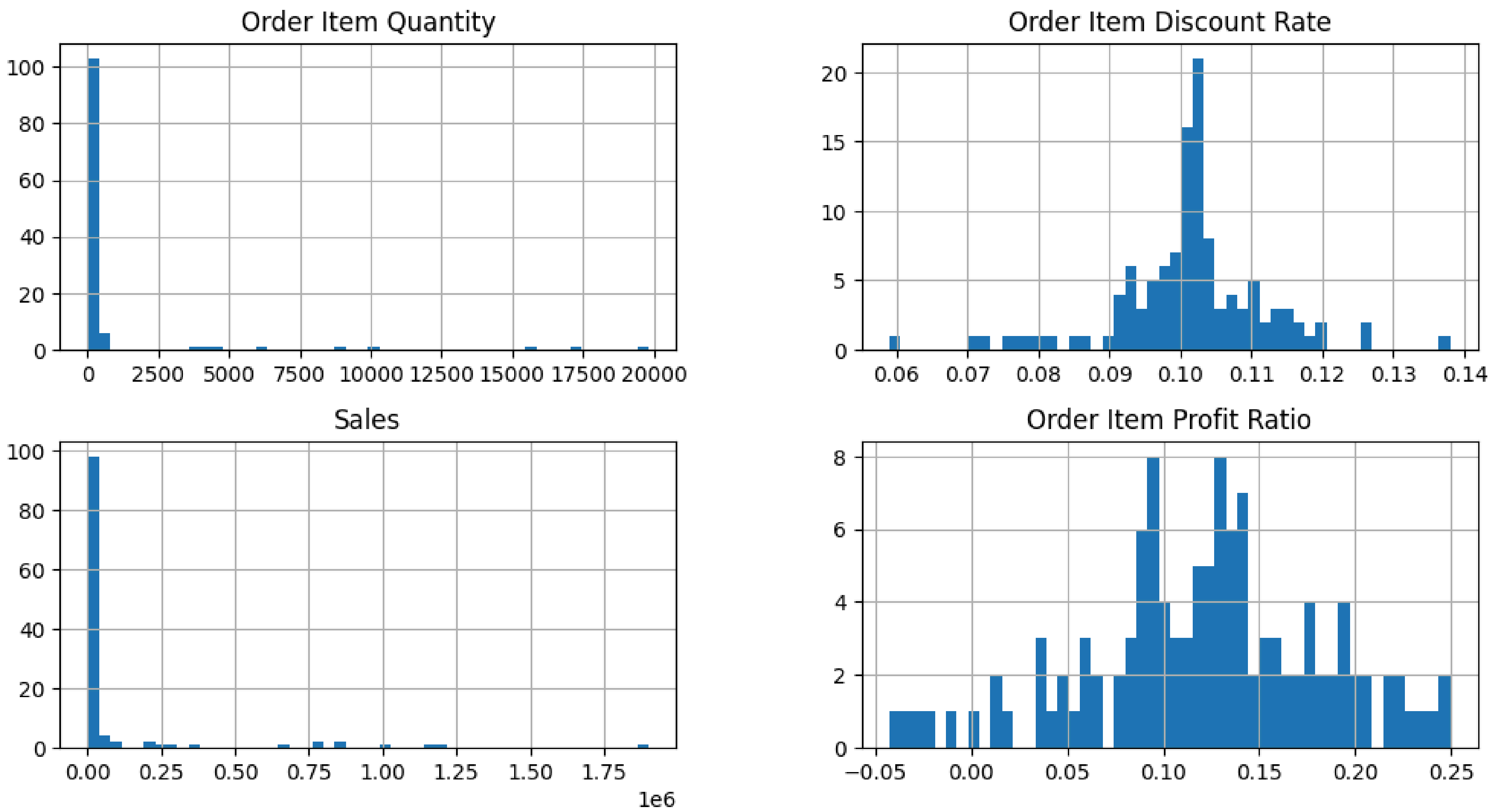
In [ ]:
```python
df_clustering_agg.shape
```

Out[ ]: (118, 5)

The company provides customers with a selection of 118 various products.

In [ ]:
```
df_clustering_agg.hist(figsize=(12, 6), bins=50)
```

Out[ ]:
```
array([[<Axes: title={'center': 'Order Item Quantity'}>,
        <Axes: title={'center': 'Order Item Discount Rate'}>],
       [<Axes: title={'center': 'Sales'}>,
        <Axes: title={'center': 'Order Item Profit Ratio'}>]],
      dtype=object)
```

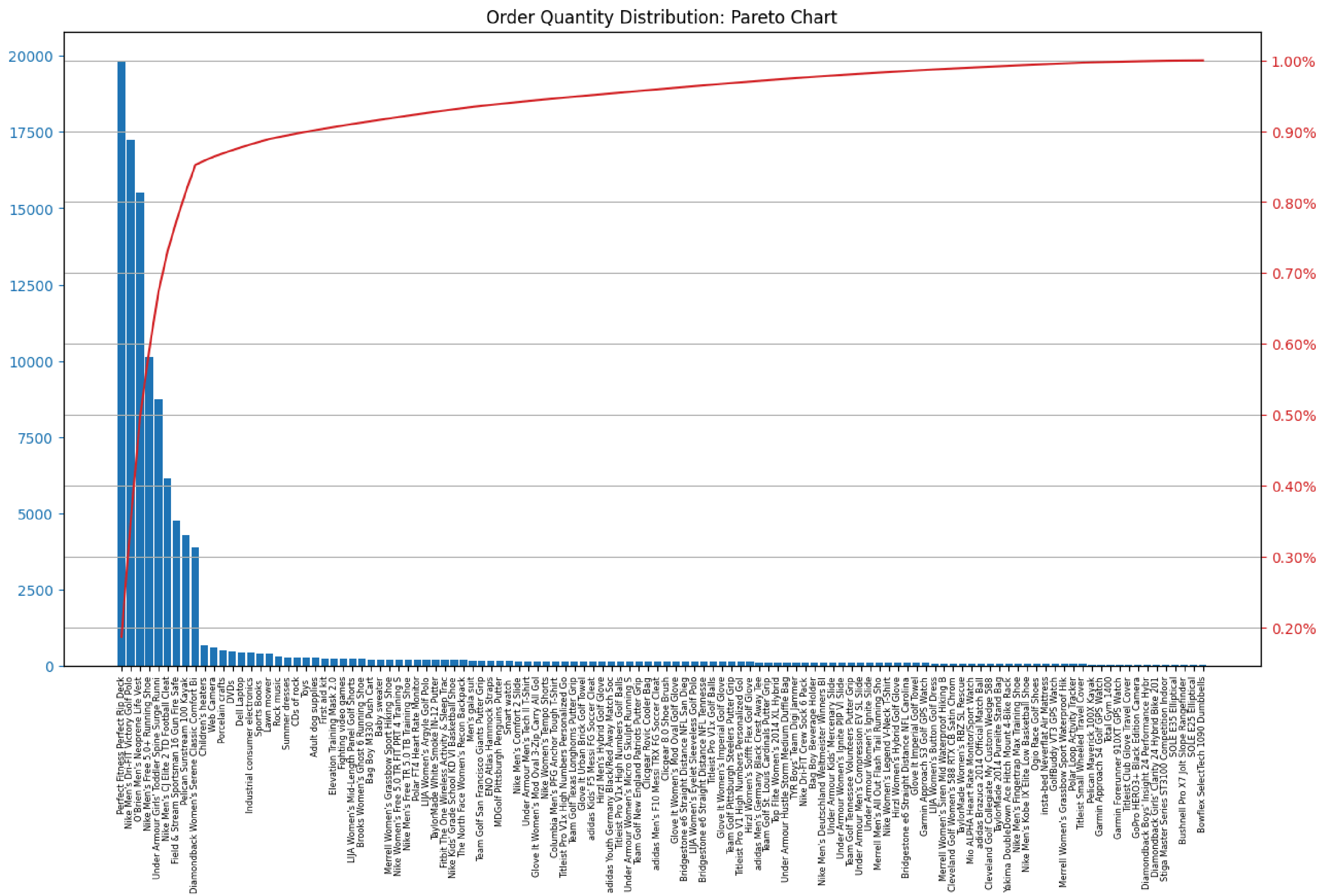


Most SKUs are rarely sold, but eight SKUs have very high sales volume, indicating that some of the company's products are very popular. To see this more clearly, let's look at it on a pareto chart.

In [ ]:
```
df_cluster_sorted_order = df_clustering_agg.sort_values(
    by="Order Item Quantity", ascending=False
).reset_index(drop=True)
```

In [ ]:
```
df_cluster_sorted_order["cum_quantity_perc"] = (
    df_cluster_sorted_order["Order Item Quantity"].cumsum()
```

```python
    / df_cluster_sorted_order["Order Item Quantity"].sum()
)

fig, ax = plt.subplots(figsize=(15, 8))

ax.bar(
    df_cluster_sorted_order["Product Name"],
    df_cluster_sorted_order["Order Item Quantity"],
)
ax.set_xticklabels(
    df_cluster_sorted_order["Product Name"], rotation=90, fontsize=6
)
ax.set_title("Order Quantity Distribution: Pareto Chart")


ax2 = ax.twinx()
ax2.plot(
    df_cluster_sorted_order["Product Name"],
    df_cluster_sorted_order["cum_quantity_perc"],
    color="tab:red",
)
ax2.yaxis.set_major_formatter(PercentFormatter())
ax2.grid(axis="y")
ax2.set_axisbelow(True)

ax.tick_params(axis="y", colors="tab:blue")
ax2.tick_params(axis="y", colors="tab:red")

plt.show()
```



As seen in the graph above, only nine out of 118 SKUs accounted for almost 85% of the total order quantity.

In [ ]:
```
# Total order quantity of 9 out of 118 SKUs
df_cluster_sorted_order.head(9)
```

Out[ ]:

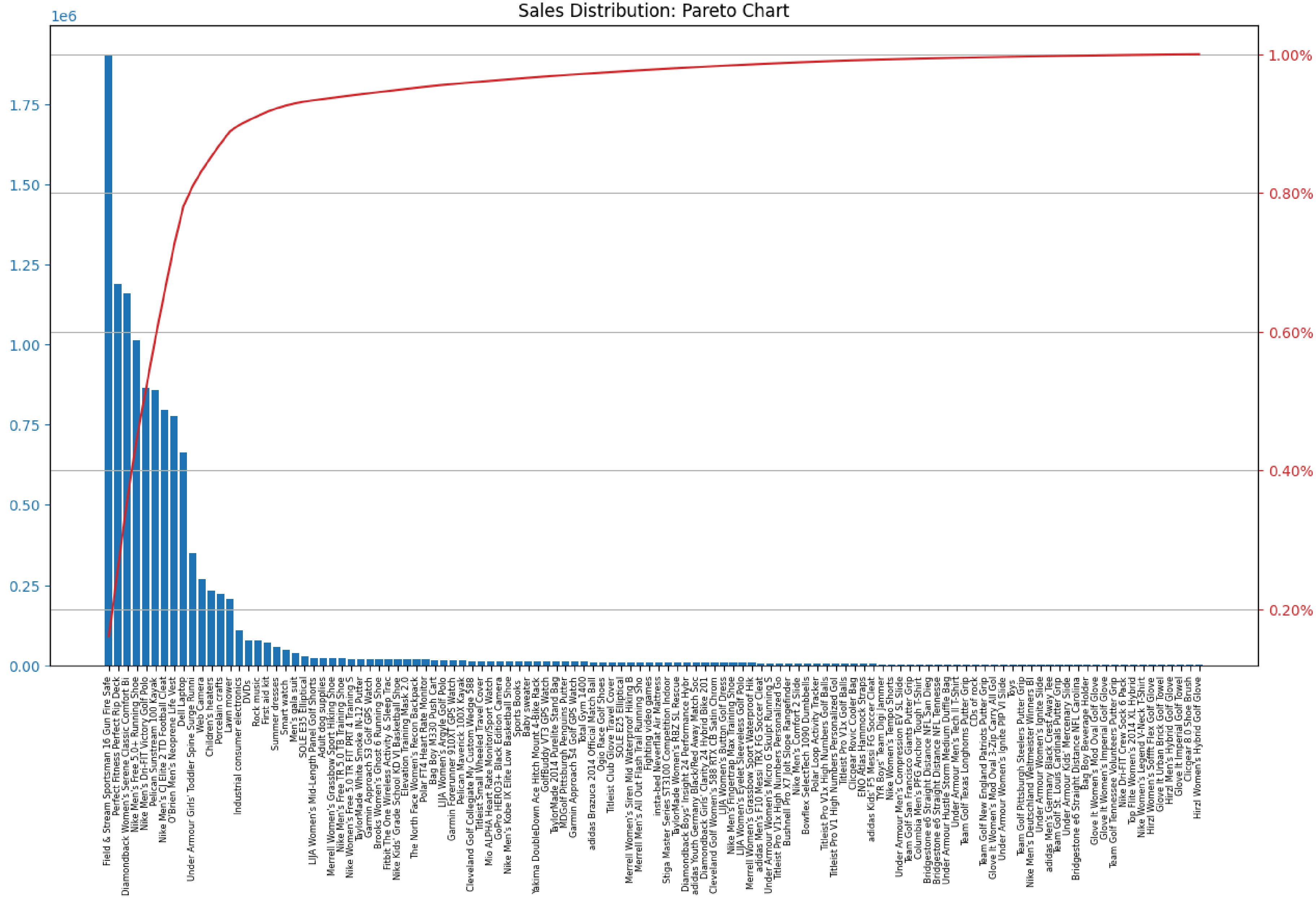
	Product Name	Order Item Quantity	Order Item Discount Rate	Sales	Order Item Profit Ratio	cum_quantity_perc
0	Perfect Fitness Perfect Rip Deck	19807	0.101641	1.188222e+06	0.135466	0.186640
1	Nike Men's Dri-FIT Victory Golf Polo	17257	0.101407	8.628500e+05	0.128004	0.349252
2	O'Brien Men's Neoprene Life Vest	15530	0.101722	7.761894e+05	0.127727	0.495590
3	Nike Men's Free 5.0+ Running Shoe	10122	0.101597	1.012099e+06	0.126268	0.590969
4	Under Armour Girls' Toddler Spine Surge Runni	8739	0.101426	3.494726e+05	0.105432	0.673316
5	Nike Men's CJ Elite 2 TD Football Cleat	6126	0.101714	7.963188e+05	0.122739	0.731041
6	Field & Stream Sportsman 16 Gun Fire Safe	4751	0.101675	1.900305e+06	0.127076	0.775809
7	Pelican Sunstream 100 Kayak	4281	0.101738	8.561572e+05	0.120500	0.816149
8	Diamondback Women's Serene Classic Comfort Bi	3867	0.101730	1.160023e+06	0.100864	0.852588

Let's look at the pareto chart for “Sales”.

In [ ]:
```
df_cluster_sorted_sales = df_clustering_agg.sort_values(
    by="Sales", ascending=False
).reset_index(drop=True)
```

In [ ]:
```
df_cluster_sorted_sales["cum_sales_perc"] = (
    df_cluster_sorted_sales["Sales"].cumsum() / df_cluster_sorted_sales["Sales"].sum()
)
```

```python
fig, ax = plt.subplots(figsize=(15, 8))

ax.bar(df_cluster_sorted_sales["Product Name"], df_cluster_sorted_sales["Sales"])
ax.set_xticklabels(
    df_cluster_sorted_sales["Product Name"], rotation=90, fontsize=6
)
ax.set_title("Sales Distribution: Pareto Chart")


ax2 = ax.twinx()
ax2.plot(
    df_cluster_sorted_sales["Product Name"],
    df_cluster_sorted_sales["cum_sales_perc"],
    color="tab:red",
)
ax2.yaxis.set_major_formatter(PercentFormatter())
ax2.grid(axis="y")
ax2.set_axisbelow(True)
ax.tick_params(axis="y", colors="tab:blue")
ax2.tick_params(axis="y", colors="tab:red")

plt.show()
```


Sales Distribution: Pareto Chart
1e6
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
0.20%
0.40%
0.60%
0.80%
1.00%
Field & Stream Sportsman 16 Gun Fire Safe
Perfect Fitness Perfect Rip Deck
Diamondback Women's Serene Classic Comfort Bi
Nike Men's Free 5.0+ Running Shoe
Nike Men's Dri-FIT Victory Golf Polo
Pelican Sunstream 100 Kayak
Nike Men's CJ Elite 2 TD Football Cleat
O'Brien Men's Neoprene Life Vest
Dell Laptop
Under Armour Girls' Toddler Spine Surge Runni
Web Camera
Children's heaters
Porcelain crafts
Lawn mower
Industrial consumer electronics
DVDs
Rock music
First aid kit
Summer dresses
Smart watch
Men's gala suit
SOLE E35 Elliptical
LIJA Women's Mid-Length Panel Golf Shorts
Adult dog supplies
Merrell Women's Grassbow Sport Hiking Shoe
Nike Men's Free TR 5.0 TB Training Shoe
Nike Women's Free 5.0 TR FIT PRT 4 Training S
TaylorMade White Smoke IN-12 Putter
Garmin Approach S3 Golf GPS Watch
Brooks Women's Ghost 6 Running Shoe
Fitbit The One Wireless Activity & Sleep Trac
Nike Kids' Grade School KD VI Basketball Shoe
Elevation Training Mask 2.0
The North Face Women's Recon Backpack
Polar FT4 Heart Rate Monitor
Bag Boy M330 Push Cart
LIJA Women's Argyle Golf Polo
Garmin Forerunner 910XT GPS Watch
Pelican Maverick 100X Kayak
Cleveland Golf Collegiate My Custom Wedge 588
Titleist Small Wheeled Travel Cover
Mio ALPHA Heart Rate Monitor/Sport Watch
GoPro HERO3+ Black Edition Camera
Nike Men's Kobe IX Elite Low Basketball Shoe
Sports Books
Baby sweater
Yakima DoubleDown Ace Hitch Mount 4-Bike Rack
GolfBuddy VT3 GPS Watch
TaylorMade 2014 Purelite Stand Bag
MDGolf Pittsburgh Penguins Putter
Garmin Approach S4 Golf GPS Watch
Total Gym 1400
adidas Brazuca 2014 Official Match Ball
Ogio Race Golf Shoes
Titleist Club Glove Travel Cover
SOLE E25 Elliptical
Merrell Women's Siren Mid Waterproof Hiking B
Merrell Men's All Out Flash Trail Running Sho
Fighting video games
insta-bed Neverflat Air Mattress
Stiga Master Series ST3100 Competition Indoor
TaylorMade Women's RBZ SL Rescue
Diamondback Boys' Insight 24 Performance Hybr
adidas Youth Germany Black/Red Away Match Soc
Diamondback Girls' Clarity 24 Hybrid Bike 201
Cleveland Golf Women's 588 RTX CB Satin Chrom
LIJA Women's Button Golf Dress
Nike Men's Fingertrap Max Training Shoe
LIJA Women's Eyelet Sleeveless Golf Polo
Merrell Women's Grassbow Sport Waterproof Hik
adidas Men's F10 Messi TRX FG Soccer Cleat
Under Armour Women's Micro G Skulpt Running S
Titleist Pro V1x High Numbers Personalized Go
Bushnell Pro X7 Jolt Slope Rangefinder
Nike Men's Comfort 2 Slide
Bowflex SelectTech 1090 Dumbbells
Polar Loop Activity Tracker
Titleist Pro V1x High Numbers Golf Balls
Titleist Pro V1 High Numbers Personalized Gol
Titleist Pro V1x Golf Balls
Clicgear Rovic Cooler Bag
ENO Atlas Hammock Straps
adidas Kids' F5 Messi FG Soccer Cleat
TYR Boys' Team Digi Jammer
Nike Women's Tempo Shorts
Under Armour Men's Compression EV SL Slide
Team Golf San Francisco Giants Putter Grip
Columbia Men's PFG Anchor Tough T-Shirt
Bridgestone e6 Straight Distance NFL San Dieg
Bridgestone e6 Straight Distance NFL Tennesse
Under Armour Hustle Storm Medium Duffle Bag
Under Armour Men's Tech II T-Shirt
Team Golf Texas Longhorns Putter Grip
CDs of rock
Team Golf New England Patriots Putter Grip
Glove It Women's Mod Oval 3-Zip Carry All Gol
Under Armour Women's Ignite PIP VI Slide
Toys
Team Golf Pittsburgh Steelers Putter Grip
Nike Men's Deutschland Weltmeister Winners Bl
Under Armour Women's Ignite Slide
adidas Men's Germany Black Crest Away Tee
Team Golf St. Louis Cardinals Putter Grip
Under Armour Kids' Mercenary Slide
Bridgestone e6 Straight Distance NFL Carolina
Bag Boy Beverage Holder
Glove It Women's Mod Oval Golf Glove
Glove It Women's Imperial Golf Glove
Team Golf Tennessee Volunteers Putter Grip
Nike Dri-FIT Crew Sock 6 Pack
Top Flite Women's 2014 XL Hybrid
Nike Women's Legend V-Neck T-Shirt
Hirzl Women's Soffft Flex Golf Glove
Glove It Urban Brick Golf Towel
Hirzl Men's Hybrid Golf Glove
Glove It Imperial Golf Towel
Clicgear 8.0 Shoe Brush
Hirzl Women's Hybrid Golf Glove

The same interpretation can be made for sales value. Only nine SKUs contribute around 80% of the total sales value over the observed period.

In [ ]:
```
# Total sales of 9 out of 118 SKUs
df_cluster_sorted_sales.head(9)
```

Out[ ]:

	Product Name	Order Item Quantity	Order Item Discount Rate	Sales	Order Item Profit Ratio	cum_sales_perc
0	Field & Stream Sportsman 16 Gun Fire Safe	4751	0.101675	1.900305e+06	0.127076	0.160928
1	Perfect Fitness Perfect Rip Deck	19807	0.101641	1.188222e+06	0.135466	0.261553
2	Diamondback Women's Serene Classic Comfort Bi	3867	0.101730	1.160023e+06	0.100864	0.359789
3	Nike Men's Free 5.0+ Running Shoe	10122	0.101597	1.012099e+06	0.126268	0.445499
4	Nike Men's Dri-FIT Victory Golf Polo	17257	0.101407	8.628500e+05	0.128004	0.518570
5	Pelican Sunstream 100 Kayak	4281	0.101738	8.561572e+05	0.120500	0.591074
6	Nike Men's CJ Elite 2 TD Football Cleat	6126	0.101714	7.963188e+05	0.122739	0.658510
7	O'Brien Men's Neoprene Life Vest	15530	0.101722	7.761894e+05	0.127727	0.724242
8	Dell Laptop	442	0.102240	6.630000e+05	0.117059	0.780388

Combination of ABCXYZ-Classification

ABC Classification:

- ABC classification is a method based on the Pareto Principle. It categorizes items in inventory into three categories: A, B, and C, based on their importance in terms of value or usage.
- Categories:

- A: High-value or high-usage items requiring close monitoring.
    - B: Moderate-value or moderate-usage items managed with standard control.
    - C: Low-value or low-usage items managed with minimal attention.

XYZ Classification:

- Categorizes items based on demand variability or predictability.
- Categories:
    - X: Items with stable and predictable demand.
    - Y: Items with moderate variability in demand.
    - Z: Items with highly unpredictable demand.

Combining ABCXYZ-Classification:

- Provides a comprehensive view of inventory.
- Example: AX might be a high-value product with stable demand, needing tight control and accurate forecasting.
- Example: CZ might be a low-value product with highly unpredictable demand, requiring less control but more safety stock.

This approach helps businesses focus their resources on the most valuable items (A) while spending less time on less critical ones (C), saving time and money. It also helps reduce inventory holding costs and prevent stockouts by considering demand variability.

In [ ]:
```
df_abc = df_cluster_sorted_sales[["Product Name", "Sales"]]

# Calculate cumulative sum of Sales and add it as a new column
df_abc["cum_sum"] = df_abc["Sales"].cumsum()

# Calculate cumulative percentage of Sales and add it as a new column
df_abc["cum_per"] = df_abc["cum_sum"] / df_abc["Sales"].sum() * 100

# Add the percentage of each SKU as a new column
df_abc["per"] = df_abc["cum_per"] - df_abc["cum_per"].shift(1)

# Add the first missing value in column "per" to be the first of cumulative percentage
df_abc.loc[0, "per"] = df_abc["cum_per"][0]
```

In [ ]:
```
# Define function to classify the SKUs based on their cumlated percentage revenue
def abc_classification(data):
```

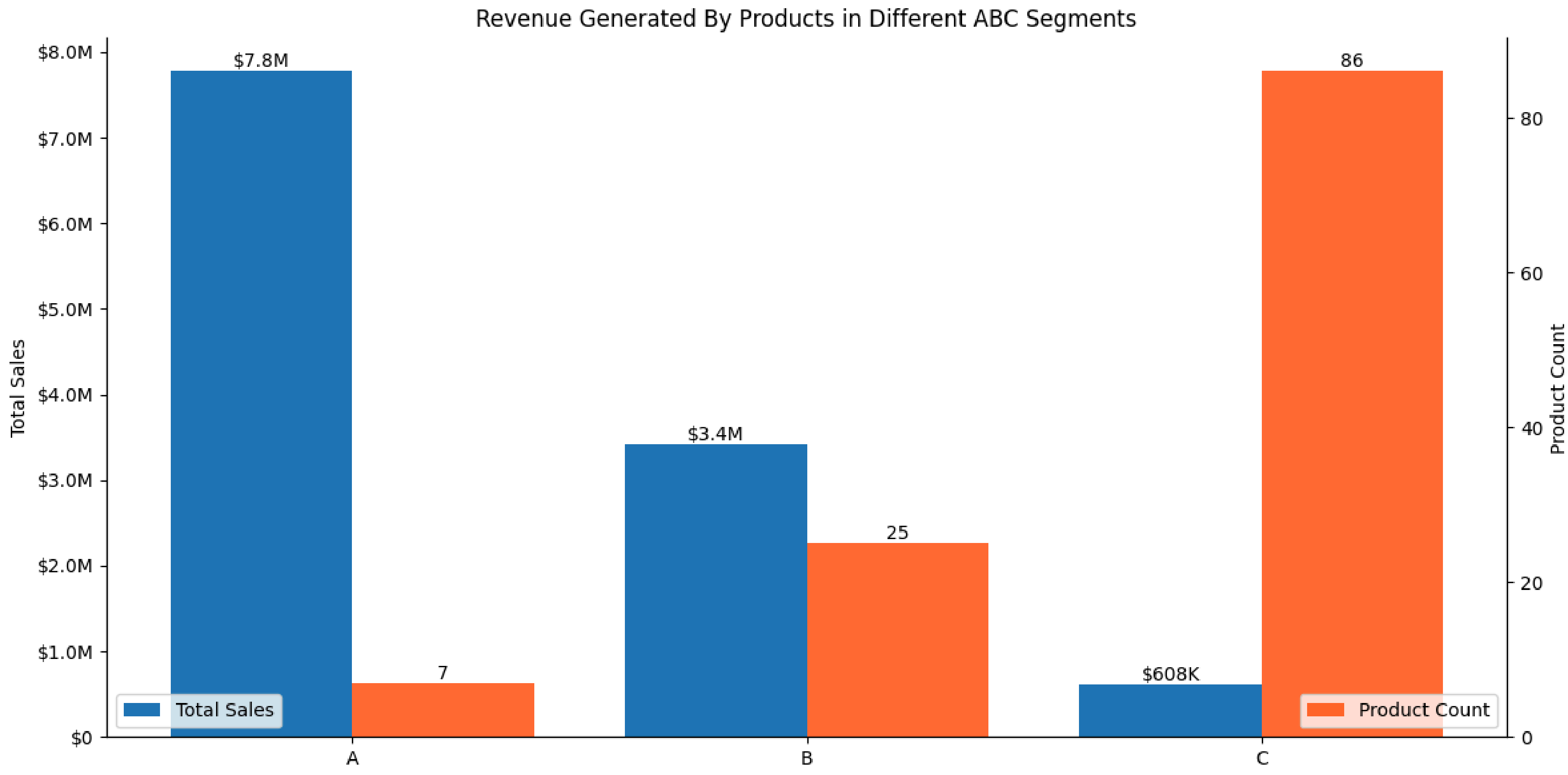
```python
    if data["cum_per"] <= 70:
        return "A"
    elif data["cum_per"] > 70 and data["cum_per"] <= 95:
        return "B"
    elif data["cum_per"] > 95:
        return "C"
```

In [ ]:
```python
df_abc["abc"] = df_abc.apply(abc_classification, axis=1)

abc_summary = (
    df_abc[["abc", "Product Name", "Sales"]]
    .groupby("abc")
    .agg(Revenue=("Sales", "sum"), count=("Product Name", "count"))
)
```

In [ ]:
```python
# Function to display bar values
def display_bar_values(bars, ax, formatter=None):
    for bar in bars:
        height = bar.get_height()
        # Apply the formatter if provided
        if formatter:
            formatted_height = formatter(height)
        else:
            formatted_height = str(height)
        ax.text(
            bar.get_x() + bar.get_width() / 2,
            height,
            formatted_height,
            ha="center",
            va="bottom",
        )


# Wrap currency_formatter to accept a single argument
def currency_formatter_wrapper(x):
    return currency_formatter(x, 0)


fig, ax = plt.subplots(figsize=(12, 6))
```

```python
cat_index = list(range(len(abc_summary.index)))
offset = 0.2
bar_width = 0.4

# Plot "Revenue" on the first y-axis
x_revenue = [i - offset for i in cat_index]
bars1 = ax.bar(
    x_revenue,
    abc_summary["Revenue"],
    0.4,
    label="Total Sales",
    alpha=1,
    color="tab:blue",
)
ax.set_ylabel("Total Sales")
ax.set_xticks(range(len(abc_summary.index)))
ax.set_xticklabels(abc_summary.index)
ax.yaxis.set_major_formatter(FuncFormatter(currency_formatter))

# Create a secondary y-axis for the "Product Count"
ax2 = ax.twinx()

# Plot "Product Count" on the secondary y-axis
x_product_count = [i + offset for i in cat_index]
bars2 = ax2.bar(
    x_product_count,
    abc_summary["count"],
    0.4,
    label="Product Count",
    alpha=0.8,
    color="orangered",
)
ax2.set_ylabel("Product Count")

# Set the title and legend
plt.title("Revenue Generated By Products in Different ABC Segments")
ax.legend(loc="lower left")
ax2.legend(loc="lower right")

# Hide the top and right spines
ax.spines["top"].set_visible(False)
```

```
ax2.spines["top"].set_visible(False)


# Display values for "Revenue" bars
display_bar_values(bars1, ax, formatter=currency_formatter_wrapper)

# Display values for "Product Count" bars
display_bar_values(bars2, ax2)


# Adjust layout
plt.tight_layout()
plt.show()
```



- Only 7 products contribute around 67% of our total sales, while 86 contribute only 5%. These products are vital to our store, demanding a high level of service. Maintaining safety stock is imperative to ensure we never run out of them. It is important to have various suppliers for A-class products to prevent revenue loss and customer migration to competitors due to product shortages.
- The 25 products in category B contribute 28% of total sales. This category may represent products of medium importance. Procurement processes and inventory management may need to be planned more carefully.
- The 86 products in category C contribute around 5% of total sales. This category may represent lower value and more common products. Supply chain managers must continuously make improvements to optimize stock levels of these products and increase efficiency.
- Priority should be given to class A products when allocating capital and stocking space, followed by class B products. Class C products, which generate the least revenue, should have minimal inventory. With 86 products in Class C, excess inventory not only takes up significant stocking space but also ties up capital unnecessarily.

Let's analyze segment A products by country to prioritize inventory based on regional customer preferences

In [ ]:
```
# Selecting the top 5 country based on total order item revenue
top5_countries = df_.groupby("Order Country")["Sales"].sum().nlargest(5).index.tolist()
```

In [ ]:
```
# Filtering the data for the top 6 cities and grouping by city and product name to calculate total revenue
country_sales = (
    df_[df_["Order Country"].isin(top5_countries)]
    .groupby(["Order Country", "Product Name"], as_index=False)
    .agg(Revenue=("Sales", "sum"))
)
```

In [ ]:
```
# Replace country names with formal names
country_sales["Order Country"].replace(
    {
        "Reino Unido": "United Kingdom",
        "México": "Mexico",
        "Francia": "France",
        "Brasil": "Brazil",
        "Alemania": "Germany",
    },
```

```
    inplace=True,
)
```

In [ ]:
```
city_product_revenue_sorted = country_sales.sort_values(
    by=["Order Country", "Revenue"], ascending=False
)
```

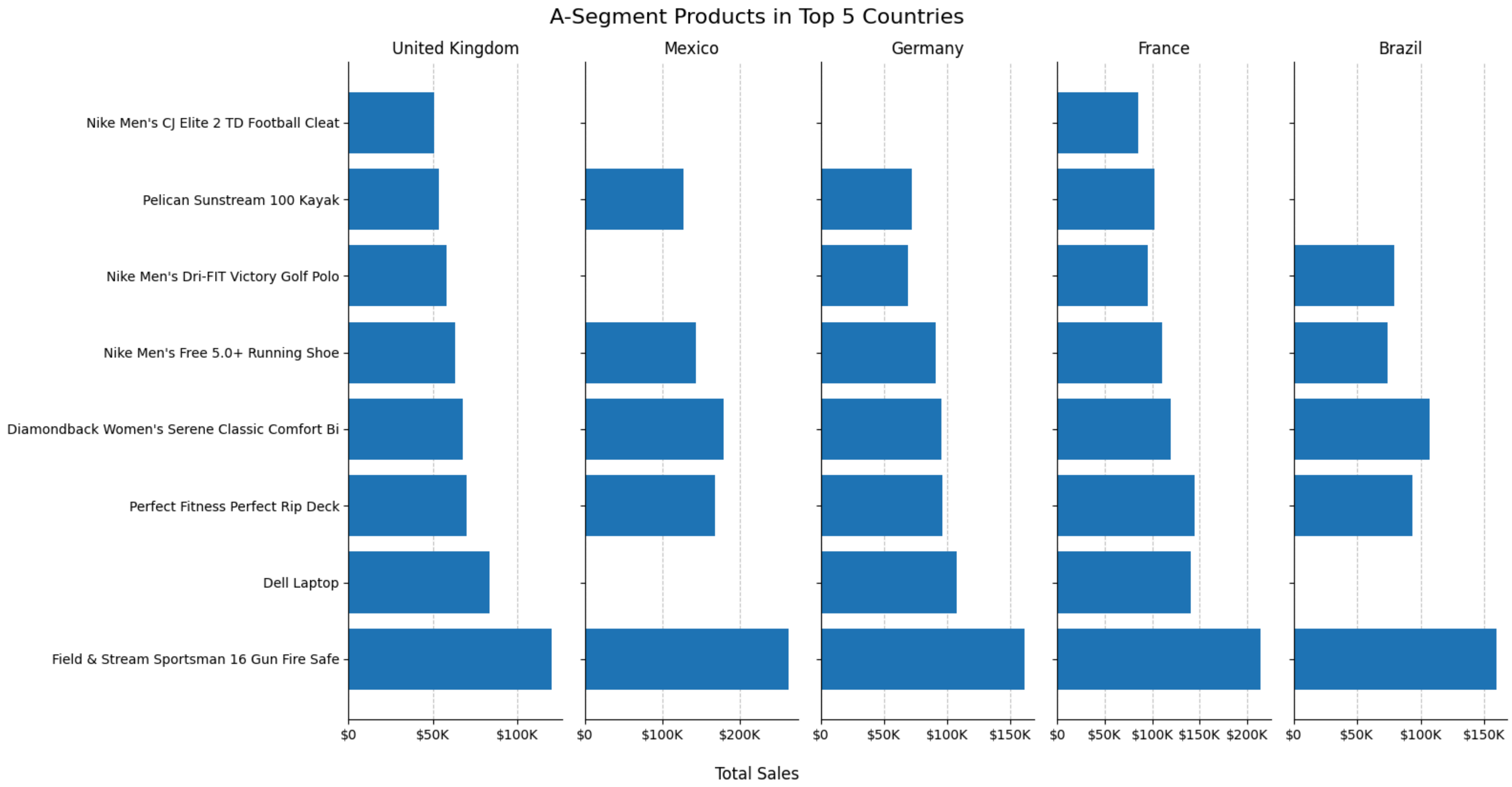
In [ ]:
```
# Calculating the total revenue for each order country again for later use
city_product_revenue_sorted["Total_Country_Revenue"] = (
    city_product_revenue_sorted.groupby("Order Country")["Revenue"].transform("sum")
)
```

In [ ]:
```
# Calculating the cumulative percentage of total revenue per country per product
city_product_revenue_sorted["cum_per"] = (
    city_product_revenue_sorted.groupby("Order Country")["Revenue"].cumsum()
    / city_product_revenue_sorted["Total_Country_Revenue"]
    * 100
)
```

In [ ]:
```
# Applying the ABC segmentation function to determine the segment for each product in each country
city_product_revenue_sorted["Segment"] = city_product_revenue_sorted.apply(
    abc_classification, axis=1
)
```

In [ ]:
```
segment_A_data = city_product_revenue_sorted[
    city_product_revenue_sorted["Segment"] == "A"
]

fig, axs = plt.subplots(
    1, len(segment_A_data["Order Country"].unique()), figsize=(16, 8), sharey=True
)

for i, country in enumerate(segment_A_data["Order Country"].unique()):
    country_data = segment_A_data[segment_A_data["Order Country"] == country]
    country_data_sorted = country_data.sort_values(by="Revenue", ascending=True)
    ax = axs[i]
    bars = ax.barh(country_data["Product Name"], country_data["Revenue"])
    ax.set_title(country)
    ax.xaxis.set_major_formatter(FuncFormatter(currency_formatter))
```

```
    ax.spines[["top", "right"]].set_visible(False)

    # Set the zorder of the bars to a higher value than the grid lines
    for bar in bars:
        bar.set_zorder(2)

    # Add grid and set the zorder of the grid lines to a lower value than the bars
    ax.grid(axis="x", linestyle="--", alpha=0.7, fillstyle="left")
    for line in ax.get_xgridlines():
        line.set_zorder(1)

plt.suptitle("A-Segment Products in Top 5 Countries", fontsize=16)
fig.text(0.5, -0.03, "Total Sales", ha="center", fontsize=12)
plt.tight_layout()
plt.show()
```



- Overall, the "Field & Stream Sportsman 16 Gun Fire Safe" consistently shows the highest sales across all five countries, indicating it is a top-performing product in the A-segment. Other products show variability in sales performance depending on the country, highlighting regional preferences and market dynamics.

XYZ Classification

In [ ]:
```
df_clustering_cp = df_clustering.copy()
```

In [ ]:
```
df_clustering_cp["Year"] = df_clustering_cp["order date (DateOrders)"].dt.year
df_clustering_cp["Month"] = df_clustering_cp["order date (DateOrders)"].dt.month
```

In [ ]:
```
df_cp_agg = (
    df_clustering_cp.groupby(["Product Name", "Year", "Month"])["Order Item Quantity"]
    .sum()
    .reset_index()
)
```

In [ ]:
```
df_cp_agg["Month"] = df_cp_agg["Month"].map("{:02}".format)
df_cp_agg["Year_Month"] = (
    df_cp_agg["Year"].astype(str) + "-" + df_cp_agg["Month"].astype(str)
)
```

In [ ]:
```
df_cp_agg.head()
```

Out[ ]:

	Product Name	Year	Month	Order Item Quantity	Year_Month
0	Adult dog supplies	2017	11	127	2017-11
1	Adult dog supplies	2017	12	119	2017-12
2	Baby sweater	2017	10	82	2017-10
3	Baby sweater	2017	12	125	2017-12
4	Bag Boy Beverage Holder	2017	01	11	2017-01

In [ ]:
```
df_cp_wide = (
    df_cp_agg.pivot(
        index="Product Name", columns="Year_Month", values="Order Item Quantity"
    )
    .reset_index()
    .fillna(0)
)
```

In [ ]:
```
df_cp_wide.head()
```

Out[ ]:

Year_Month	Product Name	2017-01	2017-02	2017-03	2017-04	2017-05	2017-06	2017-07	2017-08	2017-09	2017-10	2017-11	2017-12
0	Adult dog supplies	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	127.0	119.0
1	Baby sweater	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	82.0	0.0	125.0
2	Bag Boy Beverage Holder	11.0	30.0	33.0	24.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3	Bag Boy M330 Push Cart	0.0	0.0	0.0	4.0	70.0	33.0	25.0	52.0	24.0	0.0	0.0	0.0
4	Bowflex SelectTech 1090 Dumbbells	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	7.0	3.0	0.0	0.0

In [ ]:

```
df_cp_wide["total_demand"] = df_cp_wide.iloc[:, 1:13].sum(axis=1)
```

In [ ]:

```
# calculating average monthly demand by Product Name
df_cp_wide["avg_demand"] = df_cp_wide.iloc[:, 1:13].mean(axis=1)
```

In [ ]:

```
df_cp_wide["std_dev"] = df_cp_wide.iloc[:, 1:13].std(axis=1)
```

In [ ]:

```
df_cp_wide["cov"] = df_cp_wide["std_dev"] / df_cp_wide["avg_demand"]
```

In [ ]:

```
print("Minimum Covariance:", df_cp_wide["cov"].min())
print("Mean Covariance:", df_cp_wide["cov"].mean())
print("Maximum Covariance:", df_cp_wide["cov"].max())
```

```
Minimum Covariance: 0.5920622207504581
Mean Covariance: 1.8221988285468964
Maximum Covariance: 3.4641016151377553
```

- The minimum Covariance of 0.59 suggests that some products have relatively stable demand patterns.
- The overall mean Covariance of 1.82 implies a moderate level of demand variability across the dataset.

- The maximum Covariance of 3.46 indicates significant variability in demand for certain products, potentially due to factors like seasonality or fluctuations in customer preferences.

That means this dataset includes lots of products with fluctuating or seasonal demand, which is going to make things much harder for procurement staff to keep in check.

In [ ]:
```
def xyz_classification(cov):

    if cov <= 0.6:
        return "X"
    elif cov >= 0.6 and cov <= 1.0:
        return "Y"
    else:
        return "Z"
```

In [ ]:
```
df_cp_wide["xyz"] = df_cp_wide["cov"].apply(xyz_classification)
```

In [ ]:
```
df_cp_wide[["xyz", "Product Name", "total_demand"]].groupby("xyz").agg(
    total_demand=("total_demand", "sum"), count=("Product Name", "count")
)
```

Out[ ]:

	total_demand	count
xyz		
X	81741.0	8
Y	8739.0	1
Z	15644.0	109

In [ ]:
```
df_cp_wide.head()
```

Out[ ]:

Year_Month	Product Name	2017-01	2017-02	2017-03	2017-04	2017-05	2017-06	2017-07	2017-08	2017-09	2017-10	2017-11	2017-12	total_demand	avg_demand

0	Adult dog supplies	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	127.0	119.0	246.0	20.500000	4
1	Baby sweater	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	82.0	0.0	125.0	207.0	17.250000	4
2	Bag Boy Beverage Holder	11.0	30.0	33.0	24.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	98.0	8.166667	1
3	Bag Boy M330 Push Cart	0.0	0.0	0.0	4.0	70.0	33.0	25.0	52.0	24.0	0.0	0.0	0.0	208.0	17.333333	2
4	Bowflex SelectTech 1090 Dumbbells	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	7.0	3.0	0.0	0.0	10.0	0.833333	

In [ ]:

```
total_demand_by_month_xyz = df_cp_wide.groupby("xyz").agg(
    Jan=("2017-01", "sum"),
    Feb=("2017-02", "sum"),
    Mar=("2017-03", "sum"),
    Apr=("2017-04", "sum"),
    May=("2017-05", "sum"),
    Jun=("2017-06", "sum"),
    Jul=("2017-07", "sum"),
    Aug=("2017-08", "sum"),
    Sep=("2017-09", "sum"),
    Oct=("2017-10", "sum"),
    Nov=("2017-11", "sum"),
    Dec=("2017-12", "sum"),
)
```

In [ ]:

```
total_demand_by_month_xyz
```

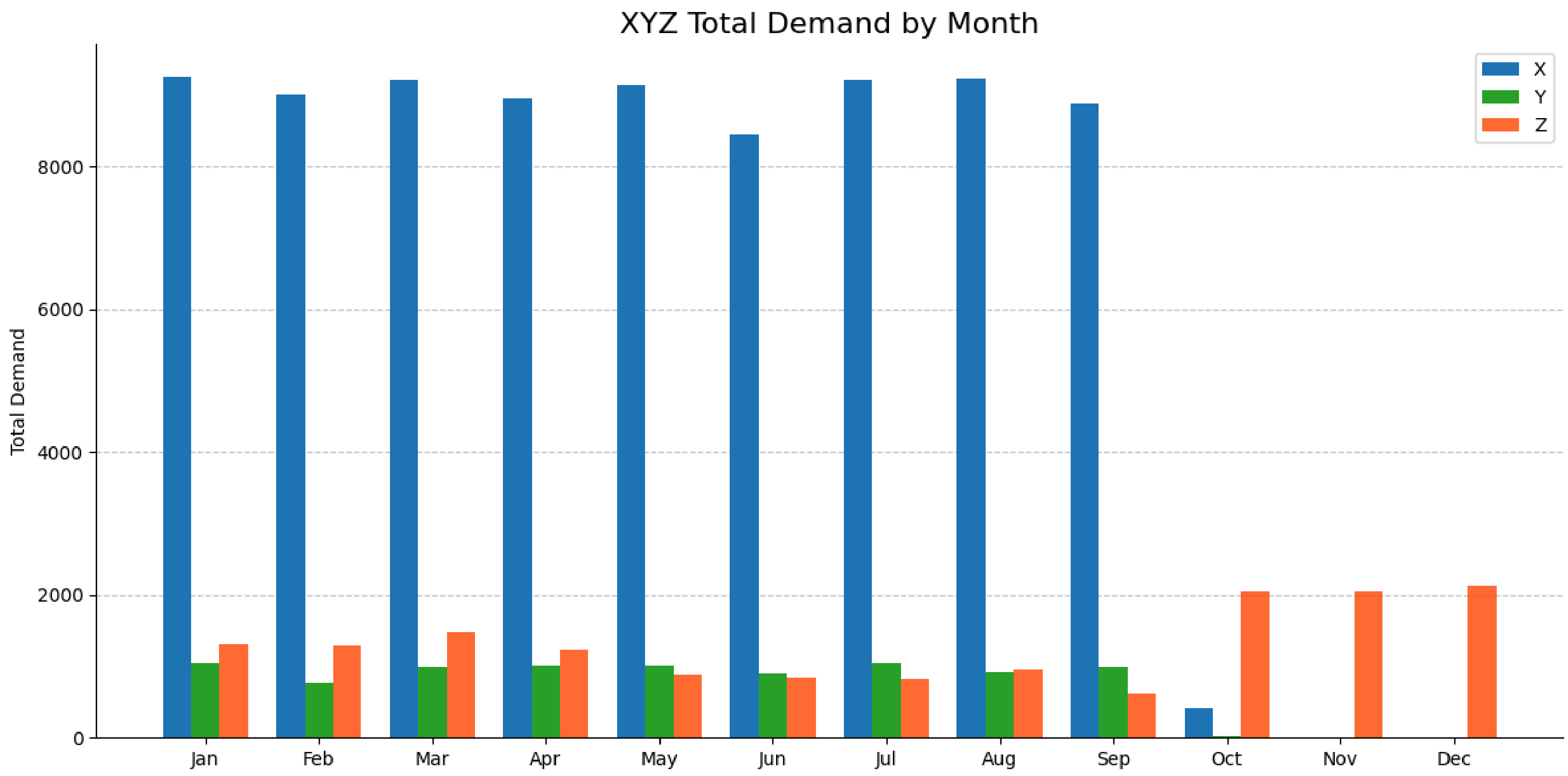
Out[ ]:

xyz	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
X	9247.0	9013.0	9208.0	8946.0	9146.0	8444.0	9210.0	9225.0	8883.0	419.0	0.0	0.0
Y	1053.0	771.0	992.0	1014.0	1015.0	906.0	1054.0	917.0	992.0	25.0	0.0	0.0
Z	1305.0	1286.0	1476.0	1229.0	872.0	844.0	827.0	953.0	627.0	2046.0	2055.0	2124.0

In [ ]:

```
plt.figure(figsize=(12, 6))

bar_width = 0.25
index = total_demand_by_month_xyz.columns
x = range(len(index))

# Plot the bars
plt.bar(
    x, total_demand_by_month_xyz.loc["X"], width=bar_width, label="X", color="tab:blue"
)
plt.bar(
    [i + bar_width for i in x],
    total_demand_by_month_xyz.loc["Y"],
    width=bar_width,
    label="Y",
    color="tab:green",
)
plt.bar(
    [i + 2 * bar_width for i in x],
    total_demand_by_month_xyz.loc["Z"],
    width=bar_width,
    label="Z",
    alpha=0.8,
    color="orangered",
)

# Adjust the spines
plt.gca().spines["top"].set_visible(False)
plt.gca().spines["right"].set_visible(False)
```

```
# Set labels and title
plt.ylabel("Total Demand")
plt.title("XYZ Total Demand by Month", fontsize=16)

# Set x-ticks
plt.xticks([i + bar_width for i in x], index)

# Add grid
plt.grid(axis="y", linestyle="--", alpha=0.7, fillstyle="left")

# Set the zorder of the bars to a higher value than the grid lines
for container in plt.gca().containers:
    for bar in container:
        bar.set_zorder(2)

# Access the grid lines through the current axes and set their zorder
for line in plt.gca().get_ygridlines():
    line.set_zorder(1)

# Add legend
plt.legend()
# Adjust layout
plt.tight_layout()
# Show the plot
plt.show()
```

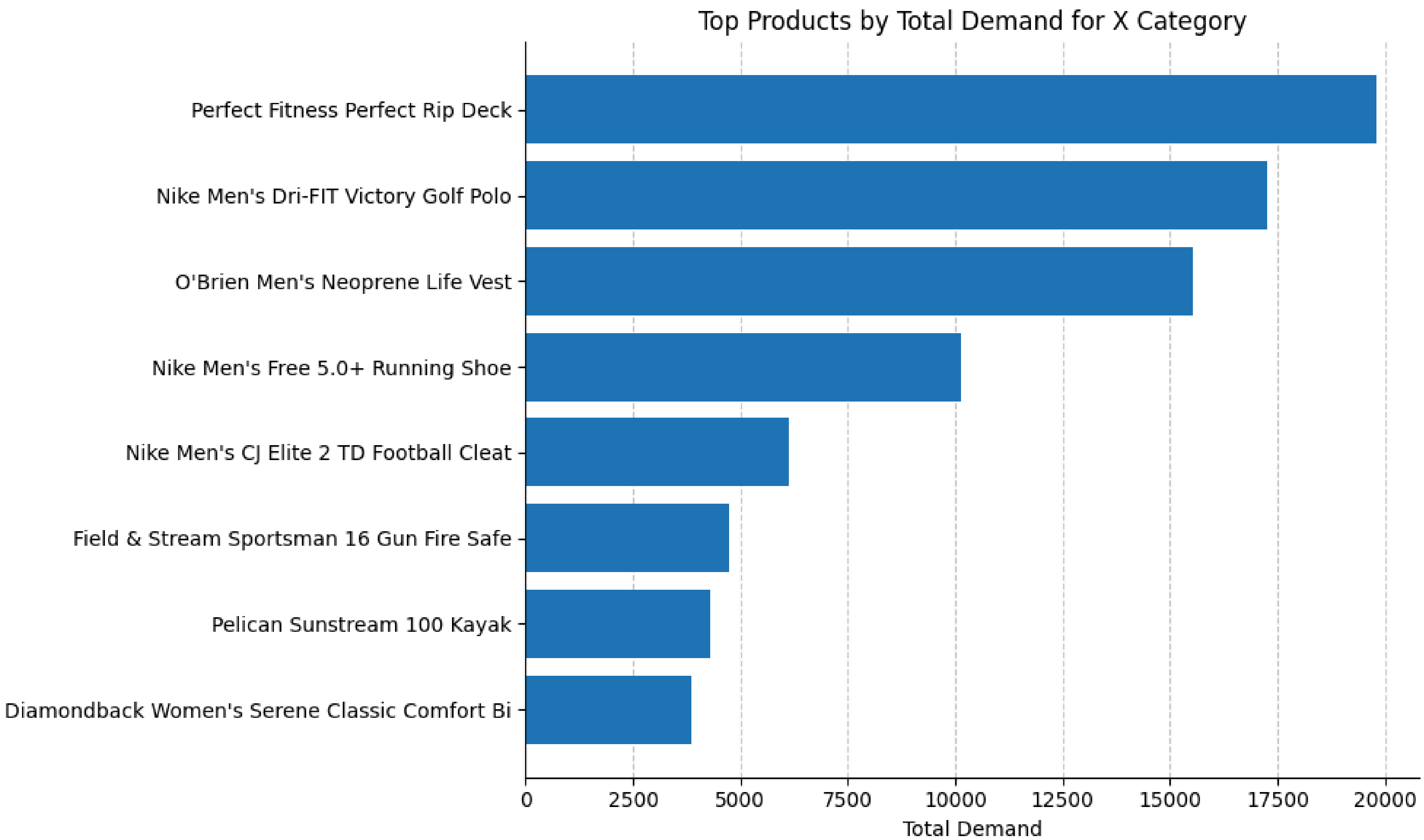


Based on the data in the table:

- There is a noticeable seasonal variation among the XYZ categories. Particularly, category Z's sales show a significant increase in October, November, and December compared to other months. This indicates that category Z is more seasonal and experiences higher demand during these months.
- Category X's sales have a more balanced distribution, but there is a noticeable decrease in October compared to other months. This suggests that the category receives lower demand in October compared to other months.
- Similarly, category Y's sales are generally evenly distributed, but there is a significant decrease in October compared to other months. This indicates that the category experiences lower demand in October.

In conclusion, based on the data in the table, there is seasonal variability among the XYZ categories, with category Z showing higher demand in October, November, and December.

In [ ]:
```python
df_x = df_cp_wide[df_cp_wide["xyz"] == "X"].sort_values(
    by="total_demand", ascending=False
)

plt.figure(figsize=(10, 6))
bars = plt.barh(df_x["Product Name"], df_x["total_demand"], color="tab:blue")

# Set the zorder of the bars to a higher value than the grid lines
for bar in bars:
    bar.set_zorder(2)

plt.gca().spines["top"].set_visible(False)
plt.gca().spines["right"].set_visible(False)
plt.xlabel("Total Demand")
plt.title("Top Products by Total Demand for X Category")
plt.gca().invert_yaxis()

# Add the grid and set the zorder of the grid lines to a lower value than the bars
plt.grid(axis="x", linestyle="--", alpha=0.7, fillstyle="left")

# Access the grid lines through the current axes and set their zorder
for line in plt.gca().get_xgridlines():
    line.set_zorder(1)

plt.tight_layout()
plt.show()
```



- **High-Demand SKUs**: The "Perfect Fitness Perfect Rip Deck" and "Nike Men's Dri-FIT Victory Golf Polo" show significantly higher total demands. These products are key drivers of revenue and require robust inventory management to ensure consistent availability.
- **Moderate-Demand SKUs**: Products like the "O'Brien Men's Neoprene Life Vest" and "Nike Men's Free 5.0+ Running Shoe" have moderate demand. They benefit from automatic replenishment but may not need as high a buffer as high-demand items.

- **Lower-Demand SKUs**: Items such as the "Diamondback Women's Serene Classic Comfort Bike" have lower demand, suggesting a need for careful management to avoid overstocking while ensuring availability when needed.

In [ ]:
```
df_abc_xyz = df_abc.merge(df_cp_wide, on="Product Name", how="left")
```

In [ ]:
```
df_abc_xyz["abc_xyz"] = df_abc_xyz["abc"].astype(str) + df_abc_xyz["xyz"].astype(str)
```

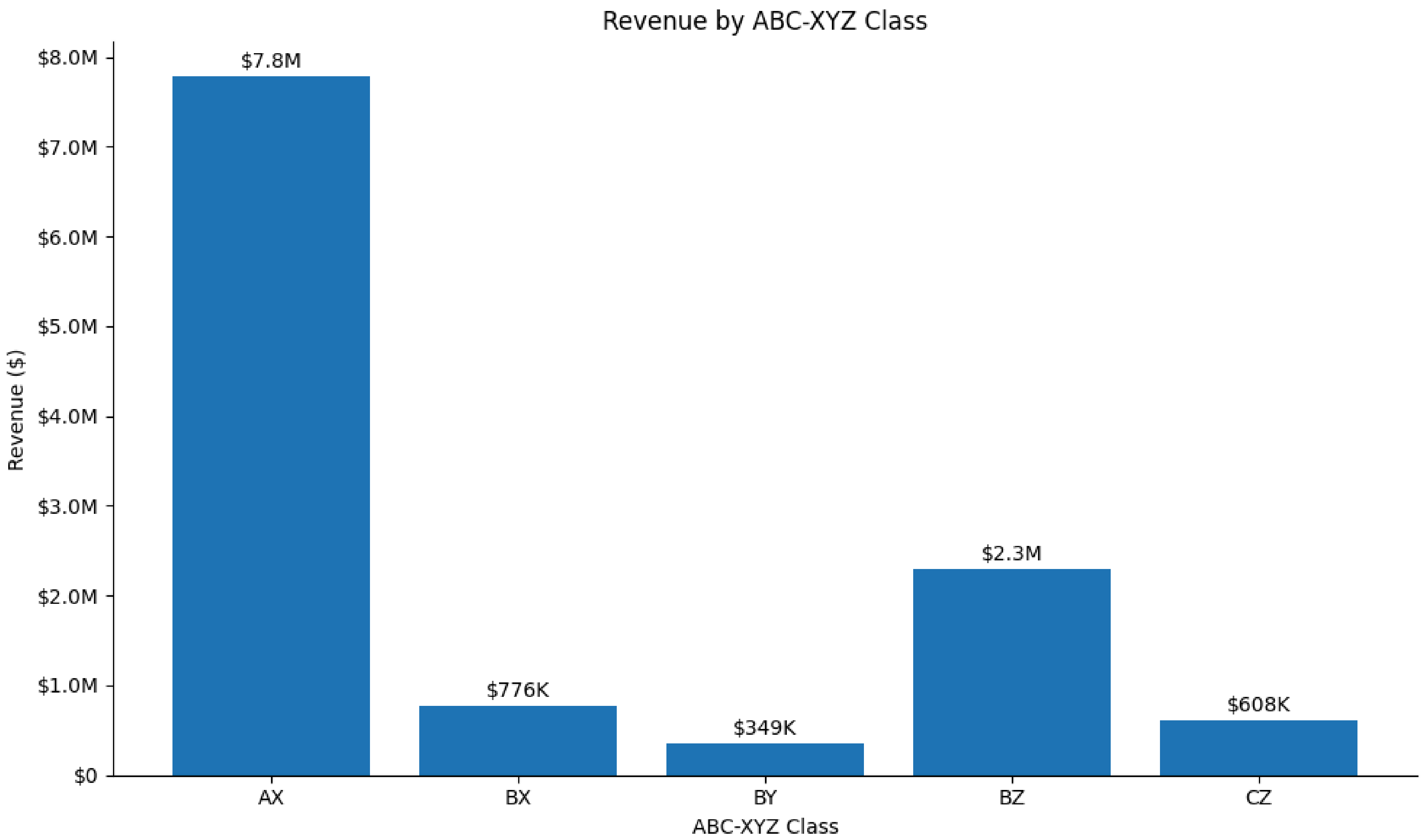
In [ ]:
```
df_abc_xyz_summary = (
    df_abc_xyz.groupby("abc_xyz")
    .agg(
        total_skus=("Product Name", "nunique"),
        total_demand=("total_demand", sum),
        avg_demand=("avg_demand", "mean"),
        total_revenue=("Sales", sum),
    )
    .reset_index()
)

df_abc_xyz_summary.sort_values(by="total_revenue", ascending=False)
```

Out[ ]:

	abc_xyz	total_skus	total_demand	avg_demand	total_revenue
0	AX	7	66211.0	788.226190	7.775974e+06
3	BZ	23	6550.0	23.731884	2.299083e+06
1	BX	1	15530.0	1294.166667	7.761894e+05
4	CZ	86	9094.0	8.812016	6.077169e+05
2	BY	1	8739.0	728.250000	3.494726e+05

In [ ]:
```
# Create the bar plot
plt.figure(figsize=(10, 6))
plt.bar(
    df_abc_xyz_summary["abc_xyz"], df_abc_xyz_summary["total_revenue"], color="tab:blue"
)
```

```python
# Add labels and title
plt.xlabel("ABC-XYZ Class")
plt.ylabel("Revenue ($)")
plt.title("Revenue by ABC-XYZ Class")
plt.gca().spines["top"].set_visible(False)
plt.gca().spines["right"].set_visible(False)
# Add value labels on top of each bar
for i in range(len(df_abc_xyz_summary["abc_xyz"])):
    plt.text(
        i,
        df_abc_xyz_summary["total_revenue"][i] + 100000,
        currency_formatter_wrapper(df_abc_xyz_summary["total_revenue"][i]),
        ha="center",
    )

# Format y-axis ticks using the currency_formatter function
plt.gca().yaxis.set_major_formatter(plt.FuncFormatter(currency_formatter))

# Display the plot
plt.tight_layout()
plt.show()
```



- Combining ABC and XYZ data yields nine distinct classes that offer key insights for supply chain management. Classes with an A prefix significantly contribute to high revenue, making them crucial for resource allocation. B Classes generate medium revenue, requiring efficient planning, while C Classes contribute low revenue but still need attention for overall balance.

- X suffixed Classes have stable, predictable demand, making them easier to forecast and manage. Y Classes have variable but manageable demand, necessitating a flexible approach. Z Classes are the most challenging, with sporadic and varying demand, requiring robust forecasting and agile strategies.
- Understanding these classes' revenue contributions and demand patterns allows supply chain analysts to optimize resources, improve forecasting accuracy, and enhance overall supply chain performance.

The Association of International Certified Professional Accountants provides practical guidance on applying ABC XYZ classifications for procurement managers to maximize revenue and profit without excessive capital investment in stock. They recommend the following approaches:

Management Approaches for XYZ Inventory Analysis

Class	Value	Demand	Forecastability	Management
AX	High	Steady	Easy	Easy
BX	Medium	Steady	Easy	Easy
BY	Medium	Variable	Hard	Hard
BZ	Medium	Sporadic	Difficult	Difficult
CZ	Low	Sporadic	Difficult	Difficult

1. **AX Class (High Revenue, Stable Demand)**:
   - Implement automatic replenishment systems to ensure stock levels are maintained.
   - Use a low buffer inventory strategy, JIT (Just-In-Time) approach, or consignment transfers to minimize excess stock.
   - Utilize perpetual inventory tracking for real-time visibility into stock levels.
2. **BX Class (Moderate Revenue, Stable Demand)**:
   - Adopt automatic replenishment systems to streamline stock management.
   - Conduct periodic counting to verify inventory accuracy and adjust stock levels as needed.
   - Maintain a low buffer inventory to balance stock availability and capital tied up.

3. **CX Class (Low Revenue, Stable Demand)**:
    - Employ automatic replenishment systems for efficient stock replenishment.
    - Use periodic estimation methods to forecast demand and adjust stock levels accordingly.
    - Maintain a low buffer inventory to optimize capital utilization.
4. **AY Class (High Revenue, Variable Demand)**:
    - Opt for semi-automatic replenishment methods to manage fluctuating demand effectively.
    - Maintain a low buffer inventory to avoid overstocking while meeting demand variations.
5. **BY Class (Moderate Revenue, Variable Demand)**:
    - Implement semi-automatic replenishment processes with manual adjustments for seasonal demand changes.
    - Manage stock with a carefully adjusted seasonal buffer to optimize stock levels.
6. **CY Class (Low Revenue, Variable Demand)**:
    - Use semi-automatic replenishment approaches to handle demand fluctuations efficiently.
    - Maintain a higher buffer inventory to ensure stock availability during demand peaks.
7. **AZ Class (Buy to Order, No Buffer)**:
    - Source products on-demand to minimize inventory holding costs.
    - Avoid stocking these items and display lead times to customers to manage expectations.
8. **BZ Class (Buy to Order, No Buffer with Lead Time Shown)**:
    - Procure items based on customer orders to reduce inventory costs.
    - Clearly communicate lead times to customers to manage delivery expectations.
9. **CZ Class (Automatic Replenishment, High Buffer)**:
    - Use automatic replenishment systems with a higher buffer inventory to meet variable demand.
    - Conduct periodic inspections to ensure stock levels align with demand patterns.

Implementing these management approaches based on ABC XYZ classifications can help optimize inventory management, reduce stockouts, and improve overall supply chain efficiency.

Demand Forecasting

In this section, we explore time series demand forecasting, a critical part of supply chain and inventory management.

Objectives

- Forecasting demand for the upcoming month (4 weeks ahead)

Evaluation Metrics

- Symmetric Mean Absolute Percentage Error
- Mean Absolute Error

Methods

- We will focus on using Nixtla open-source libraries
    - Statistical model
        - MSTL model (Multiple Seasonal-Trend decomposition using LOESS)
    - Generative pre-trained transformer model
        - TimeGPT

In [ ]:

```
# Import libraries
import os
import time

import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
from datasetsforecast.losses import mae, smape
from dotenv import load_dotenv
from nixtla import NixtlaClient
from statsforecast import StatsForecast as sf
from statsforecast.models import MSTL, AutoARIMA
```

```python
from statsmodels.tsa.stattools import adfuller
from utilsforecast.evaluation import evaluate
```

In [ ]:
```python
demand_df = pd.read_csv("data/ts_demand_forecasting_train.csv")
```

In [ ]:
```python
demand_df.shape
```

Out[ ]:
```
(8589, 13)
```

In [ ]:
```python
demand_df.head()
```

Out[ ]:

	STORE_SKU	DATE	UNITS	UNITS_MIN	UNITS_MAX	UNITS_MEAN	UNITS_STD	TRANSACTIONS_SUM	PROMO_MAX
0	store_130_SKU_120931082	2019-05-06	388.0	44.0	69.0	55.428571	8.182443	243.0	1.0
1	store_130_SKU_120931082	2019-05-13	318.0	37.0	62.0	45.428571	8.079958	210.0	1.0
2	store_130_SKU_120931082	2019-05-20	126.0	13.0	23.0	18.000000	3.915780	118.0	0.0
3	store_130_SKU_120931082	2019-05-27	285.0	23.0	65.0	40.714286	14.067863	197.0	1.0
4	store_130_SKU_120931082	2019-06-03	93.0	10.0	20.0	13.285714	3.352327	87.0	0.0

In [ ]:
```python
demand_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8589 entries, 0 to 8588
Data columns (total 13 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   STORE_SKU         8589 non-null   object 
 1   DATE              8589 non-null   object 
 2   UNITS             8589 non-null   float64
```

```
 3   UNITS_MIN         8589 non-null   float64
 4   UNITS_MAX         8589 non-null   float64
 5   UNITS_MEAN        8589 non-null   float64
 6   UNITS_STD         8589 non-null   float64
 7   TRANSACTIONS_SUM  8589 non-null   float64
 8   PROMO_MAX         8589 non-null   float64
 9   PRICE_MEAN        8589 non-null   float64
 10  STORE             8589 non-null   object
 11  SKU               8589 non-null   object
 12  SKU_CATEGORY      8589 non-null   object
dtypes: float64(8), object(5)
memory usage: 872.4+ KB
```

In [ ]:
```
date_col = "DATE"
series_id = "STORE_SKU"
target = "UNITS"
```

In [ ]:
```
# Convert the date column to datetime format
demand_df[date_col] = pd.to_datetime(demand_df[date_col])

print(f"Min date: {demand_df[date_col].min()}")
print(f"Max date: {demand_df[date_col].max()}")
```

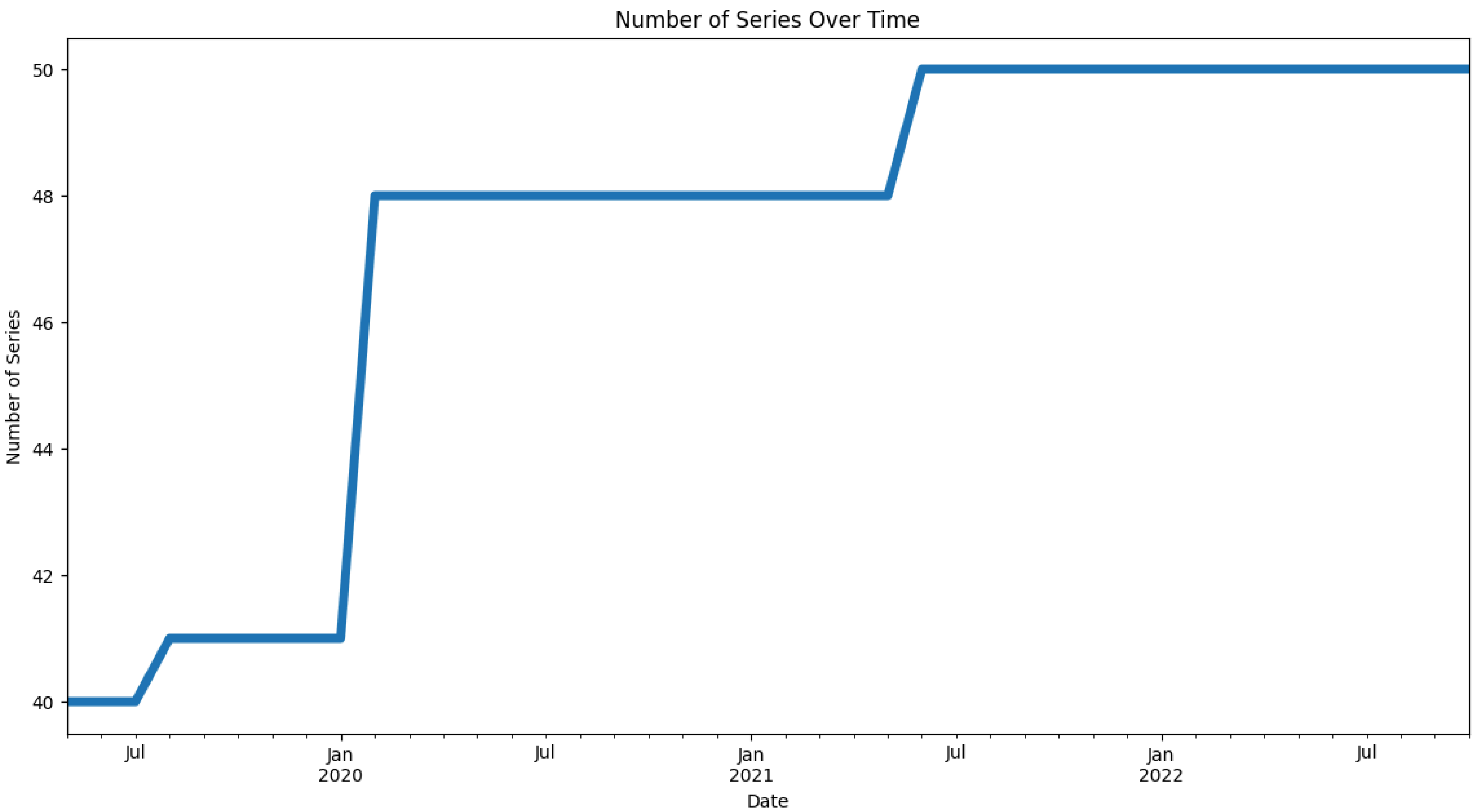
```
Min date: 2019-05-06 00:00:00
Max date: 2022-10-24 00:00:00
```

In [ ]:
```
series_dupl_dates = demand_df.groupby([series_id, date_col]).size()
series_dupl_dates = series_dupl_dates[series_dupl_dates > 1]
print("# of series with duplicate dates:", len(series_dupl_dates))
```

```
# of series with duplicate dates: 0
```

In [ ]:
```
# Check the number of series over time
series_over_time = demand_df.groupby(demand_df[date_col].dt.to_period("M"))[
    series_id
].nunique()
series_over_time.plot(
    kind="line", figsize=(14, 7), title="Number of Series Over Time", linewidth=5
)
plt.xlabel("Date")
```

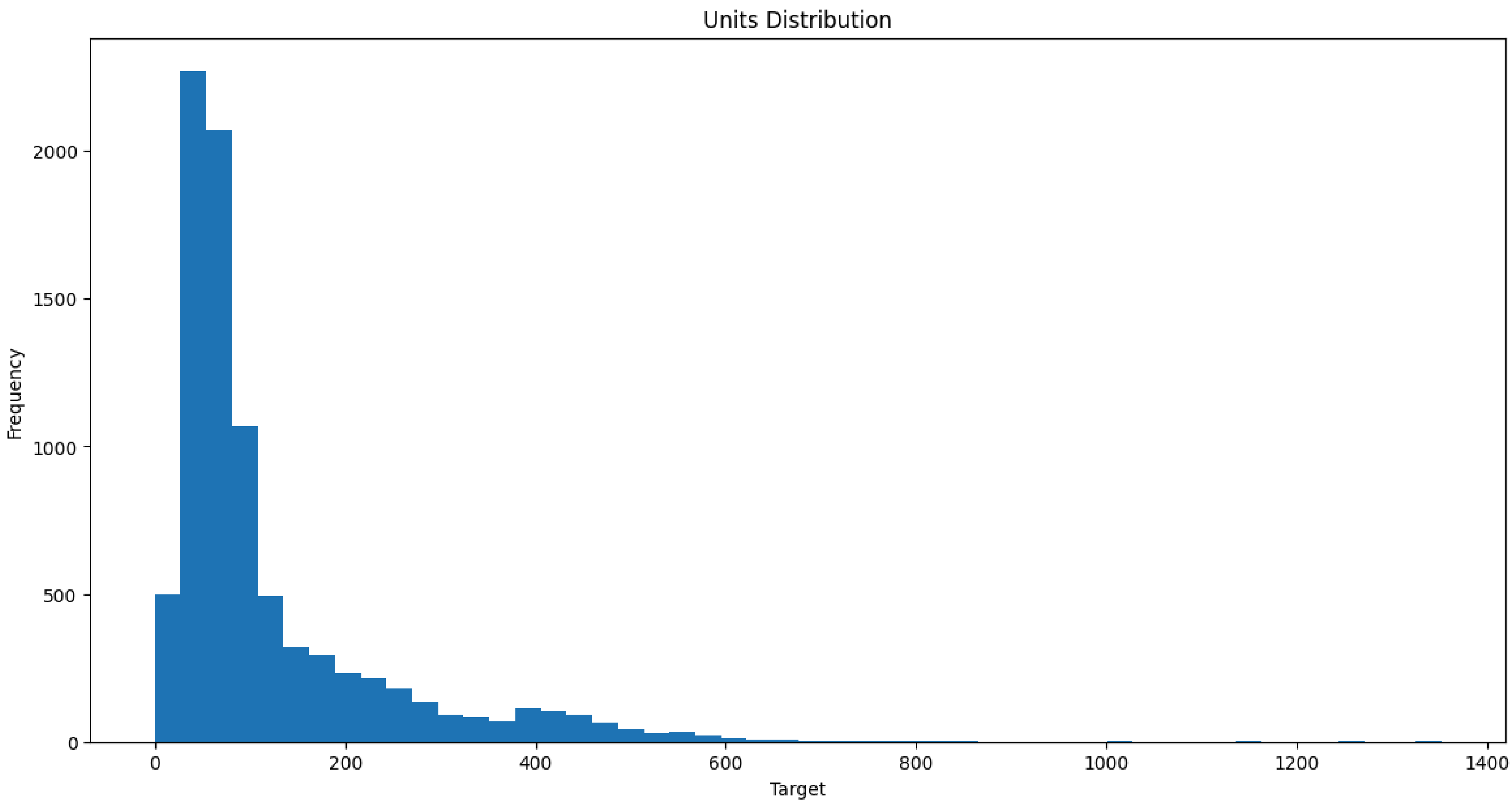
```
plt.ylabel("Number of Series")
plt.show()
```



In [ ]:

```
# Plot the target distribution
demand_df[target].plot(
    kind="hist", bins=50, figsize=(14, 7), title="Units Distribution"
)
plt.xlabel("Target")
```

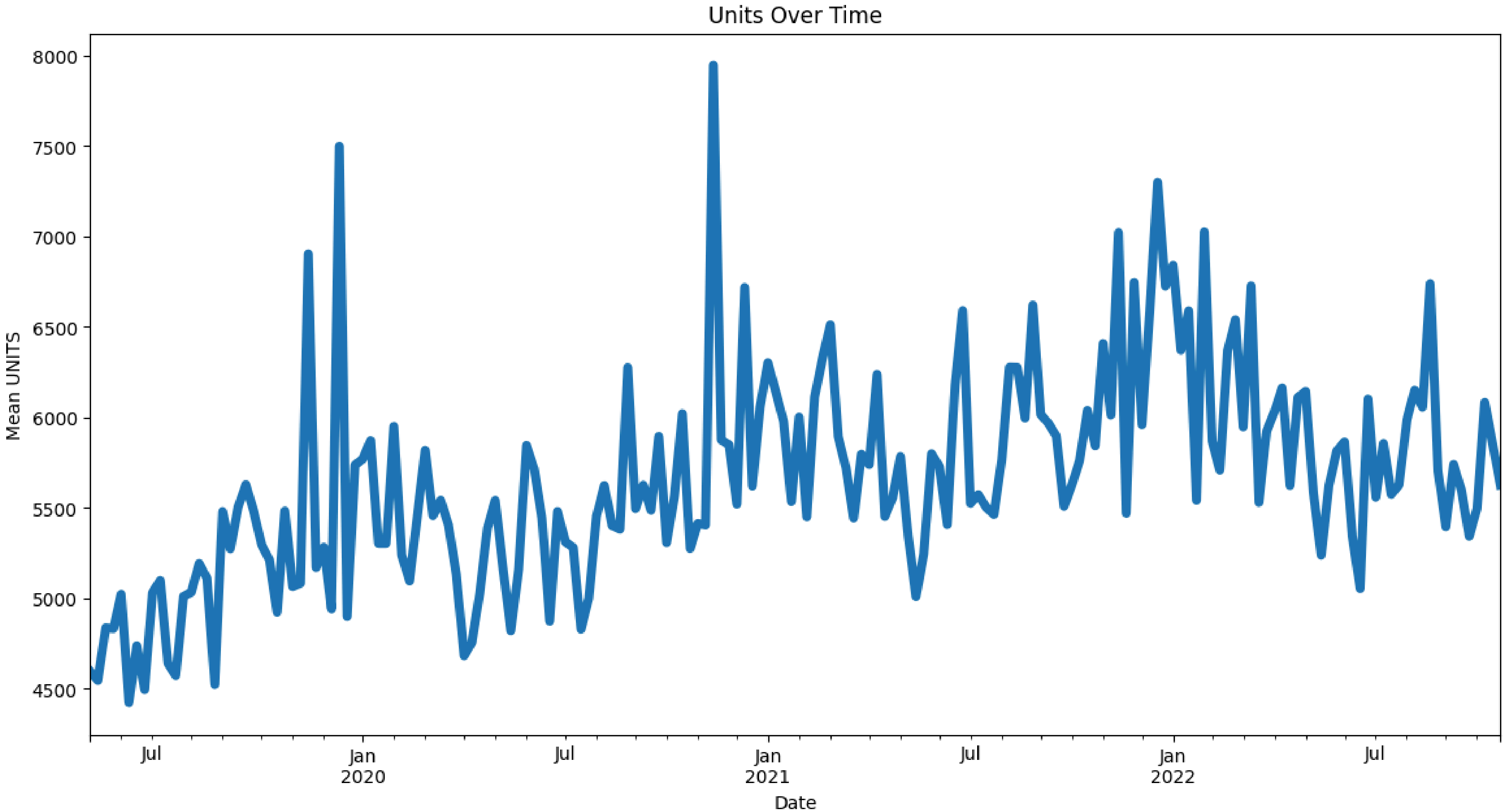
```
plt.ylabel("Frequency")
plt.show()
```



- The target variable shows a right-skewed distribution. Most of the data points are clustered between 0 and 200 units.
- We might consider transforming the target variable (using a logarithmic transformation) to normalize the distribution.

In [ ]:
```
# Plot the target over time
target_over_time = demand_df.groupby(demand_df[date_col].dt.to_period("W-MON"))[
    target
].sum()
```

```python
target_over_time.plot(
    kind="line", figsize=(14, 7), title="Units Over Time", linewidth=5
)
plt.xlabel("Date")
plt.ylabel("Mean UNITS")
plt.show()
```



In [ ]:

```python
# Compute and print missing data
total_entries = demand_df.shape[0]
non_missing_entries = demand_df[target].notnull().sum()
```

```python
sparsity = (total_entries - non_missing_entries) / total_entries
print(f"Data sparsity: {sparsity:.2%}")
```

```
Data sparsity: 0.00%
```

In [ ]:

```python
# Compute per series statistics
per_series_stats = demand_df.groupby(series_id)[target].agg(
    ["count", "mean", "std", "min", "max"]
)
print("Per series statistics:")
pd.DataFrame(per_series_stats)
```

```
Per series statistics:
```

Out[ ]:

STORE_SKU	count	mean	std	min	max
store_130_SKU_120931082	182	127.401099	75.008129	32.00	415.00
store_130_SKU_120969795	182	46.098901	20.505789	9.00	111.00
store_133_SKU_9888998	182	46.986264	16.841909	13.57	95.72
store_136_SKU_120973845	182	88.274725	19.139249	48.00	141.00
store_137_SKU_120949681	182	232.565934	63.624534	122.00	715.00
store_137_SKU_909891669	182	55.846154	30.827778	17.00	155.00
store_139_SKU_120939045	141	50.503546	18.971642	0.00	84.00
store_140_SKU_120931082	182	83.461538	51.095363	27.00	278.00
store_141_SKU_120930437	182	396.197802	56.082855	243.00	547.00
store_141_SKU_120939045	141	73.900709	28.990960	0.00	130.00
store_143_SKU_120970410	182	79.714286	25.745154	24.00	160.00
store_144_SKU_120939426	182	54.065934	18.833849	15.00	103.00

store_144_SKU_120970431	182	53.516484	20.356688	21.00	136.00
store_144_SKU_209939185	182	199.681319	93.603947	28.00	728.00
store_144_SKU_9888794	182	83.035714	24.078400	37.08	206.14
store_146_SKU_120969553	182	166.582418	45.718709	0.00	402.00
store_146_SKU_120971333	182	30.664835	6.834490	7.00	49.00
store_146_SKU_667079807	182	169.774725	66.204428	29.00	428.00
store_146_SKU_9935203	182	43.692308	28.192586	7.00	153.00
store_147_SKU_120939419	182	64.164835	14.946877	21.00	109.00
store_147_SKU_120970437	182	62.939560	27.200944	18.00	176.00
store_147_SKU_56889100	182	182.214286	41.657287	74.00	385.00
store_147_SKU_667079809	182	85.082418	35.606487	19.00	222.00
store_147_SKU_673092026	182	37.269231	11.251963	11.00	75.00
store_148_SKU_809896993	182	87.802198	44.714372	8.00	219.00
store_174_SKU_409905079	182	87.060440	90.321230	27.00	1152.00
store_175_SKU_120939350	182	444.450549	105.523401	187.00	657.00
store_175_SKU_120949681	182	395.049451	106.279953	180.00	777.00
store_175_SKU_120969012	182	237.461538	142.811455	79.00	1328.00
store_175_SKU_409929345	182	75.258242	39.905196	0.00	230.00
store_175_SKU_9888909	182	445.835165	118.522839	212.00	1004.00
store_181_SKU_120939043	182	41.186813	14.669028	7.00	77.00

store_182_SKU_120969792	182	34.186813	20.727334	13.00	216.00
store_182_SKU_409905066	182	101.730769	118.469517	29.00	1352.00
store_182_SKU_56889087	168	49.797619	19.835418	8.00	122.00
store_191_SKU_120969553	182	64.681319	22.323775	0.00	161.00
store_191_SKU_673091552	182	67.159341	20.982284	27.00	142.00
store_192_SKU_909893792	182	74.543956	44.354495	23.00	270.00
store_193_SKU_209888946	182	128.895604	72.251671	20.00	310.00
store_194_SKU_120970412	182	66.379121	28.162987	0.00	142.00
store_194_SKU_120973848	182	63.296703	15.750818	3.00	110.00
store_194_SKU_233718998	182	59.153846	56.201772	2.00	668.00
store_194_SKU_9479889782	182	69.989011	25.510476	17.00	136.00
store_196_SKU_120931489	72	33.097222	8.378644	17.00	71.00
store_196_SKU_9888908	72	238.805417	78.561633	119.78	695.62
store_198_SKU_120972554	143	58.608392	26.090588	13.00	122.00
store_198_SKU_209939182	143	229.965035	147.161472	21.00	1263.00
store_198_SKU_667082810	143	66.881119	20.567816	21.00	111.00
store_198_SKU_9479889787	143	67.489510	18.408077	25.00	107.00
store_198_SKU_9888792	143	188.398601	61.927165	64.00	478.00

- The mean values represent the average sales volume for each SKU-store combination, which is essential for establishing baseline demand levels.

- High standard deviations indicate fluctuating demand, which suggests the need for advanced forecasting techniques to account for variability.
- Low standard deviations indicate more consistent demand, suitable for simpler forecasting models.
- Minimum values of zero are present in several series, indicating periods with no sales, which could be due to stockouts, low demand, or product lifecycle events.
- Maximum values vary widely, reflecting peak sales periods likely influenced by promotions, seasonality, or other factors.

Identify Series with High Variability

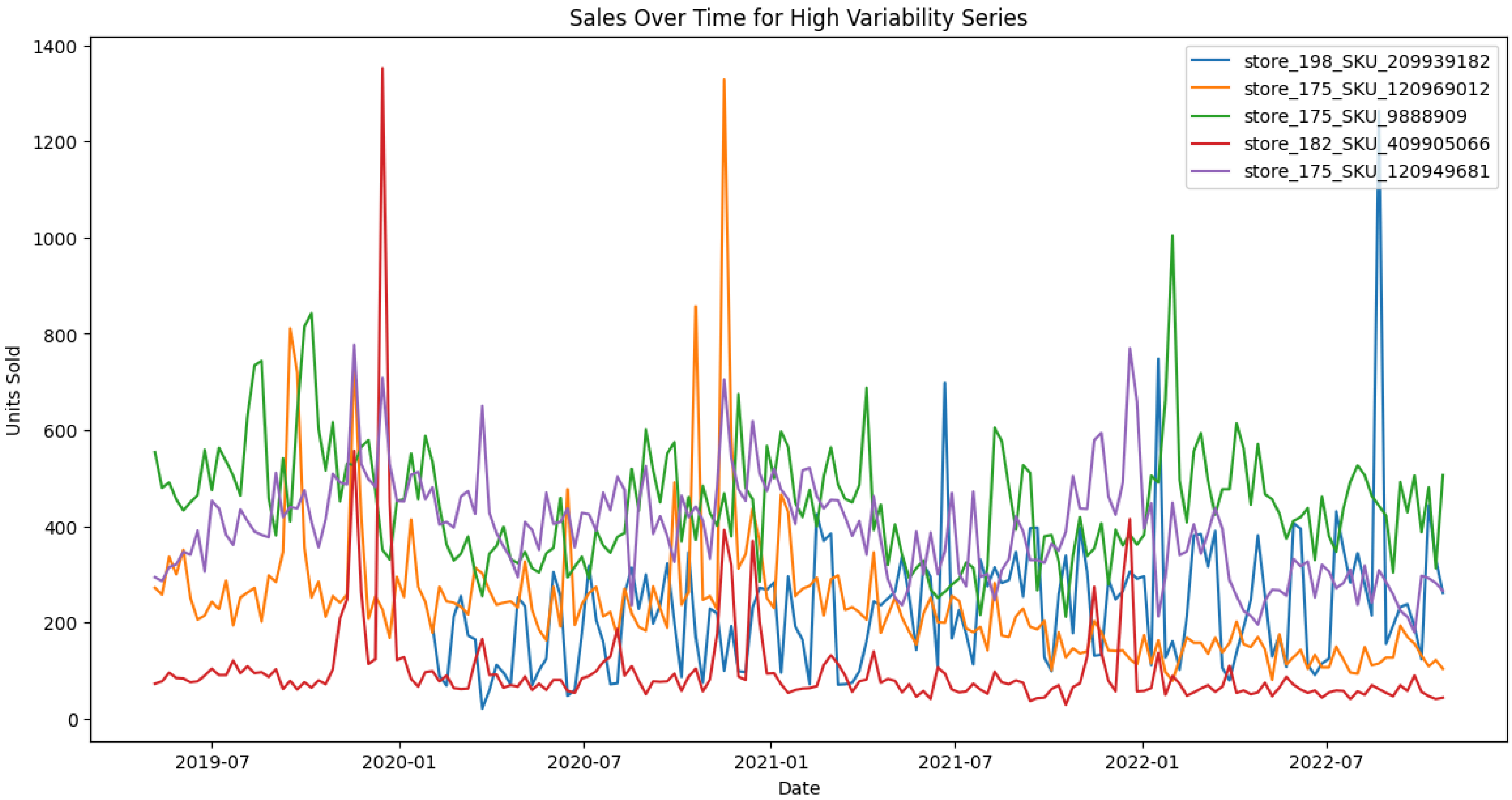
First, let's identify the series with the highest standard deviations, which indicate high variability in units.

In [ ]:
```
# Identify series with the highest standard deviations
top_var_series = per_series_stats.sort_values(by="std", ascending=False).head().index
```

Plot Sales Over Time for High Variability Series

We will plot the sales data for these high variability series to visually inspect the spikes and dips.

In [ ]:
```
# Identify series with the highest standard deviations
top_var_series = per_series_stats.sort_values(by="std", ascending=False).head().index

# Plot sales over time for high variability series
plt.figure(figsize=(14, 7))
for series in top_var_series:
    series_data = demand_df[demand_df[series_id] == series].set_index(date_col)["UNITS"]
    plt.plot(series_data, label=series)
plt.title("Sales Over Time for High Variability Series")
plt.xlabel("Date")
plt.ylabel("Units Sold")
plt.legend()
plt.show()
```



The plot illustrates the sales over time for the series with the highest standard deviations.

Spikes:

- Several series, such as **store_198_SKU_209939182**, **store_175_SKU_120969012**, and **store_175_SKU_9888909**, show notable spikes in sales. These spikes may correspond to specific events like promotions, seasonal demand, or market interventions.
- The spikes are particularly noticeable around early 2020 and late 2021, suggesting potential external influences or business activities that led to increased sales during these periods.

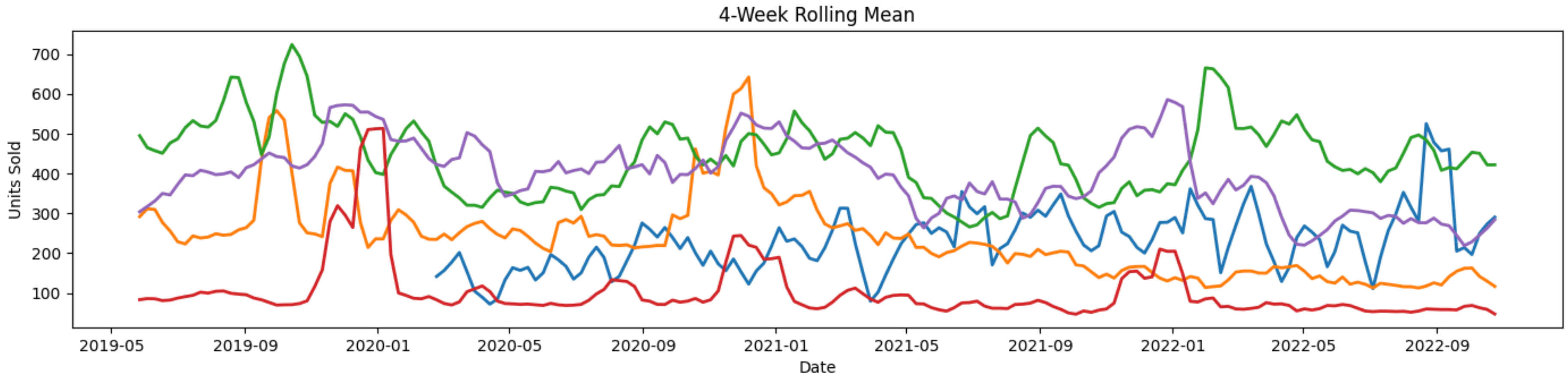
Dips:

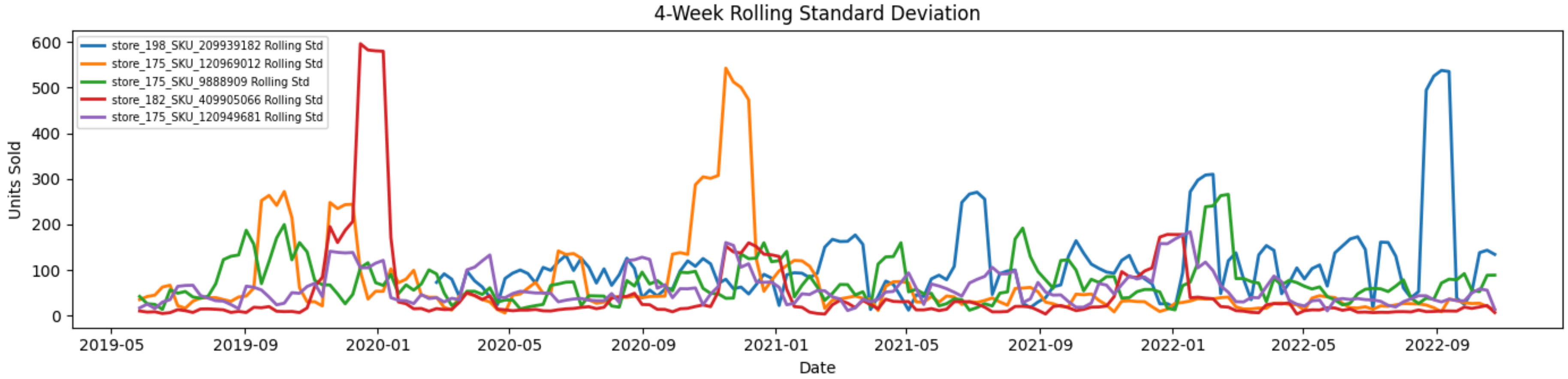
- Dips in sales are also evident in the series, notably around mid-2020 and early 2021. These dips might indicate periods of low demand, stockouts, or changes in market conditions.

Calculate and Plot Rolling Statistics

To further analyze the variability, we will calculate and plot the rolling mean and standard deviation.

In [ ]:
```
# Plot rolling mean and standard deviation for high variability series
window = 4
plt.figure(figsize=(14, 7))
for series in top_var_series:
    series_data = demand_df[demand_df[series_id] == series].set_index(date_col)["UNITS"]
    rolling_mean = series_data.rolling(window=window).mean()
    rolling_std = series_data.rolling(window=window).std()

    plt.subplot(2, 1, 1)
    plt.plot(rolling_mean, label=f"{series} Rolling Mean", linewidth=2)
    plt.title(f"{window}-Week Rolling Mean")
    plt.xlabel("Date")
    plt.ylabel("Units Sold")

    plt.subplot(2, 1, 2)
    plt.plot(rolling_std, label=f"{series} Rolling Std", linewidth=2)
    plt.title(f"{window}-Week Rolling Standard Deviation")
    plt.xlabel("Date")
    plt.ylabel("Units Sold")

plt.legend(fontsize="x-small")
plt.tight_layout()
plt.show()
```





Rolling Mean

The plot (top) shows the rolling mean of the sales data for the top variability series, providing insight into the overall trends over time.

- Series like **store_175_SKU_120969012** show a generally decreasing trend over time, suggesting a decline in sales.
- Conversely, some series like **store_198_SKU_209939182** exhibit an increasing trend towards the end of the period, indicating growing sales.

Rolling Standard Deviation

The plot (bottom) illustrates the rolling standard deviation, which indicates the variability in sales over time.

- Series such as **store_182_SKU_409905066** and **store_175_SKU_120969012** show high rolling standard deviations, highlighting periods of significant fluctuation in sales.
- Notably, store_182_SKU_409905066 has a period of very high variability around early 2020, followed by a sharp decrease, suggesting a period of high volatility in sales followed by stabilization.
- Some series exhibit relatively stable variability over time, such as **store_175_SKU_120949681**. These series may have more predictable sales patterns.

Note: It is seen that **store_198_SKU_209939182** started selling on 2020-09.

Check if any series start after the the minimum datetime and if any series end before the maximum datetime

In [ ]:
```
def analyze_series_dates(df, date_col, series_id):
    """
    Analyzes the date range of each series in the DataFrame and identifies series that start
    after the overall minimum date or end before the overall maximum date.

    Parameters:
    df (pd.DataFrame): The DataFrame containing demand data.
    date_col (str): The name of the column containing date information.
    series_id (str): The name of the column that uniquely identifies the series.

    Returns:
    tuple: A tuple containing the overall minimum date, overall maximum date,
           DataFrame of series that start after the overall minimum date,
           and DataFrame of series that end before the overall maximum date.
    """
    # Calculate overall min and max dates
    min_date = df[date_col].min()
    max_date = df[date_col].max()

    # Calculate min and max dates for each series
    series_start_end = df.groupby(series_id)[date_col].agg(["min", "max"])

    # Identify series that start after the overall minimum date
    series_start_after_min = series_start_end[series_start_end["min"] > min_date]

    # Identify series that end before the overall maximum date
    series_end_before_max = series_start_end[series_start_end["max"] < max_date]
```

```
    # Prepare the result string
    return print(
        f"Overall min date: {min_date}\n"
        f"Overall max date: {max_date}\n\n"
        f"Series that start after the overall minimum date:\n{series_start_after_min}\n\n"
        f"Series that end before the overall maximum date:\n{series_end_before_max}"
    )
```

In [ ]:
```
analyze_series_dates(df=demand_df, date_col=date_col, series_id=series_id)
```

```
Overall min date: 2019-05-06 00:00:00
Overall max date: 2022-10-24 00:00:00

Series that start after the overall minimum date:
                                min        max
STORE_SKU
store_139_SKU_120939045  2020-02-17 2022-10-24
store_141_SKU_120939045  2020-02-17 2022-10-24
store_182_SKU_56889087   2019-08-12 2022-10-24
store_196_SKU_120931489  2021-06-14 2022-10-24
store_196_SKU_9888908    2021-06-14 2022-10-24
store_198_SKU_120972554  2020-02-03 2022-10-24
store_198_SKU_209939182  2020-02-03 2022-10-24
store_198_SKU_667082810  2020-02-03 2022-10-24
store_198_SKU_9479889787 2020-02-03 2022-10-24
store_198_SKU_9888792    2020-02-03 2022-10-24

Series that end before the overall maximum date:
Empty DataFrame
Columns: [min, max]
Index: []
```

- The dataset includes 10 series that lack data from the start of the entire time range (2019-05-06). Instead, they start at various points later:
    - 2019-08-12 has 1 series
    - 2020-02-03 has 5 series
    - 2020-02-17 has 2 series

  - 2021-06-14 has 2 series
- There are no series that end before the overall maximum date.

I will drop the series that starts on 2019-08-12 and the series that starts on 2021-06-14 and use data from 2020-02-03. I will use the interpolation technique to fill the gaps in the other remaining series.

In [ ]:
```
to_drop = ["store_196_SKU_120931489", "store_196_SKU_9888908"]

filtered_df_ = demand_df[~demand_df["STORE_SKU"].isin(to_drop)]

filtered_df = filtered_df_.loc[filtered_df_["DATE"].between("2021-06-14", "2022-10-24")]
```

In [ ]:
```
filtered_df.shape
```

Out[ ]:
```
(3456, 13)
```

In [ ]:
```
analyze_series_dates(df=filtered_df, date_col=date_col, series_id=series_id)
```

```
Overall min date: 2021-06-14 00:00:00
Overall max date: 2022-10-24 00:00:00

Series that start after the overall minimum date:
Empty DataFrame
Columns: [min, max]
Index: []

Series that end before the overall maximum date:
Empty DataFrame
Columns: [min, max]
Index: []
```

There are no series that start after the overall minimum date.

Time Series Analysis

In [ ]:
```
def prepare_forecast_data(df, date_col, series_id):
    """
    Prepares the forecast DataFrame by resetting the index, dropping specific columns,
```

```
    renaming columns, and converting the series_id column to category type.

    Parameters:
    df (pd.DataFrame): The filtered DataFrame to process.
    date_col (str): The name of the column containing date information.
    series_id (str): The name of the column that uniquely identifies the series.

    Returns:
    pd.DataFrame: The prepared DataFrame for forecasting.
    """

    # Drop rows with UNITS = 0
    df = df[df["UNITS"] != 0]

    # Reset the index and drop it
    df.reset_index(inplace=True, drop=True)

    # Drop specific columns
    df_forecast = df.drop(columns=["STORE", "SKU", "SKU_CATEGORY"])

    # Rename columns
    df_forecast.rename(
        columns={date_col: "ds", "UNITS": "y", series_id: "unique_id"}, inplace=True
    )

    # Convert the unique_id column to category type
    df_forecast["unique_id"] = df_forecast["unique_id"].astype("category")

    return df_forecast
```

In [ ]:
```
df_forecast = prepare_forecast_data(
    df=filtered_df, date_col=date_col, series_id=series_id
)
```

Time Series Stationarity

In [ ]:
```
def augmented_dickey_fuller_test(series, significance_level=0.05):
    results = {}
    dftest = adfuller(series, autolag="AIC")
```

```python
    results["Test Statistic"] = dftest[0]
    results["p-value"] = dftest[1]
    results["No Lags Used"] = dftest[2]
    results["Number of Observations Used"] = dftest[3]
    results["Stationarity"] = dftest[1] <= significance_level

    return results
```

In [ ]:
```python
def apply_adf_test(df, column, diff=False, significance_level=0.05):
    results_adf = []
    for uid in df["unique_id"].unique():
        subset = df[df["unique_id"] == uid].copy()
        series = subset[column]

        diff_order = 0
        if diff:
            # First differencing
            diff_series = series.diff().dropna()
            result = augmented_dickey_fuller_test(diff_series, significance_level)
            diff_order = 1

            # Check if first differencing made the series stationary
            if not result["Stationarity"]:
                # Second differencing
                diff_series = diff_series.diff().dropna()
                result = augmented_dickey_fuller_test(diff_series, significance_level)
                diff_order = 2

        else:
            result = augmented_dickey_fuller_test(series, significance_level)

        results_adf.append({
            "unique_id": uid,
            "Test Statistic": result["Test Statistic"],
            "p-value": result["p-value"],
            "No Lags Used": result["No Lags Used"],
            "Number of Observations Used": result["Number of Observations Used"],
            "Stationarity": result["Stationarity"],
            "Differencing Order": diff_order
```

```python
        })
    return pd.DataFrame(results_adf)
```

In [ ]:
```python
results_adf = apply_adf_test(df_forecast, "y")
```

In [ ]:
```python
def get_non_stationary_stores(results_adf):
    nonst_df = results_adf[results_adf["Stationarity"] == False]
    nonst_df_ = nonst_df[["unique_id", "p-value", "Stationarity"]]
    print(f"Total number of non-stationary store_sku {nonst_df_.shape[0]}")
    return nonst_df_
```

In [ ]:
```python
nonst_df = get_non_stationary_stores(results_adf)
nonst_df
```

```
Total number of non-stationary store_sku 16
```

Out[ ]:

	unique_id	p-value	Stationarity
6	store_139_SKU_120939045	0.308797	False
8	store_141_SKU_120930437	0.097703	False
10	store_143_SKU_120970410	0.111458	False
12	store_144_SKU_120970431	0.256850	False
15	store_146_SKU_120969553	0.175221	False
16	store_146_SKU_120971333	0.051884	False
17	store_146_SKU_667079807	0.367783	False
20	store_147_SKU_120970437	0.487991	False
21	store_147_SKU_56889100	0.124301	False
22	store_147_SKU_667079809	0.091617	False
23	store_147_SKU_673092026	0.184395	False

25	store_174_SKU_409905079	0.177542	False
26	store_175_SKU_120939350	0.566427	False
33	store_182_SKU_409905066	0.139246	False
35	store_191_SKU_120969553	0.345574	False
43	store_198_SKU_120972554	0.124673	False

Making the series stationary

In [ ]:
```
results_adf_ = apply_adf_test(df_forecast, "y", diff=True)
```

In [ ]:
```
nonst_df_diff = get_non_stationary_stores(results_adf_)
nonst_df_diff
```

```
Total number of non-stationary store_sku 0
```

Out[ ]:

unique_id	p-value	Stationarity

When using machine learning models for time series forecasting, it is not strictly necessary to make the data stationary. Unlike traditional time series methods (e.g., ARIMA), which rely on stationarity to make accurate predictions, machine learning models can often handle non-stationary data well. However, it is possible to make the time series stationary by using methods such as differencing, STL, and log transformations.

The **MSTL** (Multiple Seasonal-Trend decomposition using LOESS) model can provide more accurate forecasts by decomposing the time series into seasonal, trend, and residual components. This makes it suitable for handling non-stationary data, which is why we will use this model.

Demand Forecasting with MSTL Model

The MSTL (Multiple Seasonal-Trend decomposition using LOESS) model decomposes the time series in multiple seasonalities using a Local Polynomial Regression (LOESS). Then it forecasts the trend using a custom non-seasonal model and each seasonality using a SeasonalNaive model.

In [ ]:
```python
def split_by_unique_id(group):
    split_date = "2022-09-26"
    train = group[group["ds"] <= split_date]
    test = group[group["ds"] > split_date]
    return train, test


train_list = []
test_list = []

grouped = df_forecast.groupby("unique_id")
for name, group in grouped:
    train, test = split_by_unique_id(group)
    train_list.append(train)
    test_list.append(test)

train_data = pd.concat(train_list)
test_data = pd.concat(test_list)
```

In [ ]:
```python
train_data.shape,test_data.shape
```

Out[ ]:
```
((3263, 10), (192, 10))
```

In [ ]:
```python
train_df_u = train_data.drop(
    columns=[
        "UNITS_MIN",
        "UNITS_MAX",
        "UNITS_MEAN",
        "UNITS_STD",
        "TRANSACTIONS_SUM",
        "PROMO_MAX",
        "PRICE_MEAN",
    ]
)
exog_df = test_data.drop(columns=["y"])
test_y = test_data[["unique_id", "ds", "y"]]
exog_df["ds"] = pd.to_datetime(exog_df["ds"])
test_y["ds"] = pd.to_datetime(test_y["ds"])
```

```
In [ ]: HORIZON = 4  # forecast horizon: 4 weeks ahead
        LEVEL = [90]  # means that the range of values should include the actual future value with probability 90%.
        S_LENGTH = [4]  # length of the seasonal period of the time series
        N_WINDOWS = 8  # number of windows used for cross-validation, meaning the number of forecasting processes in the pas
        STEP_SIZE = 2  # step size between each window, meaning how often do you want to run the forecasting process.

        # Create a baseline forecast
        models_mstl = [
            MSTL(season_length=S_LENGTH, trend_forecaster=AutoARIMA()),
        ]
        sf_model = sf(models=models_mstl, freq="W-MON")
```

```
In [ ]: forecasts_df = sf_model.forecast(df=train_data,h=HORIZON, X_df=exog_df,level=LEVEL)
        forecasts_df.head()
```

Out[ ]:

	ds	MSTL	MSTL-lo-90	MSTL-hi-90
unique_id				
store_130_SKU_120931082	2022-10-03	85.253983	80.861099	89.646866
store_130_SKU_120931082	2022-10-10	101.088570	91.992538	110.184601
store_130_SKU_120931082	2022-10-17	65.764618	55.961220	75.568008
store_130_SKU_120931082	2022-10-24	69.487785	59.684387	79.291176
store_130_SKU_120969795	2022-10-03	63.681263	61.214573	66.147957

```
In [ ]: forecasts_df.reset_index(inplace=True)
```

```
In [ ]: res = test_y.merge(forecasts_df, how="left", on=["unique_id", "ds"])
```

```
In [ ]: mae_exg = mae(res["y"],res["MSTL"])
        smape_exg_mean = smape(res["y"],res["MSTL"])
```

```
In [ ]: print(f"With exogenous variable:\nMAE: {mae_exg:.2f}\nSMAPE: {smape_exg_mean:.2f}")
```

```
With exogenous variable:
MAE: 6.97
SMAPE: 7.84
```

- A MAE of 6.97 means that, on average, your model's predictions deviate from the actual values by approximately 6.97 units.
- A SMAPE of 7.84 indicates that, on average, the forecast error is 7.84 of the magnitude of the actual and forecasted values.

In [ ]:

```
# univariate model
fcst_u = sf_model.forecast(df=train_df_u, h=HORIZON)
res_u = test_y.merge(fcst_u, how="left", on=["unique_id", "ds"])

mae_u = mae(res_u["y"],res_u["MSTL"])

# Calculate SMAPE
smape_mean_u = smape(res_u["y"],res_u["MSTL"])

print(f"Without exogenous variable:\nMAE: {round(mae_u,2)}\nSMAPE: {round(smape_mean_u,2)}")
```

```
Without exogenous variable:
MAE: 28.85
SMAPE: 29.19
```

The model performed better with exogenous variables.

In [ ]:

```
sf.plot(train_df_u,forecasts_df,engine="plotly",level=LEVEL)
```

MSTL Cross-Validation

In [ ]:

```
crossvalidation_df_mstl = sf_model.cross_validation(
    df=df_forecast, h=HORIZON, n_windows=N_WINDOWS,step_size=STEP_SIZE,
)
```

In [ ]:

```
crossvalidation_df_mstl.head()
```

Out[ ]:

	ds	cutoff	y	MSTL
unique_id				

store_130_SKU_120931082	2022-06-27	2022-06-20	96.0	94.234886
store_130_SKU_120931082	2022-07-04	2022-06-20	70.0	69.967743
store_130_SKU_120931082	2022-07-11	2022-06-20	89.0	88.396660
store_130_SKU_120931082	2022-07-18	2022-06-20	90.0	96.498802
store_130_SKU_120931082	2022-07-11	2022-07-04	89.0	86.595596

In [ ]:
```
def evaluate_cross_validation(df, metric):
    models = [c for c in df.columns if c not in ('unique_id','ds', 'cutoff', 'y')]
    evals = []
    for model in models:
        eval_ = df.groupby(['unique_id', 'cutoff']).apply(lambda x: metric(x['y'].values, x[model].values)).to_frame
        if metric == mae:
            eval_.columns = [model+'_mae']
        else:
            eval_.columns = [model+'_smape']

        evals.append(eval_)
    evals = pd.concat(evals, axis=1)
    evals = evals.groupby(['unique_id']).mean(numeric_only=True)
    return evals
```

In [ ]:
```
evaluation_mstl_cv_mae = evaluate_cross_validation(crossvalidation_df_mstl,mae)
```

In [ ]:
```
mae_mstl_cv_std = evaluation_mstl_cv_mae.std()[0]
mae_mstl_cv = evaluation_mstl_cv_mae.mean()[0]
```

In [ ]:
```
print(f"MAE: {mae_mstl_cv:.2f}\nMAE: std: {mae_mstl_cv_std:.2f}")
```

```
MAE: 6.49
MAE: std: 7.13
```

The mean MAE value for the Cross Validation is 6.49, with a standard deviation of 7.13.

In [ ]:
```
evaluation_mstl_cv_smape = evaluate_cross_validation(crossvalidation_df_mstl,smape)
```

In [ ]:
```
smape_mstl_cv_std = evaluation_mstl_cv_smape.std()[0]
smape_mstl_cv = evaluation_mstl_cv_smape.mean()[0]
```

In [ ]:
```
print(f"SMAPE: {smape_mstl_cv:.2f}\nSMAPE std: {smape_mstl_cv_std:.2f}")
```

```
SMAPE: 8.33
SMAPE std: 9.01
```

The mean SMAPE value for the Cross Validation is 8.33, with a standard deviation of 9.01.

In [ ]:
```
sf.plot(
    df_forecast,
    crossvalidation_df_mstl[["ds","MSTL"]],
    engine="plotly",
)
```

Although there isn't much intermittent data in my dataset, the following metrics can be helpful

> **Error Metrics for Intermittent Demand (CFE, PIS, MSR)**
>
> Intermittent demand is present in many retail settings and when forecasting stock requirements, businesses must strike a balance between the cost of goods and loss of sales due to a lack of stock. When training a forecasting model, using common accuracy measures, such as the MAE or MSE, do not always translate to ideal real-world outcomes. Due to the intermittence, forecasts at or near zero may reduce the error but would result in shelves being empty. We will explore a new range of error metrics targeted towards intermittent demand, such as the Cumulative Forecasting Error (CFE), Periods in Stock (PIS) and Mean Squared Rate (MSR).
>
> Source

In [ ]:
```
crossvalidation_df_mstl["error"] = crossvalidation_df_mstl["y"] - crossvalidation_df_mstl["MSTL"]
crossvalidation_df_mstl["abs_error"] = crossvalidation_df_mstl["error"].abs()

# Calculate cumulative forecast error
crossvalidation_df_mstl["CFE"] = crossvalidation_df_mstl["error"].cumsum()

# Calculate period-in-stock
```

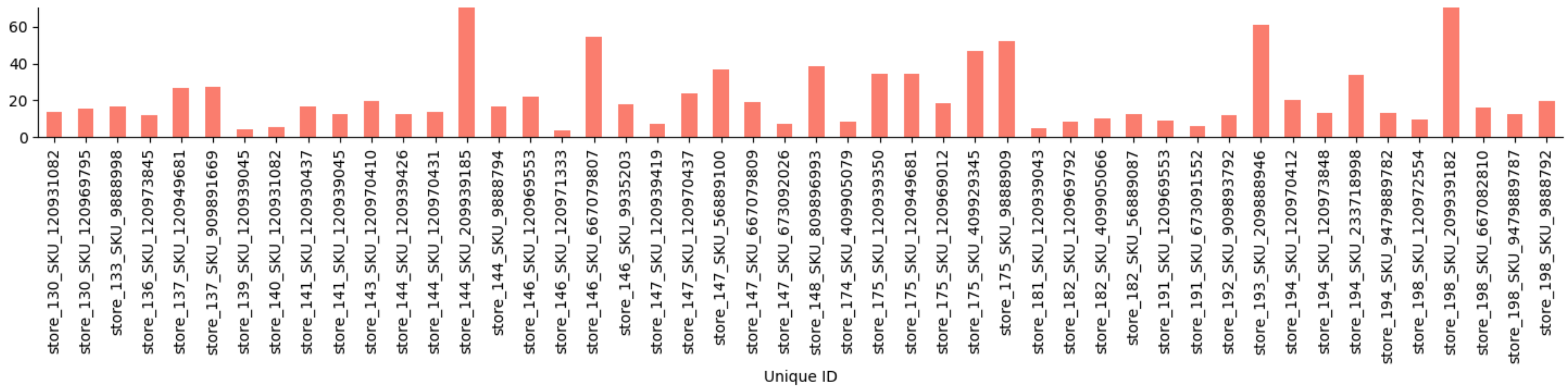
```
crossvalidation_df_mstl["in_stock"] = crossvalidation_df_mstl["MSTL"] >= crossvalidation_df_mstl["y"]
crossvalidation_df_mstl["PIS"] = crossvalidation_df_mstl["in_stock"].cumsum() / range(1, len(crossvalidation_df_mstl

# Calculate mean absolute rate
crossvalidation_df_mstl["cumulative_mean"] = crossvalidation_df_mstl.groupby("unique_id")["y"].cumsum() / crossvalid
crossvalidation_df_mstl["rate"] = crossvalidation_df_mstl["MSTL"] - crossvalidation_df_mstl["cumulative_mean"]
crossvalidation_df_mstl["abs_rate"] = crossvalidation_df_mstl["rate"].abs()
crossvalidation_df_mstl["MAR"] = crossvalidation_df_mstl.groupby("unique_id")["abs_rate"].transform("mean")

# Calculate number of stockouts
crossvalidation_df_mstl["stockout"] = crossvalidation_df_mstl["MSTL"] < crossvalidation_df_mstl["y"]
crossvalidation_df_mstl["NOS"] = crossvalidation_df_mstl.groupby("unique_id")["stockout"].transform("sum")

# Aggregate Metrics by unique_id
metrics_df = crossvalidation_df_mstl.groupby("unique_id").agg(
    CFE=("CFE", "last"),  # Last value of CFE for the cumulative effect
    PIS=("PIS", "last"),  # Last value of PIS for cumulative percentage
    MAR=("MAR", "mean"),
    NOS=("NOS", "mean")     )

metrics_df.reset_index(inplace=True)
```

In [ ]:

```
fig, axes = plt.subplots(4, 1, figsize=(15, 15),sharex=True)

# CFE
metrics_df.plot(kind="bar", x="unique_id", y="CFE", ax=axes[0], legend=False, color="skyblue")
axes[0].set_title("Cumulative Forecast Error (CFE)")
axes[0].set_xlabel("Unique ID")
axes[0].set_ylabel("CFE")

# NOS P
metrics_df.plot(kind="bar", x="unique_id", y="NOS", ax=axes[1], legend=False, color="orchid")
axes[1].set_title("Number of Stockouts (NOS)")
axes[1].set_ylabel("NOS")
axes[1].set_xlabel("Unique ID")

# PIS
metrics_df.plot(kind="bar", x="unique_id", y="PIS", ax=axes[2], legend=False, color="lightgreen")
axes[2].set_title("Period-In-Stock (PIS)")
axes[2].set_xlabel("Unique ID")
```

```
axes[2].set_ylabel("PIS")

# MAE
metrics_df.plot(kind="bar", x="unique_id", y="MAR", ax=axes[3], legend=False, color="salmon")
axes[3].set_title("Mean Absolute Rate (MAR)")
axes[3].set_xlabel("Unique ID")
axes[3].set_ylabel("MAR")

for ax in axes:
    # Remove top and right spines
    ax.spines["top"].set_visible(False)
    ax.spines["right"].set_visible(False)


# Adjust layout
plt.tight_layout()
plt.show()
```


Cumulative Forecast Error (CFE)
CFE
300
200
100
0
−100
−200
Number of Stockouts (NOS)
NOS
25
20
15
10
5
0
Period-In-Stock (PIS)
PIS
0.5
0.4
0.3
0.2
0.1
0.0
Mean Absolute Rate (MAR)
MAR
160
140
120
100
80



Cumulative Forecast Error (CFE)

The CFE is the sum of the difference between a forecast and the observed demand.

- **Positive CFE**: Indicates over-forecasting (the model predicts higher demand than actual).
- **Negative CFE**: Indicates under-forecasting (the model predicts lower demand than actual).
- The **CFE plot** shows fluctuations, suggesting varying forecasting accuracy across different `unique_ids`.

Number of Stockouts (NOS)

Count of instances where the forecasted stock is less than the actual demand. Reveals the frequency of stockouts, crucial for inventory management.

- **Higher NOS Values**: Indicate more frequent stockouts.
- Several unique_ids have higher NOS values, suggesting frequent instances of stockouts.
- Some unique_ids have lower NOS values, indicating better stock management or more accurate forecasts.

Period-In-Stock (PIS)

This is the accumulation of the CFE, which will give insight into what is happening throughout the period. Shows the reliability of the forecast in maintaining stock levels.

- Values close to 1 indicate good performance, where the stock is frequently in supply.

- Lower values indicate more frequent stockouts.
- Most unique_ids have a relatively high PIS, indicating that the forecasted stock was sufficient to meet demand for a significant portion of the time.
- Some unique_ids show slightly lower PIS values, suggesting more frequent stockouts or periods where the forecast did not meet actual demand.

Mean Absolute Rate (MAR)

MAR is a measure of the average absolute deviation of the forecasted demand rate from the cumulative mean demand rate. It reflects how well the forecast matches the variability of demand over time.

- The MAR values show significant variation across unique IDs, with some having very high MAR values, indicating large deviations between forecasted and actual demand rates.
- A few unique IDs stand out with exceptionally high MAR values, suggesting these forecasts are less reliable and deviate substantially from the actual demand.
- The MAR metric highlights the overall accuracy and reliability of the forecast in capturing demand trends.
- The **MAR plot** highlights significant variability, with some `unique_ids` showing high error, suggesting areas where the model needs improvement.

The CFE, NOS, and PIS metrics help identify areas where the forecast tends to overestimate or underestimate demand, leading to stockouts or overstocks.

Demand Forecasting with TimeGPT

Nixtla's TimeGPT is a generative pre-trained forecasting model for time series data. TimeGPT can produce accurate forecasts for new time series without training, using only historical values as inputs. TimeGPT can be used across a plethora of tasks including demand forecasting, anomaly detection, financial forecasting, and more.

Splitting the data

In [ ]:
```
test_df = df_forecast.groupby('unique_id').tail(4)
input_df = df_forecast.drop(test_df.index).reset_index(drop=True)
```

```python
exog_df = test_df.drop(columns=["y"])
```

In [ ]:
```python
# Load environment variables from a .env file and retrieve the NIXTLA API key
load_dotenv(".env")
api_key=os.getenv("NIXTLA_API_KEY")
```

Initialize NixtlaClient

Create and validate the Nixtla client using the API key.

In [ ]:
```python
nixtla_client = NixtlaClient(api_key=api_key)
```

In [ ]:
```python
nixtla_client.validate_api_key()
```

```
INFO:nixtla.nixtla_client:Happy Forecasting! :), If you have questions or need support, please email ops@nixtla.io s
haring this response and ID: VE5FH9GRYJ
```

Out[ ]: True

In [ ]:
```python
# Check the parameters
print(f"horizon: {HORIZON}")
print(f"n_windows: {N_WINDOWS}")
print(f"step_size: {STEP_SIZE}")
print(f"level: {LEVEL}")
```

```
horizon: 4
n_windows: 8
step_size: 2
level: [90]
```

Forecast Using TimeGPT

In [ ]:
```python
start = time.time()

fcst_df = nixtla_client.forecast(
    df=input_df,
    h=HORIZON,
    X_df=exog_df,
    level=LEVEL,
```

```
    finetune_steps=10,
    finetune_loss="mae",
    time_col="ds",
    target_col="y",
    id_col="unique_id",
)

end = time.time()

timegpt_duration = end - start

print(f"Time (TimeGPT): {timegpt_duration}")
```

```
INFO:nixtla.nixtla_client:Validating inputs...
INFO:nixtla.nixtla_client:Preprocessing dataframes...
INFO:nixtla.nixtla_client:Inferred freq: W-MON
INFO:nixtla.nixtla_client:Using the following exogenous variables: UNITS_MIN, UNITS_MAX, UNITS_MEAN, UNITS_STD, TRAN
SACTIONS_SUM, PROMO_MAX, PRICE_MEAN
INFO:nixtla.nixtla_client:Calling Forecast Endpoint...
Time (TimeGPT): 4.50141453742981
```

Plot the Forecast

In [ ]:
```
nixtla_client.plot(
    test_df,
    fcst_df,
    models=["TimeGPT"],
    level=LEVEL,
    time_col="ds",
    target_col="y",
    engine="plotly",
)
```

Evaluate the Forecast

Merge the forecasted data with the validation set and evaluate the performance using MAE and RMSE metrics.

In [ ]:
```
from utilsforecast.losses import mae,smape
```

```python
fcst_df["ds"] = pd.to_datetime(fcst_df["ds"])
res_gpt = pd.merge(test_df, fcst_df, "left", ["unique_id", "ds"])


evaluation_gpt = evaluate(
    res_gpt,
    metrics=[mae,smape],
    models=["TimeGPT"],
    target_col="y",
    id_col="unique_id",

)
```

In [ ]:
```python
evaluation_gpt.groupby("metric")["TimeGPT"].agg(["mean", "std"])
```

Out[ ]:

	mean	std
metric		
mae	20.064250	26.893934
smape	0.087343	0.068339

Perform Cross-Validation

Conduct cross-validation on the entire dataset to ensure robustness of the model.

In [ ]:
```python
timegpt_cv_df = nixtla_client.cross_validation(
    df_forecast,
    h=HORIZON,
    n_windows=N_WINDOWS,
    time_col="ds",
    target_col="y",
    freq="W-MON",
)
```

```
INFO:nixtla.nixtla_client:Validating inputs...
INFO:nixtla.nixtla_client:Using the following exogenous variables: UNITS_MIN, UNITS_MAX, UNITS_MEAN, UNITS_STD, TRAN
SACTIONS_SUM, PROMO_MAX, PRICE_MEAN
INFO:nixtla.nixtla_client:Calling Cross Validation Endpoint...
```

Visualize Cross-Validation Results

In [ ]:
```
nixtla_client.plot(
    df_forecast,
    timegpt_cv_df[["unique_id","ds","TimeGPT"]],
    engine="plotly"
)
```

Evaluate Cross-Validation Performance

In [ ]:
```
evaluation_gpt_cv = evaluate(
    timegpt_cv_df,
    metrics=[mae,smape],
    models=["TimeGPT"],
    target_col="y",
    id_col="unique_id",
)
```

Cross-Validation Results

In [ ]:
```
evaluation_gpt_cv.groupby("metric")["TimeGPT"].agg(["mean", "std"])
```

Out[ ]:

metric	mean	std
mae	16.844512	19.599907
smape	0.074268	0.051462

Model Performance Visualization

In [ ]:
```
def get_eval_metrics(evaluation_gpt_cv, evaluation_mstl_cv_mae, evaluation_mstl_cv_smape):
    """
    Extracts MAE and RMSE metrics for TimeGPT and MSTL models, and merges them.

    Parameters:
    - evaluation_gpt_cv (pd.DataFrame): Evaluation DataFrame for TimeGPT containing metrics.
    - evaluation_mstl_cv_mae (pd.DataFrame): Evaluation DataFrame for MSTL containing MAE metrics.
    - evaluation_mstl_cv_smape (pd.DataFrame): Evaluation DataFrame for MSTL containing SMAPE metrics.

    Returns:
    - pd.DataFrame: Merged DataFrame with unique_id, TimeGPT MAE, and MSTL MAE and RMSE.
    """
    eval_timegpt_cv_mae = evaluation_gpt_cv[evaluation_gpt_cv["metric"] == "mae"][["unique_id", "TimeGPT"]]
    eval_timegpt_cv_smape = evaluation_gpt_cv[evaluation_gpt_cv["metric"] == "smape"][["unique_id", "TimeGPT"]]
    eval_smape_mae_mstl = pd.merge(evaluation_mstl_cv_mae, evaluation_mstl_cv_smape, on="unique_id")
    eval_smape_mae_mstl.reset_index(inplace=True)

    return eval_timegpt_cv_mae, eval_timegpt_cv_smape, eval_smape_mae_mstl
```

In [ ]:
```
eval_timegpt_cv_mae, eval_timegpt_cv_smape, eval_smape_mae_mstl = get_eval_metrics(evaluation_gpt_cv, evaluation_mst
```

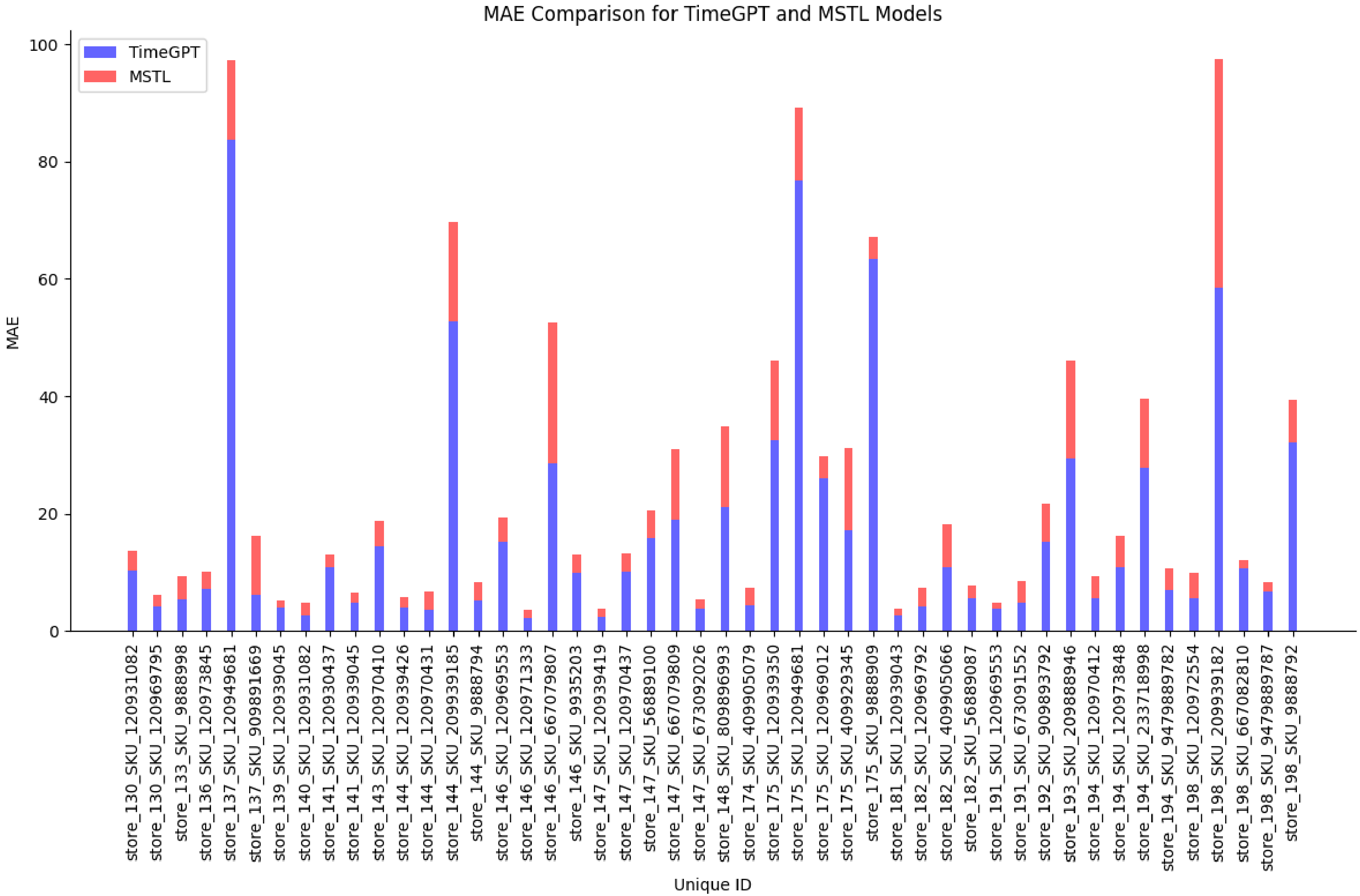
In [ ]:
```
def add_error_column(df, actual_col, predicted_col):
    """
    Adds an error column to a DataFrame based on the difference between the actual and predicted values.

    Parameters:
    df (pd.DataFrame): The DataFrame containing the actual and predicted values.
    actual_col (str): The name of the column containing the actual values.
    predicted_col (str): The name of the column containing the predicted values.

    Returns:
    pd.DataFrame: The DataFrame with the new error column added.
    """

    df["error_abs"] = np.abs(df[actual_col] - df[predicted_col])
```

```python
    df["error_"] = df[actual_col] - df[predicted_col]
    return df
```

In [ ]:
```python
crossvalidation_df_mstl = add_error_column(crossvalidation_df_mstl, "y", "MSTL")
timegpt_cv_df = add_error_column(timegpt_cv_df, "y", "TimeGPT")
```

In [ ]:
```python
width = 0.35

fig, axs = plt.subplots(figsize=(12, 8))

axs.bar(
    eval_timegpt_cv_mae["unique_id"],
    eval_timegpt_cv_mae["TimeGPT"],
    width,
    label="TimeGPT",
    color="b",
    alpha=0.6,
)
axs.bar(
    eval_smape_mae_mstl["unique_id"],
    eval_smape_mae_mstl["MSTL_mae"],
    width,
    label="MSTL",
    color="r",
    alpha=0.6,
    bottom=eval_timegpt_cv_mae["TimeGPT"],
)

# Customizing the bar plot
axs.set_xlabel("Unique ID")
axs.set_ylabel("MAE")
axs.set_title("MAE Comparison for TimeGPT and MSTL Models")
axs.legend()
axs.spines["top"].set_visible(False)
axs.spines["right"].set_visible(False)
axs.tick_params(axis="x", rotation=90)

axs.spines["top"].set_visible(False)
axs.spines["right"].set_visible(False)
```

```
# Show the combined plot
plt.tight_layout()
plt.show()
```



- The MSTL model consistently achieves lower Mean Absolute Error (MAE) values compared to the TimeGPT model across most unique IDs.
- This indicates that the MSTL model generally provides more accurate predictions for the majority of store and SKU combinations.
- The MSTL model outperforms the TimeGPT model in terms of overall accuracy, as evidenced by the lower MAE values.

Error Analysis

This error analysis helps in understanding the error distribution and identifying areas where the models can be improved.

In [ ]:
```
# MSTL error quantiles
crossvalidation_df_mstl[["y", "MSTL", "error_abs"]].describe([0.7, 0.8, 0.9, 0.95, 0.99]).T
```

Out[ ]:

	count	mean	std	min	50%	70%	80%	90%	95%	99%	m
y	1536.0	116.420860	117.729195	7.000000	73.000000	114.000000	168.000000	259.500000	398.750000	505.000000	1263.0000
MSTL	1536.0	116.534538	117.434235	-7.863361	73.506863	114.574203	166.720703	259.155624	402.694397	507.229431	1239.8222
error_abs	1536.0	6.494394	10.606213	0.001400	2.940297	6.127014	8.932001	16.441643	24.655142	51.241245	125.0586

In [ ]:
```
# TimeGPT error quantiles
timegpt_cv_df[["y", "TimeGPT", "error_abs"]].describe([0.7, 0.8, 0.9, 0.95, 0.99]).T
```

Out[ ]:

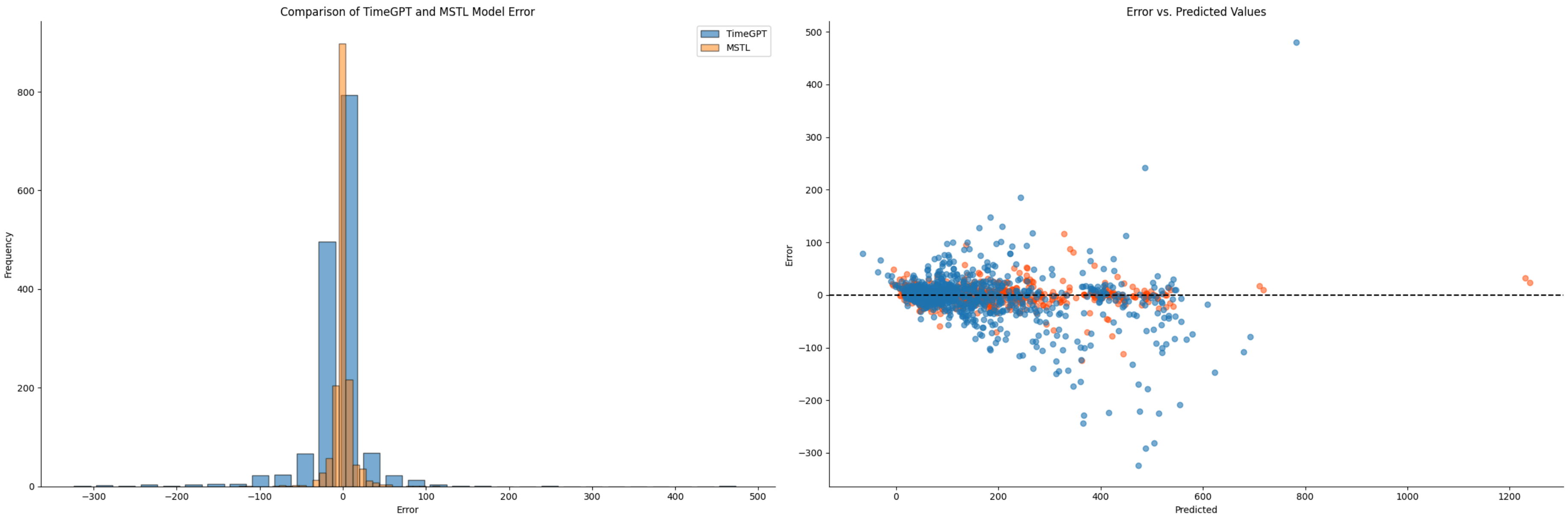
	count	mean	std	min	50%	70%	80%	90%	95%	99%	r
y	1536.0	115.186478	115.505403	2.000000	72.000000	108.805000	163.000000	254.500000	405.250000	524.600000	1263.000
TimeGPT	1536.0	118.203973	119.598659	-65.911036	71.726481	107.203879	167.513115	274.879559	412.104381	539.418692	783.144
error_abs	1536.0	16.844512	32.871438	0.006061	5.906795	13.450920	20.378603	40.325256	73.504694	159.686003	479.855

The MSTL model generally performs better than the TimeGPT model in terms of both average performance and consistency. MSTL has lower mean and median errors, a smaller standard deviation of errors, and significantly lower worst-case errors. These factors suggest that MSTL is a more reliable model for this dataset, with more accurate and consistent predictions.

In [ ]:

```
fig, axs = plt.subplots(1, 2, figsize=(24, 8))
# Plotting the histograms
axs[0].hist(
    timegpt_cv_df["error_"],
    bins=30,
    edgecolor="k",
    alpha=0.6,
    label="TimeGPT",
    width=20,
)

# Plot MSTL histogram
axs[0].hist(
    crossvalidation_df_mstl["error_"], bins=30, edgecolor="k", alpha=0.5, label="MSTL"
)

# Customizing the histograms
axs[0].set_xlabel("Error")
axs[0].set_ylabel("Frequency")
axs[0].set_title("Comparison of TimeGPT and MSTL Model Error")
axs[0].legend()

axs[1].scatter(
    crossvalidation_df_mstl["MSTL"],
    crossvalidation_df_mstl["error_"],
    alpha=0.5,
    c="orangered",
)
axs[1].scatter(
    timegpt_cv_df["TimeGPT"], timegpt_cv_df["error_"], alpha=0.6, c="tab:blue"
)

# Customizing the histograms
axs[1].set_xlabel("Predicted")
axs[1].set_ylabel("Error")
axs[1].set_title("Error vs. Predicted Values")
axs[1].axhline(y=0, color="black", linestyle="--")
```

```
for ax in axs:
    ax.spines["top"].set_visible(False)
    ax.spines["right"].set_visible(False)

# Show the combined plot
plt.tight_layout()
plt.show()
```



Histogram of Residuals

- Both models have a high concentration of residuals around zero, indicating that the majority of the predictions are close to the actual values.
- The MSTL model (orange bars) shows a slightly tighter distribution around zero compared to the TimeGPT model (blue bars), suggesting that MSTL predictions are generally more accurate.
- There are fewer extreme residuals (both positive and negative) for the MSTL model compared to the TimeGPT model. This indicates that the MSTL model has fewer large errors and is more robust.

Scatter Plot of Residuals vs. Predicted Values

- The residuals are mostly centered around the zero line, indicating no obvious bias in the predictions.

- There is a slight increase in the spread of residuals as the predicted values increase, suggesting that both models may have higher variability in their errors for larger predictions.
- Both models have a similar pattern, but the MSTL model (orange dots) seems to have fewer large residuals compared to the TimeGPT model (blue dots).
- The horizontal line at zero helps to visualize that most residuals are clustered around this line, further indicating that the predictions are generally accurate.

Conclusion

- The MSTL model generally provides more accurate and robust predictions compared to the TimeGPT model, as evidenced by the tighter distribution of residuals around zero and fewer extreme residuals.
- Both models do not show obvious bias in their predictions, as most residuals are centered around zero.
- Both models exhibit higher variability in their errors for larger predicted values, which suggests that further model tuning or additional features may be needed to improve performance for these cases.

MLflow

In [ ]:
```python
import mlflow
from statsforecast import StatsForecast
from sklearn.metrics import mean_absolute_error
import mlflavors
```

In [ ]:
```python
def custom_smape(y_true, y_pred):
    """
    Calculate Symmetric Mean Absolute Percentage Error (SMAPE)

    Parameters:
    y_true (numpy array or list): Array of actual values
    y_pred (numpy array or list): Array of predicted values

    Returns:
    float: SMAPE value
    """
    y_true, y_pred = np.array(y_true), np.array(y_pred)
    return np.mean(2 * np.abs(y_pred - y_true) / (np.abs(y_true) + np.abs(y_pred)))
```

In [ ]:
```
ARTIFACT_PATH = "model"
DATA_PATH = "./data"
# Define HORIZON and LEVEL
HORIZON = 4
LEVEL = [90]
```

In [ ]:
```
with mlflow.start_run() as run:

    X_test = test_data.drop(columns=["y"])
    y_test = test_data[["y"]]

    sf = StatsForecast(df=train_data, models=models_mstl, freq="W-MON", n_jobs=-1)

    sf.fit()

    # Evaluate model
    y_pred = sf.predict(h=HORIZON, X_df=X_test, level=LEVEL)["MSTL"]

    metrics = {
        "mae": mean_absolute_error(y_test, y_pred),
        "smape": custom_smape(y_test, y_pred),
    }

    print(f"Metrics: \n{metrics}")

    # Log metrics
    mlflow.log_metrics(metrics)

    # Log parameters
    mlflow.log_param("horizon", HORIZON)
    mlflow.log_param("level", LEVEL)

    # Log model using pickle serialization (default).
    mlflavors.statsforecast.log_model(
        statsforecast_model=sf,
        artifact_path=ARTIFACT_PATH,
        serialization_format="pickle",
    )
    model_uri = mlflow.get_artifact_uri(ARTIFACT_PATH)
```

```python
print(f"\nMLflow run id:\n{run.info.run_id}")
```

```
Metrics:
{'mae': 6.972873224218687, 'smape': 0.7521288414425913}
```

```
2024/06/12 14:45:31 WARNING mlflow.utils.environment: Encountered an unexpected error while inferring pip requirements (model URI: C:\Users\emirh\AppData\Local\Temp\tmp_jf1fmqo\model\model.pkl, flavor: statsforecast). Fall back to return ['statsforecast==1.7.4']. Set logging level to DEBUG to see the full traceback.
```

```
MLflow run id:
d862726a798e4befb5fa8f9b66fd069d
```