Saffron Sales Analysis & Trend Forecasting

1. Objective

Conduct sales trend analysis and short-term forecasting for saffron products to identify peak months, top-selling regions, and provide actionable recommendations for inventory and marketing decisions.

In [22]:
```
# Market Analysis & Sales Trend Forecasting for Saffron Products
# Author: Janet James
# Data: saffron_sales_1000rows.csv
# Date: 5-12-2025
# Objective: To analyze data and identify key trends
```

In [23]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

2. Data Description

The dataset contains 1,000 rows of saffron sales with the following columns:

- **date** – Transaction date
- **Product** – Product name
- **Quantity** – Units sold
- **Revenue** – Sales amount
- **Region** – Sales region
- **Customer Type** – Retail or Wholesale
- **Cost** – Product cost
- **Profit** – Revenue minus cost
- **Month, Year, Quarter** – Derived date features

In [24]:
```
import pandas as pd

df = pd.read_csv("saffron_sales_1000rows.csv")
df.head()
```

Out[24]:

	Date	Product	Quantity	Revenue	Region	Customer Type	Cost	Discounts	Profit	Yea
0	2023-01-01	Saffron Threads	3	3571	West	Retail	2194	17	1377	202
1	2023-01-02	Organic Saffron	21	2241	South	Retail	578	5	1663	202
2	2023-01-03	Premium Saffron	36	1194	North	Retail	836	4	358	202
3	2023-01-04	Premium Saffron	41	4818	South	Retail	707	3	4111	202
4	2023-01-05	Organic Saffron	20	914	East	Wholesale	1500	7	-586	202

In [25]:
```
df.describe()
```

Out[25]:

	Quantity	Revenue	Cost	Discounts	Profit	Year
count	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000
mean	24.916000	2751.765000	1594.075000	9.195000	1157.690000	2023.904000
std	14.101979	1299.250396	793.896026	5.815909	1500.147638	0.790828
min	1.000000	500.000000	205.000000	0.000000	-2268.000000	2023.000000
25%	13.000000	1635.250000	918.000000	4.000000	92.000000	2023.000000
50%	25.000000	2639.500000	1579.000000	9.000000	1235.500000	2024.000000
75%	37.000000	3832.000000	2293.250000	14.000000	2270.750000	2025.000000
max	49.000000	4995.000000	2998.000000	19.000000	4726.000000	2025.000000

In [26]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 13 columns):
 #   Column         Non-Null Count  Dtype 
---  ------         --------------  ----- 
 0   Date           1000 non-null   object
 1   Product        1000 non-null   object
 2   Quantity       1000 non-null   int64 
 3   Revenue        1000 non-null   int64 
 4   Region         1000 non-null   object
 5   Customer Type  1000 non-null   object
 6   Cost           1000 non-null   int64 
 7   Discounts      1000 non-null   int64 
 8   Profit         1000 non-null   int64 
 9   Year           1000 non-null   int64 
 10  Month          1000 non-null   int64 
 11  MonthName      1000 non-null   object
 12  Quarter        1000 non-null   int64 
dtypes: int64(8), object(5)
memory usage: 101.7+ KB
```

3. Data Cleaning

The following cleaning steps were performed:

- Converted the **date** column to datetime format
- Created new date features (Month, Year, Quarter)
- Stripped whitespace from Product names
- Checked and handled missing values
- Exported cleaned dataset for further analysis

In [27]:
```
#missing values
df.isnull().sum()
```

Out[27]:
```
Date             0
Product          0
Quantity         0
Revenue          0
Region           0
Customer Type    0
Cost             0
Discounts        0
Profit           0
Year             0
Month            0
MonthName        0
Quarter          0
dtype: int64
```

In [28]:
```
df.columns
```

Out[28]:
```
Index(['Date', 'Product', 'Quantity', 'Revenue', 'Region', 'Customer Type',
       'Cost', 'Discounts', 'Profit', 'Year', 'Month', 'MonthName', 'Quarter'],
      dtype='object')
```

In [29]:
```
#coverting date columns to datetime:
df['Date'] = pd.to_datetime(df['Date'])
```

In [30]:
```
# creating nrdf['Year'] = df['Date'].dt.year
df['Month'] = df['Date'].dt.month
df['MonthName'] = df['Date'].dt.strftime('%b')
df['Quarter'] = df['Date'].dt.quarter
df['Product'] = df['Product'].str.strip()
```

In [31]:
```
#data cleaning
df.isnull().sum()                                 #missing values
```

Out[31]:
```
Date             0
Product          0
Quantity         0
Revenue          0
Region           0
Customer Type    0
Cost             0
Discounts        0
Profit           0
Year             0
Month            0
MonthName        0
Quarter          0
dtype: int64
```

In [32]:
```
df=df.fillna(0)               #missing values
```

In [33]:
```
df = df.dropna()              #drop rows
```

In [34]:
```
df.to_csv('saffron_sales_1000rows.csv', index=False)
```

4. Exploratory Data Analysis (EDA)

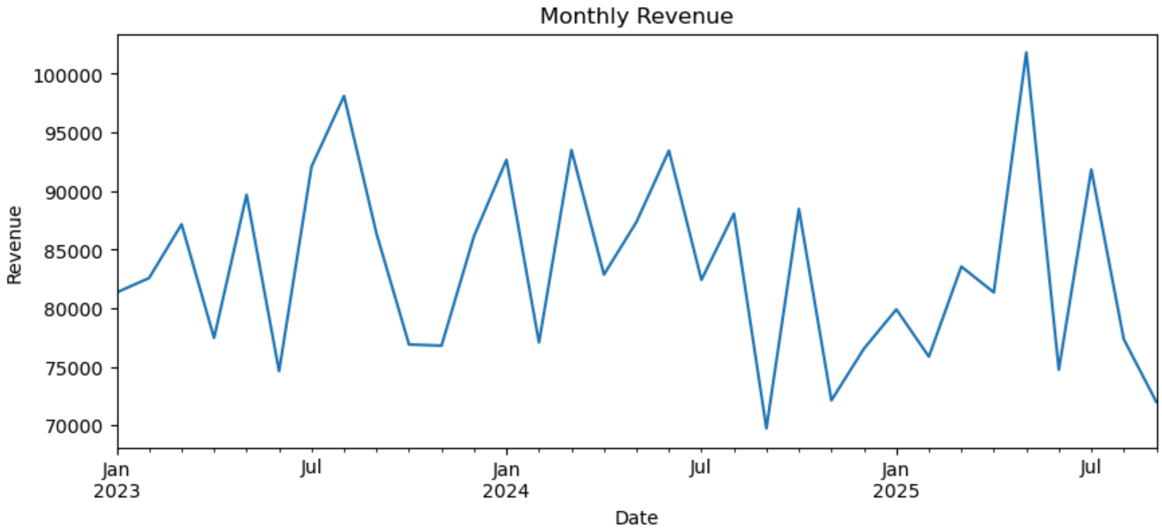
This section explores sales patterns across time, regions, customers, and products.

Plot: Monthly Revenue

Observation:
Revenue fluctuates across months, showing clear seasonal demand patterns for saffron products.

In [35]:
```
#Monthly trend (plot):
monthly = df.set_index('Date').resample('Me')['Revenue'].sum()
monthly.plot(figsize=(10,4), title='Monthly Revenue')
plt.ylabel('Revenue')
plt.show()
```

```
C:\Users\karthik\AppData\Local\Temp\ipykernel_8720\4226758972.py:2: FutureWarnin
g: 'Me' is deprecated and will be removed in a future version, please use 'ME' in
stead.
  monthly = df.set_index('Date').resample('Me')['Revenue'].sum()
```



In [36]:
```
#Total revenue & quantity:
total_rev = df['Revenue'].sum()
total_qty = df['Quantity'].sum()
print("Total revenue:", total_rev)
print("Total quantity:", total_qty)
```

```
Total revenue: 2751765
Total quantity: 24916
```

Plot: Revenue by Product

Observation:
Some saffron products contribute significantly more revenue than others, indicating key top-performing items.

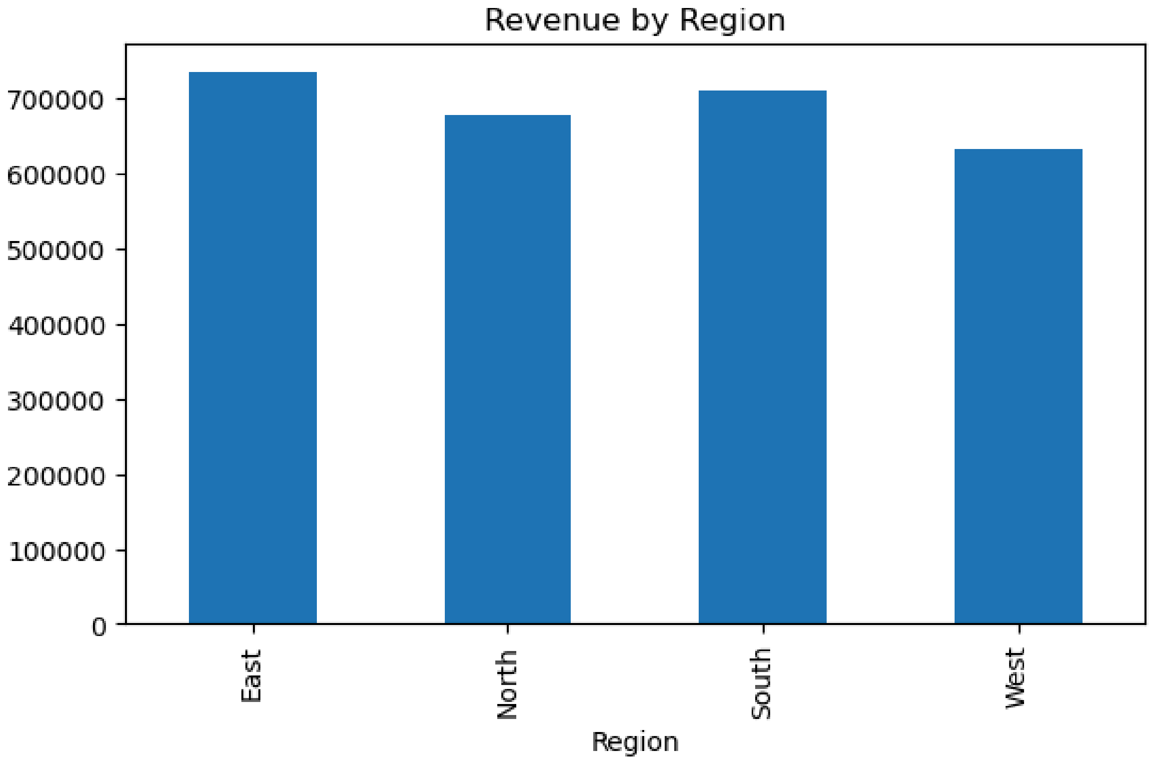
In [37]:
```
#Top products:
df.groupby('Product')['Revenue'].sum().sort_values(ascending=False).head(10)
```

Out[37]:
```
Product
Saffron Powder     746445
Premium Saffron    733678
Organic Saffron    670955
Saffron Threads    600687
Name: Revenue, dtype: int64
```

Plot: Revenue by Region

Observation:
Sales volumes differ across regions, showing uneven demand distribution geographically.

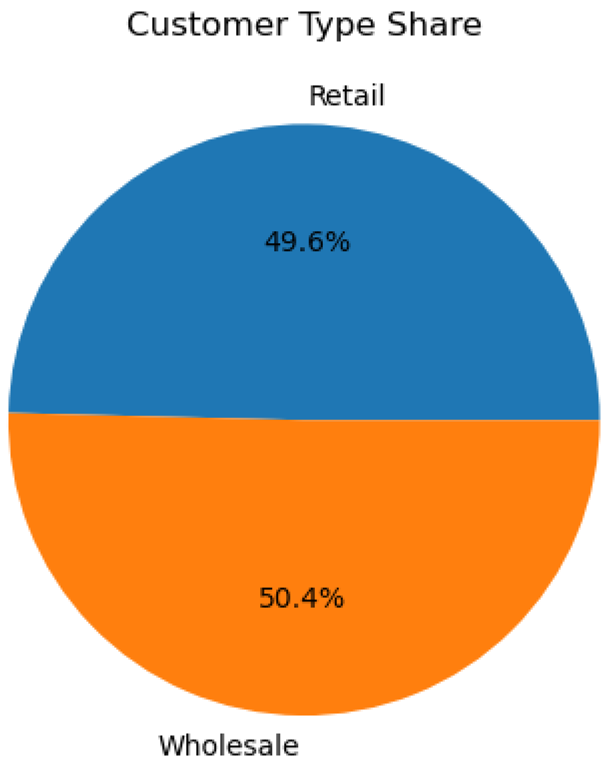
In [38]:
```
#region share
df.groupby('Region')['Revenue'].sum().plot(kind='bar', figsize=(7,4), title='Rev
plt.show()
```



Plot: Profit by Customer Type

Observation: Retail customers contribute higher overall profit than wholesale customers due to better margins.

In [39]:
```
#Customer type share:
df.groupby('Customer Type')['Revenue'].sum().plot(kind='pie', autopct='%1.1f%%',
plt.ylabel('')
plt.show()
```

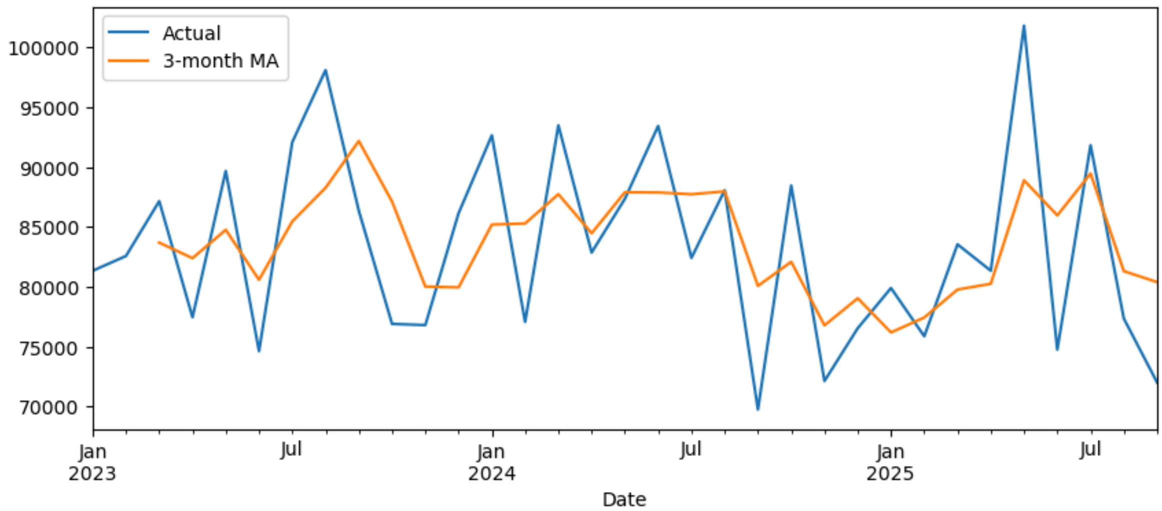


5. Forecasting

A simple model was trained to predict high vs low revenue sales using features such as Quantity, Cost, Discounts, and Month.
Evaluation metrics such as accuracy and confusion matrix were used to assess performance.

In [40]:
```
# Simple forecasting (monthly)
monthly = df.set_index('Date').resample('M')['Revenue'].sum()
monthly = monthly.asfreq('M')  # ensure regular index
# moving average
monthly_ma = monthly.rolling(3).mean()
monthly.plot(label='Actual', figsize=(10,4))
monthly_ma.plot(label='3-month MA')
plt.legend()
plt.show()
```

```
C:\Users\karthik\AppData\Local\Temp\ipykernel_8720\2665060300.py:2: FutureWarnin
g: 'M' is deprecated and will be removed in a future version, please use 'ME' ins
tead.
  monthly = df.set_index('Date').resample('M')['Revenue'].sum()
C:\Users\karthik\AppData\Local\Temp\ipykernel_8720\2665060300.py:3: FutureWarnin
g: 'M' is deprecated and will be removed in a future version, please use 'ME' ins
tead.
  monthly = monthly.asfreq('M')  # ensure regular index
```



In [41]:
```
#Note insights & save visuals
plt.savefig('monthly_revenue.png', dpi=150)
```

```
<Figure size 640x480 with 0 Axes>
```

6. Conclusions & Recommendations

- Sales show monthly seasonality, with certain months performing better.
- Retail customers provide higher profit margins.
- Some products dominate total revenue and should be prioritized.
- Regions vary in sales volume, requiring region-specific strategies.
- Discounts influence customer purchasing behavior and can be optimized.

- Premium saffron products drive the most revenue — consider promotional bundles.
- Increase inventory and marketing activities before festival months .
- Target North and West regions with focused promotions.

7.Appendix — Code Summary

This appendix provides the essential code used throughout the project for data loading, cleaning, analysis, and forecasting. Each code block supports the insights and visualizations presented in the main report.

A. Importing Libraries & Loading Dataset

This section loads all required libraries and imports the saffron sales dataset used for analysis.

B. Data Inspection

We check the structure, data types, missing values, and duplicates to understand the dataset before cleaning.

C. Data Cleaning

Data cleaning includes converting date fields, correcting text columns, removing duplicates, handling missing values, and preparing the dataset for analysis.

D. Product-wise Revenue Analysis

This analysis identifies top-performing products and highlights which saffron variants contribute the most to total revenue.

E. Region-wise Revenue Analysis

This section compares revenue across regions to understand geographical performance and business reach.

F. Monthly Sales Trend

Monthly trends reveal seasonality and demand patterns, especially peaks during festivals and special occasions.

G. Customer Type Revenue Split

Visualizing retail vs wholesale revenue helps understand customer behavior and the primary revenue source.

H. Simple Forecast (Moving Average)

A 3-month moving average provides a basic revenue forecast and smooths fluctuations in the monthly trend.

I. Saving Plots for Report

Plots are saved as image files to be included later in reports, dashboards, or your portfolio.

In [ ]: