Data Analyst project

2025

RETAIL STORE ANALYSIS

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Retail Store Performance

This dataset provides a comprehensive collection of key performance indicators (KPIs) for retail stores, offering insights into factors influencing store performance, customer engagement, and financial outcomes. The dataset is suitable for various machine learning and data analysis tasks, including regression, classification, and clustering. It can help in understanding the relationships between operational metrics, store characteristics, and sales performance.

Average Monthly Sales Revenue by Store Category

```
import warnings
warnings.filterwarnings('ignore')

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

df = pd.read_csv("Store_CA.csv")

df
```

```
      ProductVariety  MarketingSpend  CustomerFootfall  StoreSize  \
0                581              29              1723        186
1                382              31              1218        427
2                449              35              2654        142
3                666               9              2591        159
4                657              35              2151        275
...              ...             ...               ...        ...
1645             295              15              2681        235
1646             761               8              1398        456
1647             405              21              1490        465
1648             359              41              2042        350
1649             525              24              1772        178

      EmployeeEfficiency  StoreAge  CompetitorDistance
PromotionsCount  \
0                   84.9         1                  12
6
1                   75.8        18                  11
6
2                   92.8        14                  11
6
3                   66.3        11                  11
4
4                   89.1        28                  12
7
```

```
...                     ...       ...                 ...              ..
.
1645                   58.5        15                  10
5
1646                   78.5        26                  14
4
1647                   76.7        18                  12
5
1648                   67.6         2                   6
7
1649                   73.0        29                  18
6

      EconomicIndicator  StoreLocation StoreCategory
MonthlySalesRevenue
0                     108.3    Los Angeles   Electronics
284.90
1                      97.8    Los Angeles   Electronics
308.21
2                     101.1    Los Angeles       Grocery
292.11
3                     115.1     Sacramento      Clothing
279.61
4                      93.4      Palo Alto   Electronics
359.71
...                     ...            ...           ...
...
1645                   88.7     Sacramento      Clothing
273.55
1646                   95.1  San Francisco      Clothing
432.82
1647                   73.0    Los Angeles      Clothing
303.52
1648                  105.0      Palo Alto      Clothing
241.39
1649                   60.0    Los Angeles   Electronics
259.04

[1650 rows x 12 columns]
```

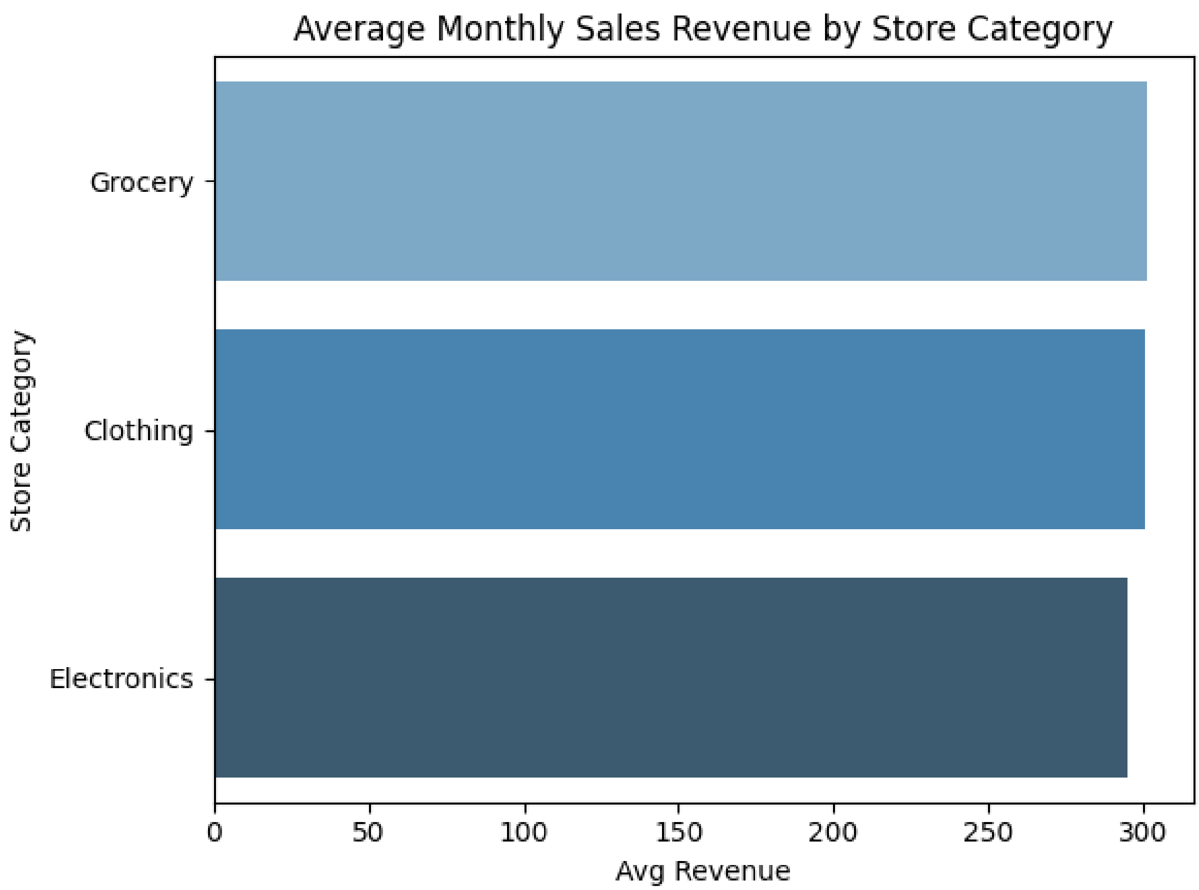
Average Monthly Sales Revenue by Store Category

```
query1 = """
SELECT StoreCategory,
```

```
       ROUND(AVG(MonthlySalesRevenue), 2) AS AvgRevenue
FROM df
GROUP BY StoreCategory
ORDER BY AvgRevenue DESC
"""
result1 = ps.sqldf(query1, locals())
print(result1)

# Graph
sns.barplot(x='AvgRevenue', y='StoreCategory', data=result1,
palette='Blues_d')
plt.title("Average Monthly Sales Revenue by Store Category")
plt.xlabel("Avg Revenue")
plt.ylabel("Store Category")
plt.tight_layout()
plt.show()
```

```
  StoreCategory  AvgRevenue
0       Grocery      301.33
1      Clothing      300.86
2   Electronics      295.39
```



This analysis shows how much revenue, on average, each store category generates. It helps identify which product categories (like Electronics, Grocery, Clothing) are the most profitable.

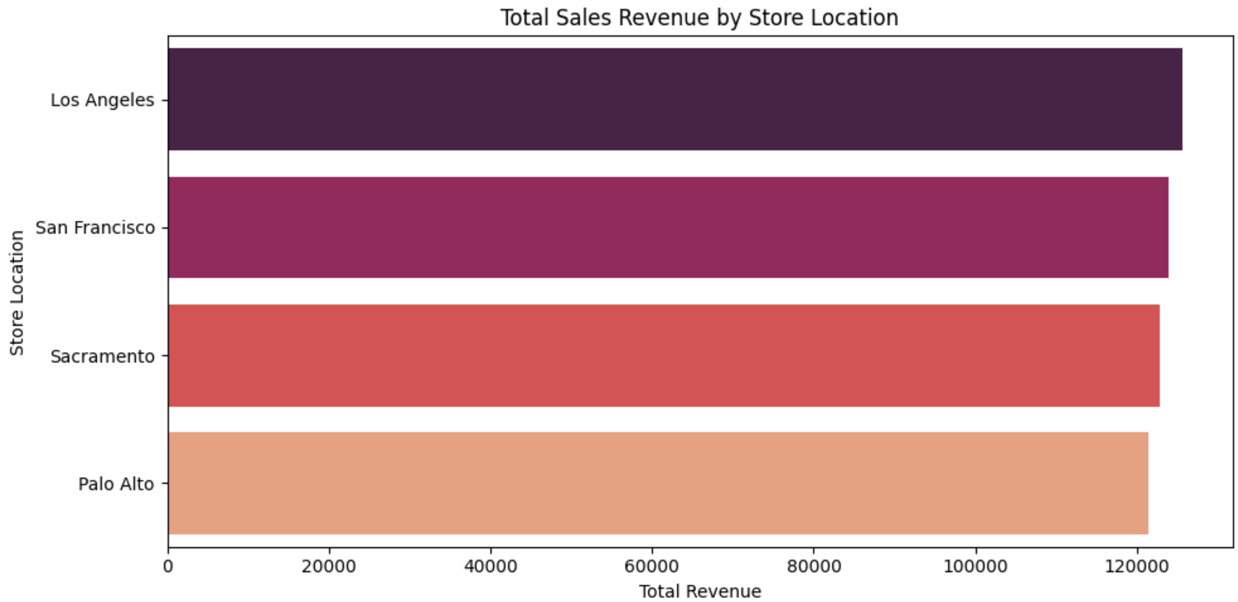
Insight: Store categories with higher average sales could receive more investments, promotions, or expansion plans.

Total Sales Revenue by Store Location

```
query2 = """
SELECT StoreLocation,
       ROUND(SUM(MonthlySalesRevenue), 2) AS TotalRevenue
FROM df
GROUP BY StoreLocation
ORDER BY TotalRevenue DESC
"""
result2 = ps.sqldf(query2, locals())
print(result2)

# Graph
plt.figure(figsize=(10, 5))
sns.barplot(x='TotalRevenue', y='StoreLocation', data=result2,
palette='rocket')
plt.title("Total Sales Revenue by Store Location")
plt.xlabel("Total Revenue")
plt.ylabel("Store Location")
plt.tight_layout()
plt.show()
```

```
   StoreLocation  TotalRevenue
0    Los Angeles     125596.79
1  San Francisco     123957.43
2     Sacramento     122778.68
3      Palo Alto     121435.02
```



We summarize the total sales generated by each store location across California. This is useful for identifying top-performing cities.

Insight:

Cities like Los Angeles or San Diego may generate more revenue and can be considered for opening new branches or allocating more resources.

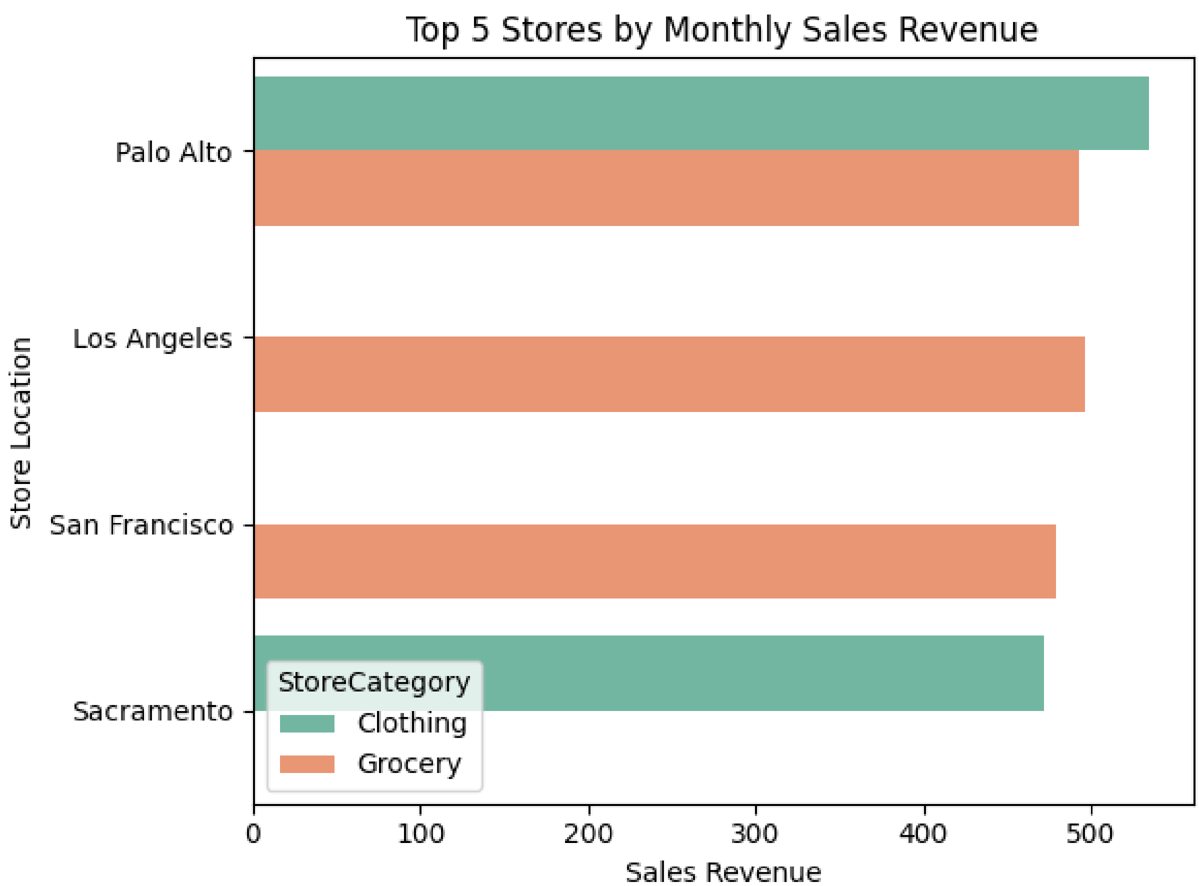
Stores with Highest Monthly Sales Revenue

```
query3 = """
SELECT StoreLocation, StoreCategory, MonthlySalesRevenue
FROM df
ORDER BY MonthlySalesRevenue DESC
LIMIT 5
"""
result3 = ps.sqldf(query3, locals())
print(result3)

# Graph
sns.barplot(x='MonthlySalesRevenue', y='StoreLocation',
hue='StoreCategory', data=result3, palette='Set2')
plt.title("Top 5 Stores by Monthly Sales Revenue")
plt.xlabel("Sales Revenue")
plt.ylabel("Store Location")
plt.tight_layout()
plt.show()
```

```
   StoreLocation StoreCategory  MonthlySalesRevenue
0      Palo Alto      Clothing               534.26
```

```
1    Los Angeles       Grocery                     496.70
2       Palo Alto      Grocery                     492.38
3  San Francisco       Grocery                     479.27
4     Sacramento      Clothing                     471.58
```



This highlights the top five performing stores in terms of individual monthly revenue. It includes both location and category.

Insight: Successful stores can be used as models or benchmarks for performance improvement in other regions.

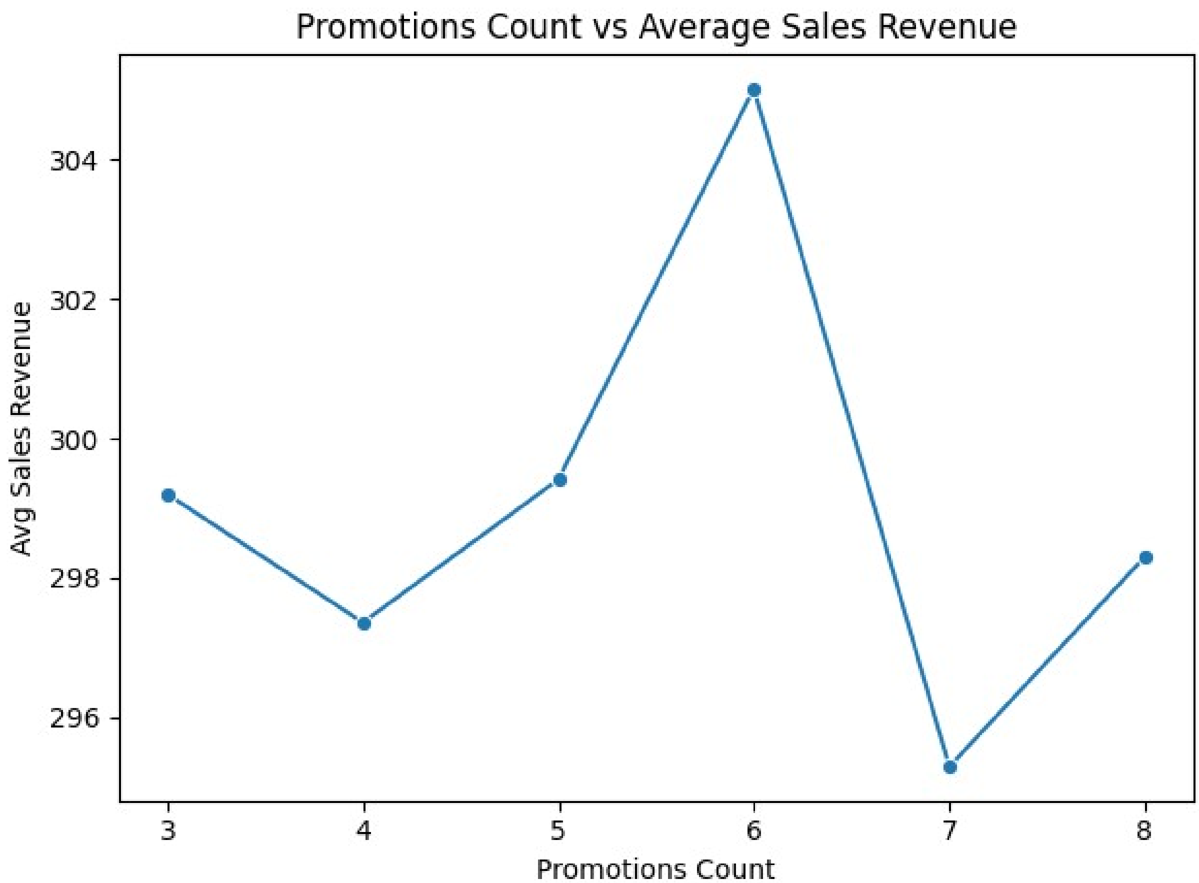
Promotions Count vs Average Sales Revenue

```
query4 = """
SELECT PromotionsCount,
       ROUND(AVG(MonthlySalesRevenue), 2) AS AvgRevenue
FROM df
GROUP BY PromotionsCount
ORDER BY PromotionsCount
"""
result4 = ps.sqldf(query4, locals())
```

```python
print(result4)

# Graph
sns.lineplot(x='PromotionsCount', y='AvgRevenue', data=result4,
marker='o')
plt.title("Promotions Count vs Average Sales Revenue")
plt.xlabel("Promotions Count")
plt.ylabel("Avg Sales Revenue")
plt.tight_layout()
plt.show()
```

	PromotionsCount	AvgRevenue
0	3	299.20
1	4	297.36
2	5	299.41
3	6	305.02
4	7	295.29
5	8	298.30



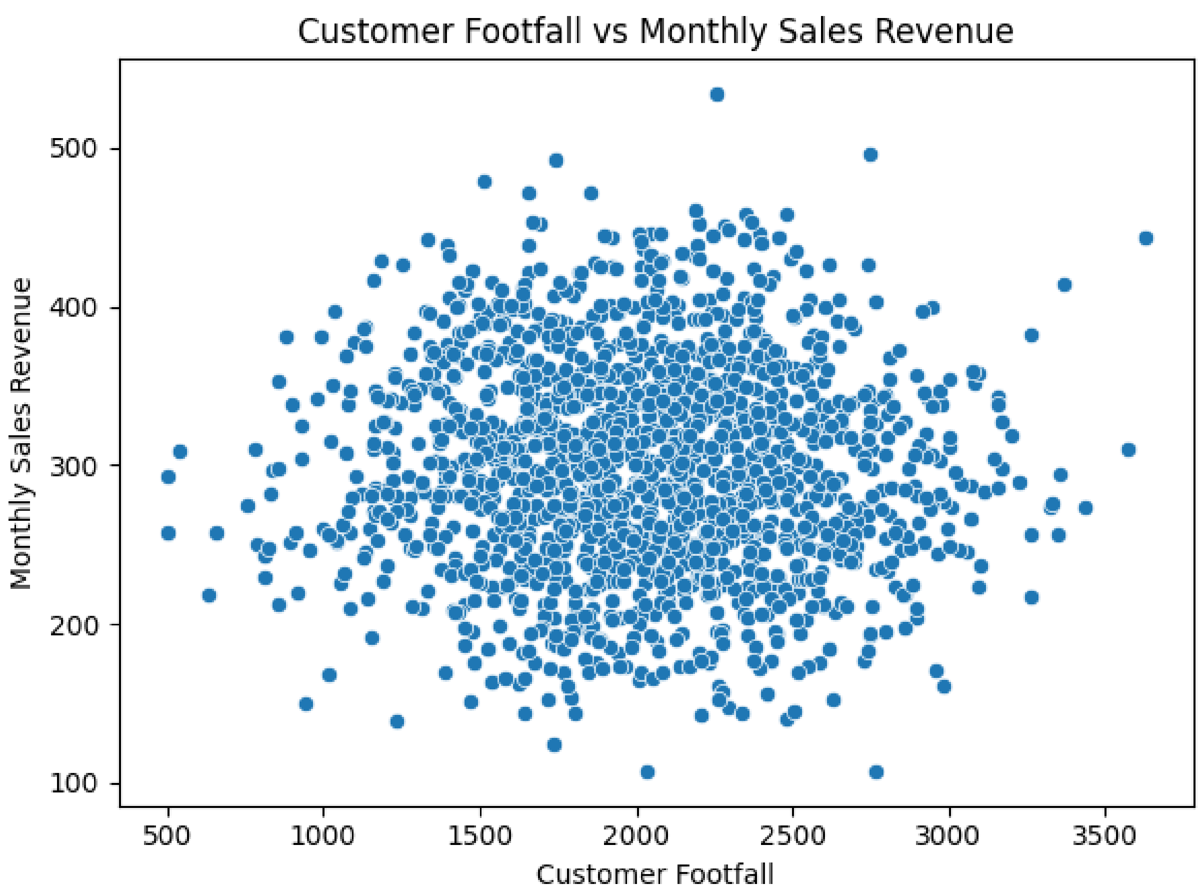
We examine how the number of promotional campaigns in a store affects its revenue performance.

Insight: There appears to be a correlation between promotions and revenue. More promotions may lead to higher sales—but this must be optimized to avoid unnecessary expense.

5. Customer Footfall vs Monthly Sales Revenue

```
query5 = """
SELECT CustomerFootfall, MonthlySalesRevenue
FROM df
"""
result5 = ps.sqldf(query5, locals())

# Graph
sns.scatterplot(x='CustomerFootfall', y='MonthlySalesRevenue',
data=result5)
plt.title("Customer Footfall vs Monthly Sales Revenue")
plt.xlabel("Customer Footfall")
plt.ylabel("Monthly Sales Revenue")
plt.tight_layout()
plt.show()
```



Description: This scatterplot investigates whether there's a direct relationship between the number of customers visiting the store and the monthly sales revenue.

Insight: Higher footfall often results in higher revenue, but some stores may have better conversion rates despite lower footfall.

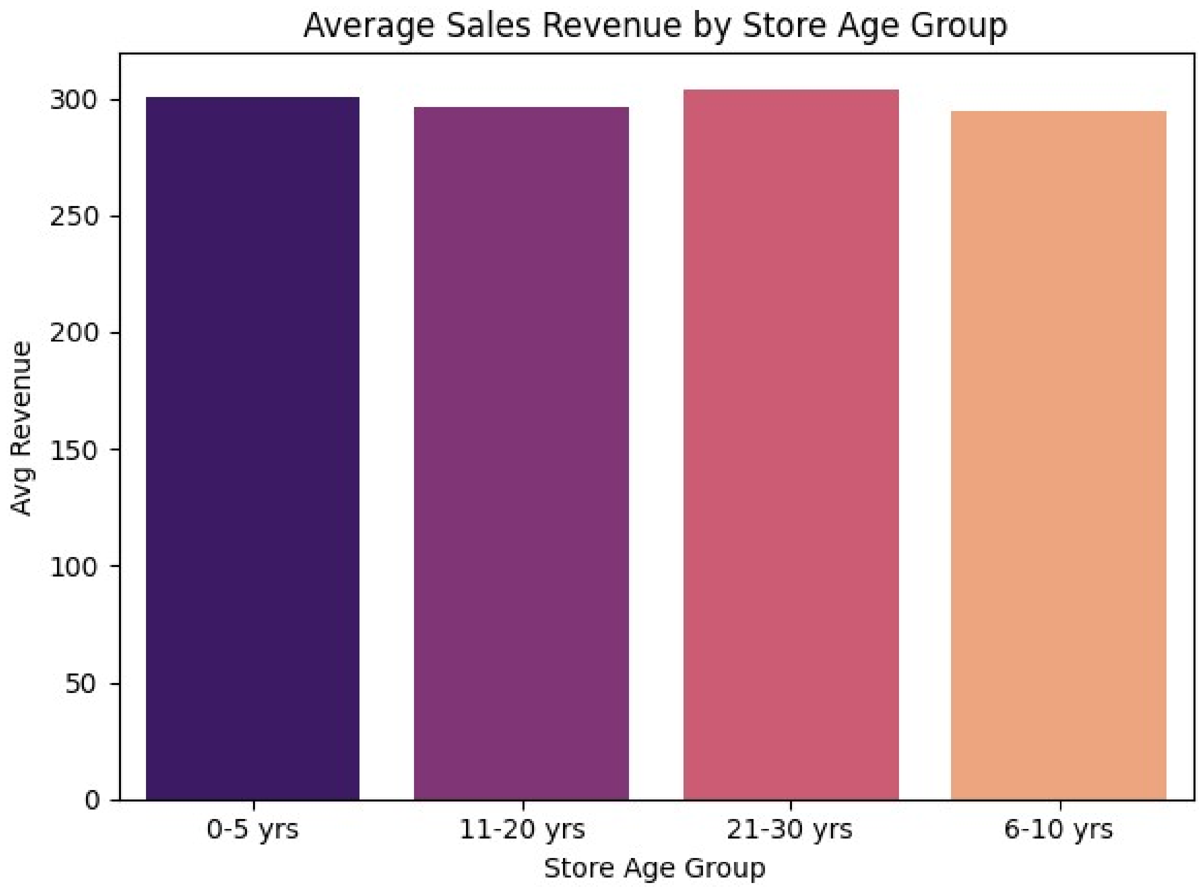
Average Revenue by Store Age Group

```
# Create age bins first (in pandas, not SQL)
df['StoreAgeGroup'] = pd.cut(df['StoreAge'], bins=[0, 5, 10, 20, 30, 50],
                             labels=['0-5 yrs', '6-10 yrs', '11-20 yrs', '21-30 yrs', '30+ yrs'])

# SQL-style query
query6 = """
SELECT StoreAgeGroup,
       ROUND(AVG(MonthlySalesRevenue), 2) AS AvgRevenue
FROM df
GROUP BY StoreAgeGroup
ORDER BY StoreAgeGroup
"""
result6 = ps.sqldf(query6, locals())
print(result6)

# Graph
sns.barplot(x='StoreAgeGroup', y='AvgRevenue', data=result6, palette='magma')
plt.title("Average Sales Revenue by Store Age Group")
plt.xlabel("Store Age Group")
plt.ylabel("Avg Revenue")
plt.tight_layout()
plt.show()
```

```
  StoreAgeGroup  AvgRevenue
0       0-5 yrs      300.47
1     11-20 yrs      296.31
2     21-30 yrs      304.07
3      6-10 yrs      294.34
```



We grouped stores by age (0–5 years, 6–10 years, etc.) to see how experience or maturity of a store affects its revenue.

Insight: Older stores might benefit from brand loyalty, but newer stores might show faster growth or higher efficiency.

Revenue by Employee Efficiency Level

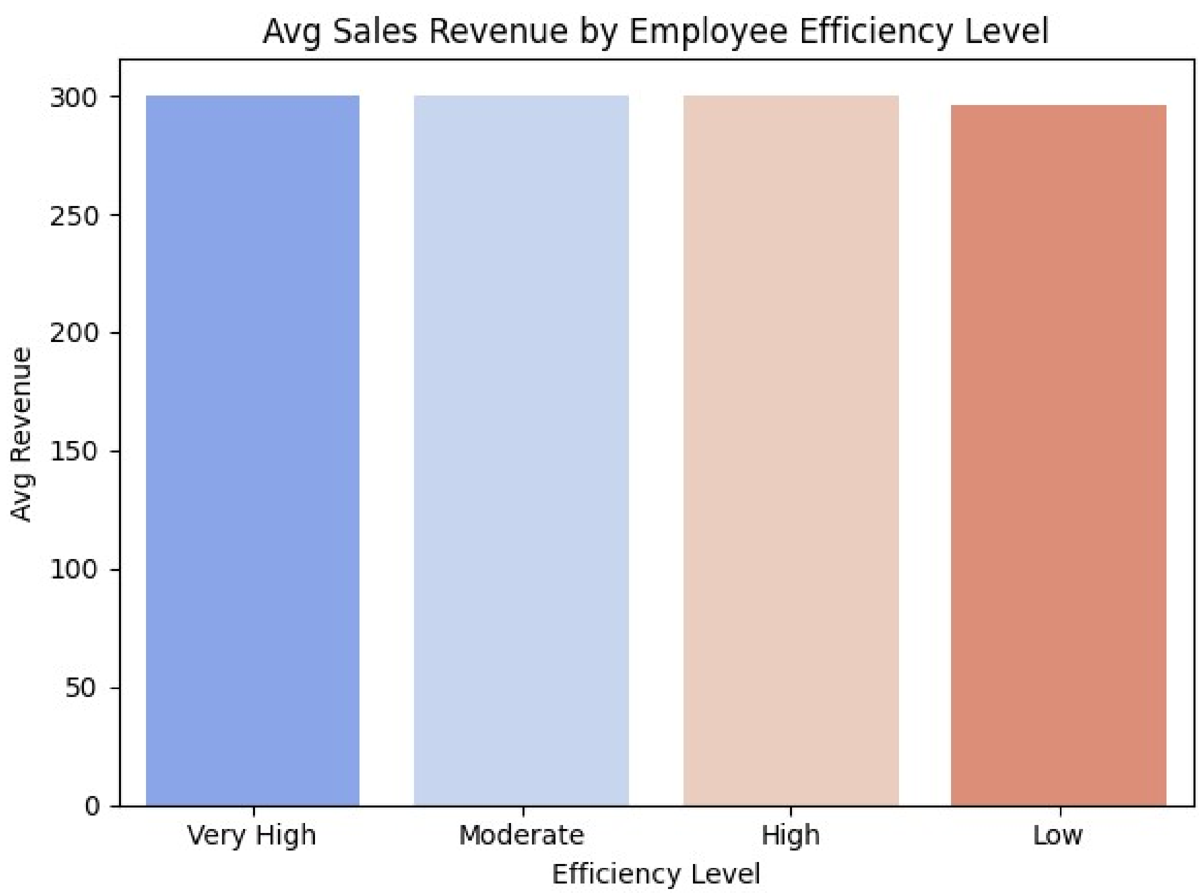
```
# Bin efficiency into categories
df['EfficiencyLevel'] = pd.cut(df['EmployeeEfficiency'], bins=[0, 60, 
75, 90, 100],
                               labels=['Low', 'Moderate', 'High', 
'Very High'])

query7 = """
SELECT EfficiencyLevel,
       ROUND(AVG(MonthlySalesRevenue), 2) AS AvgRevenue
FROM df
GROUP BY EfficiencyLevel
ORDER BY AvgRevenue DESC
"""
```

```
result7 = ps.sqldf(query7, locals())
print(result7)

# Graph
sns.barplot(x='EfficiencyLevel', y='AvgRevenue', data=result7,
palette='coolwarm')
plt.title("Avg Sales Revenue by Employee Efficiency Level")
plt.xlabel("Efficiency Level")
plt.ylabel("Avg Revenue")
plt.tight_layout()
plt.show()
```

	EfficiencyLevel	AvgRevenue
0	Very High	300.39
1	Moderate	300.24
2	High	300.20
3	Low	295.98



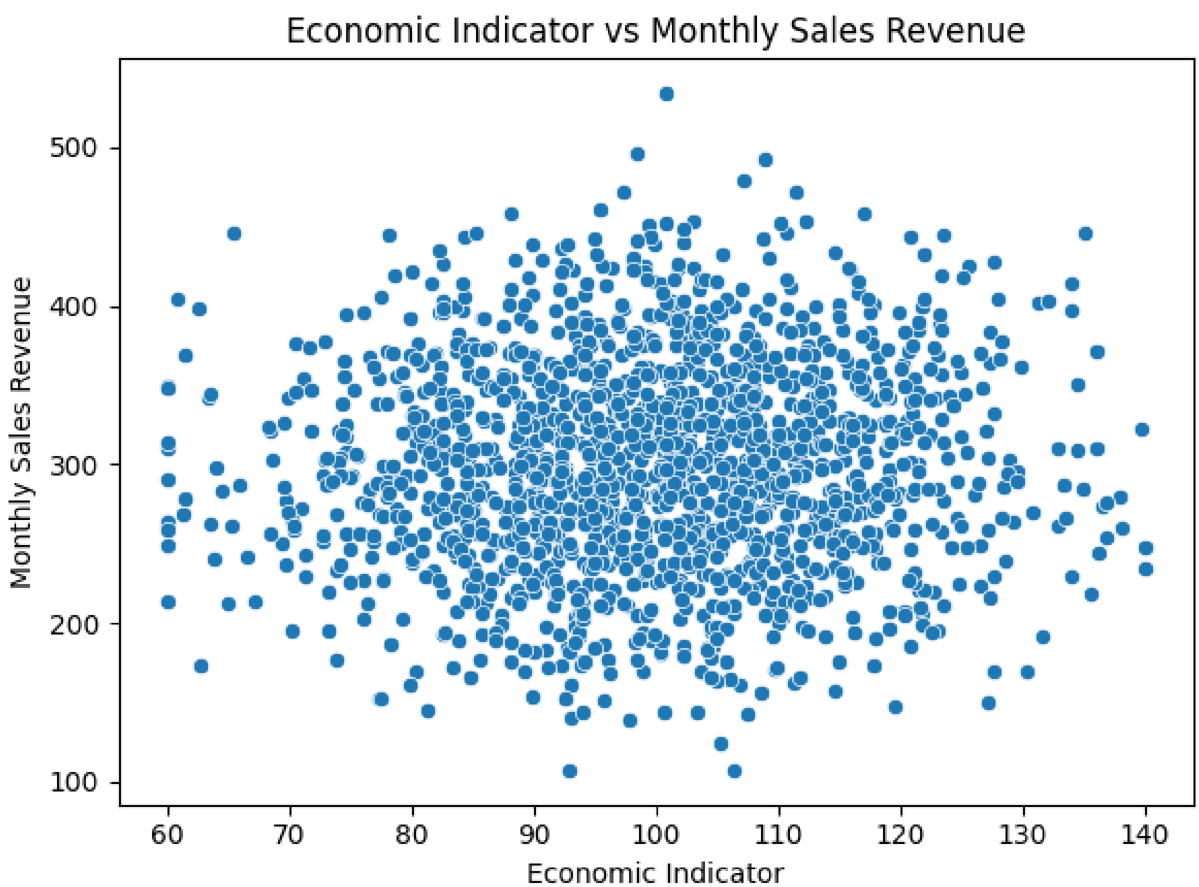
Stores are classified into efficiency levels based on employee performance. We analyze how these levels impact revenue.

Insight: Stores with high or very high employee efficiency generally report better sales outcomes.

Economic Indicator vs Monthly Sales Revenue

```
query8 = """
SELECT EconomicIndicator, MonthlySalesRevenue
FROM df
"""
result8 = ps.sqldf(query8, locals())

# Graph
sns.scatterplot(x='EconomicIndicator', y='MonthlySalesRevenue',
data=result8)
plt.title("Economic Indicator vs Monthly Sales Revenue")
plt.xlabel("Economic Indicator")
plt.ylabel("Monthly Sales Revenue")
plt.tight_layout()
plt.show()
```



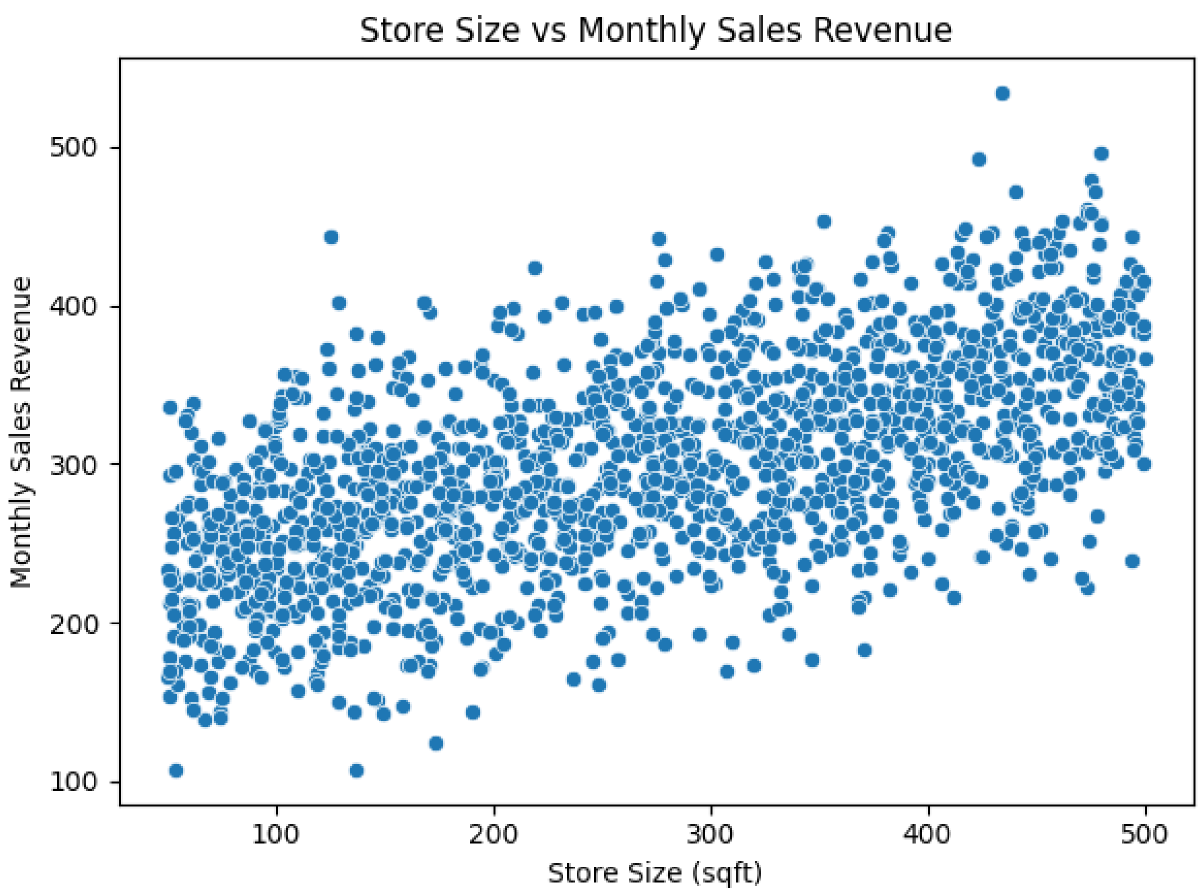
This analysis shows how local economic conditions (represented by an economic index) affect store revenue.

Insight: Stores in economically strong regions tend to perform better. This can influence location-based investment strategies.

Store Size vs Monthly Sales Revenue

```
query9 = """
SELECT StoreSize, MonthlySalesRevenue
FROM df
"""
result9 = ps.sqldf(query9, locals())

# Graph
sns.scatterplot(x='StoreSize', y='MonthlySalesRevenue', data=result9)
plt.title("Store Size vs Monthly Sales Revenue")
plt.xlabel("Store Size (sqft)")
plt.ylabel("Monthly Sales Revenue")
plt.tight_layout()
plt.show()
```



This examines whether the physical size of a store has any relationship with the revenue it generates.

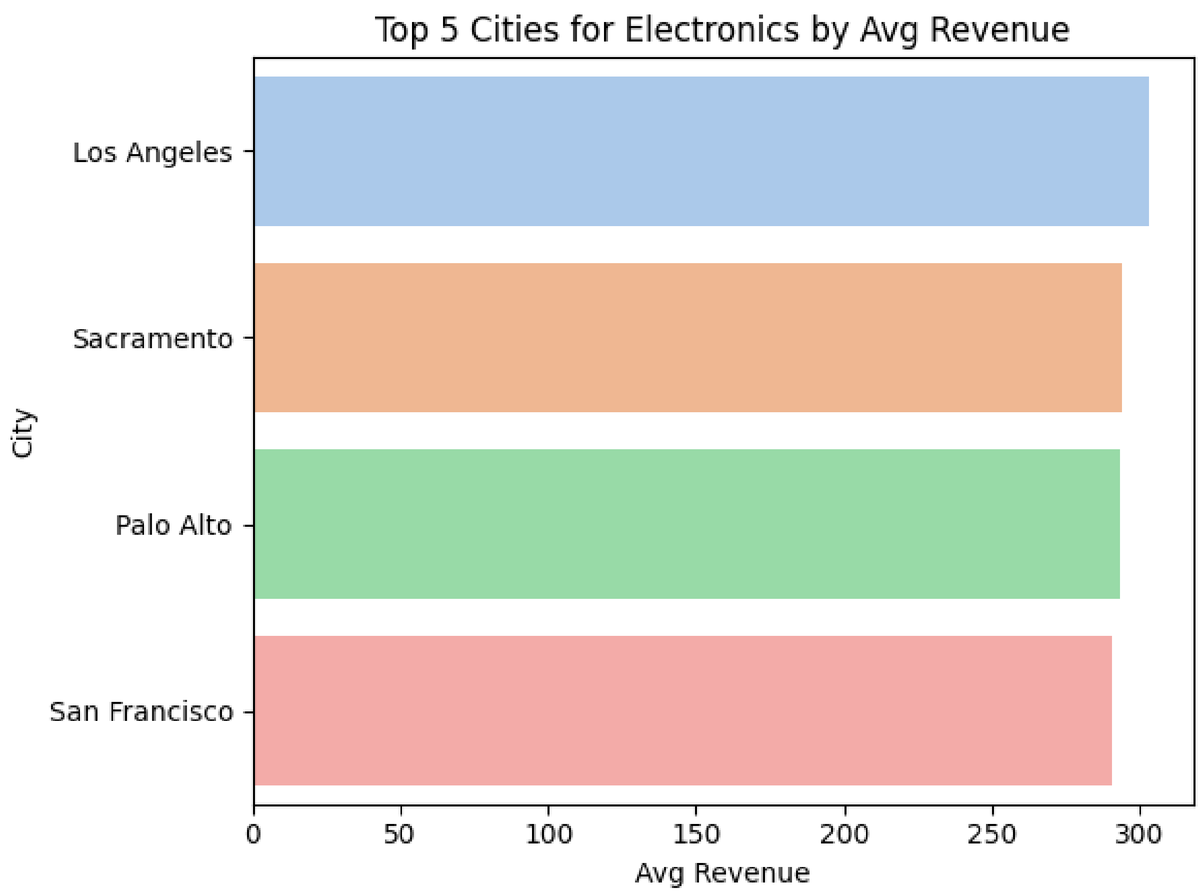
Insight: Larger stores may offer more products but also come with higher maintenance costs. Understanding this balance is crucial.

Top 5 Cities for Electronics by Avg Revenue

```
query10 = """
SELECT StoreLocation,
       ROUND(AVG(MonthlySalesRevenue), 2) AS AvgRevenue
FROM df
WHERE StoreCategory = 'Electronics'
GROUP BY StoreLocation
ORDER BY AvgRevenue DESC
LIMIT 5
"""
result10 = ps.sqldf(query10, locals())
print(result10)

# Graph
sns.barplot(x='AvgRevenue', y='StoreLocation', data=result10,
palette='pastel')
plt.title("Top 5 Cities for Electronics by Avg Revenue")
plt.xlabel("Avg Revenue")
plt.ylabel("City")
plt.tight_layout()
plt.show()
```

```
   StoreLocation  AvgRevenue
0    Los Angeles      303.07
1     Sacramento      293.89
2      Palo Alto      293.18
3  San Francisco      290.96
```



Focused analysis on Electronics stores to find out which cities generate the highest average revenue in that category.

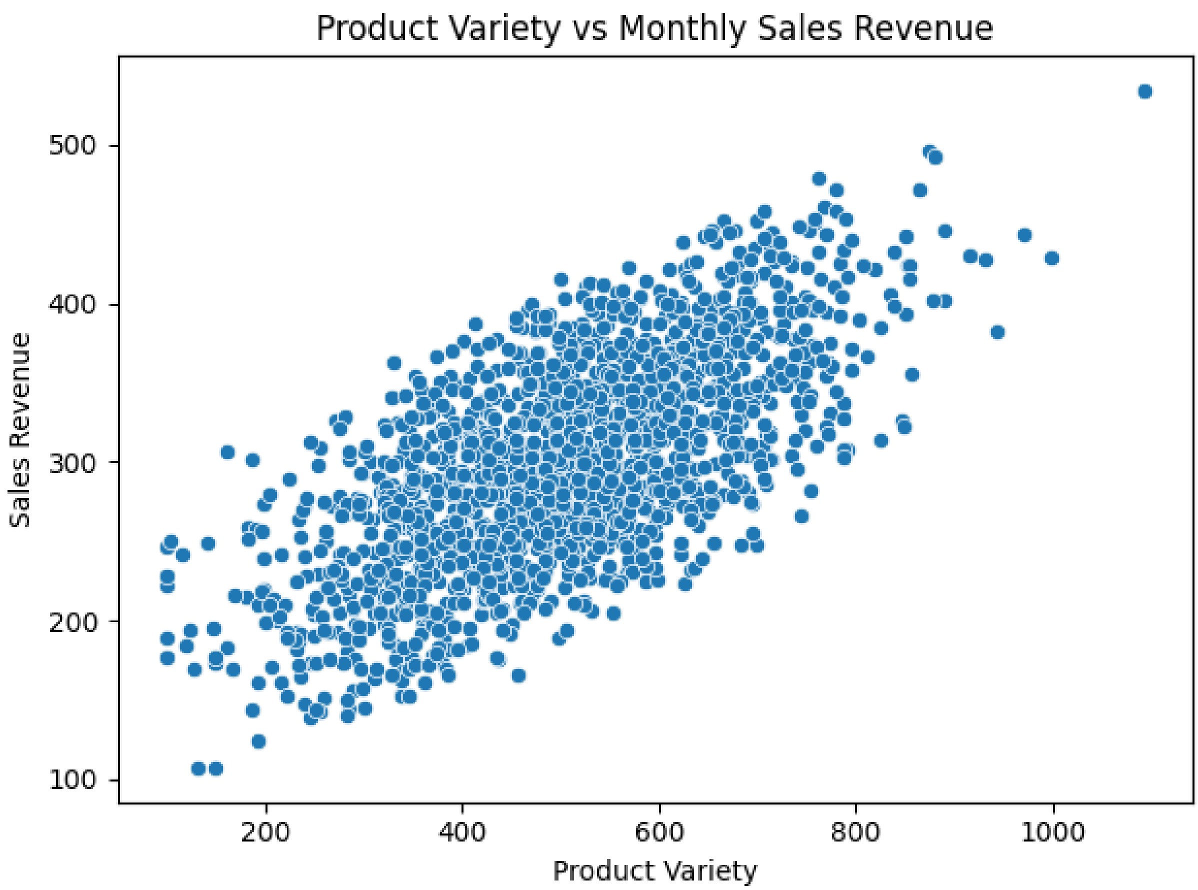
Insight: Cities with strong electronics sales can guide targeted marketing or exclusive product launches.

Product Variety vs Monthly Sales Revenue

```
query11 = """
SELECT ProductVariety, MonthlySalesRevenue
FROM df
"""
result11 = ps.sqldf(query11, locals())

# Graph
sns.scatterplot(x='ProductVariety', y='MonthlySalesRevenue', 
data=result11)
plt.title("Product Variety vs Monthly Sales Revenue")
plt.xlabel("Product Variety")
plt.ylabel("Sales Revenue")
```

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



This chart explores whether offering more product variety positively impacts sales.

Insight: A broader product range may increase customer attraction and revenue, but diminishing returns may appear beyond a certain point.

```

```