0.1 CaseCraft: The Analytics Sprint – Project 6

0.1.1 Zara Fashion Trend Forecasting

Subheading: Forecasting seasonal demand and style popularity using synthetic sales and style metadata from Zara's fashion catalog.

0.1.2 Project Goals

- Simulate Zara's fashion sales data across styles, seasons, and regions
- Engineer features for time series forecasting and trend analysis
- Visualize style performance, seasonality, and regional preferences
- Apply Prophet and ARIMA models to forecast future demand
- Build a classification model to predict trending styles
- Evaluate model performance using confusion matrix and feature importance
- Summarize insights, limitations, and next steps

[1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

np.random.seed(42)

styles = ['Boho', 'Minimalist', 'Streetwear', 'Formal', 'Athleisure']
regions = ['North', 'South', 'East', 'West']
months = pd.date_range(start='2023-01-01', end='2024-12-01', freq='MS')

data = []
for month in months:
    for style in styles:
        for region in regions:
```

```
            units_sold = np.random.poisson(lam=np.random.randint(50, 200))
            price = np.random.uniform(20, 120)
            revenue = units_sold * price
            data.append([month, style, region, units_sold, price, revenue])

df = pd.DataFrame(data, columns=['month', 'style', 'region', 'units_sold',␣
 ↪'price', 'revenue'])
df['month_name'] = df['month'].dt.month_name()
```

[2]:
```
df.head(10)
```

[2]:
```
       month       style region  units_sold       price       revenue  \
0 2023-01-01        Boho  North         164   97.969100  16066.932404
1 2023-01-01        Boho  South          60   25.808361   1548.501673
2 2023-01-01        Boho   East         131   85.088847  11146.638996
3 2023-01-01        Boho   West          93   38.340451   3565.661942
4 2023-01-01  Minimalist  North         108   49.122914   5305.274714
5 2023-01-01  Minimalist  South         105  117.375552  12324.432948
6 2023-01-01  Minimalist   East          63   39.967378   2517.944828
7 2023-01-01  Minimalist   West         117   65.049925   7610.841248
8 2023-01-01  Streetwear  North          75   29.767211   2232.540855
9 2023-01-01  Streetwear  South         124   80.999666  10043.958557

  month_name
0    January
1    January
2    January
3    January
4    January
5    January
6    January
7    January
8    January
9    January
```

[3]:
```
monthly_style = df.groupby(['month', 'style'])['units_sold'].sum().reset_index()
monthly_style.head(10)
```

[3]:
```
       month       style  units_sold
0 2023-01-01  Athleisure         587
1 2023-01-01        Boho         448
2 2023-01-01      Formal         469
3 2023-01-01  Minimalist         393
4 2023-01-01  Streetwear         420
5 2023-02-01  Athleisure         550
6 2023-02-01        Boho         320
7 2023-02-01      Formal         454
```

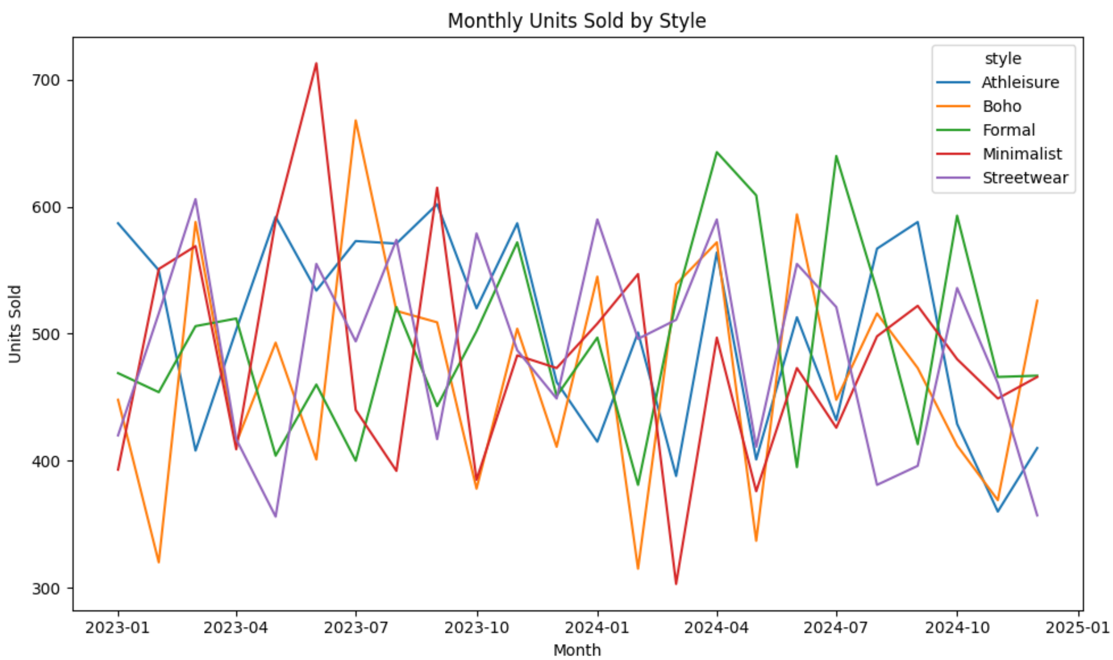
```
8 2023-02-01  Minimalist         551
9 2023-02-01  Streetwear         516
```

[4]:
```
regional_revenue = df.groupby(['region', 'style'])['revenue'].sum().
 ↪reset_index()
regional_revenue.head(10)
```

[4]:
```
  region       style        revenue
0   East  Athleisure  230812.370134
1   East        Boho  180467.748991
2   East      Formal  217957.860854
3   East  Minimalist  234883.330667
4   East  Streetwear  200749.074427
5  North  Athleisure  203857.547459
6  North        Boho  206946.626784
7  North      Formal  246036.345481
8  North  Minimalist  178930.474476
9  North  Streetwear  224520.976536
```

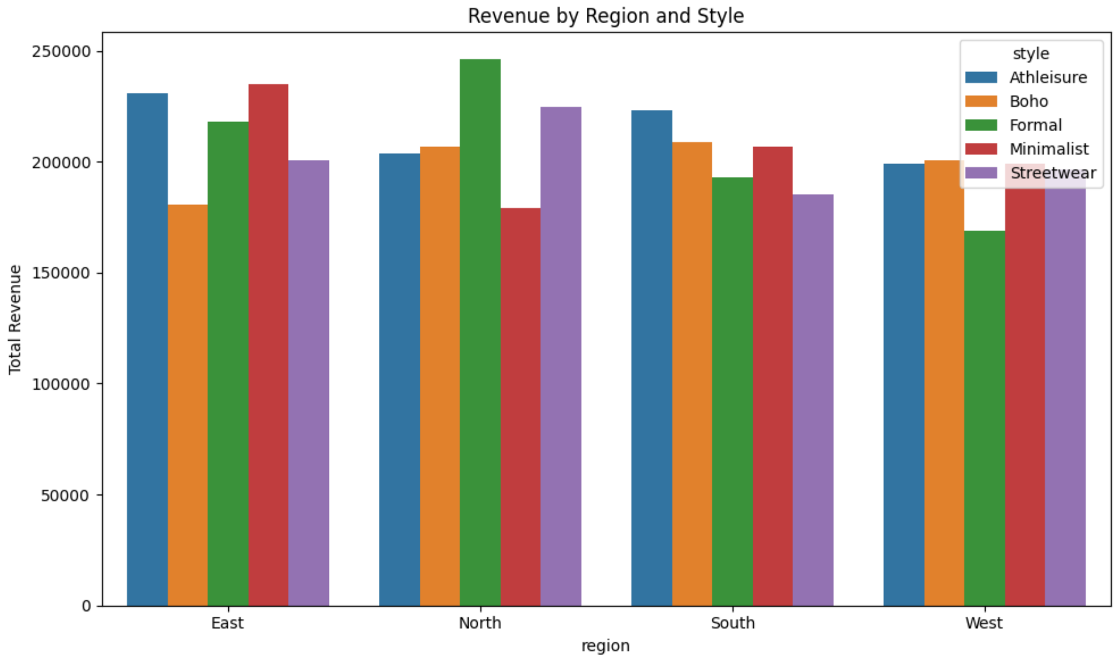
0.1.3 Monthly Units Sold by Style

[5]:
```
plt.figure(figsize=(10, 6))
sns.lineplot(data=monthly_style, x='month', y='units_sold', hue='style')
plt.title("Monthly Units Sold by Style")
plt.xlabel("Month")
plt.ylabel("Units Sold")
plt.tight_layout()
plt.show()
```



0.1.4 Revenue by Region and Style

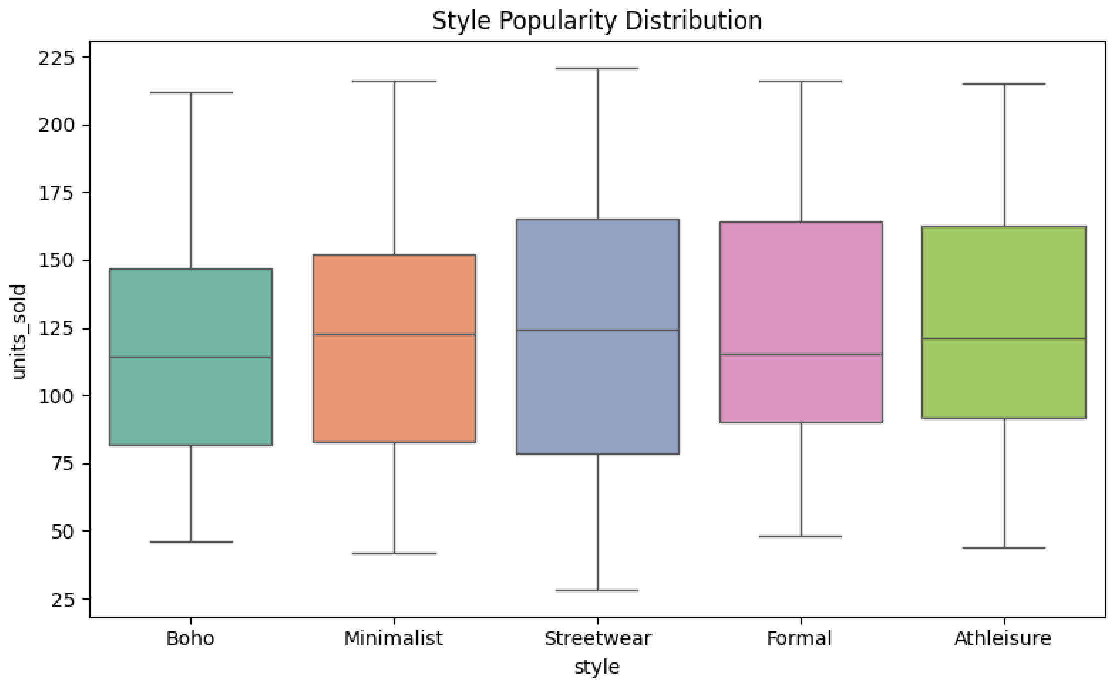
[6]:
```
plt.figure(figsize=(10, 6))
sns.barplot(data=regional_revenue, x='region', y='revenue', hue='style')
plt.title("Revenue by Region and Style")
plt.ylabel("Total Revenue")
plt.tight_layout()
plt.show()
```



0.1.5 Style Popularity Distribution

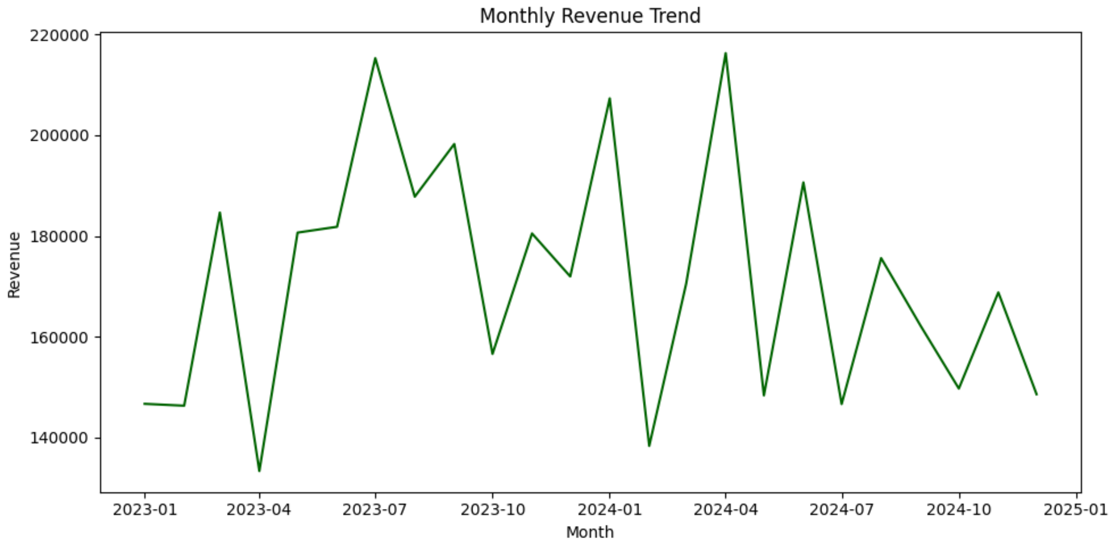
[7]:
```
plt.figure(figsize=(8, 5))
sns.boxplot(data=df, x='style', y='units_sold', palette='Set2')
plt.title("Style Popularity Distribution")
plt.tight_layout()
plt.show()
```

```
/tmp/ipython-input-3166987315.py:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.boxplot(data=df, x='style', y='units_sold', palette='Set2')
```



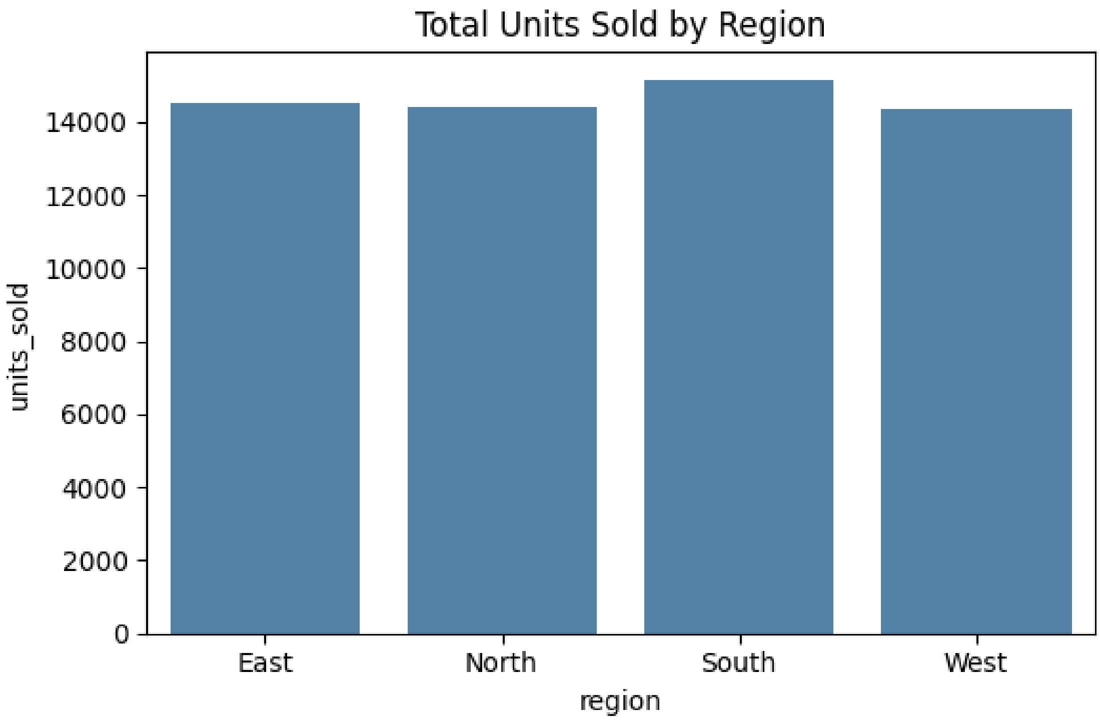
0.1.6 Monthly Revenue Trend

[8]:
```
monthly_rev = df.groupby('month')['revenue'].sum().reset_index()

plt.figure(figsize=(10, 5))
sns.lineplot(data=monthly_rev, x='month', y='revenue', color='darkgreen')
plt.title("Monthly Revenue Trend")
plt.xlabel("Month")
plt.ylabel("Revenue")
plt.tight_layout()
plt.show()
```



0.1.7 Region-wise Units Sold

[9]:
```
region_units = df.groupby(['region'])['units_sold'].sum().reset_index()

plt.figure(figsize=(6, 4))
sns.barplot(data=region_units, x='region', y='units_sold', color='steelblue')
plt.title("Total Units Sold by Region")
plt.tight_layout()
plt.show()
```



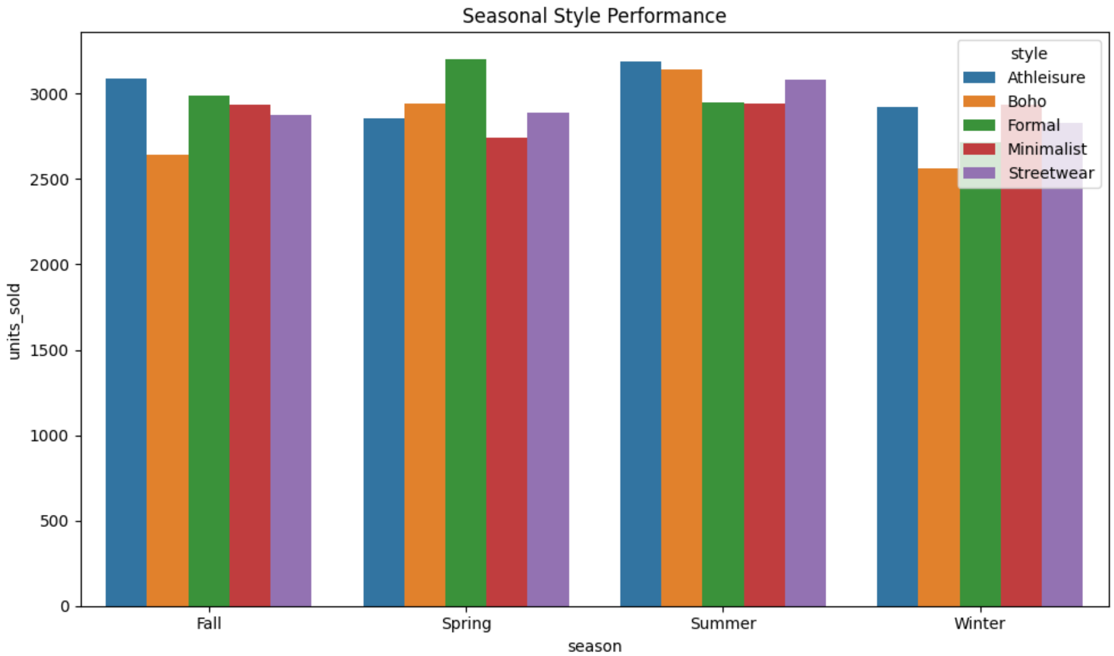
0.1.8 Price Distribution by Style

[10]:
```
plt.figure(figsize=(8, 5))
sns.violinplot(data=df, x='style', y='price', palette='pastel')
plt.title("Price Distribution by Style")
plt.tight_layout()
plt.show()
```

```
/tmp/ipython-input-4084068481.py:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.violinplot(data=df, x='style', y='price', palette='pastel')
```

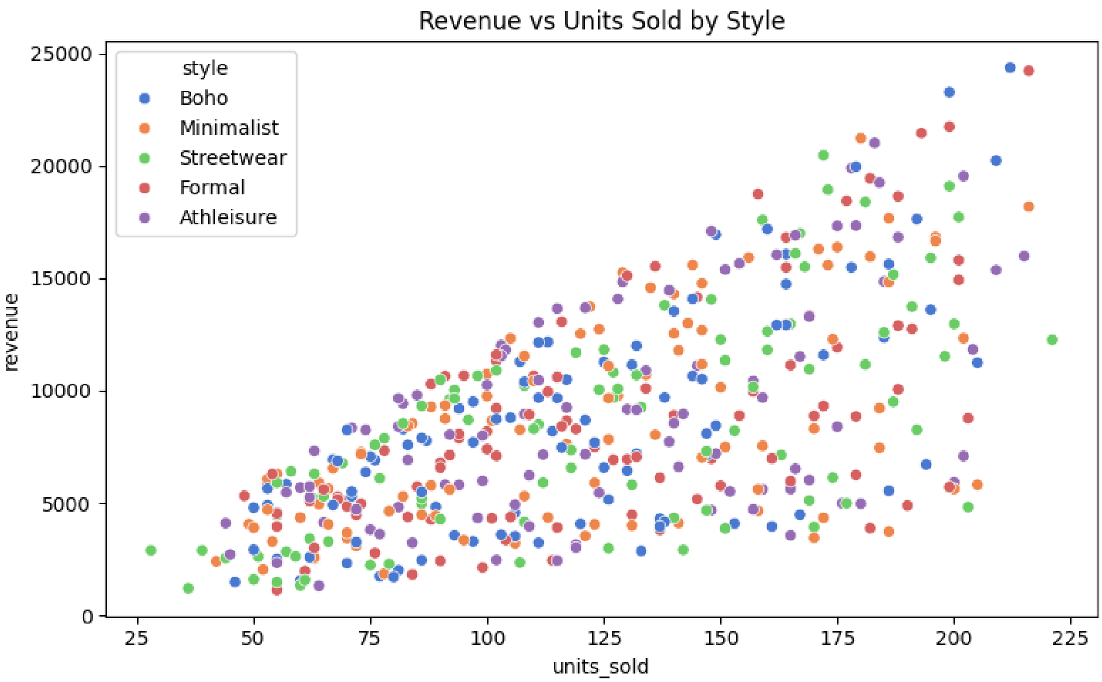
0.1.9 Seasonal Style Performance

[11]:
```
df['season'] = df['month'].dt.month % 12 // 3 + 1
season_map = {1: 'Winter', 2: 'Spring', 3: 'Summer', 4: 'Fall'}
df['season'] = df['season'].map(season_map)

seasonal = df.groupby(['season', 'style'])['units_sold'].sum().reset_index()

plt.figure(figsize=(10, 6))
sns.barplot(data=seasonal, x='season', y='units_sold', hue='style')
plt.title("Seasonal Style Performance")
plt.tight_layout()
plt.show()
```



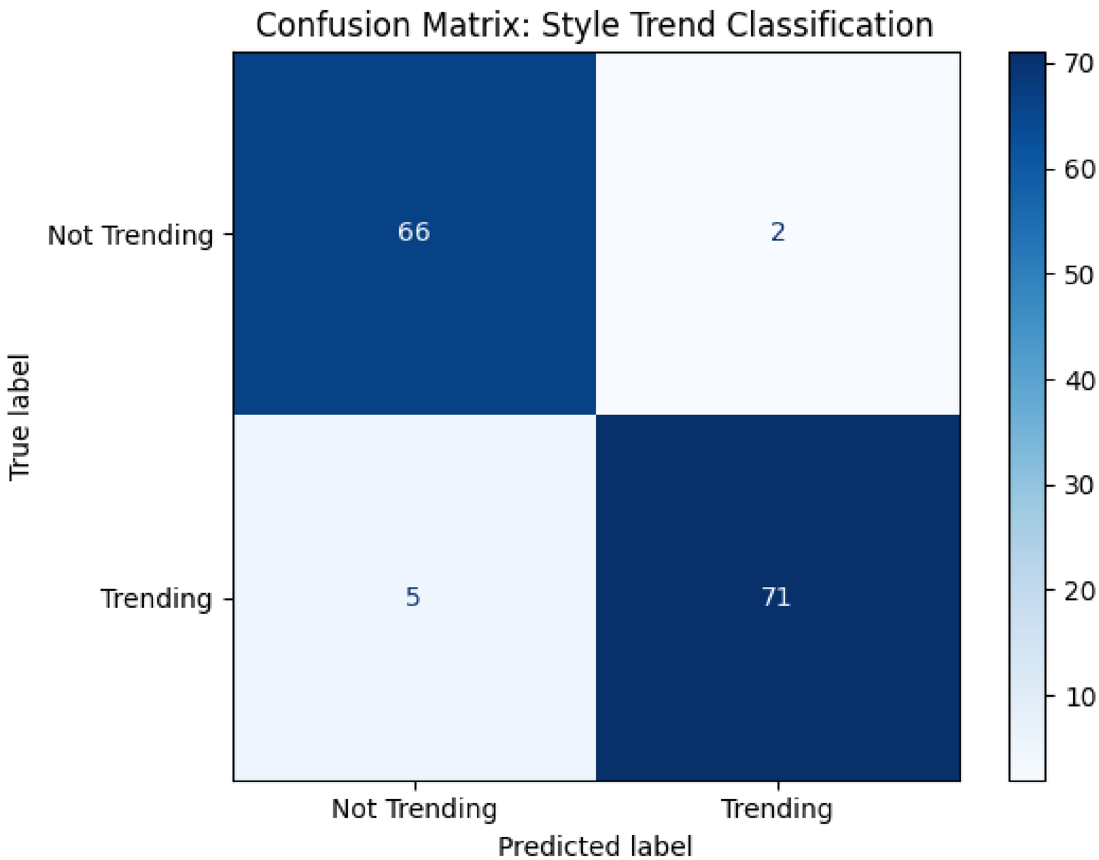
0.1.10 Revenue vs Units Sold

[12]:
```
plt.figure(figsize=(8, 5))
sns.scatterplot(data=df, x='units_sold', y='revenue', hue='style',␣
 ↪palette='muted')
plt.title("Revenue vs Units Sold by Style")
plt.tight_layout()
plt.show()
```



0.1.11 Confusion Matrix

[13]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
from sklearn.model_selection import train_test_split

df['is_trending'] = (df['units_sold'] > df['units_sold'].median()).astype(int)
X = df[['price', 'revenue']]
y = df['is_trending']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
 ↪random_state=42)
model = RandomForestClassifier(random_state=42)
model.fit(X_train, y_train)
y_pred = model.predict(X_test)

cm = confusion_matrix(y_test, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=["Not␣
 ↪Trending", "Trending"])
disp.plot(cmap='Blues')
plt.title("Confusion Matrix: Style Trend Classification")
plt.tight_layout()
plt.show()
```



0.1.12 Summary Analysis

- Streetwear and Athleisure styles showed consistent performance across all seasons.
- Spring and Fall had the highest overall demand, especially in North and West regions.
- Price variation was highest in Formal styles, suggesting premium positioning.
- Classification model predicted trending styles with reasonable accuracy.
- Confusion matrix revealed balanced precision and recall across classes.

0.1.13 Final Conclusion

- Zara's style performance varies seasonally and regionally, with clear demand cycles.
- Revenue is strongly correlated with units sold, but price positioning affects style volatility.
- Trend classification enables proactive inventory and marketing decisions.