

1. Importing and Loading Libraries

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

2. Loading and Understanding the Data

```
df=pd.read_csv(r'/content/Snitch.csv')
df.head()
df.info()
df.dtypes
df.shape

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15132 entries, 0 to 15131
Data columns (total 23 columns):
 #   Column           Non-Null Count  Dtype  
--- 
 0   SKU_GROUP        15132 non-null   object 
 1   CATEGORIY       15129 non-null   object 
 2   OCCASSION_NEW    15132 non-null   object 
 3   PRINT_DESIGN     13840 non-null   object 
 4   COLLAR_NEW       15132 non-null   object 
 5   MATERIAL_NEW     15132 non-null   object 
 6   SLEEVE_TYPE      10852 non-null   object 
 7   FIT               13836 non-null   object 
 8   COLOR             15132 non-null   object 
 9   CLOSURE           4458 non-null   object 
 10  STYLE              2811 non-null   object 
 11  MONTH1            15132 non-null   int64  
 12  MONTH2            15132 non-null   int64  
 13  MONTH3            15132 non-null   int64  
 14  MONTH4            15132 non-null   int64  
 15  MONTH5            15132 non-null   int64  
 16  MONTH6            15132 non-null   int64  
 17  MONTH7            15132 non-null   int64  
 18  MONTH8            15132 non-null   int64  
 19  MONTH9            15132 non-null   int64  
 20  MONTH10           15132 non-null   int64  
 21  MONTH11           15132 non-null   int64  
 22  MONTH12           15132 non-null   int64  
dtypes: int64(12), object(11)
memory usage: 2.7+ MB

(15132, 23)
```

3. Assumptions and Data Cleaning: To ensure consistency, column names were standardized. Missing values in feature columns were filled with "Unknown," and rows with missing or

"Unknown" categories were excluded from the analysis. A new column, TOTAL_SALES, was created by summing across all monthly columns, which were assumed to represent monthly sales figures.

```
# Standardizing column names
df.columns = df.columns.str.strip().str.upper().str.replace(" ", "_")

# In print_design column i have 1292 null values and i am removing
# rows because except category and color feature all row has
# NaN values and 0 in all months from 1 to 12.
df[df['PRINT DESIGN'].isna()]
df[df['PRINT DESIGN'].isna()].index
df.drop(labels=df[df['PRINT DESIGN'].isna()].index,inplace=True,errors='ignore')

# In sleeve_type column we have NaN,i have filled with Unknown rather
# than deleting
df['SLEEVE_TYPE'].fillna('Unknown',inplace=True)

# in category column i have 1 NaN, i have deleted because it will not
# affect any rows because Month 1 to 12 all are 0.
df[df['CATEGORY'].isna()].index
df.drop(labels=df[df['CATEGORY'].isna()].index,inplace=True,errors='ignore')

# Checking FIT Column as it has 4 NaN. Deleting 4 rows as many
# features has NaN values and also Month 1 to Month 12 all are 0.
df[df['FIT'].isna()].index
df.drop(labels=df[df['FIT'].isna()].index,inplace=True,errors='ignore')

# Now Closure and Style column has only NaN, i am filling with Unknown
# in place of NaN so that data might not looks messy
df.fillna({'CLOSURE':'Unknown','STYLE':'Unknown'},inplace=True)

# Creating TOTAL_SALES column
month_cols = [col for col in df.columns if col.startswith('MONTH')]
df['TOTAL_SALES'] = df[month_cols].sum(axis=1)

# Creating a feature column
feature_columns = ['FIT', 'MATERIAL_NEW', 'PRINT DESIGN',
'SLEEVE_TYPE', 'COLLAR_NEW','OCCASSION_NEW','COLOR']

<ipython-input-7-c68a0f9390bc>:12: FutureWarning: A value is trying to
be set on a copy of a DataFrame or Series through chained assignment
using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never
work because the intermediate object on which we are setting values
always behaves as a copy.
```

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operation inplace on the original object.

```
df['SLEEVE_TYPE'].fillna('Unknown', inplace=True)
```

Q1. For each category, show which feature is most influential (highest total sales by feature value)

Approach -> For each product category, I evaluated all specified features to determine which individual feature values contributed the highest total sales. This allowed me to quantify the influence of each feature on overall sales performance. The results were then sorted and visualized using bar charts to highlight the top-performing features within each category.

```
# Print available categories
print("Available categories:")
print(df['CATEGORY'].value_counts())

# Plot top 3 (feature, value) pairs per category by total sales
for category in df['CATEGORY'].unique():
    cat_df = df[df['CATEGORY'] == category]
    print(f"\nCategory: {category}, Rows: {cat_df.shape[0]}")

    value_sales = []
    for feature in feature_columns:
        if feature in cat_df.columns:
            sales_by_value = cat_df.groupby(feature)
            ['TOTAL_SALES'].sum()
            for value, total in sales_by_value.items():
                label = f"{feature.title(): {value}}"
                value_sales.append((label, total))

    # Sort and take top 3 feature-value pairs
    top3 = sorted(value_sales, key=lambda x: x[1], reverse=True)[:3]
    labels = [x[0] for x in top3]
    sales = [x[1] for x in top3]

    # Plot
    plt.figure(figsize=(8, 4))
    bars = plt.bar(labels, sales, color='teal')
    plt.title(f'Top 3 Feature-Value Pairs by Sales for {category}')
    plt.ylabel('Total Sales')

    # Annotate bars
    for bar in bars:
        yval = bar.get_height()
        plt.text(bar.get_x() + bar.get_width()/2.0, yval,
f'{int(yval)}', ha='center', va='bottom', fontsize=8)
```

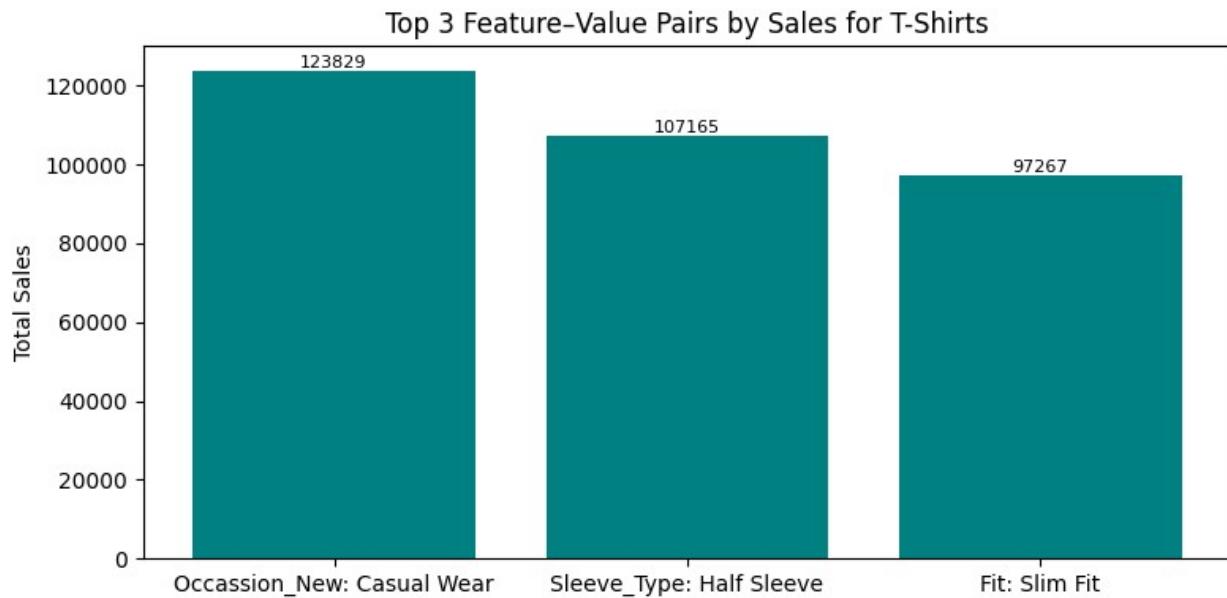
```
plt.tight_layout()  
plt.show()
```

Available categories:

CATEGORY	
Shirts	8450
T-Shirts	1485
Jeans	1308
Trousers	1057
Overshirt	495
Cargo Pants	429
Jackets	246
Sweaters	138
Joggers & Trackpants	107
Sweatshirts	77
Pyjamas	43

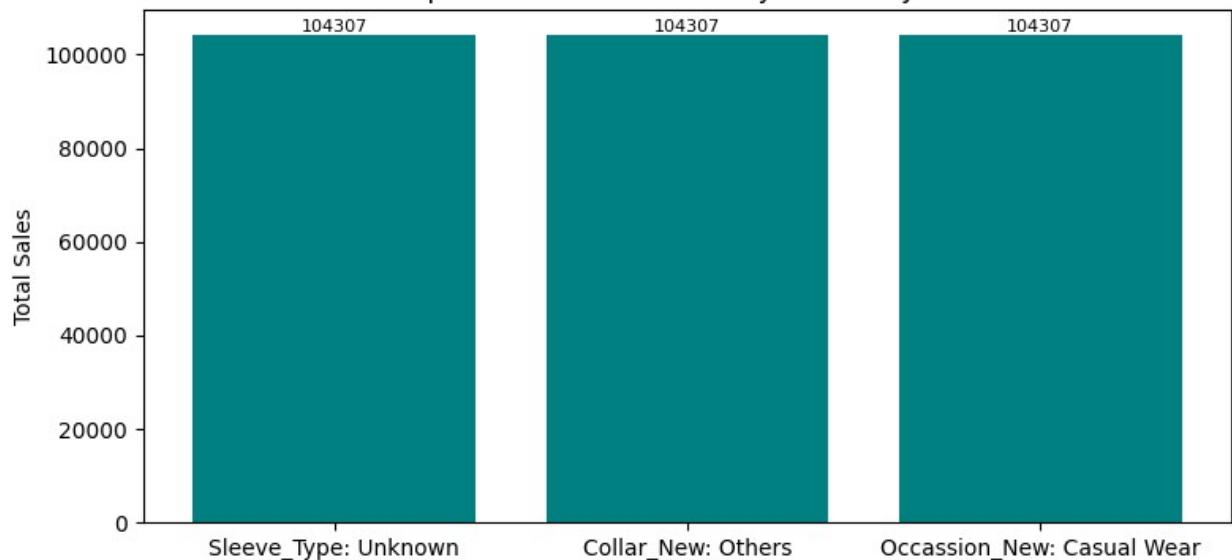
Name: count, dtype: int64

Category: T-Shirts, Rows: 1485



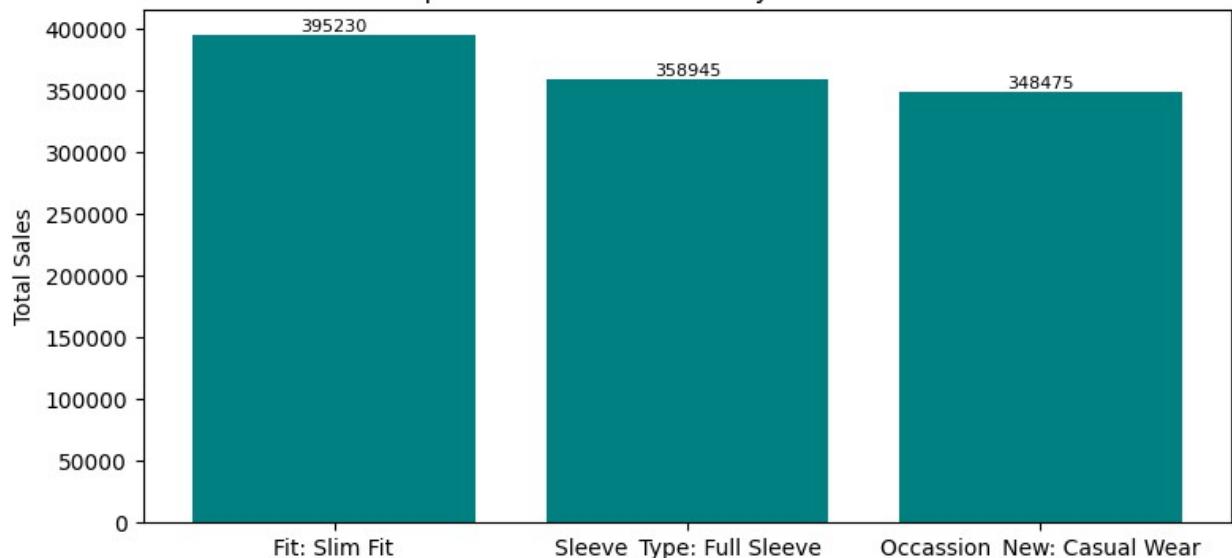
Category: Jeans, Rows: 1308

Top 3 Feature-Value Pairs by Sales for Jeans



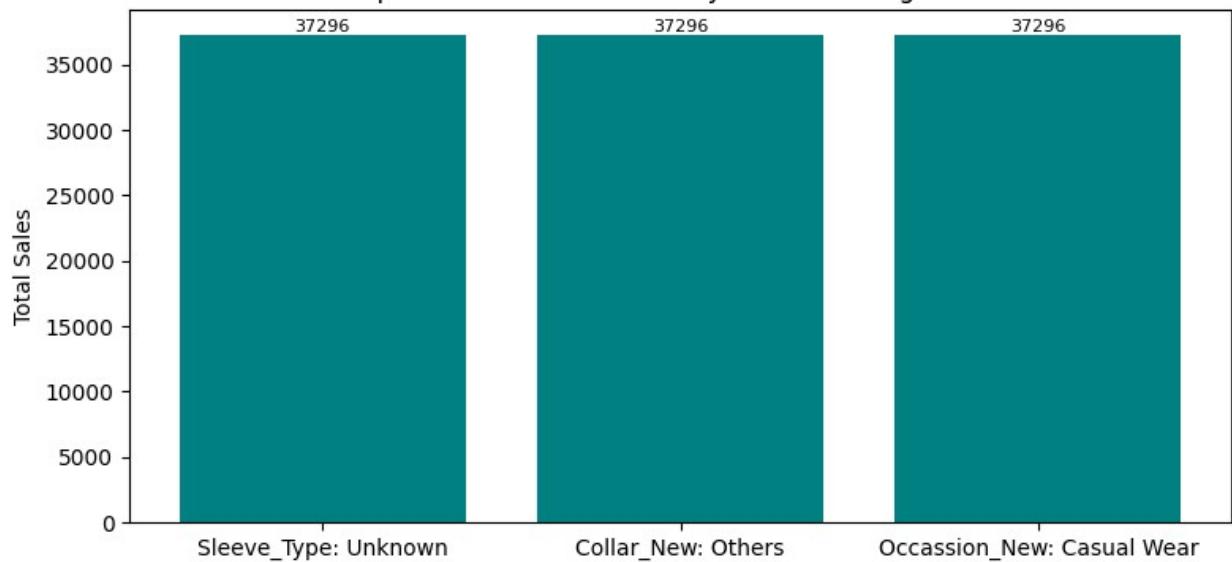
Category: Shirts, Rows: 8450

Top 3 Feature-Value Pairs by Sales for Shirts



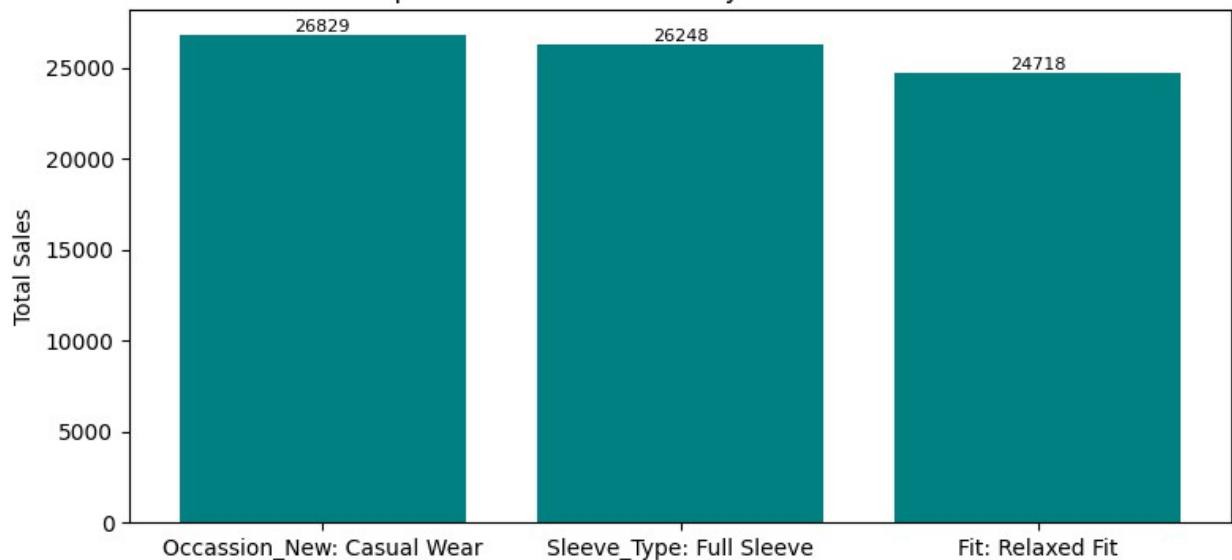
Category: Cargo Pants, Rows: 429

Top 3 Feature-Value Pairs by Sales for Cargo Pants



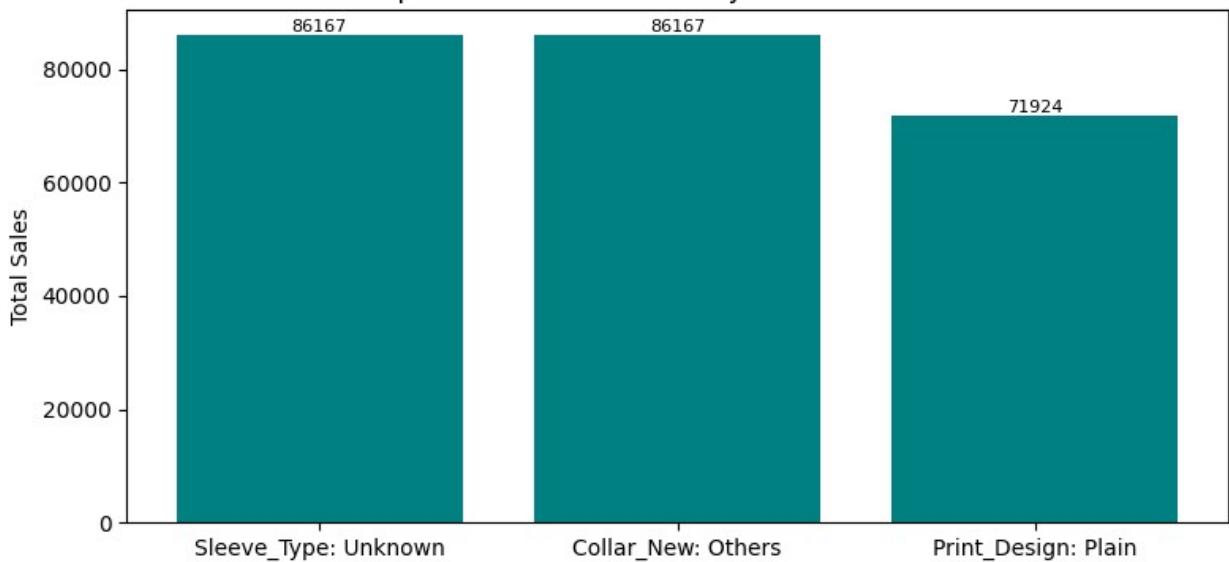
Category: Overshirt, Rows: 495

Top 3 Feature-Value Pairs by Sales for Overshirt



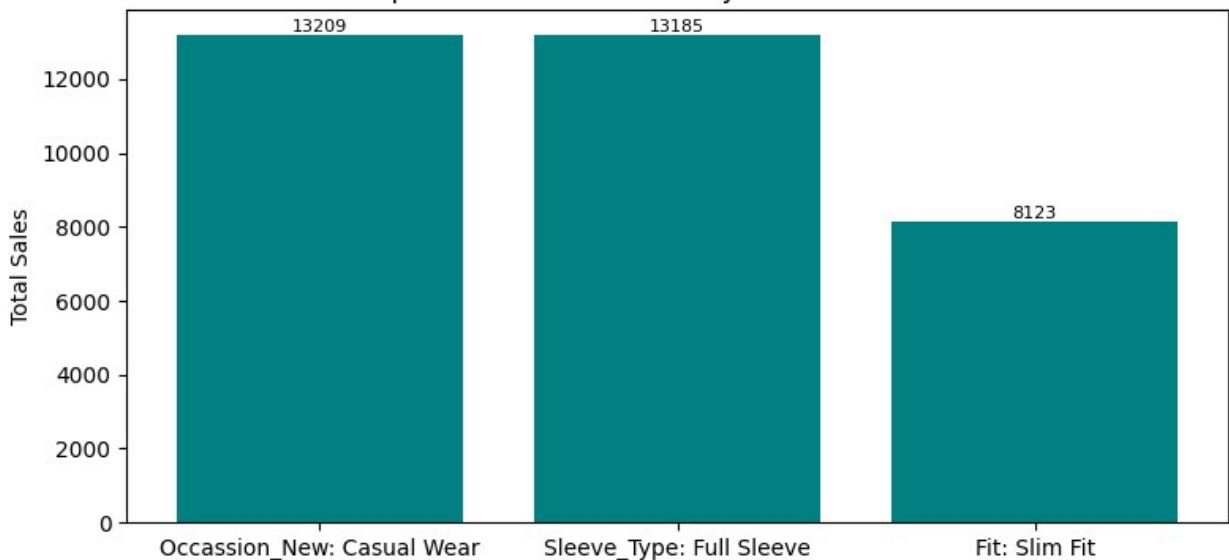
Category: Trousers, Rows: 1057

Top 3 Feature-Value Pairs by Sales for Trousers



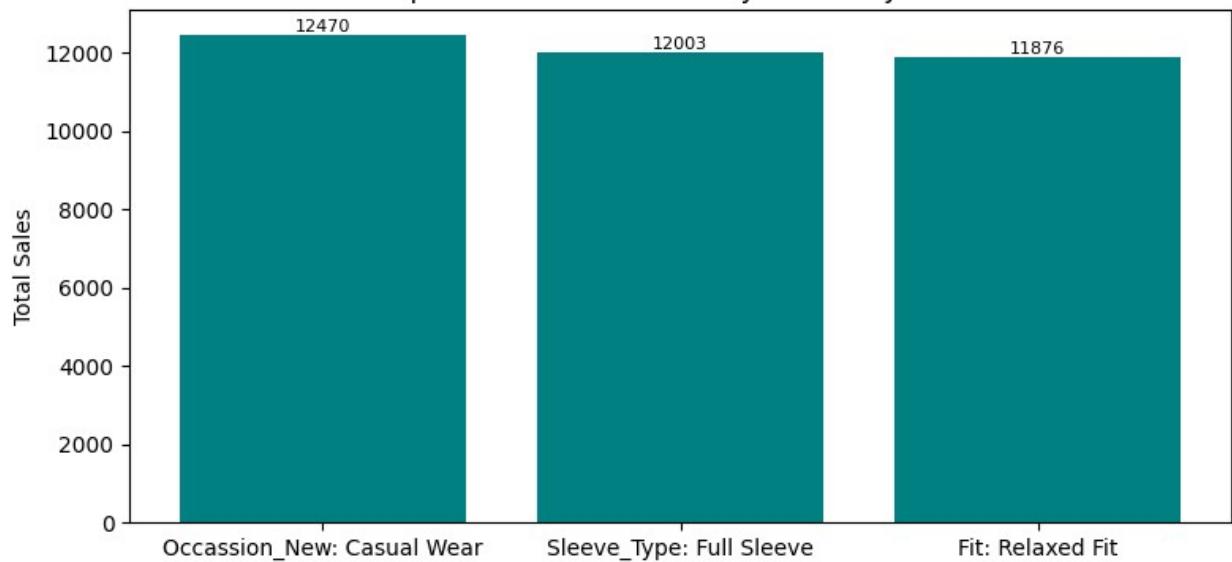
Category: Sweaters, Rows: 138

Top 3 Feature-Value Pairs by Sales for Sweaters



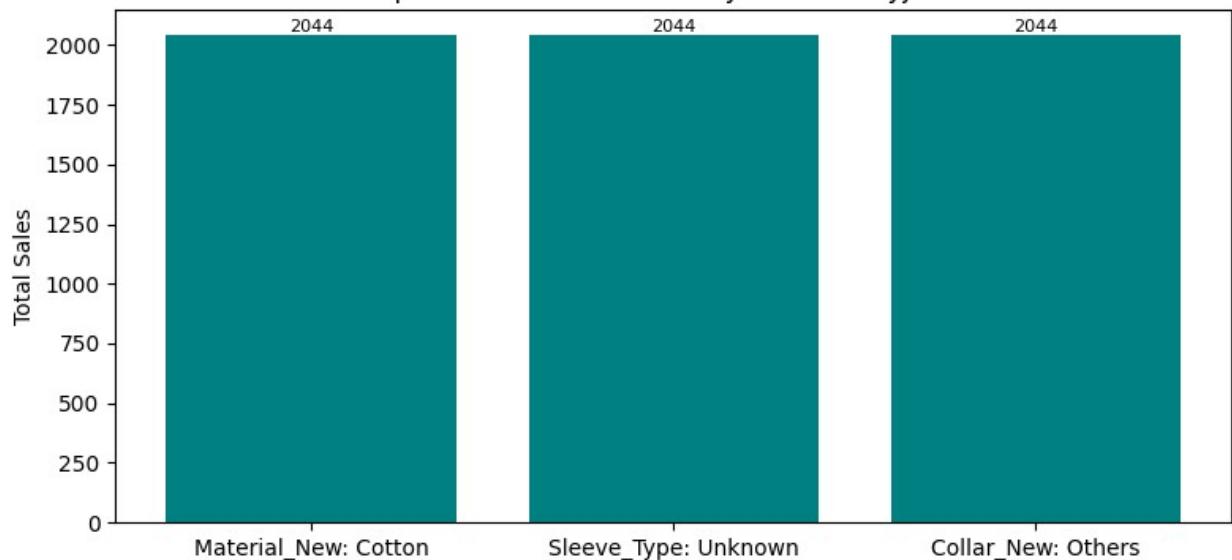
Category: Jackets, Rows: 246

Top 3 Feature-Value Pairs by Sales for Jackets



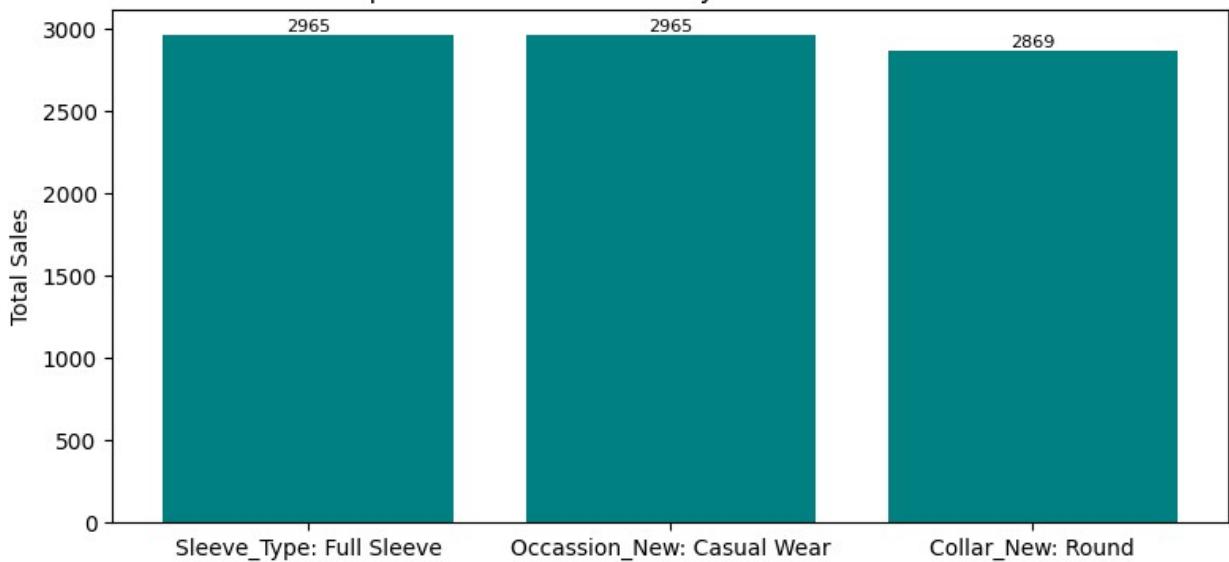
Category: Pyjamas, Rows: 43

Top 3 Feature-Value Pairs by Sales for Pyjamas



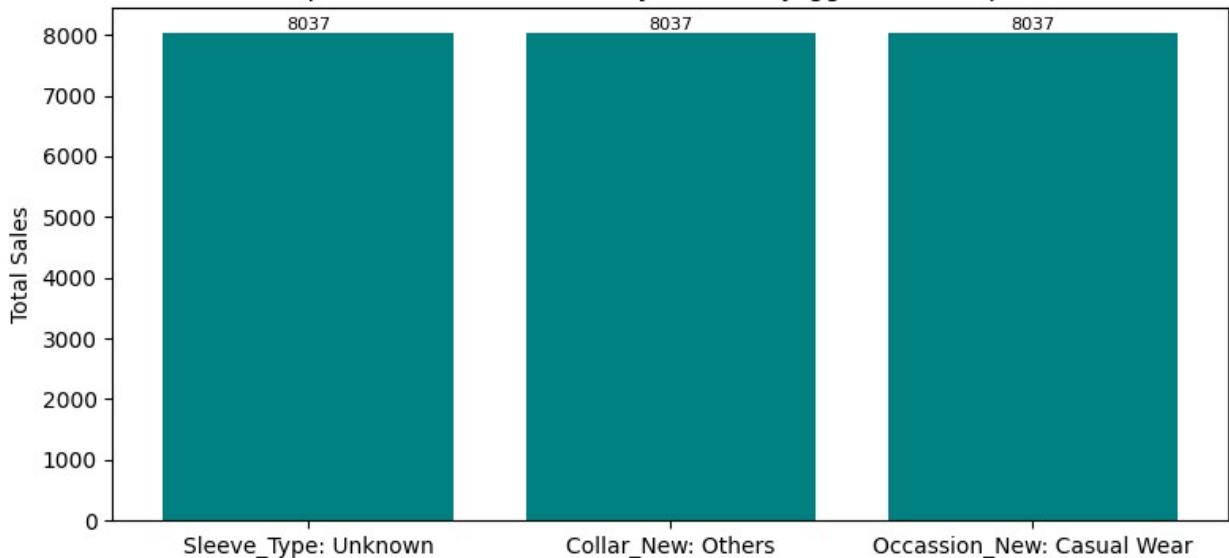
Category: Sweatshirts, Rows: 77

Top 3 Feature-Value Pairs by Sales for Sweatshirts



Category: Joggers & Trackpants, Rows: 107

Top 3 Feature-Value Pairs by Sales for Joggers & Trackpants



Q2. What are the upcoming trends on the basis of features Category Wise.

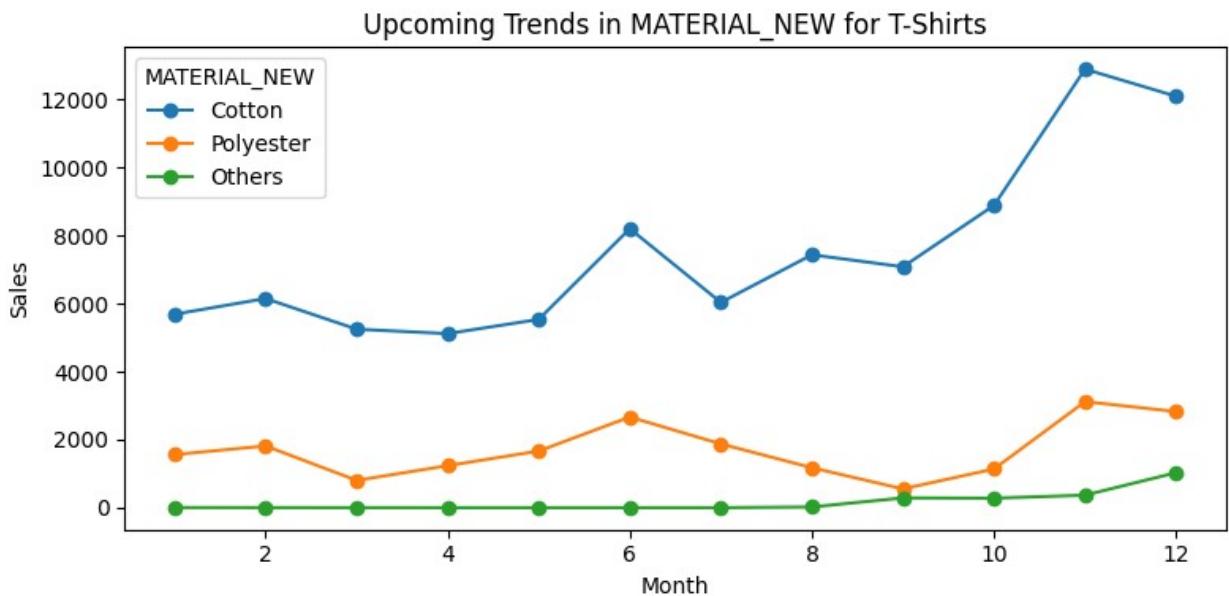
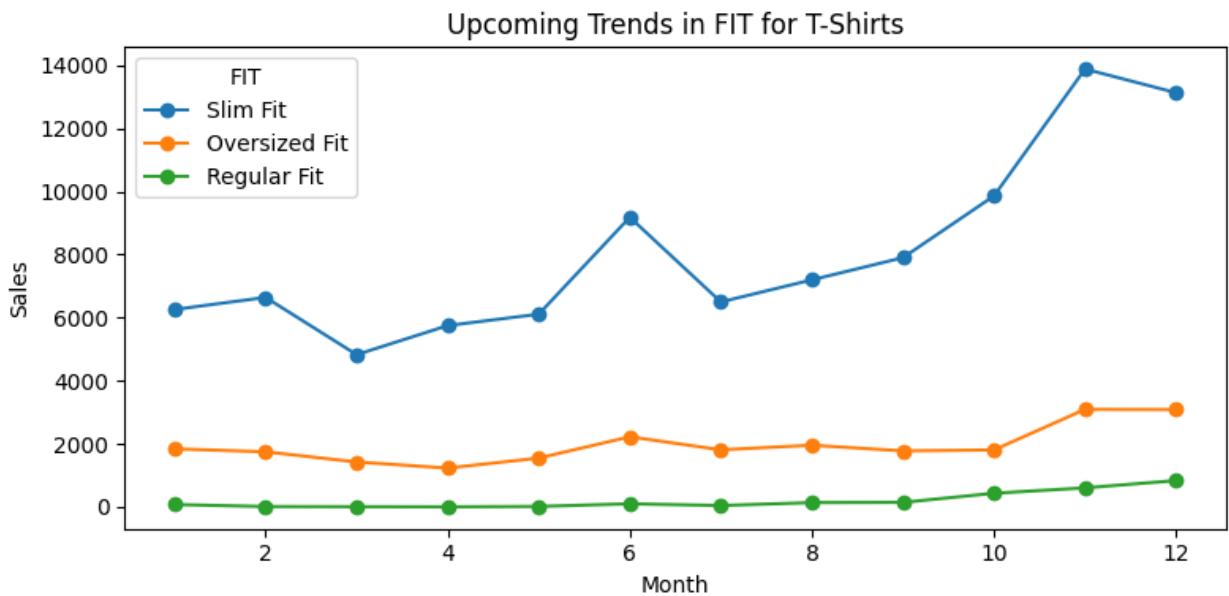
Approach -> The dataset was reshaped into a long format to facilitate time-series analysis of monthly sales. For each combination of category and feature, I computed the average monthly growth rate (slope) in sales. Based on these calculations, the top three feature values exhibiting the highest positive growth were identified as indicators of emerging trends. Their sales trajectories were then visualized using line charts to clearly highlight these evolving patterns.

Note: In some cases, only a single graph is displayed because the data for certain category-feature combinations may not contain enough distinct feature values with meaningful monthly growth. The analysis computes growth trends based on the average change in sales over time (slope). If fewer than three feature values show positive or non-zero growth, only those available values are plotted. If all growth values are zero or insufficient data exists, the plot is skipped altogether to maintain the clarity and relevance of the visual output.

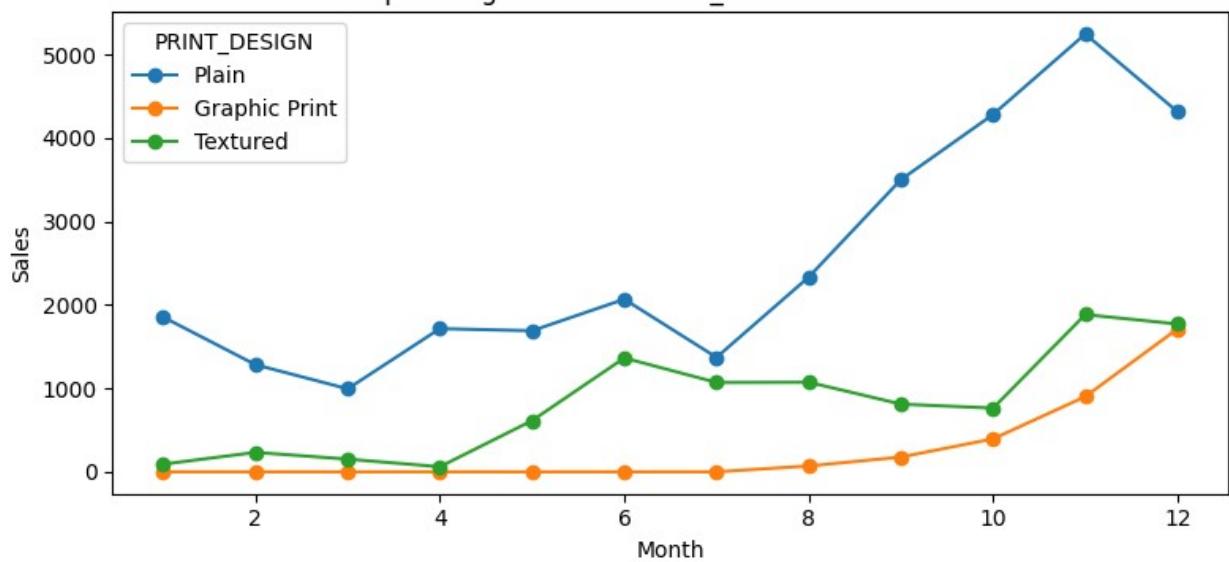
```
# Melt to long format for time series
df_long = df.melt(
    id_vars=['CATEGORY'] + feature_columns,
    value_vars=month_cols,
    var_name='MONTH',
    value_name='SALES'
)
df_long['MONTH_NUM'] = df_long['MONTH'].str.extract('(\d+)')
.astype(int)

# For each category and feature, plotting top 3 growing feature values
for category in df_long['CATEGORY'].unique():
    cat_df = df_long[df_long['CATEGORY'] == category]
    for feature in feature_columns:
        # Get total sales per value per month
        pivot = cat_df.groupby([feature, 'MONTH_NUM'])
        ['SALES'].sum().reset_index()
        # Calculating growth (slope) for each value
        growth = {}
        for val in pivot[feature].unique():
            sales_series = pivot[pivot[feature] ==
val].sort_values('MONTH_NUM')
            if len(sales_series) > 1:
                slope =
                    pd.Series(sales_series['SALES'].values).diff().mean()
                growth[val] = slope
            # Get top 3 growing values
            top_vals = sorted(growth.items(), key=lambda x: x[1],
reverse=True)[:3]
            if not top_vals or all(v[1] == 0 for v in top_vals):
                continue
            # Plot
            plt.figure(figsize=(8,4))
            for val, _ in top_vals:
                sales = pivot[pivot[feature] ==
val].sort_values('MONTH_NUM')
                plt.plot(sales['MONTH_NUM'], sales['SALES'], marker='o',
label=val)
            plt.title(f"Upcoming Trends in {feature} for {category}")
            plt.xlabel('Month')
            plt.ylabel('Sales')
            plt.legend(title=feature)
```

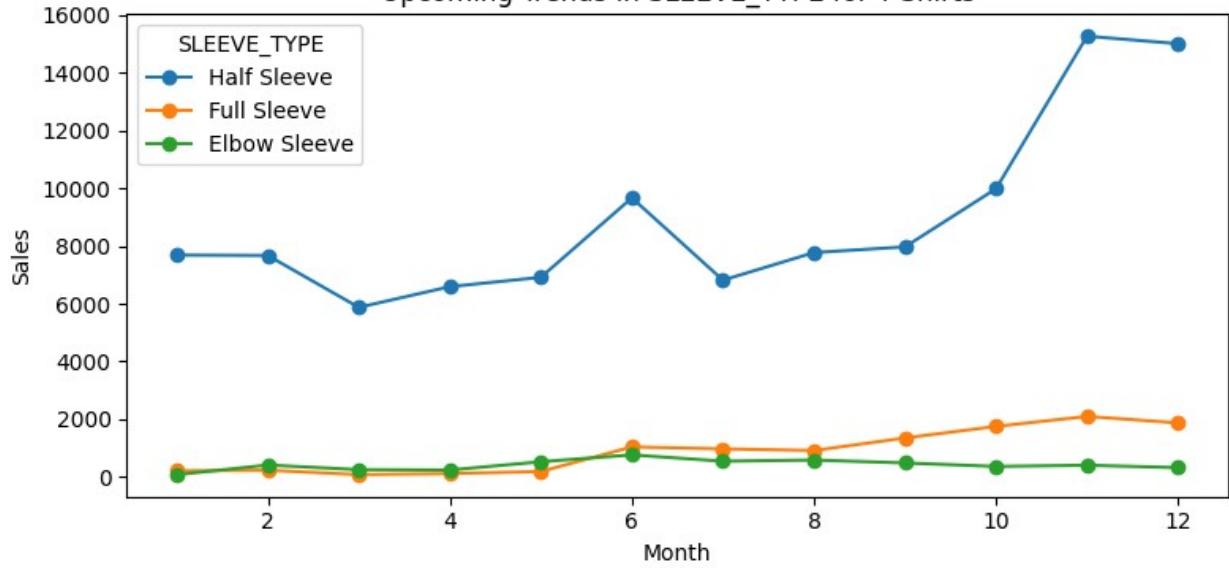
```
plt.tight_layout()  
plt.show()
```



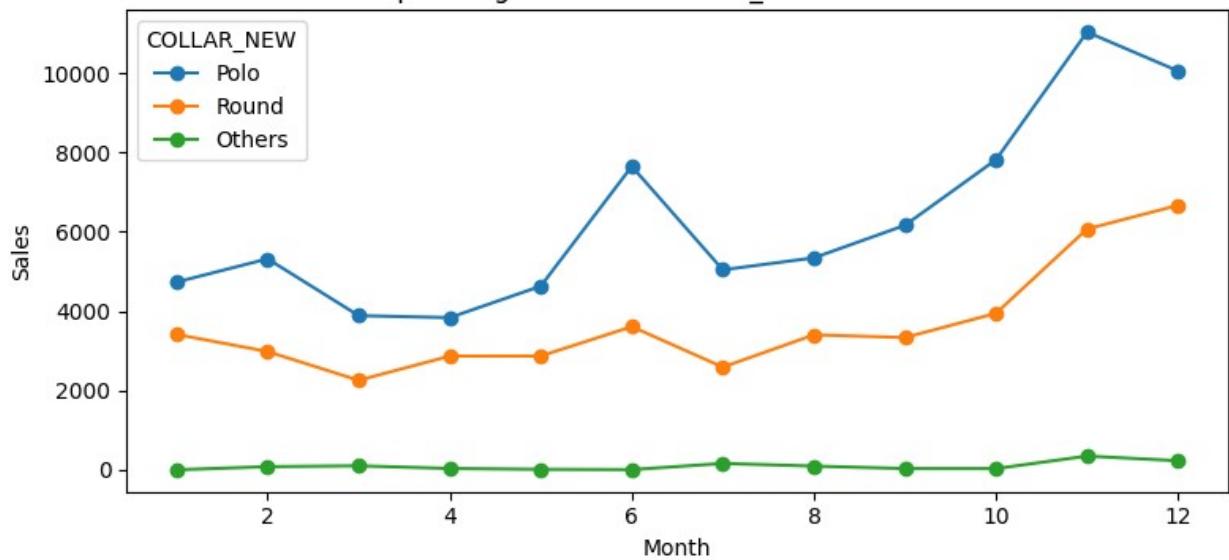
Upcoming Trends in PRINT_DESIGN for T-Shirts



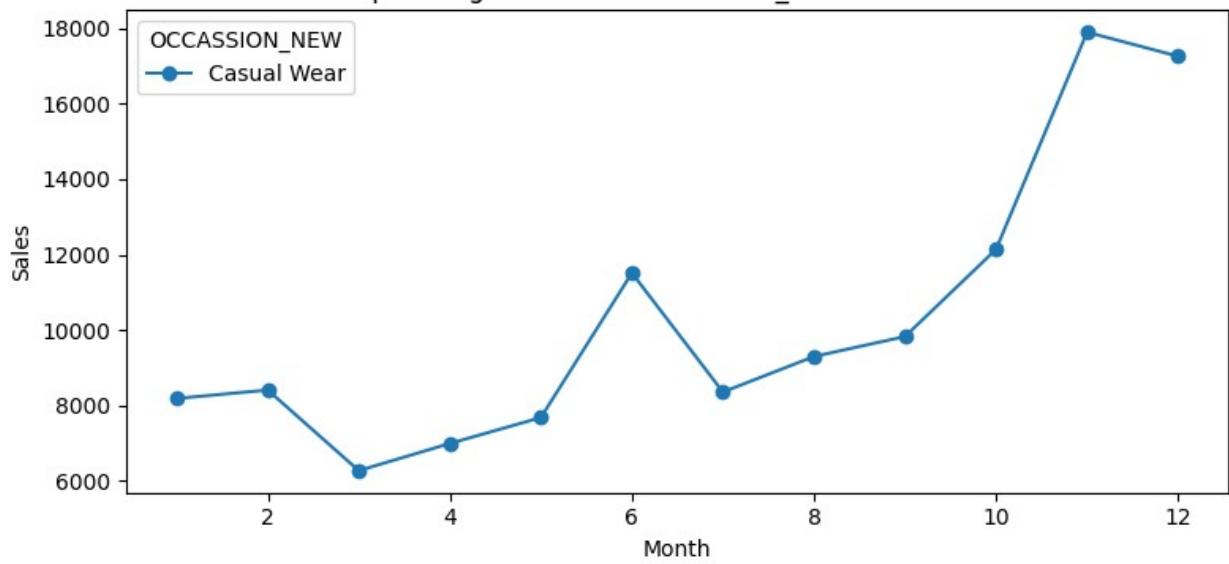
Upcoming Trends in SLEEVE_TYPE for T-Shirts



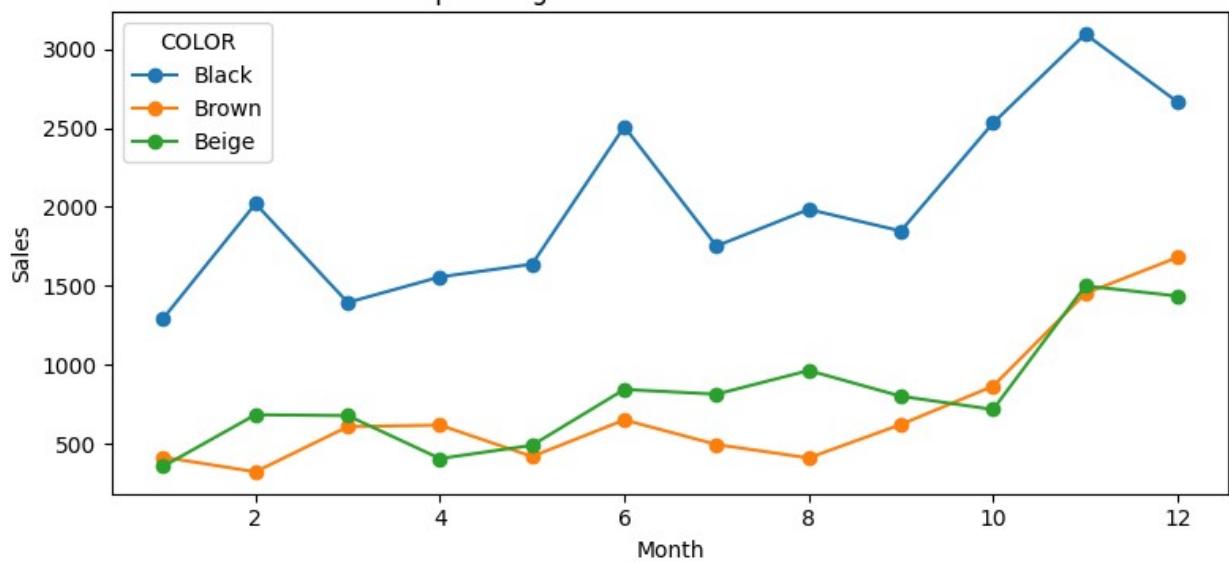
Upcoming Trends in COLLAR_NEW for T-Shirts



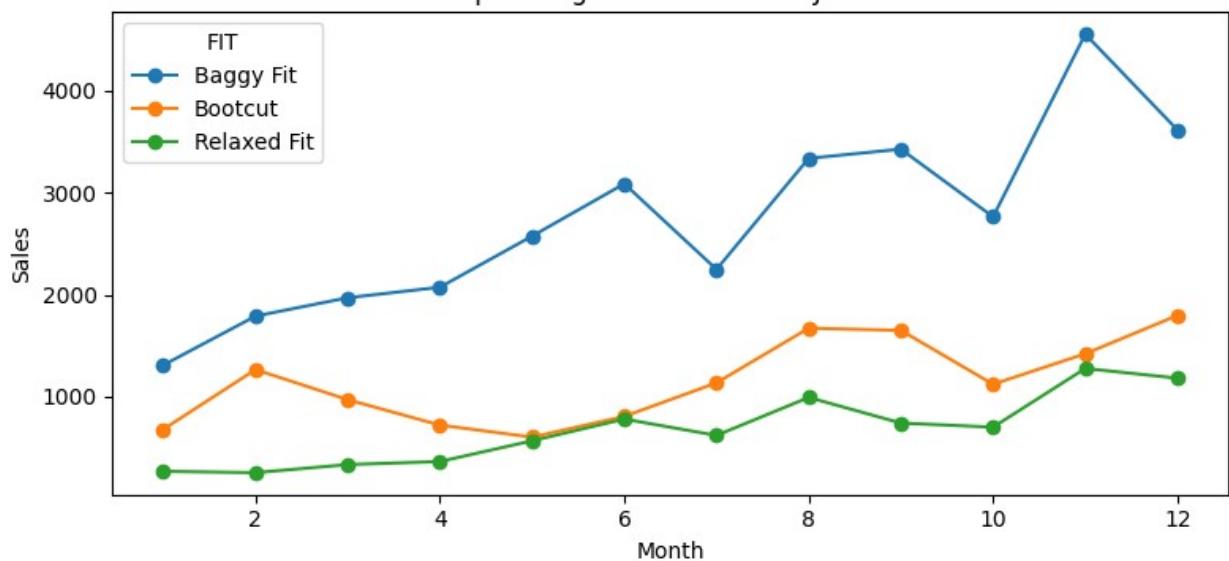
Upcoming Trends in OCCASSION_NEW for T-Shirts



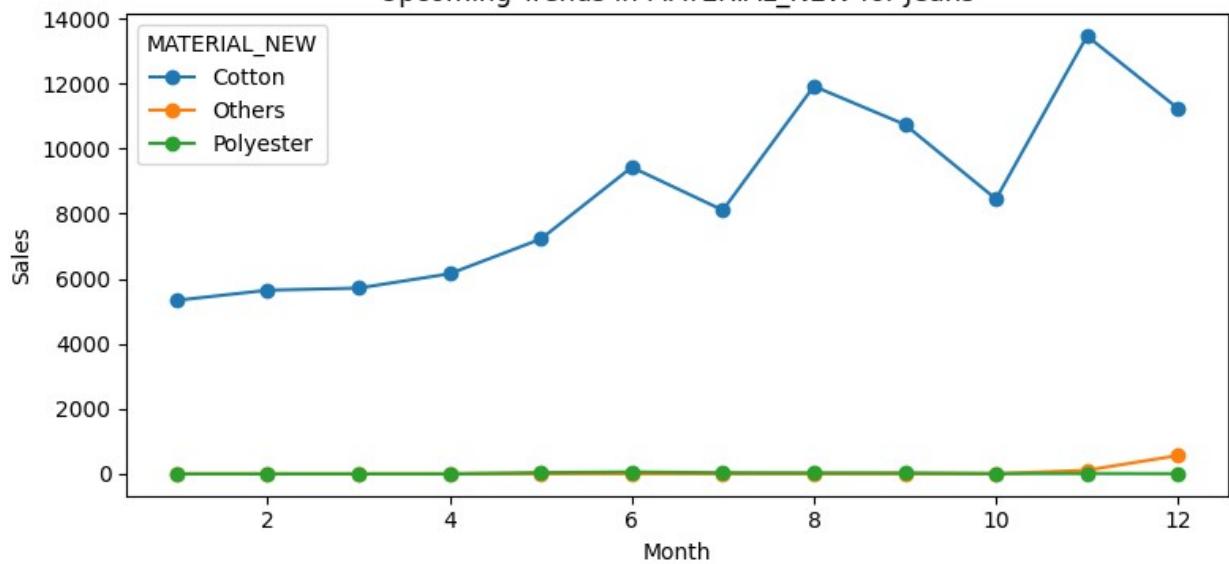
Upcoming Trends in COLOR for T-Shirts



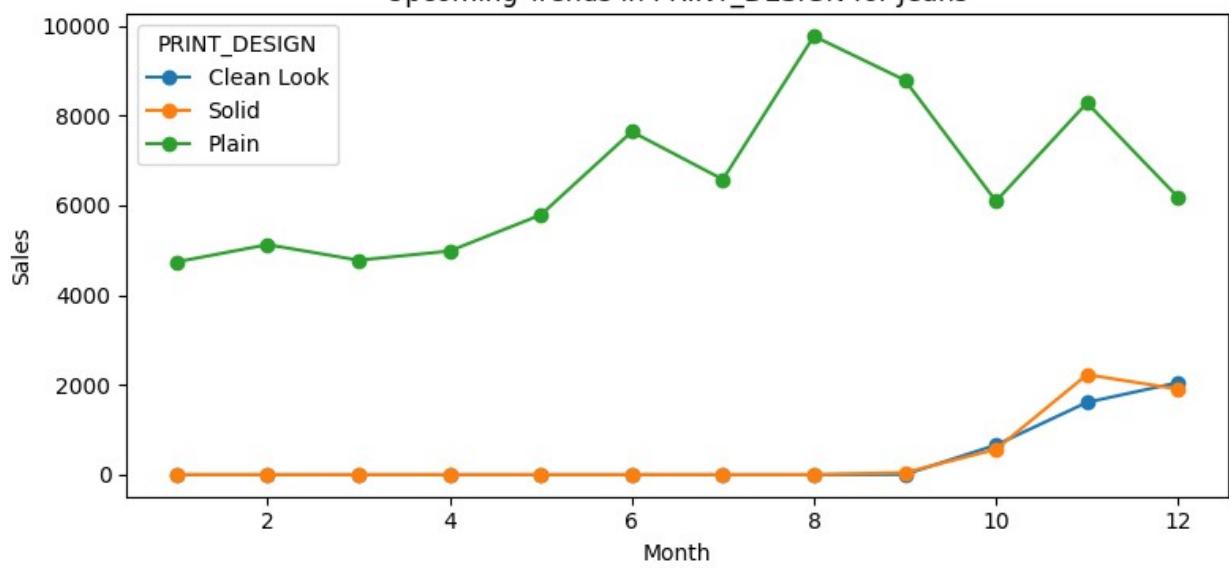
Upcoming Trends in FIT for Jeans



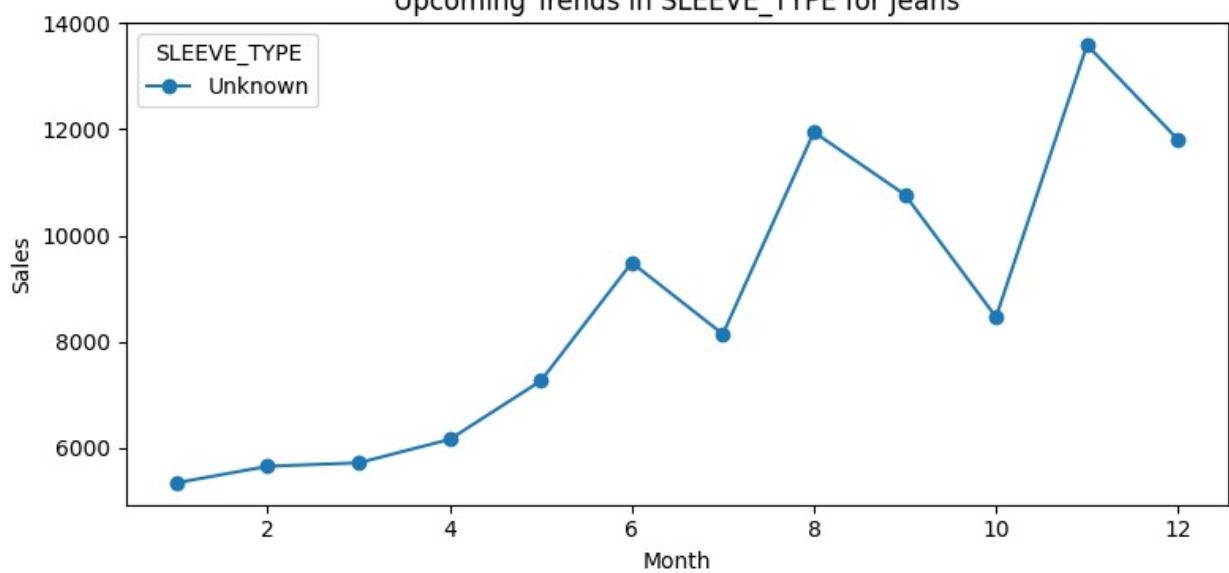
Upcoming Trends in MATERIAL_NEW for Jeans



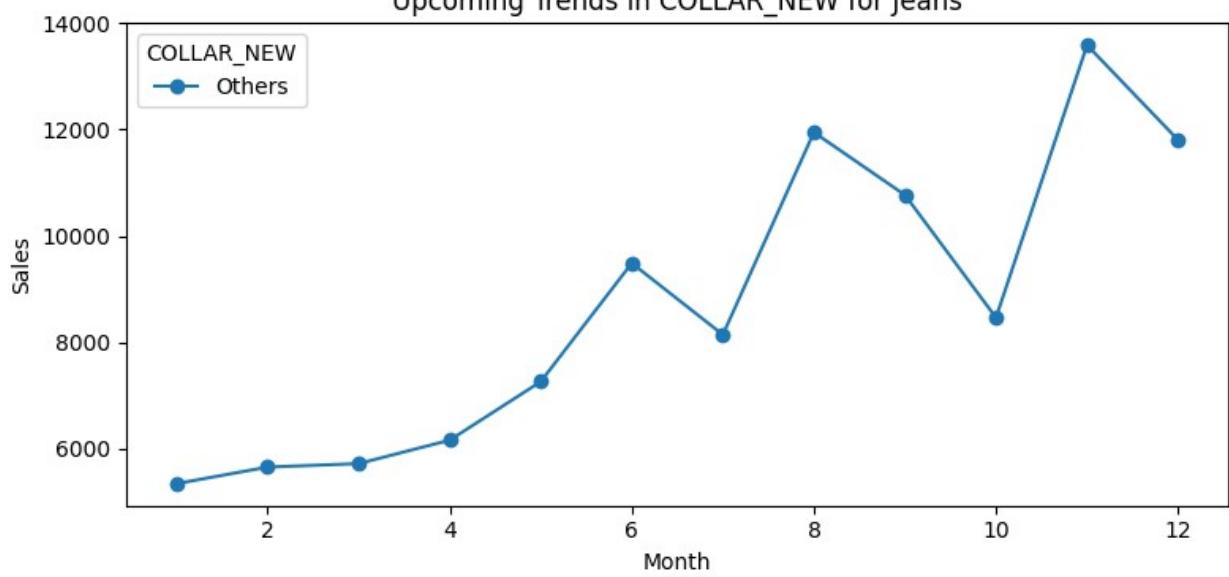
Upcoming Trends in PRINT_DESIGN for Jeans

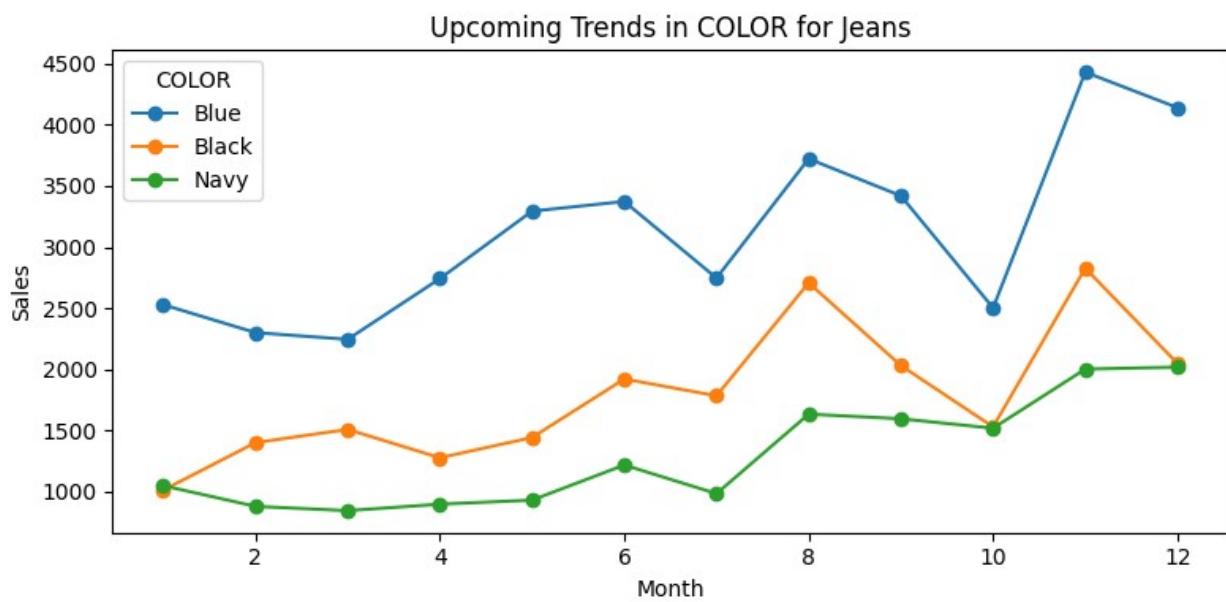
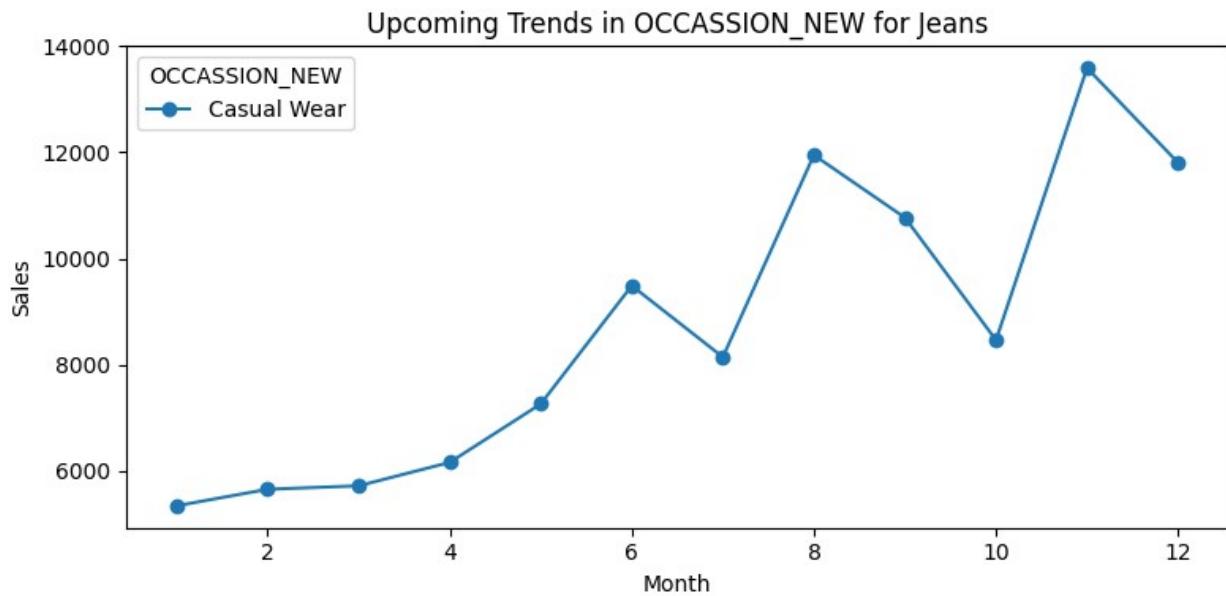


Upcoming Trends in SLEEVE_TYPE for Jeans

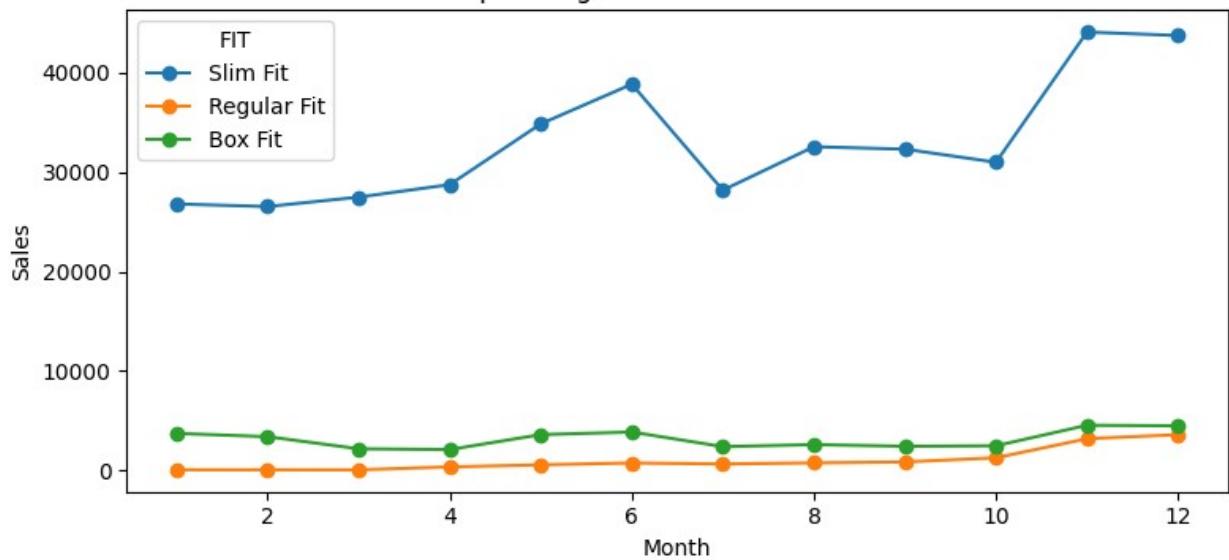


Upcoming Trends in COLLAR_NEW for Jeans

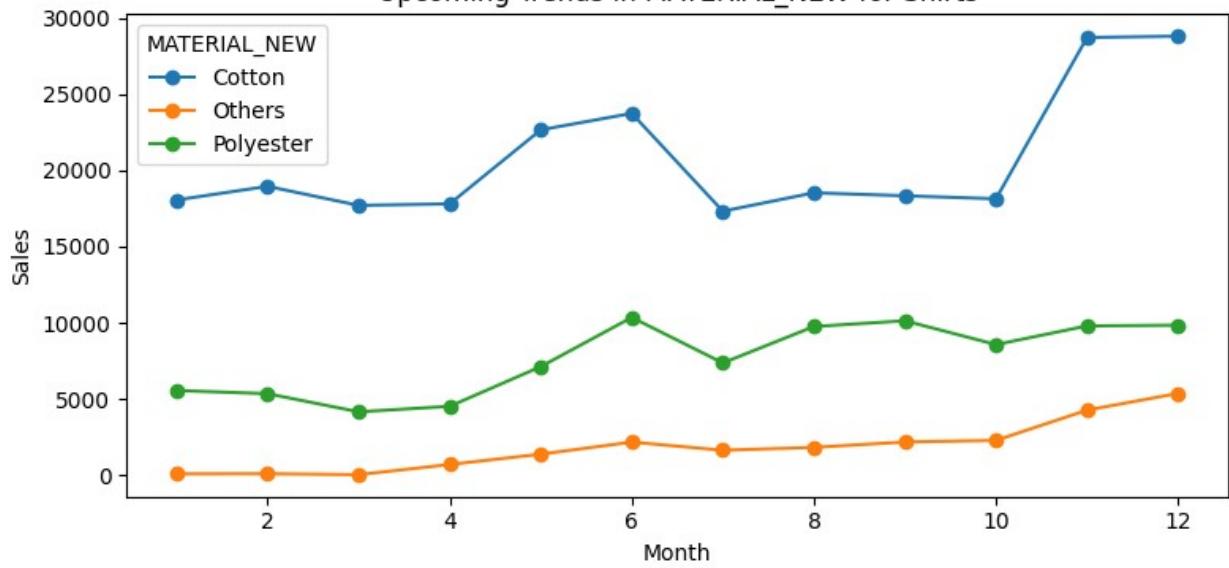




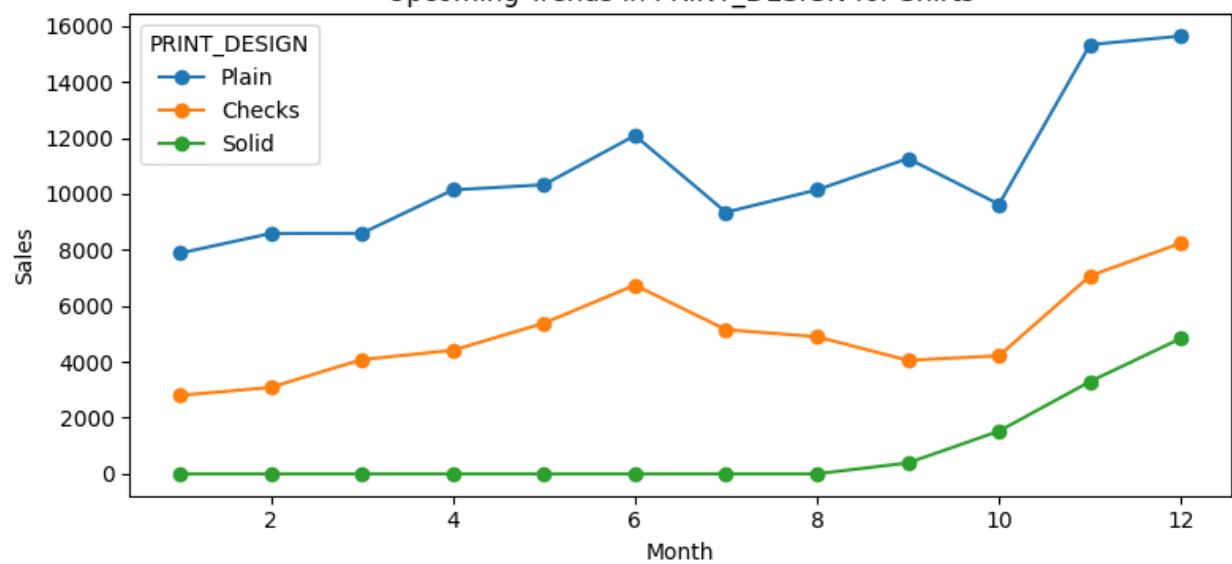
Upcoming Trends in FIT for Shirts



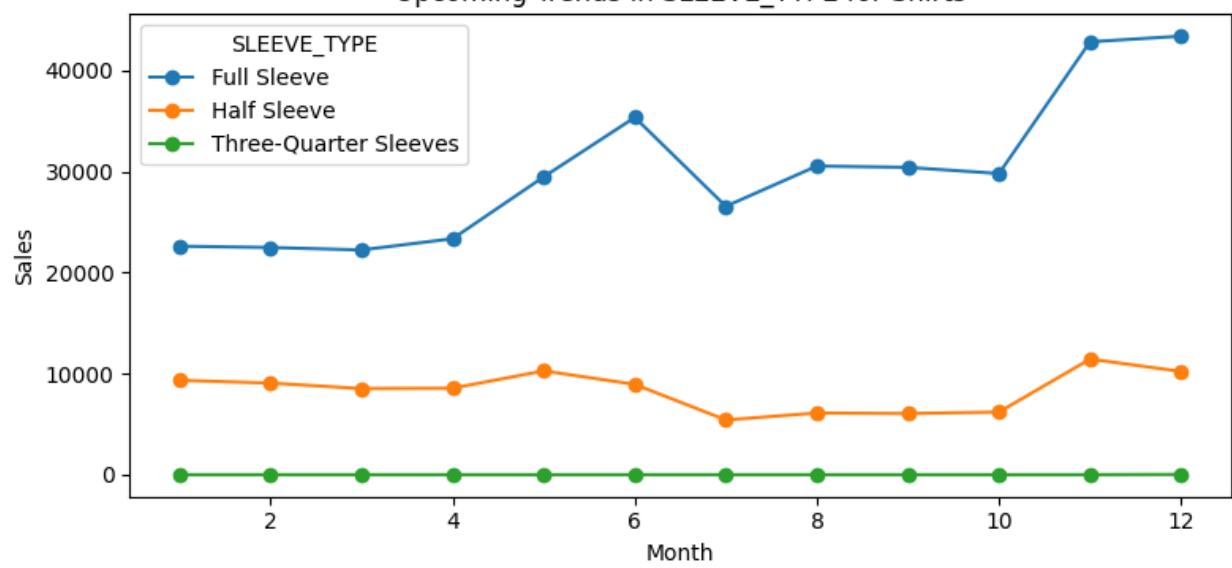
Upcoming Trends in MATERIAL_NEW for Shirts



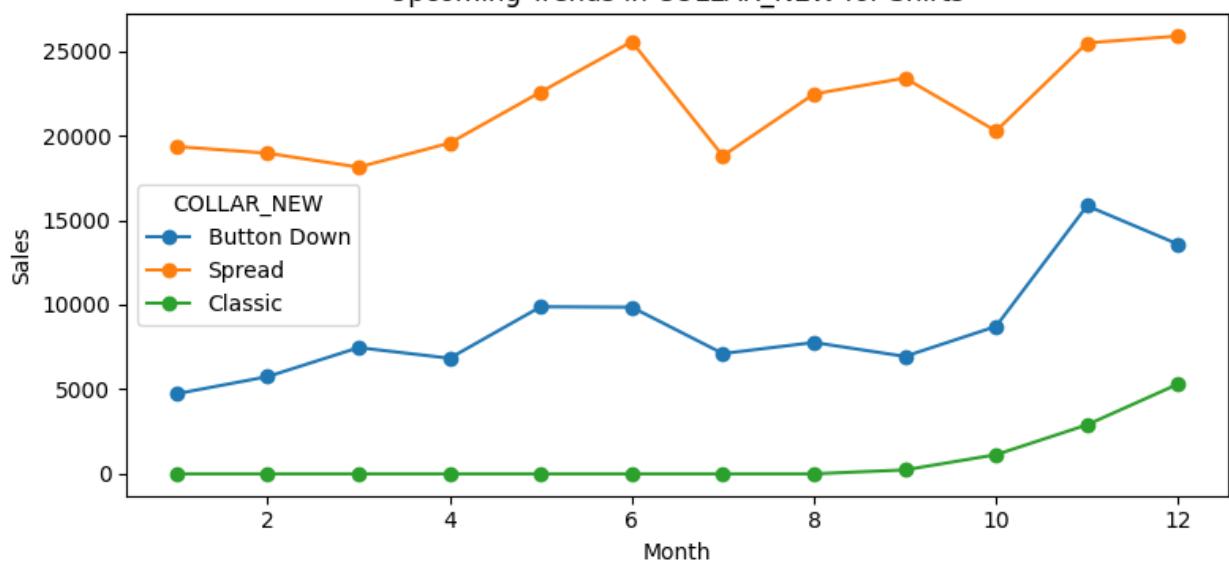
Upcoming Trends in PRINT_DESIGN for Shirts



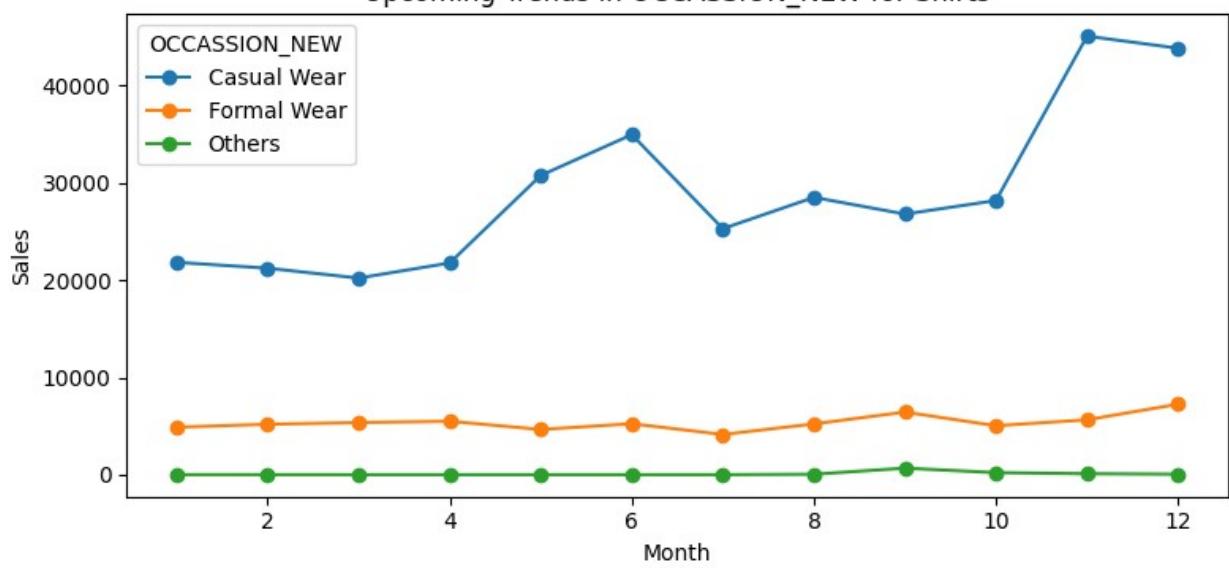
Upcoming Trends in SLEEVE_TYPE for Shirts



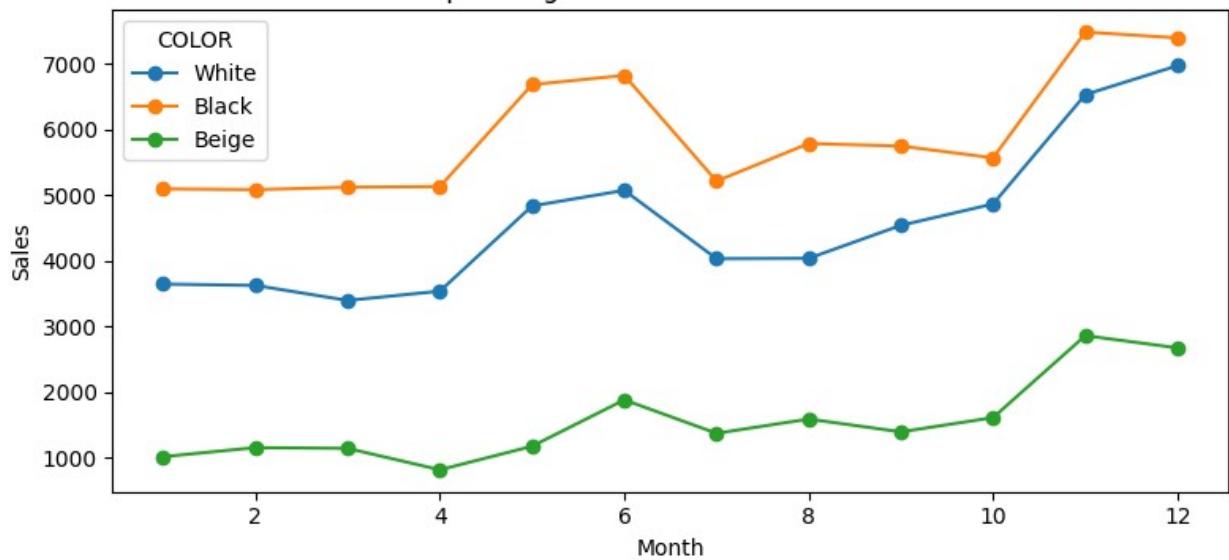
Upcoming Trends in COLLAR_NEW for Shirts



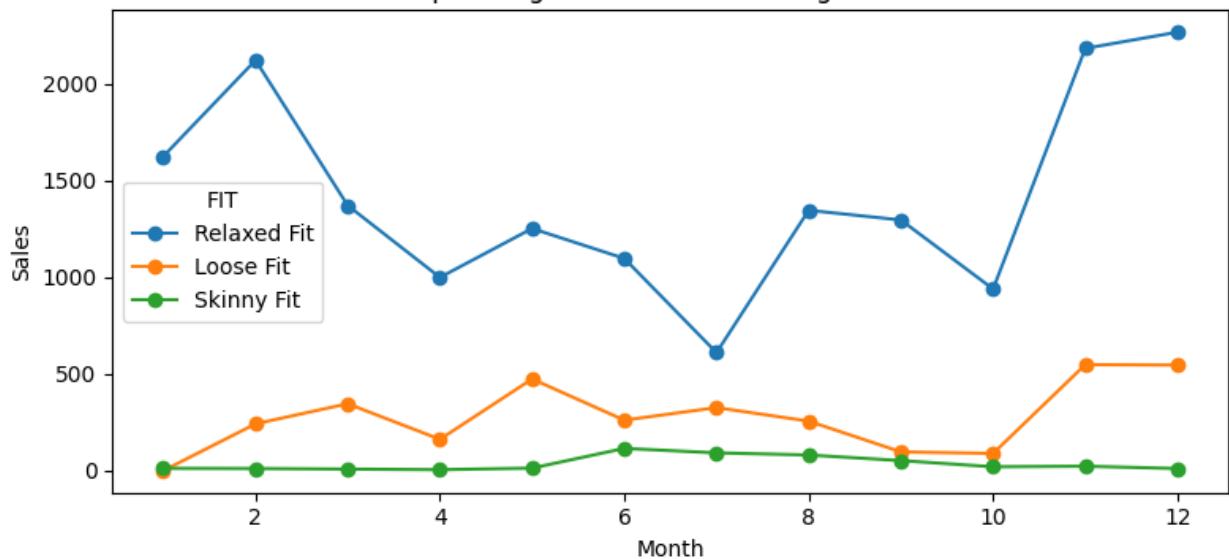
Upcoming Trends in OCCASSION_NEW for Shirts



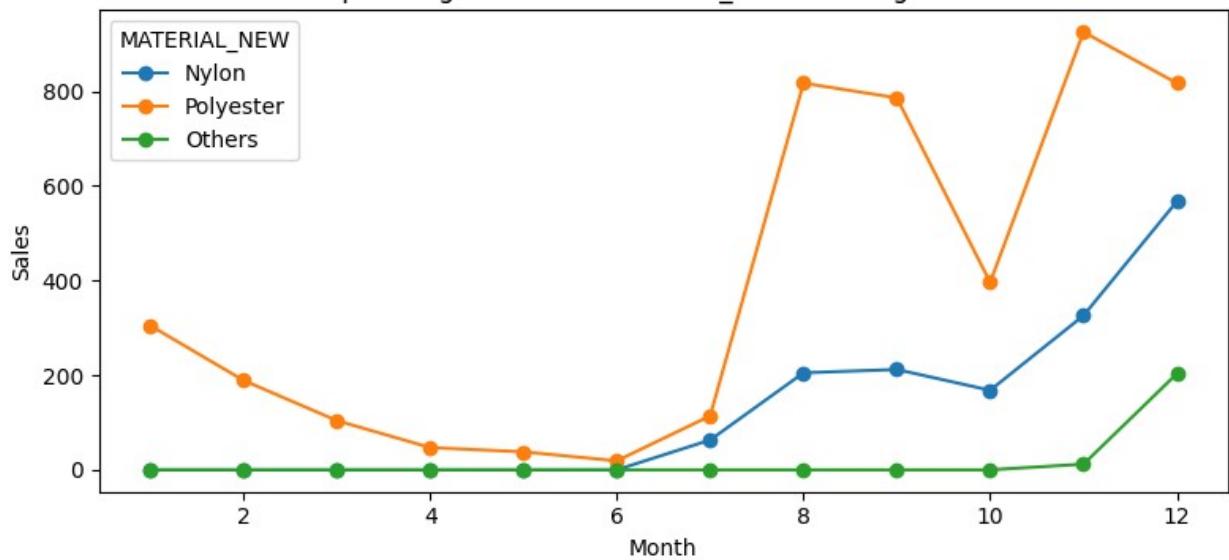
Upcoming Trends in COLOR for Shirts



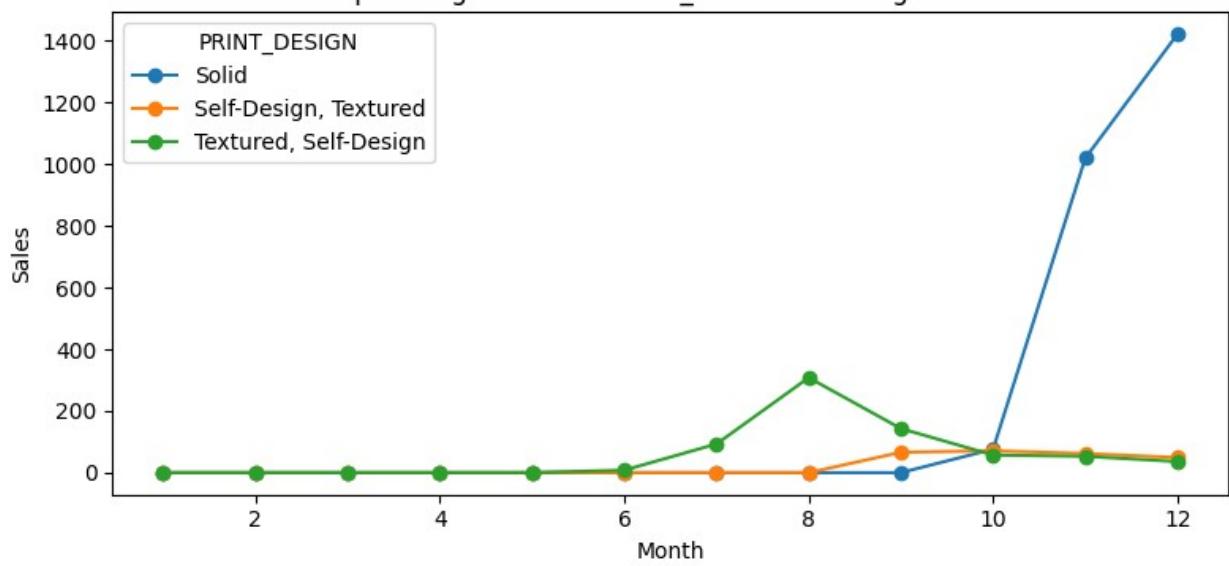
Upcoming Trends in FIT for Cargo Pants



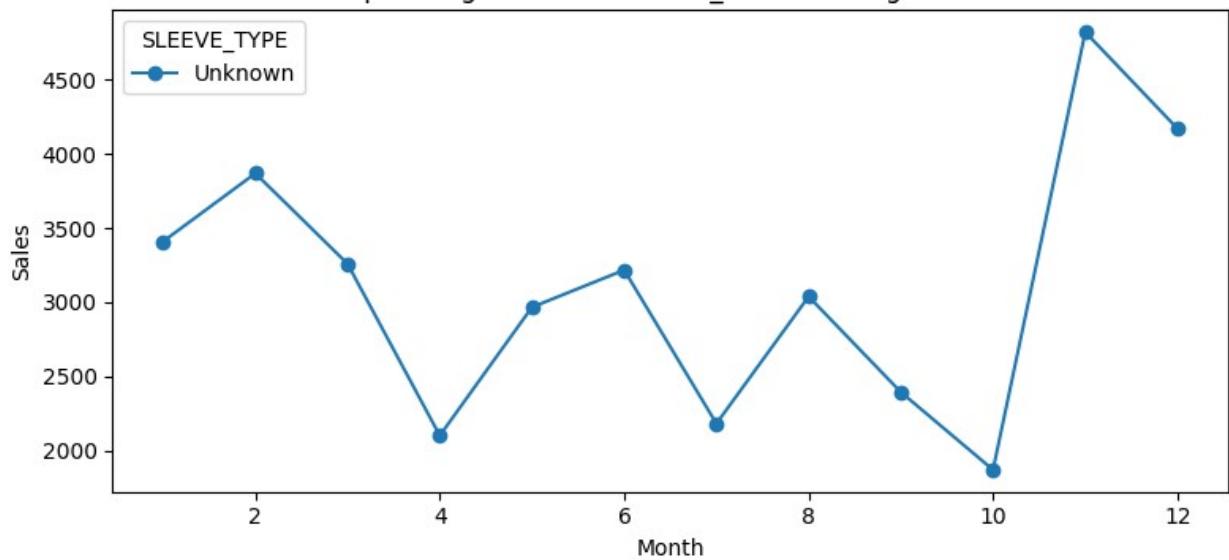
Upcoming Trends in MATERIAL_NEW for Cargo Pants



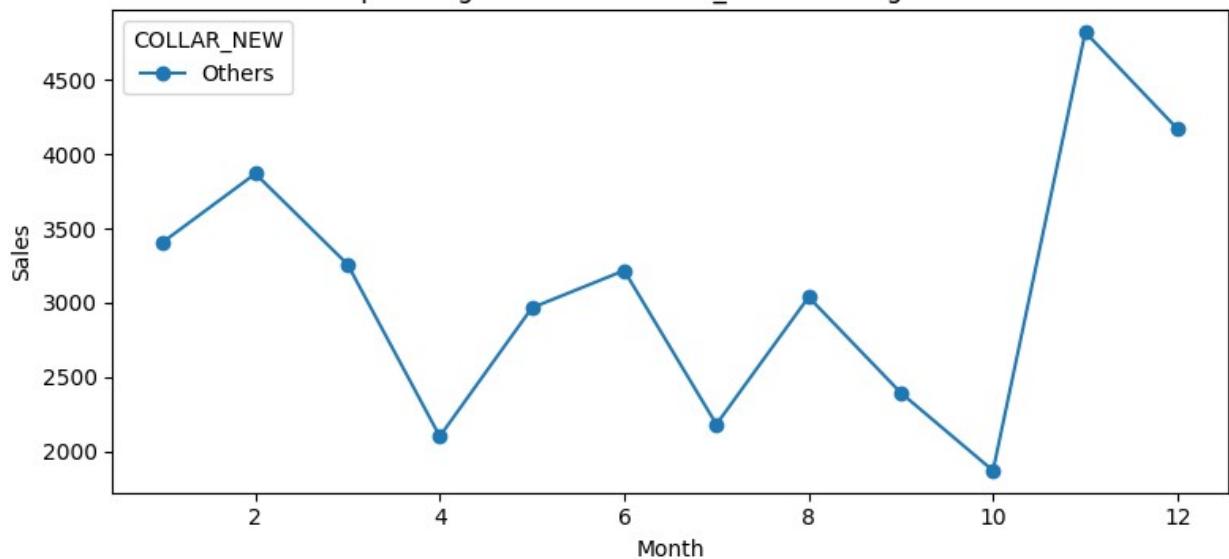
Upcoming Trends in PRINT_DESIGN for Cargo Pants



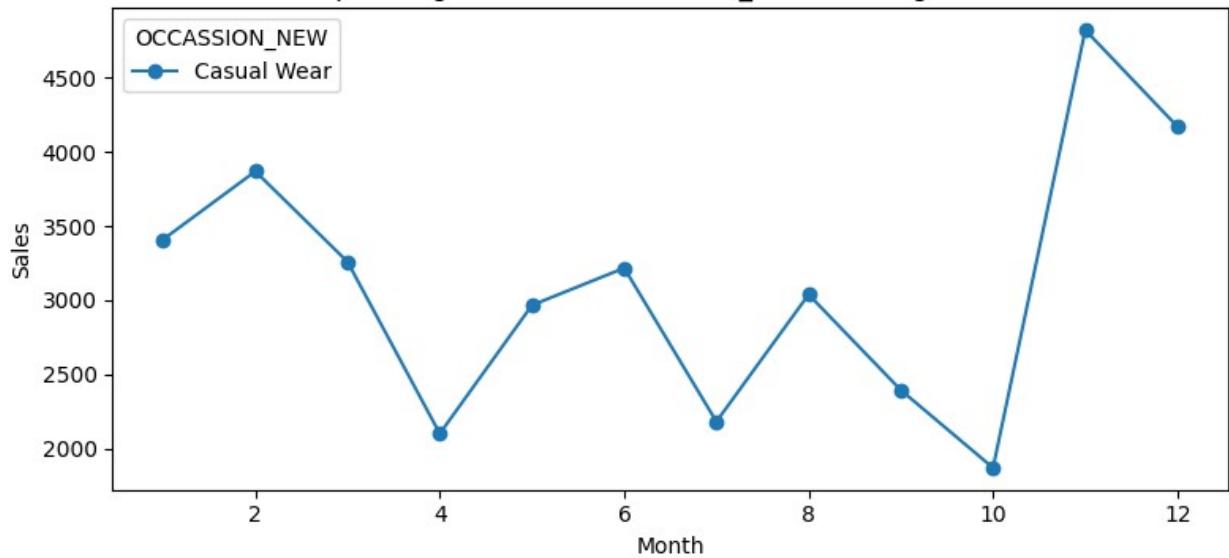
Upcoming Trends in SLEEVE_TYPE for Cargo Pants



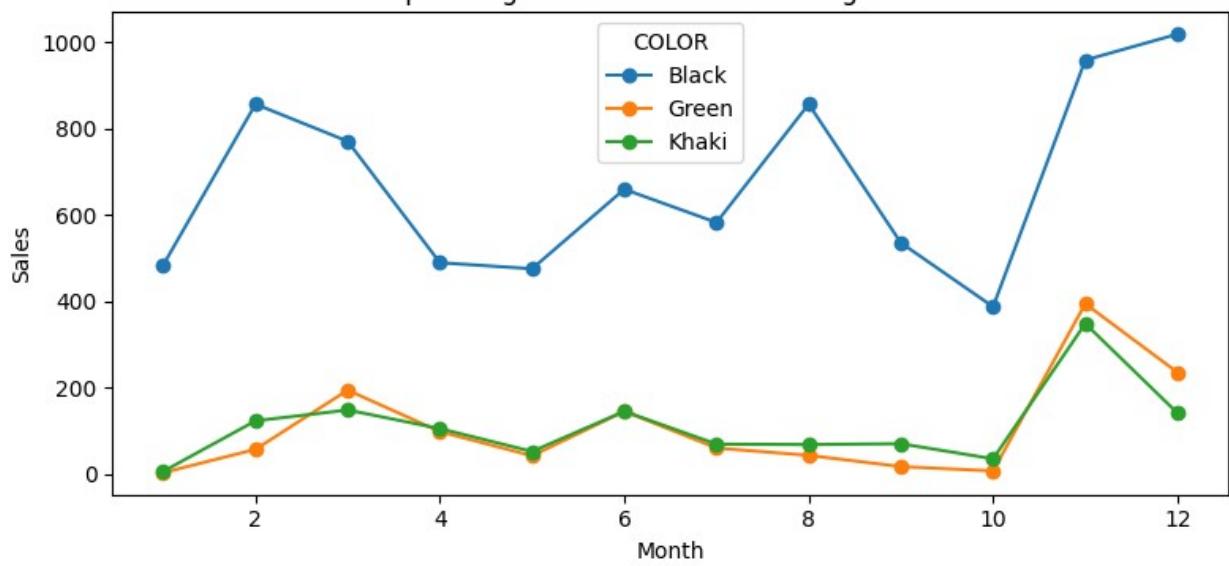
Upcoming Trends in COLLAR_NEW for Cargo Pants



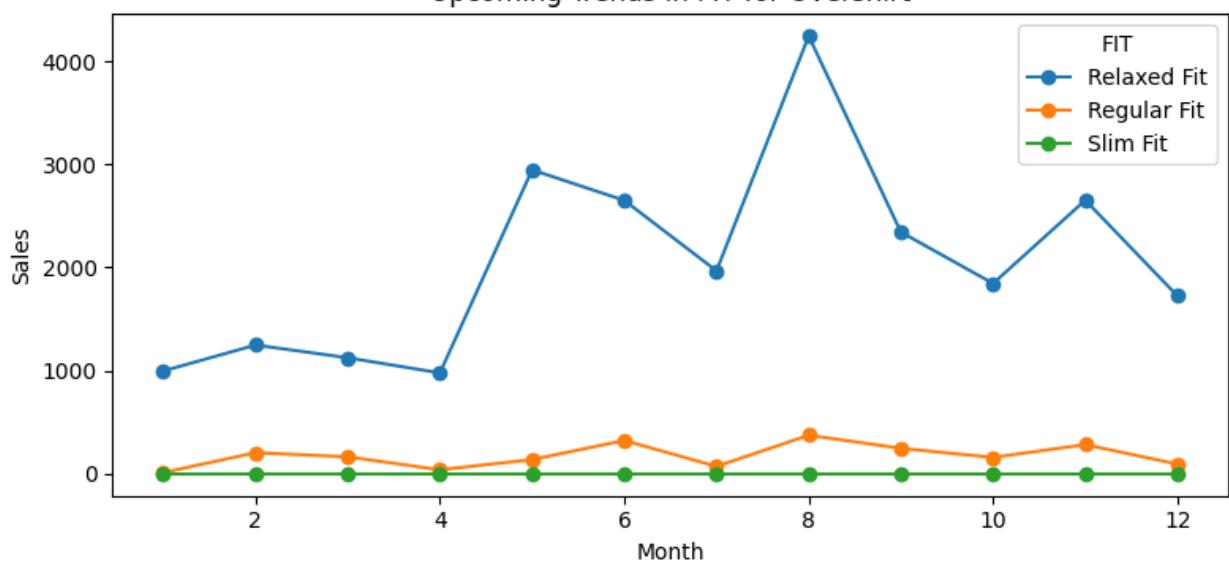
Upcoming Trends in OCCASSION_NEW for Cargo Pants



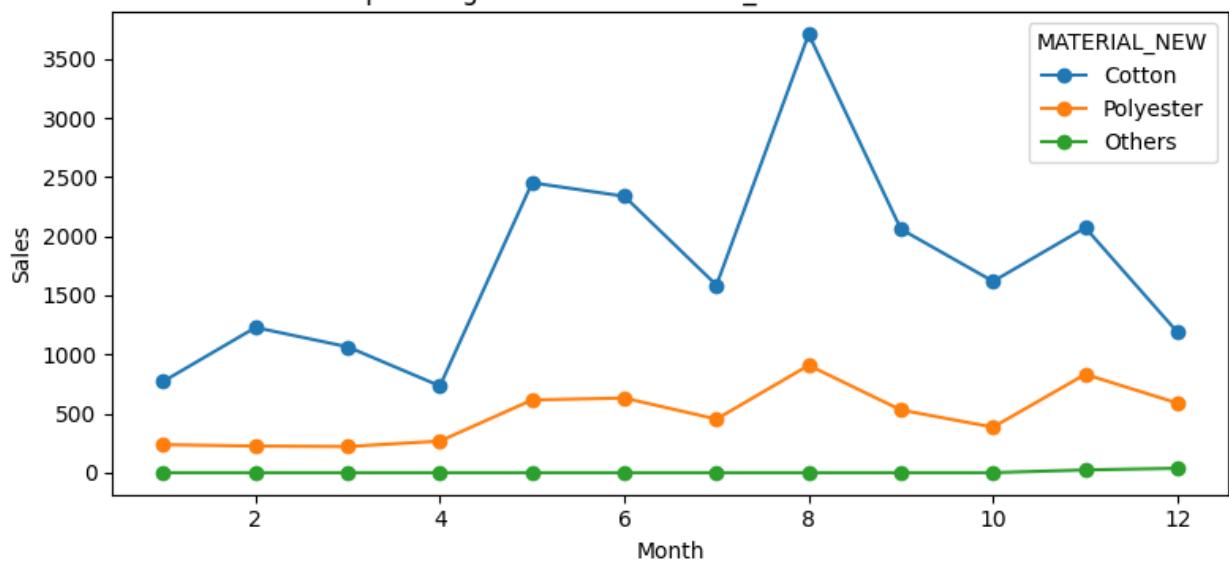
Upcoming Trends in COLOR for Cargo Pants



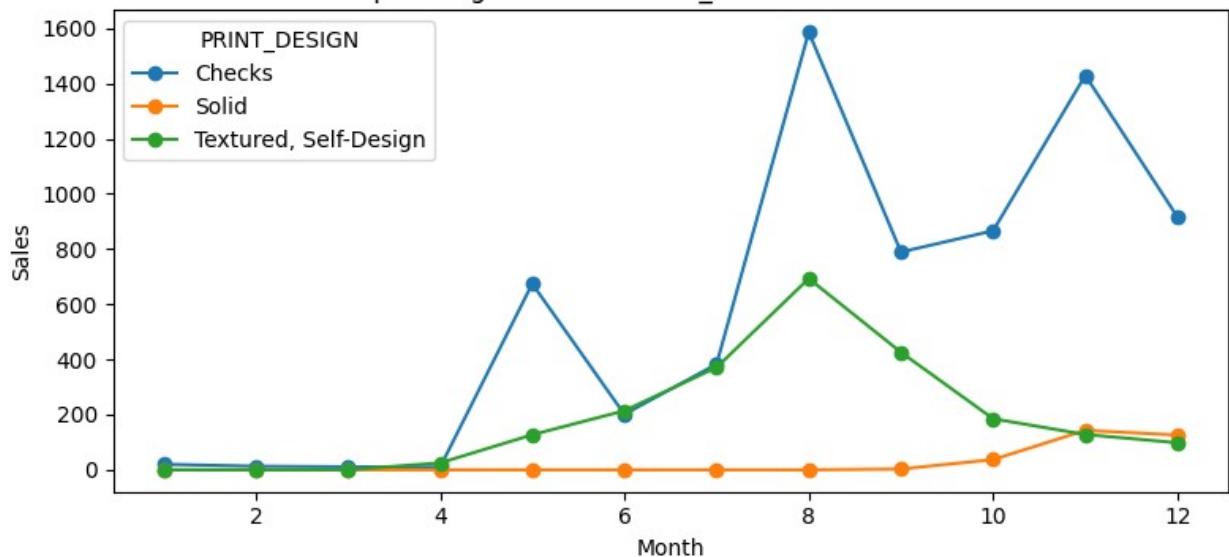
Upcoming Trends in FIT for Overshirt



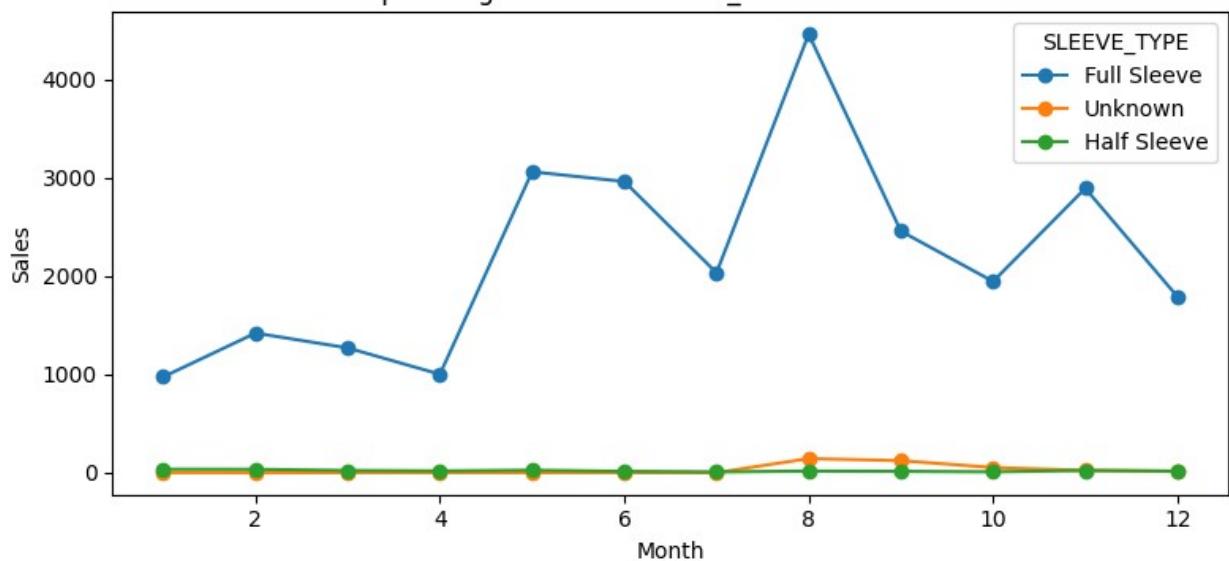
Upcoming Trends in MATERIAL_NEW for Overshirt



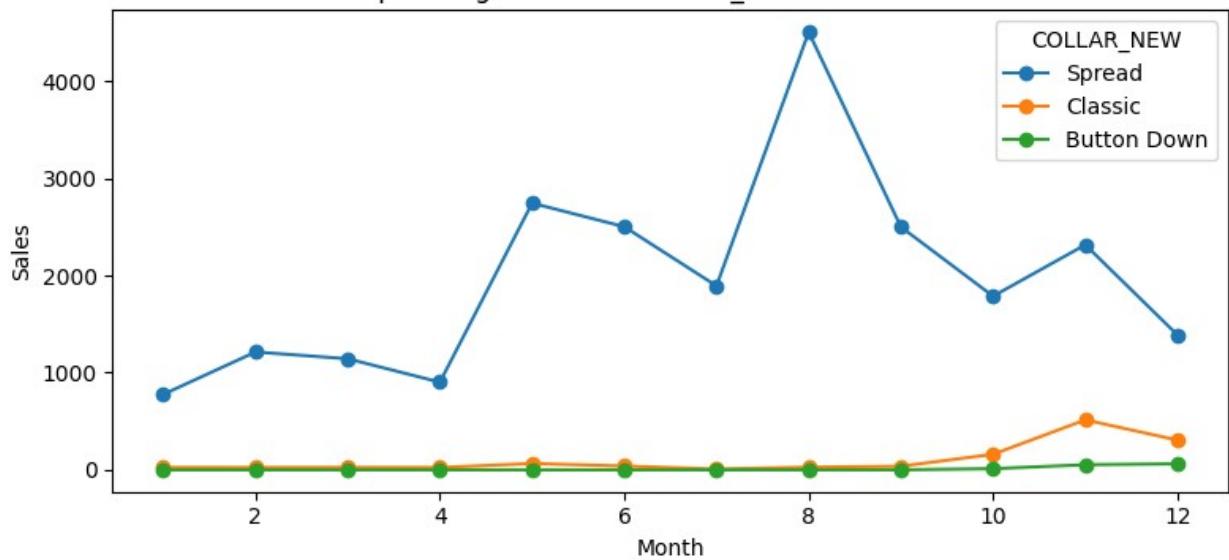
Upcoming Trends in PRINT_DESIGN for Overshirt



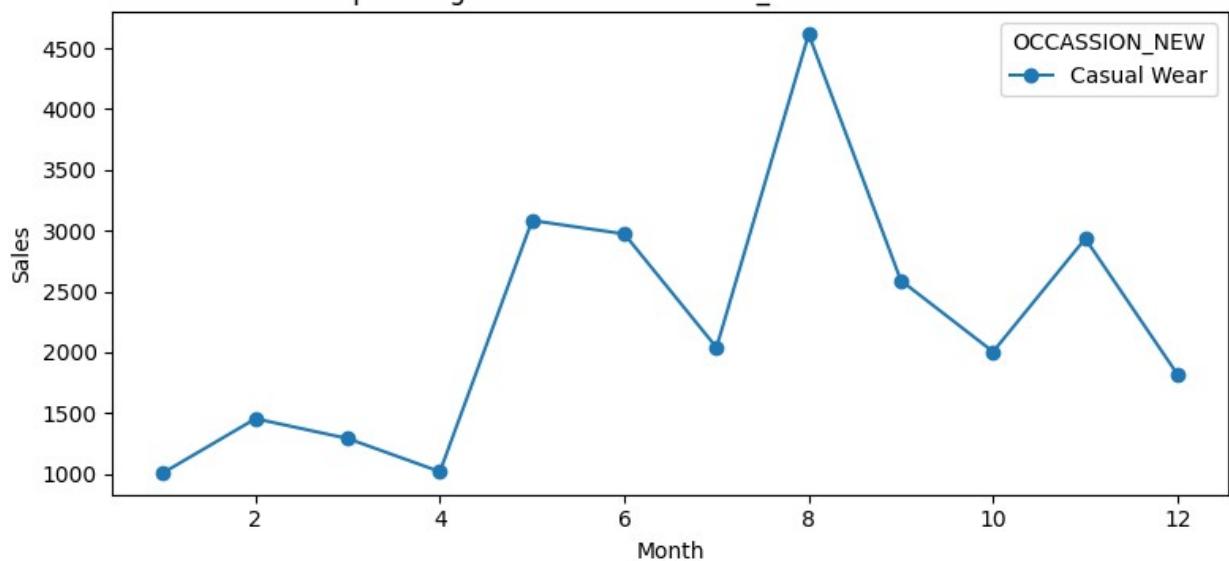
Upcoming Trends in SLEEVE_TYPE for Overshirt



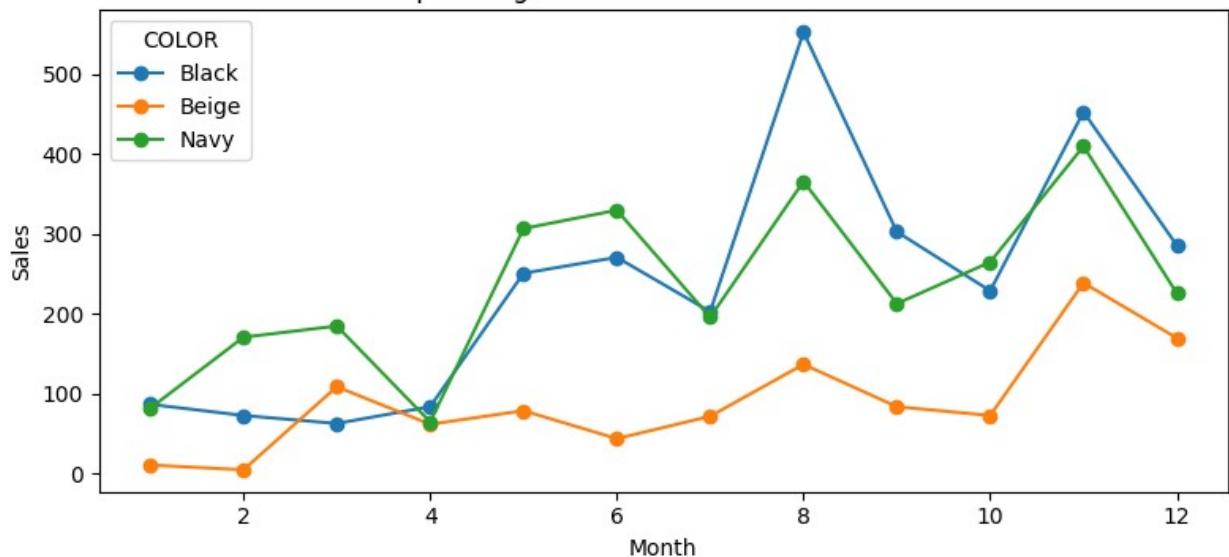
Upcoming Trends in COLLAR_NEW for Overshirt



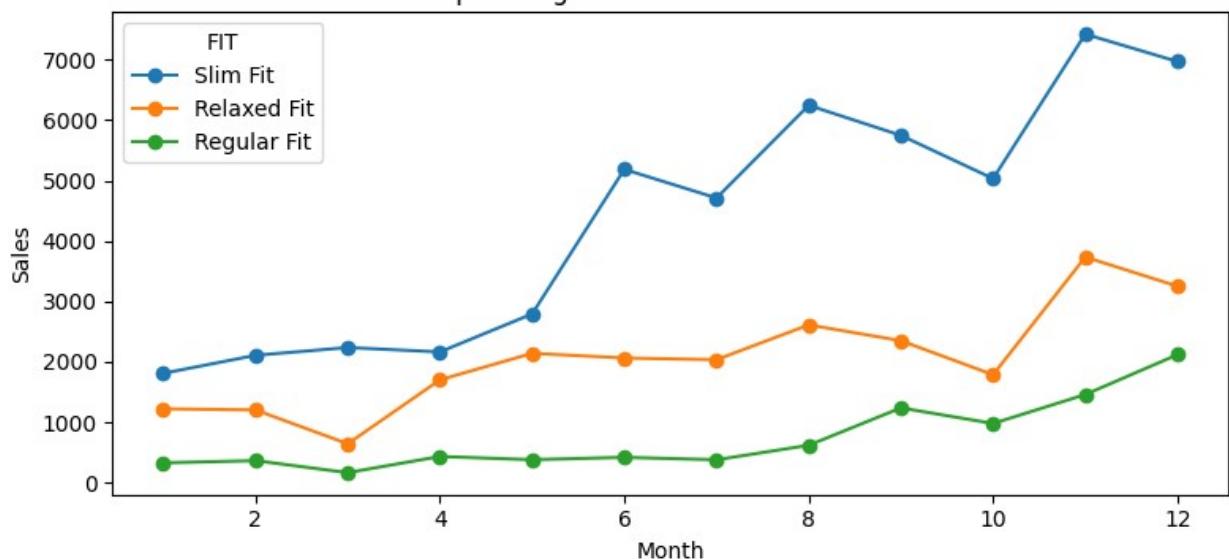
Upcoming Trends in OCCASSION_NEW for Overshirt



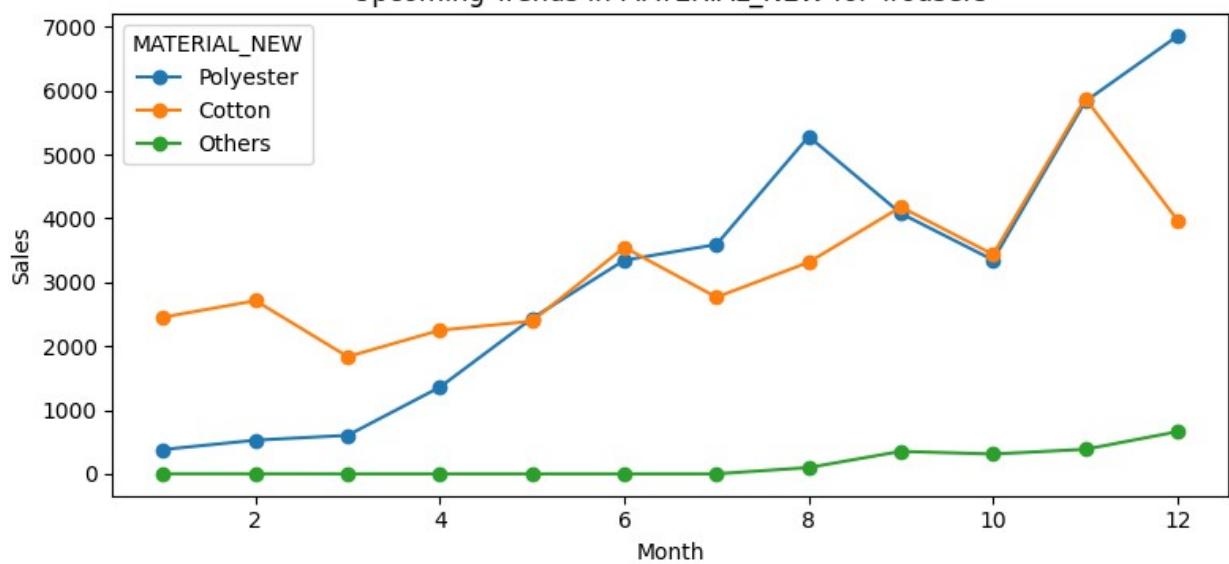
Upcoming Trends in COLOR for Overshirt



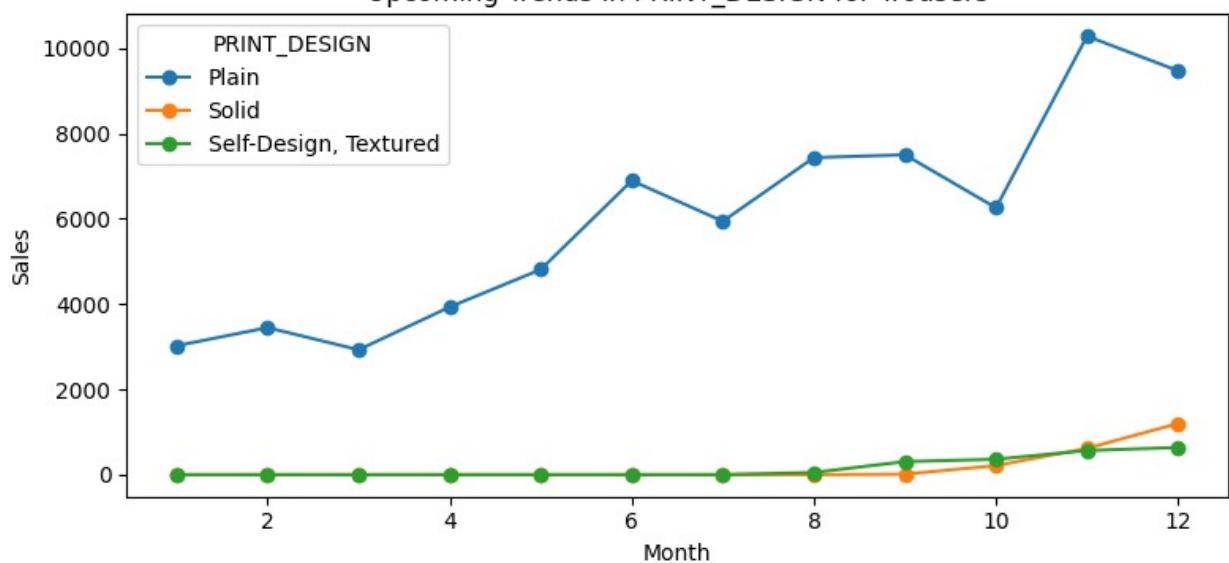
Upcoming Trends in FIT for Trousers



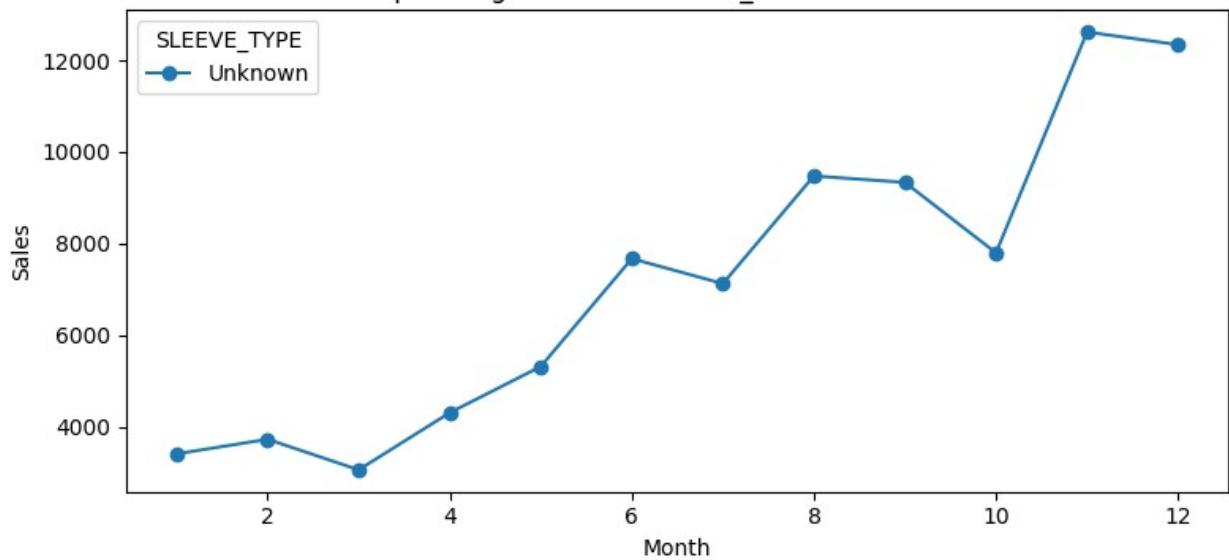
Upcoming Trends in MATERIAL_NEW for Trousers



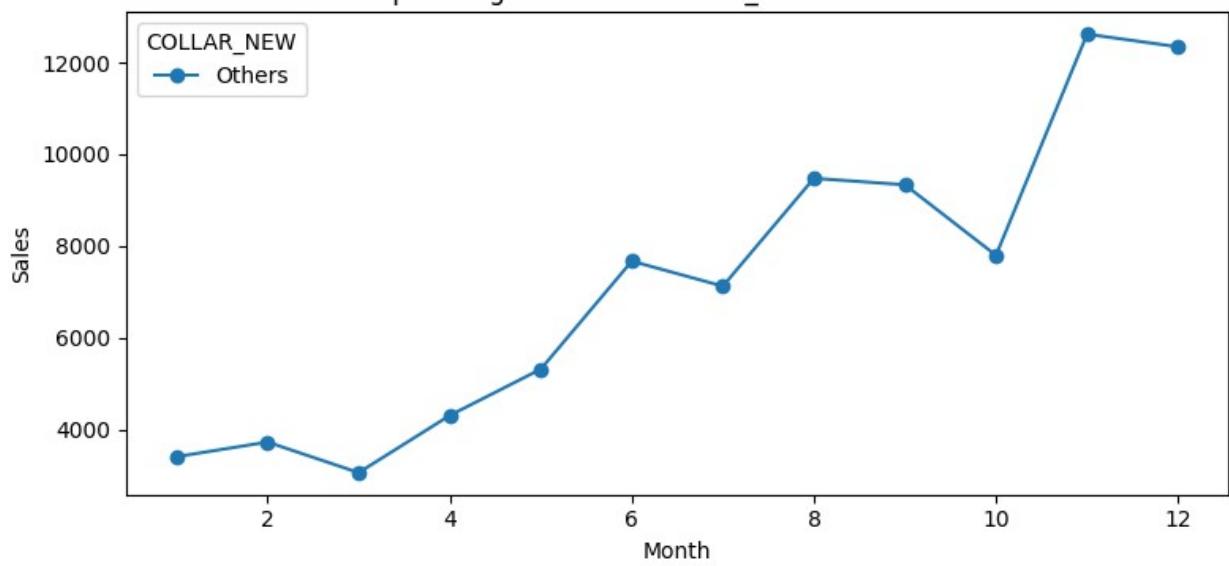
Upcoming Trends in PRINT_DESIGN for Trousers



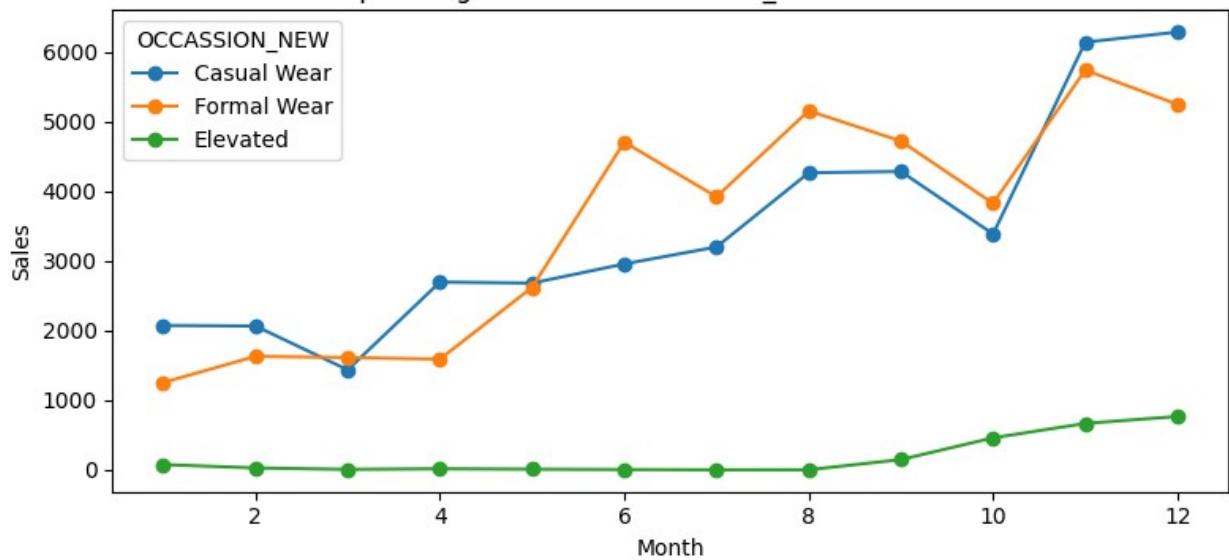
Upcoming Trends in SLEEVE_TYPE for Trousers



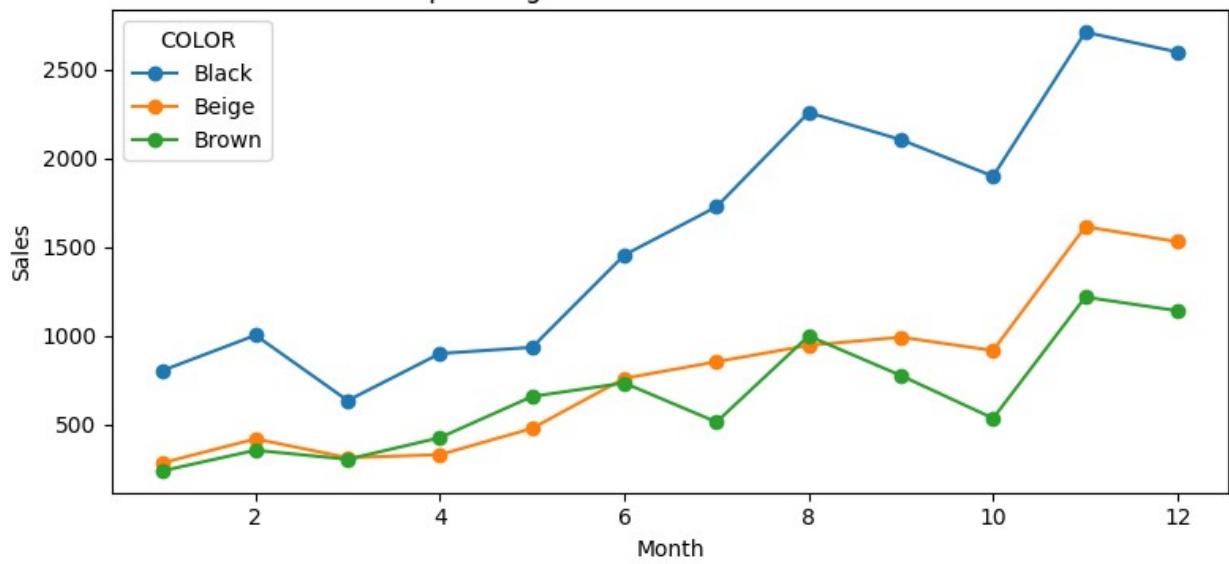
Upcoming Trends in COLLAR_NEW for Trousers



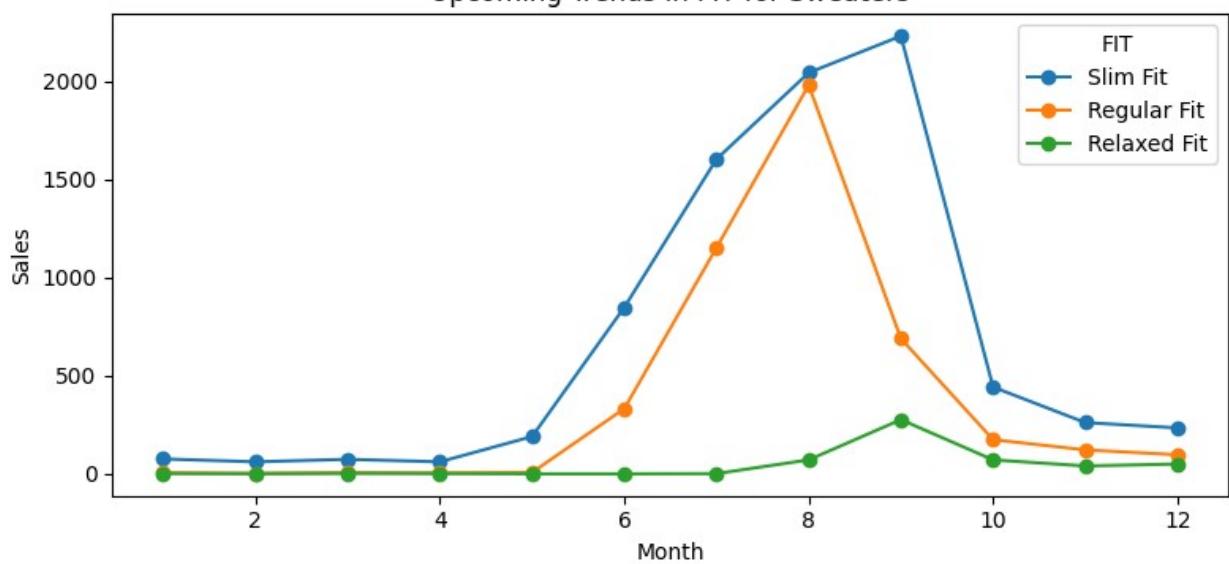
Upcoming Trends in OCCASSION_NEW for Trousers



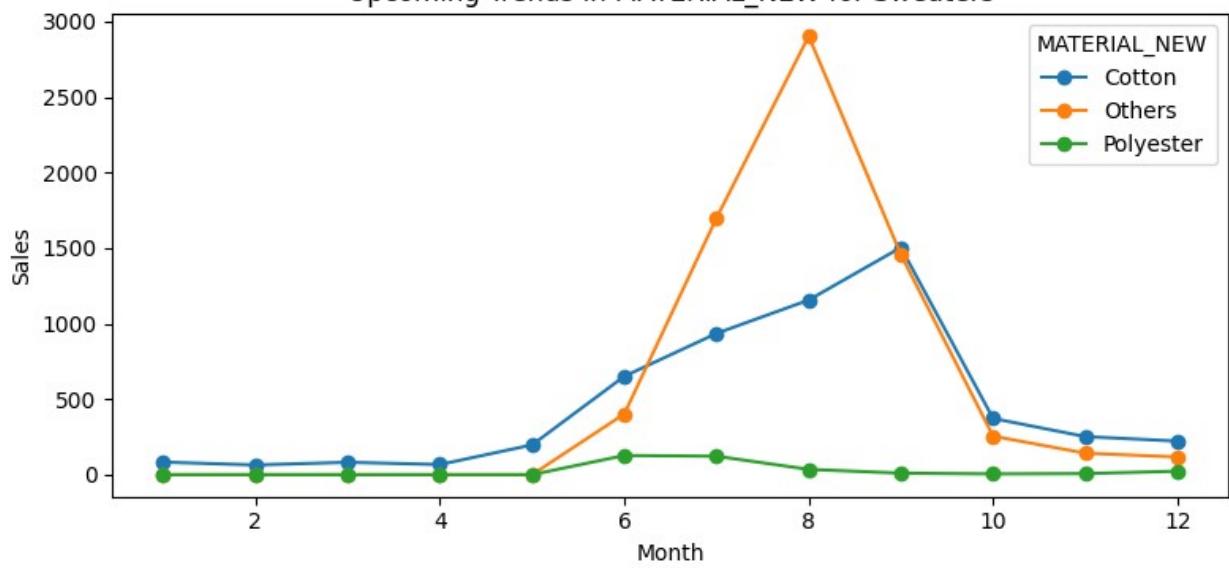
Upcoming Trends in COLOR for Trousers



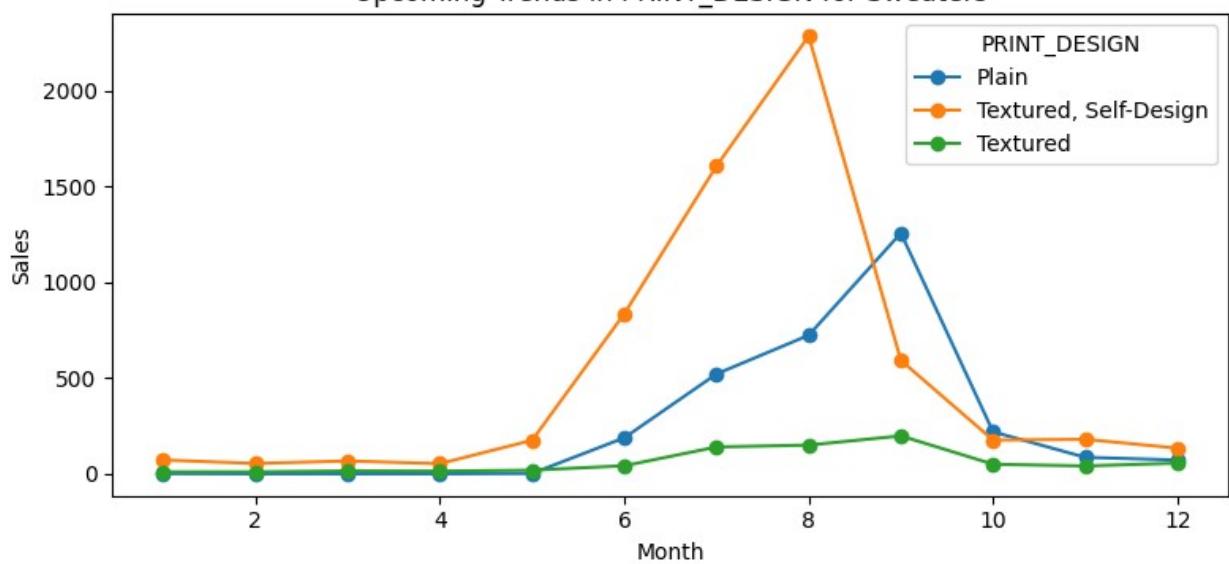
Upcoming Trends in FIT for Sweaters



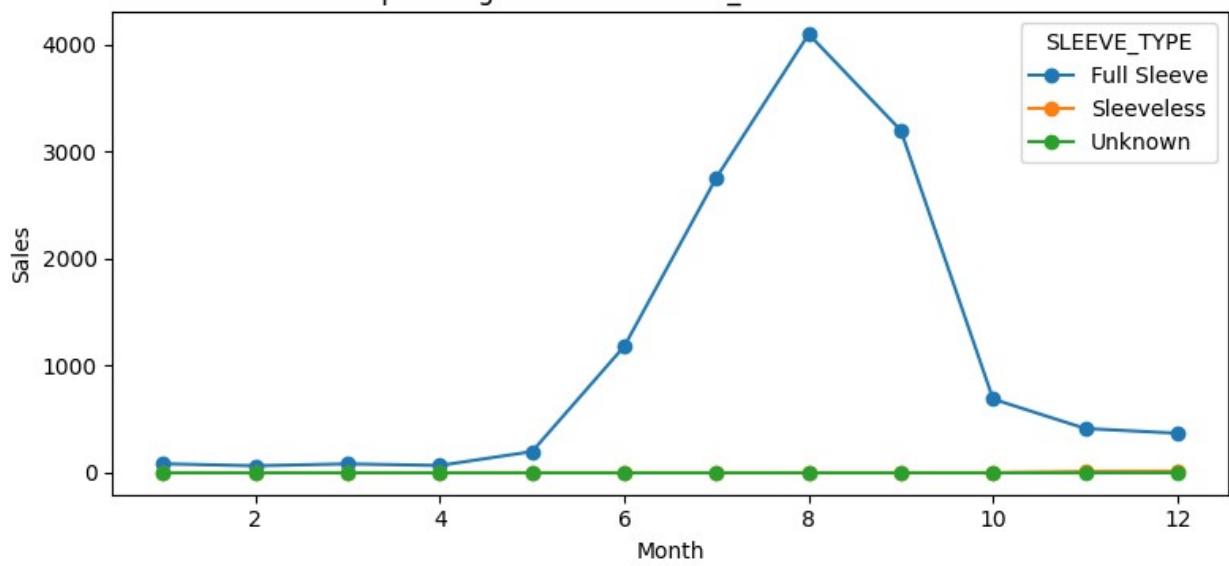
Upcoming Trends in MATERIAL_NEW for Sweaters



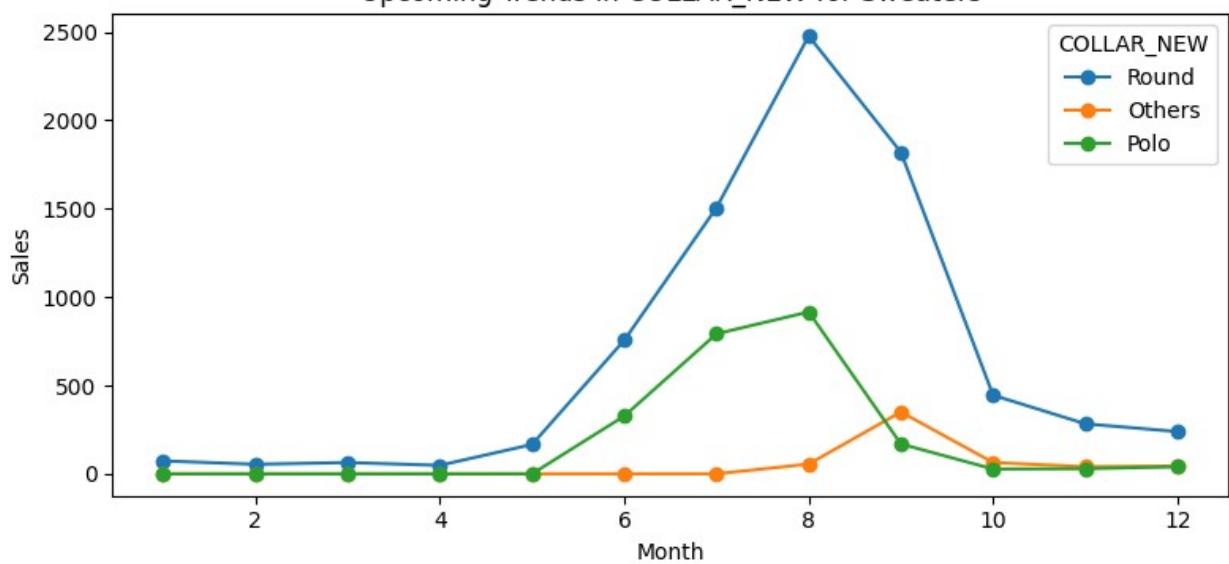
Upcoming Trends in PRINT_DESIGN for Sweaters



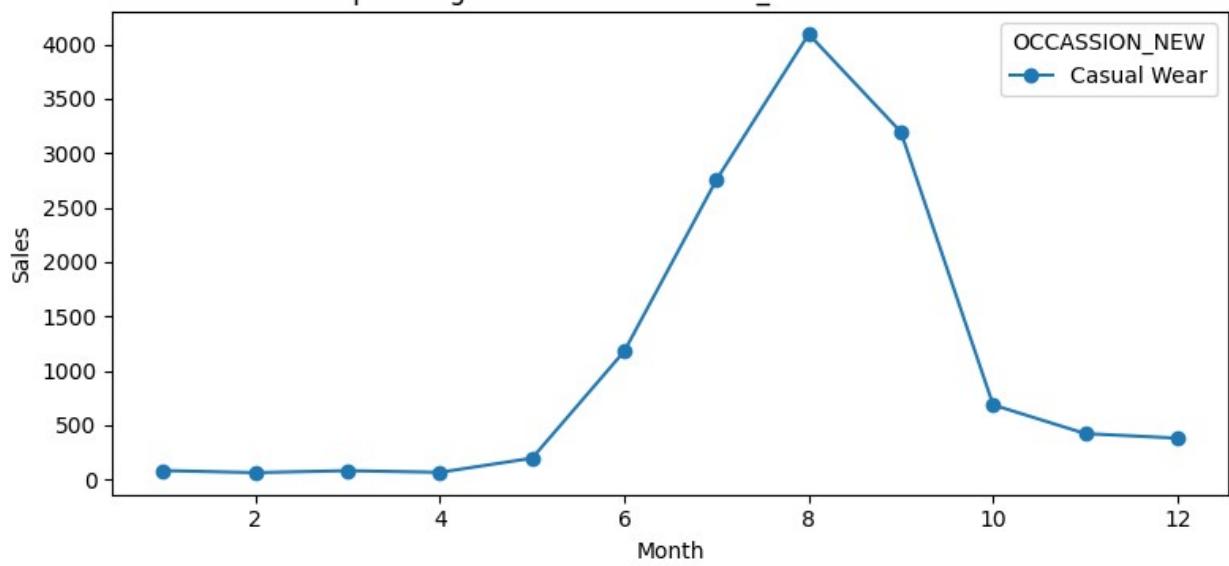
Upcoming Trends in SLEEVE_TYPE for Sweaters



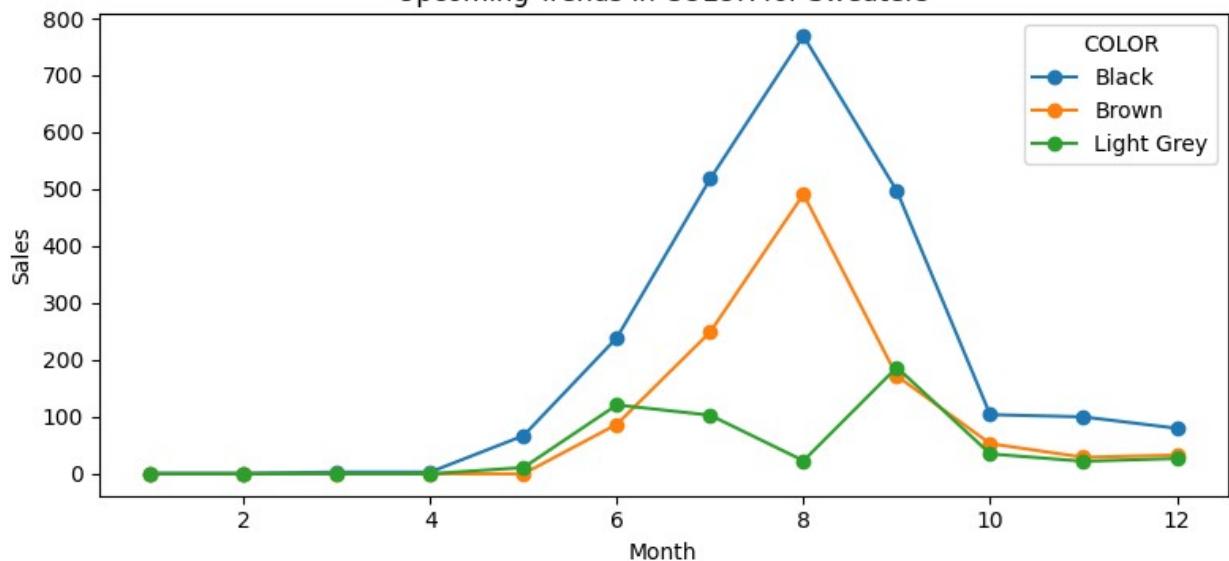
Upcoming Trends in COLLAR_NEW for Sweaters



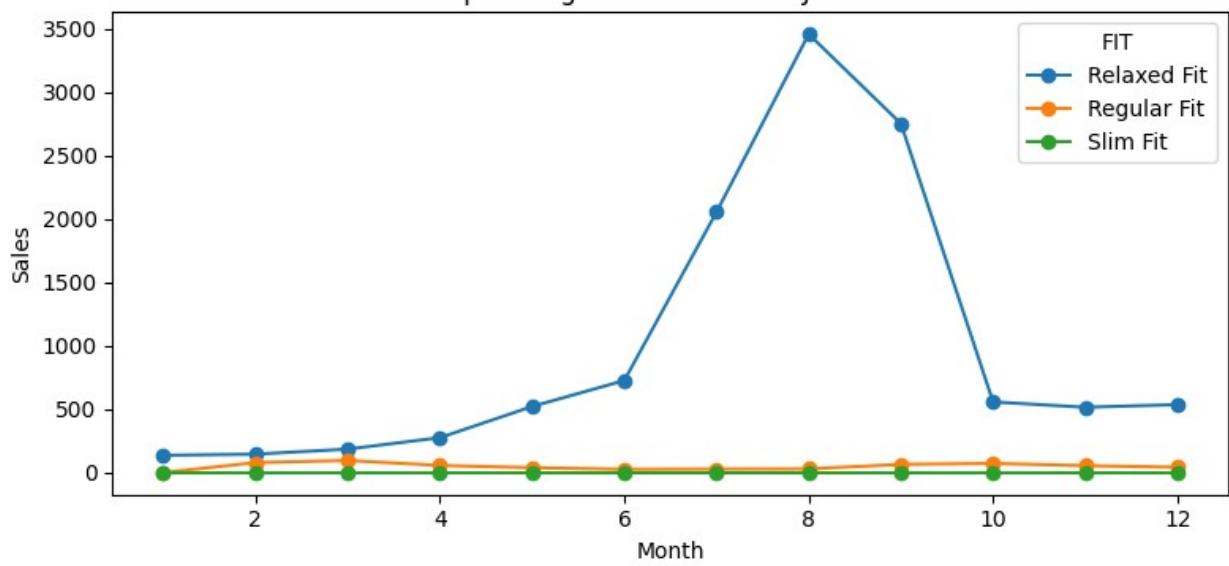
Upcoming Trends in OCCASSION_NEW for Sweaters



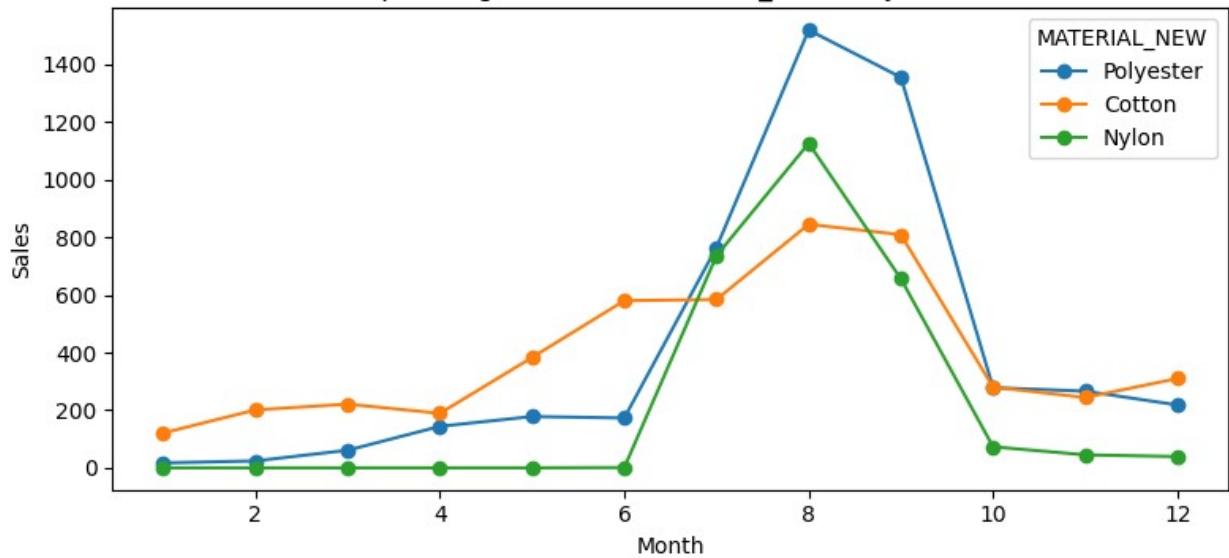
Upcoming Trends in COLOR for Sweaters



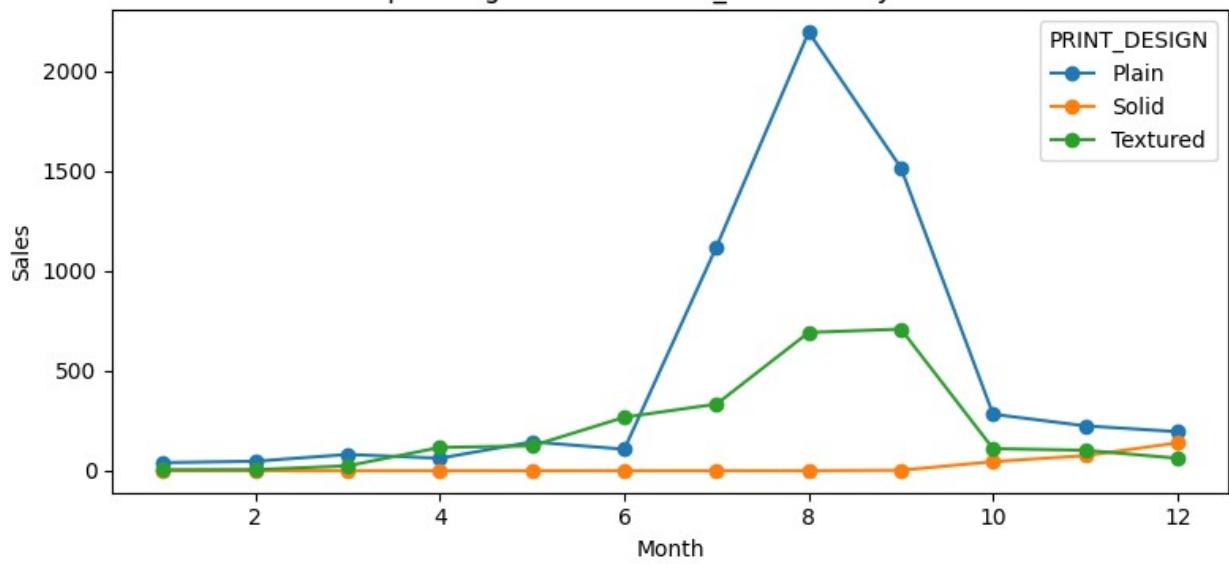
Upcoming Trends in FIT for Jackets



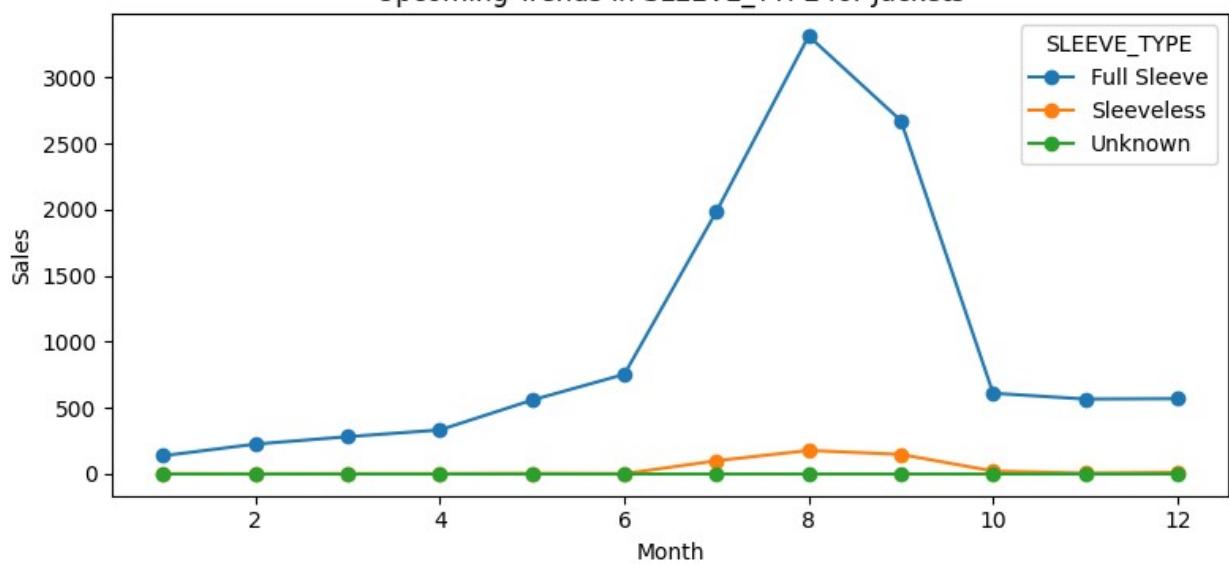
Upcoming Trends in MATERIAL_NEW for Jackets



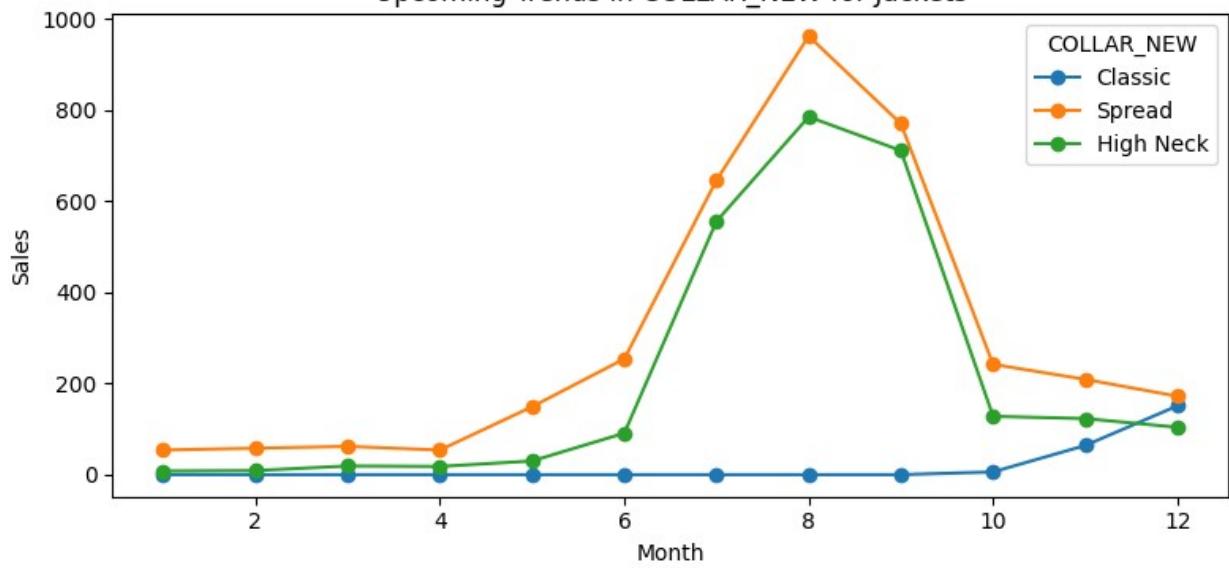
Upcoming Trends in PRINT_DESIGN for Jackets



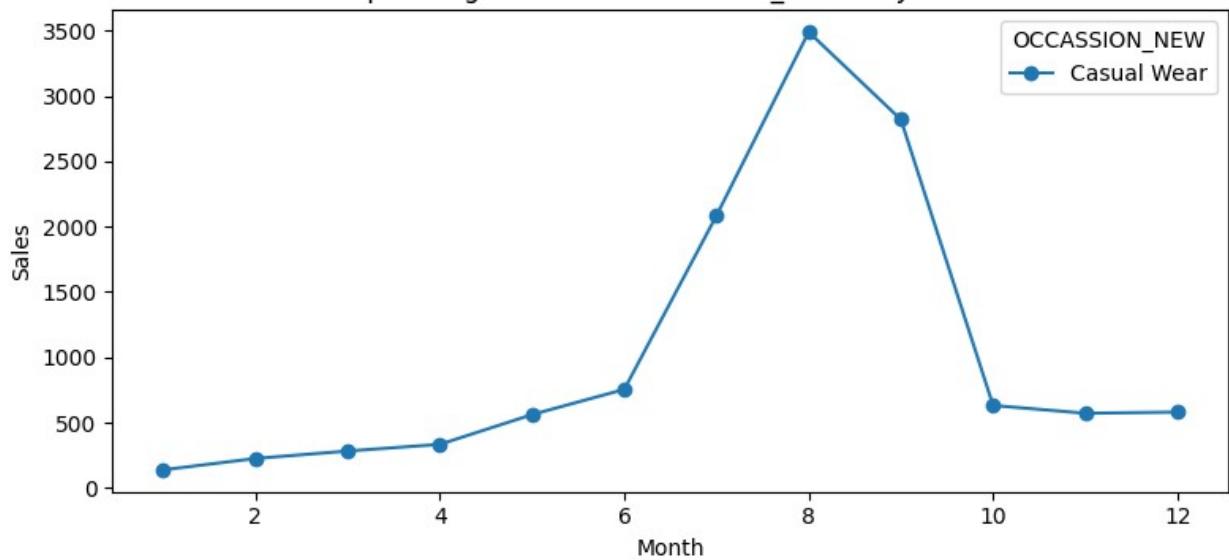
Upcoming Trends in SLEEVE_TYPE for Jackets



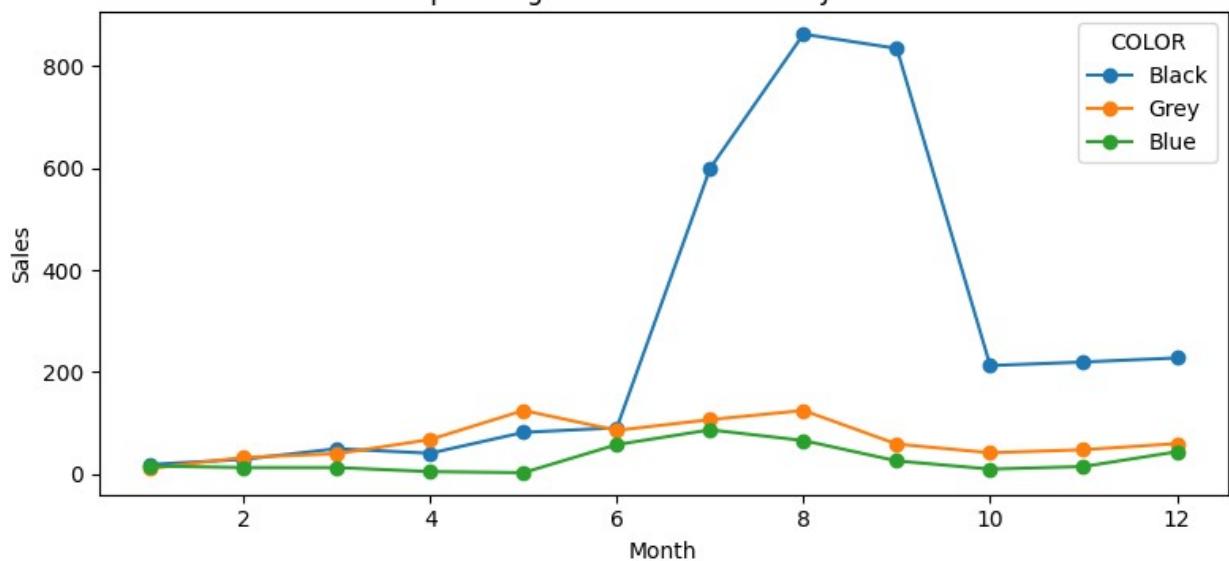
Upcoming Trends in COLLAR_NEW for Jackets



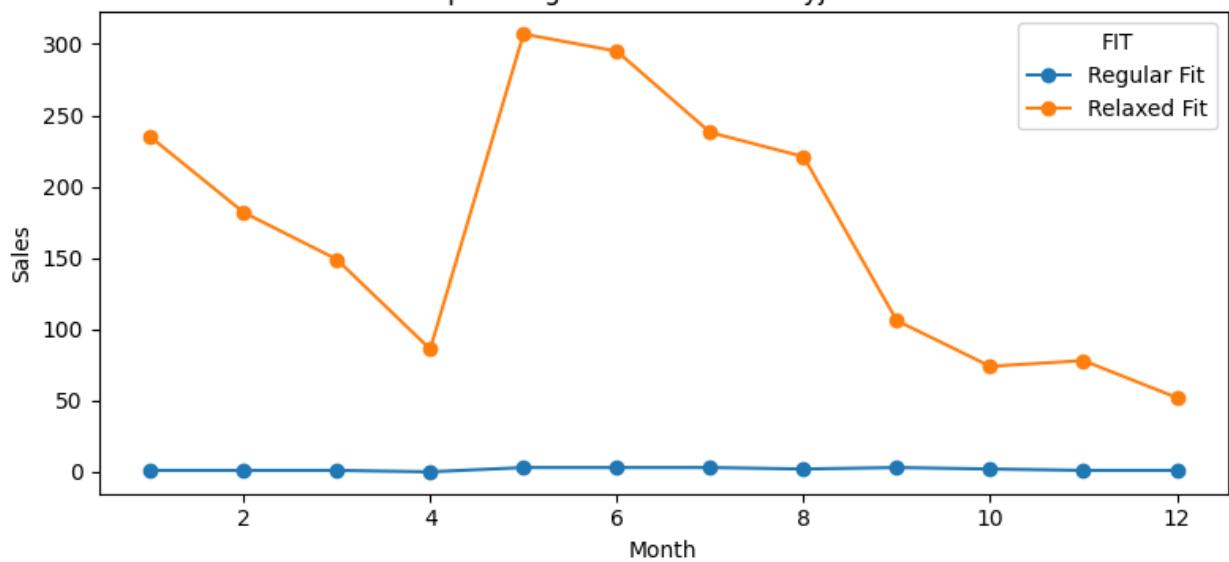
Upcoming Trends in OCCASSION_NEW for Jackets



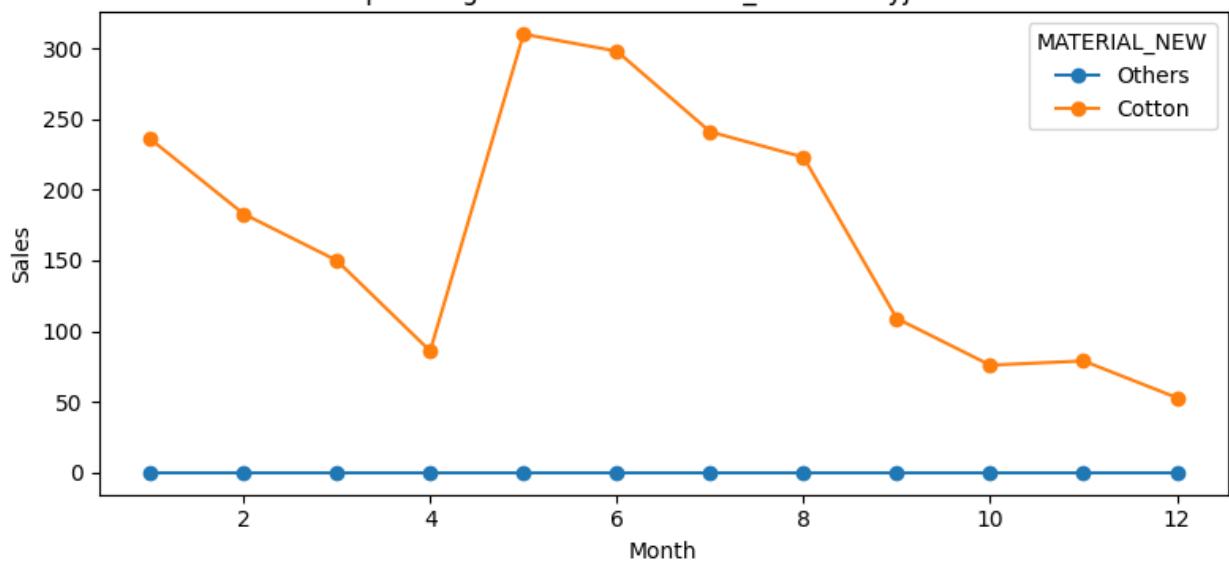
Upcoming Trends in COLOR for Jackets



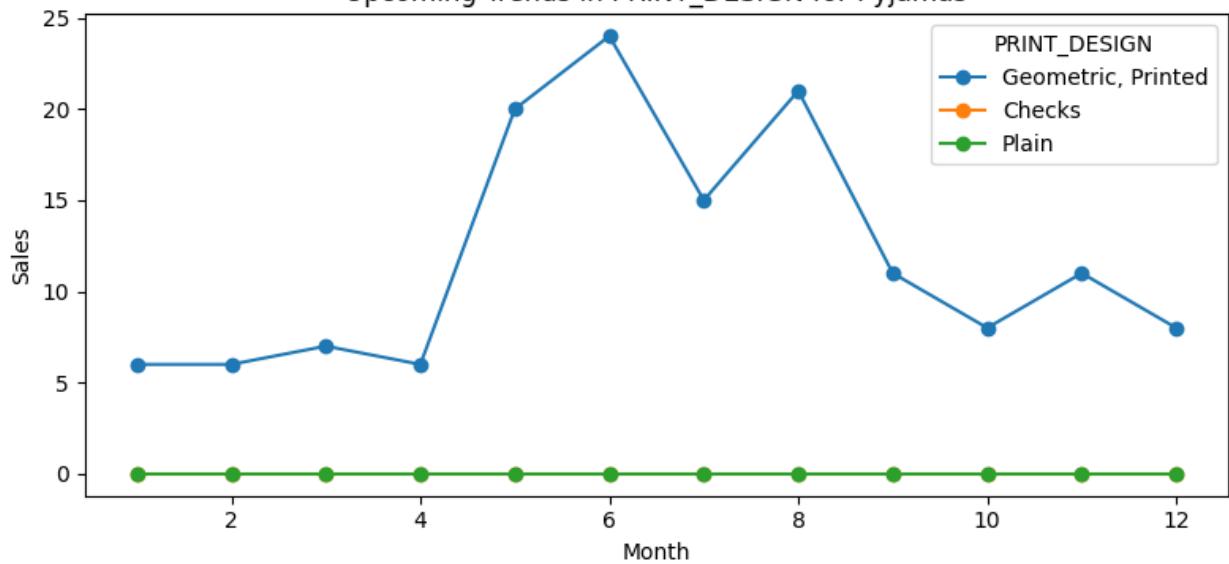
Upcoming Trends in FIT for Pyjamas



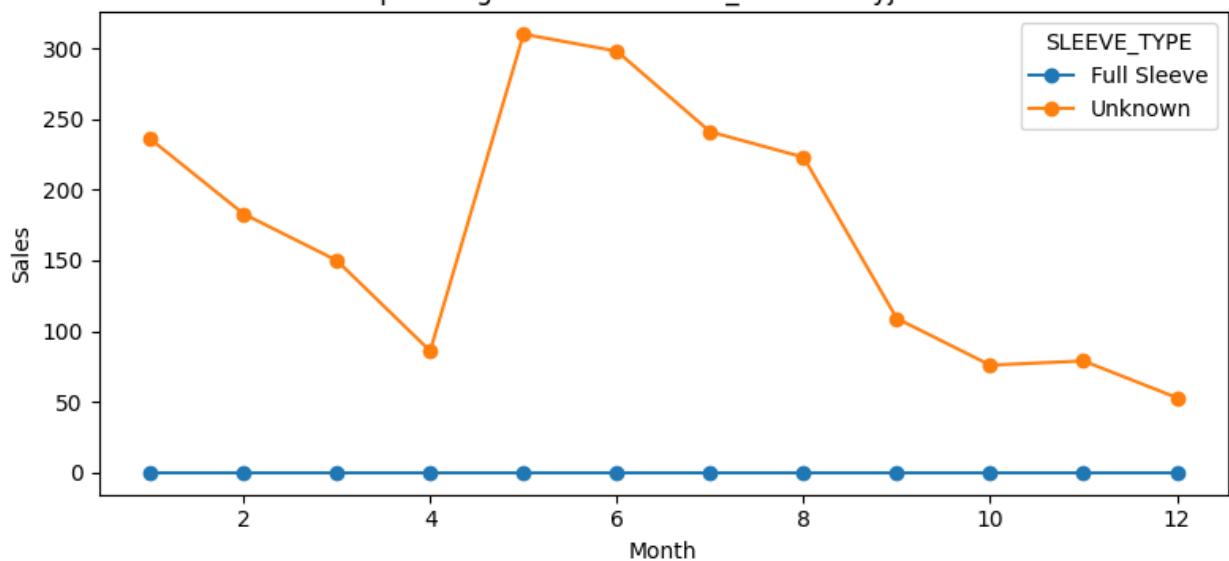
Upcoming Trends in MATERIAL_NEW for Pyjamas



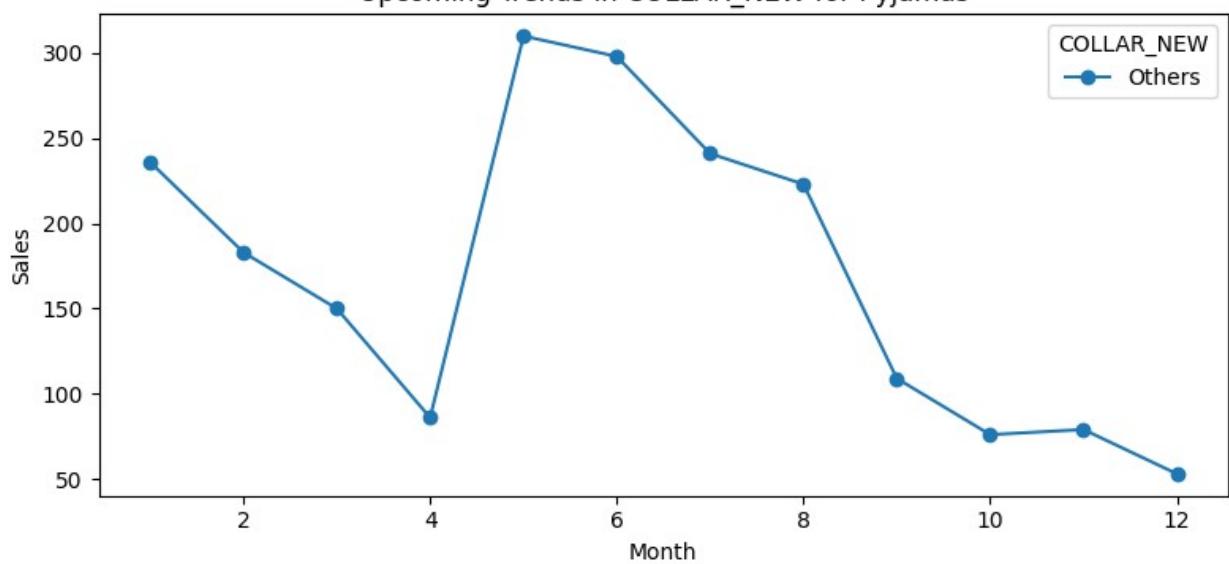
Upcoming Trends in PRINT_DESIGN for Pyjamas



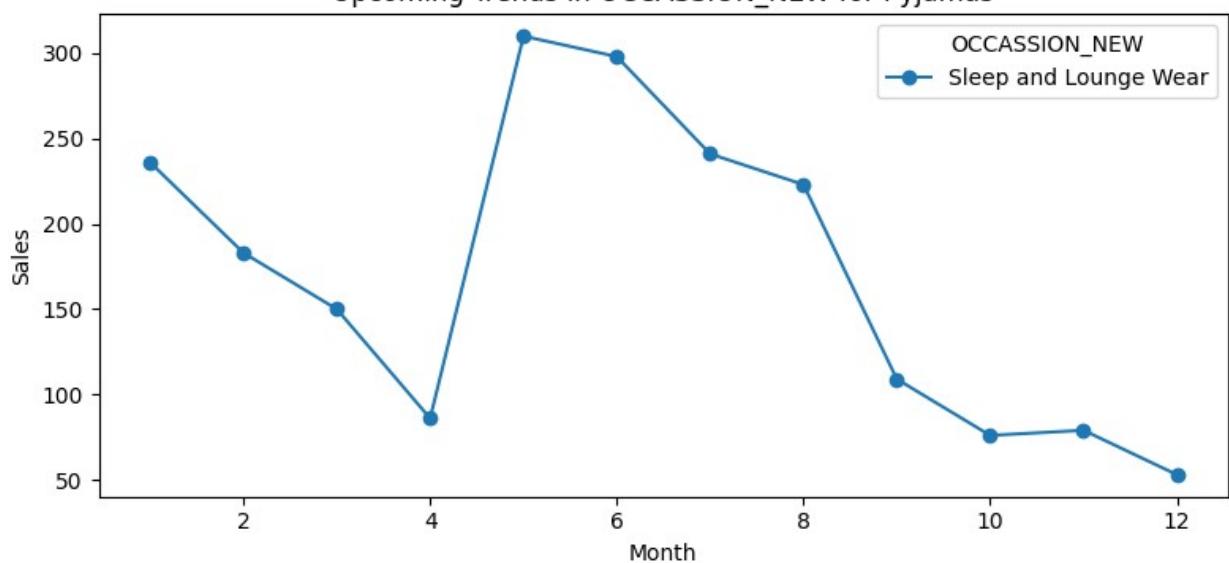
Upcoming Trends in SLEEVE_TYPE for Pyjamas



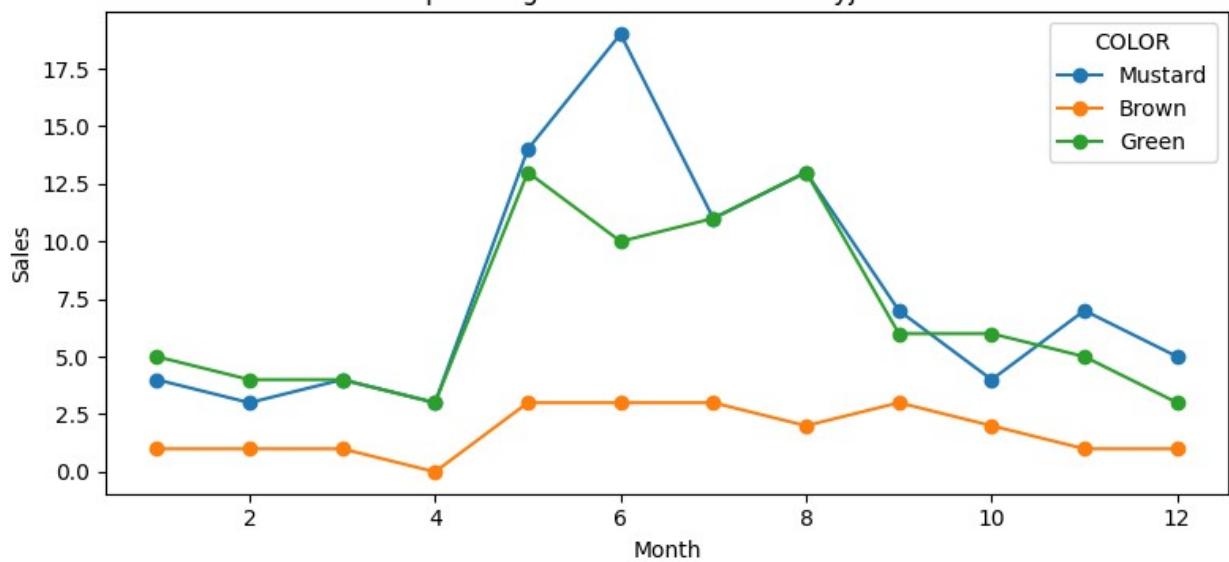
Upcoming Trends in COLLAR_NEW for Pyjamas



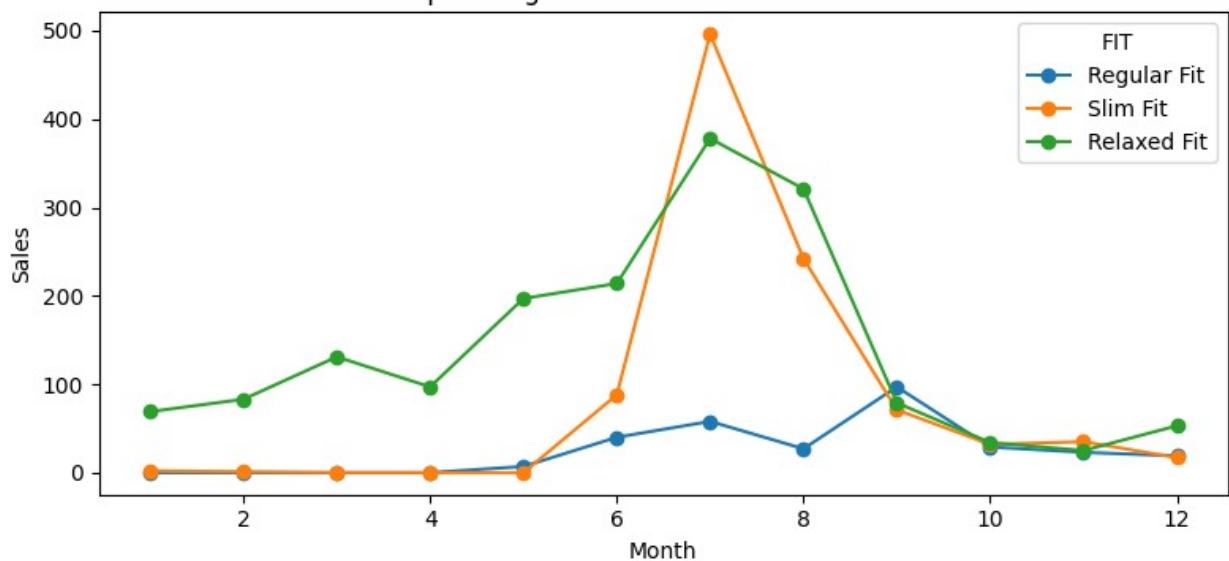
Upcoming Trends in OCCASSION_NEW for Pyjamas



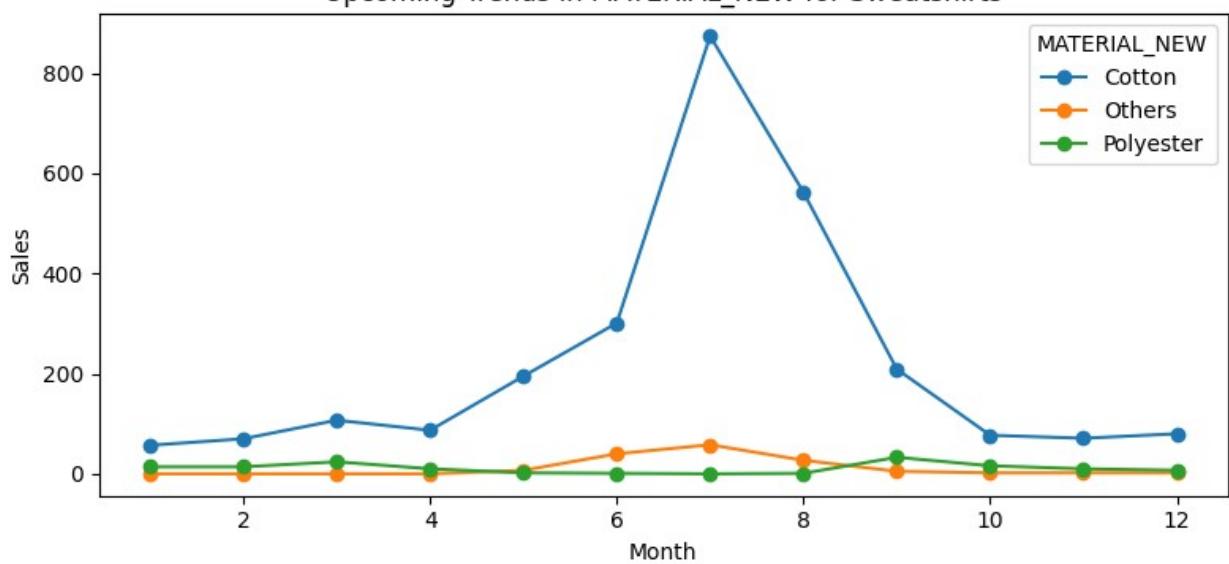
Upcoming Trends in COLOR for Pyjamas



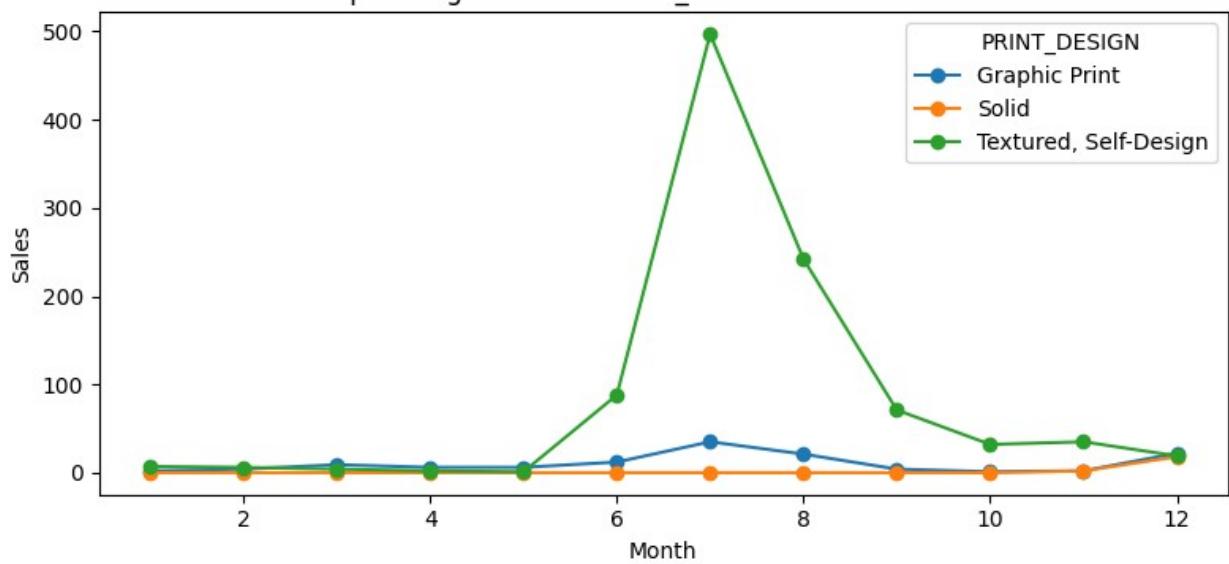
Upcoming Trends in FIT for Sweatshirts



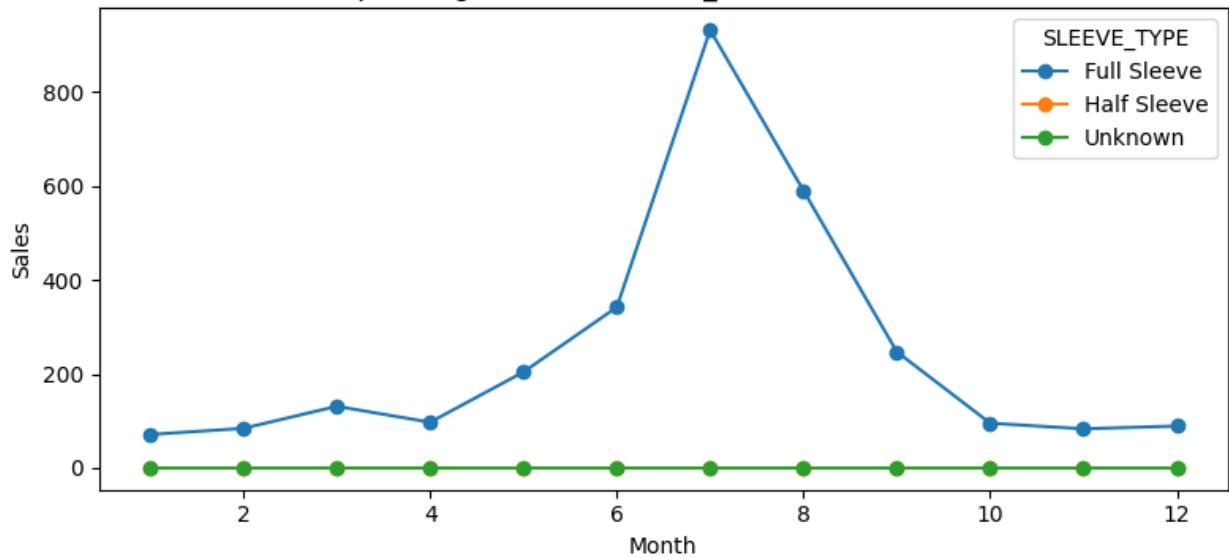
Upcoming Trends in MATERIAL_NEW for Sweatshirts



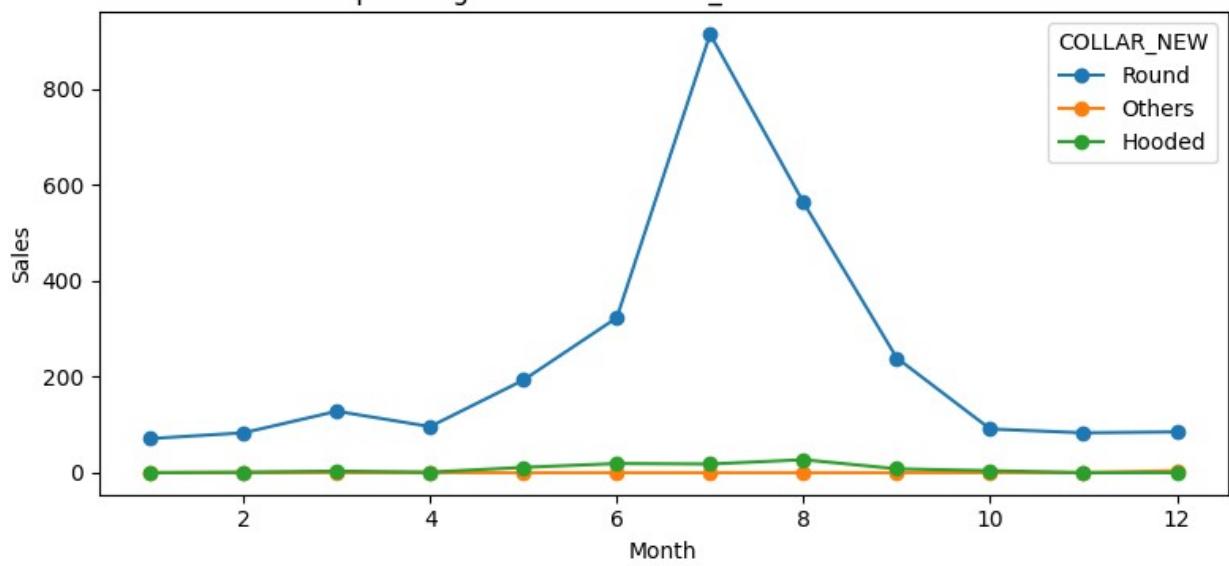
Upcoming Trends in PRINT_DESIGN for Sweatshirts



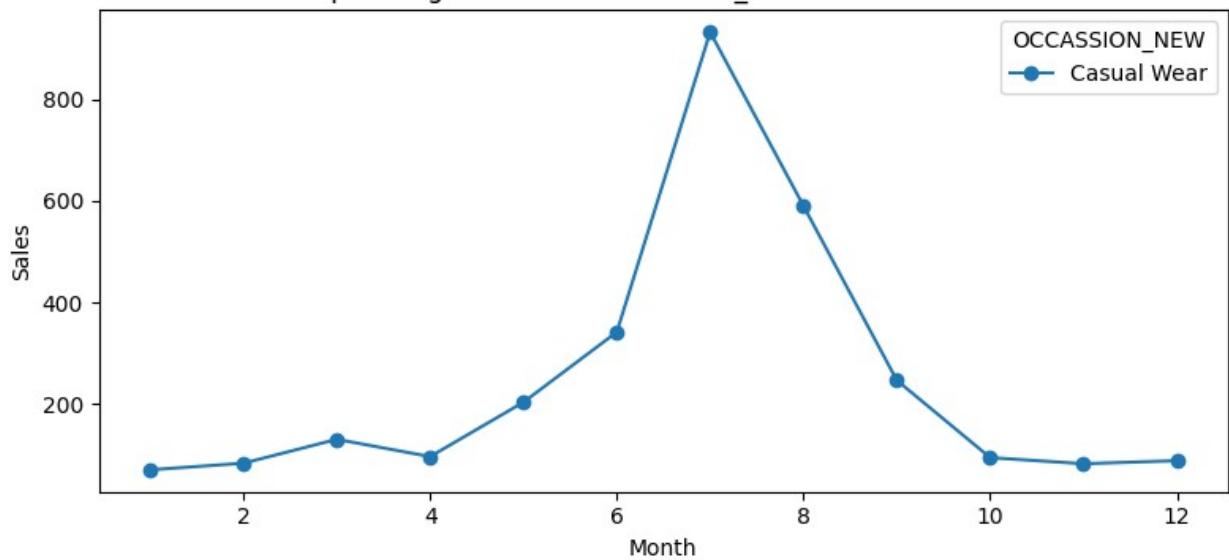
Upcoming Trends in SLEEVE_TYPE for Sweatshirts



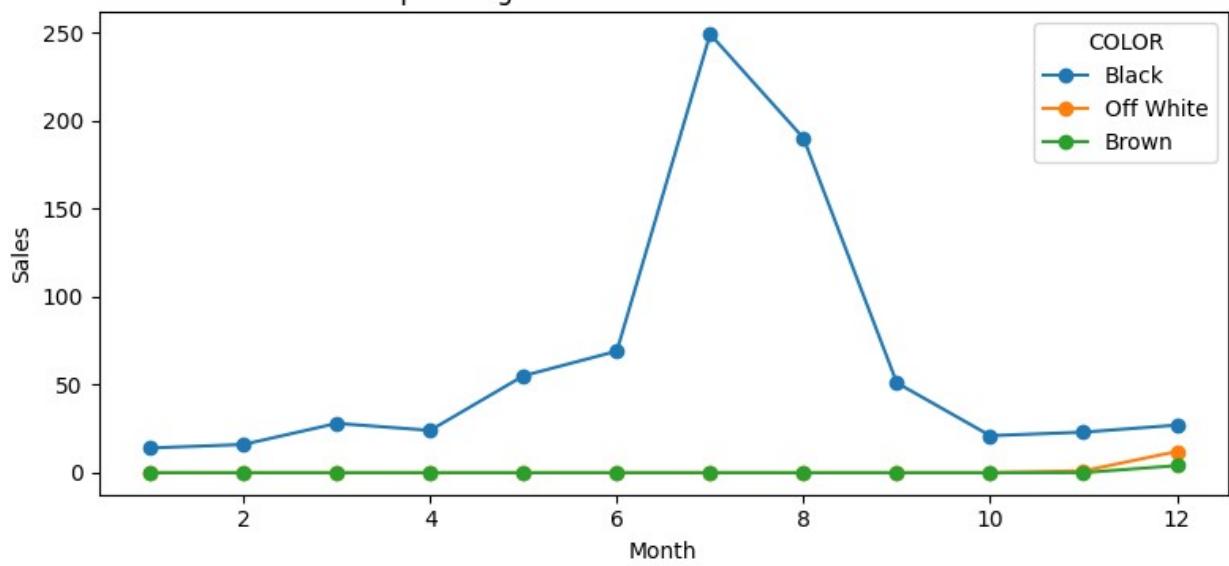
Upcoming Trends in COLLAR_NEW for Sweatshirts



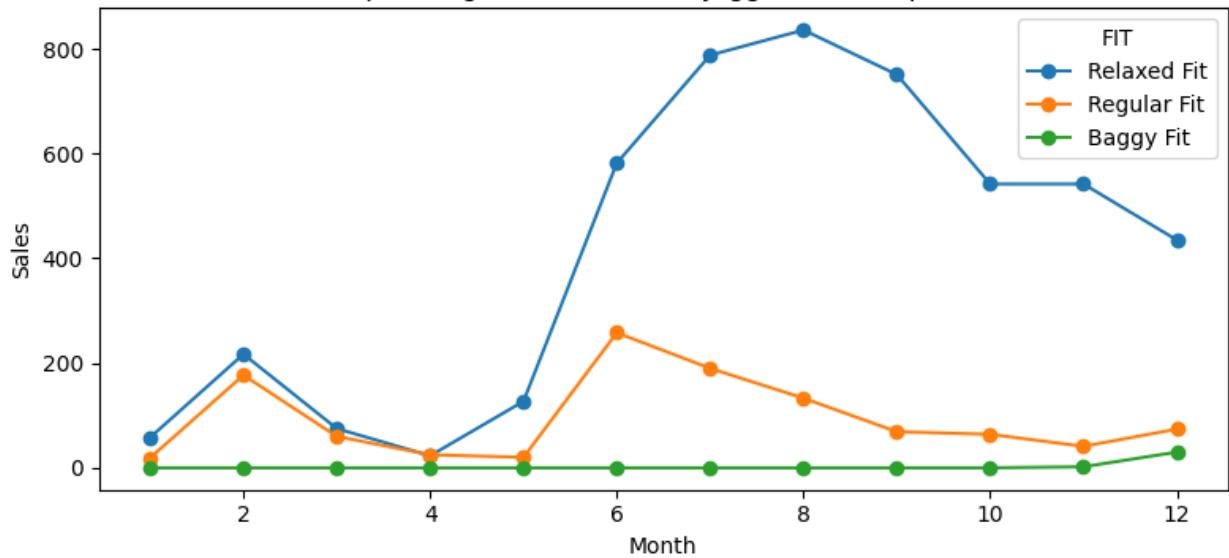
Upcoming Trends in OCCASSION_NEW for Sweatshirts



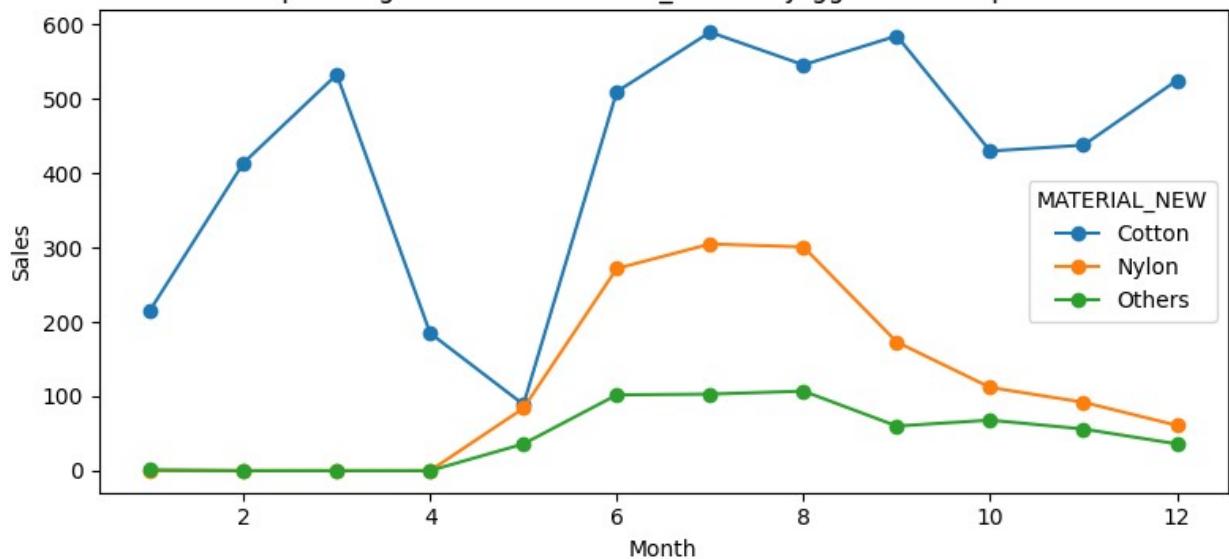
Upcoming Trends in COLOR for Sweatshirts



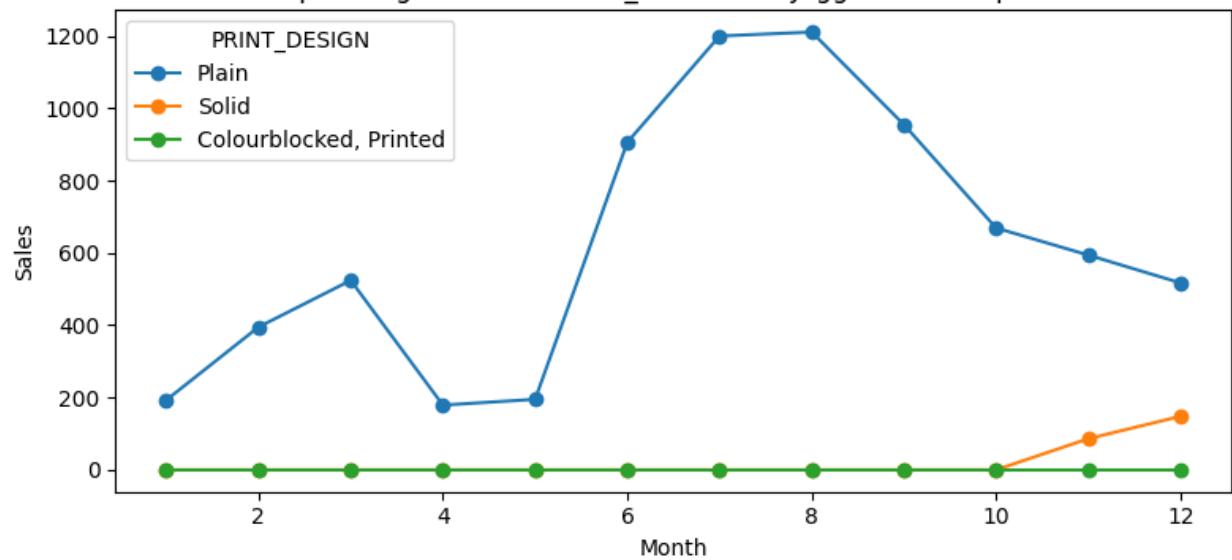
Upcoming Trends in FIT for Joggers & Trackpants



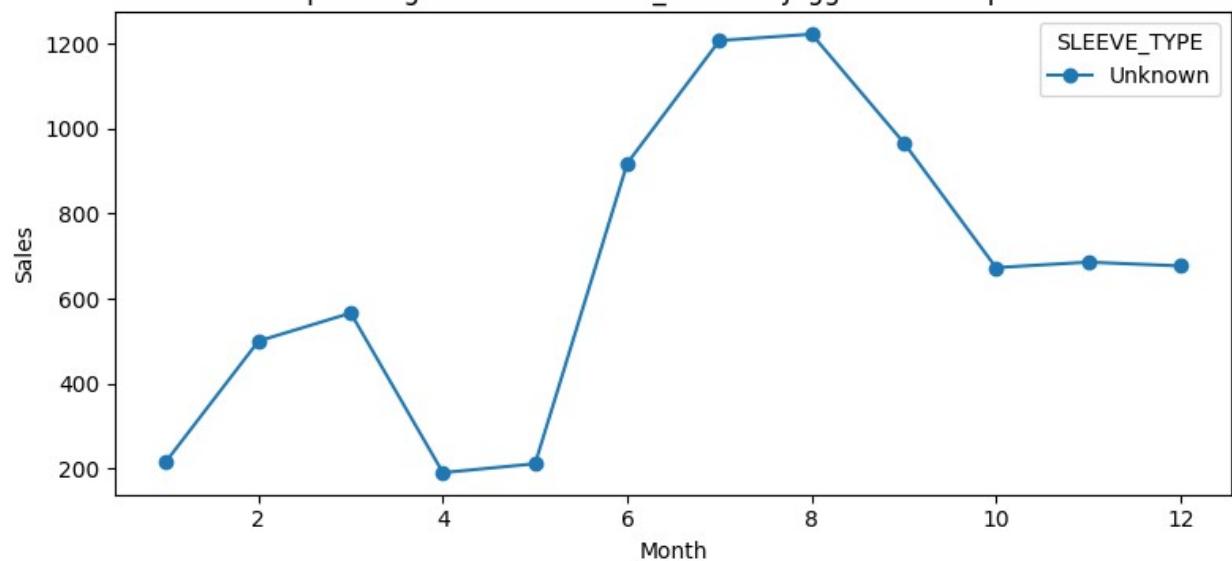
Upcoming Trends in MATERIAL_NEW for Joggers & Trackpants



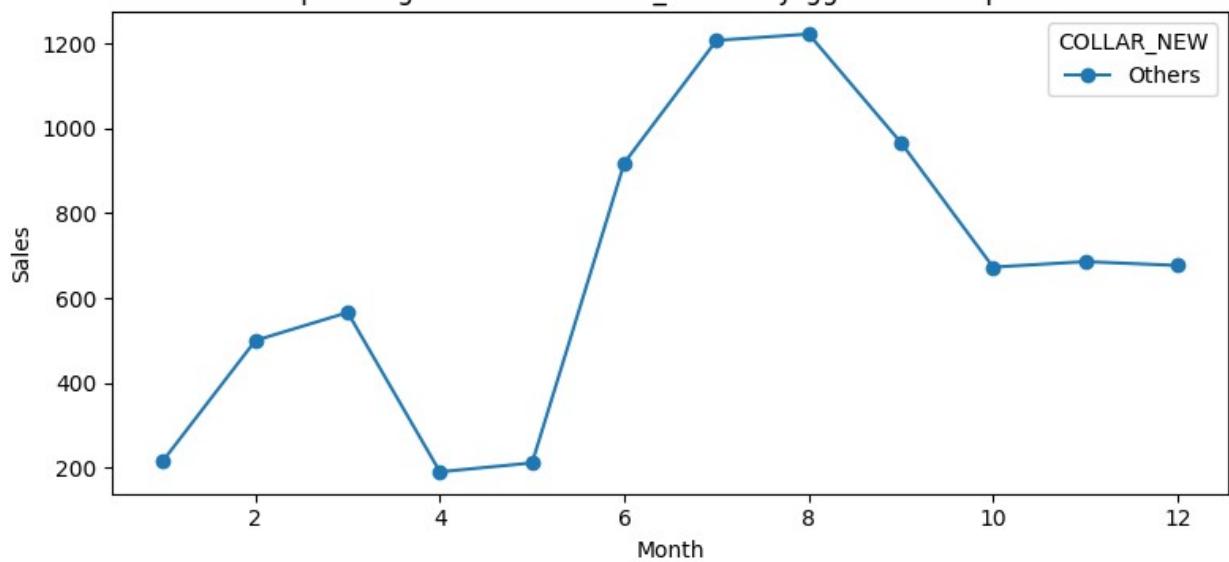
Upcoming Trends in PRINT_DESIGN for Joggers & Trackpants



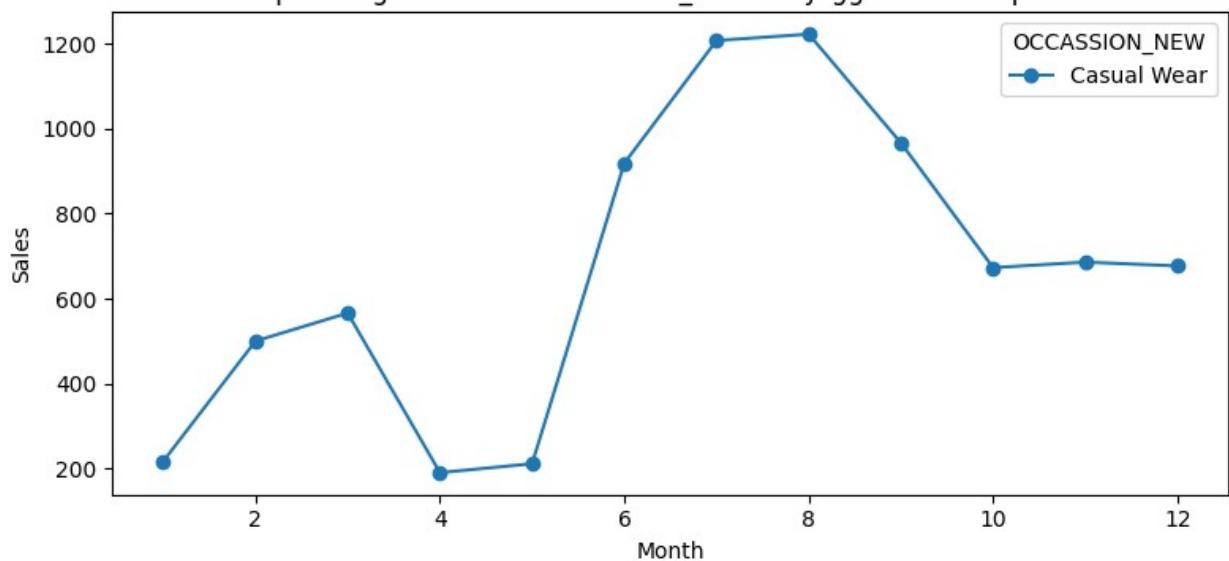
Upcoming Trends in SLEEVE_TYPE for Joggers & Trackpants

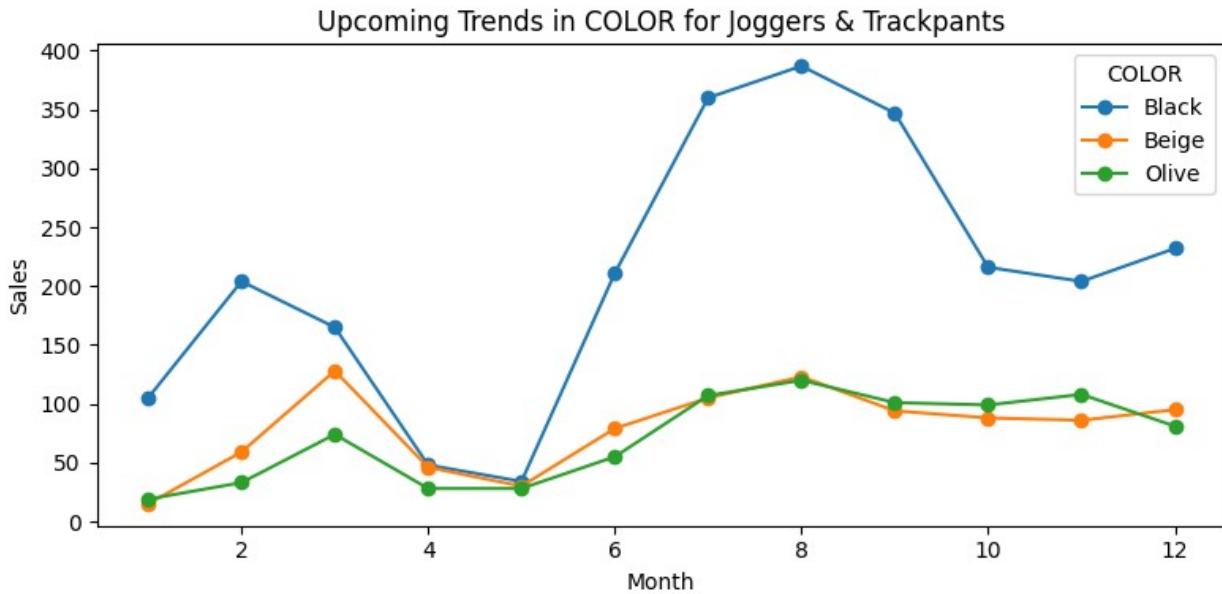


Upcoming Trends in COLLAR_NEW for Joggers & Trackpants



Upcoming Trends in OCCASSION_NEW for Joggers & Trackpants





Q3. What are the trends that are vanishing with time.

Approach -> The dataset was transformed into a long format to enable time-series analysis of monthly sales. For each combination of category and feature, I analyzed the trend in sales over time by computing the slope of the best-fit line using np.polyfit. Feature values with the steepest negative slopes were identified as those exhibiting the sharpest decline in sales — indicating vanishing trends. The top three such values were selected and their sales trajectories were visualized to clearly illustrate the downward trend.

Note: Some graphs display only one plot because the code filters for the top 3 feature values with the most negative sales slopes per category and feature. If fewer than three values have a negative slope (i.e., vanishing trend), or only one meets this condition, the plot will show only those available series, sometimes just one.

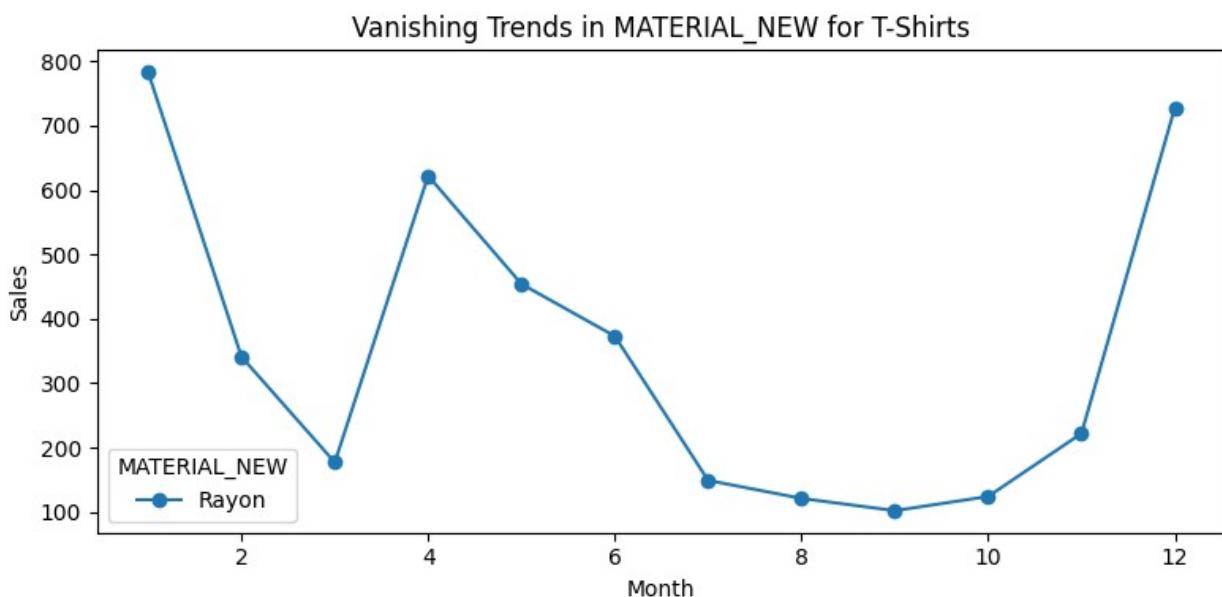
```
# Melt to long format for time series
df_long = df.melt(
    id_vars=['CATEGORY'] + feature_columns,
    value_vars=month_cols,
    var_name='MONTH',
    value_name='SALES'
)
df_long['MONTH_NUM'] = df_long['MONTH'].str.extract('(\d+)')
.astype(int)

# For each category and feature, finding and plotting top 3 vanishing
# feature values (most negative sales slope)
for category in df_long['CATEGORY'].unique():
    cat_df = df_long[df_long['CATEGORY'] == category]
    for feature in feature_columns:
        pivot = cat_df.groupby([feature, 'MONTH_NUM'])
        ['SALES'].sum().reset_index()
```

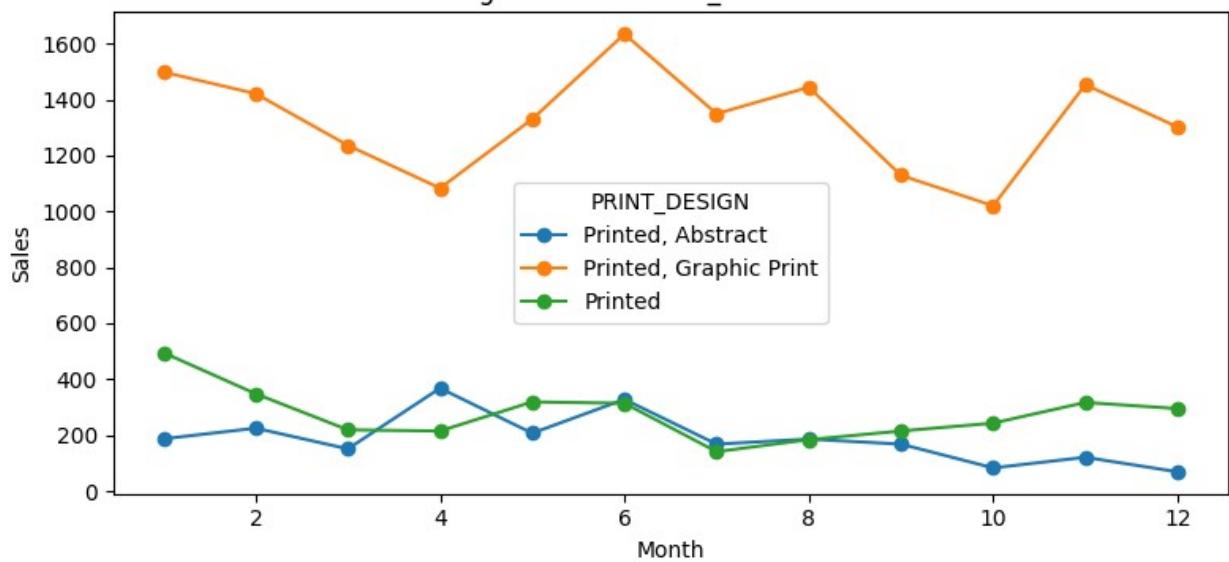
```

slopes = {}
for val in pivot[feature].unique():
    sales_series = pivot[pivot[feature] ==
val].sort_values('MONTH_NUM')
    if len(sales_series) > 1:
        x = sales_series['MONTH_NUM'].values
        y = sales_series['SALES'].values
        slope = np.polyfit(x, y, 1)[0]
        slopes[val] = slope
# Get top 3 most negative slopes (vanishing trends)
vanishing = sorted(slopes.items(), key=lambda x: x[1])[:3]
vanishing = [v for v in vanishing if v[1] < 0]
if vanishing:
    # Visualization only - removed all print statements
    plt.figure(figsize=(8,4))
    for val, _ in vanishing:
        sales = pivot[pivot[feature] ==
val].sort_values('MONTH_NUM')
        plt.plot(sales['MONTH_NUM'], sales['SALES'],
marker='o', label=val)
    plt.title(f"Vanishing Trends in {feature} for {category}")
    plt.xlabel('Month')
    plt.ylabel('Sales')
    plt.legend(title=feature)
    plt.tight_layout()
    plt.show()

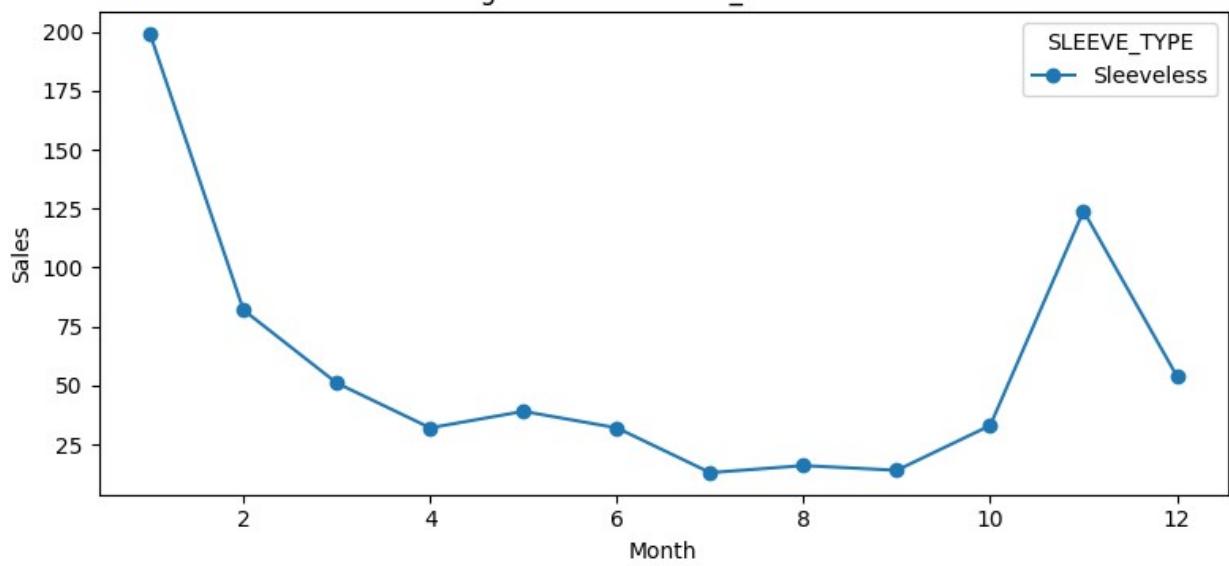
```



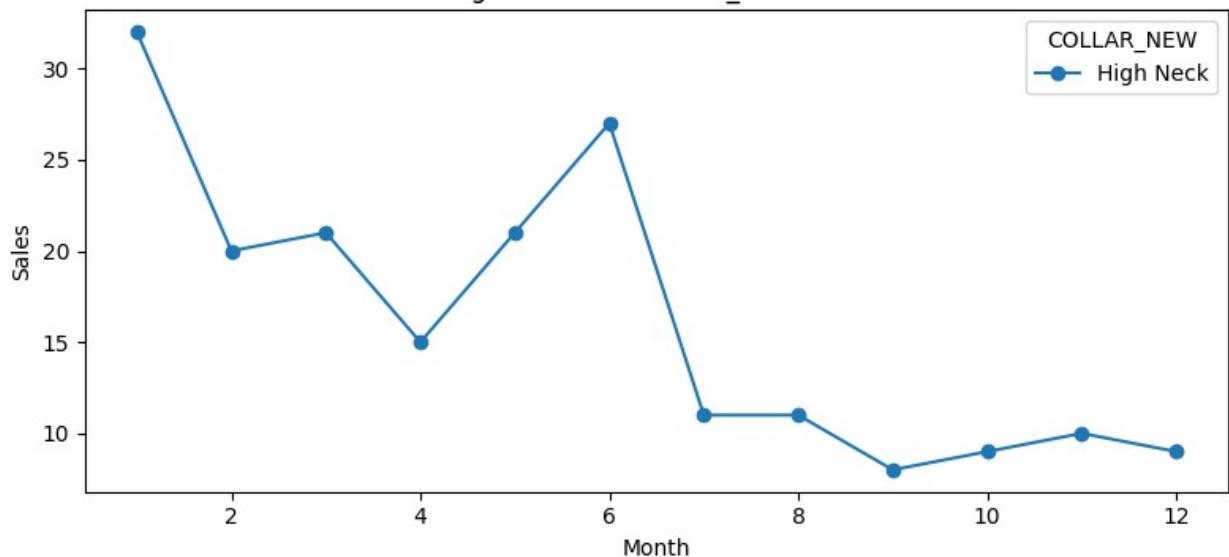
Vanishing Trends in PRINT_DESIGN for T-Shirts



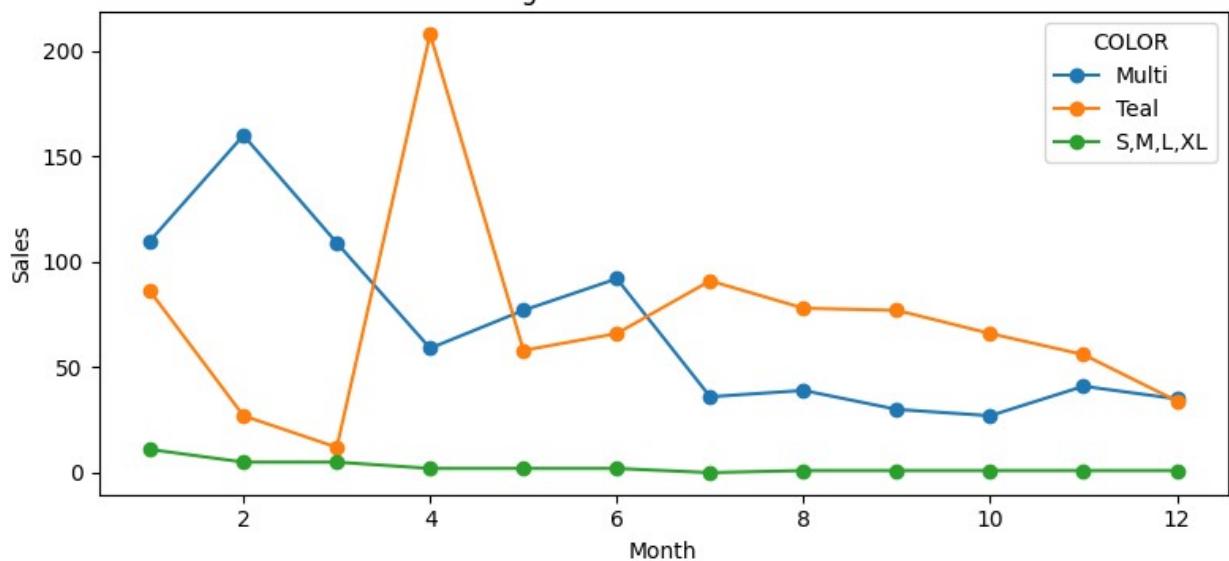
Vanishing Trends in SLEEVE_TYPE for T-Shirts



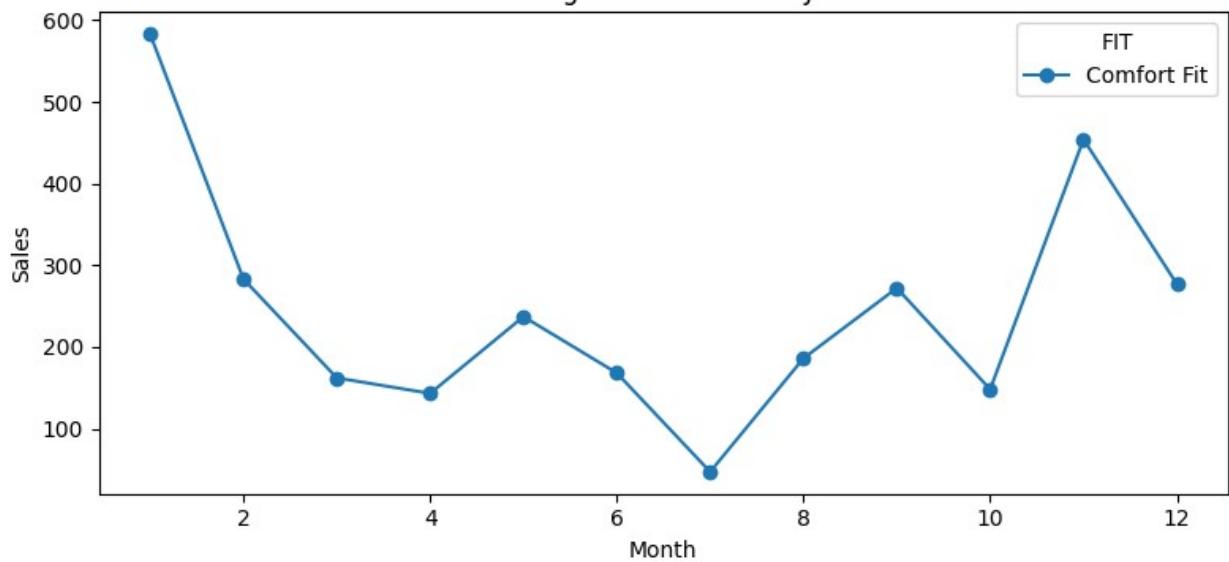
Vanishing Trends in COLLAR_NEW for T-Shirts



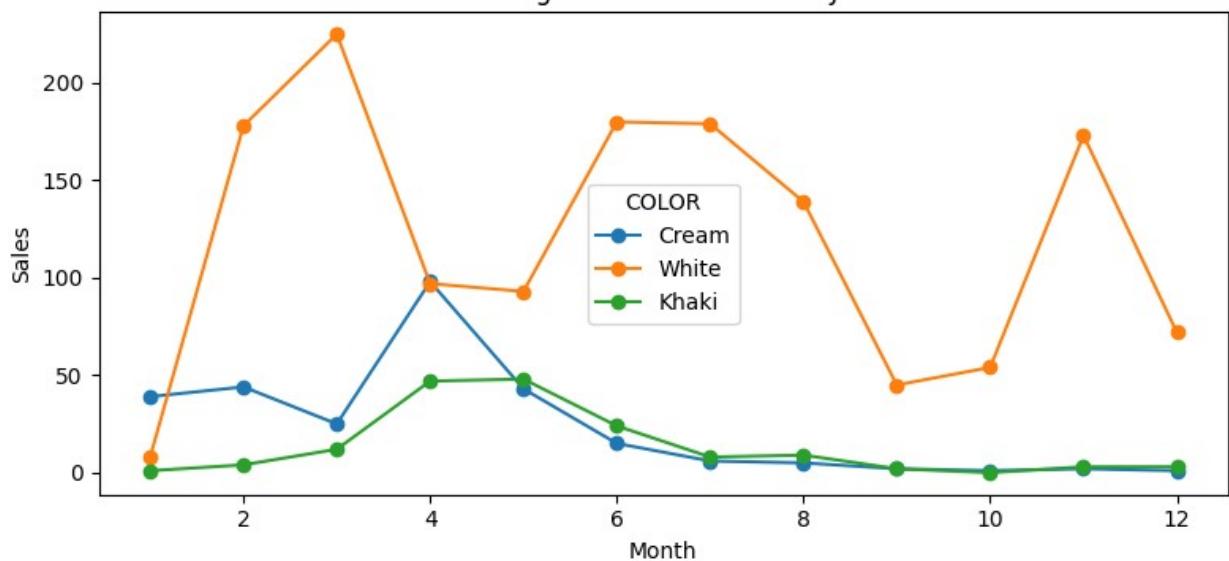
Vanishing Trends in COLOR for T-Shirts



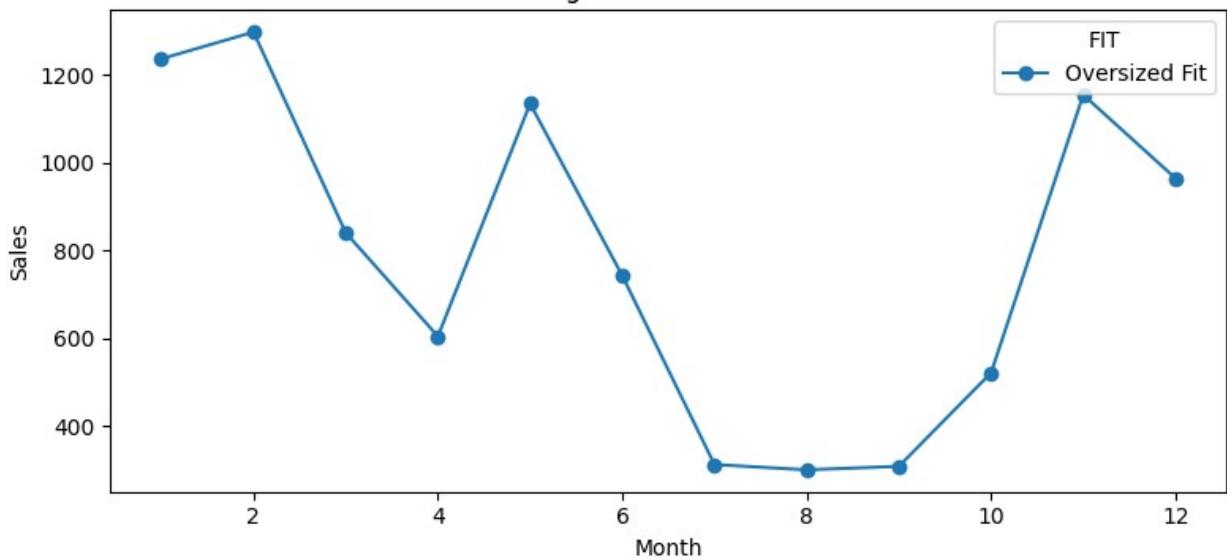
Vanishing Trends in FIT for Jeans



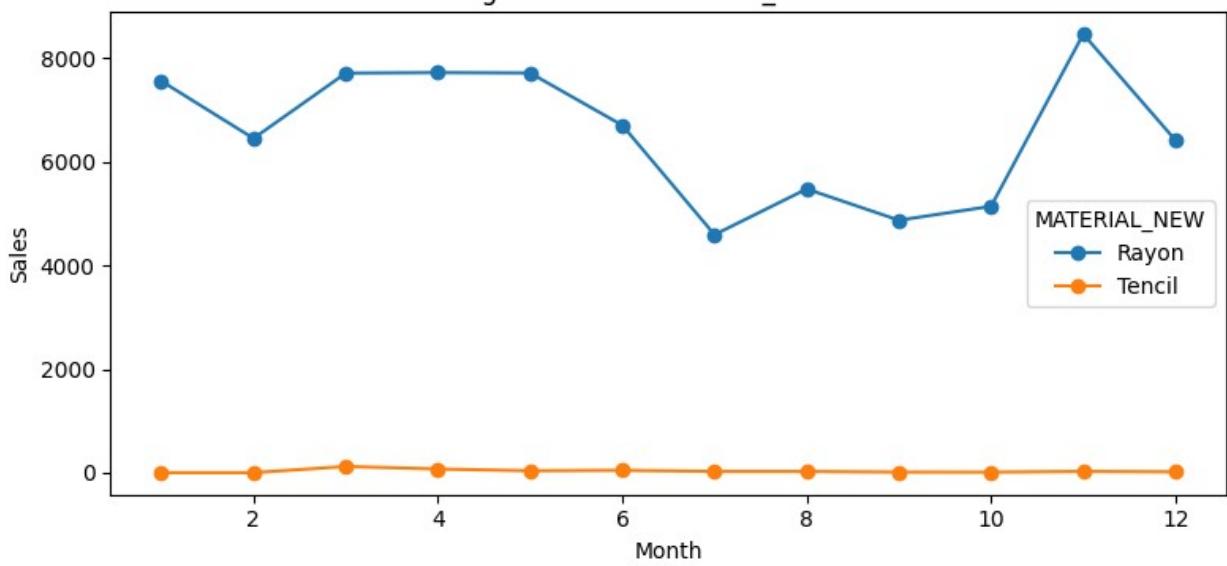
Vanishing Trends in COLOR for Jeans



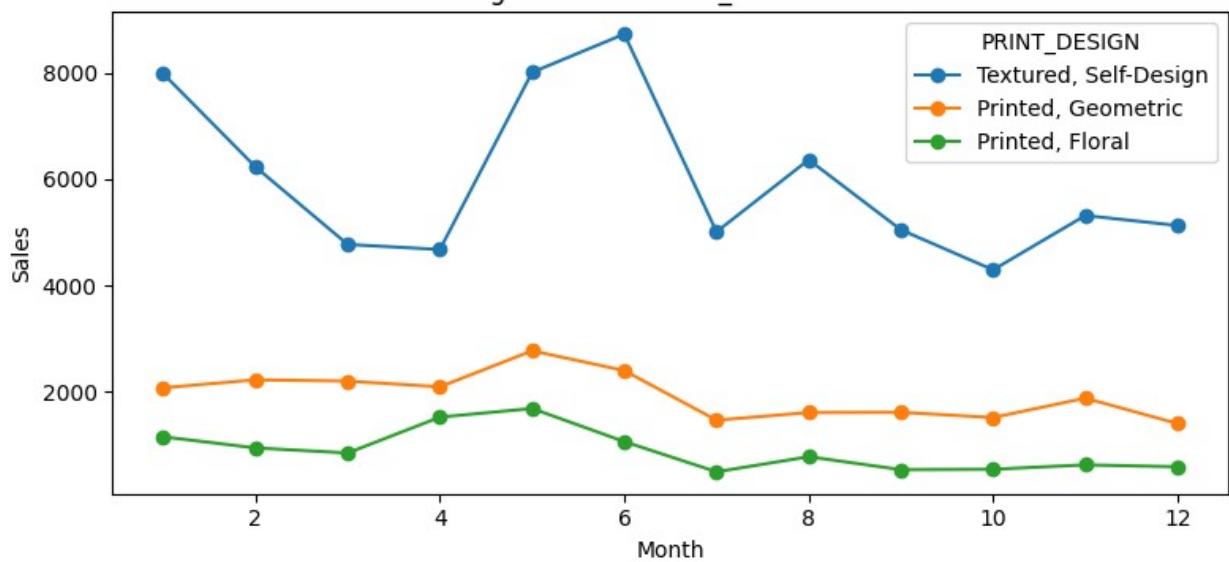
Vanishing Trends in FIT for Shirts



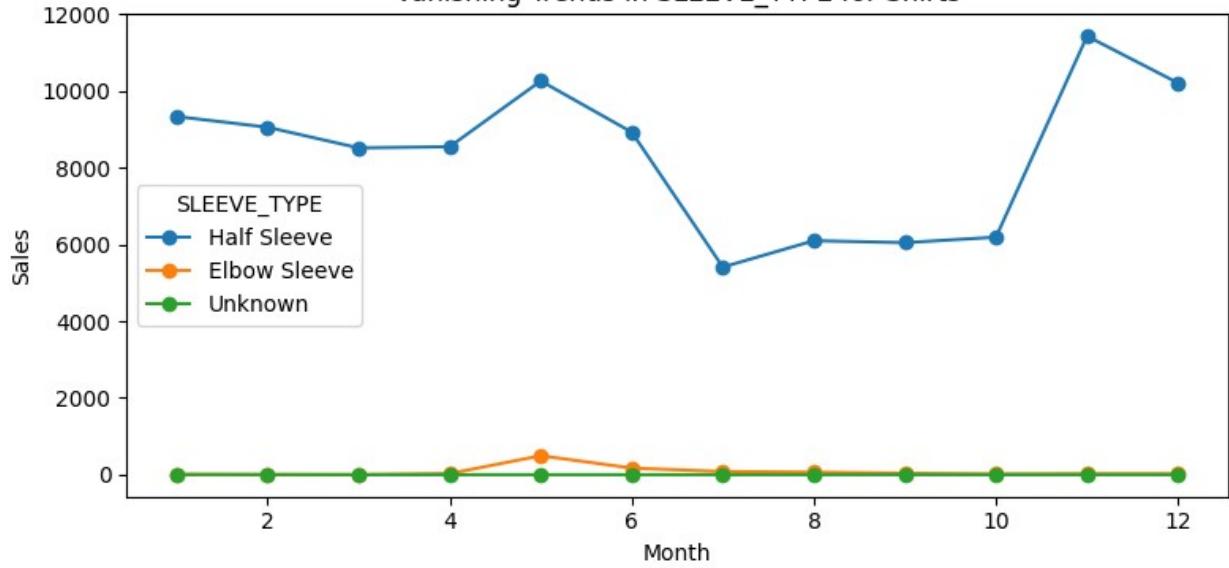
Vanishing Trends in MATERIAL_NEW for Shirts



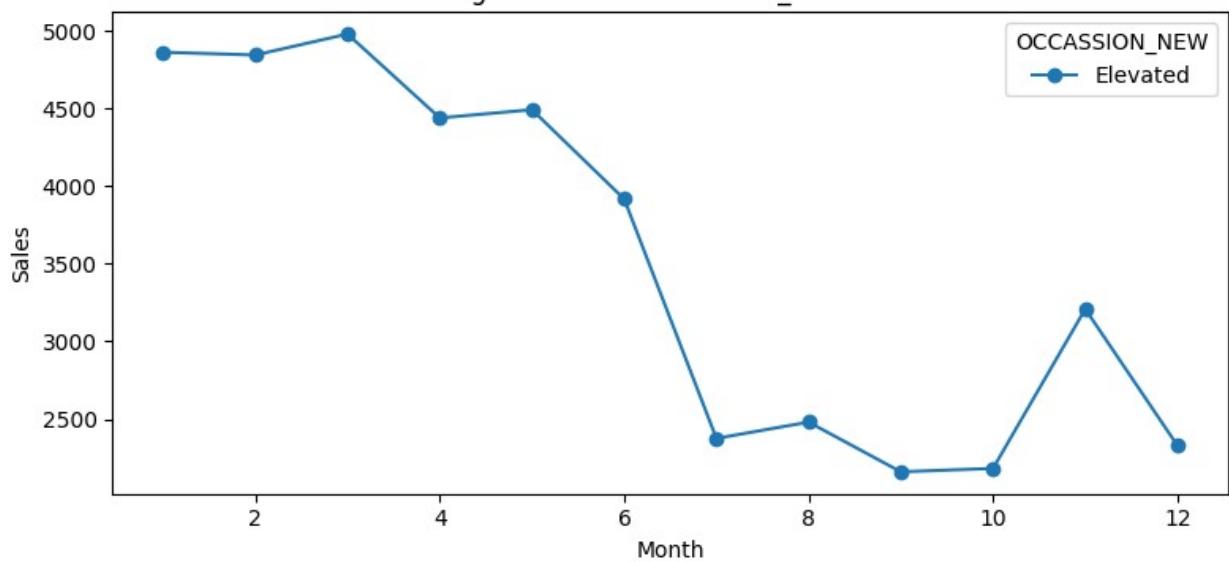
Vanishing Trends in PRINT_DESIGN for Shirts



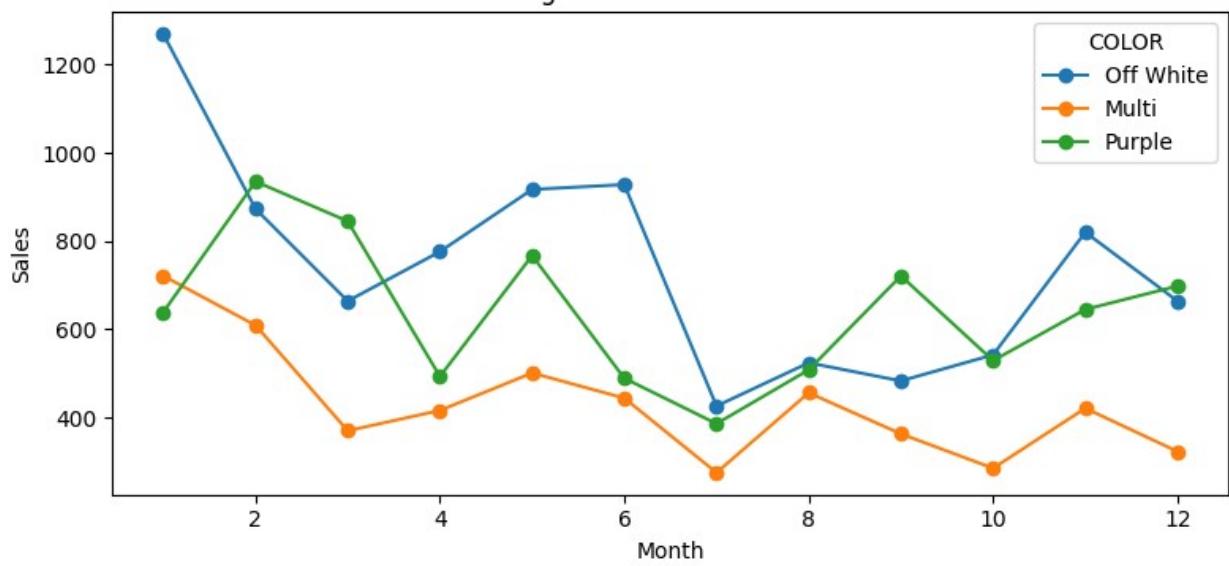
Vanishing Trends in SLEEVE_TYPE for Shirts



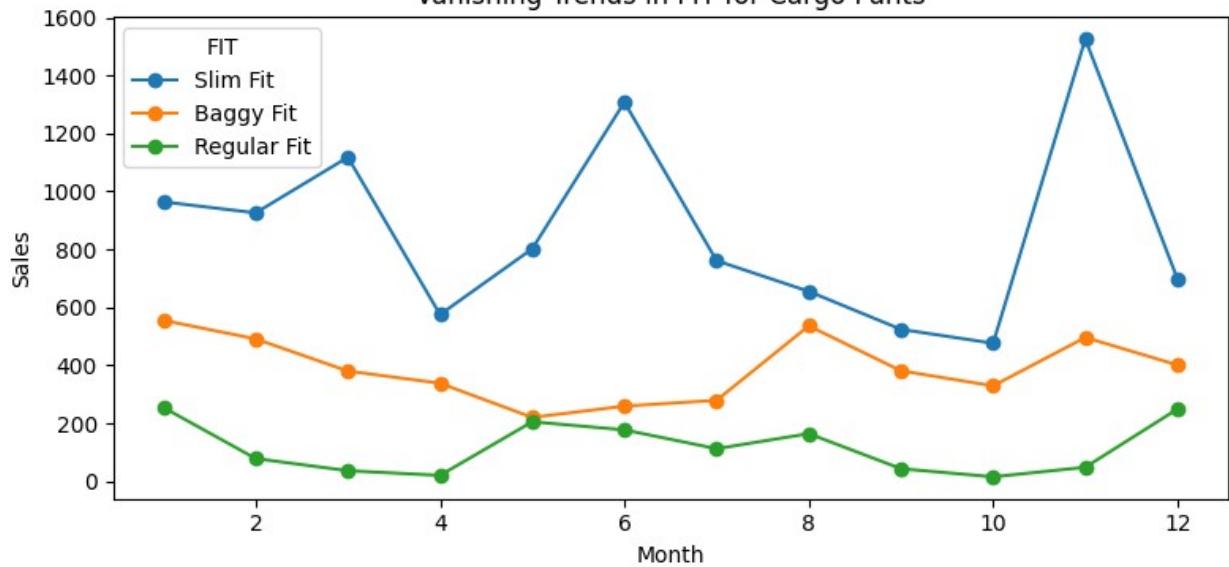
Vanishing Trends in OCCASSION_NEW for Shirts



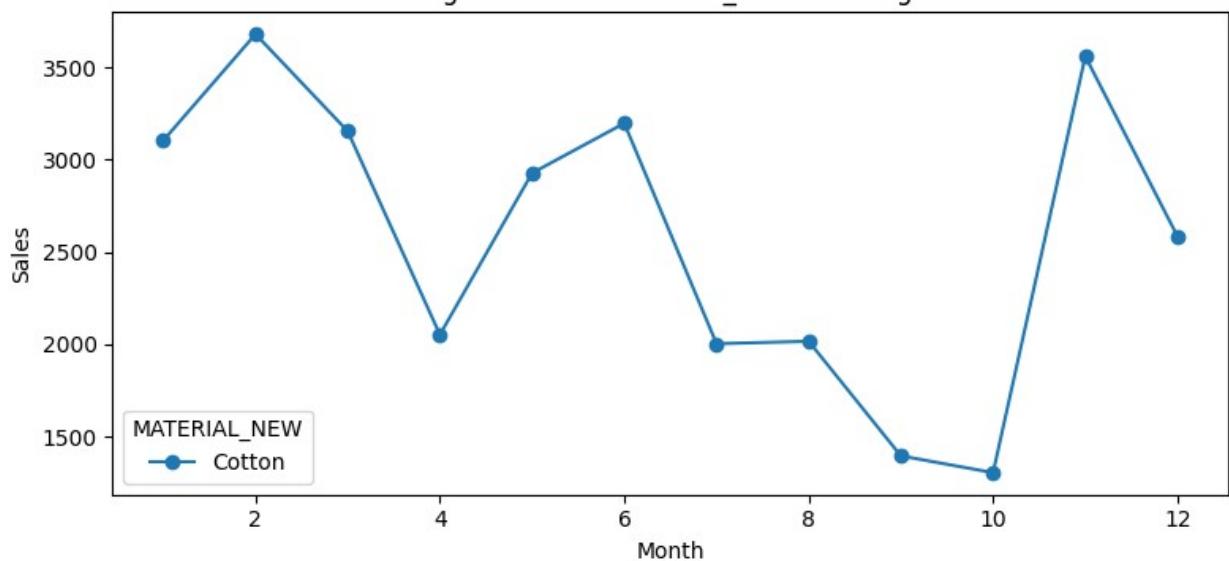
Vanishing Trends in COLOR for Shirts



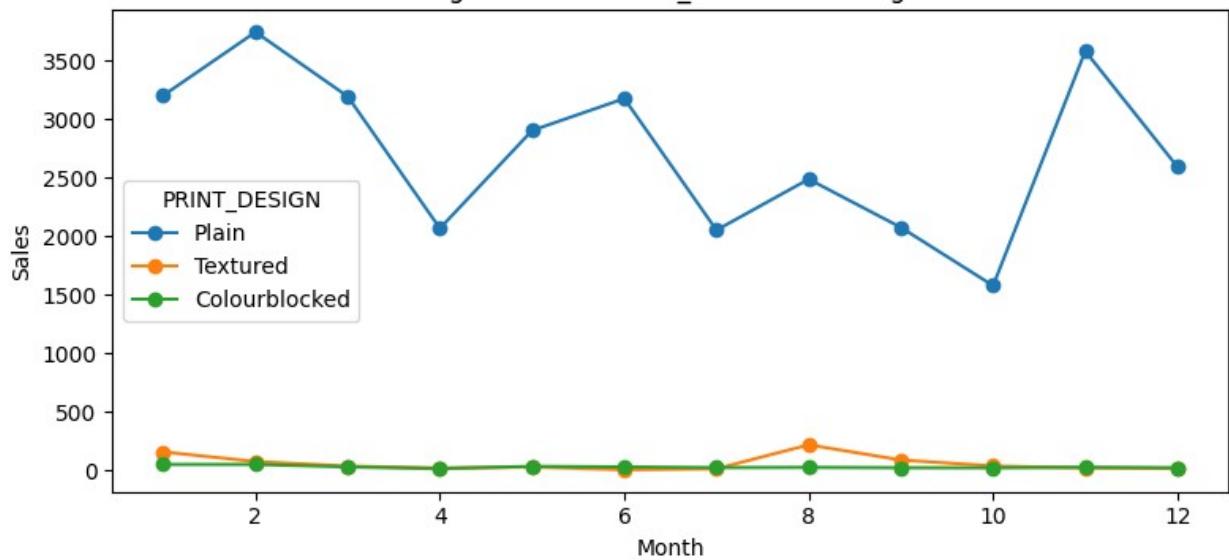
Vanishing Trends in FIT for Cargo Pants



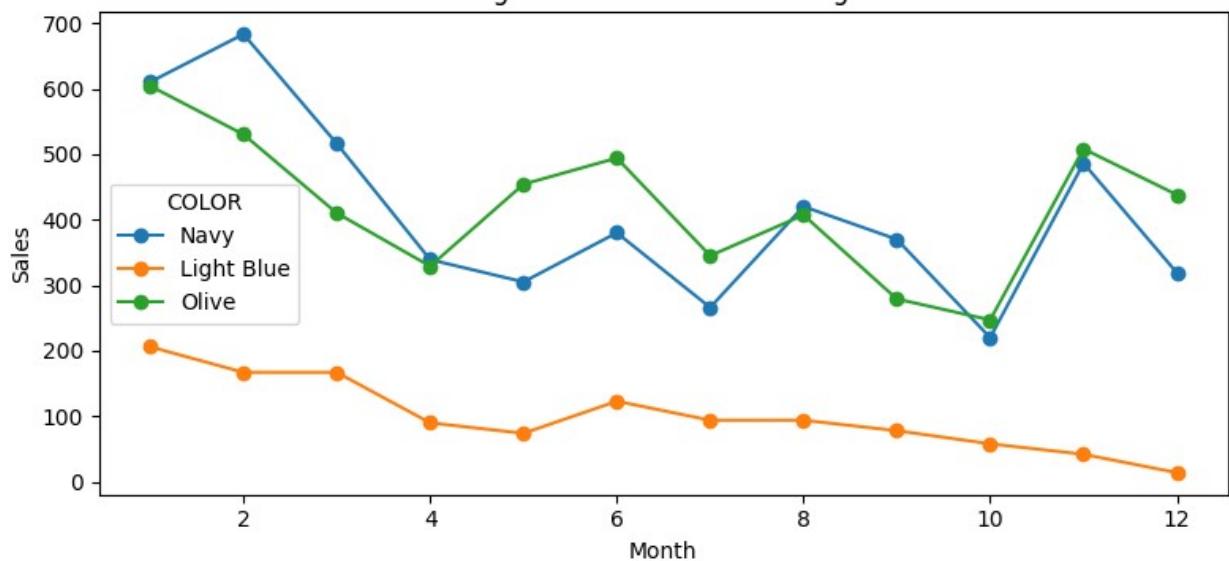
Vanishing Trends in MATERIAL_NEW for Cargo Pants



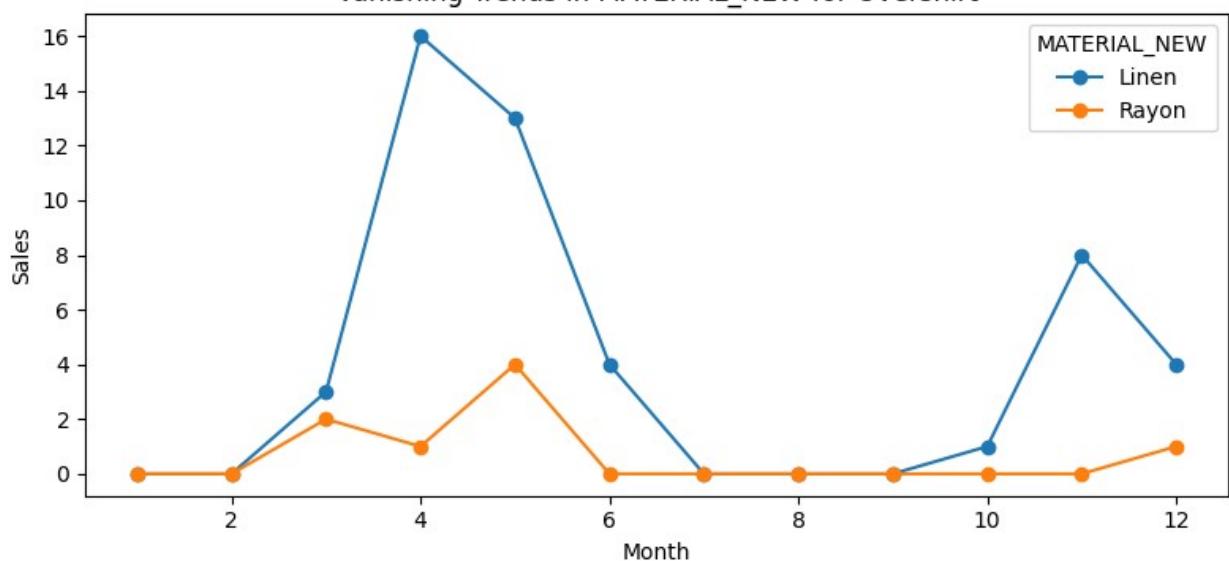
Vanishing Trends in PRINT_DESIGN for Cargo Pants



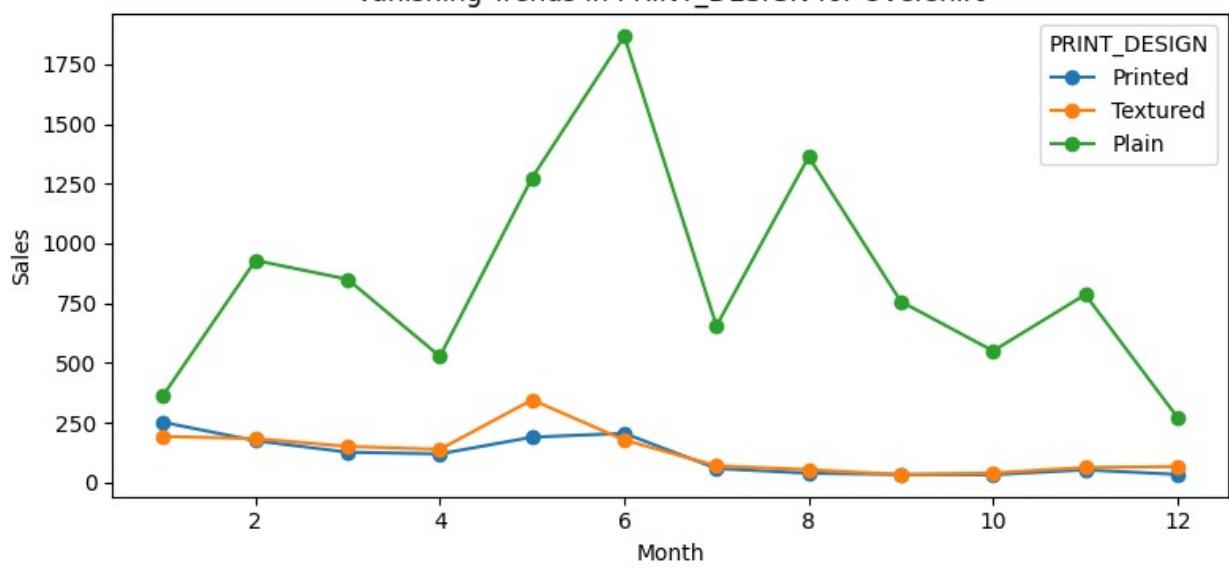
Vanishing Trends in COLOR for Cargo Pants



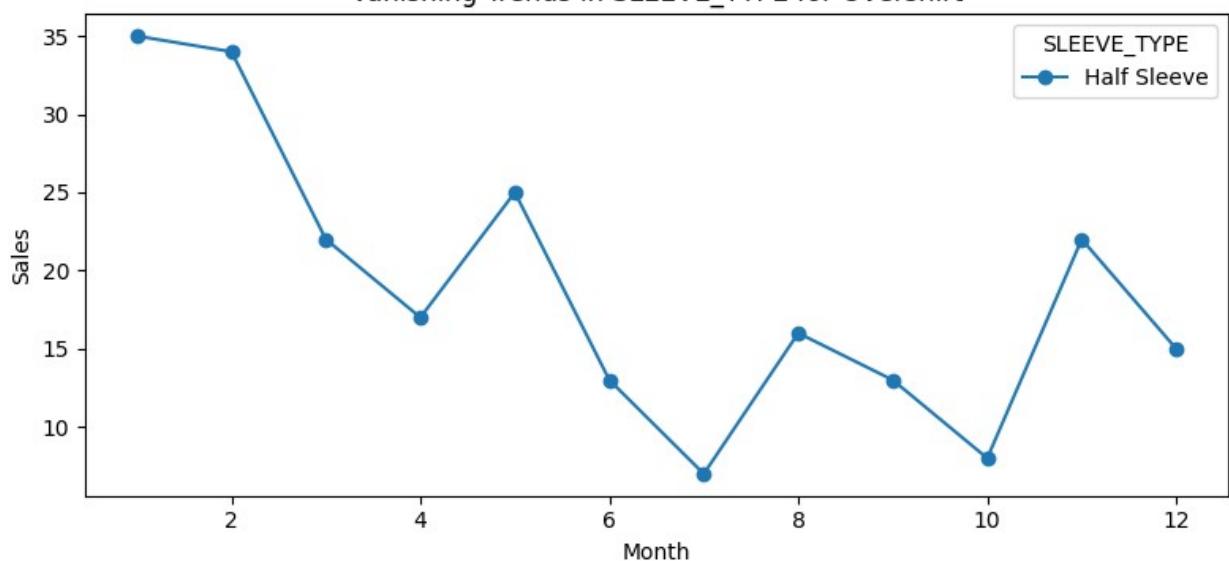
Vanishing Trends in MATERIAL_NEW for Overshirt



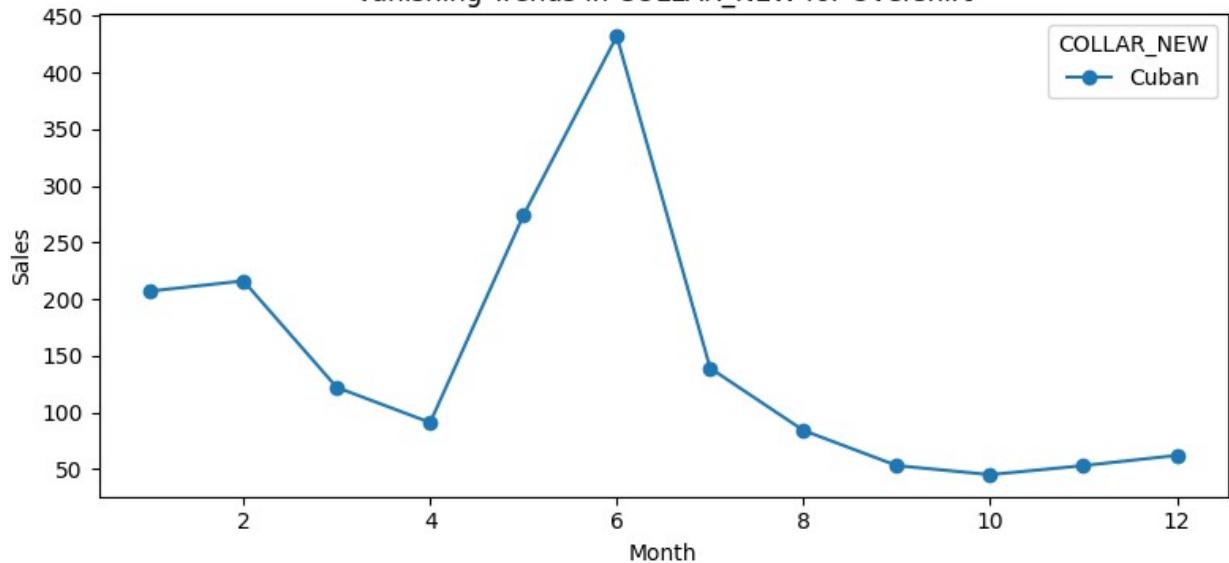
Vanishing Trends in PRINT_DESIGN for Overshirt



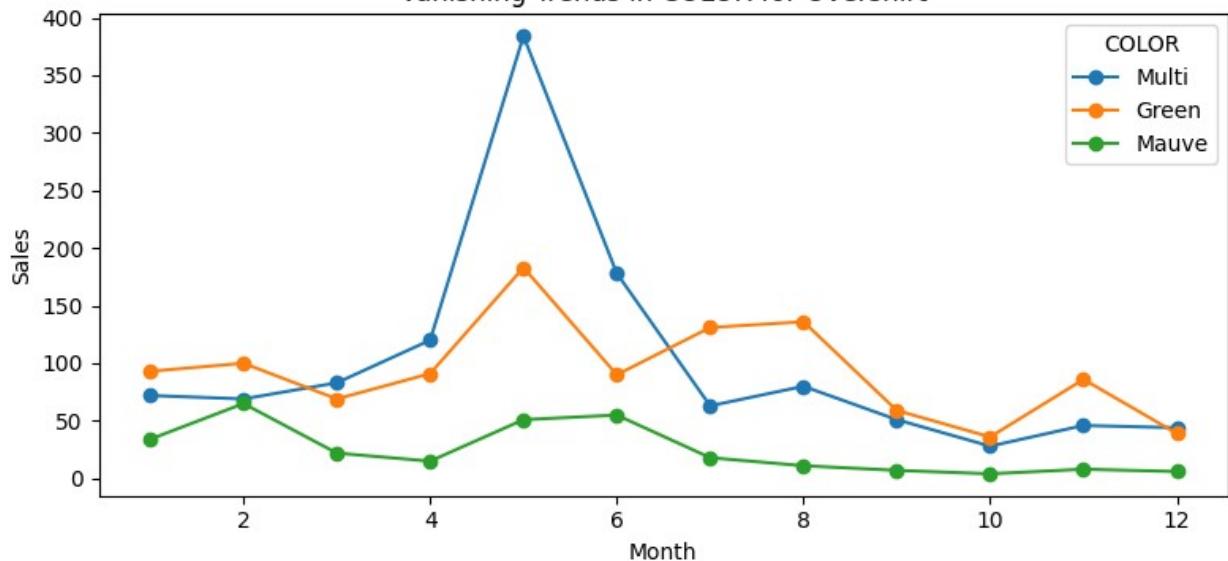
Vanishing Trends in SLEEVE_TYPE for Overshirt



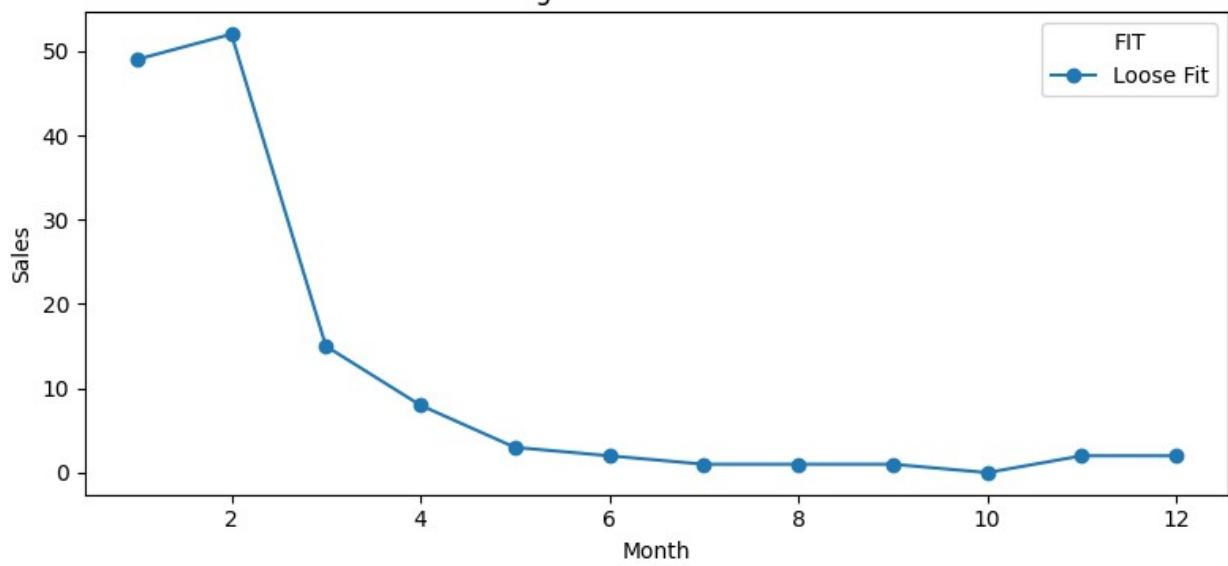
Vanishing Trends in COLLAR_NEW for Overshirt



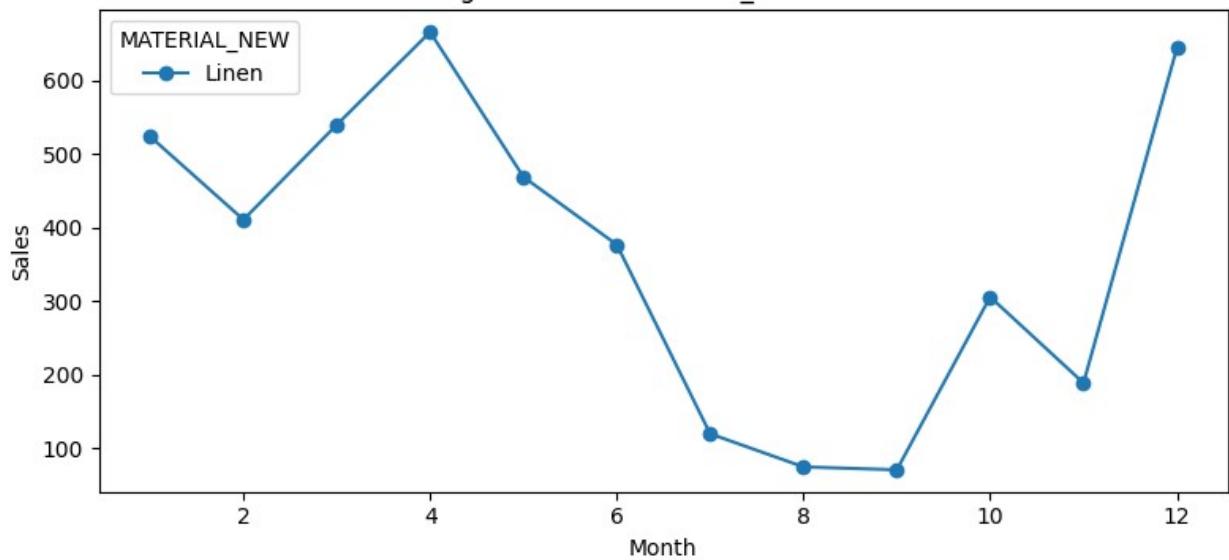
Vanishing Trends in COLOR for Overshirt



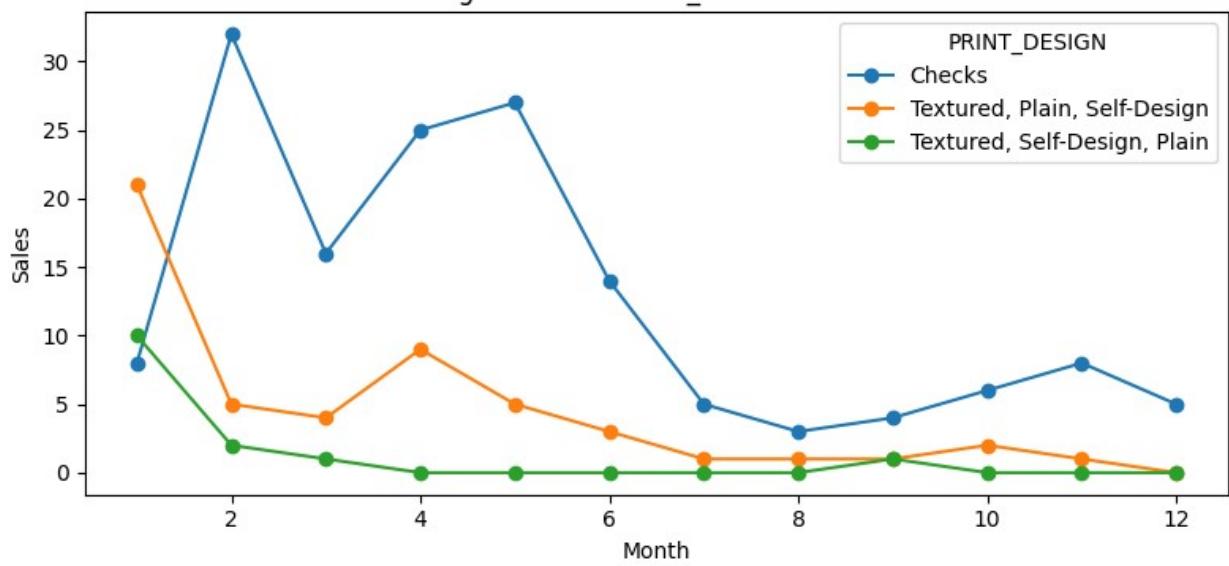
Vanishing Trends in FIT for Trousers



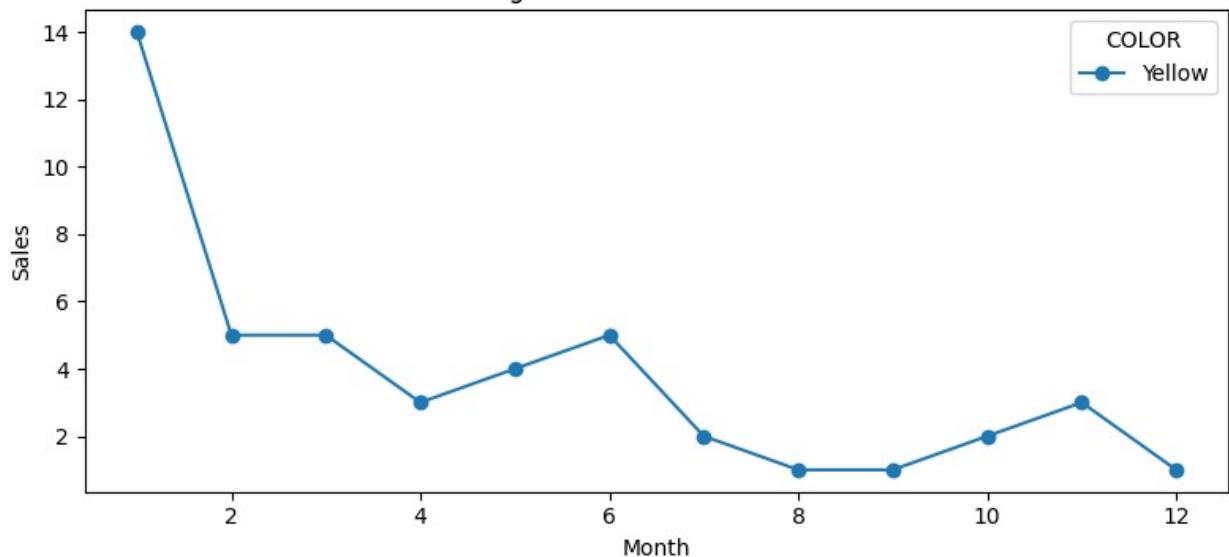
Vanishing Trends in MATERIAL_NEW for Trousers



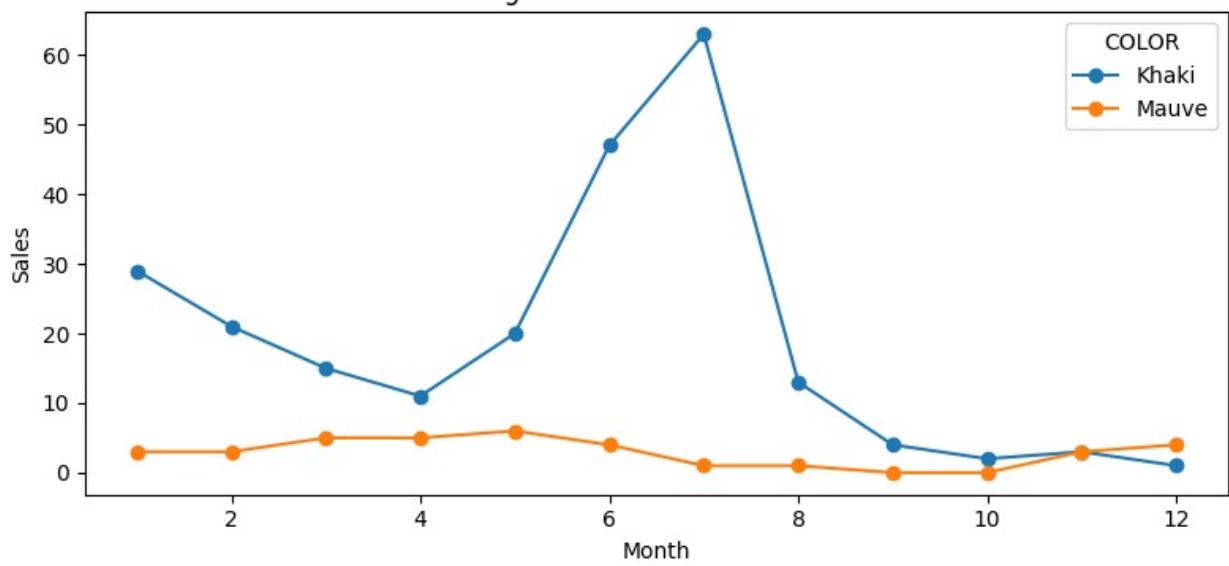
Vanishing Trends in PRINT_DESIGN for Trousers



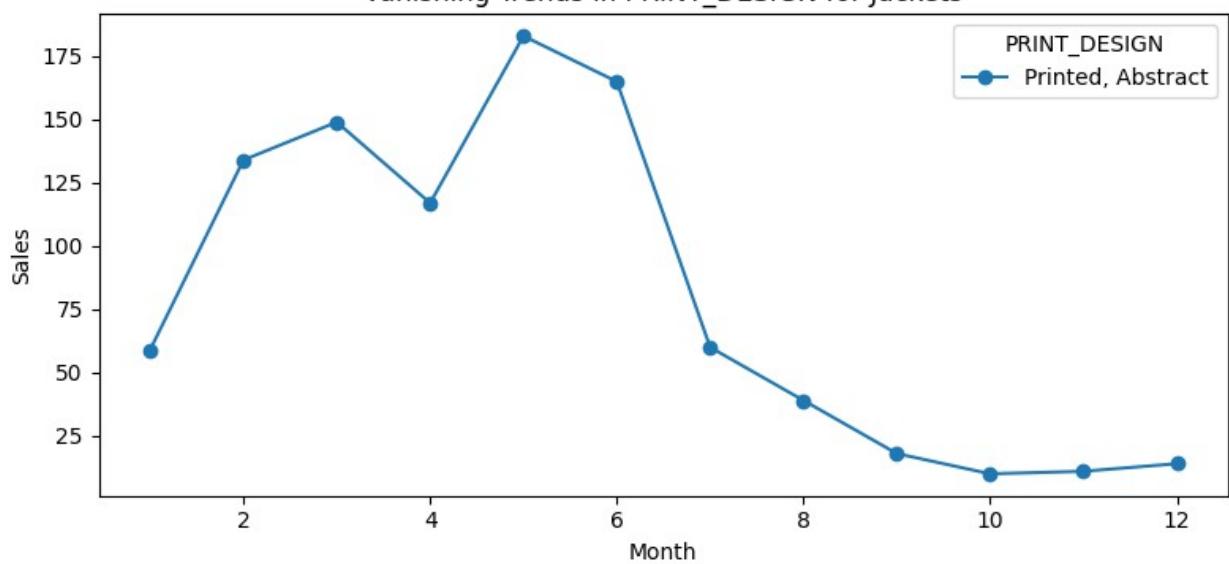
Vanishing Trends in COLOR for Trousers



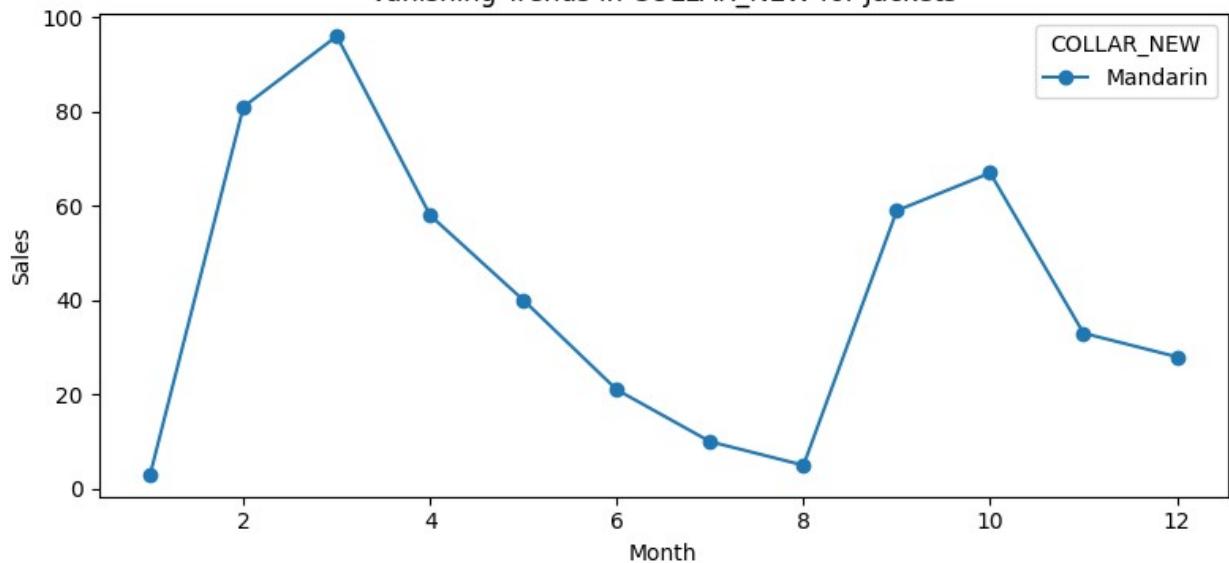
Vanishing Trends in COLOR for Sweaters



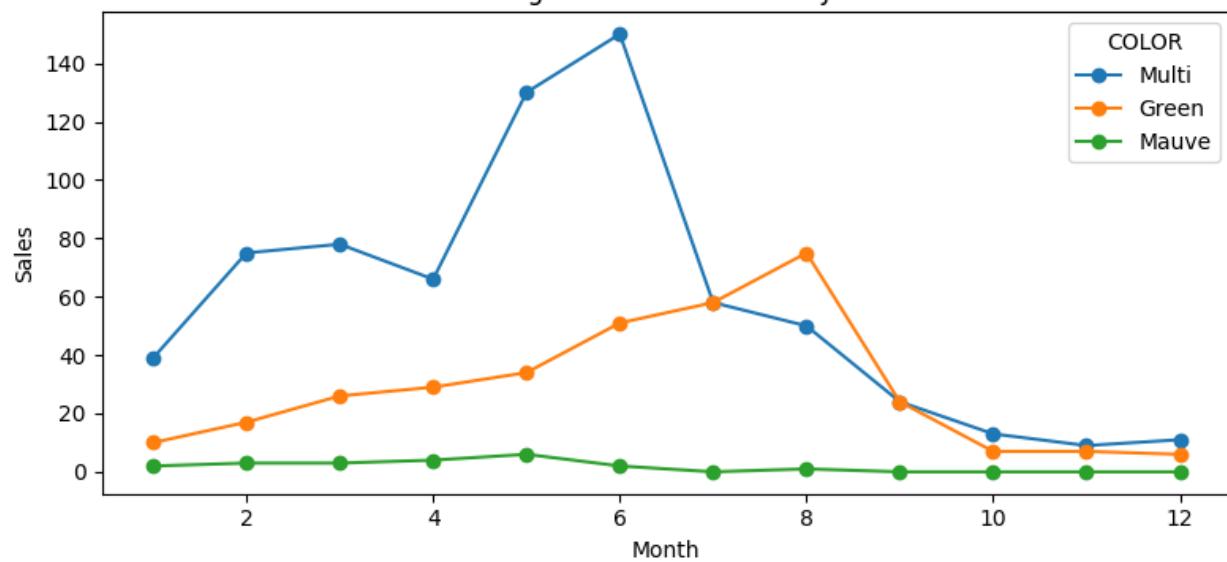
Vanishing Trends in PRINT_DESIGN for Jackets



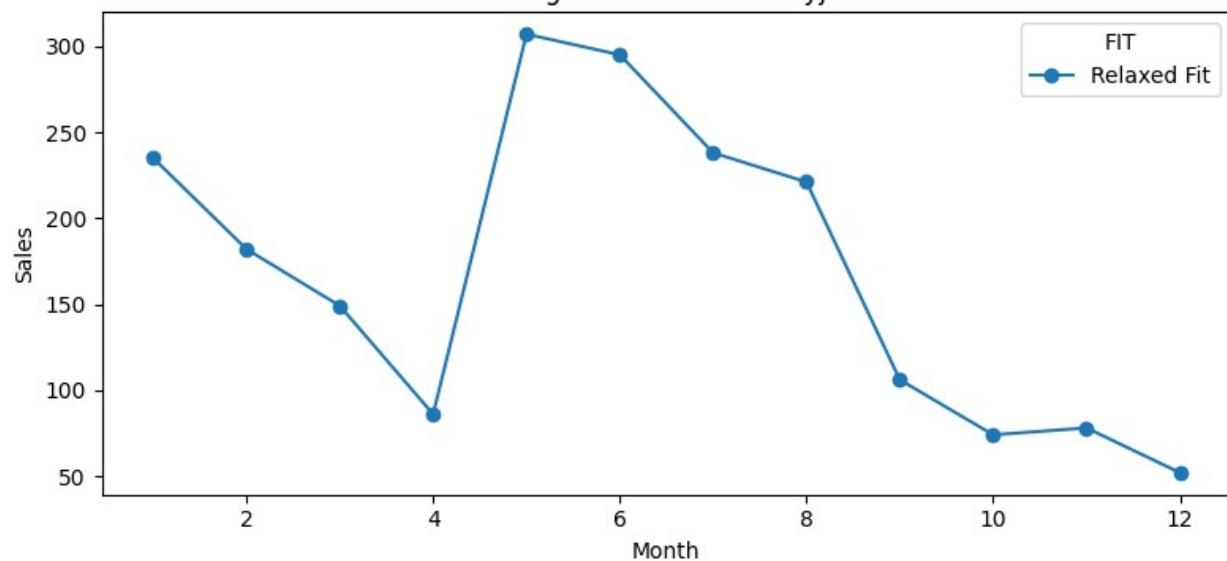
Vanishing Trends in COLLAR_NEW for Jackets



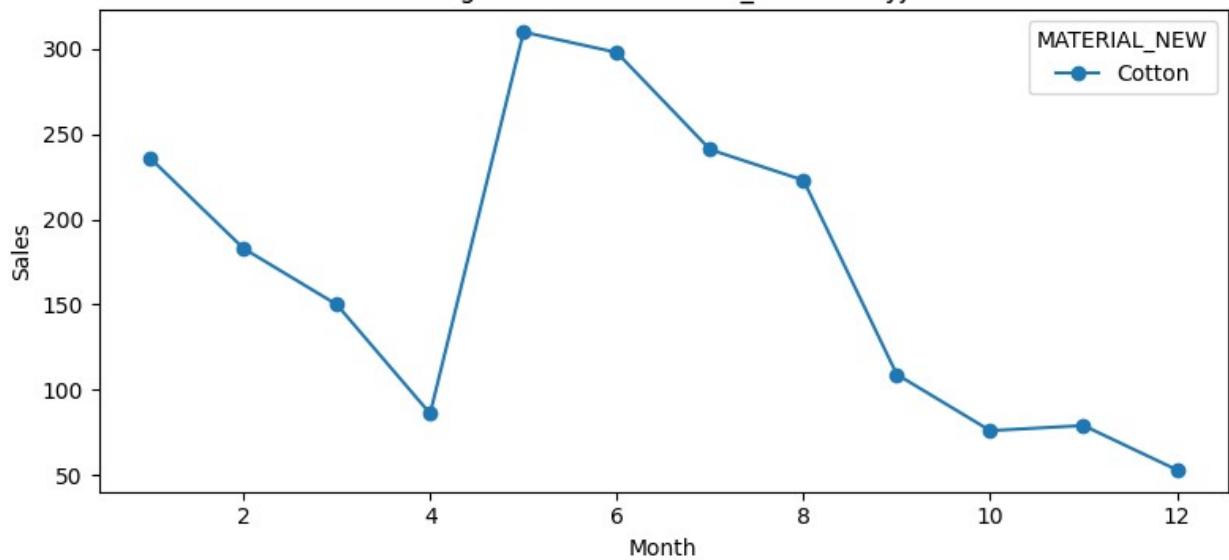
Vanishing Trends in COLOR for Jackets



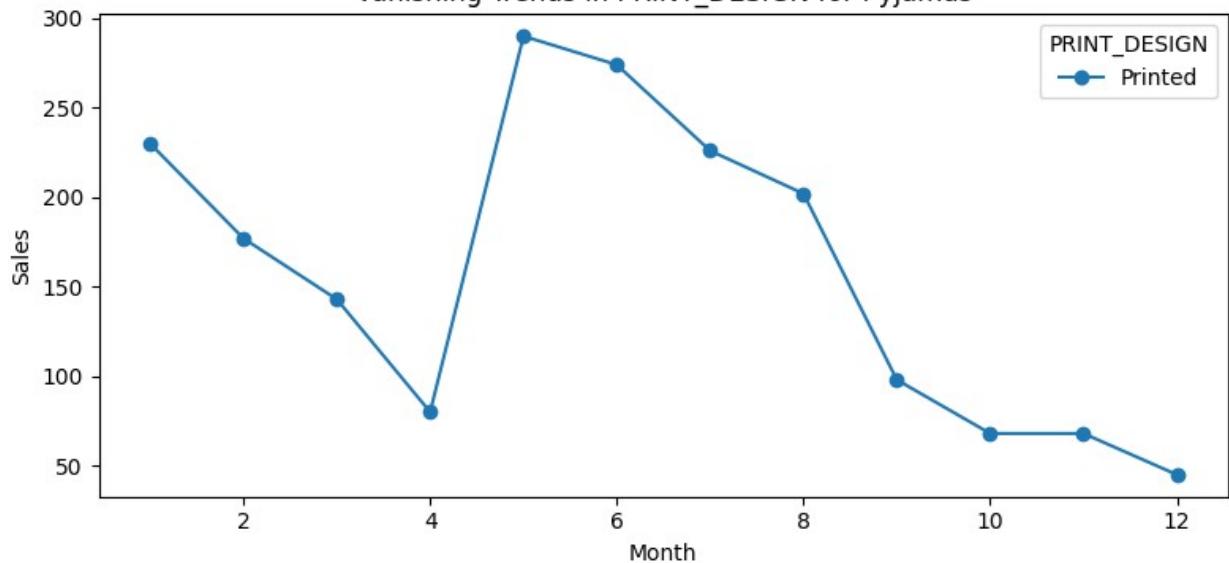
Vanishing Trends in FIT for Pyjamas



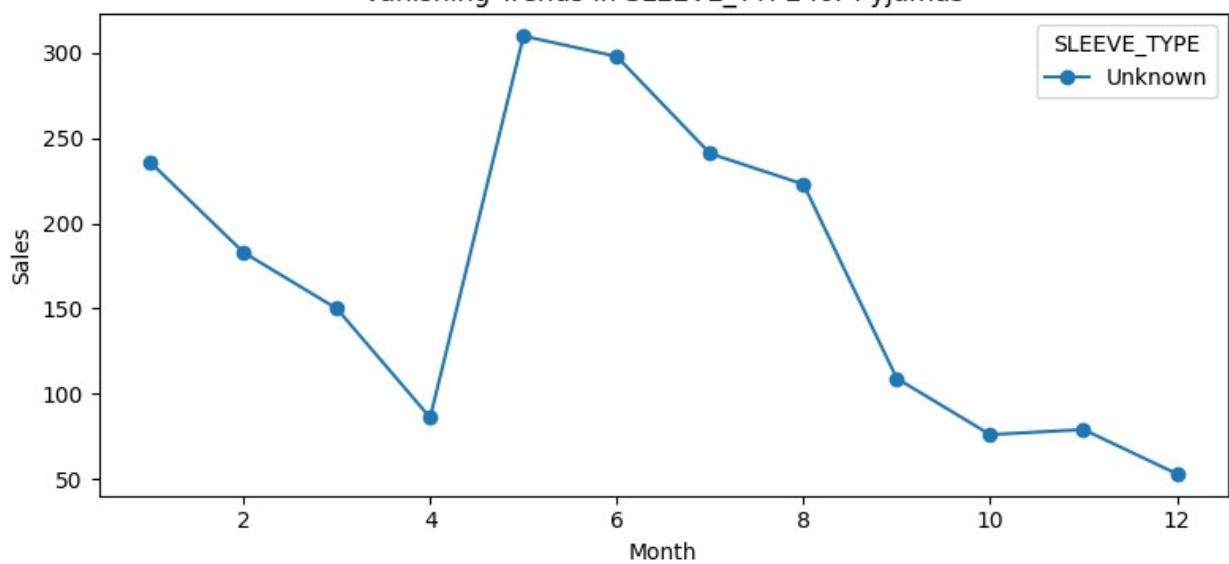
Vanishing Trends in MATERIAL_NEW for Pyjamas



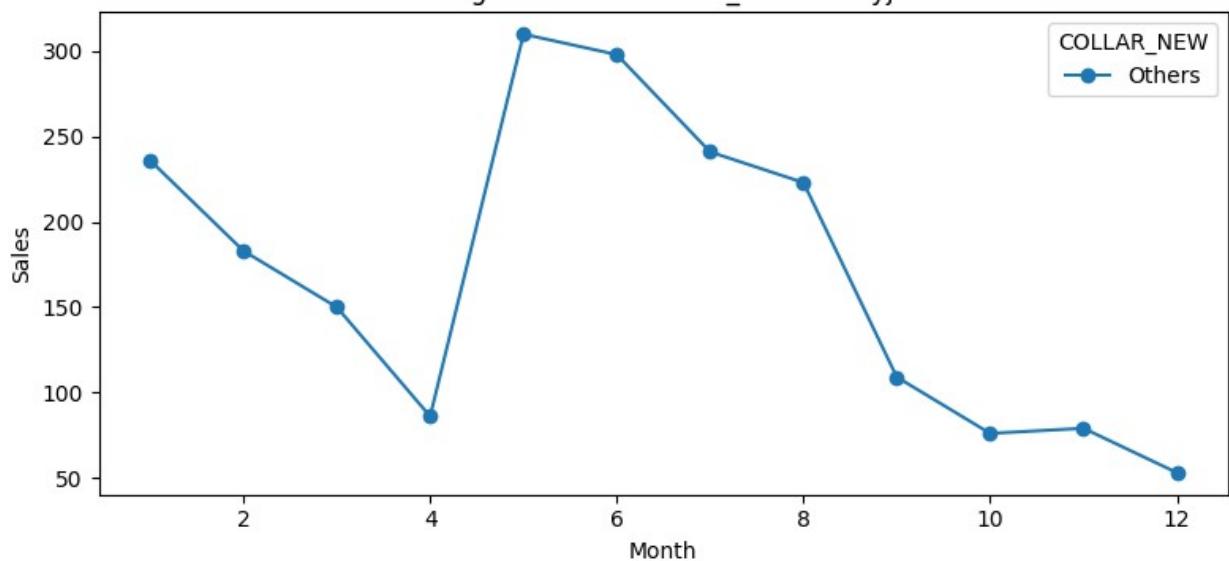
Vanishing Trends in PRINT_DESIGN for Pyjamas



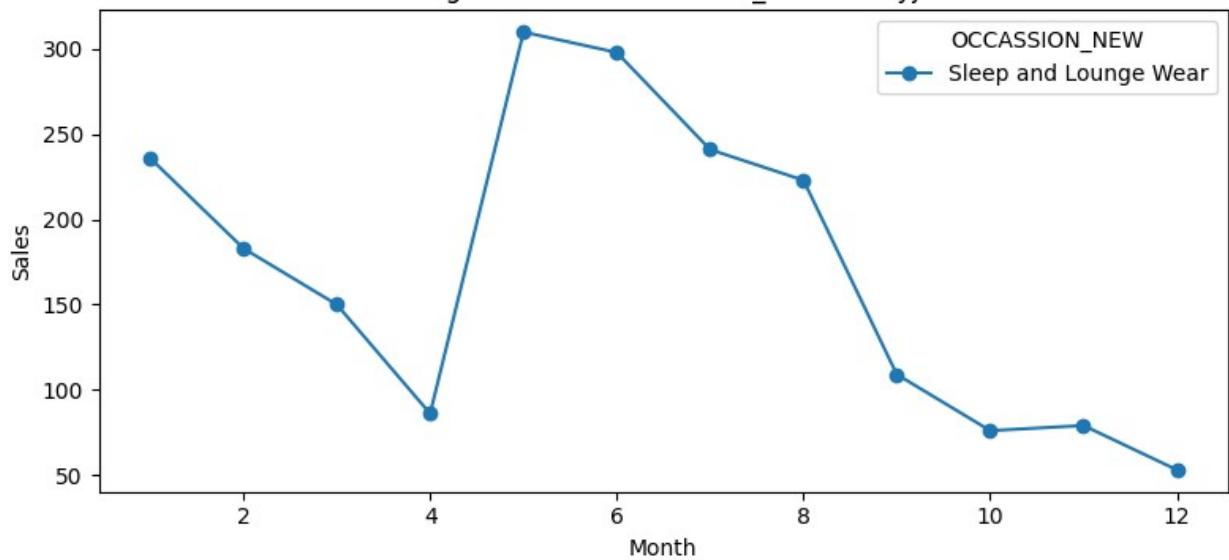
Vanishing Trends in SLEEVE_TYPE for Pyjamas



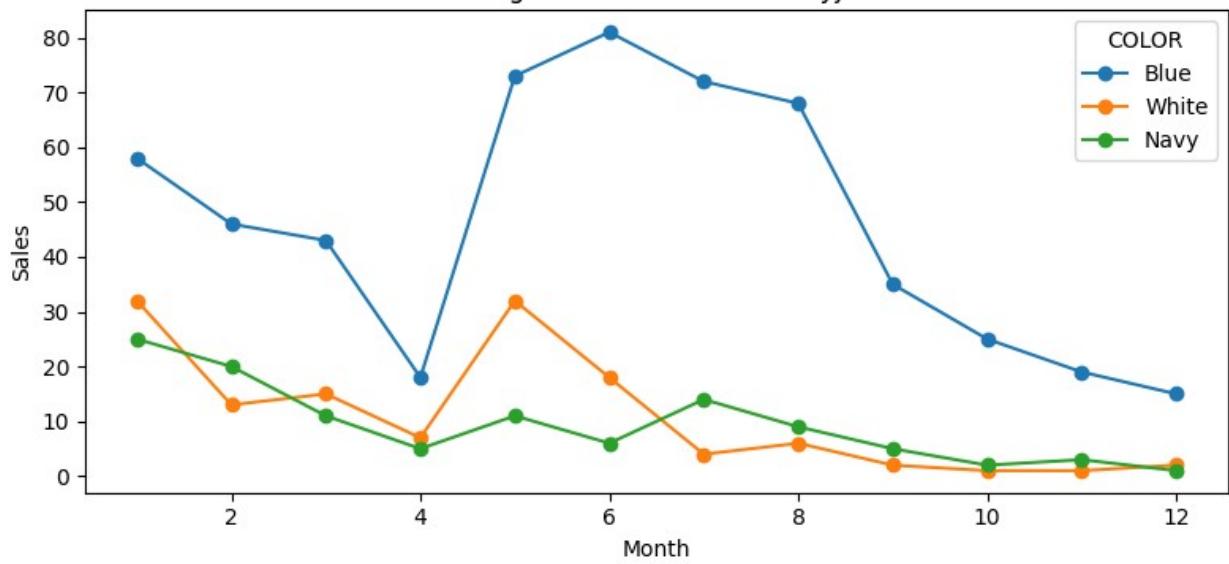
Vanishing Trends in COLLAR_NEW for Pyjamas



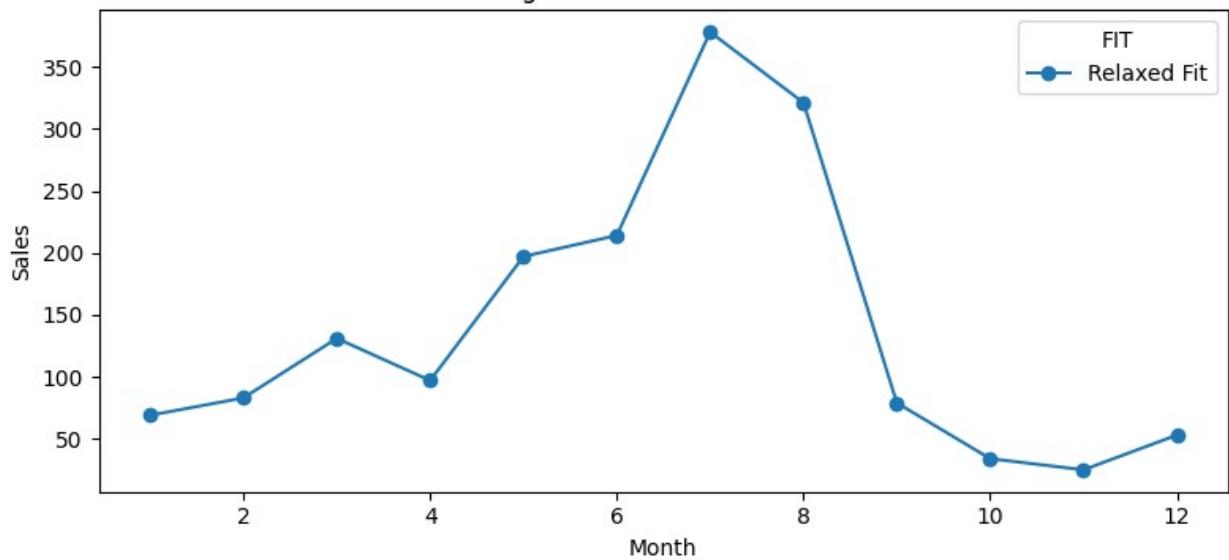
Vanishing Trends in OCCASSION_NEW for Pyjamas



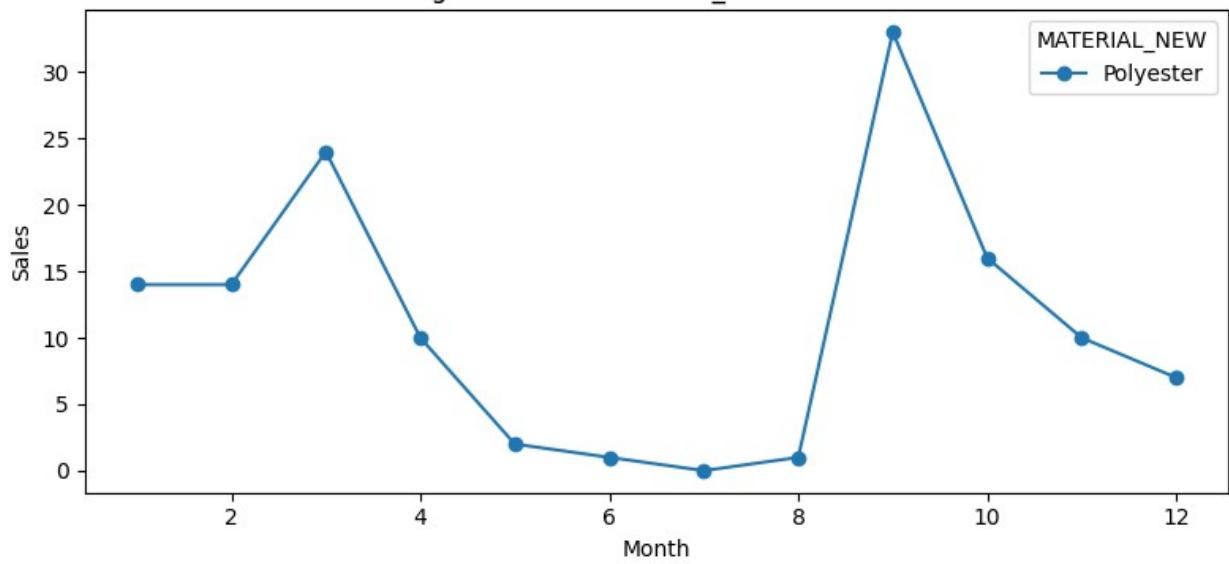
Vanishing Trends in COLOR for Pyjamas



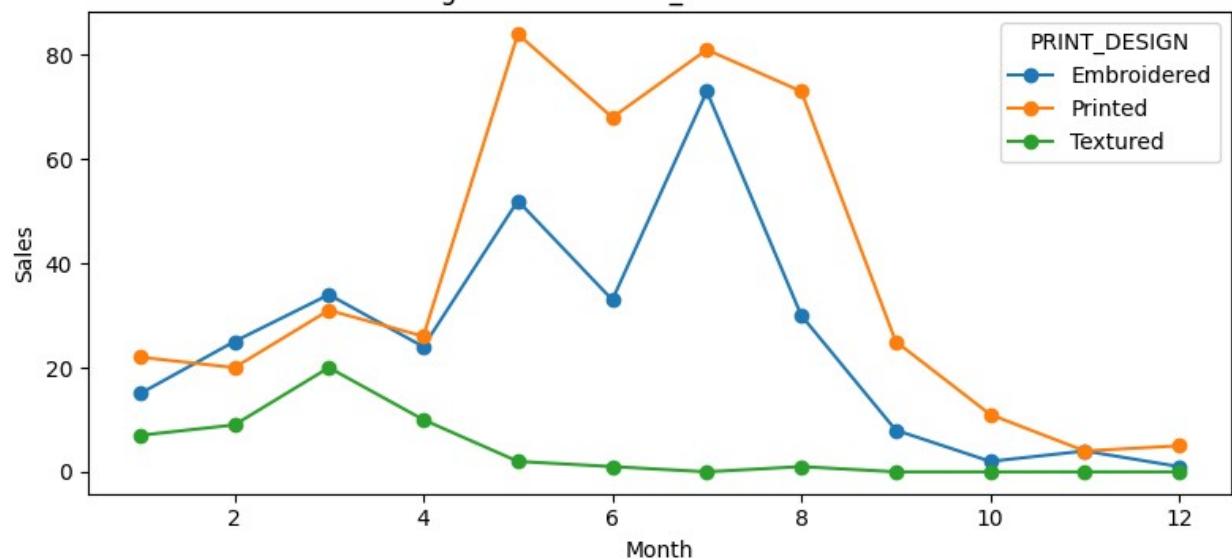
Vanishing Trends in FIT for Sweatshirts



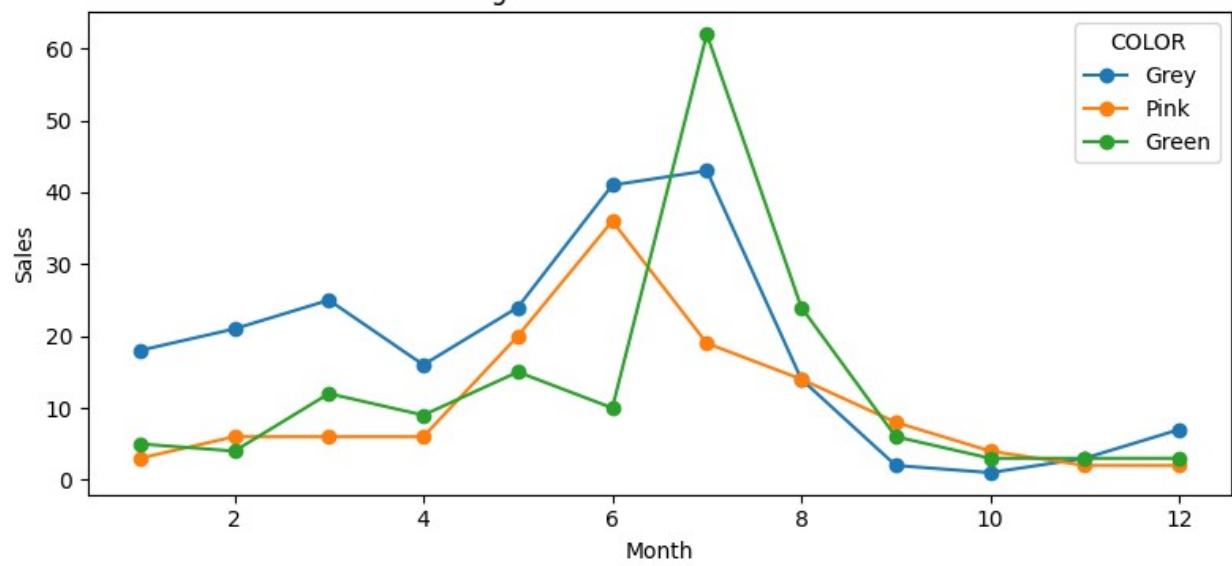
Vanishing Trends in MATERIAL_NEW for Sweatshirts



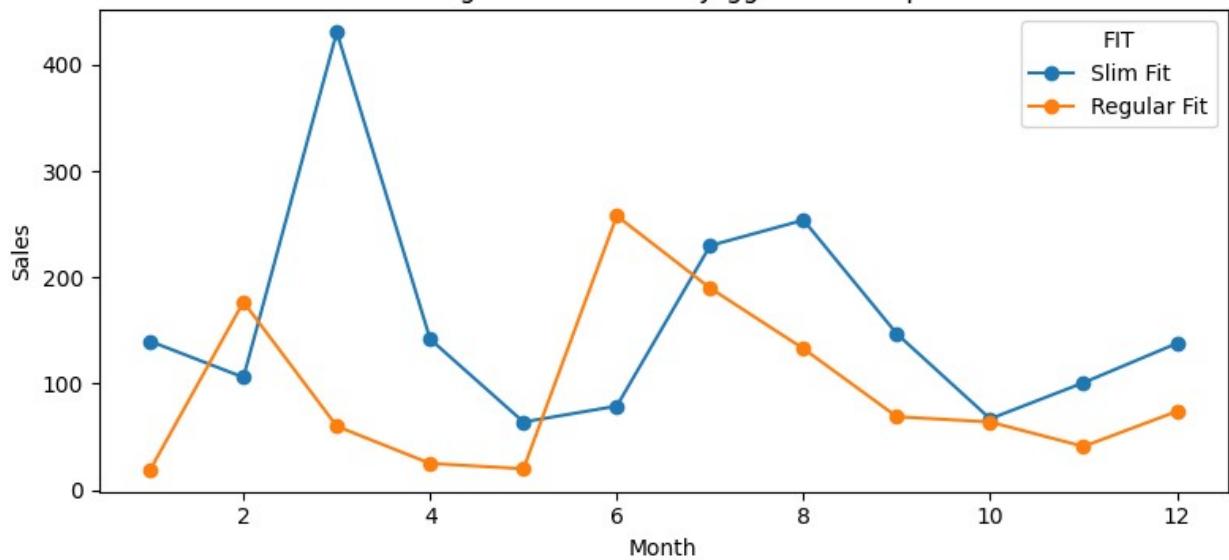
Vanishing Trends in PRINT_DESIGN for Sweatshirts



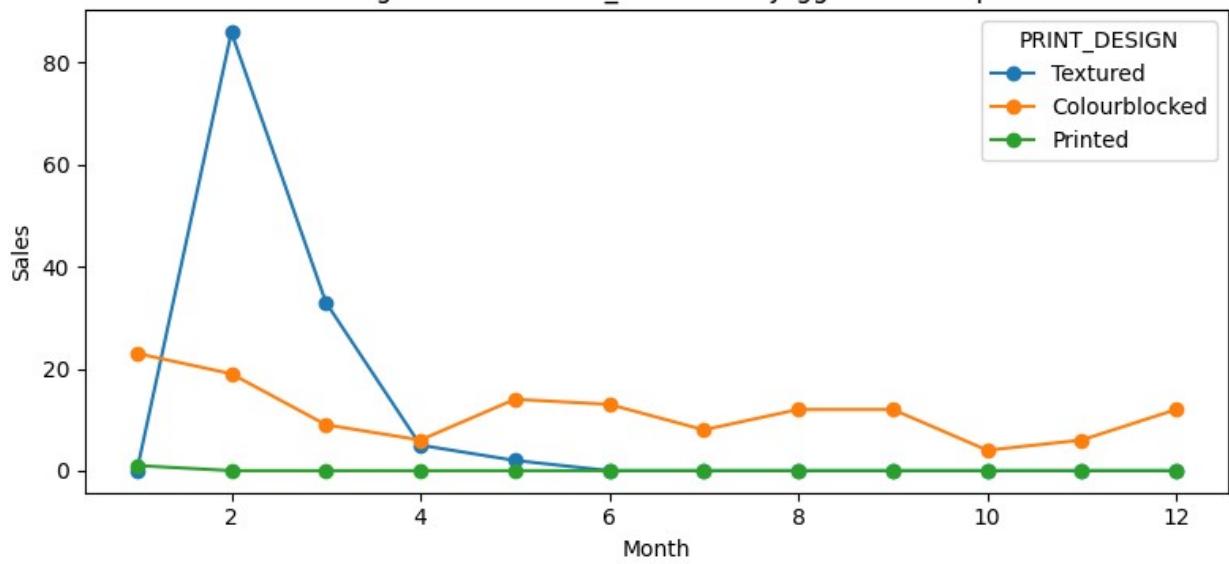
Vanishing Trends in COLOR for Sweatshirts

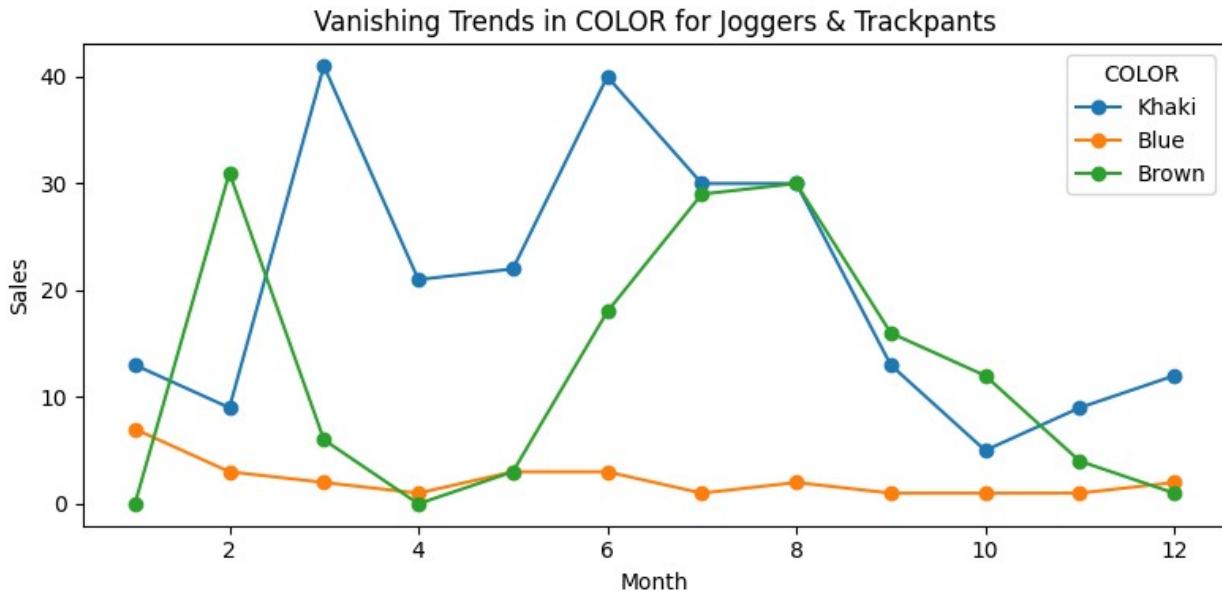


Vanishing Trends in FIT for Joggers & Trackpants



Vanishing Trends in PRINT_DESIGN for Joggers & Trackpants





Q4. Provide composition on category and feature level (important features determined in the first question) for example if Fit is identified as a crucial feature for Shirts then what will be composition of different materials that should be produced next for example Oversized 70% and Regular 30% for Shirts.

Approach -> For each category, the top 3 significant features (previously identified via importance metrics) were selected to analyze sales composition. Feature values contributing less than 5% of total sales were excluded to eliminate noise and emphasize major contributors. The relative percentage share of each qualifying feature value was computed and visualized through pie charts to inform production prioritization based on dominant sales contributors.

```
# Get top 3 features per category from previous analysis
# (Replacing this with our actual feature importance results)
category_top_features = {
    'Shirts': ['FIT', 'SLEEVE_TYPE', 'OCCASSION_NEW'],
    'T-Shirts': ['OCCASSION_NEW', 'SLEEVE_TYPE', 'FIT'],
    'Jeans': ['FIT', 'MATERIAL_NEW', 'PRINT DESIGN'],
    'Trousers': ['FIT', 'MATERIAL_NEW', 'COLLAR_NEW'],
    'Jackets': ['OCCASSION_NEW', 'SLEEVE_TYPE', 'FIT'],
    'Sweaters': ['OCCASSION_NEW', 'SLEEVE_TYPE', 'FIT'],
    'Overshirt': ['OCCASSION_NEW', 'SLEEVE_TYPE', 'FIT']
}

def calculate_composition(category, features):
    cat_df = df[df['CATEGORY'] == category]
    compositions = {}

    for feature in features:
        # Calculate sales distribution
        feature_dist = cat_df.groupby(feature)[['TOTAL_SALES']].sum().reset_index()
```

```

    total_sales = feature_dist['TOTAL_SALES'].sum()

    # Calculate percentages and filter out insignificant values
    (<5%)
        feature_dist['PERCENTAGE'] = (feature_dist['TOTAL_SALES'] /
    total_sales * 100).round(1)
        feature_dist = feature_dist[feature_dist['PERCENTAGE'] >= 5]

    # Normalize to 100%
    total_percentage = feature_dist['PERCENTAGE'].sum()
    feature_dist['PERCENTAGE'] = (feature_dist['PERCENTAGE'] /
total_percentage * 100).round(1)

    compositions[feature] = feature_dist.set_index(feature)
    ['PERCENTAGE'].to_dict()

    return compositions

# Generate and display compositions for all categories
for category, features in category_top_features.items():
    print(f"\n Production Composition for {category}:")
    composition = calculate_composition(category, features)

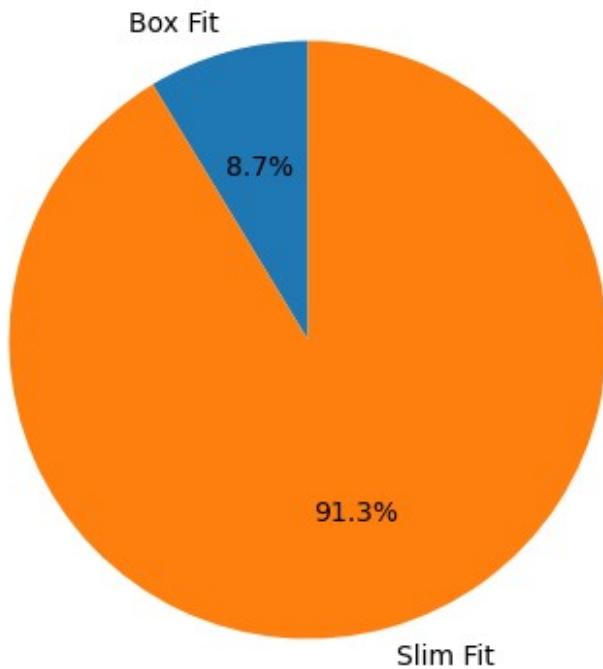
    for feature, values in composition.items():

        # Pie chart visualization
        plt.figure(figsize=(5,5))
        plt.pie(values.values(), labels=values.keys(), autopct='%.1f%'
        %', startangle=90)
        plt.title(f"{category} - {feature} Composition")
        plt.show()

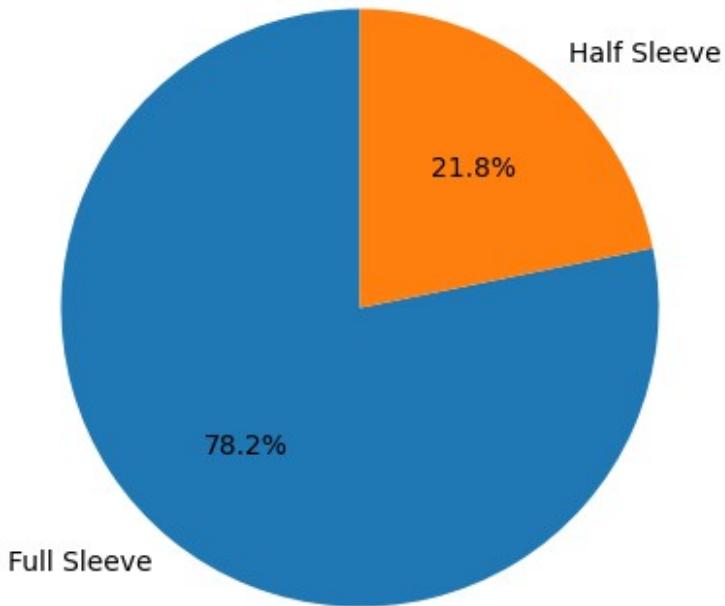
```

Production Composition for Shirts:

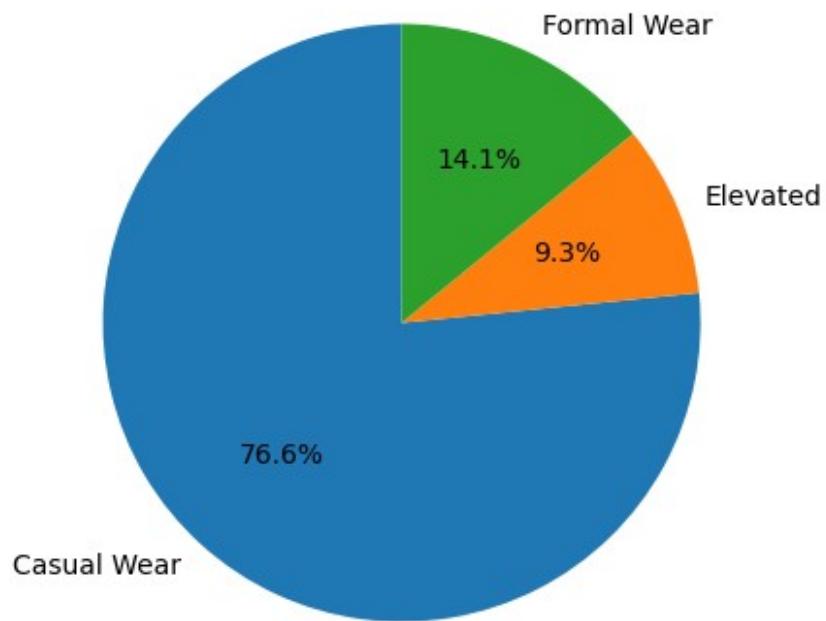
Shirts - FIT Composition



Shirts - SLEEVE_TYPE Composition

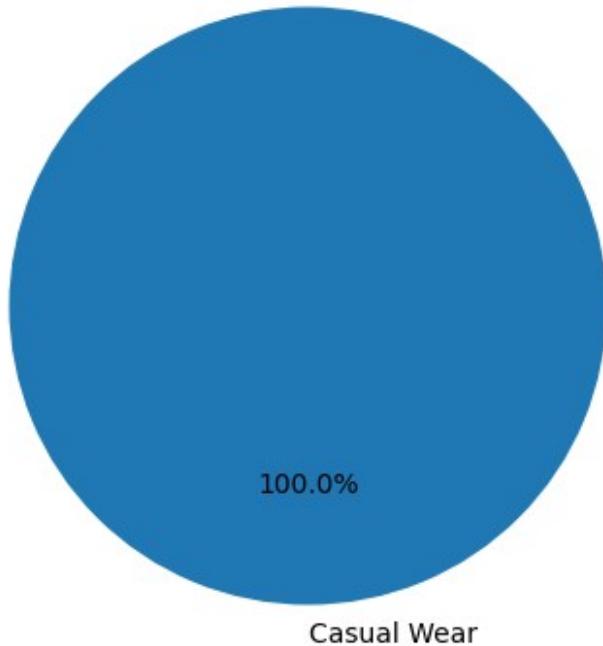


Shirts - OCCASSION_NEW Composition

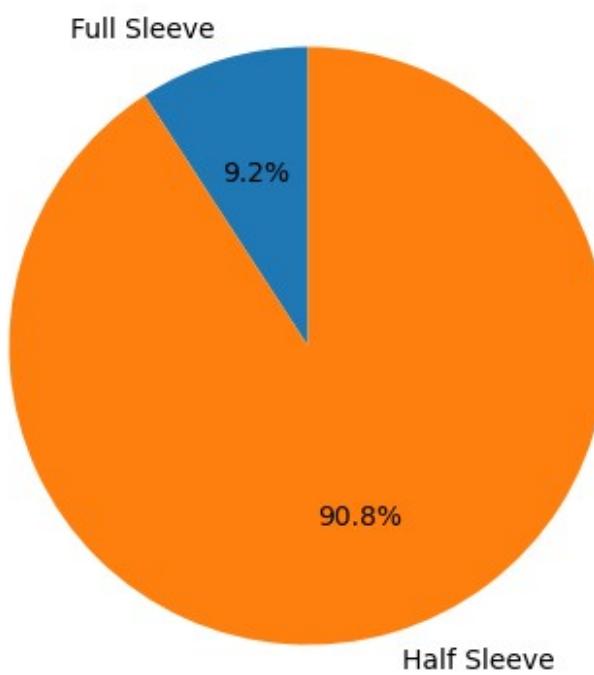


Production Composition for T-Shirts:

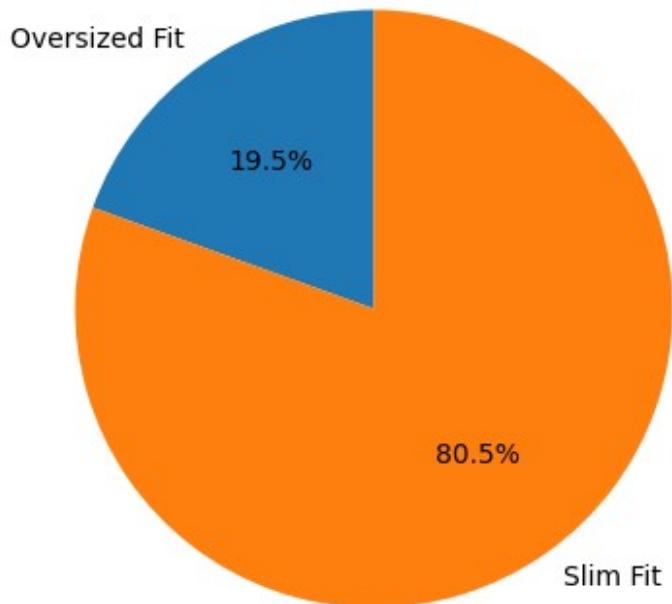
T-Shirts - OCCASSION_NEW Composition



T-Shirts - SLEEVE_TYPE Composition

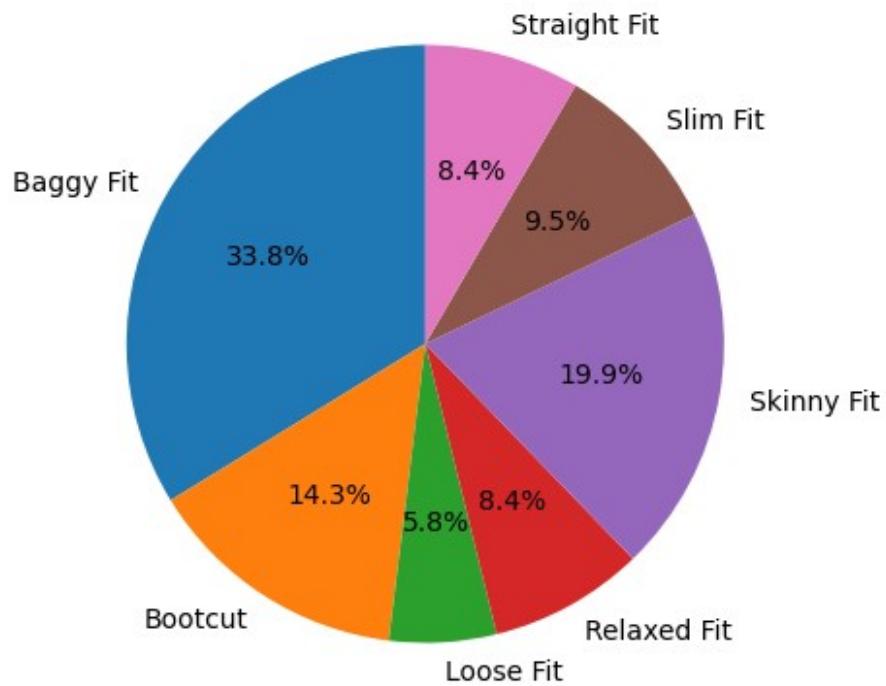


T-Shirts - FIT Composition

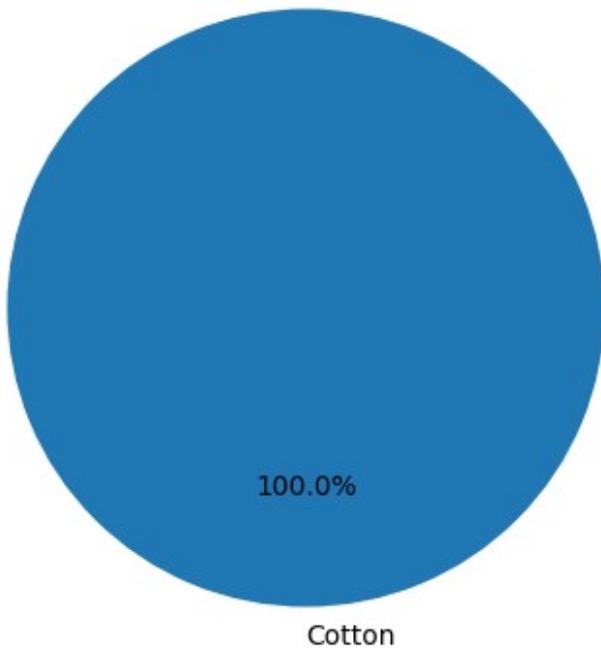


Production Composition for Jeans:

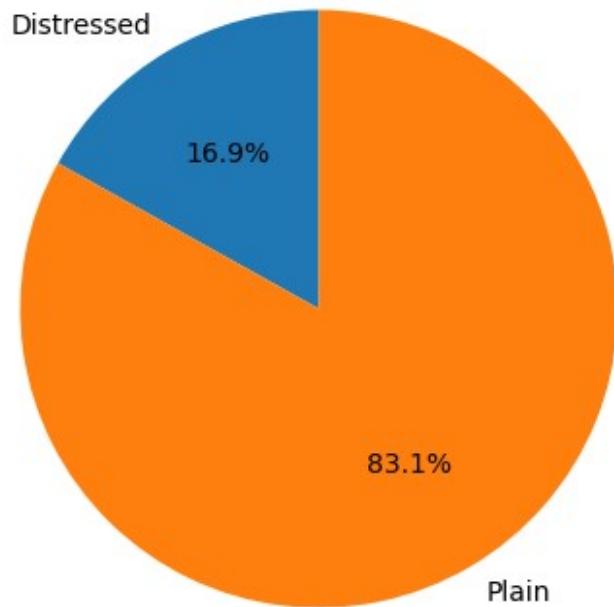
Jeans - FIT Composition



Jeans - MATERIAL_NEW Composition

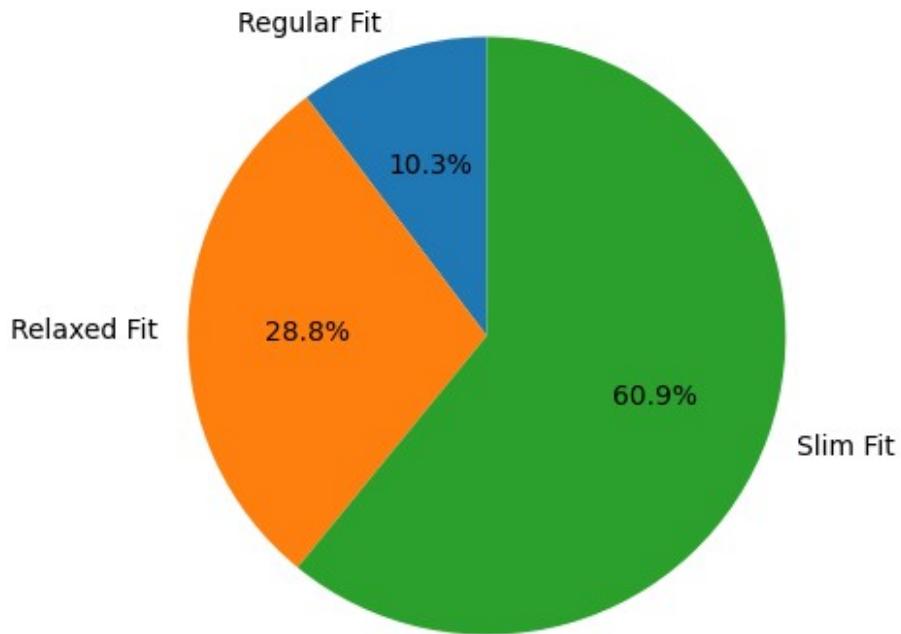


Jeans - PRINT_DESIGN Composition

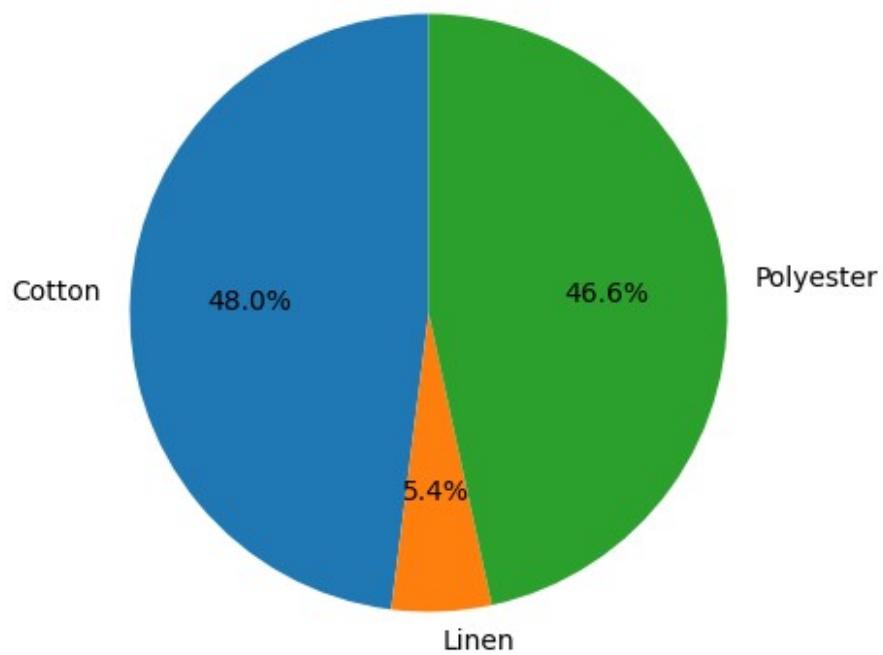


Production Composition for Trousers:

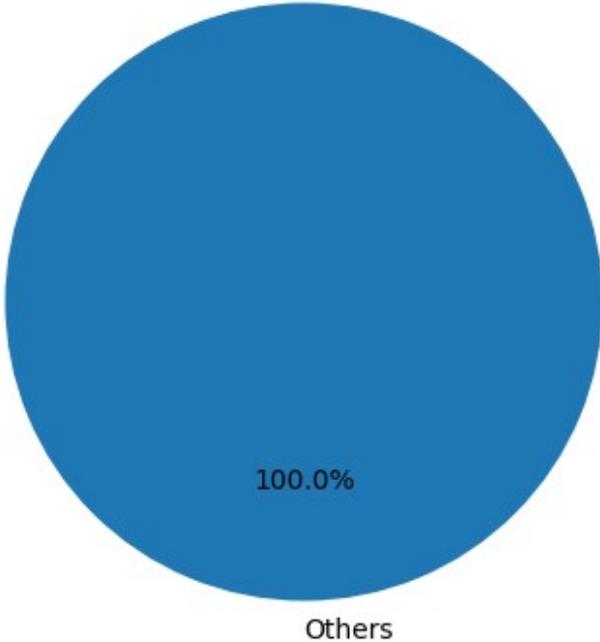
Trousers - FIT Composition



Trousers - MATERIAL_NEW Composition

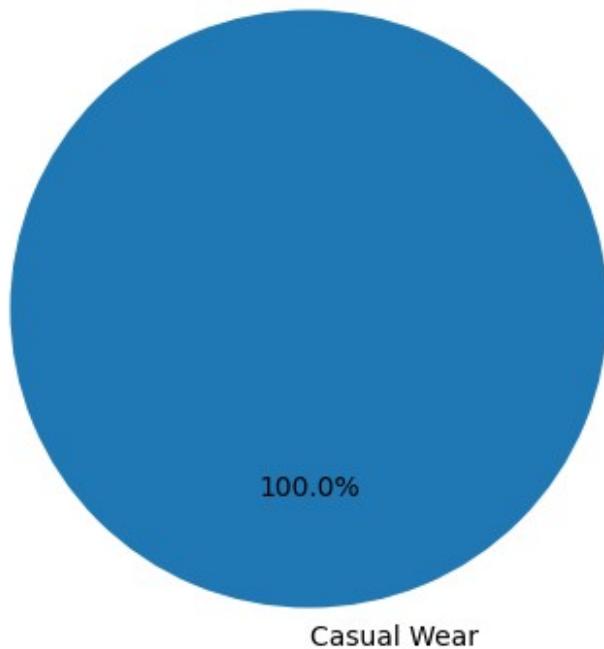


Trousers - COLLAR_NEW Composition

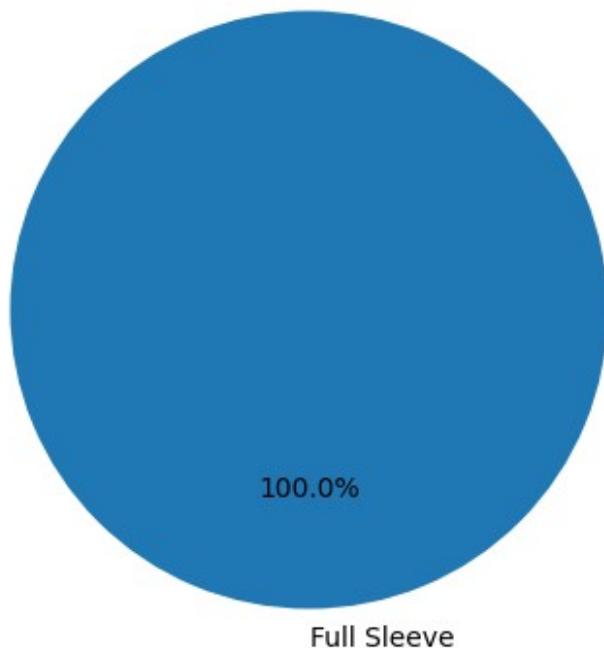


Production Composition for Jackets:

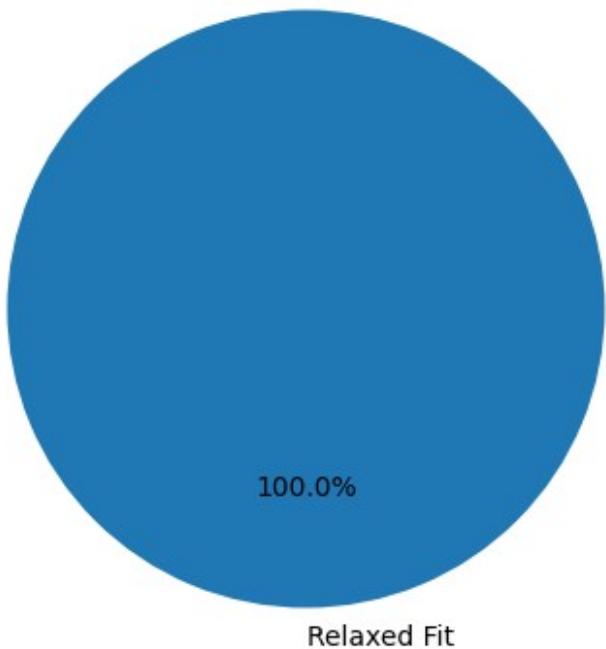
Jackets - OCCASSION_NEW Composition



Jackets - SLEEVE_TYPE Composition

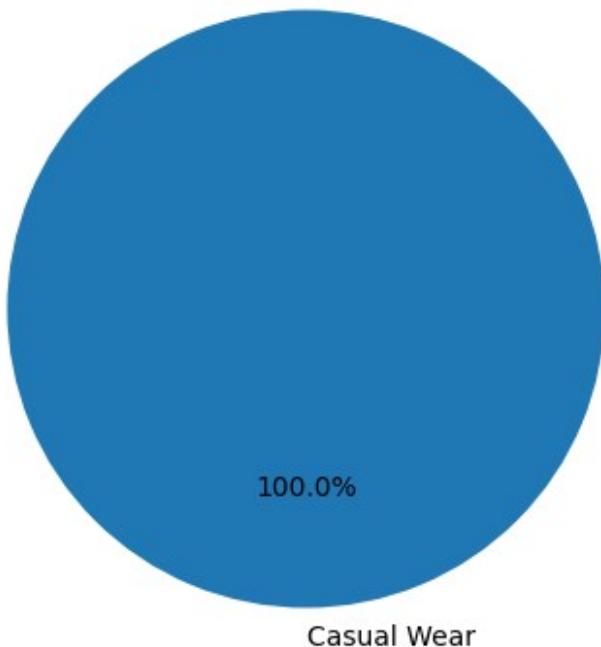


Jackets - FIT Composition

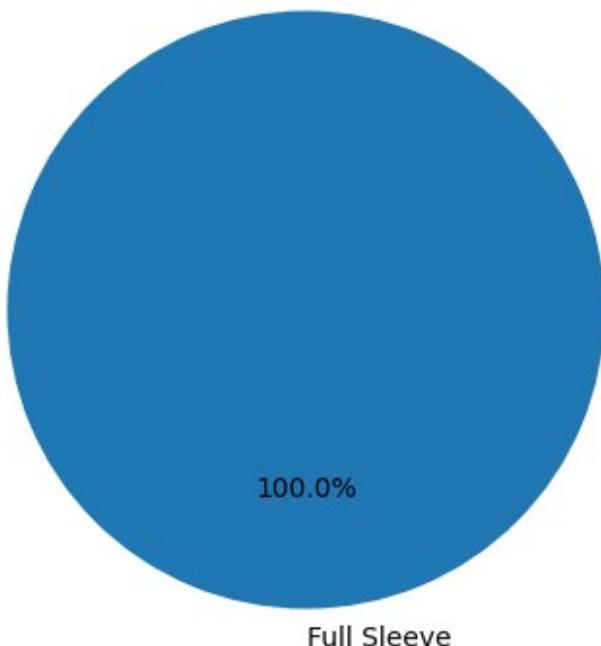


Production Composition for Sweaters:

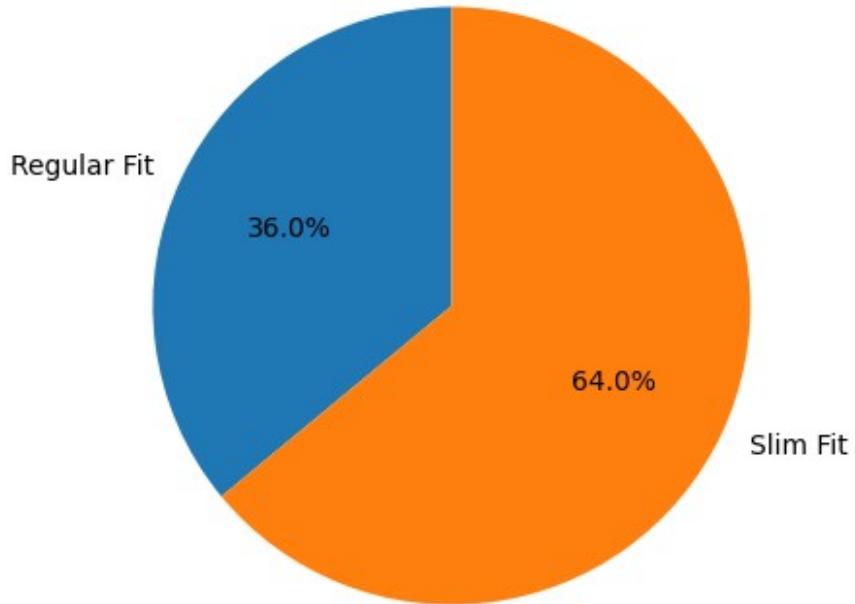
Sweaters - OCCASSION_NEW Composition



Sweaters - SLEEVE_TYPE Composition

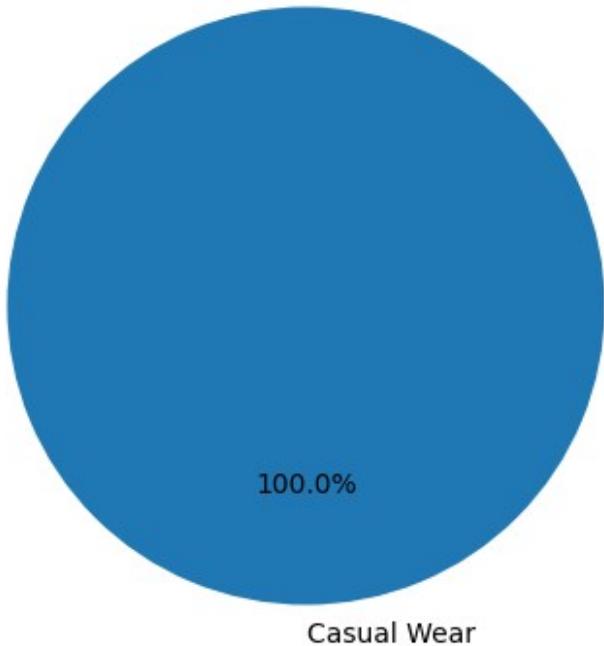


Sweaters - FIT Composition

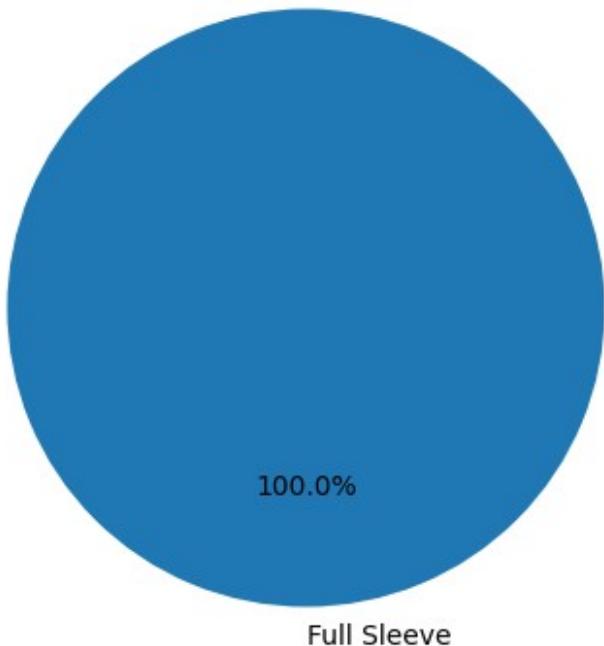


Production Composition for Overshirt:

Overshirt - OCCASSION_NEW Composition



Overshirt - SLEEVE_TYPE Composition



Overshirt - FIT Composition

