analysis_report

November 13, 2025

0.0.1 Gucci Second-Hand Market Analysis: A Strategic Plan

Project Goal: To analyze the `vestiaire.csv` dataset to understand the key drivers of sales performance on the second-hand market and provide actionable strategic recommendations to Gucci stakeholders for optimizing pricing, inventory, and seller management.

0.0.2 Part 1: Data Loading and Initial Preparation

This foundational step ensures the data is accurate, consistent, and ready for analysis. Errors or inconsistencies at this stage can lead to flawed conclusions.

1.1. Data Loading: * Load the dataset from `data/vestiaire.csv` into a pandas DataFrame.

[1]:
```
import pandas as pd
import numpy as np
import plotly.express as px
import plotly.graph_objects as go
from plotly.subplots import make_subplots
from IPython.display import Image
import os

# Note: This notebook requires the 'kaleido' package for exporting plotly␣
↪images.
# You can install it using: pip install kaleido

# Load the data
df = pd.read_csv('data/vestiaire.csv')
```

1.2. Initial Inspection & Profiling: * **Understand Dimensions:** Use `df.shape` to see the number of rows (products) and columns (features). * **Review Data Types and Nulls:** Use `df.info()` to get a summary of all columns, their data types (`Dtype`), and the count of non-null values. This is the first step in identifying missing data. * **Statistical Summary:** Use `df.describe()` for all numerical columns to understand their distribution, including mean, median (50%), standard deviation, and min/max values. This helps spot anomalies or potential outliers early (e.g., a price of $0). * **Preview Data:** Use `df.head()` to view the first few rows and get a feel for the data in each column.

[2]:
```python
print('DataFrame Dimensions:')
print(df.shape)
```

```
DataFrame Dimensions:
(900514, 36)
```

[3]:
```python
print('DataFrame Info:')
df.info()
```

```
DataFrame Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 900514 entries, 0 to 900513
Data columns (total 36 columns):
 #   Column                       Non-Null Count   Dtype
---  ------                       --------------   -----
 0   product_id                   900514 non-null  int64
 1   product_type                 900514 non-null  object
 2   product_name                 900514 non-null  object
 3   product_description          900507 non-null  object
 4   product_keywords             899331 non-null  object
 5   product_gender_target        900514 non-null  object
 6   product_category             899331 non-null  object
 7   product_season               900512 non-null  object
 8   product_condition            900514 non-null  object
 9   product_like_count           900514 non-null  float64
 10  sold                         900514 non-null  bool
 11  reserved                     900514 non-null  bool
 12  available                    900514 non-null  bool
 13  in_stock                     900514 non-null  bool
 14  should_be_gone               900514 non-null  bool
 15  brand_id                     900514 non-null  int64
 16  brand_name                   900514 non-null  object
 17  brand_url                    900514 non-null  object
 18  product_material             900510 non-null  object
 19  product_color                900513 non-null  object
 20  price_usd                    900514 non-null  float64
 21  seller_price                 900514 non-null  float64
 22  seller_earning               900514 non-null  float64
 23  seller_badge                 900514 non-null  object
 24  has_cross_border_fees        886778 non-null  object
 25  buyers_fees                  886778 non-null  float64
 26  warehouse_name               900514 non-null  object
 27  seller_id                    900514 non-null  int64
 28  seller_username              900475 non-null  object
 29  usually_ships_within         745723 non-null  object
 30  seller_country               900514 non-null  object
 31  seller_products_sold         900514 non-null  float64
 32  seller_num_products_listed   900514 non-null  float64
```

```
 33   seller_community_rank       900514 non-null  float64
 34   seller_num_followers        900514 non-null  float64
 35   seller_pass_rate            900514 non-null  float64
dtypes: bool(5), float64(10), int64(3), object(18)
memory usage: 217.3+ MB
```

[4]:
```
print('Statistical Summary of Numerical Columns:')
df.describe()
```

```
Statistical Summary of Numerical Columns:
```

[4]:
```
         product_id  product_like_count       brand_id      price_usd  \
count  9.005140e+05       900514.000000  900514.000000  900514.000000
mean   3.810003e+07            6.298326    2437.277576     386.862536
std    7.749403e+06           12.920079    3702.869580    1859.559156
min    1.113630e+05            0.000000       2.000000       6.130000
25%    3.811580e+07            1.000000      66.000000      83.070000
50%    4.174207e+07            3.000000     341.000000     168.700000
75%    4.267775e+07            7.000000    3266.000000     350.000000
max    4.324884e+07         3154.000000   18237.000000  632610.000000

        seller_price  seller_earning    buyers_fees     seller_id  \
count  900514.000000   900514.000000  886778.000000  9.005140e+05
mean      331.639409      290.436463      55.486152  1.382227e+07
std      1591.472807     1498.157606     290.259974  7.535593e+06
min         5.110000        0.000000       0.000000  1.000000e+00
25%        71.360000       58.580000      11.720000  7.977389e+06
50%       143.780000      125.370000      23.970000  1.438324e+07
75%       298.200000      261.900000      50.480000  1.946235e+07
max    527175.000000   509229.750000  105435.000000  2.608177e+07

       seller_products_sold  seller_num_products_listed  \
count         900514.000000               900514.000000
mean             664.958267                 1497.663143
std             3552.744596                 5460.166852
min                0.000000                    0.000000
25%                6.000000                   10.000000
50%               34.000000                   52.000000
75%              178.000000                  373.000000
max            79738.000000                39628.000000

       seller_community_rank  seller_num_followers  seller_pass_rate
count           9.005140e+05          9.005140e+05     900514.000000
mean            5.623160e+04          9.904618e+03         72.461753
std             1.438156e+05          3.557486e+05         34.428663
min             0.000000e+00          0.000000e+00       -180.000000
25%             0.000000e+00          1.700000e+01         68.000000
50%             0.000000e+00          7.300000e+01         88.000000
```

```
75%              2.539300e+04          2.900000e+02         95.000000
max              1.064736e+06          1.417912e+07        100.000000
```

[5]:
```
print('First 5 Rows of the DataFrame:')
df.head()
```

```
First 5 Rows of the DataFrame:
```

[5]:
```
   product_id           product_type  \
0    43247626         Wool mini skirt
1    43247441                  Jacket
2    43246517               Wool coat
3    43246507              Mini skirt
4    43246417  Vegan leather trousers

                                        product_name  \
0  Wool mini skirt Miu Miu Grey size S Internatio…
1      Jacket Barbara Bui Navy size 42 FR in Cotton
2  Wool coat Comme Des Garcons White size S Inter…
3     Mini skirt MSGM Black size 38 IT in Polyester
4  Vegan leather trousers LVIR Black size 36 FR i…

                                 product_description  \
0  Miu Miu - Pleated mini skirt Size: 36 (S)  Wai…
1  For selling nice women's suit Barbara Bui size…
2  Magnificent boiled wool coat. I bought it in t…
3  MSGM Skirt Black Printed Raw-Edge & Embroidere…
4  LVIR black grained faux leather trousers size …

              product_keywords product_gender_target product_category  \
0          Miu Miu Wool Skirts                 Women   Women Clothing
1    Barbara Bui Cotton Jackets                 Women   Women Clothing
2  Comme Des Garcons Wool Coats                 Women   Women Clothing
3         MSGM Polyester Skirts                 Women   Women Clothing
4   LVIR Vegan leather Trousers                 Women   Women Clothing

    product_season    product_condition  product_like_count  …  \
0  Autumn / Winter           Never worn                34.0  …
1      All seasons  Very good condition                 1.0  …
2  Autumn / Winter  Very good condition                 2.0  …
3      All seasons  Very good condition                 0.0  …
4      All seasons  Very good condition                 1.0  …

  warehouse_name  seller_id   seller_username  usually_ships_within  \
0      Tourcoing   25775970   vitalii25775970                   NaN
1      Tourcoing   13698770    olivia13698770                   NaN
2      Tourcoing    6042365    cecilia6042365              1-2 days
3       Brooklyn   13172949  gretchen13172949              1-2 days
```

```
4          Crawley    2578605        crunchykat              3-5 days

   seller_country  seller_products_sold seller_num_products_listed  \
0         Germany                   3.0                       14.0
1         Belgium                   0.0                        0.0
2           Spain                  58.0                       69.0
3   United States                  63.0                      274.0
4  United Kingdom                  19.0                       14.0

  seller_community_rank seller_num_followers seller_pass_rate
0                   0.0                 13.0              0.0
1                   0.0                  8.0              0.0
2                   0.0                 62.0             96.0
3              126346.0                131.0             96.0
4              102821.0                 40.0             89.0

[5 rows x 36 columns]
```

1.3. Data Cleaning and Preprocessing: * **Handling Missing Values:** * Quantify missing data for each column using `df.isnull().sum()`. * **Strategy for `product_description` and `product_keywords`:** If missing, fill with an empty string or a placeholder like 'not_specified'. These are text fields and can be handled this way. * **Strategy for `product_condition`, `product_material`, `product_color`:** These are important categorical features. If the number of missing values is small, consider dropping the rows. If it's significant, impute with the mode (most frequent value) or create a new category called 'Unknown'. * **Strategy for `seller_badge`:** This is a key indicator. Treat missing values as a separate category, e.g., 'No Badge'. * **Strategy for `usually_ships_within`:** Impute missing values with the median or mode shipping time.

[6]:
```python
print('Count of Missing Values per Column:')
df.isnull().sum()
```

```
Count of Missing Values per Column:
```

[6]:
```
product_id                      0
product_type                    0
product_name                    0
product_description             7
product_keywords             1183
product_gender_target           0
product_category             1183
product_season                  2
product_condition               0
product_like_count              0
sold                            0
reserved                        0
available                       0
in_stock                        0
should_be_gone                  0
```

```
brand_id                            0
brand_name                          0
brand_url                           0
product_material                    4
product_color                       1
price_usd                           0
seller_price                        0
seller_earning                      0
seller_badge                        0
has_cross_border_fees           13736
buyers_fees                     13736
warehouse_name                      0
seller_id                           0
seller_username                    39
usually_ships_within           154791
seller_country                      0
seller_products_sold                0
seller_num_products_listed          0
seller_community_rank               0
seller_num_followers                0
seller_pass_rate                    0
dtype: int64
```

[8]:

```python
df['product_description'].fillna('not_specified', inplace=True)
df['product_keywords'].fillna('not_specified', inplace=True)
df['product_category'].fillna('not_specified', inplace=True)

for col in ['product_condition', 'product_material', 'product_color']:
    mode_val = df[col].mode()[0]
    df[col].fillna(mode_val, inplace=True)

df['seller_badge'].fillna('No Badge', inplace=True)

mode_shipping = df['usually_ships_within'].mode()[0]
df['usually_ships_within'].fillna(mode_shipping, inplace=True)

print('Missing values after imputation:')
print(df.isnull().sum())
```

```
/var/folders/9r/_l7v_srn15z38xsssh084f4m0000gn/T/ipykernel_50017/3009039690.py:3
: 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['product_category'].fillna('not_specified', inplace=True)
/var/folders/9r/_l7v_srn15z38xsssh084f4m0000gn/T/ipykernel_50017/3009039690.py:7
: 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[col].fillna(mode_val, inplace=True)
/var/folders/9r/_l7v_srn15z38xsssh084f4m0000gn/T/ipykernel_50017/3009039690.py:9
: 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['seller_badge'].fillna('No Badge', inplace=True)

Missing values after imputation:
product_id                    0
product_type                  0
product_name                  0
product_description           0
product_keywords              0
product_gender_target         0
product_category              0
product_season                2
product_condition             0
product_like_count            0
sold                          0
reserved                      0
available                     0
in_stock                      0
should_be_gone                0
brand_id                      0
```

```
brand_name                     0
brand_url                      0
product_material               0
product_color                  0
price_usd                      0
seller_price                   0
seller_earning                 0
seller_badge                   0
has_cross_border_fees      13736
buyers_fees                13736
warehouse_name                 0
seller_id                      0
seller_username               39
usually_ships_within           0
seller_country                 0
seller_products_sold           0
seller_num_products_listed     0
seller_community_rank          0
seller_num_followers           0
seller_pass_rate               0
dtype: int64
product_id                     0
product_type                   0
product_name                   0
product_description            0
product_keywords               0
product_gender_target          0
product_category               0
product_season                 2
product_condition              0
product_like_count             0
sold                           0
reserved                       0
available                      0
in_stock                       0
should_be_gone                 0
brand_id                       0
brand_name                     0
brand_url                      0
product_material               0
product_color                  0
price_usd                      0
seller_price                   0
seller_earning                 0
seller_badge                   0
has_cross_border_fees      13736
buyers_fees                13736
warehouse_name                 0
```

```
seller_id                        0
seller_username                 39
usually_ships_within             0
seller_country                   0
seller_products_sold             0
seller_num_products_listed       0
seller_community_rank            0
seller_num_followers             0
seller_pass_rate                 0
dtype: int64
```

- **Correcting Data Types:**
  - Ensure price columns (`price_usd`, `seller_price`, `seller_earning`) are converted to `float`.
  - Ensure integer columns (`product_like_count`, `seller_products_sold`, etc.) are converted to `int`.
  - The `sold` column is our primary target variable. Ensure it is a numerical `0` or `1` for easier calculations (e.g., `mean()` to get sell-through rate).

[9]:
```python
for col in ['price_usd', 'seller_price', 'seller_earning']:
    df[col] = pd.to_numeric(df[col], errors='coerce')

for col in ['product_like_count', 'seller_products_sold',␣
 ↪'seller_num_followers']:
    df[col] = df[col].astype('int')

df['sold'] = df['sold'].astype('int')

print('Data types after correction:')
df.info()
```

```
Data types after correction:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 900514 entries, 0 to 900513
Data columns (total 36 columns):
 #   Column                      Non-Null Count   Dtype
---  ------                      --------------   -----
 0   product_id                  900514 non-null  int64
 1   product_type                900514 non-null  object
 2   product_name                900514 non-null  object
 3   product_description         900514 non-null  object
 4   product_keywords            900514 non-null  object
 5   product_gender_target       900514 non-null  object
 6   product_category            900514 non-null  object
 7   product_season              900512 non-null  object
 8   product_condition           900514 non-null  object
 9   product_like_count          900514 non-null  int64
 10  sold                        900514 non-null  int64
```

```
 11  reserved                    900514 non-null  bool
 12  available                   900514 non-null  bool
 13  in_stock                    900514 non-null  bool
 14  should_be_gone              900514 non-null  bool
 15  brand_id                    900514 non-null  int64
 16  brand_name                  900514 non-null  object
 17  brand_url                   900514 non-null  object
 18  product_material            900514 non-null  object
 19  product_color               900514 non-null  object
 20  price_usd                   900514 non-null  float64
 21  seller_price                900514 non-null  float64
 22  seller_earning              900514 non-null  float64
 23  seller_badge                900514 non-null  object
 24  has_cross_border_fees       886778 non-null  object
 25  buyers_fees                 886778 non-null  float64
 26  warehouse_name              900514 non-null  object
 27  seller_id                   900514 non-null  int64
 28  seller_username             900475 non-null  object
 29  usually_ships_within        900514 non-null  object
 30  seller_country              900514 non-null  object
 31  seller_products_sold        900514 non-null  int64
 32  seller_num_products_listed  900514 non-null  float64
 33  seller_community_rank       900514 non-null  float64
 34  seller_num_followers        900514 non-null  int64
 35  seller_pass_rate            900514 non-null  float64
dtypes: bool(4), float64(7), int64(7), object(18)
memory usage: 223.3+ MB
```

- **Handling Duplicates:**
  - Check for and remove any duplicate rows based on `product_id` to ensure each product is represented only once. Use `df.duplicated(subset=['product_id']).sum()`.

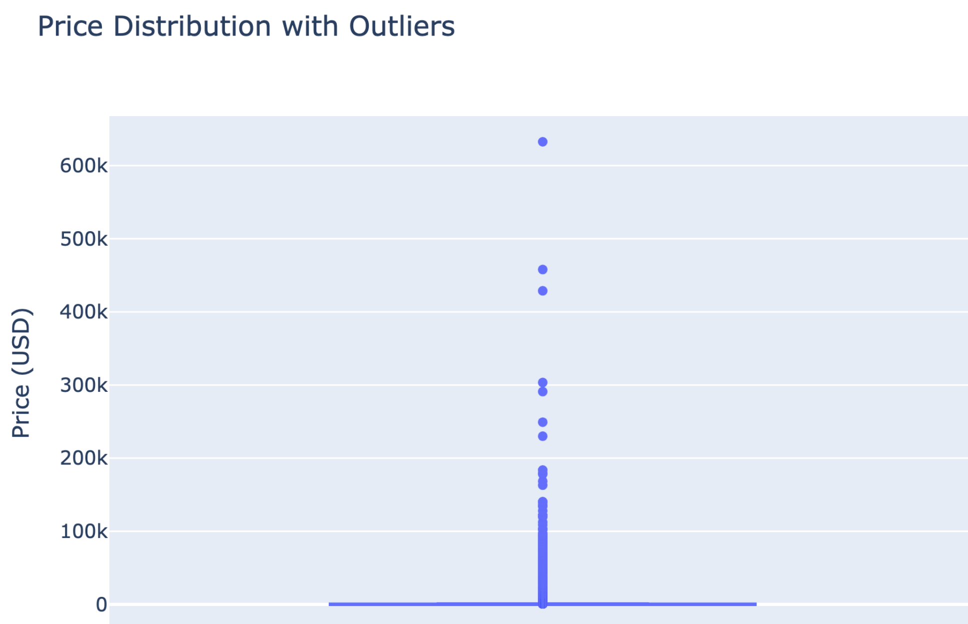
[10]:
```
print(f"Found {df.duplicated(subset=['product_id']).sum()} duplicate products␣
↪based on 'product_id'.")
df.drop_duplicates(subset=['product_id'], keep='first', inplace=True)
print(f"Shape after dropping duplicates: {df.shape}")
```

```
Found 0 duplicate products based on 'product_id'.
Shape after dropping duplicates: (900514, 36)
```

- **Outlier Treatment (for `price_usd`):**
  - Visualize the price distribution using a box plot to identify extreme outliers.
  - Calculate the Interquartile Range (IQR). Define outliers as values that fall below Q1 - 1.5 * IQR or above Q3 + 1.5 * IQR.
  - **Action:** Instead of removing outliers (which might be rare, expensive items), we will cap them at the 99th percentile to prevent them from skewing our analysis visualizations and averages, while still acknowledging their presence.

[11]:
```
fig = px.box(df, y='price_usd', title='Price Distribution with Outliers')
fig.update_layout(yaxis_title='Price (USD)')

img_bytes = fig.to_image(format="png", scale=3)
Image(img_bytes)
```

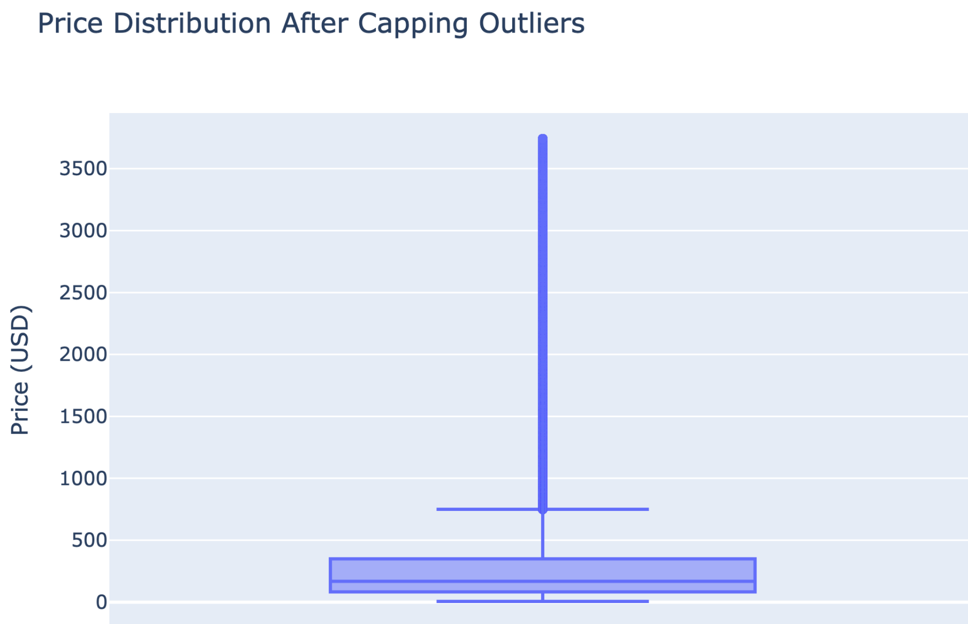
[11]:



[12]:
```
price_cap = df['price_usd'].quantile(0.99)
print(f"Capping prices at the 99th percentile: ${price_cap:,.2f}")
df['price_usd'] = np.where(df['price_usd'] > price_cap, price_cap,␣
    ↪df['price_usd'])

fig = px.box(df, y='price_usd', title='Price Distribution After Capping␣
    ↪Outliers')
fig.update_layout(yaxis_title='Price (USD)')

img_bytes = fig.to_image(format="png", scale=3)
Image(img_bytes)
```

```
Capping prices at the 99th percentile: $3,741.22
```

[12]:



- **Save Cleaned Data:**
  - Export the fully cleaned and preprocessed DataFrame to a new file named `cleaned_data.csv`. This file will be the single source of truth for the subsequent analysis.

[13]:
```
df.to_csv('cleaned_data.csv', index=False)
print("Cleaned data saved to 'cleaned_data.csv'")
```

```
Cleaned data saved to 'cleaned_data.csv'
```

0.0.3 Part 2: Exploratory Data Analysis (EDA)

This phase focuses on visualizing data and asking key questions to uncover patterns, trends, and relationships.

2.1. Sales Performance Analysis: * **Overall Sell-Through Rate:** Calculate the percentage of products marked as `sold`. This is our primary KPI.

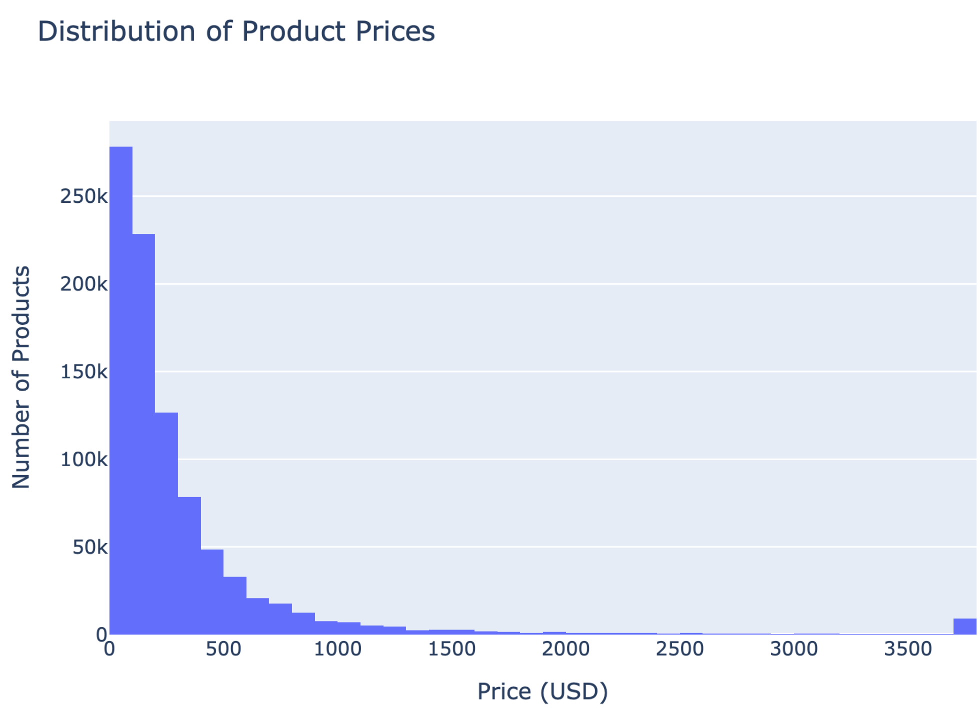
[14]:
```
sell_through_rate = df['sold'].mean()
print(f"Overall Sell-Through Rate: {sell_through_rate:.2%}")
```

```
Overall Sell-Through Rate: 1.53%
```

- **Price Distribution:**
  - Plot a histogram of `price_usd` to understand the most common price points.

[15]:
```python
fig = px.histogram(df, x='price_usd', nbins=50, title='Distribution of Product Prices')
fig.update_layout(xaxis_title='Price (USD)', yaxis_title='Number of Products')

img_bytes = fig.to_image(format="png", scale=3)
Image(img_bytes)
```

[15]:



- Analyze the relationship between `price_usd` and sales. Bin prices into logical groups (e.g., <$500, $500-$1000, $1000-$2000, $2000+) and calculate the sell-through rate for each bin. Visualize this with a bar chart.

[17]:
```python
price_bins = [0, 500, 1000, 2000, df['price_usd'].max()]
price_labels = ['<$500', '$500-$1000', '$1000-$2000', '$2000+']
df['price_bin'] = pd.cut(df['price_usd'], bins=price_bins, labels=price_labels, right=False)

sell_through_by_price = df.groupby('price_bin')['sold'].mean().reset_index()

fig = px.bar(sell_through_by_price, x='price_bin', y='sold',
             title='Sell-Through Rate by Price Bin',
             labels={'price_bin': 'Price Bin', 'sold': 'Sell-Through Rate'})
fig.update_layout(yaxis_tickformat='.0%')
```

```
img_bytes = fig.to_image(format="png", scale=3)
Image(img_bytes)
```

```
/var/folders/9r/_l7v_srn15z38xsssh084f4m0000gn/T/ipykernel_50017/923203120.py:5:
FutureWarning:

The default of observed=False is deprecated and will be changed to True in a
future version of pandas. Pass observed=False to retain current behavior or
observed=True to adopt the future default and silence this warning.
```

[17]:

2.2. Product Attribute Analysis: * **Top Performing Categories:** * Create a bar chart of `product_category` and `product_type` counts to identify the most listed item types.

[18]:

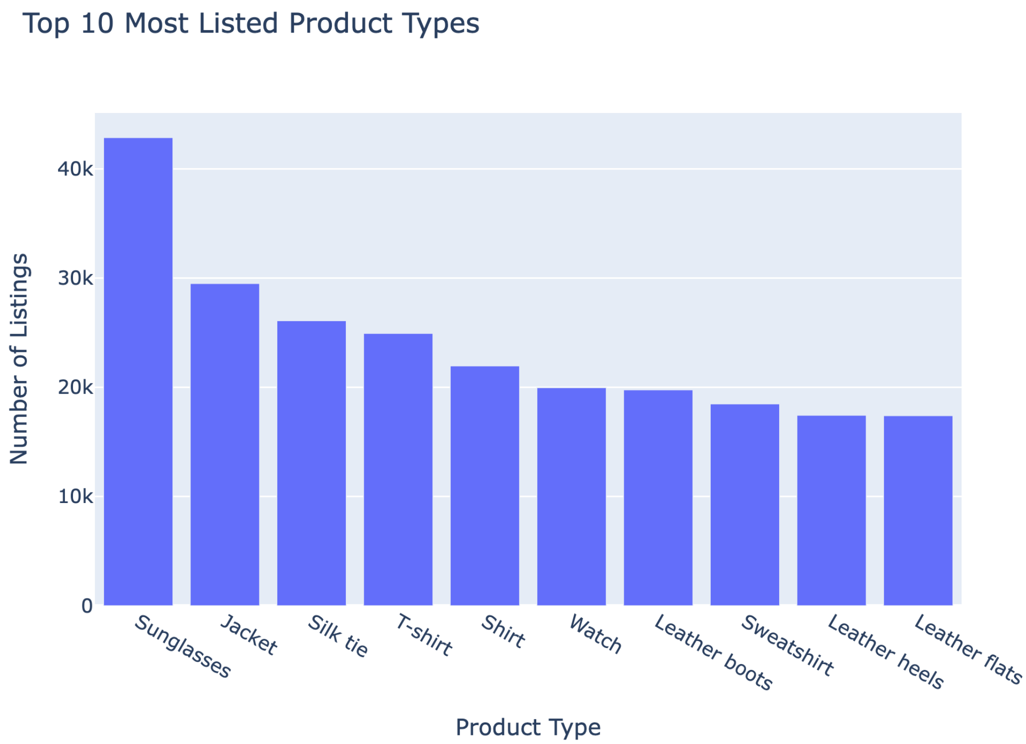
```
category_counts = df['product_category'].value_counts().reset_index()
category_counts.columns = ['Category', 'Count']

fig = px.bar(category_counts, x='Category', y='Count', title='Number of␣
↪Listings by Product Category')
fig.update_layout(xaxis_title='Product Category', yaxis_title='Number of␣
↪Listings')
```

```
img_bytes = fig.to_image(format="png", scale=3)
Image(img_bytes)
```

[18]:

[19]:
```
type_counts = df['product_type'].value_counts().nlargest(10).reset_index()
type_counts.columns = ['Type', 'Count']

fig = px.bar(type_counts, x='Type', y='Count', title='Top 10 Most Listed␣
↪Product Types')
fig.update_layout(xaxis_title='Product Type', yaxis_title='Number of Listings')

img_bytes = fig.to_image(format="png", scale=3)
Image(img_bytes)
```

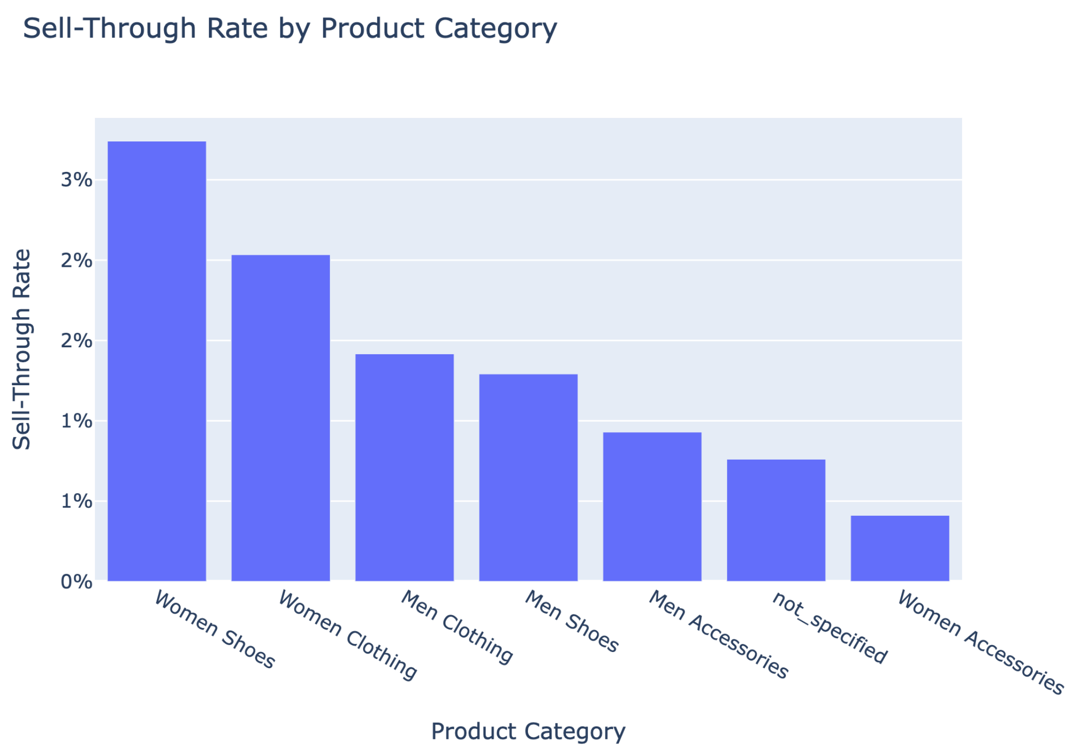
[19]:



- Create a bar chart showing the sell-through rate by `product_category`. This will reveal which categories are most in-demand.

[21]:
```
sell_through_by_category = df.groupby('product_category')['sold'].mean().
↪sort_values(ascending=False).reset_index()

fig = px.bar(sell_through_by_category, x='product_category', y='sold',
             title='Sell-Through Rate by Product Category',
             labels={'product_category': 'Product Category', 'sold':␣
↪'Sell-Through Rate'})
fig.update_layout(yaxis_tickformat='.0%')

img_bytes = fig.to_image(format="png", scale=3)
Image(img_bytes)
```

[21]:



- **Impact of Condition:**
  - Use a box plot to show the distribution of `price_usd` for each `product_condition`.
  - Use a bar chart to show the sell-through rate for each `product_condition`.

[22]:
```
condition_order = ['Like new', 'Very good condition', 'Good condition', 'Fair␣
↪condition']
df['product_condition'] = pd.Categorical(df['product_condition'],␣
↪categories=condition_order, ordered=True)

fig = px.box(df.sort_values('product_condition'), x='product_condition',␣
↪y='price_usd',
             title='Price Distribution by Product Condition',
             labels={'product_condition': 'Product Condition', 'price_usd':␣
↪'Price (USD)'})

img_bytes = fig.to_image(format="png", scale=3)
Image(img_bytes)
```

[22]:

[23]:
```
sell_through_by_condition = df.groupby('product_condition')['sold'].mean().
    ↪reset_index()

fig = px.bar(sell_through_by_condition, x='product_condition', y='sold',
             title='Sell-Through Rate by Product Condition',
             labels={'product_condition': 'Product Condition', 'sold':␣
    ↪'Sell-Through Rate'})
fig.update_layout(yaxis_tickformat='.0%')

img_bytes = fig.to_image(format="png", scale=3)
Image(img_bytes)
```

```
/var/folders/9r/_l7v_srn15z38xsssh084f4m0000gn/T/ipykernel_50017/2233563037.py:1
: FutureWarning:

The default of observed=False is deprecated and will be changed to True in a
future version of pandas. Pass observed=False to retain current behavior or
observed=True to adopt the future default and silence this warning.
```

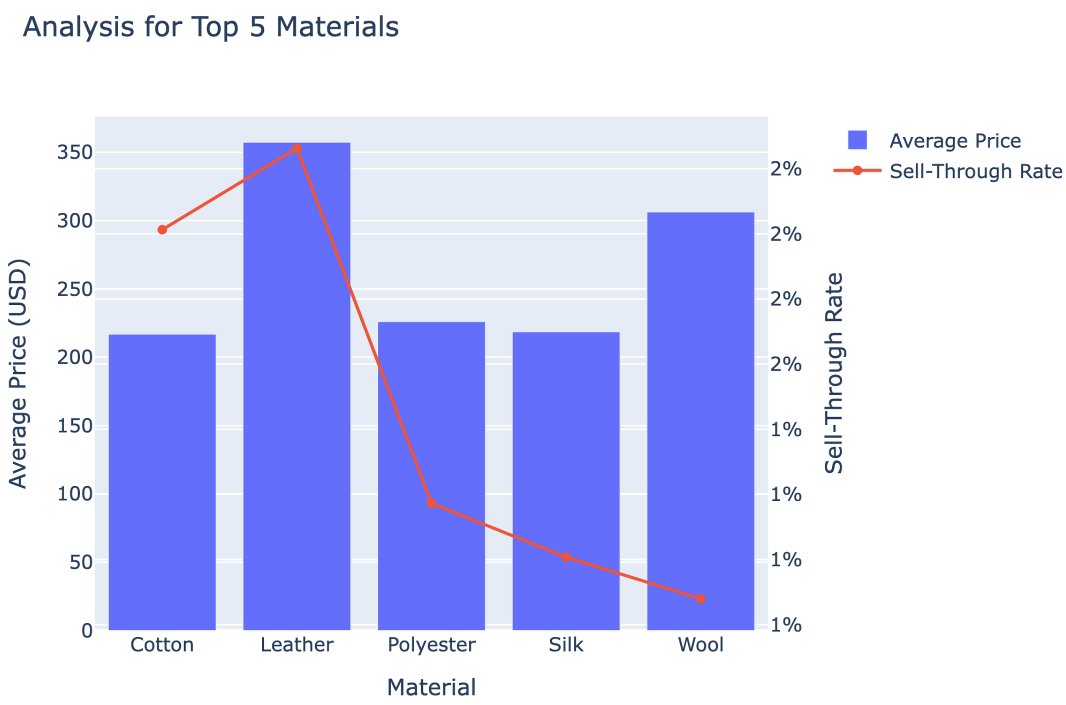
[23]:

- **Color and Material:**
  - Analyze the most common `product_material` and `product_color` combinations.
  - Calculate the average price and sell-through rate for the top 5 materials and colors to see which drive value and demand.

[24]:
```
top_materials = df['product_material'].value_counts().nlargest(5).index
material_analysis = df[df['product_material'].isin(top_materials)]

material_summary = material_analysis.groupby('product_material').agg(
    avg_price=('price_usd', 'mean'),
    sell_through_rate=('sold', 'mean')
).reset_index()

fig = make_subplots(specs=[[{"secondary_y": True}]])

fig.add_trace(go.Bar(x=material_summary['product_material'],␣
↪y=material_summary['avg_price'], name='Average Price'), secondary_y=False)
fig.add_trace(go.Scatter(x=material_summary['product_material'],␣
↪y=material_summary['sell_through_rate'], name='Sell-Through Rate',␣
↪mode='lines+markers'), secondary_y=True)
```

```
fig.update_layout(title_text='Analysis for Top 5 Materials',␣
    ↪xaxis_title='Material')
fig.update_yaxes(title_text='Average Price (USD)', secondary_y=False)
fig.update_yaxes(title_text='Sell-Through Rate', secondary_y=True, tickformat='.
    ↪0%')

img_bytes = fig.to_image(format="png", scale=3)
Image(img_bytes)
```

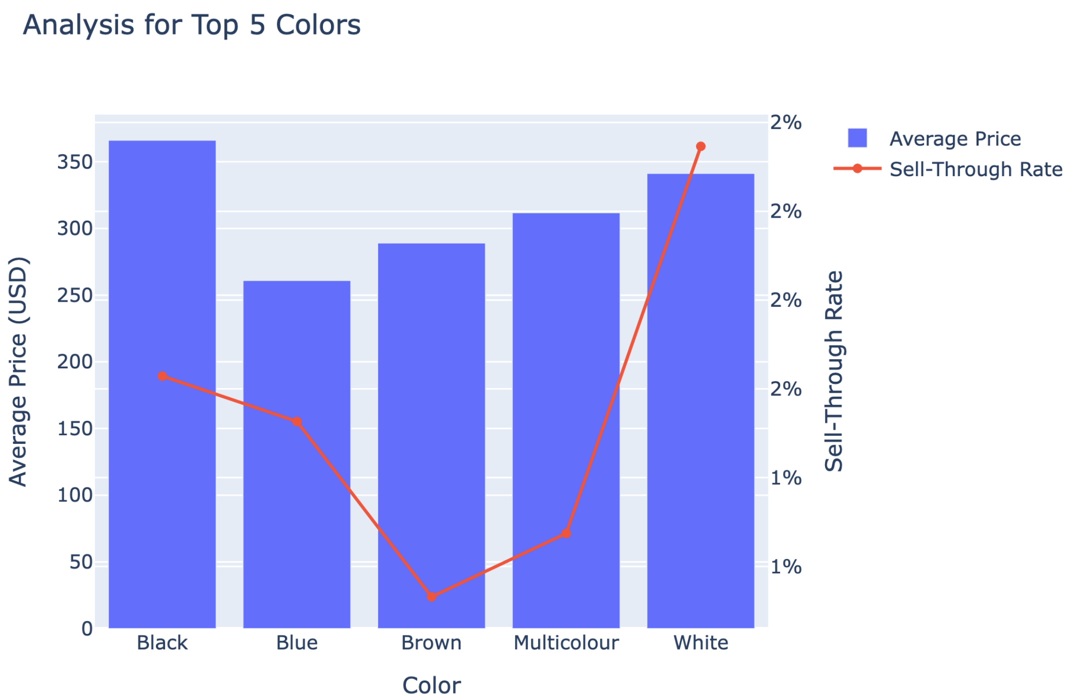
[24]:



[25]:
```
top_colors = df['product_color'].value_counts().nlargest(5).index
color_analysis = df[df['product_color'].isin(top_colors)]

color_summary = color_analysis.groupby('product_color').agg(
    avg_price=('price_usd', 'mean'),
    sell_through_rate=('sold', 'mean')
).reset_index()

fig = make_subplots(specs=[[{"secondary_y": True}]])

fig.add_trace(go.Bar(x=color_summary['product_color'],␣
    ↪y=color_summary['avg_price'], name='Average Price'), secondary_y=False)
```

```
fig.add_trace(go.Scatter(x=color_summary['product_color'],␣
 ↪y=color_summary['sell_through_rate'], name='Sell-Through Rate',␣
 ↪mode='lines+markers'), secondary_y=True)

fig.update_layout(title_text='Analysis for Top 5 Colors', xaxis_title='Color')
fig.update_yaxes(title_text='Average Price (USD)', secondary_y=False)
fig.update_yaxes(title_text='Sell-Through Rate', secondary_y=True, tickformat='.
 ↪0%')

img_bytes = fig.to_image(format="png", scale=3)
Image(img_bytes)
```

[25]:



- **Impact of Seller Reputation:**
  - Compare the average sell-through rate for products listed by sellers with different `seller_badge` types (e.g., 'Trusted Seller', 'Expert Seller' vs. 'No Badge').

[29]:

```
sell_through_by_badge = df.groupby('seller_badge')['sold'].mean().
 ↪sort_values(ascending=False).reset_index()

fig = px.bar(sell_through_by_badge, x='seller_badge', y='sold',
             title='Sell-Through Rate by Seller Badge',
```

```
                labels={'seller_badge': 'Seller Badge', 'sold': 'Sell-Through␣
↪Rate'})
fig.update_layout(yaxis_tickformat='.0%')

img_bytes = fig.to_image(format="png", scale=3)
Image(img_bytes)
```

[29]:

- **Geographic Analysis:**
  - Create a bar chart of `seller_country` to identify the top countries where sellers are located.

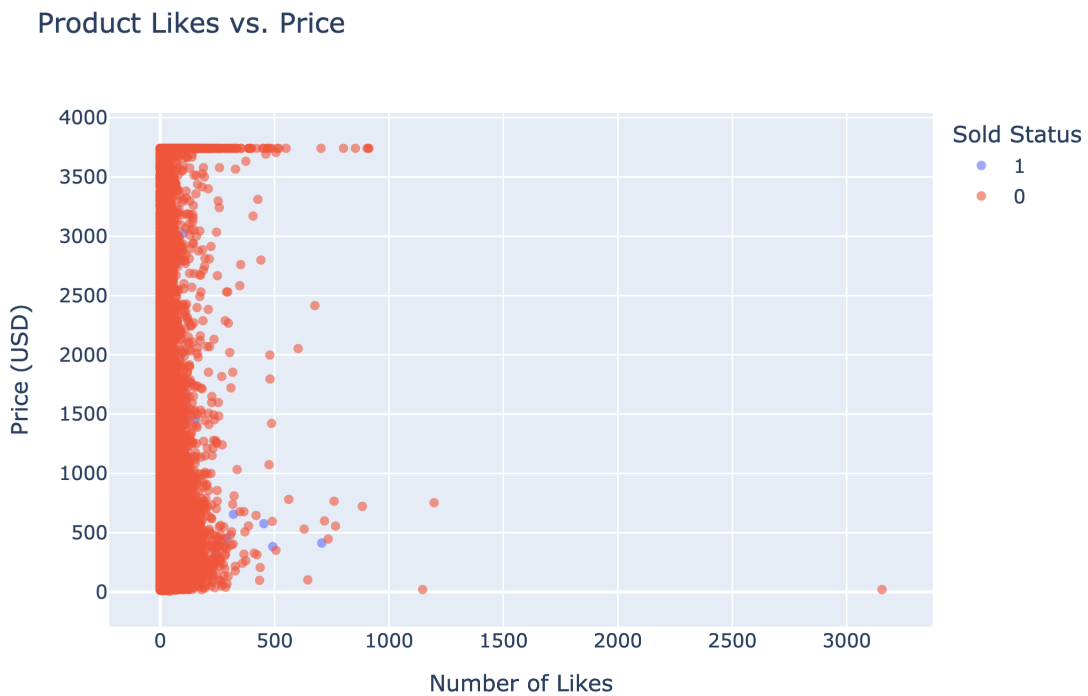
[30]:
```
country_counts = df['seller_country'].value_counts().nlargest(10).reset_index()
country_counts.columns = ['Country', 'Count']

fig = px.bar(country_counts, x='Country', y='Count', title='Top 10 Seller␣
↪Countries by Number of Listings')
fig.update_layout(xaxis_title='Seller Country', yaxis_title='Number of␣
↪Listings')

img_bytes = fig.to_image(format="png", scale=3)
Image(img_bytes)
```

[30]:

2.4. Customer Engagement Analysis: * "Likes" as a Purchase Indicator: * Create a scatter plot of `product_like_count` vs. `price_usd`. * Compare the average `product_like_count` for `sold` vs. `unsold` items. This will test the hypothesis that higher engagement correlates with sales.

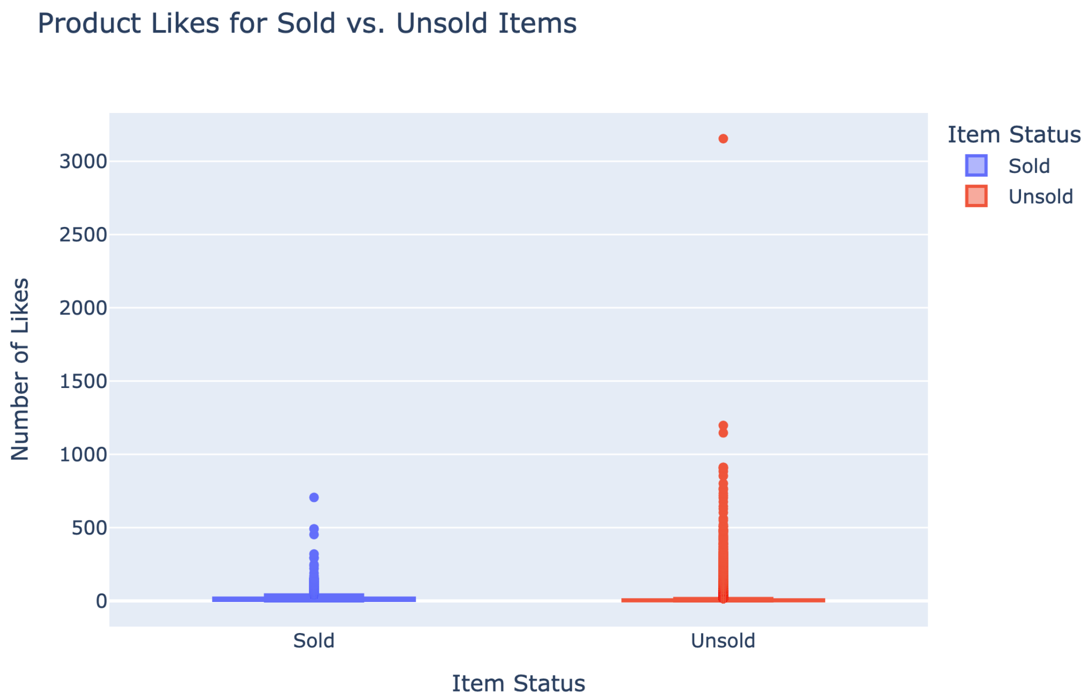
[31]:
```
fig = px.scatter(df, x='product_like_count', y='price_usd',
                 color=df['sold'].astype(str),
                 title='Product Likes vs. Price',
                 labels={'product_like_count': 'Number of Likes', 'price_usd':␣
 ↪'Price (USD)', 'color': 'Sold Status'},
                 opacity=0.6)
fig.update(layout_coloraxis_showscale=False)

img_bytes = fig.to_image(format="png", scale=3)
Image(img_bytes)
```

[31]:



[32]:
```
df['Sold Status'] = df['sold'].map({1: 'Sold', 0: 'Unsold'})
fig = px.box(df, x='Sold Status', y='product_like_count',
             color='Sold Status',
             title='Product Likes for Sold vs. Unsold Items',
             labels={'Sold Status': 'Item Status', 'product_like_count':␣
 ↪'Number of Likes'})

img_bytes = fig.to_image(format="png", scale=3)
Image(img_bytes)
```

[32]:



0.0.4 Part 3: Key Insights & Predictions

This section synthesizes the EDA findings into a compelling narrative for stakeholders.

- **Insight 1: The Pricing "Sweet Spot":** There is a specific price range where products have the highest likelihood of selling. Products priced significantly above or below this range tend to stagnate.
- **Insight 2: Condition is Non-Negotiable:** Products in "Very Good" or "Like New" condition not only sell for higher prices but also have a dramatically higher sell-through rate. Condition is a key driver of both value and velocity.
- **Insight 3: Trust Sells:** Sellers with "Trusted" or "Expert" badges consistently outperform others. This demonstrates that buyer confidence in the seller is a critical factor in the purchasing decision.
- **Insight 4: Hero Products & Categories:** Handbags and small leather goods remain the most popular and fastest-selling categories. Classic materials like leather are more sought-after than seasonal or trendy materials.
- **Insight 5: Likes Signal Intent:** A higher number of "likes" on a product is a strong positive indicator of its probability of being sold, making it a valuable metric for demand forecasting.

0.0.5 Part 4: Actionable Recommendations for Gucci Stakeholders

Translate insights into concrete, data-driven business strategies.

- **1. Implement a Dynamic Pricing Guide for Sellers:**
  - **Recommendation:** Develop an automated tool that suggests an optimal price range to sellers during the listing process.
  - **Justification:** This addresses **Insight 1**. It will help sellers price competitively, increasing their sell-through rate and boosting platform-wide sales velocity. The tool should use the product's category, condition, and material as inputs.
- **2. Refine Inventory Sourcing and Promotion:**
  - **Recommendation:** Actively encourage sellers to list items in high-demand categories (Handbags, Shoes) and pristine condition. Offer reduced commission fees or promotional visibility for these items.
  - **Justification:** This leverages **Insights 2 & 4**. It ensures a steady supply of what customers want most, improving the overall attractiveness of the platform.
- **3. Launch a "Premier Seller" Program:**
  - **Recommendation:** Create a tiered program that rewards sellers who maintain a high sell-through rate, high pass rate, and positive community feedback. Benefits could include lower fees, priority support, and a "Premier Seller" badge.
  - **Justification:** Based on **Insight 3**, this fosters a community of high-quality sellers, which in turn builds buyer trust and encourages repeat purchases.
- **4. Leverage Engagement Metrics for Marketing:**
  - **Recommendation:** Automate marketing campaigns based on engagement. For example, automatically feature products with a high number of "likes" in a "Trending Now" section on the homepage or in targeted emails.
  - **Justification:** This capitalizes on **Insight 5**. It uses social proof to create urgency and drive conversions for items that have already demonstrated popular appeal.

0.0.6 Part 5: Predictive Modeling Suggestions

Propose advanced analytical models to further enhance business intelligence and automate decision-making.

- **1. Sales Prediction Model (Classification):**
  - **Objective:** Predict if a newly listed product will sell within 90 days.
  - **Model:** Random Forest or XGBoost Classifier.
  - **Features:** `price_usd`, `product_category`, `product_condition`, `seller_badge`, `seller_pass_rate`, `product_like_count`, `product_material`.
  - **Business Value:** Can identify "at-risk" listings that are unlikely to sell, allowing for proactive interventions like recommending a price drop to the seller.
- **2. Optimal Price Recommender (Regression):**
  - **Objective:** Predict the ideal selling price of an item to maximize both profit and speed of sale.
  - **Model:** Gradient Boosting Regressor.
  - **Features:** `product_category`, `product_condition`, `product_material`, `brand_name`. The model would be trained on the prices of items that have successfully sold.

  - **Business Value:** This would be the engine powering the "Dynamic Pricing Guide" (Recommendation 1), providing data-driven, accurate price suggestions at scale.

- **3. Seller Segmentation Model (Clustering):**
  - **Objective:** Group sellers into distinct clusters (e.g., 'Power Sellers', 'Casual Sellers', 'Boutique Specialists').
  - **Model:** K-Means Clustering.
  - **Features:** `seller_products_sold`, `seller_num_products_listed`, average item price, sell-through rate.
  - **Business Value:** Enables highly targeted communication and incentive programs for different seller types, maximizing their engagement and performance on the platform.