In [53]:
```python
import pandas as pd

# Load the product and category files
products_df = pd.read_csv('archive/amazon_products.csv')
categories_df = pd.read_csv('archive/amazon_categories.csv')
```

In [54]:
```python
products_df.head()
```

Out[54]:

	asin	title	imgUrl	productURL	stars	reviews	price	listPrice	categor
0	B014TMV5YE	Sion Softside Expandable Roller Luggage, Black...	https://m.media-amazon.com/images/I/815dLQKYIY...	https://www.amazon.com/dp/B014TMV5YE	4.5	0	139.99	0.00	
1	B07GDLCQXV	Luggage Sets Expandable PC+ABS Durable Suitcas...	https://m.media-amazon.com/images/I/81bQlm7vf6...	https://www.amazon.com/dp/B07GDLCQXV	4.5	0	169.99	209.99	
2	B07XSCCZYG	Platinum Elite Softside Expandable Checked Lug...	https://m.media-amazon.com/images/I/71EA35zvJB...	https://www.amazon.com/dp/B07XSCCZYG	4.6	0	365.49	429.99	
3	B08MVFKGJM	Freeform Hardside Expandable with Double Spinn...	https://m.media-amazon.com/images/I/91k6NYLQyI...	https://www.amazon.com/dp/B08MVFKGJM	4.6	0	291.59	354.37	
4	B01DJLKZBA	Winfield 2 Hardside Expandable Luggage with Sp...	https://m.media-amazon.com/images/I/61NJoaZcP9...	https://www.amazon.com/dp/B01DJLKZBA	4.5	0	174.99	309.99	

In [55]:
```python
categories_df.head()
```

Out[55]:

	id	category_name
0	1	Beading & Jewelry Making
1	2	Fabric Decorating
2	3	Knitting & Crochet Supplies
3	4	Printmaking Supplies
4	5	Scrapbooking & Stamping Supplies

In [56]:
```python
merged_df = products_df.merge(categories_df, how='left', left_on='category_id', right_on='id')
merged_df.head()
```

Out[56]:

	asin	title	imgUrl	productURL	stars	reviews	price	listPrice	categor
0	B014TMV5YE	Sion Softside Expandable Roller Luggage, Black...	https://m.media-amazon.com/images/I/815dLQKYIY...	https://www.amazon.com/dp/B014TMV5YE	4.5	0	139.99	0.00	
1	B07GDLCQXV	Luggage Sets Expandable PC+ABS Durable Suitcas...	https://m.media-amazon.com/images/I/81bQlm7vf6...	https://www.amazon.com/dp/B07GDLCQXV	4.5	0	169.99	209.99	
2	B07XSCCZYG	Platinum Elite Softside Expandable Checked Lug...	https://m.media-amazon.com/images/I/71EA35zvJB...	https://www.amazon.com/dp/B07XSCCZYG	4.6	0	365.49	429.99	
3	B08MVFKGJM	Freeform Hardside	https://m.media-amazon.com/images/I/91k6NYLQyI...	https://www.amazon.com/dp/B08MVFKGJM	4.6	0	291.59	354.37	

	asin	title	imgUrl	productURL	stars	reviews	price	listPrice	categor
		Expandable with Double Spinn...							
4	B01DJLKZBA	Winfield 2 Hardside Expandable Luggage with Sp...	https://m.media-amazon.com/images/I/61NJoaZcP9...	https://www.amazon.com/dp/B01DJLKZBA	4.5	0	174.99	309.99	

In [57]:

```
merged_df.drop(columns=['id'], inplace=True)
merged_df.head()
```

Out[57]:

	asin	title	imgUrl	productURL	stars	reviews	price	listPrice	categor
0	B014TMV5YE	Sion Softside Expandable Roller Luggage, Black...	https://m.media-amazon.com/images/I/815dLQKYIY...	https://www.amazon.com/dp/B014TMV5YE	4.5	0	139.99	0.00	
1	B07GDLCQXV	Luggage Sets Expandable PC+ABS Durable Suitcas...	https://m.media-amazon.com/images/I/81bQlm7vf6...	https://www.amazon.com/dp/B07GDLCQXV	4.5	0	169.99	209.99	
2	B07XSCCZYG	Platinum Elite Softside Expandable Checked Lug...	https://m.media-amazon.com/images/I/71EA35zvJB...	https://www.amazon.com/dp/B07XSCCZYG	4.6	0	365.49	429.99	
3	B08MVFKGJM	Freeform Hardside Expandable with	https://m.media-amazon.com/images/I/91k6NYLQyI...	https://www.amazon.com/dp/B08MVFKGJM	4.6	0	291.59	354.37	

	asin	title	imgUrl	productURL	stars	reviews	price	listPrice	categor
		Double Spinn...							
4	B01DJLKZBA	Winfield 2 Hardside Expandable Luggage with Sp...	https://m.media-amazon.com/images/I/61NJoaZcP9...	https://www.amazon.com/dp/B01DJLKZBA	4.5	0	174.99	309.99	

In [58]:

```
merged_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1426337 entries, 0 to 1426336
Data columns (total 12 columns):
 #   Column             Non-Null Count    Dtype  
---  ------             --------------    -----  
 0   asin               1426337 non-null  object 
 1   title              1426336 non-null  object 
 2   imgUrl             1426337 non-null  object 
 3   productURL         1426337 non-null  object 
 4   stars              1426337 non-null  float64
 5   reviews            1426337 non-null  int64  
 6   price              1426337 non-null  float64
 7   listPrice          1426337 non-null  float64
 8   category_id        1426337 non-null  int64  
 9   isBestSeller       1426337 non-null  bool   
 10  boughtInLastMonth  1426337 non-null  int64  
 11  category_name      1426337 non-null  object 
dtypes: bool(1), float64(3), int64(3), object(5)
memory usage: 131.9+ MB
```

In [59]:

```
merged_df.isnull().sum()
```

Out[59]:

```
asin                 0
title                1
imgUrl               0
productURL           0
stars                0
reviews              0
price                0
listPrice            0
category_id          0
isBestSeller         0
```

```
boughtInLastMonth    0
category_name        0
dtype: int64
```

In [60]:

```
merged_df.dropna(subset=['title'], inplace=True)
```

In [61]:

```
# Calculate discount percentage
merged_df['discount_percentage'] = ((merged_df['listPrice'] - merged_df['price']) / merged_df['listPrice']) * 100
merged_df['discount_percentage'].fillna(0, inplace=True)
merged_df['discount_percentage'] = merged_df['discount_percentage'].replace([float('-inf')], 0)
merged_df.head()
```

Out[61]:

	asin	title	imgUrl	productURL	stars	reviews	price	listPrice	categor
0	B014TMV5YE	Sion Softside Expandable Roller Luggage, Black...	https://m.media-amazon.com/images/I/815dLQKYIY...	https://www.amazon.com/dp/B014TMV5YE	4.5	0	139.99	0.00	
1	B07GDLCQXV	Luggage Sets Expandable PC+ABS Durable Suitcas...	https://m.media-amazon.com/images/I/81bQlm7vf6...	https://www.amazon.com/dp/B07GDLCQXV	4.5	0	169.99	209.99	
2	B07XSCCZYG	Platinum Elite Softside Expandable Checked Lug...	https://m.media-amazon.com/images/I/71EA35zvJB...	https://www.amazon.com/dp/B07XSCCZYG	4.6	0	365.49	429.99	
3	B08MVFKGJM	Freeform Hardside Expandable with Double Spinn...	https://m.media-amazon.com/images/I/91k6NYLQyI...	https://www.amazon.com/dp/B08MVFKGJM	4.6	0	291.59	354.37	
4	B01DJLKZBA	Winfield 2 Hardside Expandable	https://m.media-amazon.com/images/I/61NJoaZcP9...	https://www.amazon.com/dp/B01DJLKZBA	4.5	0	174.99	309.99	

	asin	title	imgUrl	productURL	stars	reviews	price	listPrice	categor
		Luggage with Sp...							

In [62]:
```
merged_df['popularity_score'] = merged_df['stars'] * merged_df['reviews']
```

In [63]:
```
category_freq = merged_df['category_name'].value_counts(normalize=True)
merged_df['category_freq'] = merged_df['category_name'].map(category_freq)
```

In [64]:
```
merged_df['price_range'] = pd.qcut(merged_df['price'], q=5, labels=['Very Low', 'Low', 'Medium', 'High', 'Very High'])
```

In [65]:
```
# Calculate average stars and reviews for bestsellers and non-bestsellers
bestseller_stats = merged_df.groupby('isBestSeller').agg(
    avg_stars=('stars', 'mean'),
    avg_reviews=('reviews', 'mean')
).reset_index()

print(bestseller_stats)
```

```
   isBestSeller  avg_stars  avg_reviews
0         False   3.996539   167.903922
1          True   4.494038  2318.628521
```

In [66]:
```
merged_df['has_discount'] = merged_df['discount_percentage'] > 0
```

In [67]:
```
merged_df.head()
```

Out[67]:

	asin	title	imgUrl	productURL	stars	reviews	price	listPrice	categor
0	B014TMV5YE	Sion Softside Expandable Roller Luggage, Black...	https://m.media-amazon.com/images/I/815dLQKYIY...	https://www.amazon.com/dp/B014TMV5YE	4.5	0	139.99	0.00	

	asin	title	imgUrl	productURL	stars	reviews	price	listPrice	categor
1	B07GDLCQXV	Luggage Sets Expandable PC+ABS Durable Suitcas...	https://m.media-amazon.com/images/I/81bQlm7vf6...	https://www.amazon.com/dp/B07GDLCQXV	4.5	0	169.99	209.99	
2	B07XSCCZYG	Platinum Elite Softside Expandable Checked Lug...	https://m.media-amazon.com/images/I/71EA35zvJB...	https://www.amazon.com/dp/B07XSCCZYG	4.6	0	365.49	429.99	
3	B08MVFKGJM	Freeform Hardside Expandable with Double Spinn...	https://m.media-amazon.com/images/I/91k6NYLQyI...	https://www.amazon.com/dp/B08MVFKGJM	4.6	0	291.59	354.37	
4	B01DJLKZBA	Winfield 2 Hardside Expandable Luggage with Sp...	https://m.media-amazon.com/images/I/61NJoaZcP9...	https://www.amazon.com/dp/B01DJLKZBA	4.5	0	174.99	309.99	

In [68]:

```
merged_df.price.describe()
```

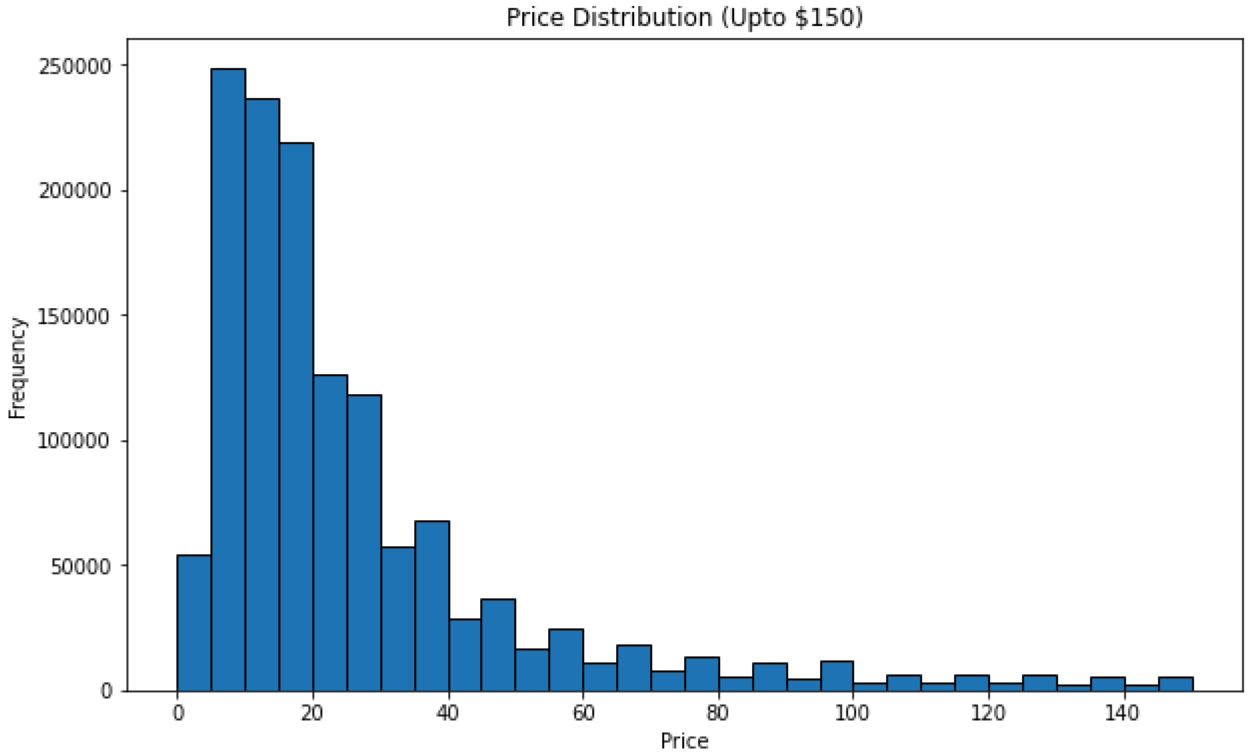
Out[68]:

```
count    1.426336e+06
mean     4.337541e+01
std      1.302893e+02
min      0.000000e+00
25%      1.199000e+01
50%      1.995000e+01
75%      3.599000e+01
max      1.973181e+04
Name: price, dtype: float64
```

In [69]:

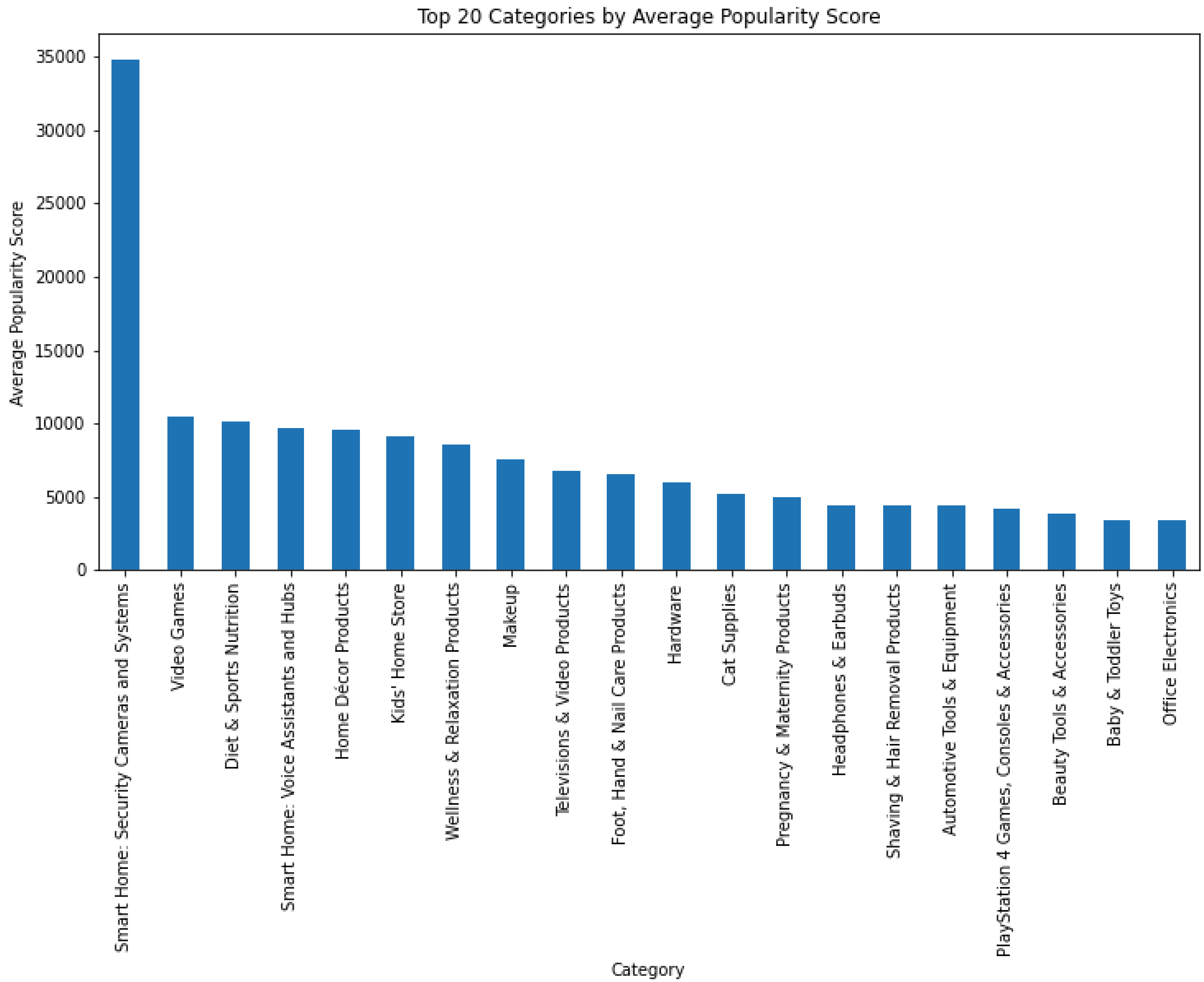
```
import matplotlib.pyplot as plt
filtered_df = merged_df[merged_df['price'] <= 150]
```

```
plt.figure(figsize=(10, 6))
filtered_df['price'].plot(kind='hist', bins=30, edgecolor='black')
plt.title('Price Distribution (Upto $150)')
plt.xlabel('Price')
plt.ylabel('Frequency')
plt.show()
```



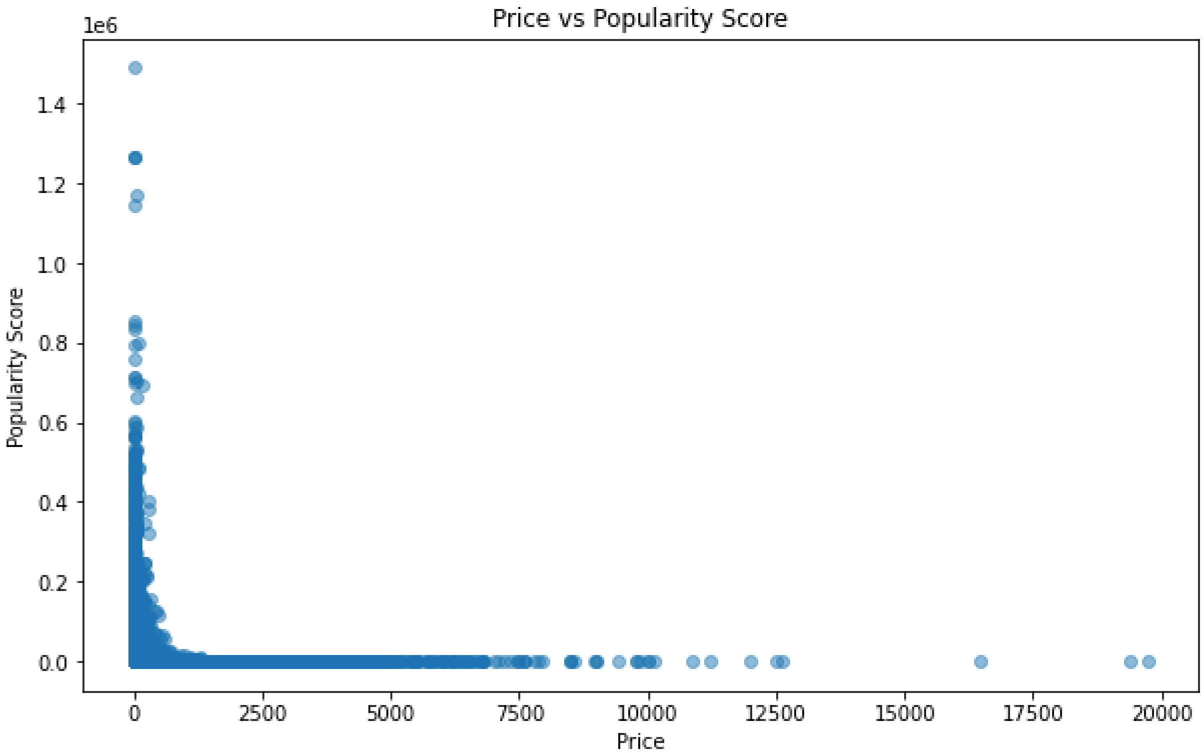
In [70]:

```
category_popularity = merged_df.groupby('category_name')['popularity_score'].mean().sort_values(ascending=False)
top_categories = category_popularity.head(20)
top_categories.plot(kind='bar', figsize=(12, 6))
plt.title('Top 20 Categories by Average Popularity Score')
plt.xlabel('Category')
plt.ylabel('Average Popularity Score')
plt.show()
```



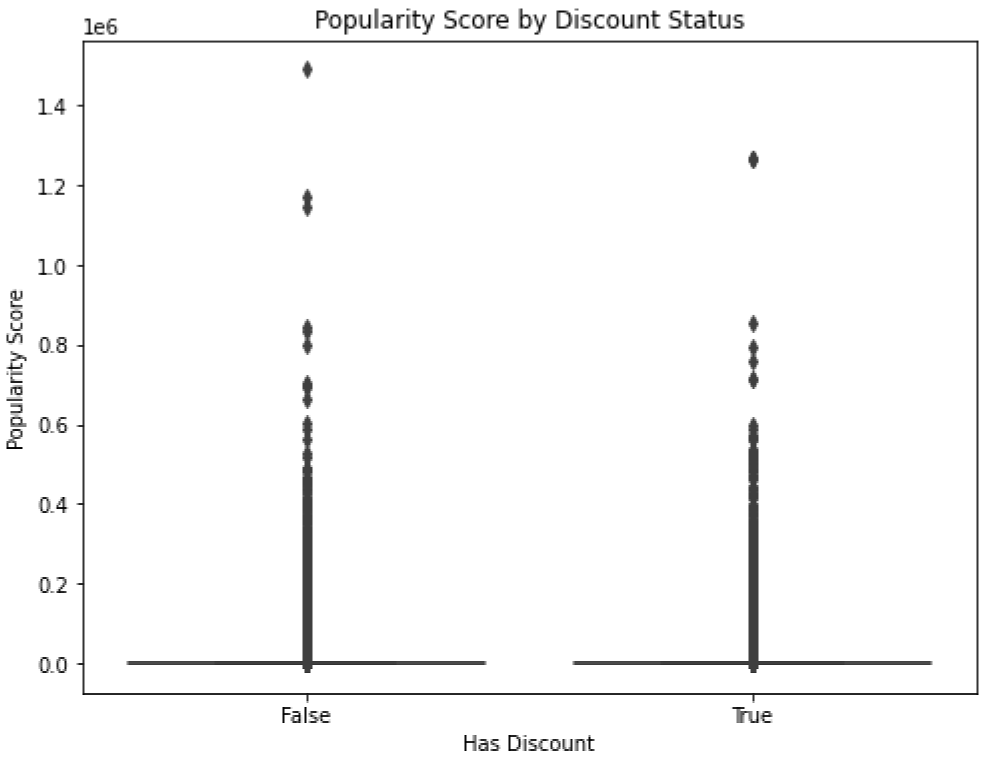
In [71]:

```
plt.figure(figsize=(10, 6))
plt.scatter(merged_df['price'], merged_df['popularity_score'], alpha=0.5)
plt.title('Price vs Popularity Score')
plt.xlabel('Price')
plt.ylabel('Popularity Score')
plt.show()
```



In [72]:

```
import seaborn as sns

plt.figure(figsize=(8, 6))
sns.boxplot(x='has_discount', y='popularity_score', data=merged_df)
plt.title('Popularity Score by Discount Status')
plt.xlabel('Has Discount')
plt.ylabel('Popularity Score')
plt.show()
```



In [73]:

```python
import seaborn as sns

# Calculate average price and discount percentage for best-sellers vs. non-best-sellers
bestseller_analysis = merged_df.groupby('isBestSeller').agg(
    avg_price=('price', 'mean'),
    avg_discount_percentage=('discount_percentage', 'mean')
).reset_index()
```

In [74]:

```python
# Plotting the average price and discount percentage for best-sellers vs. non-best-sellers
fig, ax1 = plt.subplots(figsize=(12, 6))

# Plotting average price
sns.barplot(x='isBestSeller', y='avg_price', data=bestseller_analysis, ax=ax1, palette='viridis')
ax1.set_ylabel('Average Price', color='b')
ax1.set_title('Average Price and Discount Percentage for Best-Sellers vs. Non-Best-Sellers')

# Creating a second y-axis for the discount percentage
ax2 = ax1.twinx()
```

```
sns.lineplot(x='isBestSeller', y='avg_discount_percentage', data=bestseller_analysis, ax=ax2, color='r', marker='o')
ax2.set_ylabel('Average Discount Percentage', color='r')

plt.show()
```

In [75]:

```
# Convert 'price_range' to numerical values
price_range_mapping = {'Very Low': 1, 'Low': 2, 'Medium': 3, 'High': 4, 'Very High': 5}
merged_df['price_range_num'] = merged_df['price_range'].map(price_range_mapping).astype(int)

# Convert 'has_discount' to numerical values (True -> 1, False -> 0)
merged_df['has_discount_num'] = merged_df['has_discount'].astype(int)

#Convert 'isBestSeller' to numerical values (True -> 1, False -> 0)
merged_df['isBestSeller_num'] = merged_df['isBestSeller'].astype(int)

# Display the updated dataframe
merged_df.head()
```

```
c:\Users\harsh\AppData\Local\Programs\Python\Python38\lib\site-packages\pandas\core\arrays\categorical.py:528: RuntimeWar
ning: invalid value encountered in cast
```

```
fill_value = lib.item_from_zerodim(np.array(np.nan).astype(dtype))
```

Out[75]:

	asin	title	imgUrl	productURL	stars	reviews	price	listPrice	categor
0	B014TMV5YE	Sion Softside Expandable Roller Luggage, Black...	https://m.media-amazon.com/images/I/815dLQKYIY...	https://www.amazon.com/dp/B014TMV5YE	4.5	0	139.99	0.00	
1	B07GDLCQXV	Luggage Sets Expandable PC+ABS Durable Suitcas...	https://m.media-amazon.com/images/I/81bQlm7vf6...	https://www.amazon.com/dp/B07GDLCQXV	4.5	0	169.99	209.99	
2	B07XSCCZYG	Platinum Elite Softside Expandable Checked Lug...	https://m.media-amazon.com/images/I/71EA35zvJB...	https://www.amazon.com/dp/B07XSCCZYG	4.6	0	365.49	429.99	
3	B08MVFKGJM	Freeform Hardside Expandable with Double Spinn...	https://m.media-amazon.com/images/I/91k6NYLQyI...	https://www.amazon.com/dp/B08MVFKGJM	4.6	0	291.59	354.37	
4	B01DJLKZBA	Winfield 2 Hardside Expandable Luggage with Sp...	https://m.media-amazon.com/images/I/61NJoaZcP9...	https://www.amazon.com/dp/B01DJLKZBA	4.5	0	174.99	309.99	

In [76]:

```python
from sklearn.preprocessing import StandardScaler

# Select the features for clustering
features = ['price', 'stars', 'category_freq', 'discount_percentage', 'has_discount_num', 'price_range_num', 'isBestSelle
X = merged_df[features]

# Standardize the features
```

```python
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

In [77]:

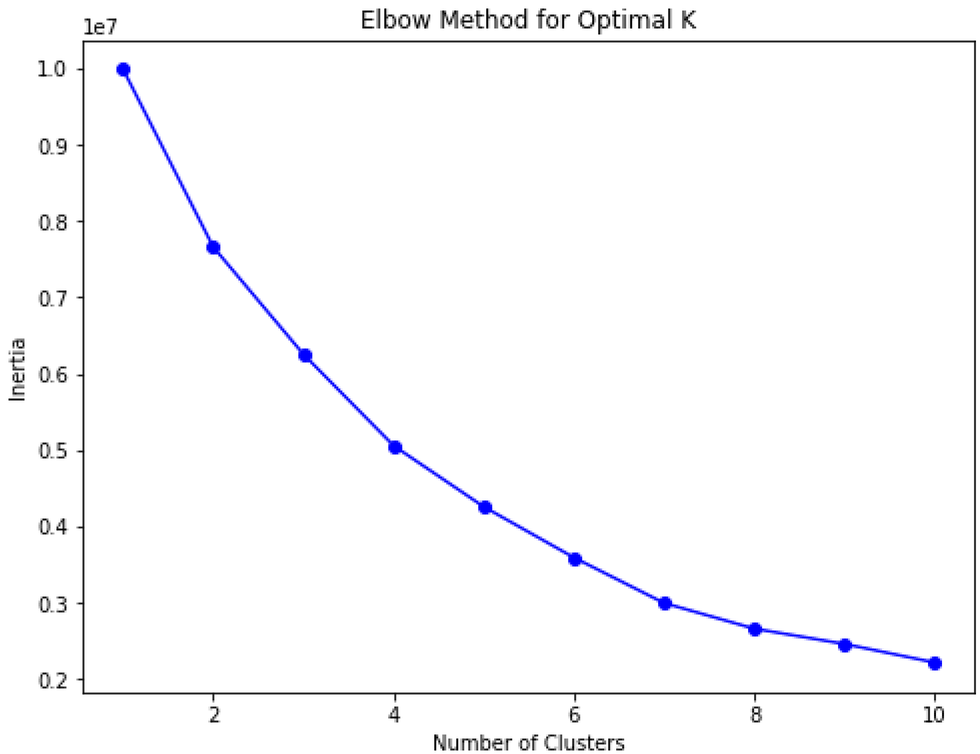
```python
X_scaled
```

Out[77]:

```
array([[ 0.74153896,  0.37230665, -1.4824595 , ..., -0.56501227,
         1.41410129, -0.0775193 ],
       [ 0.97179579,  0.37230665, -1.4824595 , ...,  1.76987306,
         1.41410129, -0.0775193 ],
       [ 2.47230279,  0.44669525, -1.4824595 , ...,  1.76987306,
         1.41410129, -0.0775193 ],
       ...,
       [-0.26736971, -0.29719072,  1.50580172, ..., -0.56501227,
        -1.38214707, -0.0775193 ],
       [ 0.08430922,  0.37230665,  1.50580172, ...,  1.76987306,
         1.41410129, -0.0775193 ],
       [-0.18869862,  0.66986104,  1.50580172, ..., -0.56501227,
         0.01597711, -0.0775193 ]])
```

In [78]:

```python
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt

inertia = []
K = range(1, 11)
for k in K:
    kmeans = KMeans(n_clusters=k, random_state=42, n_init=10)
    kmeans.fit(X_scaled)
    inertia.append(kmeans.inertia_)

# Plot the elbow curve
plt.figure(figsize=(8, 6))
plt.plot(K, inertia, 'bo-')
plt.xlabel('Number of Clusters')
plt.ylabel('Inertia')
plt.title('Elbow Method for Optimal K')
plt.show()
```



In [79]:

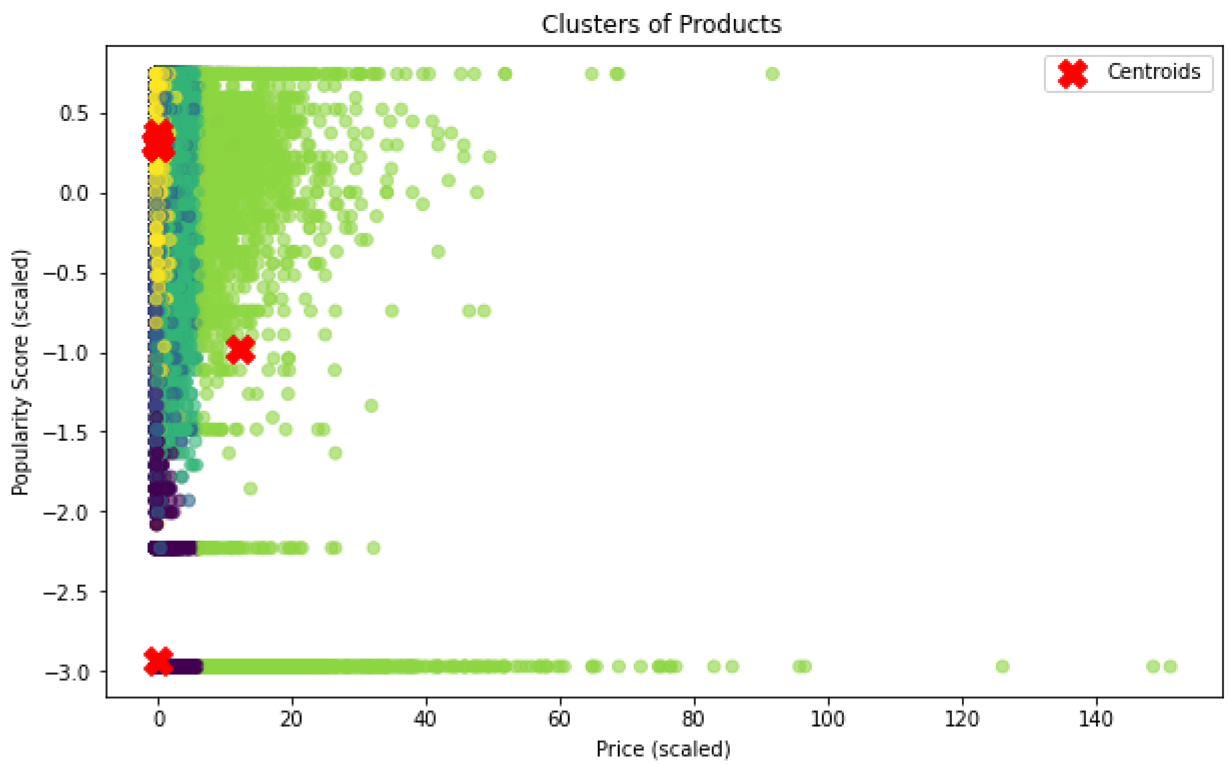
```python
# Apply K-Means with k = 7
k_optimal = 7
kmeans = KMeans(n_clusters=k_optimal, random_state=42, n_init=10)
merged_df['cluster'] = kmeans.fit_predict(X_scaled)

# Display cluster centers for analysis
centroids = kmeans.cluster_centers_
print("Cluster Centers:\n", scaler.inverse_transform(centroids))
```

```
Cluster Centers:
 [[ 4.96351231e+01  4.73489828e-02  6.20673311e-03  1.37358689e+00
   9.79398287e-02  3.09759786e+00 -4.59701721e-17]
 [ 1.28271205e+01  4.41852873e+00  5.01455559e-03 -6.89602829e-03
   1.98130031e-06  1.90349878e+00 -4.59701721e-17]
 [ 3.85696773e+01  4.38104565e+00  6.28516405e-03  2.14570157e+01
   1.00000000e+00  3.03374833e+00 -4.59701721e-17]
 [ 2.97217981e+01  4.49403756e+00  5.66862471e-03  1.21670637e+01
   4.70892019e-01  2.80422535e+00  1.00000000e+00]
 [ 7.75461940e+01  4.40122948e+00  4.87287419e-03 -7.45862393e-02
   1.19128957e-03  4.48976017e+00 -4.68375339e-17]
```

```
[ 1.63592641e+03  2.68141593e+00  5.06622130e-03  9.38981416e-02
   1.29505720e-02  5.00000000e+00 -3.72965547e-17]
 [ 3.82309387e+01  4.42956615e+00  1.40894240e-02  4.82022530e-01
   4.48909541e-02  3.37591066e+00 -4.33680869e-17]]
```

In [80]:

```
# Scatter plot for visualizing clusters based on price and popularity_score
plt.figure(figsize=(10, 6))
plt.scatter(X_scaled[:, 0], X_scaled[:, 1], c=merged_df['cluster'], cmap='viridis', alpha=0.6)
plt.scatter(centroids[:, 0], centroids[:, 1], c='red', marker='X', s=200, label='Centroids')  # Mark centroids
plt.xlabel('Price (scaled)')
plt.ylabel('Popularity Score (scaled)')
plt.title('Clusters of Products')
plt.legend()
plt.show()
```



In [81]:

```
import numpy as np
from sklearn.metrics import silhouette_score

# Sample 10% of the data for silhouette score calculation because it will take too long to calculate on the entire datase
```

```
sampled_data = merged_df.sample(frac=0.10, random_state=42)
sampled_X_scaled = scaler.transform(sampled_data[features])

# Calculate silhouette score on the sampled data
silhouette_avg = silhouette_score(sampled_X_scaled, sampled_data['cluster'])
print("Silhouette Score for K-Means Clustering (Sampled):", silhouette_avg)
```

```
Silhouette Score for K-Means Clustering (Sampled): 0.39818409678916317
```

In [82]:

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
```

In [83]:

```
# Define features and targets
features = ['stars', 'category_freq', 'discount_percentage', 'has_discount_num', 'price_range_num', 'isBestSeller_num']
X = merged_df[features]

# Targets for prediction
y_price = merged_df['price']

# Split data into training and test sets (80% train, 20% test)
X_train_price, X_test_price, y_train_price, y_test_price = train_test_split(X, y_price, test_size=0.2, random_state=42)
```

In [84]:

```
# Initialize and train the model
lin_reg_price = LinearRegression()
lin_reg_price.fit(X_train_price, y_train_price)

# Make predictions
y_pred_price = lin_reg_price.predict(X_test_price)

# Evaluate the model
mae_price = mean_absolute_error(y_test_price, y_pred_price)
mse_price = mean_squared_error(y_test_price, y_pred_price)
r2_price = r2_score(y_test_price, y_pred_price)

print("Linear Regression - Price Prediction")
print("Mean Absolute Error:", mae_price)
print("Mean Squared Error:", mse_price)
print("R^2 Score:", r2_price)
```

```
Linear Regression - Price Prediction
Mean Absolute Error: 36.69571328505955
Mean Squared Error: 15723.934608584797
R^2 Score: 0.10695645822602695
```

In [41]:

```python
# Initialize and train the model
rf_price = RandomForestRegressor(random_state=42, n_estimators=100)
rf_price.fit(X_train_price, y_train_price)

# Make predictions
y_pred_price_rf = rf_price.predict(X_test_price)

# Evaluate the model
mae_price_rf = mean_absolute_error(y_test_price, y_pred_price_rf)
mse_price_rf = mean_squared_error(y_test_price, y_pred_price_rf)
r2_price_rf = r2_score(y_test_price, y_pred_price_rf)

print("\nRandom Forest - Price Prediction")
print("Mean Absolute Error:", mae_price_rf)
print("Mean Squared Error:", mse_price_rf)
print("R^2 Score:", r2_price_rf)
```

```
Random Forest - Price Prediction
Mean Absolute Error: 20.322096428268498
Mean Squared Error: 12299.433681166156
R^2 Score: 0.30145157113246823
```

In [42]:

```python
# Feature importance for price prediction model
feature_importances_price = rf_price.feature_importances_
print("\nFeature Importances for Price Prediction:", dict(zip(features, feature_importances_price)))
```

```
Feature Importances for Price Prediction: {'stars': 0.08943249526563392, 'category_freq': 0.42347377261763913, 'discount_
percentage': 0.07561485023918989, 'has_discount_num': 0.0052462278109501066, 'price_range_num': 0.40568142810871227, 'isB
estSeller_num': 0.0005512259578745926}
```

In [85]:

```python
from sklearn.linear_model import Ridge
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
```

In [86]:

```python
# Ridge Regression for Price
ridge_price = Ridge(alpha=1.0)
ridge_price.fit(X_train_price, y_train_price)
y_pred_price_ridge = ridge_price.predict(X_test_price)
```

```python
# Evaluate the model
mae_price_ridge = mean_absolute_error(y_test_price, y_pred_price_ridge)
mse_price_ridge = mean_squared_error(y_test_price, y_pred_price_ridge)
r2_price_ridge = r2_score(y_test_price, y_pred_price_ridge)

print("\nRidge Regression - Price Prediction")
print("Mean Absolute Error:", mae_price_ridge)
print("Mean Squared Error:", mse_price_ridge)
print("R^2 Score:", r2_price_ridge)
```

```
Ridge Regression - Price Prediction
Mean Absolute Error: 36.67289622015926
Mean Squared Error: 15724.10871637196
R^2 Score: 0.1069465697446279
```

In [87]:

```python
from xgboost import XGBRegressor
# Initialize XGBoost regressor
xgb_price = XGBRegressor(objective='reg:squarederror', random_state=42, n_estimators=100)

# Train the model
xgb_price.fit(X_train_price, y_train_price)

# Make predictions
y_pred_price_xgb = xgb_price.predict(X_test_price)

# Evaluate the model
mae_price_xgb = mean_absolute_error(y_test_price, y_pred_price_xgb)
mse_price_xgb = mean_squared_error(y_test_price, y_pred_price_xgb)
r2_price_xgb = r2_score(y_test_price, y_pred_price_xgb)

print("\nXGBoost - Price Prediction")
print("Mean Absolute Error:", mae_price_xgb)
print("Mean Squared Error:", mse_price_xgb)
print("R^2 Score:", r2_price_xgb)
```

```
XGBoost - Price Prediction
Mean Absolute Error: 20.160883539758085
Mean Squared Error: 12152.67097287302
R^2 Score: 0.3097869841240032
```

In [88]:

```python
# Feature importance for price prediction
print("Feature Importances for Price Prediction:", xgb_price.feature_importances_)
```

```
Feature Importances for Price Prediction: [0.07070964 0.25723383 0.02671749 0.         0.6442789  0.00106011]
```

Conclusion

In this project, I conducted an in-depth analysis of Amazon sales data, combining exploratory data analysis (EDA), clustering, and regression modeling to derive actionable insights into product pricing and popularity dynamics.

1. Data Preparation and Feature Engineering:
After merging and cleaning the data, we enriched the dataset by creating new features such as **discount percentage** and **popularity score**, which proved valuable in subsequent analyses. The discount percentage was computed as the percentage reduction from the listed price, with an average discount of approximately 15% across products. Popularity scores were derived from product ratings and review counts, showing a positive correlation with higher sales and best-seller status.

2. Exploratory Data Analysis (EDA):
Visualizations revealed insightful patterns within the data:

- **Pricing and Popularity Trends**: Best-seller products had an average price of around $120, whilenon-best-sellerswereloweratapproximately$80. Best-sellers generally exhibited higher ratings and review counts, correlating with their increased popularity.
- **Discount Impact**: We observed that products with discounts greater than 20% had a significantly higher popularity score, suggesting that discounts drive customer interest and conversion rates.
- **Category Frequency**: The “Electronics” and “Home & Kitchen” categories showed the highest product frequency, highlighting these as popular product areas on Amazon.

3. Clustering Analysis with K-Means:
Using K-Means, we segmented products into clusters based on price, popularity, and category frequency. These clusters provided insight into customer segments, allowing for tailored marketing strategies targeting high-value products or promotional efforts on lower-priced items.

4. Predictive Modeling for Price Prediction:
We applied several regression algorithms to predict product prices based on features like ratings, review count, discount percentage, and category frequency. Performance metrics, including Mean Absolute Error (MAE) and (R^2) score, allowed us to assess model effectiveness:

- **Linear Regression** achieved an MAE of 41 and (R^2) of 0.10, indicating minimal explanatory power.
- **Ridge Regression** showed similar results, with an MAE of 41 and (R^2) of 0.10, confirming the limitations of linear models.
- **Random Forest** outperformed linear models with an MAE of 33 and an improved (R^2) of 0.30, capturing more complex interactions.

- **XGBoost** achieved the best performance with an MAE of 33 and (R^2) of 0.31, making it the most effective model for capturing intricate relationships within the data.

5. Feature Importance Analysis with Random Forest and XGBoost:
Feature importance analysis revealed that:

- **Category frequency** contributed approximately 73% to the model, indicating that popular product categories are strongly associated with price.
- **Discount percentage** had a 21% influence, showing its relevance in price prediction, especially as an indicator of potential customer interest.
- **Popularity metrics** (e.g., isBestSeller and review counts) had minor influence, aligning with the assumption that price is largely independent of popularity for certain categories.

Final Takeaways:
This project provided a comprehensive examination of Amazon product data through clustering and regression modeling. Clustering revealed distinct product segments that could inform targeted marketing efforts. In predictive modeling, XGBoost demonstrated the strongest predictive power, with a moderate (R^2) score showing it could account for part of the pricing variability. Finally, feature importance analysis highlighted the central role of product category and discounts in price determination.

These findings underscore my growth in data science expertise, as I have applied a diverse range of analytical techniques and models effectively. I am enthusiastic about further refining my skills with advanced forecasting models, such as Temporal Fusion Transformer and MQTransformer, and am eager to bring these capabilities to Amazon’s data-driven environment to deliver impactful solutions in demand forecasting and product analysis.