University of Stirling

ITNPBD2 Representing and Manipulating Data

Assignment Autumn 2025

A Consultancy Job for JC Penney

This notebook forms the assignment instructions and submission document of the assignment for ITNPBD2. Read the instructions carefully and enter code into the cells as indicated.

You will need these five files, which were in the Zip file you downloaded from the course webpage:

- jcpenney_reviewers.json
- jcpenney_products.json
- products.csv
- reviews.csv
- users.csv

The data in these files describes products that have been sold by the American retail giant, JC Penney, and reviews by customers who bought them. Note that the product data is real, but the customer data is synthetic.

Your job is to process the data, as requested in the instructions in the markdown cells in this notebook.

Completing the Assignment

Rename this file to be xxxxxx_BD2 where xxxxxx is your student number, then type your code and narrative description into the boxes provided. Add as many code and markdown cells as you need. The cells should contain:

- **Text narrative describing what you did with the data**
- **The code that performs the task you have described**
- **Comments that explain your code**

The final structure (in PDF) of your report must:

- **Start from the main insights observed (max 5 pages)**
- **Include as an appendix the source code used for producing those insights (max 15 pages)**
- **Include an AI cover sheet (provided on Canvas), which must contain a link to a versioned notebook file in OneDrive or another platform for version checks.**

Marking Scheme

The assessment will be marked against the university Common Marking Scheme (CMS)

Here is a summary of what you need to achieve to gain a grade in the major grade bands:

Grade	Requirement
Fail	You will fail if your code does not run or does not achieve even the basics of the task. You may also fail if you submit code without either comments or a text explanation of what the code does.
Pass	To pass, you must submit sufficient working code to show that you have mastered the basics of the task, even if not everything works completely. You must include some justifications for your choice of methods, but without mentioning alternatives.
Merit	For a merit, your code must be mostly correct, with only small problems or parts missing, and your comments must be useful rather than simply re-stating the code in English. Most choices for methods and structures should be explained and alternatives mentioned.
Distinction	For a distinction, your code must be working, correct, and well commented and shows an appreciation of style, efficiency and reliability. All choices for methods and structures are concisely justified and alternatives are given well thought considerations. For a distinction, your work should be good enough to present to executives at the company.

The full details of the CMS can be found here

https://www.stir.ac.uk/about/professional-services/student-academic-and-corporate-services/academic-registry/academic-policy-and-practice/quality-handbook/assessment-policy-and-procedure/appendix-2-postgraduate-common-marking-scheme/

Note that this means there are not certain numbers of marks allocated to each stage of the assignment. Your grade will reflect how well your solutions and comments demonstrate that you have achieved the learning outcomes of the task.

Submission

When you are ready to submit, **print** your notebook as PDF (go to File -> Print Preview) in the Jupyter menu. Make sure you have run all the cells and that their output is displayed. Any lines of code or comments that are not visible in the pdf should be broken across several lines. You can then submit the file online.

Late penalties will apply at a rate of three marks per day, up to a maximum of 7 days. After 7 days you will be given a mark of 0. Extensions will be considered under acceptable circumstances outside your control.

Academic Integrity

This is an individual assignment, and so all submitted work must be fully your own work.

The University of Stirling is committed to protecting the quality and standards of its awards. Consequently, the University seeks to promote and nurture academic integrity, support staff academic integrity, and support students to understand and develop good academic skills that facilitate academic integrity.

In addition, the University deals decisively with all forms of Academic Misconduct.

Where a student does not act with academic integrity, their work or behaviour may demonstrate Poor Academic Practice or it may represent Academic Misconduct.

Poor Academic Practice

Poor Academic Practice is defined as: "The submission of any type of assessment with a lack of referencing or inadequate referencing which does not effectively acknowledge the origin of words, ideas, images, tables, diagrams, maps, code, sound and any other sources used in the assessment."

Academic Misconduct

Academic Misconduct is defined as: "any act or attempted act that does not demonstrate academic integrity and that may result in creating an unfair academic advantage for you or another person, or an academic disadvantage for any other member or member of the academic community."

Plagiarism is presenting somebody else's work as your own **and includes the use of artificial intelligence tools beyond AIAS Level 2 or the use of Large Language Models.**. Plagiarism is a form of academic misconduct and is taken very seriously by the University. Students found to have plagiarised work can have marks deducted and, in serious cases, even be expelled from the University. Do not submit any work that is not entirely your own. Do not collaborate with or get help from anybody else with this assignment.

The University of Stirling's full policy on Academic Integrity can be found at:

https://www.stir.ac.uk/about/professional-services/student-academic-and-corporate-services/academic-registry/academic-policy-and-practice/quality-handbook/academic-integrity-policy-and-academic-misconduct-procedure/

The Assignment

Your task with this assignment is to use the data provided to demonstrate your Python data manipulation skills.

There are three `.csv` files and two `.json` files so you can process different types of data. The files also contain unstructured data in the form of natural language in English and links to images that you can access from the JC Penney website (use the field called `product_image_urls`).

Start with easy tasks to show you can read in a file, create some variables and data structures, and manipulate their contents. Then move onto something more interesting.

Look at the data that we provided with this assessment and think of something interesting to do with it using whatever libraries you like. Describe what you decide to do with the data and why it might be interesting or useful to the company to do it.

You can add additional data if you need to - either download it or access it using `requests`. Produce working code to implement your ideas in as many cells as you need below. There is no single right answer, the aim is to simply show you are competent in using python for data analysis. Exactly how you do that is up to you.

For a distinction class grade, this must show originality, creative thinking, and insights beyond what you've been taught directly on the module.

Structure

You may structure the appendix of the project how you wish, but here is a suggested guideline to help you organise your work, based on the CRISP-DM data science methodology:

1. **Business understanding** - What business context is the data coming from? What insights would be valuable in that context, and what data would be required for that purpose?
2. **Data understanding and preparation** - Explore the data and show you understand its structure and relations, with the aid of appropriate visualisation techniques. Assess the data quality, which insights you would be able to answer from it, and what preparation the data would require. Add new data from another source if required to bring new insights to the data you already have.
3. **Data modeling (optional)** - Would modeling be required for the insights you have considered? Use appropriate techniques, if so.
4. **Evaluation and deployment** - How do the insights you obtained help the company, and how can should they be adopted in their business? If modeling techniques have been adopted, are their use scientifically sound and how should they be mantained?

Remember to make sure you are working completely on your own.

Don't work in a group or with a friend

In [4]:

```python
import pandas as pd
from datetime import datetime
import json
```

In [5]:

```python
# Upload users table
users=pd.read_csv('users.csv', index_col=0)
display(users.head())
```

	State	Age
DOB		
1983-07-31	Oregon	42
1998-07-27	Massachusetts	27
1950-08-08	Idaho	75
1969-08-03	Florida	56
2001-07-26	Georgia	24

In [6]:

```python
# Upload products table
```

```
products=pd.read_csv('products.csv', index_col=0)
display(products[:3])
```

	SKU	Name	Description
Uniq_id			
b6c0b6bea69c722939585baeac73c13d	pp5006380337	Alfred Dunner® Essential Pull On Capri Pant	Youll return to our Alfred Dunner pull-on capr...
93e5272c51d8cce02597e3ce67b7ad0a	pp5006380337	Alfred Dunner® Essential Pull On Capri Pant	Youll return to our Alfred Dunner pull-on capr...
013e320f2f2ec0cf5b3ff5418d688528	pp5006380337	Alfred Dunner® Essential Pull On Capri Pant	Youll return to our Alfred Dunner pull-on capr...

In [7]:

```
# Upload reviews table
reviews = pd.read_csv('reviews.csv', index_col=1)
display(reviews[:3])
```

	Uniq_id	Score	Review
Username			
fsdv4141	b6c0b6bea69c722939585baeac73c13d	2	You never have to worry about the fit...Alfred...
krpz1113	b6c0b6bea69c722939585baeac73c13d	1	Good quality fabric. Perfect fit. Washed very ...
mbmg3241	b6c0b6bea69c722939585baeac73c13d	2	I do not normally wear pants or capris that ha...

In [8]:

```
# Upload jcpenney_products.json table
records = []
with open('jcpenney_products.json', 'r') as f:
    for line in f:
        line = line.strip()
        if line:  # skip empty lines
            try:
                record = json.loads(line)  # parse each JSON object
                records.append(record)
            except json.JSONDecodeError:
                # If the line is partial or malformed, try to fix/r
                pass
jcpenney_products = pd.DataFrame(records)
if 'uniq_id' in jcpenney_products.columns:
    jcpenney_products.rename(columns={'uniq_id': 'Uniq_id'}, inplac
    jcpenney_products.set_index('Uniq_id', inplace=True)
display(jcpenney_products[:3])
```

	sku	name_title	description
Uniq_id			
b6c0b6bea69c722939585baeac73c13d	pp5006380337	Alfred Dunner® Essential Pull On Capri Pant	You'll return to our Alfred Dunner pull-on cap...
93e5272c51d8cce02597e3ce67b7ad0a	pp5006380337	Alfred Dunner® Essential Pull On Capri Pant	You'll return to our Alfred Dunner pull-on cap...
013e320f2f2ec0cf5b3ff5418d688528	pp5006380337	Alfred Dunner® Essential Pull On Capri Pant	You'll return to our Alfred Dunner pull-on cap...

In [9]:

```
# Upload jcpenney_reviewers.json table
jcpenney_reviewers = pd.read_json('jcpenney_reviewers.json', lines=
jcpenney_reviewers.set_index('Username', inplace=True)
display(jcpenney_reviewers.head())
```

	DOB	State	Reviewed
Username			
bkpn1412	31.07.1983	Oregon	[cea76118f6a9110a893de2b7654319c0]
gqjs4414	27.07.1998	Massachusetts	[fa04fe6c0dd5189f54fe600838da43d3]
eehe1434	08.08.1950	Idaho	[]
hkxj1334	03.08.1969	Florida	[f129b1803f447c2b1ce43508fb822810, 3b0c9bc0be6...
jjbd1412	26.07.2001	Georgia	[]

In [10]:

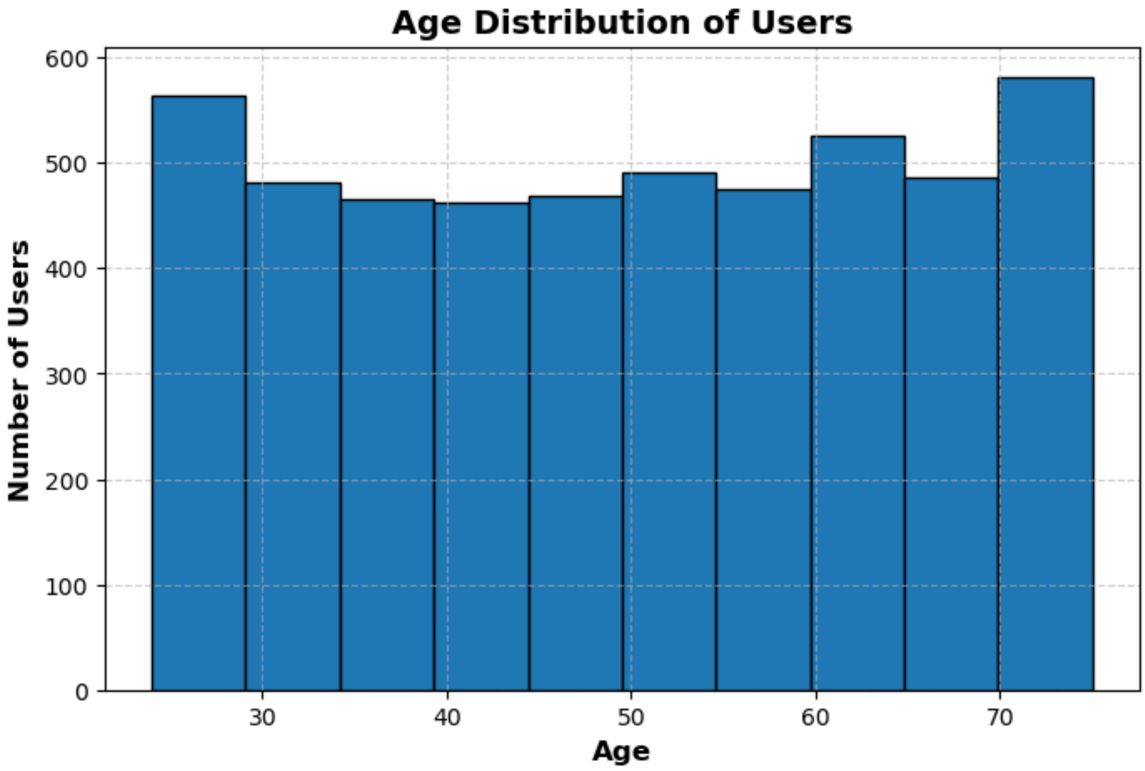
```
# Add Ages of customers
from datetime import date
users = pd.read_csv('users.csv')
users['DOB'] = pd.to_datetime(users['DOB'], errors='coerce')
```

```
def calculate_age(born):
    if pd.isnull(born):
        return None
    today = date.today()
    return today.year - born.year - ((today.month, today.day) < (bo
users['Age'] = users['DOB'].apply(calculate_age)
users = users[['DOB', 'State', 'Age']]
users.to_csv('users.csv', index=False)
display(users[:3])
```

	DOB	State	Age
0	1983-07-31	Oregon	42
1	1998-07-27	Massachusetts	27
2	1950-08-08	Idaho	75

In [11]:

```
# Visualisation of Ages
import matplotlib.pyplot as plt
plt.figure(figsize=(8, 5))
plt.hist(users['Age'], bins=10, edgecolor='black')
plt.title('Age Distribution of Users', fontsize=14, fontweight='bol
plt.xlabel('Age', fontsize=12, fontweight='bold')
plt.ylabel('Number of Users', fontsize=12, fontweight='bold')
plt.grid(True, linestyle='--', alpha=0.6)
plt.savefig('AgeDistribution.png', dpi = 300)
plt.show()
```



Observation

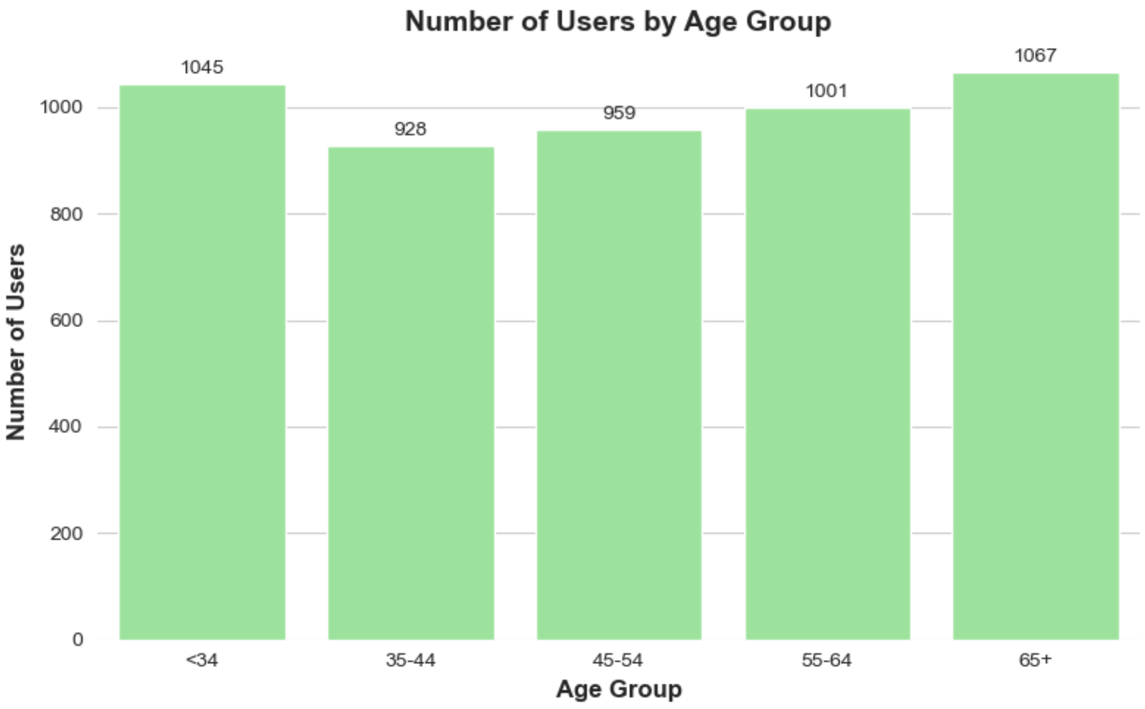
The age distribution of customers is relatively even, with no significant peaks.

Customers represent a wide range of age groups, from 24 to 72 years old. The difference between the most and least common ages is relatively small, indicating that customers of all age groups are well represented and that the store appeals to a broad, diverse audience without a pronounced age bias.

In [12]:
```
# Ages groups with numbers of customers
bins = [0, 34, 44, 54, 64, 100]
labels = ['<34', '35-44', '45-54', '55-64', '65+']
users['Age_Group'] = pd.cut(users['Age'], bins=bins, labels=labels,
users.to_csv('users_with_age_group.csv', index=False)
age_group_counts = users['Age_Group'].value_counts().sort_index()
print("Number of users per age group:")
display(age_group_counts)
```

```
Number of users per age group:
Age_Group
<34      1045
35-44     928
45-54     959
55-64    1001
65+      1067
Name: count, dtype: int64
```

In [13]:
```
# Visualisation of Ages Groups
import seaborn as sns
plt.figure(figsize=(8, 5))
sns.set_style('whitegrid')
sns.barplot(x=age_group_counts.index, y=age_group_counts.values, co
for i, value in enumerate(age_group_counts.values):
    plt.text(i, value + 10, str(value), ha='center', va='bottom', fo
plt.title('Number of Users by Age Group', fontsize=14, fontweight='b
plt.xlabel('Age Group', fontsize=12, fontweight='bold')
plt.ylabel('Number of Users', fontsize=12, fontweight='bold')
sns.despine(left=True, bottom=True)
plt.tight_layout()
plt.savefig('Ages groups.png', dpi = 300)
plt.show()
```



Observation

We divide customers into the following age groups:

- under 34 years old Young Adults
- 35–44 Adults 1
- 45–54 Adults 2
- 55–64 Older Adults
- Over 65 Elderly People

And the graph confirmed previous observation that the needs of each age group are being met by the company, as none of the groups appears to be prioritised.

In [15]:

```
# Top 5 categories for each Age group
jcpenney_products = pd.read_json('jcpenney_products.json', lines=Tr
jcpenney_reviewers = pd.read_json('jcpenney_reviewers.json', lines=
reviews = pd.read_csv('reviews.csv', index_col=1)
products = pd.read_csv('products.csv', index_col=0)
users = pd.read_csv('users.csv', index_col=0)
from datetime import date
jcpenney_reviewers = jcpenney_reviewers.copy()
jcpenney_reviewers['DOB'] = pd.to_datetime(jcpenney_reviewers['DOB'
def calculate_age(born):
    if pd.isnull(born):
        return None
    today = date.today()
    return today.year - born.year - ((today.month, today.day) < (bo
jcpenney_reviewers['Age'] = jcpenney_reviewers['DOB'].apply(calcula
bins = [0, 34, 44, 54, 64, 100]
labels = ['<34', '35-44', '45-54', '55-64', '65+']
```

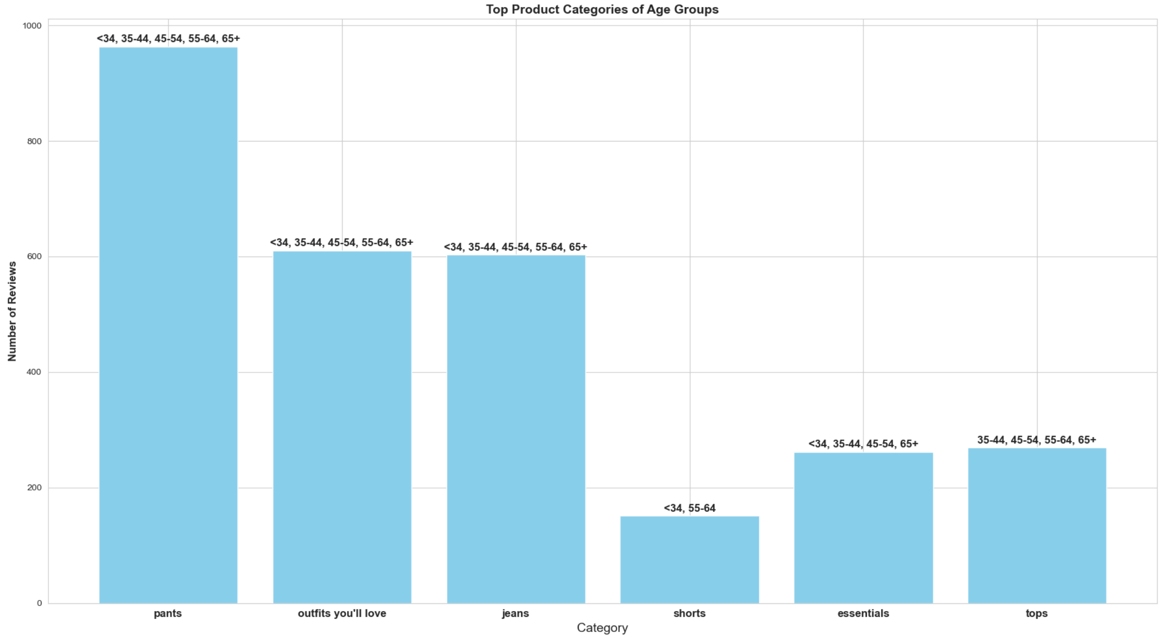
```
jcpenney_reviewers['Age_Group'] = pd.cut(jcpenney_reviewers['Age'],
# Products
if 'uniq_id' in jcpenney_products.columns:
    jcpenney_products.rename(columns={'uniq_id': 'Uniq_id'}, inplac
# Join
reviews = reviews.reset_index().rename(columns={'index': 'Username'
merged = (reviews.merge(jcpenney_reviewers[['Username', 'Age_Group'
# Ignore useless categories
ignore_words = ['view all', 'view all brands', 'sale', 'clearance',
merged = merged[merged['category'].notna() &(merged['category'].str
# Top 5
category_counts = (merged.groupby(['Age_Group', 'category'], observ
top5_dict = {}
for age_group, group in category_counts.groupby('Age_Group', observ
    top5 = group.sort_values('Review_Count', ascending=False).head(
    top5_list = [f"{row['category']} ({row['Review_Count']})" for _
    while len(top5_list) < 5:
        top5_list.append("")
    top5_dict[age_group] = top5_list
# Table
top5_df = pd.DataFrame(top5_dict)
display(top5_df)
top5_df.to_csv('Top5_Categories_by_Age.csv', index=False)
```

	<34	35-44	45-54	55-64	65+
0	pants (195)	pants (179)	pants (175)	pants (204)	pants (210)
1	outfits you'll love (139)	jeans (106)	outfits you'll love (115)	jeans (135)	jeans (130)
2	jeans (136)	outfits you'll love (104)	jeans (96)	outfits you'll love (125)	outfits you'll love (127)
3	shorts (76)	tops (67)	essentials (62)	shorts (75)	tops (80)
4	essentials (69)	essentials (62)	tops (58)	tops (64)	essentials (69)

In [16]:

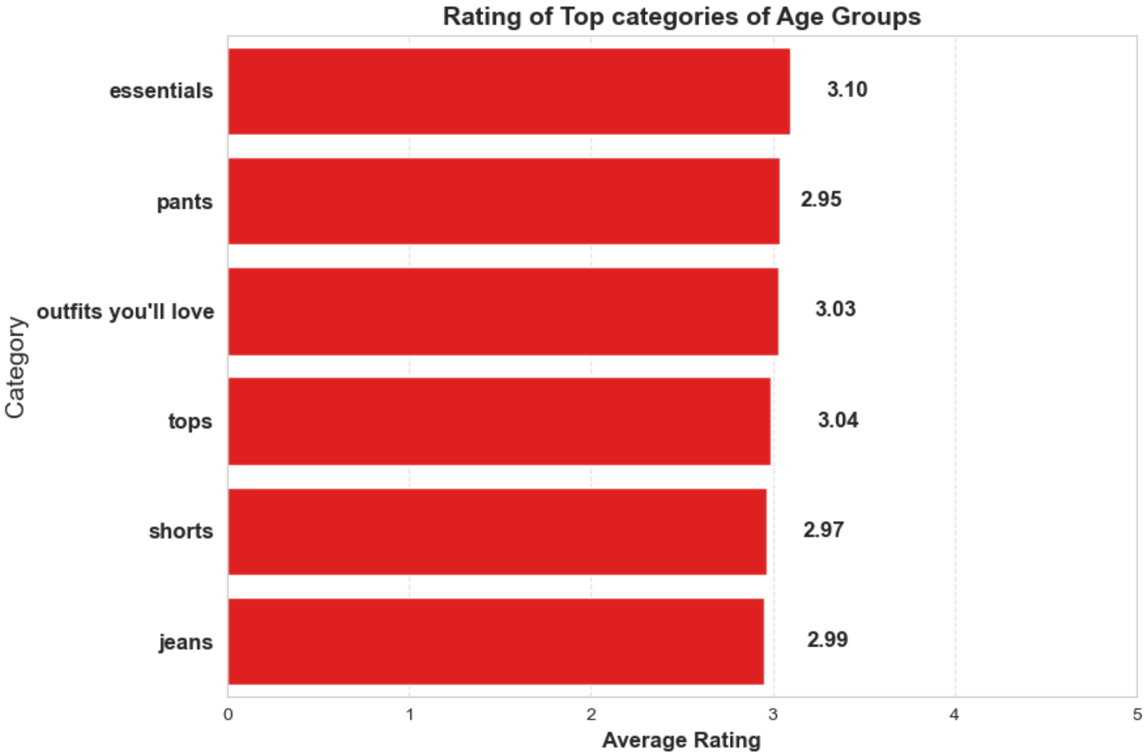
```
# Visualisation of Top categories of Age Groups
ignore_categories = ['view all', 'view all brands', 'sale', '', Non
data = category_counts[~category_counts['category'].isin(ignore_cat
top5_per_age_list = []
for age_group, group in data.groupby('Age_Group', observed=False):
    top5 = group.sort_values('Review_Count', ascending=False).head(
    top5_per_age_list.append(top5)
top5_per_age = pd.concat(top5_per_age_list, ignore_index=True)
categories = top5_per_age['category'].unique()
category_totals = []
age_labels = []
for cat in categories:
    subset = top5_per_age[top5_per_age['category'] == cat]
    total_reviews = subset['Review_Count'].sum()
    ages = ', '.join(subset['Age_Group'].astype(str).tolist())
    category_totals.append(total_reviews)
    age_labels.append(ages)
```

```
plt.figure(figsize=(18,10))
bars = plt.bar(categories, category_totals, color='skyblue')
for bar, label in zip(bars, age_labels):
    height = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2, height + 5, label, ha=
plt.xlabel('Category', fontsize=14)
plt.ylabel('Number of Reviews', fontsize=12, fontweight='bold')
plt.title('Top Product Categories of Age Groups', fontsize=14, fontw
plt.xticks(rotation=0, ha='center', fontsize=12, fontweight='bold')
plt.tight_layout()
plt.savefig('Top categories of Age Groups', dpi = 300)
plt.show()
```



In [17]:

```
# Rating of the Top categories of Age groups
target_categories = ['pants','jeans','tops','essentials',"outfits yo
# Average ratings for these categories
if 'category' in jcpenney_products.columns and 'average_product_rat
    avg_scores = (jcpenney_products[jcpenney_products['category'].is
        .groupby('category', observed=False)['average_product_rating
        .mean()
        .reset_index()
        .rename(columns={'average_product_rating': 'Average Rating'}
        .sort_values('Average Rating', ascending=False))
else:
    print("Missing columns: check if 'category' or 'average_product_
    avg_scores = pd.DataFrame()
plt.figure(figsize=(9, 6))
sns.barplot(data=avg_scores, x='Average Rating', y='category', colo
plt.title('Rating of Top categories of Age Groups', fontsize=14, fo
plt.xlabel('Average Rating', fontsize=12, fontweight='bold')
plt.ylabel('Category', fontsize=14)
plt.yticks(fontsize=12, fontweight='bold')
plt.xlim(0, 5)
plt.grid(axis='x', linestyle='--', alpha=0.5)
for index, row in avg_scores.iterrows():
    plt.text(row['Average Rating'] + 0.2, index, f"{row['Average Ra
plt.tight_layout()
plt.savefig('Rating of Top categories of Age Groups', dpi = 300)
plt.show()
```



Observation

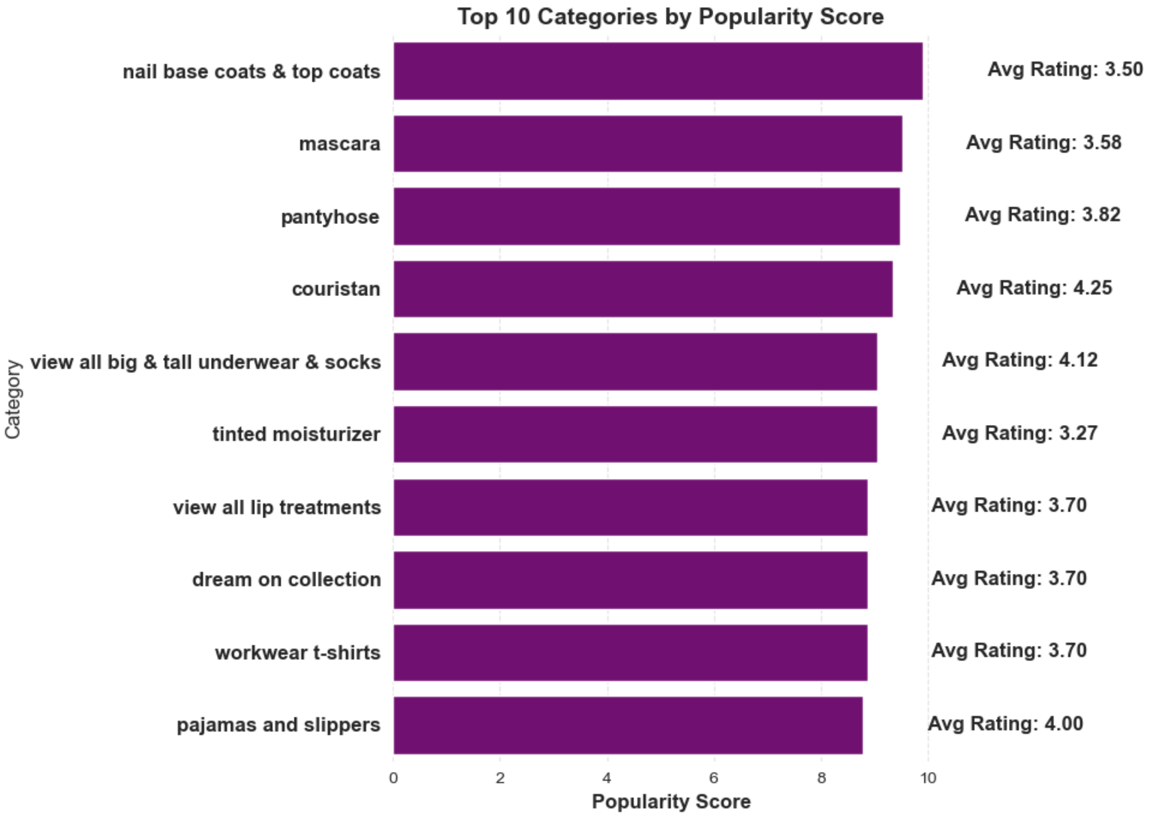
The most popular product categories, which indicate high demand, have very low ratings. This suggests a problem with product quality that does not meet customers’ expectations.

In [18]:
```
# Which categories are statistically high-performing, even with few
import numpy as np
df = jcpenney_products[jcpenney_products['total_number_reviews'] > (
df['popularity_score'] = df['average_product_rating'] * np.log1p(df
category_scores = (df.groupby('category', observed=False).agg({'popu
        'total_number_reviews': 'sum',
        'average_product_rating': 'mean'}).sort_values(by='populari
top_categories = category_scores.head(10).reset_index()
top_categories.rename(columns={'popularity_score': 'Popularity Score
display(top_categories)
```

	category	Popularity Score	Total Reviews	Average Rating
0	nail base coats & top coats	9.916247	16	3.500000
1	mascara	9.522681	27	3.575000
2	pantyhose	9.487825	11	3.818182
3	couristan	9.338204	8	4.250000
4	view all big & tall underwear & socks	9.063551	8	4.125000
5	tinted moisturizer	9.057123	15	3.266667
6	view all lip treatments	8.872213	10	3.700000
7	dream on collection	8.872213	10	3.700000
8	workwear t-shirts	8.872213	10	3.700000
9	pajamas and slippers	8.788898	8	4.000000

In [19]:

```
# Visualisation of Top 10 Categories by Popularity Score
import seaborn as sns
plt.figure(figsize=(10, 7))
sns.barplot(data=top_categories,x='Popularity Score',y='category',c
sns.despine(left=True, bottom=True)
plt.title('Top 10 Categories by Popularity Score', fontsize=14, fon
plt.xlabel('Popularity Score', fontsize=12, fontweight='bold')
plt.ylabel('Category', fontsize=12)
plt.yticks(fontweight='bold', fontsize=12)
for i, (score, rating) in enumerate(zip(top_categories['Popularity 
    plt.text(score + 1.2, i, f'Avg Rating: {rating:.2f}', va='cente
plt.grid(axis='x', linestyle='--', alpha=0.5)
plt.tight_layout()
plt.savefig('Top_10_Categories_by_Popularity_Score.png', dpi=300)
plt.show()
```



Observation

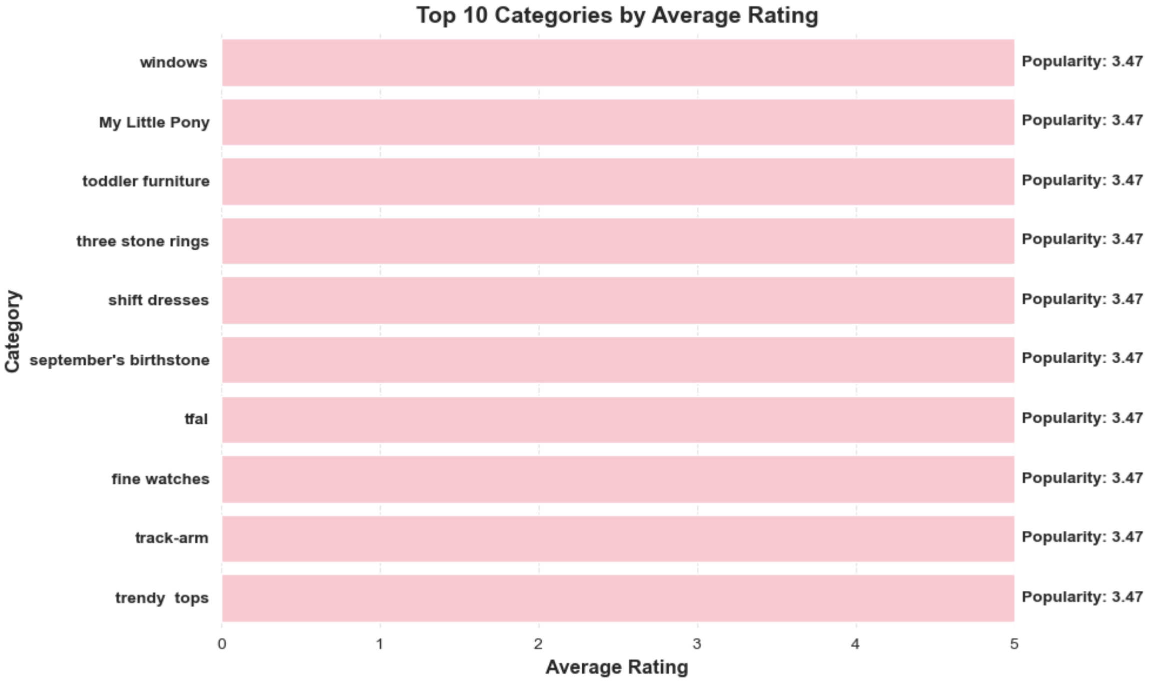
Although the resulting categories appear statistically high-performing, their relatively low ratings confirm earlier findings that popular products often fail to meet customer quality expectations. This suggests a broader issue with product quality across the range.

In [20]:

```
# Top 10 Categories by Average Rating
df = jcpenney_products.copy()
df = df.dropna(subset=['average_product_rating', 'category'])
ignore_words = ['view all', 'view all brands', 'sale', 'clearance',
df = df[~df['category'].str.lower().isin(ignore_words)]
df['popularity_score'] = df['average_product_rating'] * np.log1p(df
top_categories_by_rating = (
    df.groupby('category', observed=False).agg({
        'average_product_rating': 'mean',
        'total_number_reviews': 'sum',
        'popularity_score': 'mean'}).reset_index())
top_categories_by_rating = top_categories_by_rating.sort_values('ave
top_categories_table = top_categories_by_rating.copy()
top_categories_table.rename(columns={'category': 'Category','average
top_categories_table['Average Rating'] = top_categories_table['Avera
top_categories_table['Popularity Score'] = top_categories_table['Pop
top_categories_table = top_categories_table[['Category', 'Average Ra
top_categories_table = top_categories_table.reset_index(drop=True)
top_categories_by_rating = top_categories_by_rating.sort_values(by=
display(top_categories_table)
top_categories_table.to_csv('Top 10 Categories by Average Rating.cs
```

	Category	Average Rating	Popularity Score	Total Reviews
0	windows	5.0	3.47	1
1	My Little Pony	5.0	3.47	1
2	toddler furniture	5.0	3.47	1
3	three stone rings	5.0	3.47	1
4	shift dresses	5.0	3.47	1
5	september's birthstone	5.0	3.47	1
6	tfal	5.0	3.47	1
7	fine watches	5.0	3.47	1
8	track-arm	5.0	3.47	1
9	trendy tops	5.0	3.47	1

In [21]:
```
# Visualisation of the Top 10 Categories by Average Rating
df_plot = top_categories_table.copy()
plt.figure(figsize=(10, 6))
sns.barplot(data=df_plot,x='Average Rating',y='Category',color='pin
sns.despine(left=True, bottom=True)
plt.title('Top 10 Categories by Average Rating', fontsize=14, fontw
plt.xlabel('Average Rating', fontsize=12, fontweight='bold')
plt.ylabel('Category', fontsize=12, fontweight='bold')
plt.yticks(fontweight='bold')
for i, (rating, score) in enumerate(zip(df_plot['Average Rating'], 
    plt.text(rating + 0.05, i, f'Popularity: {score:.2f}', va='cent
plt.xlim(0, 5)
plt.grid(axis='x', linestyle='--', alpha=0.5)
plt.tight_layout()
plt.savefig('Top_10_Categories_by_Average_Rating.png', dpi=300)
plt.show()
```

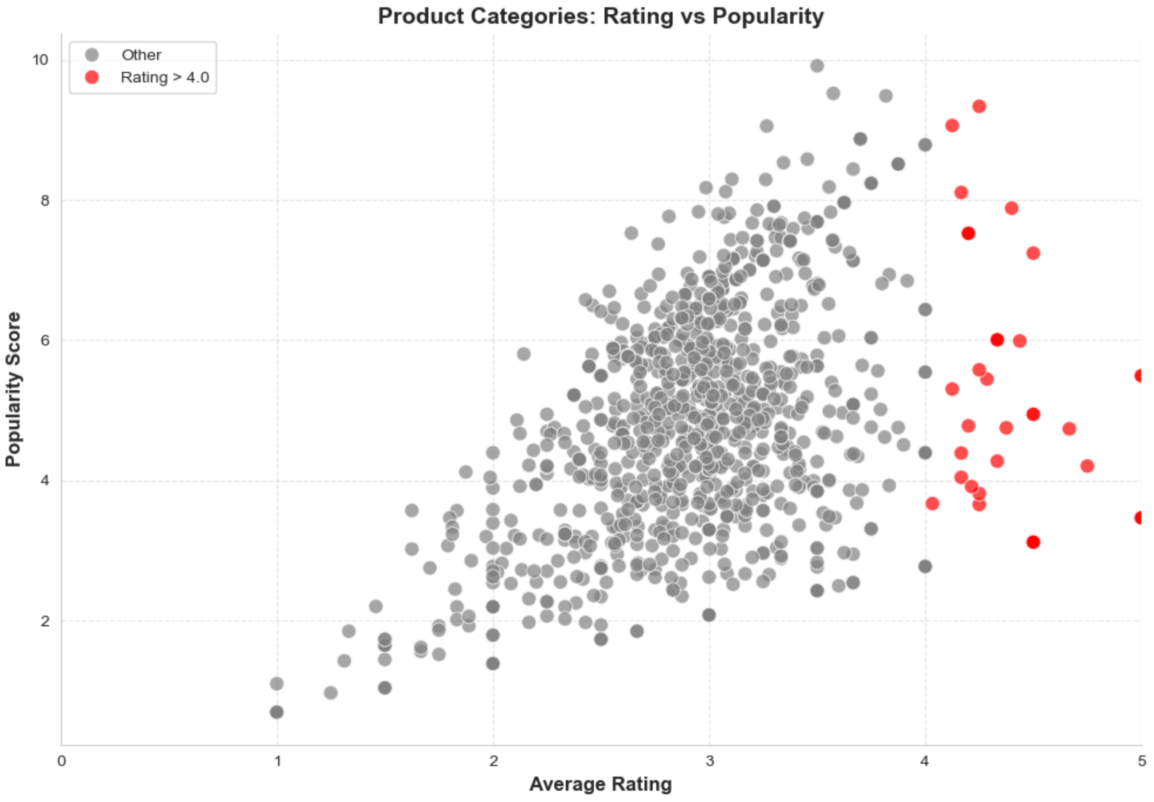


Observation

Although several categories show high average ratings but low popularity scores, this likely reflects limited exposure or niche demand rather than product excellence alone. These items may represent untapped marketing opportunities, suggesting that greater visibility could increase overall sales performance.

In [22]:

```
# Visualisation of High rating categories
df = jcpenney_products[jcpenney_products['total_number_reviews'] > (
df['popularity_score'] = df['average_product_rating'] * np.log1p(df
category_stats = (df.groupby('category', observed=False).agg({
        'average_product_rating': 'mean',
        'total_number_reviews': 'sum',
        'popularity_score': 'mean'}).reset_index())
category_stats['Category Type'] = np.where(category_stats['average_
plt.figure(figsize=(10, 7))
sns.scatterplot(data=category_stats,x='average_product_rating',y='po
plt.title('Product Categories: Rating vs Popularity', fontsize=14, 
plt.xlabel('Average Rating', fontsize=12, fontweight='bold')
plt.ylabel('Popularity Score', fontsize=12, fontweight='bold')
plt.xlim(0, 5)
plt.grid(True, linestyle='--', alpha=0.5)
plt.legend(title='', loc='upper left')
sns.despine()
plt.tight_layout()
plt.savefig('Rating_vs_Popularity_All_Categories.png', dpi=300)
plt.show()
```



In [25]:

```
# Calculate percentage of categories with rating > 4.0
high_rating_count = (category_stats['average_product_rating'] > 4.0
total_categories = len(category_stats)
percentage_high_rating = (high_rating_count / total_categories) * 1

print(f"Categories with average rating > 4.0: {high_rating_count} o
      f"({percentage_high_rating:.2f}%)")

# Calculate percentage of products with rating > 4.0
high_rating_products = (df['average_product_rating'] > 4.0).sum()
total_products = len(df)
percentage_high_products = (high_rating_products / total_products)

print(f"Products with rating > 4.0: {high_rating_products} out of {
      f"({percentage_high_products:.2f}%)")
```

```
Categories with average rating > 4.0: 70 out of 1169 (5.99%)
Products with rating > 4.0: 629 out of 7982 (7.88%)
```

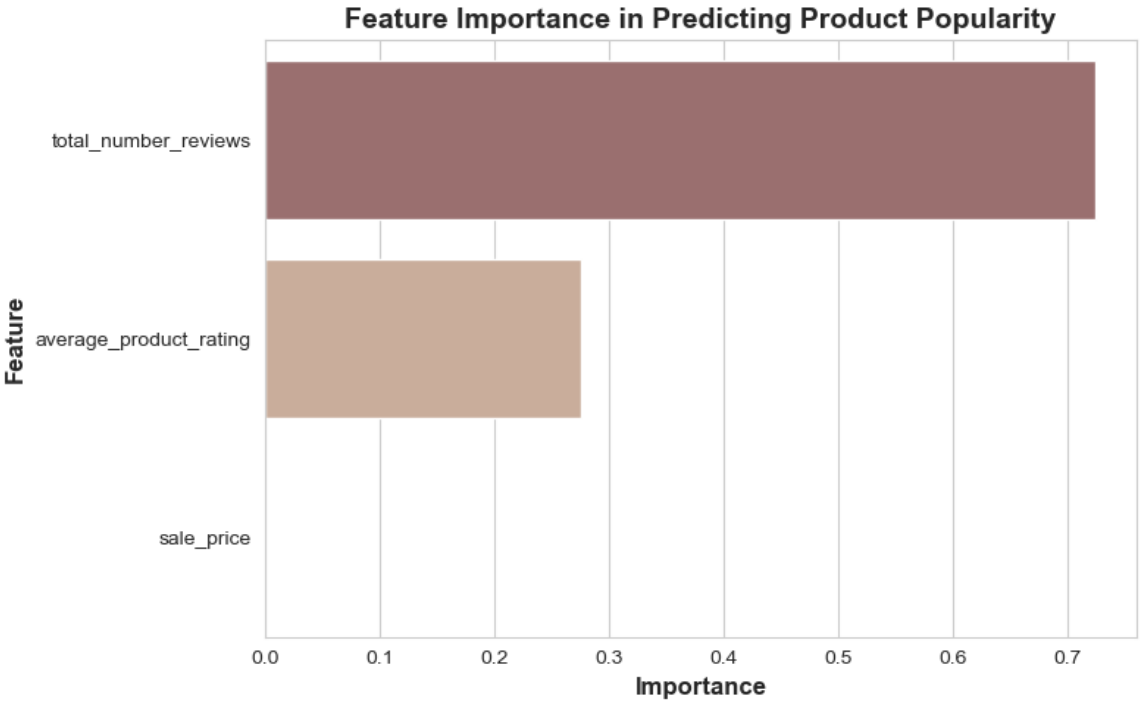
Observation

This scatter plot presents all product categories.
Categories highlighted in red represent those achieving exceptionally high customer satisfaction (average rating above 4.0).
The fact that only a few categories meet this standard underscores a broader challenge in maintaining consistent product quality.
These high-rated categories should be viewed as strategic benchmarks for improving the quality of other products and enhancing overall customer satisfaction.

In [26]:

```
# Forecast of popularity factors
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split
df = jcpenney_products.copy()
df = df[df['total_number_reviews'] > 0]
df = df.dropna(subset=['average_product_rating', 'sale_price'])
import re
def clean_price(price):
    if pd.isna(price):
        return np.nan
    price = str(price).replace('$', '').strip()
    if '-' in price:
        parts = re.split(r'[-–]', price)
        parts = [float(p) for p in parts if p.replace('.', '', 1).i
        if len(parts) == 2:
            return np.mean(parts)
    try:
        return float(price)
    except:
        return np.nan
df['sale_price'] = df['sale_price'].apply(clean_price)
df = df.dropna(subset=['sale_price'])
```

```
df['popularity_score'] = df['average_product_rating'] * np.log1p(df
X = df[['sale_price', 'average_product_rating', 'total_number_revie
y = df['popularity_score']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size
model = RandomForestRegressor(random_state=42)
model.fit(X_train, y_train)
importances = pd.DataFrame({'Feature': X.columns,'Importance': mode
plt.figure(figsize=(8, 5))
sns.barplot(x='Importance',y='Feature',hue='Feature',          data=
plt.title('Feature Importance in Predicting Product Popularity', fo
plt.xlabel('Importance', fontsize=12, fontweight='bold')
plt.ylabel('Feature', fontsize=12, fontweight='bold')
plt.tight_layout()
plt.savefig('Forecast of popularity factors.png', dpi=300)
plt.show()
display(importances)
```



	Feature	Importance
2	total_number_reviews	0.724028
1	average_product_rating	0.275901
0	sale_price	0.000070

Observation

The feature importance analysis shows that the number of reviews is the strongest predictor of product popularity, followed by average customer rating, while price has almost no impact.
This indicates that encouraging customers to leave more reviews and maintaining high satisfaction levels will be far more effective for increasing product popularity than changing prices.