🛒 BigBasket Exploratory Data Analysis (EDA)

In [1]:
```
# importing major libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px

# additional libraries
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
#importing dataset
df = pd.read_csv('BigBasket.csv')
```

Data Assessing

About Company

BigBasket is one of India’s largest online grocery and supermarket companies, known for delivering fresh produce, household essentials and everyday groceries right to customers’ doorsteps.

- What BigBasket Does ?

BigBasket operates as an online supermarket where users can shop for thousands of items — from fresh fruits and vegetables to packaged foods, dairy, personal care and household products. Orders can be placed via the website or mobile app, and deliveries are made directly to customers’ homes.

In [3]:
```
# overview data
df.head()
```

Out[3]:

	index	product	category	sub_category	brand	sale_price	market_pric
0	1	Garlic Oil - Vegetarian Capsule 500 mg	Beauty & Hygiene	Hair Care	Sri Sri Ayurveda	220.0	220
1	2	Water Bottle - Orange	Kitchen, Garden & Pets	Storage & Accessories	Mastercook	180.0	180
2	3	Brass Angle Deep - Plain, No.2	Cleaning & Household	Pooja Needs	Trm	119.0	250
3	4	Cereal Flip Lid Container/ Storage Jar - Assort...	Cleaning & Household	Bins & Bathroom Ware	Nakoda	149.0	176
4	5	Creme Soft Soap - For Hands & Body	Beauty & Hygiene	Bath & Hand Wash	Nivea	162.0	162

In [4]:

```
#shape
df.shape
```

Out[4]: (27555, 10)

In [5]:

```
df.columns
```

Out[5]:

```
Index(['index', 'product', 'category', 'sub_category', 'brand', 'sale_price',
       'market_price', 'type', 'rating', 'description'],
      dtype='object')
```

Data Card – BigBasket Product Dataset

Dataset Name

BigBasket Product Listings Dataset

Dataset Description

This dataset contains detailed information about products listed on **BigBasket**, one of India's largest online grocery and retail platforms.
It includes product names, categories, sub-categories, brand details, pricing information, customer ratings, and product descriptions.

The dataset can be used for **Exploratory Data Analysis (EDA)**, **price comparison**, **product categorization**, **customer rating analysis**, and **recommendation system development**.

Source of Data

- Extracted from BigBasket product listings
- Represents e-commerce grocery and household product data

Number of Records

- **Total Records:** N
- Each row represents one unique product

Number of Features

- **Total Features:** 10

Dataset Structure

The dataset is organized in a tabular format where each row corresponds to a single product and each column represents a specific attribute of that product.

Feature Description

Column Name	Description
index	Unique numerical identifier for each product

Column Name	Description
product	Name of the product
category	Main product category
sub_category	Sub-category within the main category
brand	Brand or manufacturer name
sale_price	Selling price of the product (INR)
market_price	Original market price (MRP) of the product (INR)
type	Product type or functional classification
rating	Average customer rating (1–5 scale)
description	Textual description of product features

Data Types Overview

Feature	Data Type
index	Integer
product	Categorical (Text)
category	Categorical
sub_category	Categorical
brand	Categorical
sale_price	Numerical (Float)
market_price	Numerical (Float)
type	Categorical
rating	Numerical (Float)
description	Text

📌 Types of Data Errors

✅ Summary Table

Error Type	Description	Example
Completeness	Missing data	Age = NULL
Validity	Rule or datatype violation	Salary = -10000

Error Type	Description	Example
Accuracy	Unrealistic values	Age = 200
Inconsistency	Multiple formats	NYC vs New York City

In [6]:
```
# Seaking Information
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 27555 entries, 0 to 27554
Data columns (total 10 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   index         27555 non-null  int64  
 1   product       27554 non-null  object 
 2   category      27555 non-null  object 
 3   sub_category  27555 non-null  object 
 4   brand         27554 non-null  object 
 5   sale_price    27549 non-null  float64
 6   market_price  27555 non-null  float64
 7   type          27555 non-null  object 
 8   rating        18919 non-null  float64
 9   description   27440 non-null  object 
dtypes: float64(3), int64(1), object(6)
memory usage: 2.1+ MB
```

Data Quality Observations – BigBasket Product Dataset

Completeness

- Missing values observed in **product**, **brand**, **sale_price**, **rating**, and **description** columns.
- **Rating** has a significant number of missing values, indicating many unrated products.

Accuracy

- Missing **sale_price** can affect price and discount analysis.
- Incomplete **product** or **brand** information may impact product-level insights.

Validity

- **Rating** values should fall within an expected range (e.g., 1–5).
- **Sale price** should not exceed **market price**; such cases need

validation.

Consistency

- Text columns may contain inconsistent naming or formatting.
- Products with equal **sale_price** and **market_price** indicate no discount and should be checked for consistency.

In [7]:
```
# Seeking description
df.describe()
```

Out[7]:

	index	sale_price	market_price	rating
count	27555.00000	27549.000000	27555.000000	18919.000000
mean	13778.00000	334.648391	382.056664	3.943295
std	7954.58767	1202.102113	581.730717	0.739217
min	1.00000	2.450000	3.000000	1.000000
25%	6889.50000	95.000000	100.000000	3.700000
50%	13778.00000	190.320000	220.000000	4.100000
75%	20666.50000	359.000000	425.000000	4.300000
max	27555.00000	112475.000000	12500.000000	5.000000

In [8]:
```
# Completness
df.isnull().sum().sum()
# Percentage
df.isnull().mean()*100
```

Out[8]:
```
index            0.000000
product          0.003629
category         0.000000
sub_category     0.000000
brand            0.003629
sale_price       0.021775
market_price     0.000000
type             0.000000
rating          31.340954
description      0.417347
dtype: float64
```

In [9]:
```
df['product'].fillna('Unknown Product', inplace=True)
df['brand'].fillna('Unknown Brand', inplace=True)
```

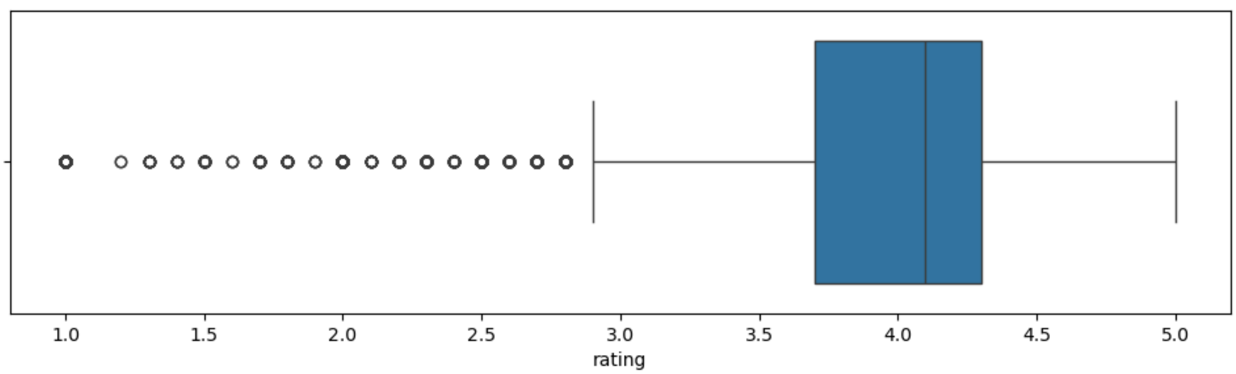
In [10]:
```
df['sale_price'].fillna(df['market_price'], inplace=True)
```

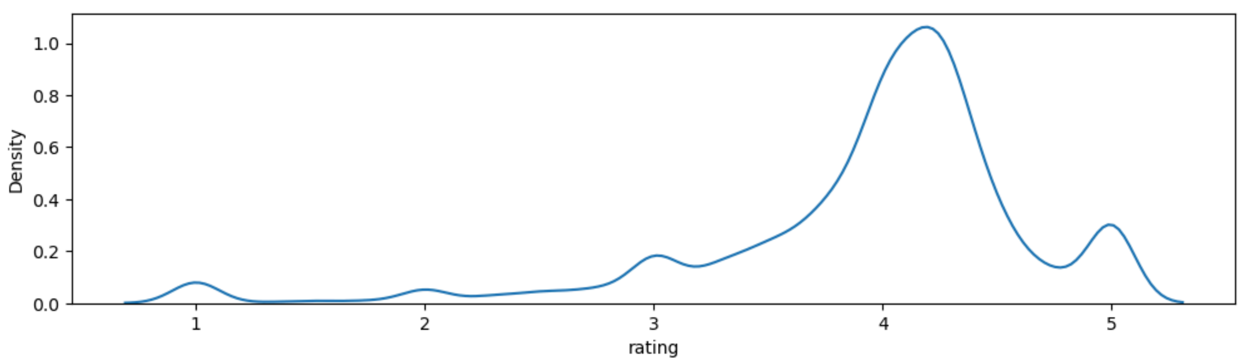
In [11]:
```python
df['description'].fillna('', inplace=True)
```

In [12]:
```python
# Completeness
df.isnull().sum().sum()
# Percentage
df.isnull().mean()*100
```

Out[12]:
```
index            0.000000
product          0.000000
category         0.000000
sub_category     0.000000
brand            0.000000
sale_price       0.000000
market_price     0.000000
type             0.000000
rating          31.340954
description      0.000000
dtype: float64
```

In [13]:
```python
plt.figure(figsize=(12,3))
sns.boxplot(x=df.rating)
plt.show()
plt.figure(figsize=(12,3))
sns.kdeplot(x=df.rating)
plt.show()
df.rating.skew()
```





Out[13]:
```
np.float64(-1.73020990761911)
```

In [14]:
```python
#CORRECT PRICEING
```

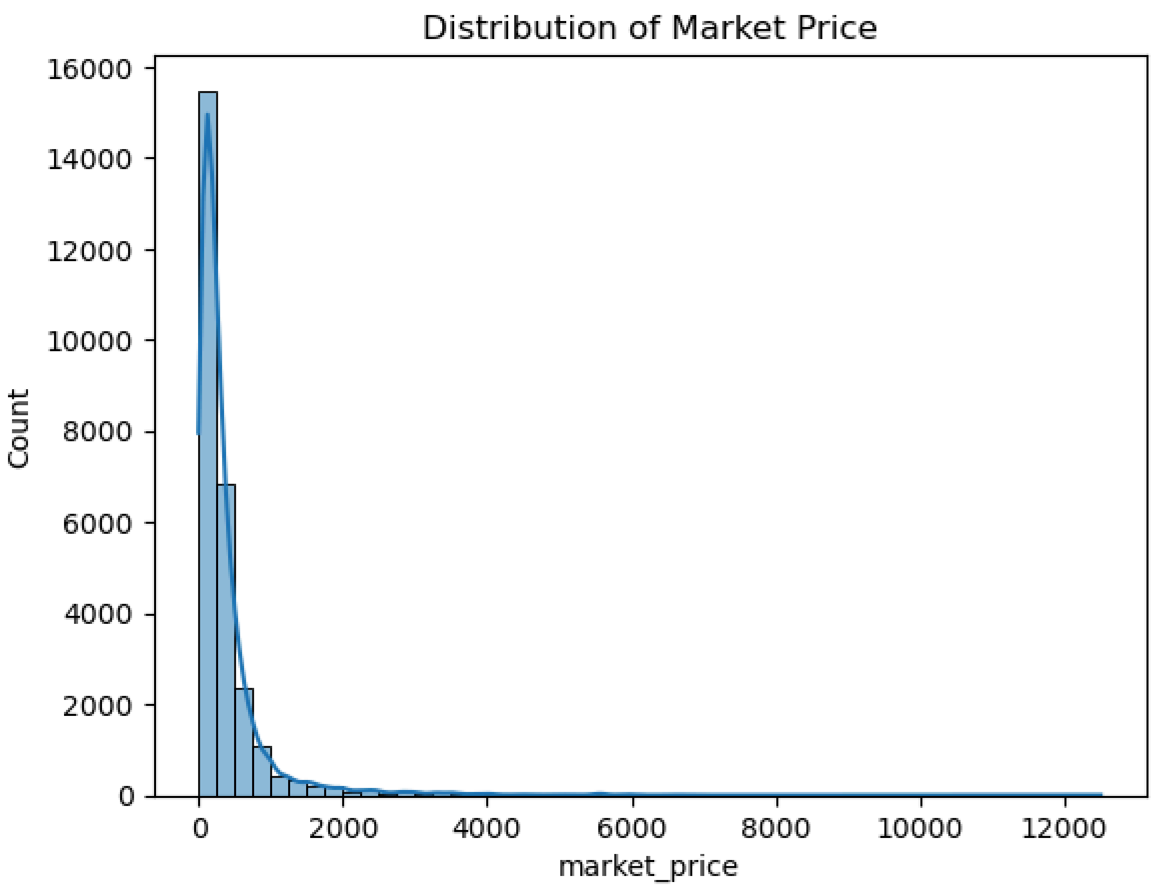
```
df.loc[df['sale_price'] > df['market_price'], 'sale_price'] = df['market_price
```

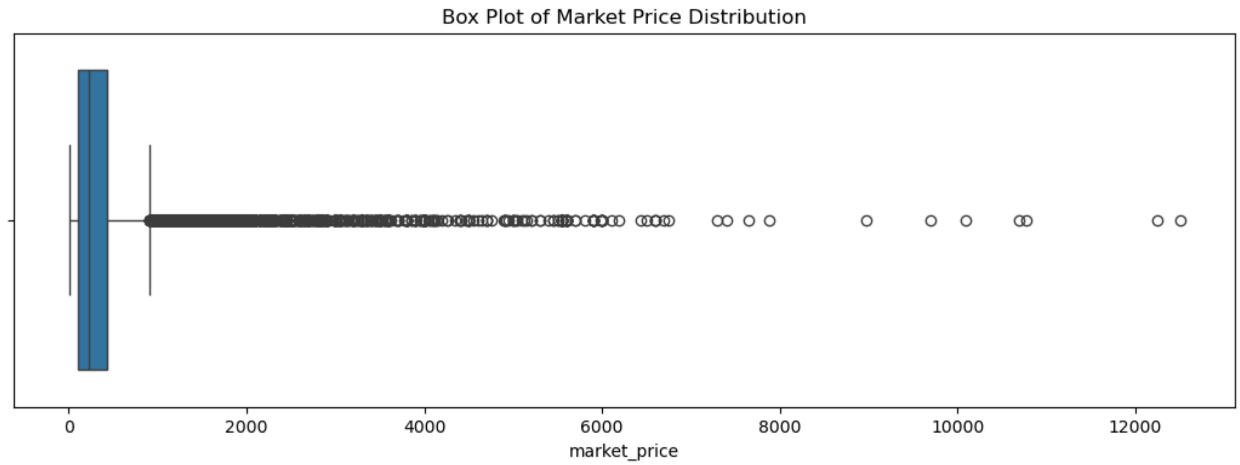
In [15]:
```
df.duplicated().sum()
df.drop_duplicates(inplace=True)
```

Data Analysis & Visualization

Univariate Analysis

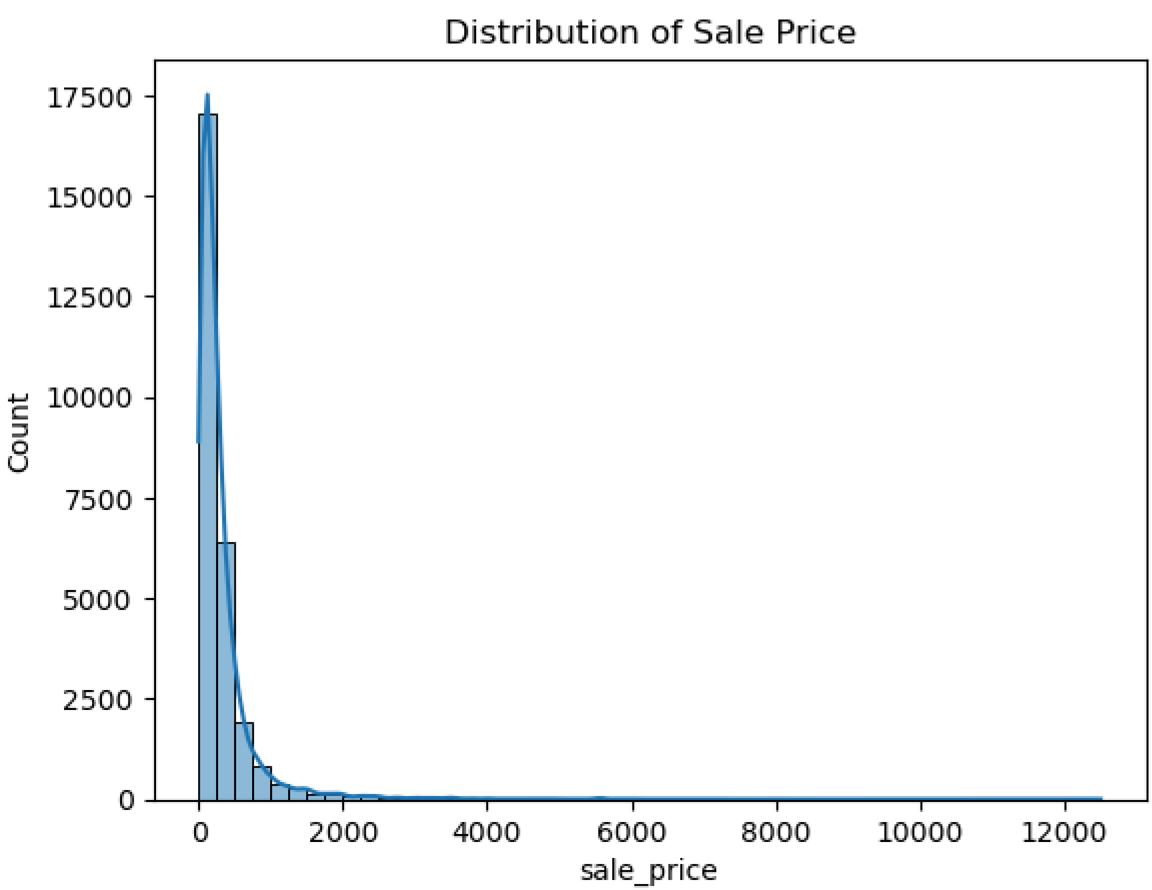
In [16]:
```
# Univariate Analysis
# Numerical columns
# Distribution
# Market Price
plt.title("Distribution of Market Price")
sns.histplot(df.market_price,bins=50,kde=True)
plt.show()

plt.figure(figsize=(13,4))
plt.title("Box Plot of Market Price Distribution")
sns.boxplot(x=df.market_price)
plt.show()
df.market_price.skew()
```

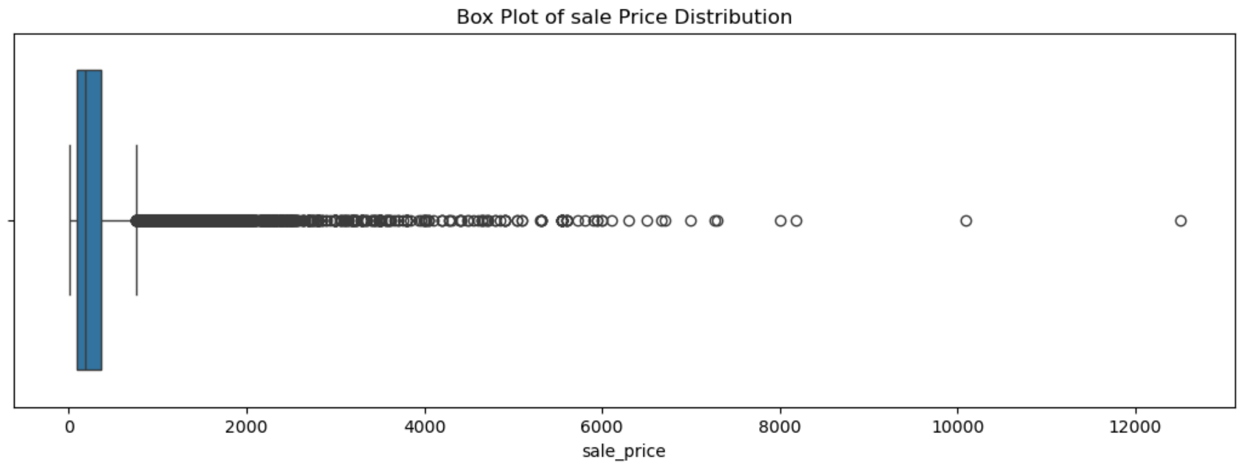




Out[16]: np.float64(5.788868514337814)

In [17]:
```
# Sale Price
plt.title("Distribution of Sale Price")
sns.histplot(df.sale_price,bins=50,kde=True)
plt.show()

plt.figure(figsize=(13,4))
plt.title("Box Plot of sale Price Distribution")
sns.boxplot(x=df.sale_price)
plt.show()
df.sale_price.skew()
```



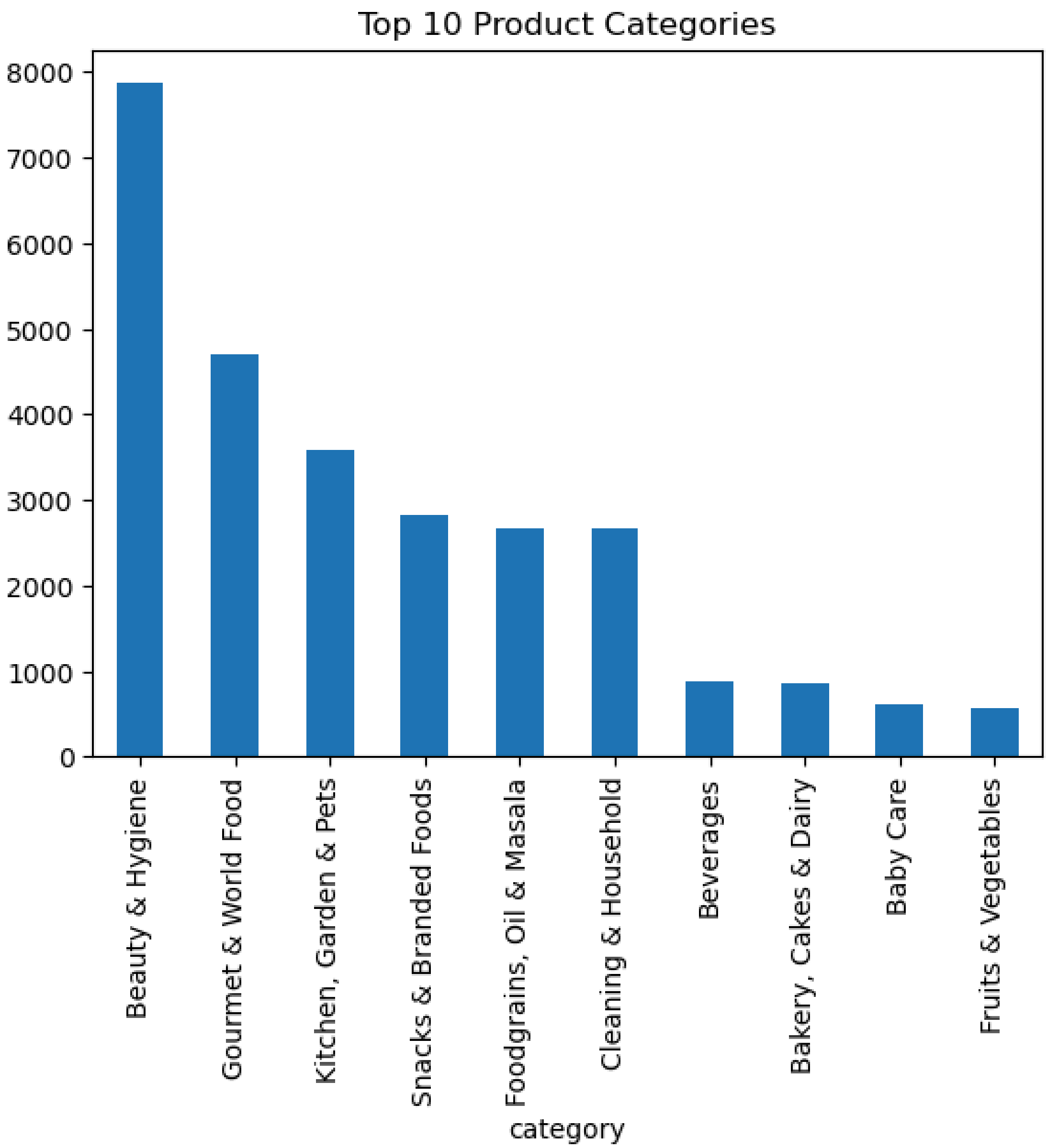


Out[17]:
```
np.float64(6.17469685556941)
```

Insights – Market Price and Sale Price

- Market price is generally higher than or equal to sale price, confirming the presence of discounts across most products.
- Sale price closely follows market price, indicating a strong linear pricing relationship.
- The majority of products are concentrated in lower to mid price ranges, suggesting a mass-market pricing strategy.
- A small number of products show very high market and sale prices, which appear as outliers in box plots.
- Equal market and sale prices indicate products sold without discounts, commonly seen in daily-use or essential items.

In [18]:
```
# Category
df['category'].value_counts().head(10).plot(kind='bar')
plt.title("Top 10 Product Categories")
plt.show()
```



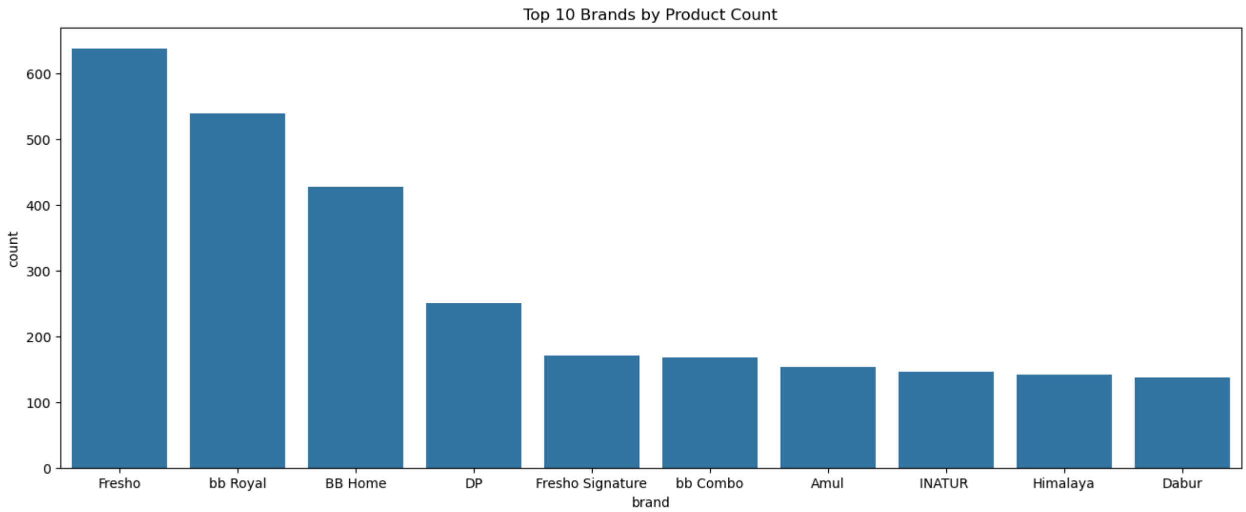
Insights – Top 10 Product Categories

- A small number of categories contribute to a large proportion of products listed on BigBasket.
- This indicates that BigBasket focuses heavily on high-demand everyday categories such as household and personal care items.
- Category dominance suggests strong customer demand and frequent purchases in these segments.

In [19]:

```
#BRAND
plt.figure(figsize=(16,6))
sns.countplot(data=df, x='brand', order=df['brand'].value_counts().head(10).ir
plt.title("Top 10 Brands by Product Count")
```

```
plt.show()

temp = df['brand'].value_counts().head(10).reset_index()
temp.columns = ['brand', 'count']
temp
px.pie(temp,names='brand',values='count',
       color_discrete_sequence=px.colors.sequential.Blues,
       height=400,title='Top 10 Brands Distribution')
```



Insights – Top 10 Brands

- Only a few brands appear repeatedly across the dataset, showing brand

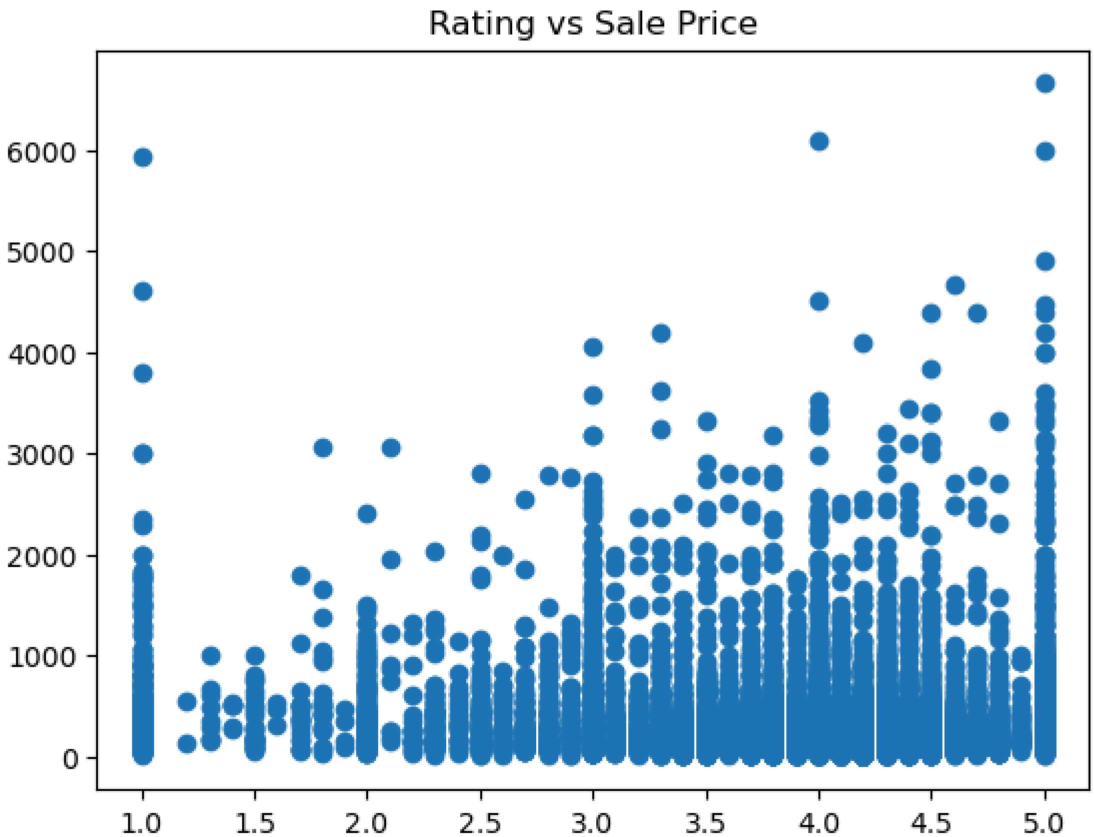
concentration.
- Popular brands likely have higher customer trust and better availability on the platform.
- The presence of dominant brands suggests that BigBasket prioritizes well-known and reliable suppliers.

Bivariate Analysis

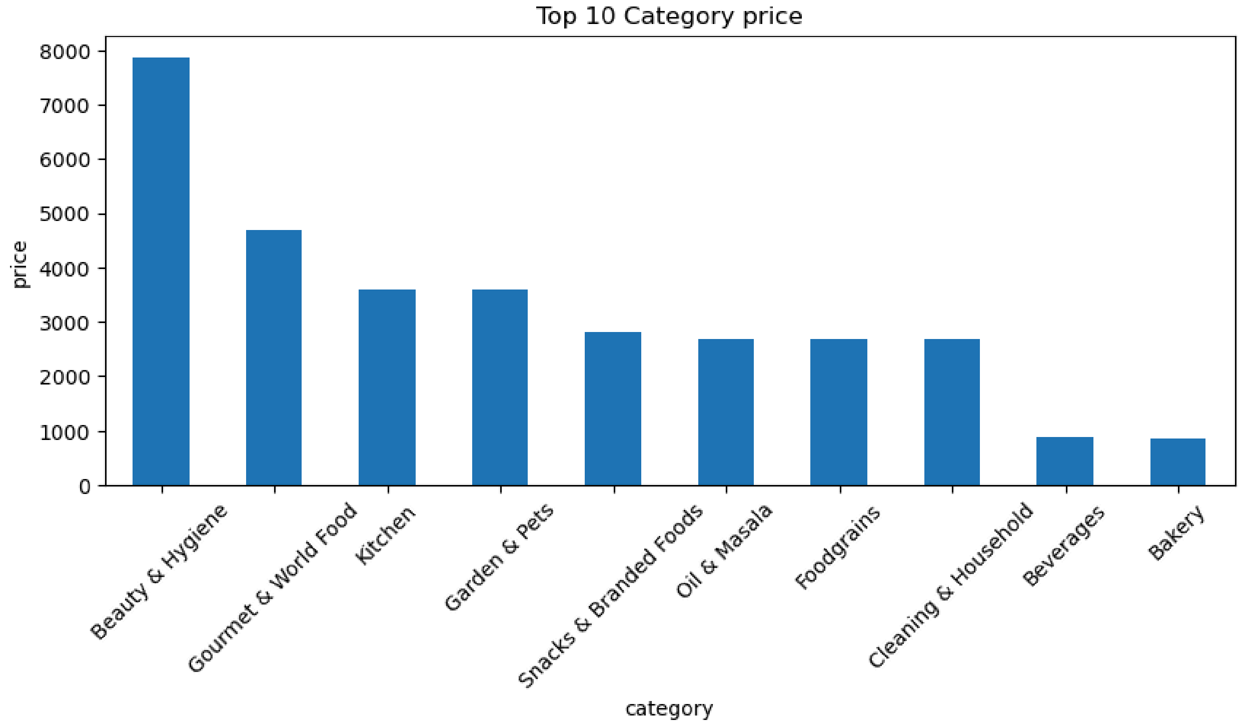
In [20]:
```
#plotly
df['discount'] = df['market_price'] - df['sale_price']

px.scatter(df,x='sale_price', y='market_price',color='discount',
    hover_data=['product','sale_price','market_price','discount'],
    height=500,
    title='Market Price vs Sale Price with Discount Intensity')
```

- A sale price lower than the market price indicates the presence of discounts, which is a common pricing strategy in e-commerce platforms to drive customer demand and increase sales volume.

In [21]:
```
# Rating vs sale price
plt.scatter(df['rating'], df['sale_price'])
plt.title("Rating vs Sale Price")
plt.show()
```

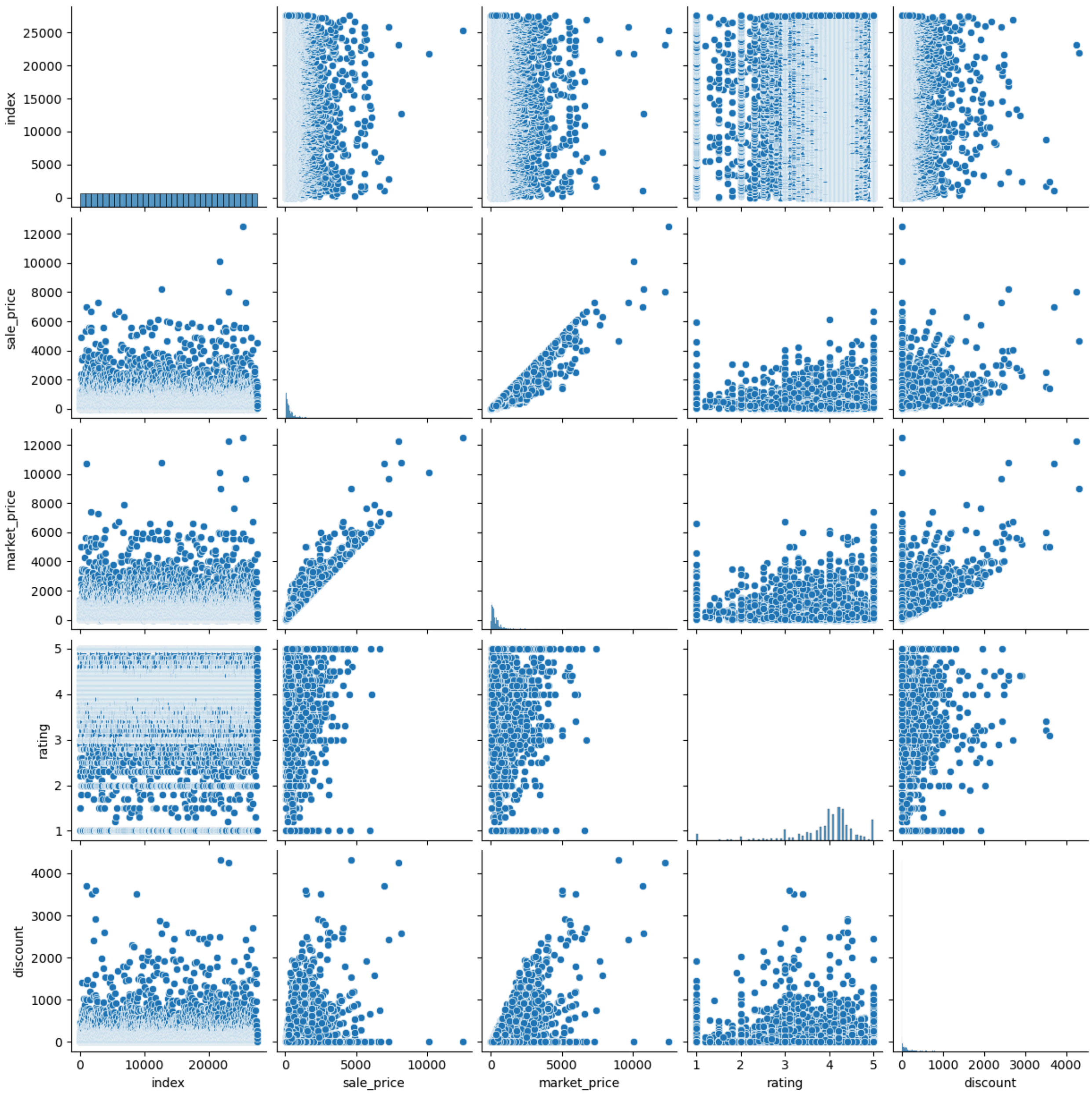


In [22]:
```
#Top 10 Category price
category = df['category'].str.split(', ').explode().value_counts().head(10)

plt.figure(figsize=(10,4))
category.plot(kind='bar')
plt.title('Top 10 Category price')
plt.xlabel('category')
plt.ylabel('price')
plt.xticks(rotation=45)
plt.show()
```

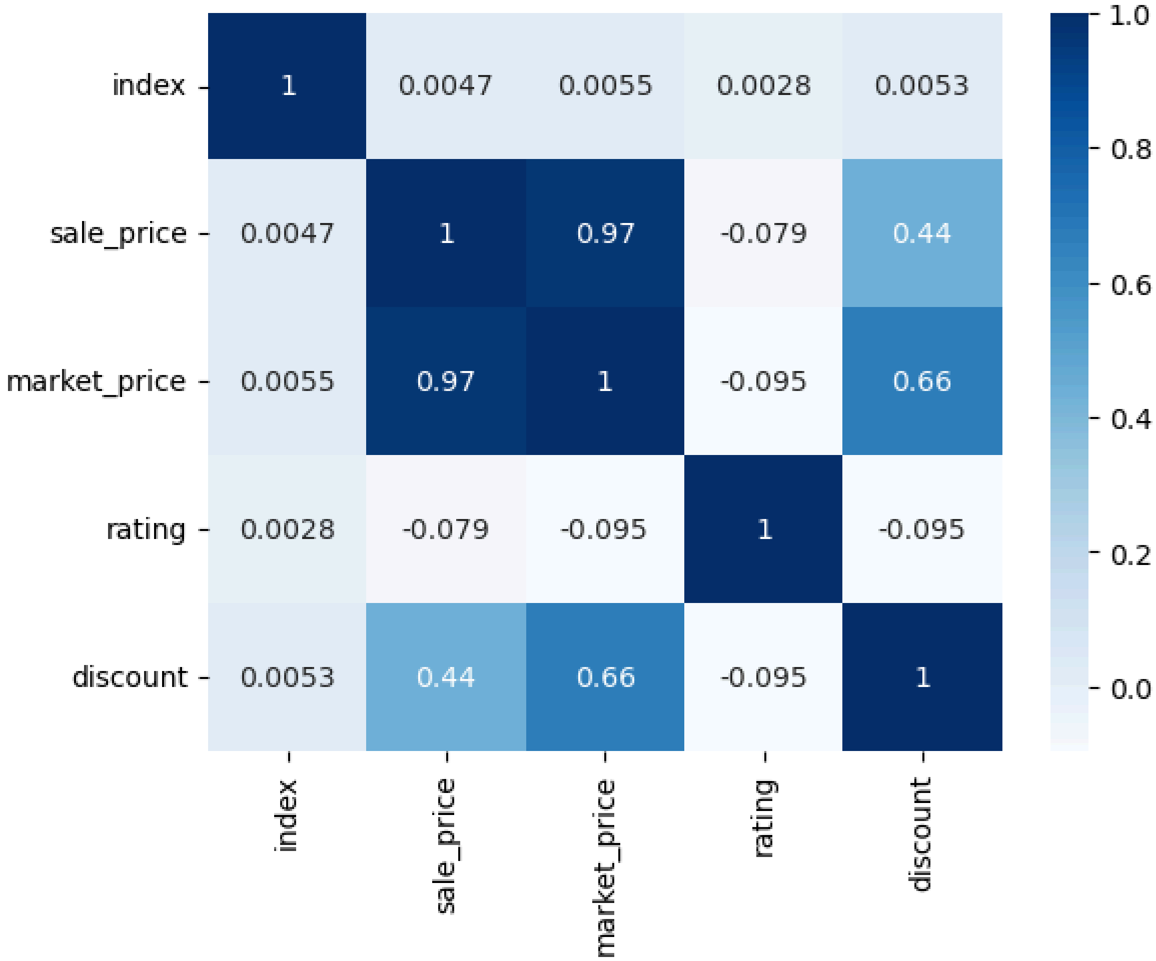


Multivariate Analysis

In [23]:
```
# multivariate analysis

sns.pairplot(df)
plt.show()
```



In [24]:
```
# corr
# heat map
sns.heatmap(df.corr(numeric_only=True),cmap="Blues",annot=True)
plt.show()
```



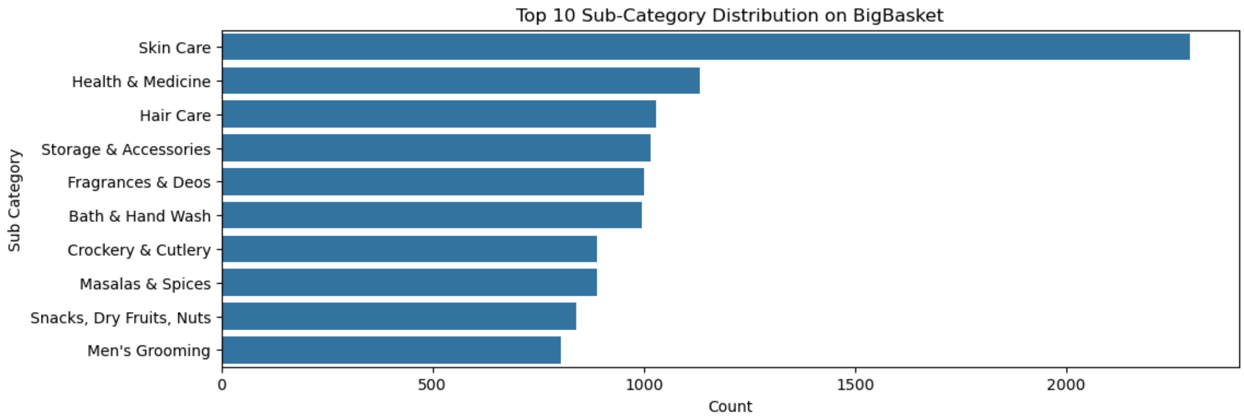
Correlation Analysis (Heatmap Summary)

- **Sale Price & Market Price:** Strong positive correlation (0.97), both increase together.
- **Discount & Market Price:** Moderate positive correlation (0.66).
- **Discount & Sale Price:** Moderate positive correlation (0.44).
- **Rating & Prices:** Very weak negative correlation, almost no relationship.
- **Rating & Discount:** Very weak negative correlation.
- **Index:** No meaningful correlation, can be removed.

Conclusion:
Market price strongly influences sale price, discount has moderate impact, and rating is independent of price factors.

In [25]:
```
# Top 10 Sub-Categories
temp = df['sub_category'].value_counts().head(10).reset_index()
temp.columns = ['sub_category', 'count']
plt.figure(figsize=(12,4))
```

```
sns.countplot(data=df,y='sub_category',order=temp['sub_category'])
plt.title('Top 10 Sub-Category Distribution on BigBasket')
plt.xlabel('Count')
plt.ylabel('Sub Category')
plt.show()

# Pie chart
px.pie(temp,values='count',names='sub_category',height=400,
    color_discrete_sequence=px.colors.sequential.RdBu,hole=0.5,
    title='Top 10 Sub-Category Listing Distribution on BigBasket').show()
temp
```



Out[25]:

	sub_category	count
0	Skin Care	2294
1	Health & Medicine	1133
2	Hair Care	1028
3	Storage & Accessories	1015
4	Fragrances & Deos	1000
5	Bath & Hand Wash	996
6	Crockery & Cutlery	890
7	Masalas & Spices	889
8	Snacks, Dry Fruits, Nuts	840
9	Men's Grooming	805

Top 10 Sub-Category Insights (BigBasket)

- A few sub-categories dominate the product listings.
- The top sub-category has the highest number of products, showing strong demand.
- Product distribution is uneven, indicating a long-tail pattern.
- BigBasket focuses more on daily-need sub-categories.
- Lower-ranked sub-categories have significantly fewer listings.

Conclusion:
BigBasket’s inventory is concentrated in popular sub-categories, reflecting customer demand and core business focus.

In [31]:

```
# Top 10 products by frequency
temp = df['product'].value_counts().head(10).reset_index()
temp.columns = ['product', 'count']
px.pie(temp,names='product',values='count',title='Top 10 Product Distribution'
    color_discrete_sequence=px.colors.sequential.Plasma,height=500).show()
```

Top 10 Product Insights

- A small number of products dominate the total listings.
- The top products indicate high customer demand and popularity.
- Product distribution follows a skewed pattern, with few products contributing most of the volume.
- High-priced products appear less frequently compared to mid-range products.
- BigBasket focuses inventory on fast-moving and essential products.

Conclusion:

The Top 10 products represent BigBasket’s core offerings and drive the majority of platform activity.

Conclusion

- **This project analyzed BigBasket product data through univariate, bivariate, and multivariate analysis. Data cleaning improved reliability by addressing missing values and pricing inconsistencies. Visual insights reveal strong category dominance, pricing strategies, and customer rating behavior. The dataset is suitable for recommendation systems, pricing optimization, and market analysis.**

In [ ]: