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February 22, 2025

1 Bagpack Price Prediction

[1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

1.1 Reading the dataset

[2]:
```python
df = pd.read_csv("./train.csv")
```

1.2 Exploring the dataset

[3]:
```python
print("Information of the dataset: ")
print(df.info())
```

```
Information of the dataset:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 300000 entries, 0 to 299999
Data columns (total 11 columns):
 #   Column                Non-Null Count   Dtype
---  ------                --------------   -----
 0   id                    300000 non-null  int64
 1   Brand                 290295 non-null  object
 2   Material              291653 non-null  object
 3   Size                  293405 non-null  object
 4   Compartments          300000 non-null  float64
 5   Laptop Compartment    292556 non-null  object
 6   Waterproof            292950 non-null  object
 7   Style                 292030 non-null  object
 8   Color                 290050 non-null  object
 9   Weight Capacity (kg)  299862 non-null  float64
 10  Price                 300000 non-null  float64
dtypes: float64(3), int64(1), object(7)
memory usage: 25.2+ MB
None
```

```python
print("Description of the dataset: ")
print(df.describe())
```

```
Description of the dataset:
                  id   Compartments  Weight Capacity (kg)          Price
count  300000.000000  300000.000000         299862.000000  300000.000000
mean   149999.500000       5.443590             18.029994      81.411107
std     86602.684716       2.890766              6.966914      39.039340
min         0.000000       1.000000              5.000000      15.000000
25%     74999.750000       3.000000             12.097867      47.384620
50%    149999.500000       5.000000             18.068614      80.956120
75%    224999.250000       8.000000             24.002375     115.018160
max    299999.000000      10.000000             30.000000     150.000000
```

```python
print("Shape of the dataset ", df.shape)
```

```
Shape of the dataset  (300000, 11)
```

1.3 Exploring the null values

```python
df.isnull().sum()
```

```
id                         0
Brand                   9705
Material                8347
Size                    6595
Compartments               0
Laptop Compartment      7444
Waterproof              7050
Style                   7970
Color                   9950
Weight Capacity (kg)     138
Price                      0
dtype: int64
```

1.4 Handling the null values

```python
df['Brand'] = df['Brand'].fillna("Non Branded")

df['Material'] = df['Material'].fillna("Unknown")

df['Size'] = df['Size'].fillna('Unknown')

df['Laptop Compartment'] = df['Laptop Compartment'].fillna("Unknown")

df['Waterproof'] = df['Waterproof'].fillna("Unknown")
```

```
df['Style'] = df['Style'].fillna("Unknown")

df['Color'] = df['Color'].fillna('Unique')

weight_mean = df['Weight Capacity (kg)'].mean()
df['Weight Capacity (kg)'] = df['Weight Capacity (kg)'].fillna(weight_mean)

print("After removing all the outliers")
df.isnull().sum()
```

```
After removing all the outliers
```

[7]:
```
id                      0
Brand                   0
Material                0
Size                    0
Compartments            0
Laptop Compartment      0
Waterproof              0
Style                   0
Color                   0
Weight Capacity (kg)    0
Price                   0
dtype: int64
```

1.5 Adding Columns for better Graph plotting

[8]:
```
bins = [0, 13, 21, 30]
labels = ['Light', 'Medium', 'Heavy']
df['Weight Category'] = pd.cut(df['Weight Capacity (kg)'], bins = bins, labels␣
 ↪= labels, right = True)

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

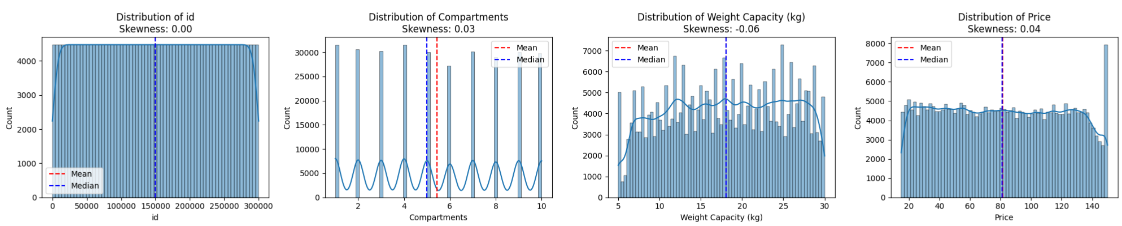
[9]:
```
bins = [15, 60, 105, 150]
labels = ['Affordable', 'Medium', 'Expensive']
df['Price Category'] = pd.cut(df['Price'], bins = bins, labels = labels, right␣
 ↪= True)
```

1.6 Skewness

[10]:
```
numerical_cols = df.select_dtypes(include=['float64', 'int64'])
skewness = numerical_cols.skew()

# Print skewness values
print("Skewness of numerical columns:")
```

```python
print(skewness)

# Plotting skewness using subplots for numerical columns
n_cols = len(numerical_cols.columns)

# Set up the subplots
fig, axes = plt.subplots(nrows=1, ncols=n_cols, figsize=(5 * n_cols, 4))

# Plot each numerical column
for ax, col in zip(axes, numerical_cols.columns):
    sns.histplot(df[col], ax=ax, kde=True)
    ax.set_title(f'Distribution of {col}\nSkewness: {skewness[col]:.2f}')
    ax.axvline(df[col].mean(), color='red', linestyle='--', label='Mean')
    ax.axvline(df[col].median(), color='blue', linestyle='--', label='Median')
    ax.legend()

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

```
Skewness of numerical columns:
id                     0.000000
Compartments           0.029125
Weight Capacity (kg)  -0.064254
Price                  0.036883
dtype: float64
```



[11]:
```python
df.isnull().sum()
```

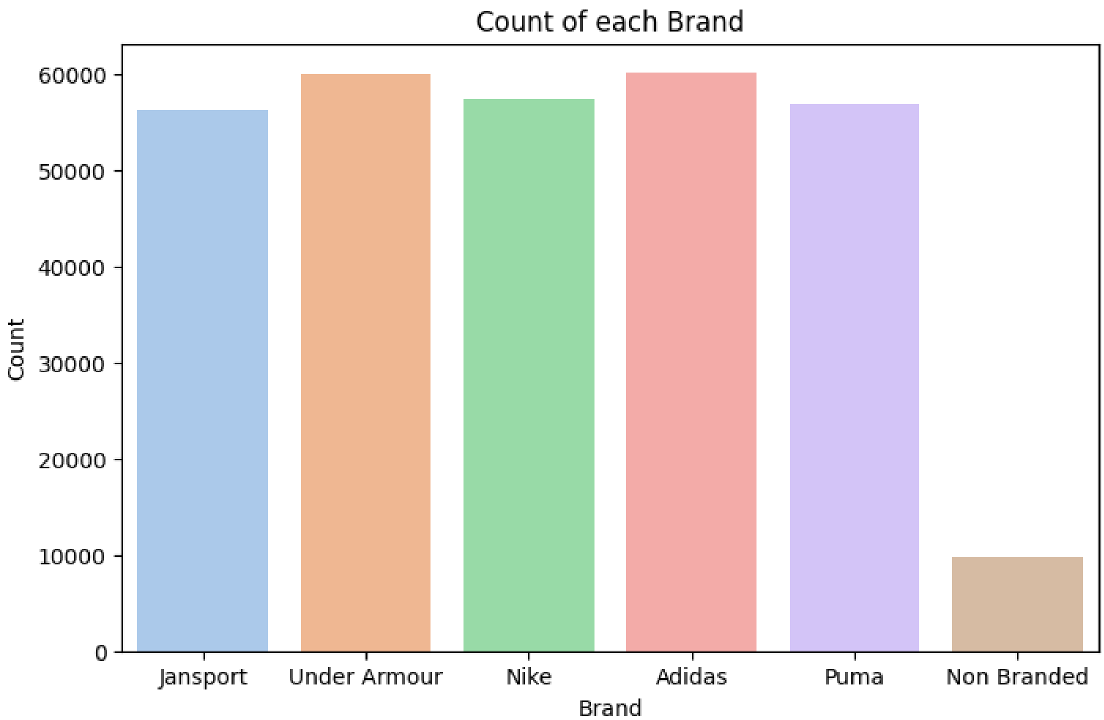
[11]:
```
id                      0
Brand                   0
Material                0
Size                    0
Compartments            0
Laptop Compartment      0
Waterproof              0
Style                   0
Color                   0
Weight Capacity (kg)    0
```

```
Price                    0
Weight Category          0
Price Category         693
dtype: int64
```

1.7 Univariate Analysis

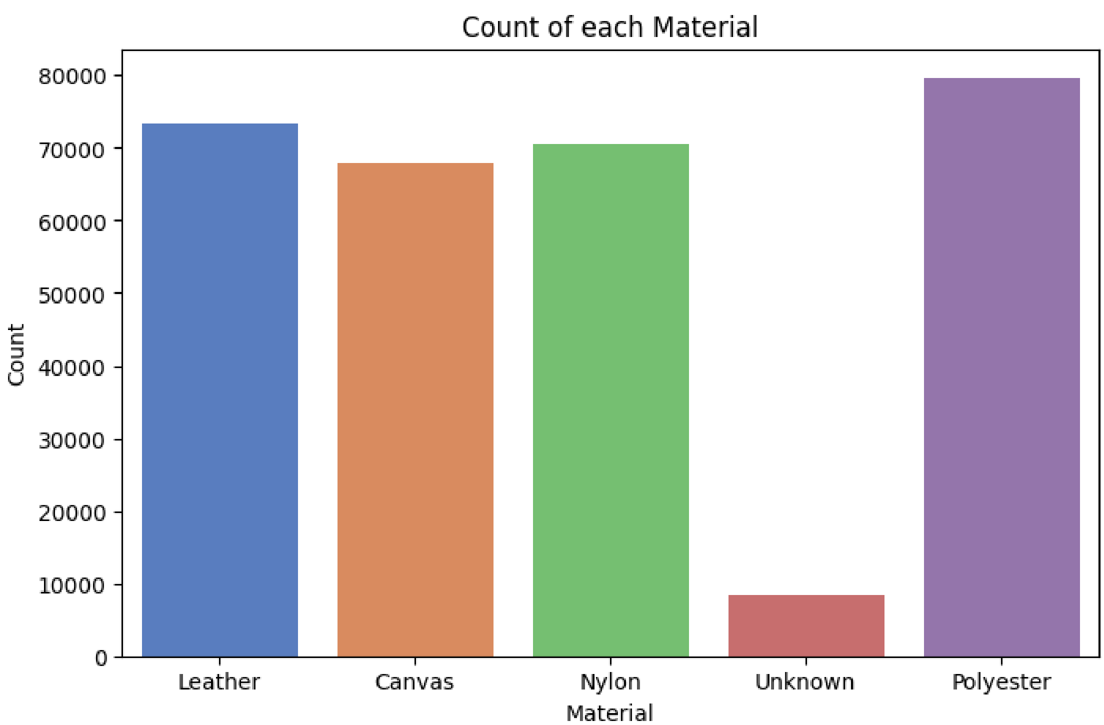
```python
[12]: # Brand
plt.figure(figsize = (8, 5))
sns.countplot(x = df['Brand'], data = df, palette = 'pastel', hue = None)

plt.title('Count of each Brand')
plt.xlabel('Brand')
plt.ylabel('Count')

plt.show()
```

```
<ipython-input-12-4aeb48e43e68>:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.countplot(x = df['Brand'], data = df, palette = 'pastel', hue = None)
```



[13]:
```python
# Brand
plt.figure(figsize = (8, 5))
sns.countplot(x = df['Material'], data = df, palette = 'muted', hue = None)

plt.title('Count of each Material')
plt.xlabel('Material')
plt.ylabel('Count')

plt.show()
```

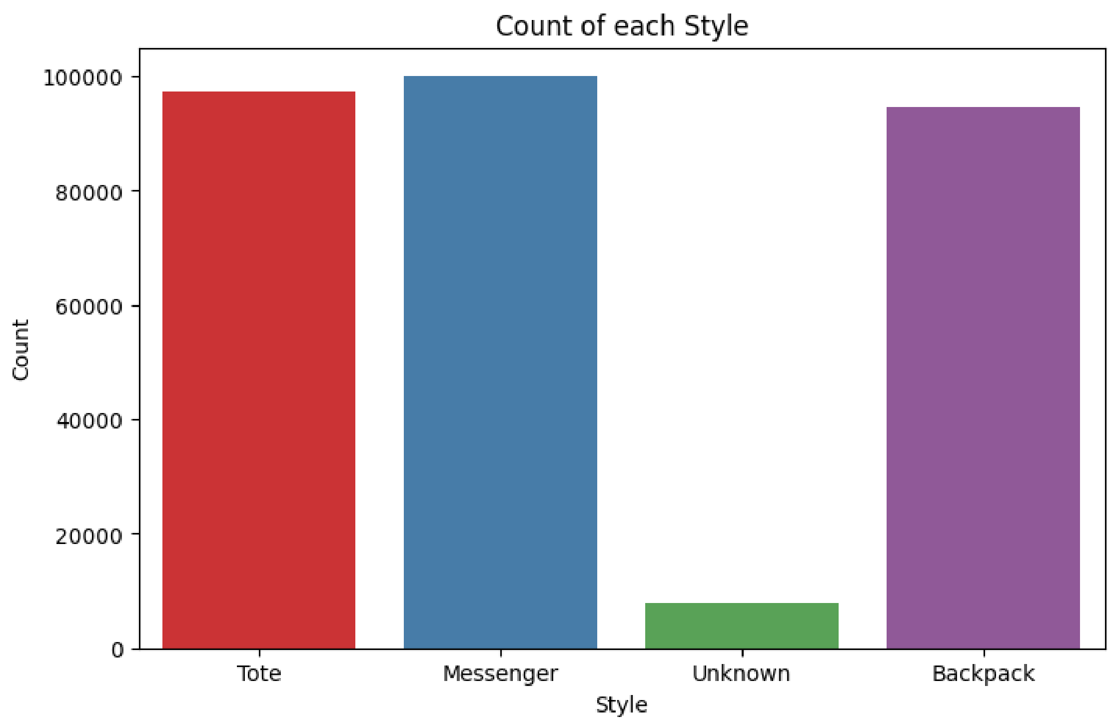
```
<ipython-input-13-71edb78387b0>:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.countplot(x = df['Material'], data = df, palette = 'muted', hue = None)
```



[14]:
```python
# Brand
plt.figure(figsize = (8, 5))
sns.countplot(x = df['Style'], data = df, palette = 'Set1', hue = None)
```

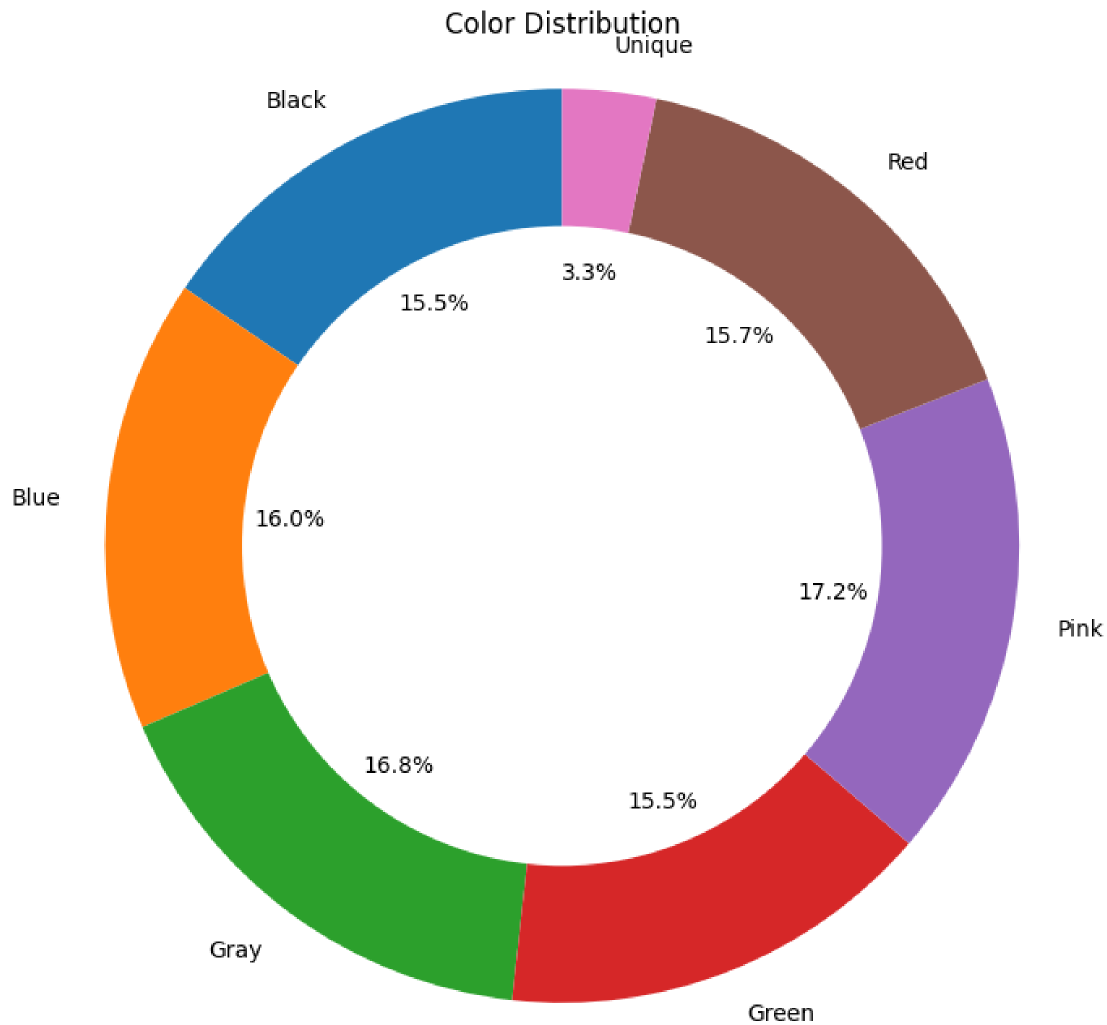
```python
plt.title('Count of each Style')
plt.xlabel('Style')
plt.ylabel('Count')

plt.show()
```

```
&lt;ipython-input-14-eef356250b69&gt;:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.countplot(x = df['Style'], data = df, palette = 'Set1', hue = None)
```



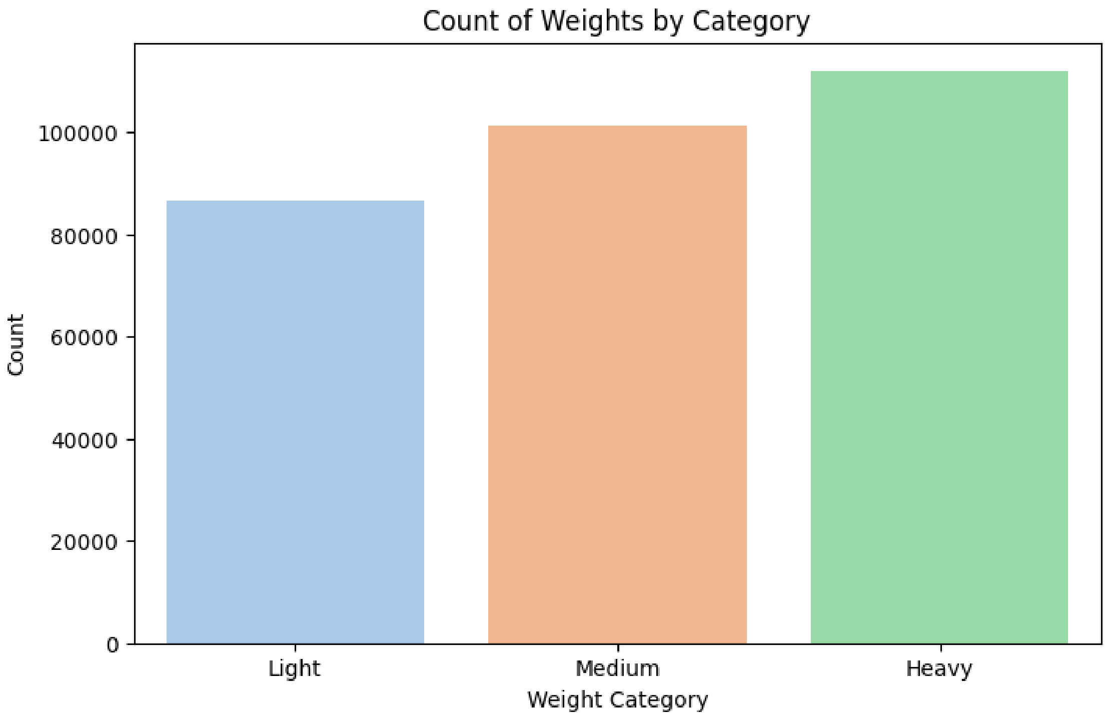
[15]:
```python
# Color
color = df.groupby('Color', as_index = False).count()

plt.figure(figsize=(8, 8))
plt.pie(color['Brand'], labels=color['Color'], autopct='%1.1f%%', startangle=90)

# Draw a white circle in the center to create a doughnut effect
centre_circle = plt.Circle((0, 0), 0.70, fc='white')
fig = plt.gcf()
fig.gca().add_artist(centre_circle)
```

```
# Equal aspect ratio ensures that pie is drawn as a circle
plt.axis('equal')
plt.title('Color Distribution')
plt.show()
```



[16]:
```
# Weight category
plt.figure(figsize=(8, 5))
sns.barplot(x='Weight Category', y='Count', data=category_counts,␣
↪palette='pastel')
plt.title('Count of Weights by Category')
plt.xlabel('Weight Category')
plt.ylabel('Count')
plt.show()
```

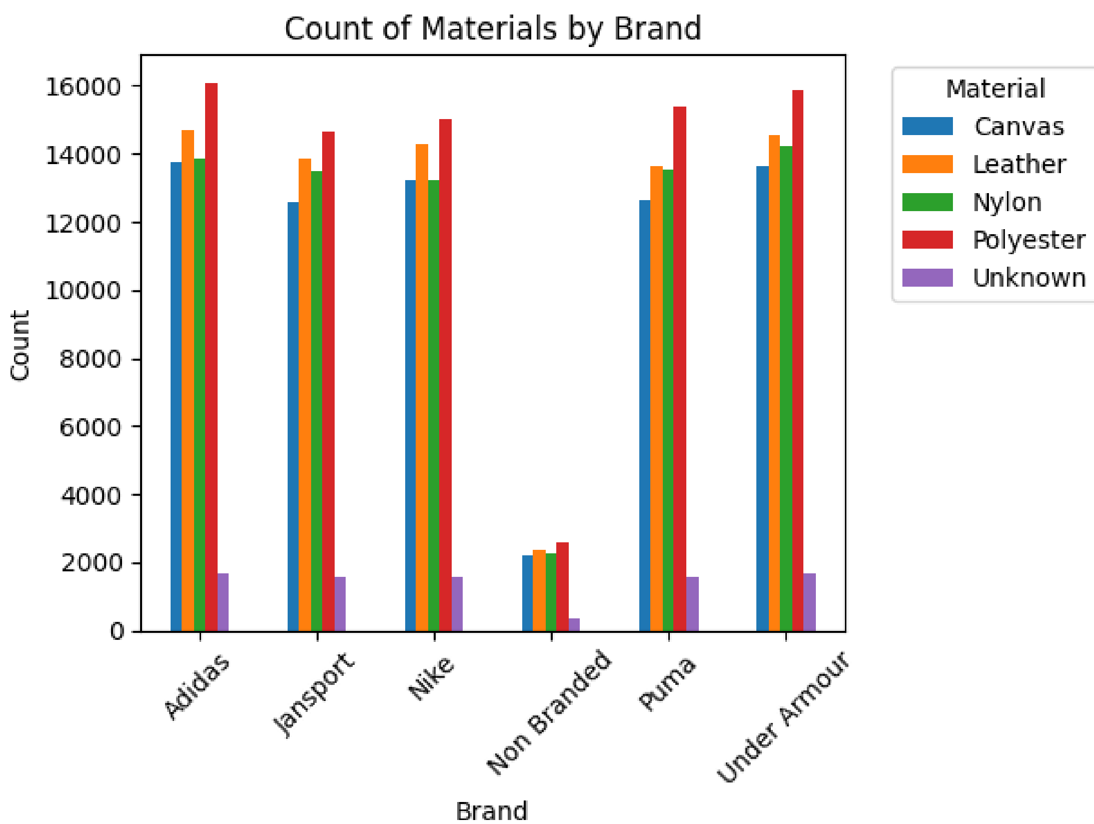
```
<ipython-input-16-2c15eedf876d>:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.barplot(x='Weight Category', y='Count', data=category_counts,
palette='pastel')
```



1.8 Bivariate analysis

[17]:

```python
# Brand vs Material
grouped = df.groupby(['Brand', 'Material']).size().reset_index(name='Count')
pivoted = grouped.pivot(index='Brand', columns='Material', values='Count').
    ↪fillna(0)

pivoted.plot(kind='bar', stacked=False)
plt.title('Count of Materials by Brand')
plt.xlabel('Brand')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.legend(title='Material', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.tight_layout()
plt.show()
```



[18]:

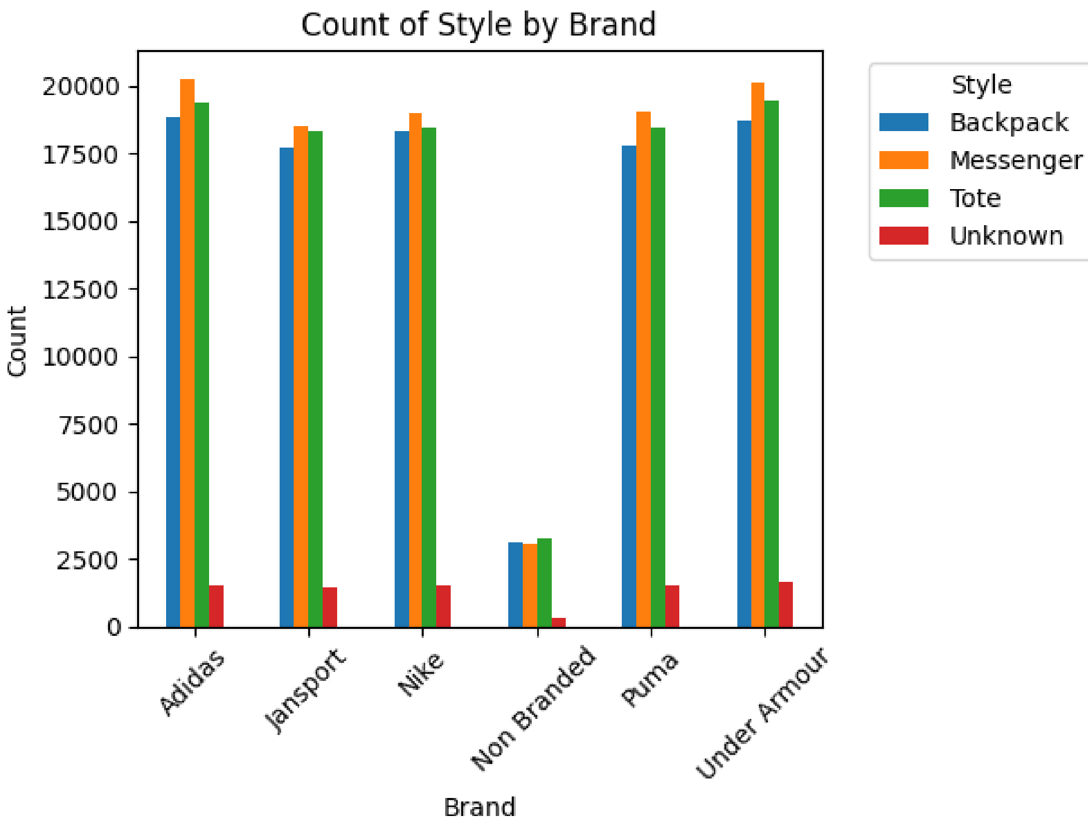
```python
# Brand vs Price
grouped = df.groupby(['Brand', 'Price Category']).size().
    ↪reset_index(name='Count')
pivoted = grouped.pivot(index='Brand', columns='Price Category',␣
    ↪values='Count').fillna(0)
```

```
pivoted.plot(kind='bar', stacked=False)
plt.title('Count of Brand by Price Category')
plt.xlabel('Brand')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.legend(title='Price Category', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.tight_layout()
plt.show()
```

```
<ipython-input-18-facb2f982896>:2: 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.
  grouped = df.groupby(['Brand', 'Price
Category']).size().reset_index(name='Count')
```

[19]:
```
# Brand vs Style
grouped = df.groupby(['Brand', 'Style']).size().reset_index(name='Count')
pivoted = grouped.pivot(index='Brand', columns='Style', values='Count').
 ↪fillna(0)
```

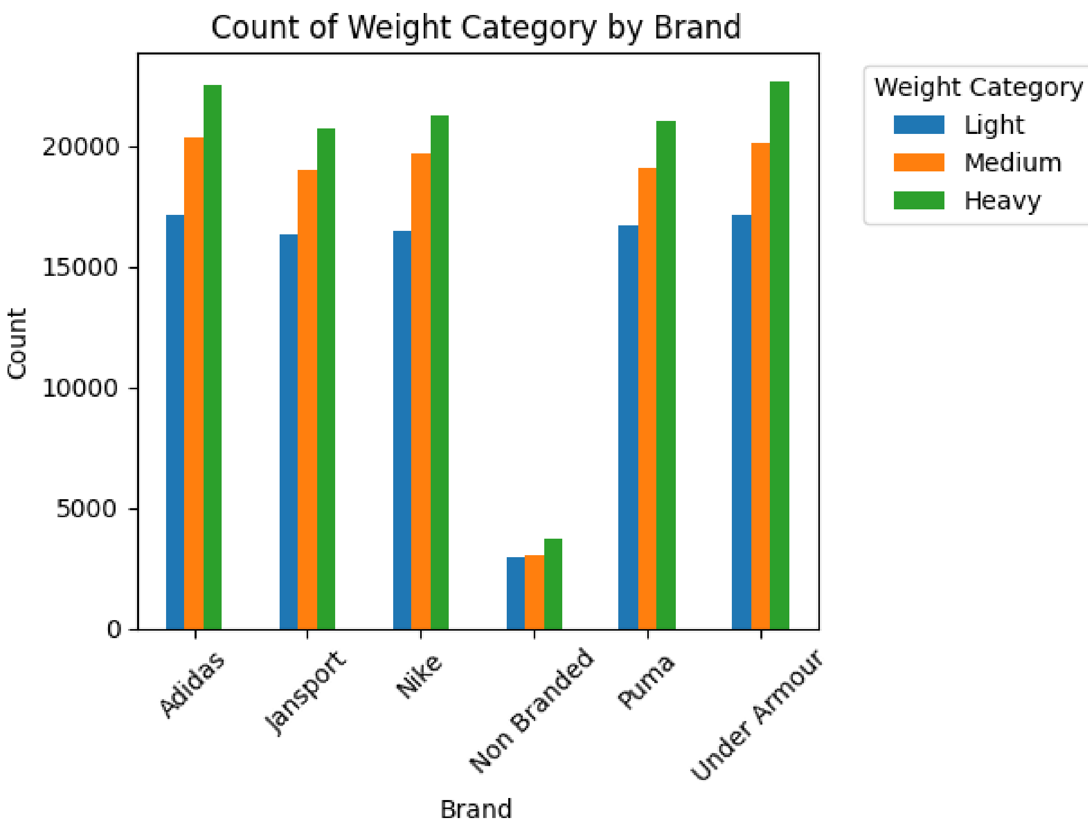
```
pivoted.plot(kind='bar', stacked=False)
plt.title('Count of Style by Brand')
plt.xlabel('Brand')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.legend(title='Style', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.tight_layout()
plt.show()
```



[20]:
```
# Brand vs Weight Category
grouped = df.groupby(['Brand', 'Weight Category']).size().
  ↪reset_index(name='Count')
pivoted = grouped.pivot(index='Brand', columns='Weight Category',␣
  ↪values='Count').fillna(0)

pivoted.plot(kind='bar', stacked=False)
plt.title('Count of Weight Category by Brand')
plt.xlabel('Brand')
plt.ylabel('Count')
plt.xticks(rotation=45)
```

```
plt.legend(title='Weight Category', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.tight_layout()
plt.show()
```

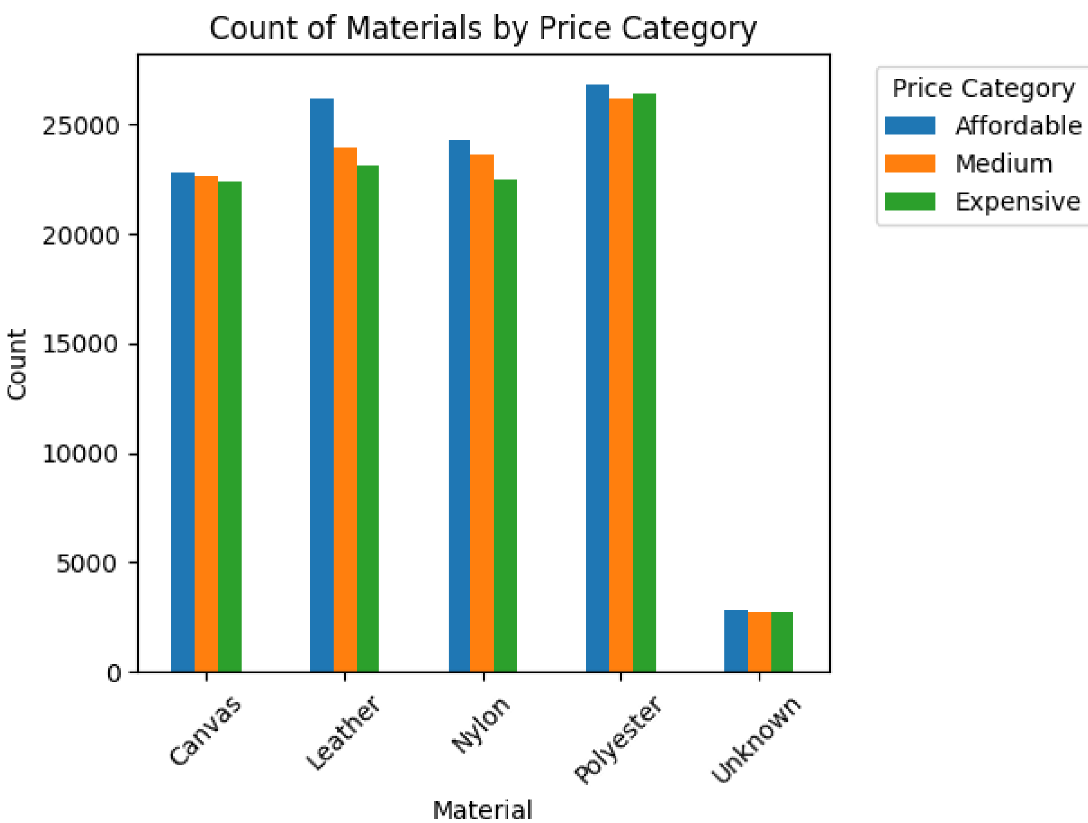
```
<ipython-input-20-ca41bccade79>:2: FutureWarning: The default of observed=False
is deprecated and will be changed to True in a future version of pandas. Pass
observed=False to retain current behavior or observed=True to adopt the future
default and silence this warning.
  grouped = df.groupby(['Brand', 'Weight
Category']).size().reset_index(name='Count')
```



[21]:
```
# Material vs Price
grouped = df.groupby(['Material', 'Price Category']).size().
  ↪reset_index(name='Count')
pivoted = grouped.pivot(index='Material', columns='Price Category',␣
  ↪values='Count').fillna(0)

pivoted.plot(kind='bar', stacked=False)
plt.title('Count of Materials by Price Category')
plt.xlabel('Material')
```

```
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.legend(title='Price Category', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.tight_layout()
plt.show()
```

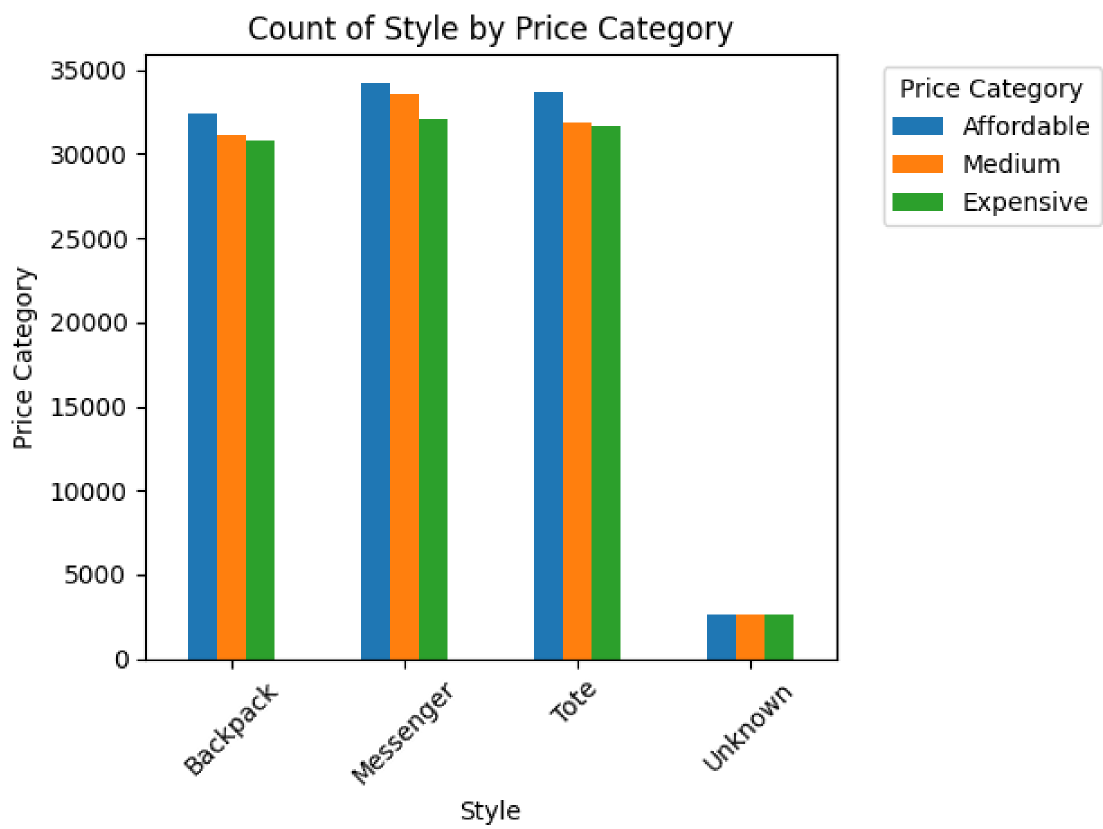
```
<ipython-input-21-aa9cd85781be>:2: FutureWarning: The default of observed=False
is deprecated and will be changed to True in a future version of pandas. Pass
observed=False to retain current behavior or observed=True to adopt the future
default and silence this warning.
  grouped = df.groupby(['Material', 'Price
Category']).size().reset_index(name='Count')
```



[22]:
```
# Style vs Price
grouped = df.groupby(['Style', 'Price Category']).size().
  ↪reset_index(name='Count')
pivoted = grouped.pivot(index='Style', columns='Price Category',␣
  ↪values='Count').fillna(0)

pivoted.plot(kind='bar', stacked=False)
```

```
plt.title('Count of Style by Price Category')
plt.xlabel('Style')
plt.ylabel('Price Category')
plt.xticks(rotation=45)
plt.legend(title='Price Category', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.tight_layout()
plt.show()
```

```
<ipython-input-22-421eda627aae>:2: 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.
  grouped = df.groupby(['Style', 'Price
Category']).size().reset_index(name='Count')
```



[23]:
```
# Color vs Price
grouped = df.groupby(['Color', 'Price Category']).size().
 ↪reset_index(name='Count')
pivoted = grouped.pivot(index='Color', columns='Price Category',␣
 ↪values='Count').fillna(0)
```

```python
pivoted.plot(kind='bar', stacked=False)
plt.title('Count of Color by Price Category')
plt.xlabel('Color')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.legend(title='Price Category', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.tight_layout()
plt.show()
```

```
<ipython-input-23-555c3cb96ee6>:2: 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.
  grouped = df.groupby(['Color', 'Price
Category']).size().reset_index(name='Count')
```

1.9 Feature Engineering for Model Training

[24]:
```
# Drop unwanted columns
new_df = df.drop(['id', 'Waterproof', 'Laptop Compartment', 'Weight Category',␣
 ↪'Price Category'], axis = 1)
```

[25]:
```
# Change the float values to int as some models give error for float values
new_df['Compartments'] = new_df['Compartments'].astype(int)
new_df['Price'] = new_df['Price'].astype(int)
new_df['Weight Capacity (kg)'] = new_df['Weight Capacity (kg)'].astype(int)
```

1.10 Model Training

[26]:
```
# Defining X and Y dataset
X = new_df.drop(columns = ['Price'])
Y = new_df['Price']
```

[27]:
```
# Data preprocessing
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test = train_test_split(X,Y,test_size=0.
 ↪15,random_state=2)
```

1.10.1 Import libraries

[28]:
```
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import OneHotEncoder
from sklearn.metrics import r2_score,mean_absolute_error

from xgboost import XGBRegressor
from sklearn.linear_model import LinearRegression, Ridge, Lasso, ElasticNet
from sklearn.neighbors import KNeighborsRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.cluster import KMeans, DBSCAN, AgglomerativeClustering
from sklearn.ensemble import␣
 ↪RandomForestRegressor,GradientBoostingRegressor,AdaBoostRegressor,ExtraTreesRegressor
from sklearn.ensemble import VotingRegressor, BaggingRegressor,␣
 ↪StackingRegressor
from sklearn.svm import SVR
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error
from sklearn.model_selection import train_test_split
```

1.11 Linear Regression

[29]:
```
step1 = ColumnTransformer(
    ␣
  ↪transformers=[('col_tnf',OneHotEncoder(sparse_output=False,drop='first'),[0,1,2,4,5])],
    remainder='passthrough'
)

step2 = LinearRegression()

pipe = Pipeline([
    ('step1',step1),
    ('step2',step2)
])

pipe.fit(X_train,y_train)

y_pred = pipe.predict(X_test)

print('RMSE score', np.sqrt(mean_squared_error(y_test, y_pred)))
```

```
RMSE score 39.18521675416943
```

1.12 Ridge Regression

[30]:
```
step1 = ColumnTransformer(
    ␣
  ↪transformers=[('col_tnf',OneHotEncoder(sparse_output=False,drop='first'),[0,1,2,4,5])],
    remainder='passthrough'
)

step2 = Ridge()

pipe = Pipeline([
    ('step1',step1),
    ('step2',step2)
])

pipe.fit(X_train,y_train)

y_pred = pipe.predict(X_test)

print('RMSE score', np.sqrt(mean_squared_error(y_test, y_pred)))
```

```
RMSE score 39.18521621559453
```

1.13 Lasso Regression

[31]:
```
step1 = ColumnTransformer(
    ␣
  ↪transformers=[('col_tnf',OneHotEncoder(sparse_output=False,drop='first'),[0,1,2,4,5])],
    remainder='passthrough'
)

step2 = Lasso()

pipe = Pipeline([
    ('step1',step1),
    ('step2',step2)
])

pipe.fit(X_train,y_train)

y_pred = pipe.predict(X_test)

print('RMSE score', np.sqrt(mean_squared_error(y_test, y_pred)))
```

```
RMSE score 39.19518883212979
```

1.14 ElasticNet Regression

[32]:
```
step1 = ColumnTransformer(
    ␣
  ↪transformers=[('col_tnf',OneHotEncoder(sparse_output=False,drop='first'),[0,1,2,4,5])],
    remainder='passthrough'
)

step2 = ElasticNet()

pipe = Pipeline([
    ('step1',step1),
    ('step2',step2)
])

pipe.fit(X_train,y_train)

y_pred = pipe.predict(X_test)

print('RMSE score', np.sqrt(mean_squared_error(y_test, y_pred)))
```

```
RMSE score 39.19413509444018
```

1.15 Decision Tree

[33]:
```
step1 = ColumnTransformer(
    transformers=[('col_tnf',OneHotEncoder(sparse_output=False,drop='first'),[0,1,2,4,5])],
    remainder='passthrough'
)

step2 = DecisionTreeRegressor()

pipe = Pipeline([
    ('step1',step1),
    ('step2',step2)
])

pipe.fit(X_train,y_train)

y_pred = pipe.predict(X_test)

print('RMSE score', np.sqrt(mean_squared_error(y_test, y_pred)))
```

```
RMSE score 53.4981778839449
```

1.16 Extra tree

[34]:
```
step1 = ColumnTransformer(
    transformers=[('col_tnf',OneHotEncoder(sparse_output=False,drop='first'),[0,1,2,4,5])],
    remainder='passthrough'
)

step2 = ExtraTreesRegressor(n_estimators=100,
                              random_state=3,
                              max_samples=None,
                              max_features=0.75,
                              max_depth=15)

pipe = Pipeline([
    ('step1',step1),
    ('step2',step2)
])

pipe.fit(X_train,y_train)

y_pred = pipe.predict(X_test)

print('RMSE score', np.sqrt(mean_squared_error(y_test, y_pred)))
```

RMSE score 39.49093458977512

1.17 Voting

[35]:
```
step1 = ColumnTransformer(
    transformers=[('col_tnf', OneHotEncoder(sparse_output=False, drop='first'),␣
 ↪[0, 1, 2, 4, 5])],
    remainder='passthrough'
)

ridge_model = Ridge()
linear_model = LinearRegression()
lasso_model = Lasso()

voting_regressor = VotingRegressor(estimators=[
    ('ridge', ridge_model),
    ('linear', linear_model),
    ('lasso', lasso_model)
])

pipe = Pipeline([
    ('step1', step1),
    ('step2', voting_regressor)
])

pipe.fit(X_train, y_train)

y_pred = pipe.predict(X_test)

print('RMSE:', np.sqrt(mean_squared_error(y_test, y_pred)))
```

RMSE: 39.184375647684455

1.18 Bagging

[36]:
```
step1 = ColumnTransformer(
    transformers=[('col_tnf', OneHotEncoder(sparse_output=False, drop='first'),␣
 ↪[0, 1, 2, 4, 5])],
    remainder='passthrough'
)

base_model = Ridge()  # You can change this to LinearRegression() or␣
 ↪DecisionTreeRegressor()

bagging_regressor = BaggingRegressor(estimator=base_model, n_estimators=50,␣
 ↪random_state=42)
```

```
pipe = Pipeline([
    ('step1', step1),
    ('step2', bagging_regressor)
])

pipe.fit(X_train, y_train)

y_pred = pipe.predict(X_test)

print('RMSE:', np.sqrt(mean_squared_error(y_test, y_pred)))
```

```
RMSE: 39.184898304234295
```

1.19 Random Forest

[37]:
```
step1 = ColumnTransformer(
    
 ↪transformers=[('col_tnf',OneHotEncoder(sparse_output=False,drop='first'),[0,1,2,4,5])],
    remainder='passthrough'
)

step2 = RandomForestRegressor(n_estimators = 100, random_state = 42)

pipe = Pipeline([
    ('step1',step1),
    ('step2',step2)
])

pipe.fit(X_train,y_train)

y_pred = pipe.predict(X_test)

print('RMSE', np.sqrt(mean_squared_error(y_test, y_pred)))
```

```
RMSE 43.9357107695224
```

1.20 AdaBoost

[38]:
```
step1 = ColumnTransformer(
    
 ↪transformers=[('col_tnf',OneHotEncoder(sparse_output=False,drop='first'),[0,1,2,4,5,6])],
    remainder='passthrough'
)

step2 = AdaBoostRegressor(n_estimators=50, random_state=42)

pipe = Pipeline([
```

```
    ('step1',step1),
    ('step2',step2)
])

pipe.fit(X_train,y_train)

y_pred = pipe.predict(X_test)

print('RMSE', np.sqrt(mean_squared_error(y_test, y_pred)))
```

```
RMSE 39.207410208141226
```

1.21 K Means Clustering

[39]:
```
step1 = ColumnTransformer(
    ␣
 ↪transformers=[('col_tnf',OneHotEncoder(sparse_output=False,drop='first'),[0,1,2,4,5,6])],
    remainder='passthrough'
)

step2 = KMeans(n_clusters = 3, random_state = 42)

pipe = Pipeline([
    ('step1',step1),
    ('step2',step2)
])

pipe.fit(X_train,y_train)

y_pred = pipe.predict(X_test)

print('RMSE', np.sqrt(mean_squared_error(y_test, y_pred)))
```

```
RMSE 89.14747095559008
```

1.22 Gradient Boosting

[40]:
```
step1 = ColumnTransformer(
    transformers=[('col_tnf', OneHotEncoder(sparse_output=False, drop='first'),␣
 ↪[0, 1, 2, 4, 5, 6])],
    remainder='passthrough'
)

step2 = GradientBoostingRegressor(random_state=42)

pipe = Pipeline([
    ('step1', step1),
```

```
    ('step2', step2)
])

pipe.fit(X_train, y_train)

y_pred = pipe.predict(X_test)

print('RMSE', np.sqrt(mean_squared_error(y_test, y_pred)))
```

RMSE 39.187112181786034

1.23 Stacking

[41]:
```
step1 = ColumnTransformer(
    transformers=[('col_tnf', OneHotEncoder(sparse_output=False, drop='first'),␣
 ↪[0, 1, 2, 4, 5, 6])],
    remainder='passthrough'
)

base_learners = [
    ('lr', LinearRegression()),
    ('gb', GradientBoostingRegressor(random_state=42)),
]

final_estimator = GradientBoostingRegressor(random_state=42)

stacking_model = StackingRegressor(estimators=base_learners,␣
 ↪final_estimator=final_estimator)

pipe = Pipeline([
    ('step1', step1),
    ('stacking', stacking_model)
])

pipe.fit(X_train, y_train)

y_pred = pipe.predict(X_test)

print('RMSE', np.sqrt(mean_squared_error(y_test, y_pred)))
```

RMSE 39.18726052784003

1.24 K Nearest Neighbors

[42]:
```
step1 = ColumnTransformer(
    ␣
  ↪transformers=[('col_tnf',OneHotEncoder(sparse_output=False,drop='first'),[0,1,2,4,5,6])],
    remainder='passthrough'
)

step2 = KNeighborsRegressor(n_neighbors = 5)

pipe = Pipeline([
    ('step1',step1),
    ('step2',step2)
])

pipe.fit(X_train,y_train)

y_pred = pipe.predict(X_test)

print('RMSE', np.sqrt(mean_squared_error(y_test, y_pred)))
```

```
RMSE 42.959242254852576
```

1.25 XG Boost

[43]:
```
step1 = ColumnTransformer(
    ␣
  ↪transformers=[('col_tnf',OneHotEncoder(sparse_output=False,drop='first'),[0,1,2,4,5,6])],
    remainder='passthrough'
)

step2 = XGBRegressor(random_state=42)

pipe = Pipeline([
    ('step1',step1),
    ('step2',step2)
])

pipe.fit(X_train,y_train)

y_pred = pipe.predict(X_test)

print('RMSE', np.sqrt(mean_squared_error(y_test, y_pred)))
```

```
RMSE 39.33804068980177
```