# fds-blog

January 22, 2024

[260]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

[261]:
```
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
import sklearn
import warnings
import random
warnings.filterwarnings('ignore')
```

[262]:
```
pip install faker
```

```
Requirement already satisfied: faker in /usr/local/lib/python3.10/dist-packages
(22.4.0)
Requirement already satisfied: python-dateutil>=2.4 in
/usr/local/lib/python3.10/dist-packages (from faker) (2.8.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-
packages (from python-dateutil>=2.4->faker) (1.16.0)
```

## 1 Creating Synthetic Dataset Generation using Faker

[263]:
```
from faker import Faker
np.random.seed(32)
fake = Faker()
Faker.seed(32)

# Number of rows in the dataset
start_index = 1
num_rows = 1500
# Generate synthetic data
battery_values = [3000, 3500, 4000, 4500, 5000, 5500, 6000]

data = {
```

```
    'Unnamed: 0': list(range(start_index, start_index + num_rows)),
    'Company': [fake.random_element(['Apple', 'Samsung', 'Google', 'Huawei',␣
 ↪'OnePlus', 'Sony', 'LG', 'Motorola', 'Xiaomi', 'Nokia', 'Oppo', 'Vivo',␣
 ↪'Realme']) for _ in range(num_rows)],
    'Weight(gm)': [fake.pyfloat(right_digits=2, positive=True, min_value=100,␣
 ↪max_value=250) for _ in range(num_rows)],
    'PPI': [fake.random_int(min=100, max=800) for _ in range(num_rows)],
    'CPU_core': [fake.random_int(min=1, max=8) for _ in range(num_rows)],
    'CPU_freq': [fake.pyfloat(left_digits=1, right_digits=1, positive=True,␣
 ↪min_value=1, max_value=2.7) for _ in range(num_rows)],
    'Dual_sim' :[fake.random_element(['Yes','No']) for _ in range(num_rows)],
    'Internal_mem(GB)': [fake.random_element(['16GB', '32GB',␣
 ↪'64GB','128GB','256GB']) for _ in range(num_rows)],
    'RAM': [fake.random_int(min=4, max=16) for _ in range(num_rows)],
    'RearCam': [fake.random_int(min=20, max=108) for _ in range(num_rows)],
    'Front_Cam': [fake.random_int(min=10, max=32) for _ in range(num_rows)],
    'Gen_5G' :[fake.random_element(['Yes','No']) for _ in range(num_rows)],
    'Battery': [fake.random_element(battery_values) for _ in range(num_rows)],
    'Thickness': [fake.random_int(min=5, max=18) for _ in range(num_rows)],
    # 'Price': [fake.random_int(min=5000, max=100000) for _ in range(num_rows)]
}

df = pd.DataFrame(data)
df.head()
```

[263]:

```
   Unnamed: 0  Company  Weight(gm)  PPI  CPU_core  CPU_freq Dual_sim  \
0           1  Samsung      180.32  312         1       1.5       No
1           2   Huawei      159.12  362         1       1.6       No
2           3   Google      159.29  241         1       1.0       No
3           4  OnePlus      214.38  555         4       1.2      Yes
4           5     Vivo      102.43  607         8       1.8      Yes

  Internal_mem(GB)  RAM  RearCam  Front_Cam Gen_5G  Battery  Thickness
0             16GB    8       77         31    Yes     5000         17
1             64GB    8       51         13     No     3000         12
2             16GB   11       84         23     No     5000         11
3             32GB    7       91         10     No     6000          8
4            128GB   12       71         27     No     4500         11
```

## 2 Removing unwanted rows and unwanted data

[264]:

```
df.drop(columns=['Unnamed: 0'],inplace=True)
df["Internal_mem(GB)"] = df["Internal_mem(GB)"].str.replace('GB', '').
 ↪astype(int)
```

[265]:
```
df_copy = df.copy()
df_copy.head()
```

[265]:

| | Company | Weight(gm) | PPI | CPU_core | CPU_freq | Dual_sim | Internal_mem(GB) |
|---|---|---|---|---|---|---|---|
| 0 | Samsung | 180.32 | 312 | 1 | 1.5 | No | 16 |
| 1 | Huawei | 159.12 | 362 | 1 | 1.6 | No | 64 |
| 2 | Google | 159.29 | 241 | 1 | 1.0 | No | 16 |
| 3 | OnePlus | 214.38 | 555 | 4 | 1.2 | Yes | 32 |
| 4 | Vivo | 102.43 | 607 | 8 | 1.8 | Yes | 128 |

| | RAM | RearCam | Front_Cam | Gen_5G | Battery | Thickness |
|---|---|---|---|---|---|---|
| 0 | 8 | 77 | 31 | Yes | 5000 | 17 |
| 1 | 8 | 51 | 13 | No | 3000 | 12 |
| 2 | 11 | 84 | 23 | No | 5000 | 11 |
| 3 | 7 | 91 | 10 | No | 6000 | 8 |
| 4 | 12 | 71 | 27 | No | 4500 | 11 |

# 3 Performing label encoding (converting catogirical data to numerical data)

[266]:
```
from sklearn.preprocessing import LabelEncoder
label_encoder = LabelEncoder()
df_copy['Gen_5G'] = label_encoder.fit_transform(df_copy['Gen_5G']).astype(int)
df_copy['Dual_sim'] = label_encoder.fit_transform(df_copy['Dual_sim']).
 ↪astype(int)
```

[267]:
```
df_copy.describe()
```

[267]:

| | Weight(gm) | PPI | CPU_core | CPU_freq | Dual_sim |
|---|---|---|---|---|---|
| count | 1500.000000 | 1500.000000 | 1500.000000 | 1500.000000 | 1500.000000 |
| mean | 176.520353 | 449.583333 | 4.427333 | 1.451667 | 0.518667 |
| std | 43.239296 | 200.174228 | 2.345006 | 0.287249 | 0.499818 |
| min | 100.120000 | 100.000000 | 1.000000 | 1.000000 | 0.000000 |
| 25% | 139.862500 | 272.750000 | 2.000000 | 1.200000 | 0.000000 |
| 50% | 175.975000 | 451.000000 | 4.000000 | 1.500000 | 1.000000 |
| 75% | 214.347500 | 624.000000 | 6.000000 | 1.700000 | 1.000000 |
| max | 249.940000 | 799.000000 | 8.000000 | 1.900000 | 1.000000 |

| | Internal_mem(GB) | RAM | RearCam | Front_Cam | Gen_5G |
|---|---|---|---|---|---|
| count | 1500.000000 | 1500.000000 | 1500.000000 | 1500.000000 | 1500.000000 |
| mean | 98.570667 | 10.054667 | 63.491333 | 21.166667 | 0.491333 |
| std | 86.612660 | 3.786983 | 25.918573 | 6.680767 | 0.500092 |
| min | 16.000000 | 4.000000 | 20.000000 | 10.000000 | 0.000000 |
| 25% | 32.000000 | 7.000000 | 41.000000 | 15.000000 | 0.000000 |
| 50% | 64.000000 | 10.000000 | 63.000000 | 21.000000 | 0.000000 |
| 75% | 128.000000 | 14.000000 | 86.000000 | 27.000000 | 1.000000 |

```
max          256.000000    16.000000   108.000000    32.000000     1.000000

           Battery    Thickness
count  1500.000000  1500.000000
mean   4525.333333    11.478000
std    1006.992674     4.028938
min    3000.000000     5.000000
25%    3500.000000     8.000000
50%    4500.000000    11.000000
75%    5500.000000    15.000000
max    6000.000000    18.000000
```

# 4 Generating Price based on the features weights(How much the feature contributes in price)

[268]:
```
#comapany wegihts
user_defined_values = {'Apple': 250,'Samsung': 160,'Google': 85,'Huawei':␣
↪100,'OnePlus': 180,'Sony': 90,'LG': 70,
    'Motorola': 60,'Xiaomi': 45,'Nokia': 50,'Oppo': 20,'Vivo': 40,'Realme': 30,}
df_copy['Company'] = df_copy['Company'].map(user_defined_values)
```

# 5 Maximum Absolute scaler

[269]:
```
max_vals = np.max(np.abs(df_copy))
max_vals
```

[269]:
```
Company              250.00
Weight(gm)           249.94
PPI                  799.00
CPU_core               8.00
CPU_freq               1.90
Dual_sim               1.00
Internal_mem(GB)     256.00
RAM                   16.00
RearCam              108.00
Front_Cam             32.00
Gen_5G                 1.00
Battery             6000.00
Thickness             18.00
dtype: float64
```

[270]:
```
r=(df_copy) / max_vals
r.head()
```

[270]:

| | Company | Weight(gm) | PPI | CPU_core | CPU_freq | Dual_sim |
|---|---|---|---|---|---|---|
| 0 | 0.64 | 0.721453 | 0.390488 | 0.125 | 0.789474 | 0.0 |
| 1 | 0.40 | 0.636633 | 0.453066 | 0.125 | 0.842105 | 0.0 |
| 2 | 0.34 | 0.637313 | 0.301627 | 0.125 | 0.526316 | 0.0 |
| 3 | 0.72 | 0.857726 | 0.694618 | 0.500 | 0.631579 | 1.0 |
| 4 | 0.16 | 0.409818 | 0.759700 | 1.000 | 0.947368 | 1.0 |

| | Internal_mem(GB) | RAM | RearCam | Front_Cam | Gen_5G | Battery | Thickness |
|---|---|---|---|---|---|---|---|
| 0 | 0.0625 | 0.5000 | 0.712963 | 0.96875 | 1.0 | 0.833333 | 0.944444 |
| 1 | 0.2500 | 0.5000 | 0.472222 | 0.40625 | 0.0 | 0.500000 | 0.666667 |
| 2 | 0.0625 | 0.6875 | 0.777778 | 0.71875 | 0.0 | 0.833333 | 0.611111 |
| 3 | 0.1250 | 0.4375 | 0.842593 | 0.31250 | 0.0 | 1.000000 | 0.444444 |
| 4 | 0.5000 | 0.7500 | 0.657407 | 0.84375 | 0.0 | 0.750000 | 0.611111 |

[271]:
```
def calculate_price(data):
  # weight_vector = [17,1,7,8,7,4,14,15,7,6,3,13,2]
  weight_vector = [0.15, 0.04, 0.05, 0.11, 0.08, 0.04, 0.14, 0.17, 0.06, 0.02,␣
 ↪0.04, 0.09, 0.01]
  x = pd.DataFrame(np.array(weight_vector * data))
  x = x*1000
  x.columns = df.columns
  return x
df_new = calculate_price(r)
df_new.head()
```

[271]:

| | Company | Weight(gm) | PPI | CPU_core | CPU_freq | Dual_sim |
|---|---|---|---|---|---|---|
| 0 | 96.0 | 28.858126 | 19.524406 | 13.75 | 63.157895 | 0.0 |
| 1 | 60.0 | 25.465312 | 22.653317 | 13.75 | 67.368421 | 0.0 |
| 2 | 51.0 | 25.492518 | 15.081352 | 13.75 | 42.105263 | 0.0 |
| 3 | 108.0 | 34.309034 | 34.730914 | 55.00 | 50.526316 | 40.0 |
| 4 | 24.0 | 16.392734 | 37.984981 | 110.00 | 75.789474 | 40.0 |

| | Internal_mem(GB) | RAM | RearCam | Front_Cam | Gen_5G | Battery | Thickness |
|---|---|---|---|---|---|---|---|
| 0 | 8.75 | 85.000 | 42.777778 | 19.375 | 40.0 | 75.0 | 9.444444 |
| 1 | 35.00 | 85.000 | 28.333333 | 8.125 | 0.0 | 45.0 | 6.666667 |
| 2 | 8.75 | 116.875 | 46.666667 | 14.375 | 0.0 | 75.0 | 6.111111 |
| 3 | 17.50 | 74.375 | 50.555556 | 6.250 | 0.0 | 90.0 | 4.444444 |
| 4 | 70.00 | 127.500 | 39.444444 | 16.875 | 0.0 | 67.5 | 6.111111 |

[272]:
```
df_new['Price'] = df_new.sum(axis=1)
df_new['Price'] = df_new['Price'].round(-1)
df_new
```

[272]:

| | Company | Weight(gm) | PPI | CPU_core | CPU_freq | Dual_sim |
|---|---|---|---|---|---|---|
| 0 | 96.0 | 28.858126 | 19.524406 | 13.75 | 63.157895 | 0.0 |
| 1 | 60.0 | 25.465312 | 22.653317 | 13.75 | 67.368421 | 0.0 |
| 2 | 51.0 | 25.492518 | 15.081352 | 13.75 | 42.105263 | 0.0 |

```
3       108.0   34.309034  34.730914     55.00  50.526316      40.0
4        24.0   16.392734  37.984981    110.00  75.789474      40.0
…         …        …          …           …        …
1495     42.0   34.566696  39.236546     41.25  67.368421       0.0
1496    150.0   24.767544  28.848561     27.50  54.736842      40.0
1497     54.0   33.880131  29.161452     55.00  58.947368       0.0
1498     42.0   16.115868  46.433041     27.50  71.578947      40.0
1499     27.0   35.048412  42.365457     55.00  63.157895       0.0

      Internal_mem(GB)      RAM    RearCam  Front_Cam  Gen_5G  Battery  \
0                 8.75   85.000  42.777778     19.375    40.0     75.0
1                35.00   85.000  28.333333      8.125     0.0     45.0
2                 8.75  116.875  46.666667     14.375     0.0     75.0
3                17.50   74.375  50.555556      6.250     0.0     90.0
4                70.00  127.500  39.444444     16.875     0.0     67.5
…                  …       …         …       …        …       …
1495              8.75  116.875  30.000000      6.875    40.0     67.5
1496             17.50   42.500  35.000000     15.625     0.0     75.0
1497            140.00   74.375  42.777778     15.625     0.0     90.0
1498             17.50   63.750  23.888889     19.375     0.0     45.0
1499            140.00   53.125  23.888889     13.750    40.0     52.5

      Thickness  Price
0      9.444444  500.0
1      6.666667  400.0
2      6.111111  420.0
3      4.444444  570.0
4      6.111111  630.0
…           …     …
1495   8.333333  500.0
1496   3.333333  510.0
1497   7.222222  600.0
1498   2.777778  420.0
1499   3.333333  550.0

[1500 rows x 14 columns]
```

[273]:
```python
# df_new['Price'].value_counts()
```

[274]:
```python
df_merged = pd.merge(df, df_new[['Price']], left_index=True, right_index=True)
```

[275]:
```python
df_merged.describe()
```

[275]:
```
         Weight(gm)          PPI     CPU_core     CPU_freq  Internal_mem(GB)  \
count   1500.000000  1500.000000  1500.000000  1500.000000       1500.000000
mean     176.520353   449.583333     4.427333     1.451667         98.570667
std       43.239296   200.174228     2.345006     0.287249         86.612660
```

```
min      100.120000   100.000000     1.000000     1.000000       16.000000
25%      139.862500   272.750000     2.000000     1.200000       32.000000
50%      175.975000   451.000000     4.000000     1.500000       64.000000
75%      214.347500   624.000000     6.000000     1.700000      128.000000
max      249.940000   799.000000     8.000000     1.900000      256.000000

               RAM      RearCam    Front_Cam      Battery    Thickness  \
count  1500.000000  1500.000000  1500.000000  1500.000000  1500.000000
mean     10.054667    63.491333    21.166667  4525.333333    11.478000
std       3.786983    25.918573     6.680767  1006.992674     4.028938
min       4.000000    20.000000    10.000000  3000.000000     5.000000
25%       7.000000    41.000000    15.000000  3500.000000     8.000000
50%      10.000000    63.000000    21.000000  4500.000000    11.000000
75%      14.000000    86.000000    27.000000  5500.000000    15.000000
max      16.000000   108.000000    32.000000  6000.000000    18.000000

             Price
count  1500.000000
mean    558.093333
std      91.443640
min     310.000000
25%     490.000000
50%     550.000000
75%     620.000000
max     860.000000
```

[276]:
```
# Base_Price = {'Apple': 30000,'Samsung': 5000,'Google': 5000,'Huawei':
 ↪4500,'OnePlus': 8000,'Sony': 3000,'LG': 5000,
#      'Motorola': 6000,'Xiaomi': 4500,'Nokia': 6000,'Oppo': 5000,'Vivo':
 ↪5000,'Realme': 5500,}
Base_Price = {'Apple': 30000,'Samsung': 16000,'Google': 20000,'Huawei':
 ↪15000,'OnePlus': 17000,'Sony': 9000,'LG': 6000,
    'Motorola': 4500,'Xiaomi': 6500,'Nokia': 6000,'Oppo': 5000,'Vivo':
 ↪7000,'Realme': 8000,}

base_price_cpucore = {1: 500, 2: 1000, 3: 1500, 4: 2000, 5: 2500, 6: 3000, 7:
 ↪3500, 8: 4000,}
base_price_dual_sim = {'Yes': 3000, 'No': 0,}
base_price_Internal_mem = {16: 2000, 32: 3000, 64: 4000,128: 5000, 256:6000,}
base_price_RAM = {4: 500, 5: 1000, 6: 1500, 7: 2000, 8: 2500, 9: 3000, 10:
 ↪3000, 11: 4000, 12: 5000, 13: 6000, 14: 6000, 15: 6000, 16: 7000,}
base_price_Gen_5G = {'Yes': 4000, 'No': 0,}
base_price_battery = {3000: 1000, 3500: 1500, 4000: 2000, 4500: 2500, 5000:
 ↪3000, 5500: 4000, 6000: 5500,}


# Map user-defined values to the 'Company' column
```

```python
df_merged['Base_Price'] = df_merged['Company'].map(Base_Price)
df_merged['base_price_cpucore'] = df_merged['CPU_core'].map(base_price_cpucore)
df_merged['base_price_dual_sim'] = df_merged['Dual_sim'].
↪map(base_price_dual_sim)
df_merged['base_price_Internal_mem'] = df_merged['Internal_mem(GB)'].
↪map(base_price_Internal_mem)
df_merged['base_price_RAM'] = df_merged['RAM'].map(base_price_RAM)
df_merged['base_price_Gen_5G'] = df_merged['Gen_5G'].map(base_price_Gen_5G)
df_merged['base_price_battery'] = df_merged['Battery'].map(base_price_battery)

for i in range(3):
    df_merged['Price'] += df_merged['Base_Price']

for i in range(1):
  df_merged['Price'] += df_merged['base_price_cpucore']

for i in range(1):
  df_merged['Price'] += df_merged['base_price_dual_sim']

for i in range(1):
  df_merged['Price'] += df_merged['base_price_Internal_mem']

for i in range(1):
  df_merged['Price'] += df_merged['base_price_RAM']

for i in range(1):
  df_merged['Price'] += df_merged['base_price_Gen_5G']

for i in range(1):
  df_merged['Price'] += df_merged['base_price_battery']

# df_merged = df_merged.drop(['Base_Price'], axis=1)
columns_to_drop = ['Base_Price', 'base_price_cpucore', 'base_price_dual_sim',␣
↪'base_price_Internal_mem', 'base_price_RAM', 'base_price_Gen_5G',␣
↪'base_price_battery']
df_merged.drop(columns=columns_to_drop, inplace=True)
```

[277]:
```python
df_merged
```

[277]:
```
      Company  Weight(gm)  PPI  CPU_core  CPU_freq Dual_sim  Internal_mem(GB)  \
0     Samsung      180.32  312         1       1.5       No                16
1      Huawei      159.12  362         1       1.6       No                64
2      Google      159.29  241         1       1.0       No                16
3     OnePlus      214.38  555         4       1.2      Yes                32
4        Vivo      102.43  607         8       1.8      Yes               128
…         …           …   …         …         …                           …
1495       LG      215.99  627         3       1.6       No                16
```

```
1496     Apple      154.76  461          2        1.3      Yes             32
1497      Sony      211.70  466          4        1.4       No            256
1498        LG      100.70  742          2        1.7      Yes             32
1499    Xiaomi      219.00  677          4        1.5       No            256

      RAM  RearCam  Front_Cam Gen_5G  Battery  Thickness     Price
0       8       77         31    Yes     5000         17   60500.0
1       8       51         13     No     3000         12   53400.0
2      11       84         23     No     5000         11   69920.0
3       7       91         10     No     6000          8   67070.0
4      12       71         27     No     4500         11   41130.0
…    …      …        …     …      …        …       …
1495   11       54         11    Yes     4500         15   32500.0
1496    4       63         25     No     5000          6  101010.0
1497    7       77         25     No     6000         13   43100.0
1498    6       43         31     No     3000          5   27920.0
1499    5       43         22    Yes     3500          6   34550.0

[1500 rows x 14 columns]
```

[278]:
```python
df_merged['Price'] = np.abs(df_merged['Price'])
df_merged['Price'] = df_merged['Price'].round(-3)
```

# 6 Describe about dataframe(df)

[279]:
```python
df_merged.describe()
```

[279]:
```
        Weight(gm)          PPI     CPU_core     CPU_freq  Internal_mem(GB)  \
count  1500.000000  1500.000000  1500.000000  1500.000000       1500.000000
mean    176.520353   449.583333     4.427333     1.451667         98.570667
std      43.239296   200.174228     2.345006     0.287249         86.612660
min     100.120000   100.000000     1.000000     1.000000         16.000000
25%     139.862500   272.750000     2.000000     1.200000         32.000000
50%     175.975000   451.000000     4.000000     1.500000         64.000000
75%     214.347500   624.000000     6.000000     1.700000        128.000000
max     249.940000   799.000000     8.000000     1.900000        256.000000

               RAM      RearCam    Front_Cam      Battery    Thickness  \
count  1500.000000  1500.000000  1500.000000  1500.000000  1500.000000
mean     10.054667    63.491333    21.166667  4525.333333    11.478000
std       3.786983    25.918573     6.680767  1006.992674     4.028938
min       4.000000    20.000000    10.000000  3000.000000     5.000000
25%       7.000000    41.000000    15.000000  3500.000000     8.000000
50%      10.000000    63.000000    21.000000  4500.000000    11.000000
75%      14.000000    86.000000    27.000000  5500.000000    15.000000
max      16.000000   108.000000    32.000000  6000.000000    18.000000
```

```
               Price
count     1500.000000
mean     52260.000000
std      22552.564054
min      22000.000000
25%      35000.000000
50%      42000.000000
75%      67000.000000
max     119000.000000
```

[280]:
```
# df_merged['Price'] = np.where((df_merged['Dual_sim'] == 0) &
 ↪(df_merged['Gen_5G'] == 0), df_merged['Price'] - 10000, df_merged['Price'])
# df_merged['Price'] = np.where((df_merged['Dual_sim'] == 0) &
 ↪(df_merged['Gen_5G'] == 1), df_merged['Price'] - 5000, df_merged['Price'])
# df_merged['Price'] = np.where((df_merged['Dual_sim'] == 1) &
 ↪(df_merged['Gen_5G'] == 1), df_merged['Price'], df_merged['Price'])
# df_merged['Price'] = np.where((df_merged['Dual_sim'] == 1) &
 ↪(df_merged['Gen_5G'] == 0), df_merged['Price'] - 5000, df_merged['Price'])
```

[281]:
```
df_merged
```

[281]:
```
      Company  Weight(gm)  PPI  CPU_core  CPU_freq Dual_sim  Internal_mem(GB)  \
0     Samsung      180.32  312         1       1.5       No                16
1      Huawei      159.12  362         1       1.6       No                64
2      Google      159.29  241         1       1.0       No                16
3     OnePlus      214.38  555         4       1.2      Yes                32
4        Vivo      102.43  607         8       1.8      Yes               128
…         …          … …     …        …        …                 …
1495       LG      215.99  627         3       1.6       No                16
1496    Apple      154.76  461         2       1.3      Yes                32
1497     Sony      211.70  466         4       1.4       No               256
1498       LG      100.70  742         2       1.7      Yes                32
1499   Xiaomi      219.00  677         4       1.5       No               256

      RAM  RearCam  Front_Cam Gen_5G  Battery  Thickness     Price
0       8       77         31    Yes     5000         17   60000.0
1       8       51         13     No     3000         12   53000.0
2      11       84         23     No     5000         11   70000.0
3       7       91         10     No     6000          8   67000.0
4      12       71         27     No     4500         11   41000.0
…   …       …         …     …      …        …        …
1495   11       54         11    Yes     4500         15   32000.0
1496    4       63         25     No     5000          6  101000.0
1497    7       77         25     No     6000         13   43000.0
1498    6       43         31     No     3000          5   28000.0
1499    5       43         22    Yes     3500          6   35000.0
```

[1500 rows x 14 columns]

[282]:
```
numeric_columns = df_merged.select_dtypes(include=[np.float, np.int]).columns.
↪tolist()
non_numeric_columns = df_merged.select_dtypes(exclude=[np.number]).columns.
↪tolist()
print("Numeric Columns:", numeric_columns)
print("Non-Numeric Columns:", non_numeric_columns)
```

```
Numeric Columns: ['Weight(gm)', 'PPI', 'CPU_core', 'CPU_freq',
'Internal_mem(GB)', 'RAM', 'RearCam', 'Front_Cam', 'Battery', 'Thickness',
'Price']
Non-Numeric Columns: ['Company', 'Dual_sim', 'Gen_5G']
```

[283]:
```
csv_file_path = 'mobile_price_data.csv'
df_merged.to_csv(csv_file_path, index=False)
print(f"DataFrame has been successfully converted to CSV: {csv_file_path}")
```

```
DataFrame has been successfully converted to CSV: mobile_price_data.csv
```

# 7 finding Max and Min price for each company

[284]:
```
# Assuming df is your DataFrame
company_list = df_merged['Company'].unique()

for company in company_list:
    max_price = df_merged[df_merged['Company'] == company]['Price'].max()
    min_price = df_merged[df_merged['Company'] == company]['Price'].min()
    print(f"Company: {company}, Max Price: {max_price}, Min Price:␣
↪{min_price}\n")
```

```
Company: Samsung, Max Price: 76000.0, Min Price: 56000.0

Company: Huawei, Max Price: 73000.0, Min Price: 51000.0

Company: Google, Max Price: 87000.0, Min Price: 67000.0

Company: OnePlus, Max Price: 78000.0, Min Price: 58000.0

Company: Vivo, Max Price: 49000.0, Min Price: 27000.0

Company: Motorola, Max Price: 40000.0, Min Price: 22000.0

Company: Apple, Max Price: 119000.0, Min Price: 95000.0

Company: Sony, Max Price: 53000.0, Min Price: 34000.0
```

```
Company: Xiaomi, Max Price: 46000.0, Min Price: 27000.0

Company: Nokia, Max Price: 47000.0, Min Price: 25000.0

Company: Realme, Max Price: 52000.0, Min Price: 29000.0

Company: LG, Max Price: 45000.0, Min Price: 26000.0

Company: Oppo, Max Price: 42000.0, Min Price: 23000.0
```

# 8 Performing label encoding (converting catogirical data to numerical data)

[285]:
```python
from sklearn.preprocessing import LabelEncoder

label_encoder = LabelEncoder()

# Define the columns to encode
columns_to_encode = ['Company', 'Gen_5G', 'Dual_sim']

# Create a dictionary to store encoding mappings
encoding_mappings = {}

# Encode each column and store the mappings
for column in columns_to_encode:
    df_merged[column] = label_encoder.fit_transform(df_merged[column]).
 ↪astype(int)

    # Store encoding mappings in the dictionary
    encoding_mapping = dict(zip(label_encoder.classes_, label_encoder.
 ↪transform(label_encoder.classes_)))
    encoding_mappings[column] = encoding_mapping

# Display the encoding mappings
for column, mappings in encoding_mappings.items():
    print(f"\nEncoding for {column}:")
    for category, encoded_number in mappings.items():
        print(f"{category}: {encoded_number}")
```

```
Encoding for Company:
Apple: 0
Google: 1
Huawei: 2
```

```
LG: 3
Motorola: 4
Nokia: 5
OnePlus: 6
Oppo: 7
Realme: 8
Samsung: 9
Sony: 10
Vivo: 11
Xiaomi: 12

Encoding for Gen_5G:
No: 0
Yes: 1

Encoding for Dual_sim:
No: 0
Yes: 1
```

[286]:
```
df_merged
```

[286]:
```
      Company  Weight(gm)  PPI  CPU_core  CPU_freq  Dual_sim  \
0           9      180.32  312         1       1.5         0
1           2      159.12  362         1       1.6         0
2           1      159.29  241         1       1.0         0
3           6      214.38  555         4       1.2         1
4          11      102.43  607         8       1.8         1
…         …          …   …        …         …       …
1495        3      215.99  627         3       1.6         0
1496        0      154.76  461         2       1.3         1
1497       10      211.70  466         4       1.4         0
1498        3      100.70  742         2       1.7         1
1499       12      219.00  677         4       1.5         0

      Internal_mem(GB)  RAM  RearCam  Front_Cam  Gen_5G  Battery  Thickness  \
0                   16    8       77         31       1     5000         17
1                   64    8       51         13       0     3000         12
2                   16   11       84         23       0     5000         11
3                   32    7       91         10       0     6000          8
4                  128   12       71         27       0     4500         11
…                  …   …        …         …       …       …        …
1495                16   11       54         11       1     4500         15
1496                32    4       63         25       0     5000          6
1497               256    7       77         25       0     6000         13
1498                32    6       43         31       0     3000          5
1499               256    5       43         22       1     3500          6
```

```
          Price
0       60000.0
1       53000.0
2       70000.0
3       67000.0
4       41000.0
…           …
1495    32000.0
1496   101000.0
1497    43000.0
1498    28000.0
1499    35000.0

[1500 rows x 14 columns]
```

[287]:
```python
df_merged['Weight(gm)'] = df_merged['Weight(gm)'].round(-1)
df_merged.head()
```

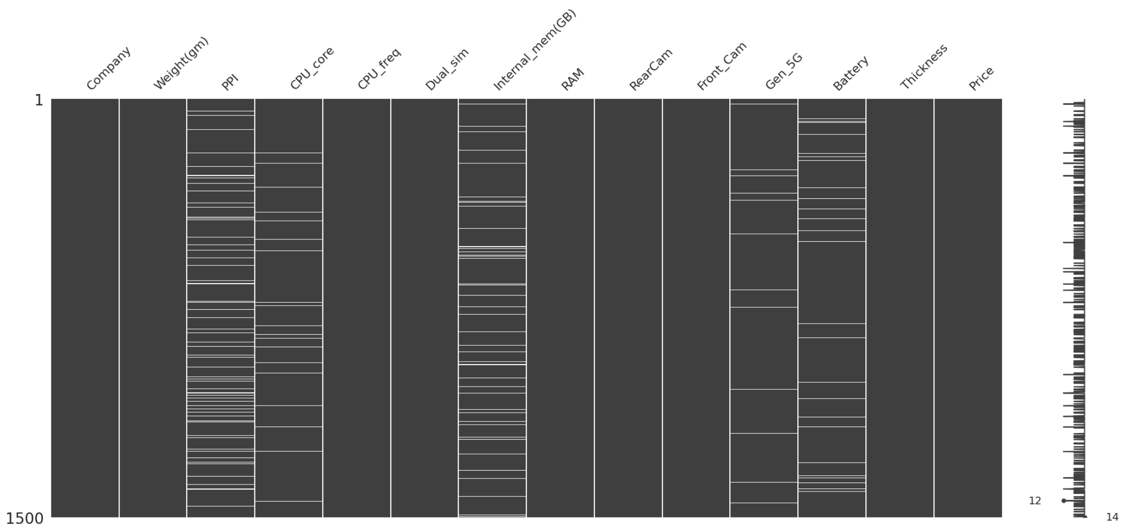
[287]:
```
   Company  Weight(gm)  PPI  CPU_core  CPU_freq  Dual_sim  Internal_mem(GB)  \
0        9       180.0  312         1       1.5         0                16
1        2       160.0  362         1       1.6         0                64
2        1       160.0  241         1       1.0         0                16
3        6       210.0  555         4       1.2         1                32
4       11       100.0  607         8       1.8         1               128

   RAM  RearCam  Front_Cam  Gen_5G  Battery  Thickness    Price
0    8       77         31       1     5000         17  60000.0
1    8       51         13       0     3000         12  53000.0
2   11       84         23       0     5000         11  70000.0
3    7       91         10       0     6000          8  67000.0
4   12       71         27       0     4500         11  41000.0
```

# 9 Inserting some null values

[288]:
```python
import numpy as np
df_merged.loc[df.sample(130).index, 'PPI'] = np.nan
df_merged.loc[df.sample(90).index, 'Internal_mem(GB)'] = np.nan
df_merged.loc[df.sample(50).index, 'Battery'] = np.nan
df_merged.loc[df.sample(30).index, 'CPU_core'] = np.nan
df_merged.loc[df.sample(30).index, 'Gen_5G'] = np.nan
```

[289]:
```python
import missingno as msno
msno.matrix(df_merged)
```

[289]: <Axes: >




[290]:
```
df_merged.isnull().sum()
```

[290]:
```
Company              0
Weight(gm)           0
PPI                130
CPU_core            30
CPU_freq             0
Dual_sim             0
Internal_mem(GB)    90
RAM                  0
RearCam              0
Front_Cam            0
Gen_5G              30
Battery             50
Thickness            0
Price                0
dtype: int64
```

[291]:
```
df_merged
```

[291]:
```
      Company  Weight(gm)    PPI  CPU_core  CPU_freq  Dual_sim  \
0           9       180.0  312.0       1.0       1.5         0
1           2       160.0  362.0       1.0       1.6         0
2           1       160.0  241.0       1.0       1.0         0
3           6       210.0  555.0       4.0       1.2         1
4          11       100.0  607.0       8.0       1.8         1
…         …          …      …        …         …        …
1495        3       220.0  627.0       3.0       1.6         0
1496        0       150.0  461.0       2.0       1.3         1
```

```
1497      10       210.0  466.0      4.0      1.4        0
1498       3       100.0  742.0      2.0      1.7        1
1499      12       220.0  677.0      4.0      1.5        0

      Internal_mem(GB)  RAM  RearCam  Front_Cam  Gen_5G  Battery  Thickness  \
0                 16.0    8       77         31     1.0   5000.0         17
1                 64.0    8       51         13     0.0   3000.0         12
2                 16.0   11       84         23     0.0   5000.0         11
3                 32.0    7       91         10     0.0   6000.0          8
4                128.0   12       71         27     0.0   4500.0         11
…                  …  …    …        …      …       …         …
1495              16.0   11       54         11     1.0   4500.0         15
1496              32.0    4       63         25     NaN   5000.0          6
1497               NaN    7       77         25     0.0   6000.0         13
1498               NaN    6       43         31     0.0   3000.0          5
1499             256.0    5       43         22     1.0   3500.0          6

         Price
0      60000.0
1      53000.0
2      70000.0
3      67000.0
4      41000.0
…         …
1495   32000.0
1496  101000.0
1497   43000.0
1498   28000.0
1499   35000.0

[1500 rows x 14 columns]
```

[292]:
```python
df_merged['Company'].value_counts()
```

[292]:
```
2     144
0     128
4     120
9     116
10    116
11    115
12    113
1     110
8     109
6     108
3     108
5     107
7     106
```

```
Name: Company, dtype: int64
```

# 10 Imputation of missing values using various techniques

[293]:
```python
# from sklearn.experimental import enable_iterative_imputer
# from sklearn.impute import IterativeImputer

# # Assuming df is your DataFrame and 'Company' is the column you want to impute
# imputer_multiple = IterativeImputer(random_state=42)
# df_merged['Company'] = imputer_multiple.fit_transform(df_merged[['Company']])
```

[294]:
```python
# from sklearn.impute import KNNImputer
# imputer_knn = KNNImputer(n_neighbors=5)
# df_merged['Company'] = imputer_knn.fit_transform(df_merged[['Company']]).
 ↪astype(int)
# df_merged
```

# 11 Using median

[295]:
```python
import pandas as pd
from sklearn.impute import SimpleImputer

imputer = SimpleImputer(strategy='median')
df_merged['Battery'] = imputer.fit_transform(df_merged[['Battery']])

df_merged
```

[295]:
```
      Company  Weight(gm)    PPI  CPU_core  CPU_freq  Dual_sim  \
0           9       180.0  312.0       1.0       1.5         0
1           2       160.0  362.0       1.0       1.6         0
2           1       160.0  241.0       1.0       1.0         0
3           6       210.0  555.0       4.0       1.2         1
4          11       100.0  607.0       8.0       1.8         1
…         …           …      …         …         …        …
1495        3       220.0  627.0       3.0       1.6         0
1496        0       150.0  461.0       2.0       1.3         1
1497       10       210.0  466.0       4.0       1.4         0
1498        3       100.0  742.0       2.0       1.7         1
1499       12       220.0  677.0       4.0       1.5         0

      Internal_mem(GB)  RAM  RearCam  Front_Cam  Gen_5G  Battery  Thickness  \
0                 16.0    8       77         31     1.0   5000.0         17
1                 64.0    8       51         13     0.0   3000.0         12
2                 16.0   11       84         23     0.0   5000.0         11
3                 32.0    7       91         10     0.0   6000.0          8
```

```
4                128.0   12      71         27      0.0    4500.0          11
…                …   …     …       …      …      …      …
1495              16.0   11      54         11      1.0    4500.0          15
1496              32.0    4      63         25      NaN    5000.0           6
1497               NaN    7      77         25      0.0    6000.0          13
1498               NaN    6      43         31      0.0    3000.0           5
1499             256.0    5      43         22      1.0    3500.0           6

         Price
0      60000.0
1      53000.0
2      70000.0
3      67000.0
4      41000.0
…          …
1495   32000.0
1496  101000.0
1497   43000.0
1498   28000.0
1499   35000.0

[1500 rows x 14 columns]
```

## 12 Using Mode

[296]:
```python
imputer = SimpleImputer(strategy='most_frequent')
df_merged['Internal_mem(GB)'] = imputer.
 ↪fit_transform(df_merged[['Internal_mem(GB)']])
df_merged
```

[296]:
```
      Company  Weight(gm)    PPI  CPU_core  CPU_freq  Dual_sim  \
0           9       180.0  312.0       1.0       1.5         0
1           2       160.0  362.0       1.0       1.6         0
2           1       160.0  241.0       1.0       1.0         0
3           6       210.0  555.0       4.0       1.2         1
4          11       100.0  607.0       8.0       1.8         1
…         …          …     …       …        …       …
1495        3       220.0  627.0       3.0       1.6         0
1496        0       150.0  461.0       2.0       1.3         1
1497       10       210.0  466.0       4.0       1.4         0
1498        3       100.0  742.0       2.0       1.7         1
1499       12       220.0  677.0       4.0       1.5         0

      Internal_mem(GB)  RAM  RearCam  Front_Cam  Gen_5G  Battery  Thickness  \
0                 16.0    8       77         31     1.0   5000.0         17
1                 64.0    8       51         13     0.0   3000.0         12
```

```
2                 16.0    11        84         23     0.0    5000.0          11
3                 32.0     7        91         10     0.0    6000.0           8
4                128.0    12        71         27     0.0    4500.0          11
…                 …  …     …         …      …     …      …
1495              16.0    11        54         11     1.0    4500.0          15
1496              32.0     4        63         25     NaN    5000.0           6
1497              16.0     7        77         25     0.0    6000.0          13
1498              16.0     6        43         31     0.0    3000.0           5
1499             256.0     5        43         22     1.0    3500.0           6

         Price
0      60000.0
1      53000.0
2      70000.0
3      67000.0
4      41000.0
…        …
1495   32000.0
1496  101000.0
1497   43000.0
1498   28000.0
1499   35000.0

[1500 rows x 14 columns]
```

# 13 Using Knn

[297]:
```python
from sklearn.impute import KNNImputer
imputer_knn = KNNImputer(n_neighbors=5)
df_merged['PPI'] = imputer_knn.fit_transform(df_merged[['PPI']]).astype(int)
df_merged
```

[297]:
```
      Company  Weight(gm)  PPI  CPU_core  CPU_freq  Dual_sim  \
0           9       180.0  312       1.0       1.5         0
1           2       160.0  362       1.0       1.6         0
2           1       160.0  241       1.0       1.0         0
3           6       210.0  555       4.0       1.2         1
4          11       100.0  607       8.0       1.8         1
…        …           …  …       …         …       …
1495        3       220.0  627       3.0       1.6         0
1496        0       150.0  461       2.0       1.3         1
1497       10       210.0  466       4.0       1.4         0
1498        3       100.0  742       2.0       1.7         1
1499       12       220.0  677       4.0       1.5         0

      Internal_mem(GB)  RAM  RearCam  Front_Cam  Gen_5G  Battery  Thickness  \
```

```
0                   16.0    8         77          31      1.0    5000.0           17
1                   64.0    8         51          13      0.0    3000.0           12
2                   16.0   11         84          23      0.0    5000.0           11
3                   32.0    7         91          10      0.0    6000.0            8
4                  128.0   12         71          27      0.0    4500.0           11
…                  …   …       …         …      …       …      …
1495                16.0   11         54          11      1.0    4500.0           15
1496                32.0    4         63          25      NaN    5000.0            6
1497                16.0    7         77          25      0.0    6000.0           13
1498                16.0    6         43          31      0.0    3000.0            5
1499               256.0    5         43          22      1.0    3500.0            6

         Price
0      60000.0
1      53000.0
2      70000.0
3      67000.0
4      41000.0
…          …
1495   32000.0
1496  101000.0
1497   43000.0
1498   28000.0
1499   35000.0

[1500 rows x 14 columns]
```

## 14 Multivariate feature imputation

[298]:

```python
from sklearn.experimental import enable_iterative_imputer
from sklearn.impute import IterativeImputer
mice_imputer = IterativeImputer(random_state=0)
df_merged['CPU_core'] = mice_imputer.fit_transform(df_merged[['CPU_core']]).
  ↪astype(int)
df_merged
```

[298]:

```
      Company  Weight(gm)  PPI  CPU_core  CPU_freq  Dual_sim  \
0           9       180.0  312         1       1.5         0
1           2       160.0  362         1       1.6         0
2           1       160.0  241         1       1.0         0
3           6       210.0  555         4       1.2         1
4          11       100.0  607         8       1.8         1
…       …         …  …       …        …        …
1495        3       220.0  627         3       1.6         0
1496        0       150.0  461         2       1.3         1
1497       10       210.0  466         4       1.4         0
```

```
1498        3       100.0  742         2       1.7         1
1499       12       220.0  677         4       1.5         0

      Internal_mem(GB)  RAM  RearCam  Front_Cam  Gen_5G  Battery  Thickness  \
0                 16.0    8       77         31     1.0   5000.0         17
1                 64.0    8       51         13     0.0   3000.0         12
2                 16.0   11       84         23     0.0   5000.0         11
3                 32.0    7       91         10     0.0   6000.0          8
4                128.0   12       71         27     0.0   4500.0         11
…                  …  …      …          …     …      …         …
1495              16.0   11       54         11     1.0   4500.0         15
1496              32.0    4       63         25     NaN   5000.0          6
1497              16.0    7       77         25     0.0   6000.0         13
1498              16.0    6       43         31     0.0   3000.0          5
1499             256.0    5       43         22     1.0   3500.0          6

         Price
0      60000.0
1      53000.0
2      70000.0
3      67000.0
4      41000.0
…          …
1495   32000.0
1496  101000.0
1497   43000.0
1498   28000.0
1499   35000.0

[1500 rows x 14 columns]
```

[299]:
```
df_merged['CPU_core'].value_counts()
```

[299]:
```
1    219
6    199
4    196
7    190
2    180
3    178
8    175
5    163
Name: CPU_core, dtype: int64
```

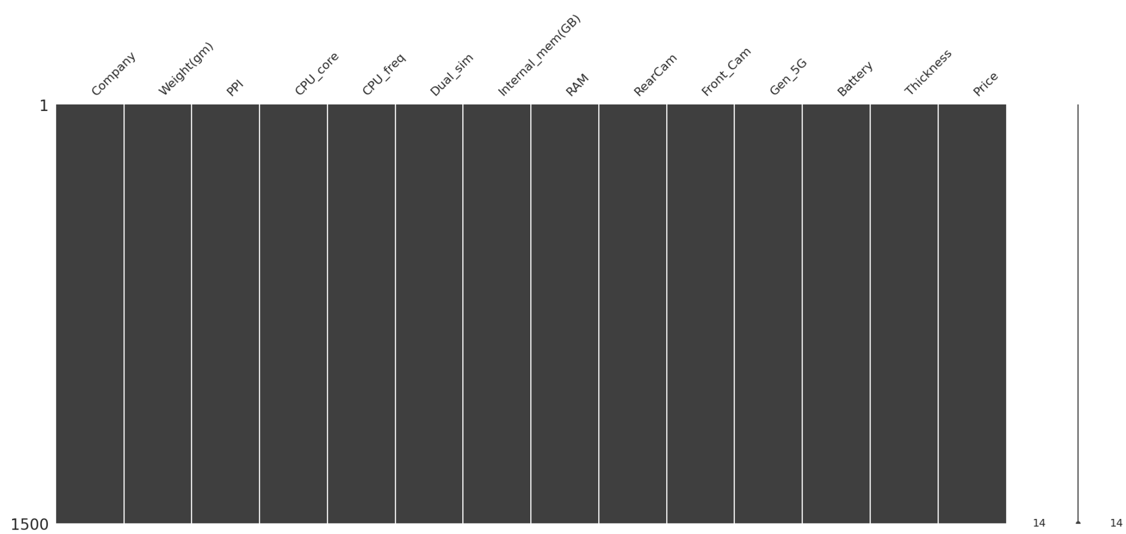
[300]:
```
df_merged['Gen_5G'] = df_merged['Gen_5G'].fillna(method='bfill')
```

[301]:
```
df_merged.isnull().sum()
```

[301]:
```
Company             0
Weight(gm)          0
PPI                 0
CPU_core            0
CPU_freq            0
Dual_sim            0
Internal_mem(GB)    0
RAM                 0
RearCam             0
Front_Cam           0
Gen_5G              0
Battery             0
Thickness           0
Price               0
dtype: int64
```

[302]:
```
msno.matrix(df_merged)
```

[302]:
```
<Axes: >
```




[303]:
```
df_merged.corr()
```

[303]:
```
                   Company  Weight(gm)       PPI  CPU_core  CPU_freq  \
Company           1.000000   -0.033894 -0.035367 -0.001696 -0.043763
Weight(gm)       -0.033894    1.000000 -0.024519  0.044470 -0.004677
PPI              -0.035367   -0.024519  1.000000  0.024396  0.055434
CPU_core         -0.001696    0.044470  0.024396  1.000000 -0.008669
CPU_freq         -0.043763   -0.004677  0.055434 -0.008669  1.000000
Dual_sim         -0.016431    0.008557  0.019944 -0.003378 -0.007419
```

```
Internal_mem(GB)  0.007243    0.017536  0.003930  0.002807  0.037610
RAM               0.024401   -0.025259  0.019059  0.005788  0.047505
RearCam          -0.026918    0.027723  0.025406  0.009979 -0.038035
Front_Cam         0.013403    0.042453  0.042920  0.023586 -0.002926
Gen_5G           -0.014889    0.021557  0.031871  0.018104 -0.014477
Battery          -0.001666    0.023796 -0.008695  0.016072  0.005073
Thickness         0.037313    0.011519  0.018738  0.019412 -0.035592
Price            -0.556091    0.034972  0.056383  0.039368  0.005700

                  Dual_sim  Internal_mem(GB)       RAM   RearCam  Front_Cam  \
Company          -0.016431          0.007243  0.024401 -0.026918   0.013403
Weight(gm)        0.008557          0.017536 -0.025259  0.027723   0.042453
PPI               0.019944          0.003930  0.019059  0.025406   0.042920
CPU_core         -0.003378          0.002807  0.005788  0.009979   0.023586
CPU_freq         -0.007419          0.037610  0.047505 -0.038035  -0.002926
Dual_sim          1.000000         -0.023921 -0.010760  0.027898   0.007459
Internal_mem(GB) -0.023921          1.000000  0.054864 -0.021540  -0.006787
RAM              -0.010760          0.054864  1.000000 -0.034495  -0.033373
RearCam           0.027898         -0.021540 -0.034495  1.000000  -0.043369
Front_Cam         0.007459         -0.006787 -0.033373 -0.043369   1.000000
Gen_5G           -0.007012          0.029458  0.014478  0.015769   0.032820
Battery          -0.027663         -0.037936  0.047197  0.003270  -0.033193
Thickness        -0.035409          0.016175  0.046950  0.026683   0.024301
Price             0.050466          0.054010  0.056190  0.042059   0.006234

                    Gen_5G   Battery  Thickness     Price
Company          -0.014889 -0.001666   0.037313 -0.556091
Weight(gm)        0.021557  0.023796   0.011519  0.034972
PPI               0.031871 -0.008695   0.018738  0.056383
CPU_core          0.018104  0.016072   0.019412  0.039368
CPU_freq         -0.014477  0.005073  -0.035592  0.005700
Dual_sim         -0.007012 -0.027663  -0.035409  0.050466
Internal_mem(GB)  0.029458 -0.037936   0.016175  0.054010
RAM               0.014478  0.047197   0.046950  0.056190
RearCam           0.015769  0.003270   0.026683  0.042059
Front_Cam         0.032820 -0.033193   0.024301  0.006234
Gen_5G            1.000000  0.052340   0.009293  0.078342
Battery           0.052340  1.000000  -0.037837  0.048829
Thickness         0.009293 -0.037837   1.000000 -0.001714
Price             0.078342  0.048829  -0.001714  1.000000
```

[304]:
```python
df_merged['Internal_mem(GB)'].value_counts()
```

[304]:
```
16.0     387
64.0     290
128.0    289
256.0    283
```

```
32.0     251
Name: Internal_mem(GB), dtype: int64
```

[305]:
```
df_merged['Battery'].value_counts()
```

[305]:
```
5000.0    234
4500.0    224
5500.0    215
6000.0    213
4000.0    208
3000.0    204
3500.0    202
Name: Battery, dtype: int64
```

## 15 Data Quality

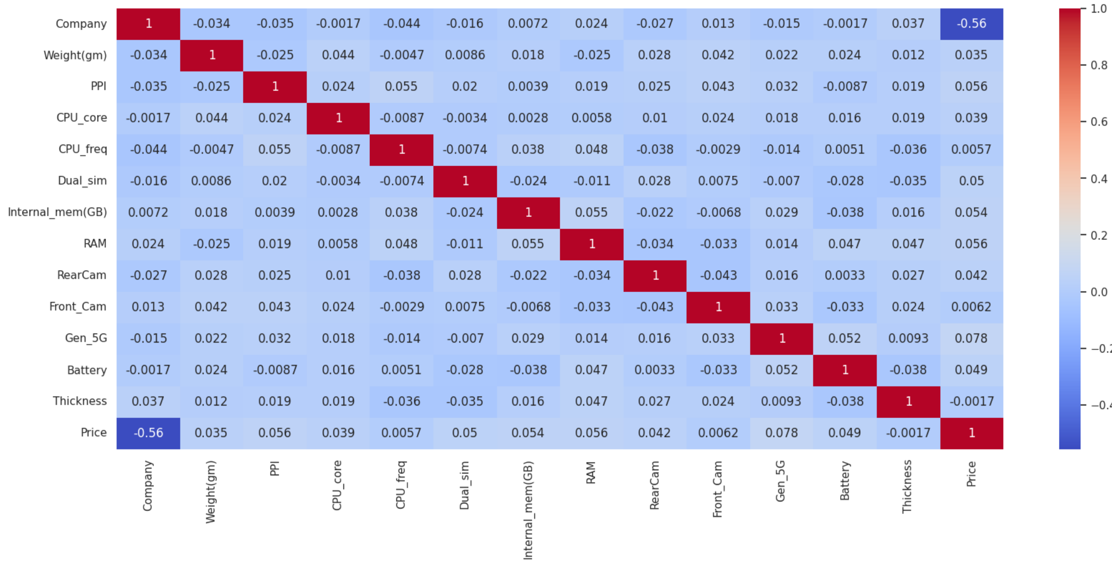
[306]:
```
import pandas as pd
duplicate_rows = df_merged[df_merged.duplicated()]
duplicate_rows.shape
```

[306]:
```
(0, 14)
```

So there are no duplicates

## 16 HeatMap

[307]:
```
plt.figure(figsize=(20, 8))
correlation_matrix = df_merged.corr()
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
plt.show()
```



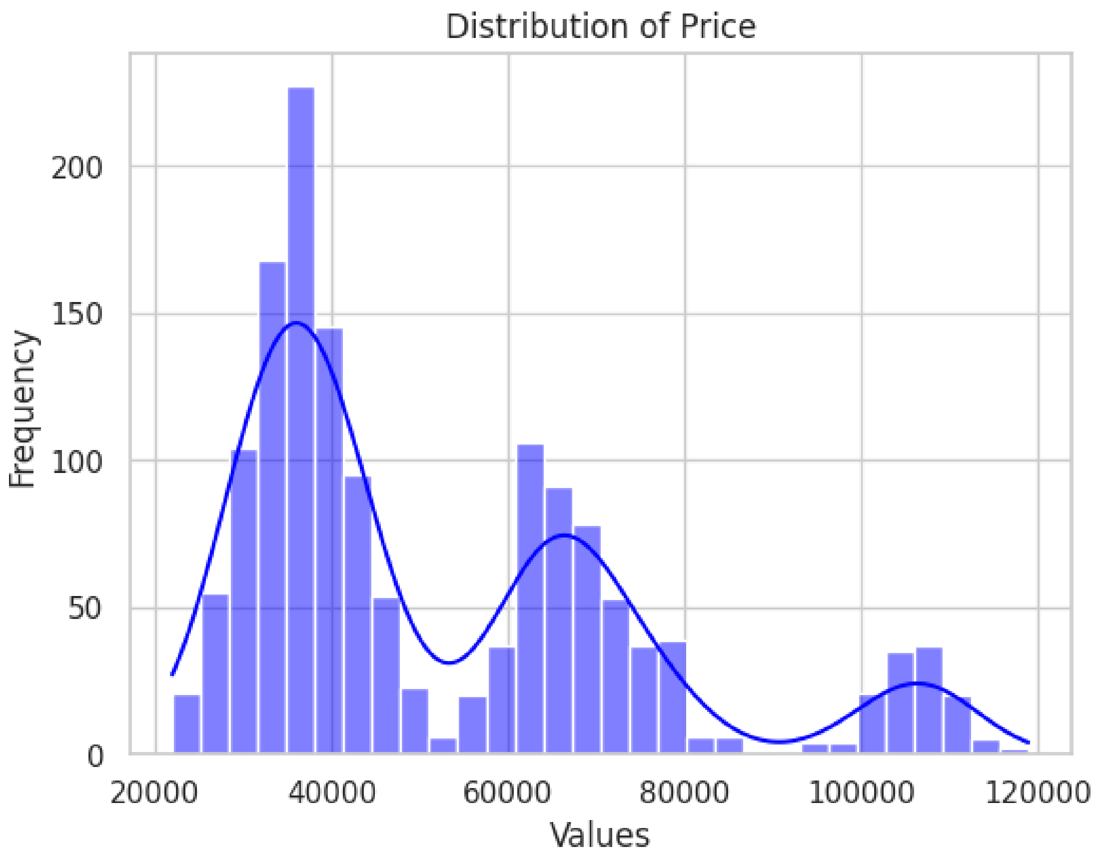

# 17 Data Skewness

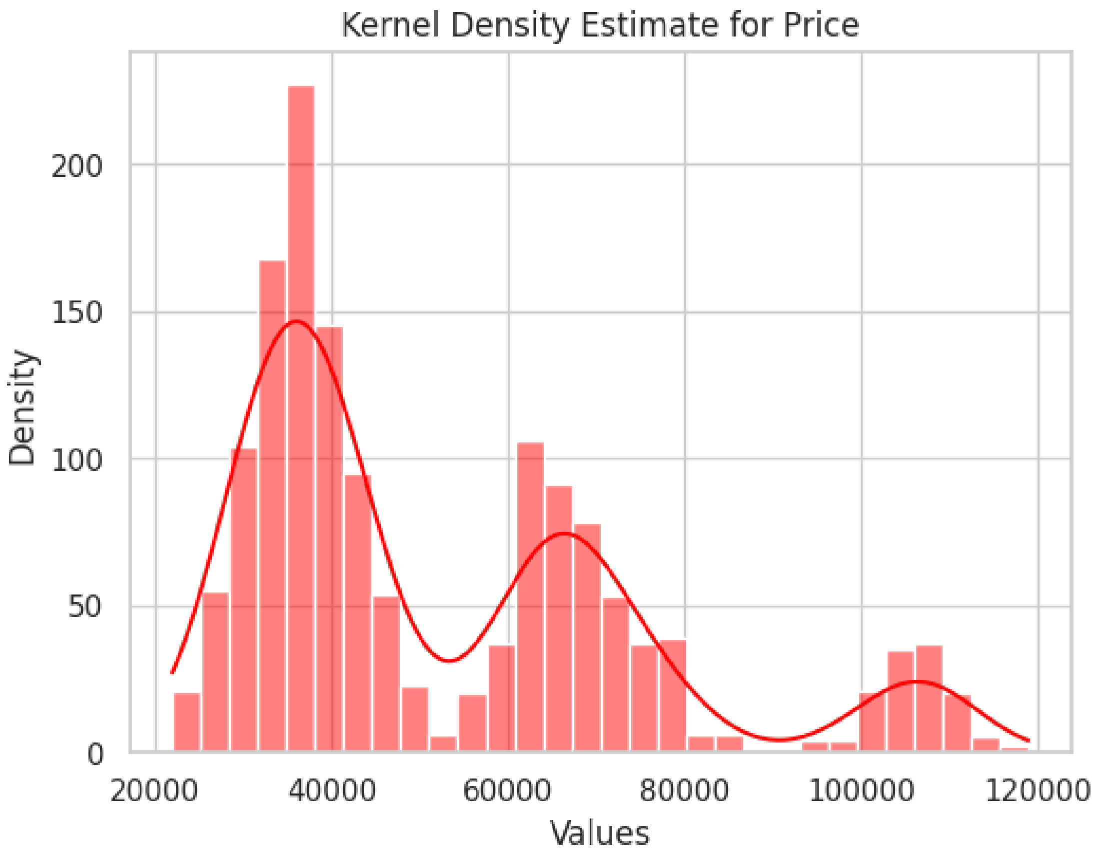
[308]:
```python
numeric_columns = df_merged.select_dtypes(include=['float64', 'int']).columns
skewness = df_merged[numeric_columns].apply(lambda x: x.skew())
print(skewness)
```

```
Company             0.040592
Weight(gm)         -0.052652
PPI                 0.015320
CPU_core            0.009454
CPU_freq           -0.017846
Dual_sim           -0.074794
Internal_mem(GB)    0.949655
RAM                -0.025163
RearCam             0.025589
Front_Cam          -0.022150
Gen_5G              0.053406
Battery            -0.047799
Thickness           0.019966
Price               1.057614
dtype: float64
```

[309]:
```python
columns_to_analyze = ["Price"]
for column in columns_to_analyze:
    sns.histplot(df_merged[column], kde=True, color='blue', bins=30)
    plt.title(f'Distribution of {column}')
    plt.xlabel('Values')
```

```
    plt.ylabel('Frequency')
    plt.show()

    sns.histplot(df_merged[column], kde=True, color='red', bins=30)
    plt.title(f'Kernel Density Estimate for {column}')
    plt.xlabel('Values')
    plt.ylabel('Density')
    plt.show()
```






[310]:
```
dfcopy = df_merged.copy()
```

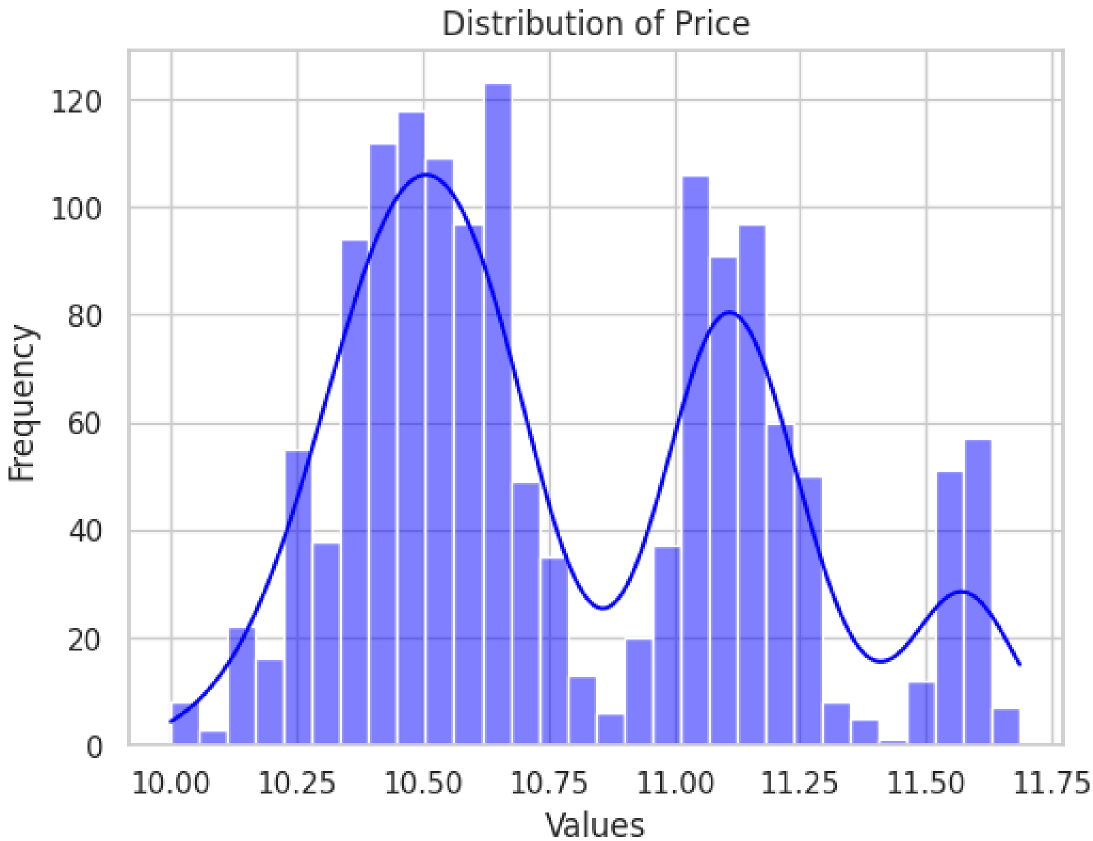
## 18 Skneness after Transformation

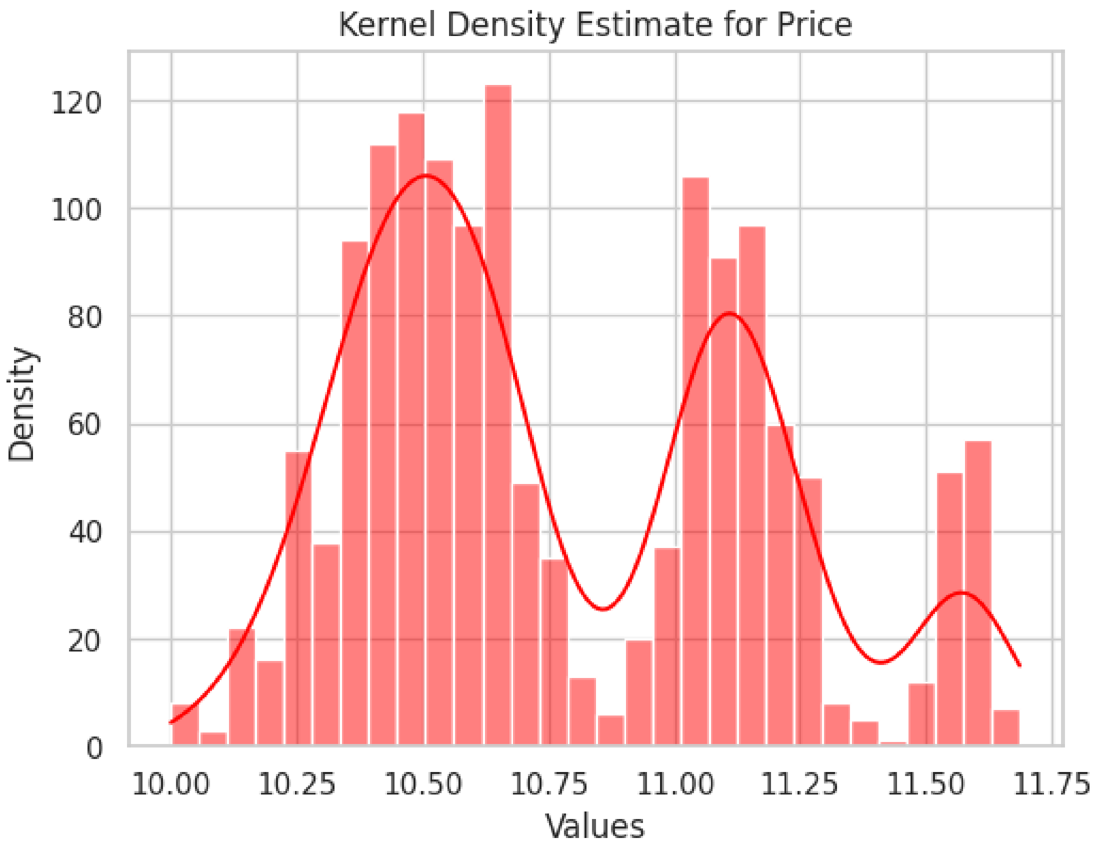
[311]:
```
columns_to_analyze = ["Price"]
for column in columns_to_analyze:
  df_merged[column] = df_merged[column].apply(lambda x: np.log1p(x) if x > 0␣
 ↪else 0)
  transformed_skewness = df_merged[column].skew()
  print(f"Skewness after transformation for {column}: {transformed_skewness}")
```

```
Skewness after transformation for Price: 0.4522692673157849
```

[312]:
```
columns_to_analyze = ["Price"]
for column in columns_to_analyze:
    sns.histplot(df_merged[column], kde=True, color='blue', bins=30)
    plt.title(f'Distribution of {column}')
    plt.xlabel('Values')
    plt.ylabel('Frequency')
```

```
plt.show()

sns.histplot(df_merged[column], kde=True, color='red', bins=30)
plt.title(f'Kernel Density Estimate for {column}')
plt.xlabel('Values')
plt.ylabel('Density')
plt.show()
```






## 19 Normalization

[313]:
```
df_Normalize=df_merged.copy()
```

[314]:
```
from sklearn.preprocessing import MinMaxScaler
columns_to_normalize = ['Price']
scaler = MinMaxScaler()
df_Normalize[columns_to_normalize] = scaler.
 ↪fit_transform(df_Normalize[columns_to_normalize])
df_Normalize.head(n=3)
```

[314]:

| | Company | Weight(gm) | PPI | CPU_core | CPU_freq | Dual_sim | Internal_mem(GB) | \ |
|---|---|---|---|---|---|---|---|---|
| 0 | 9 | 180.0 | 312 | 1 | 1.5 | 0 | 16.0 | |
| 1 | 2 | 160.0 | 362 | 1 | 1.6 | 0 | 64.0 | |
| 2 | 1 | 160.0 | 241 | 1 | 1.0 | 0 | 16.0 | |

| | RAM | RearCam | Front_Cam | Gen_5G | Battery | Thickness | Price |
|---|---|---|---|---|---|---|---|
| 0 | 8 | 77 | 31 | 1.0 | 5000.0 | 17 | 0.594341 |
| 1 | 8 | 51 | 13 | 0.0 | 3000.0 | 12 | 0.520853 |

```
2    11        84          23      0.0    5000.0          11   0.685658
```

[315]:
```
df_merged=df_Normalize.copy()
```

# 20 Binning

[316]:
```
import pandas as pd
column_name = 'Price'
num_bins = 10

df_Normalize['Binned_Column'] = pd.cut(df_Normalize[column_name],␣
    ↪bins=num_bins, labels=False)

binned_means = df_Normalize.groupby('Binned_Column')[column_name].mean()
binned_medians = df_Normalize.groupby('Binned_Column')[column_name].median()

df_Normalize['Binned_Column_Means'] = df_Normalize['Binned_Column'].
    ↪map(binned_means)
df_Normalize['Binned_Column_Medians'] = df_Normalize['Binned_Column'].
    ↪map(binned_medians)

df_Normalize[['Binned_Column', 'Binned_Column_Means', 'Binned_Column_Medians',␣
    ↪column_name]]
```

[316]:

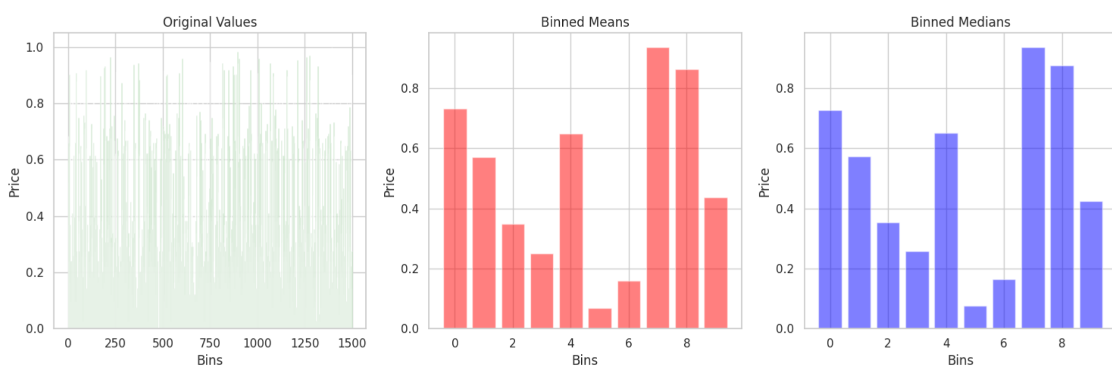
| | Binned_Column | Binned_Column_Means | Binned_Column_Medians | Price |
|---|---|---|---|---|
| 0 | 5 | 0.570393 | 0.574258 | 0.594341 |
| 1 | 5 | 0.570393 | 0.574258 | 0.520853 |
| 2 | 6 | 0.649945 | 0.650802 | 0.685658 |
| 3 | 6 | 0.649945 | 0.650802 | 0.659710 |
| 4 | 3 | 0.348768 | 0.354147 | 0.368775 |
| … | … | … | … | … |
| 1495 | 2 | 0.250888 | 0.257874 | 0.221961 |
| 1496 | 9 | 0.937023 | 0.937031 | 0.902845 |
| 1497 | 3 | 0.348768 | 0.354147 | 0.396989 |
| 1498 | 1 | 0.159285 | 0.163646 | 0.142859 |
| 1499 | 2 | 0.250888 | 0.257874 | 0.275045 |

[1500 rows x 4 columns]

# 21 Equi width

[317]:
```
import pandas as pd
import matplotlib.pyplot as plt

column_name = 'Price'
```

```
fig, axes = plt.subplots(nrows=1, ncols=3, figsize=(15, 5))

# Original column values
axes[0].bar(df_Normalize.index, df_Normalize[column_name], color='green', alpha=0.5)
axes[0].set_title('Original Values')

# Binned means
axes[1].bar(df_Normalize['Binned_Column'].unique(), df_Normalize.groupby('Binned_Column')[column_name].mean(), color='red', alpha=0.5)
axes[1].set_title('Binned Means')

# Binned medians
axes[2].bar(df_Normalize['Binned_Column'].unique(), df_Normalize.groupby('Binned_Column')[column_name].median(), color='blue', alpha=0.5)
axes[2].set_title('Binned Medians')

# Set common labels
for ax in axes:
    ax.set_xlabel('Bins')
    ax.set_ylabel(column_name)

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




## 22 Equi depth

[318]:
```
import pandas as pd
column_name = 'Price'
num_bins = 5
# Calculate bin edges using pandas' qcut function
```

```
df_Normalize['EquiDepth_Binned_Column'], bin_edges = pd.
 ↪qcut(df_Normalize[column_name], q=num_bins, retbins=True, labels=False)
print("Bin Edges:", bin_edges)
df_Normalize[['EquiDepth_Binned_Column', column_name]].head()
```

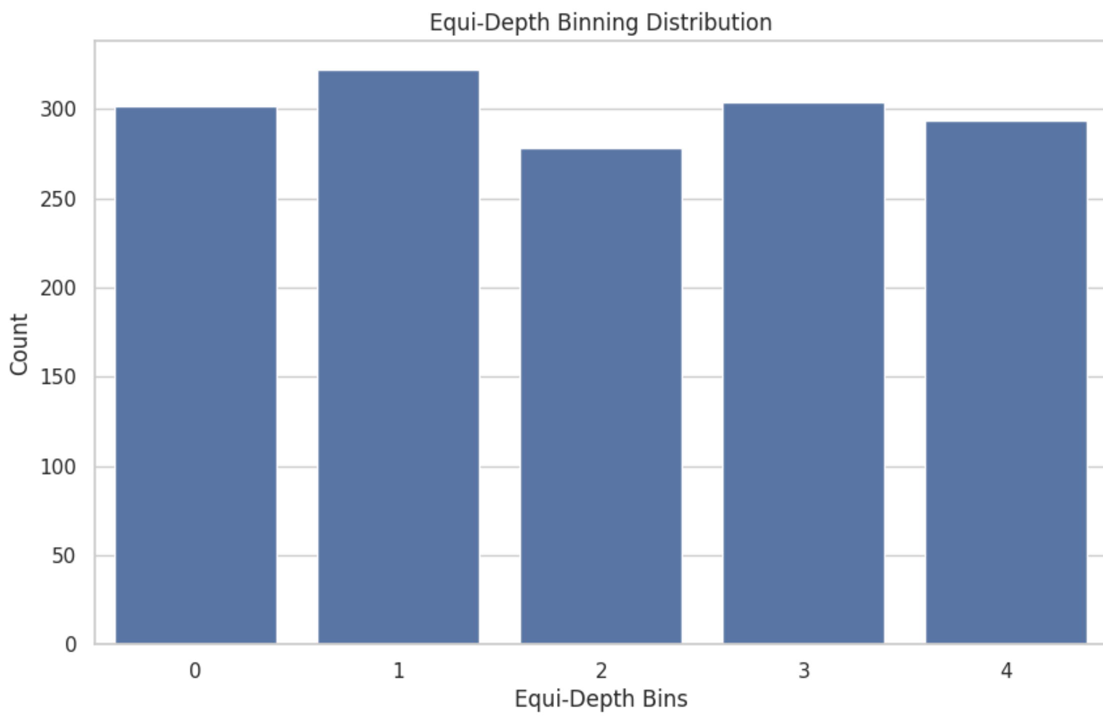
```
Bin Edges: [0.         0.24018921 0.33914956 0.54279596 0.67713466 1.        ]
```

[318]:

| | EquiDepth_Binned_Column | Price |
|---|---|---|
| 0 | 3 | 0.594341 |
| 1 | 2 | 0.520853 |
| 2 | 4 | 0.685658 |
| 3 | 3 | 0.659710 |
| 4 | 2 | 0.368775 |

[319]:

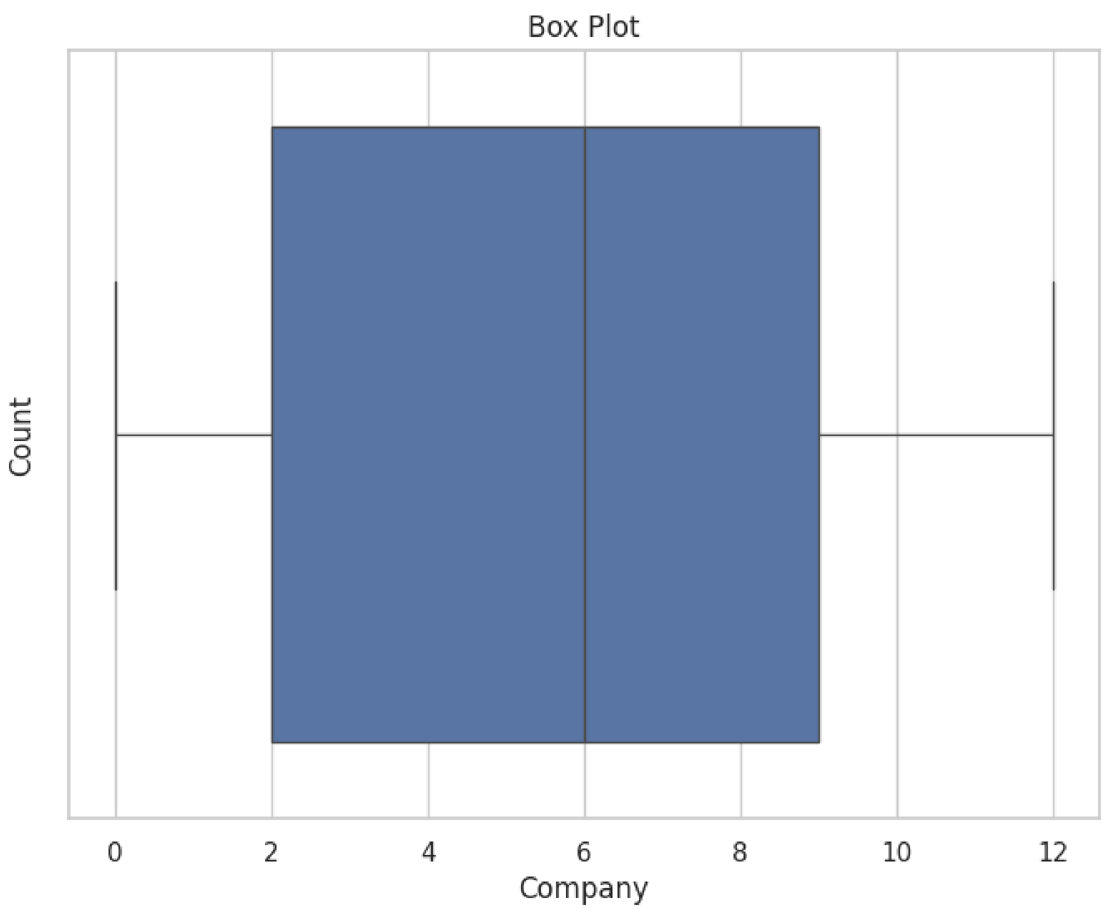
```
sns.set(style="whitegrid")
# Create a bar plot to visualize the distribution of the equi-depth bins
plt.figure(figsize=(10, 6))
sns.countplot(x='EquiDepth_Binned_Column', data=df_Normalize)
plt.xlabel('Equi-Depth Bins')
plt.ylabel('Count')
plt.title('Equi-Depth Binning Distribution')
plt.show()
```

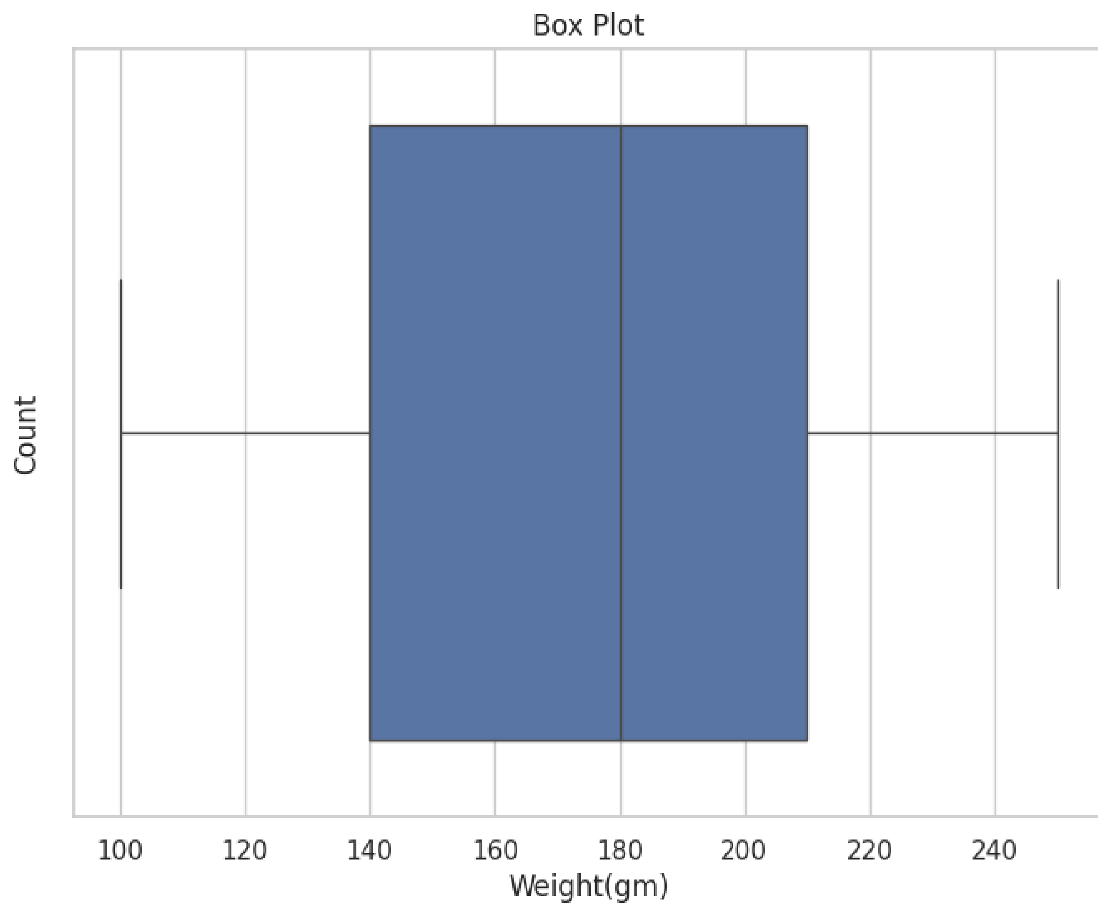


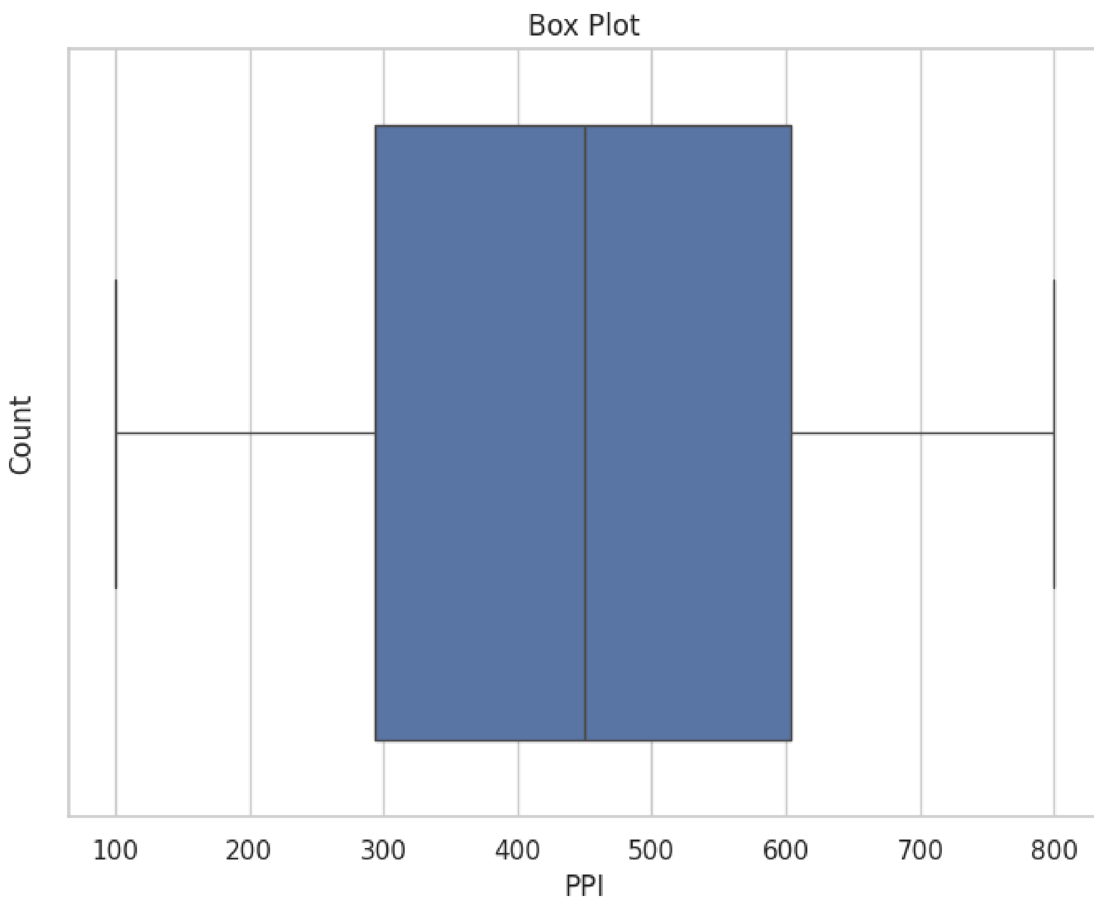
[320]:
```
df_Normalize.drop('Binned_Column', axis=1, inplace=True)
df_Normalize.drop('Binned_Column_Means', axis=1, inplace=True)
df_Normalize.drop('Binned_Column_Medians', axis=1, inplace=True)
df_Normalize.drop('EquiDepth_Binned_Column', axis=1, inplace=True)
```

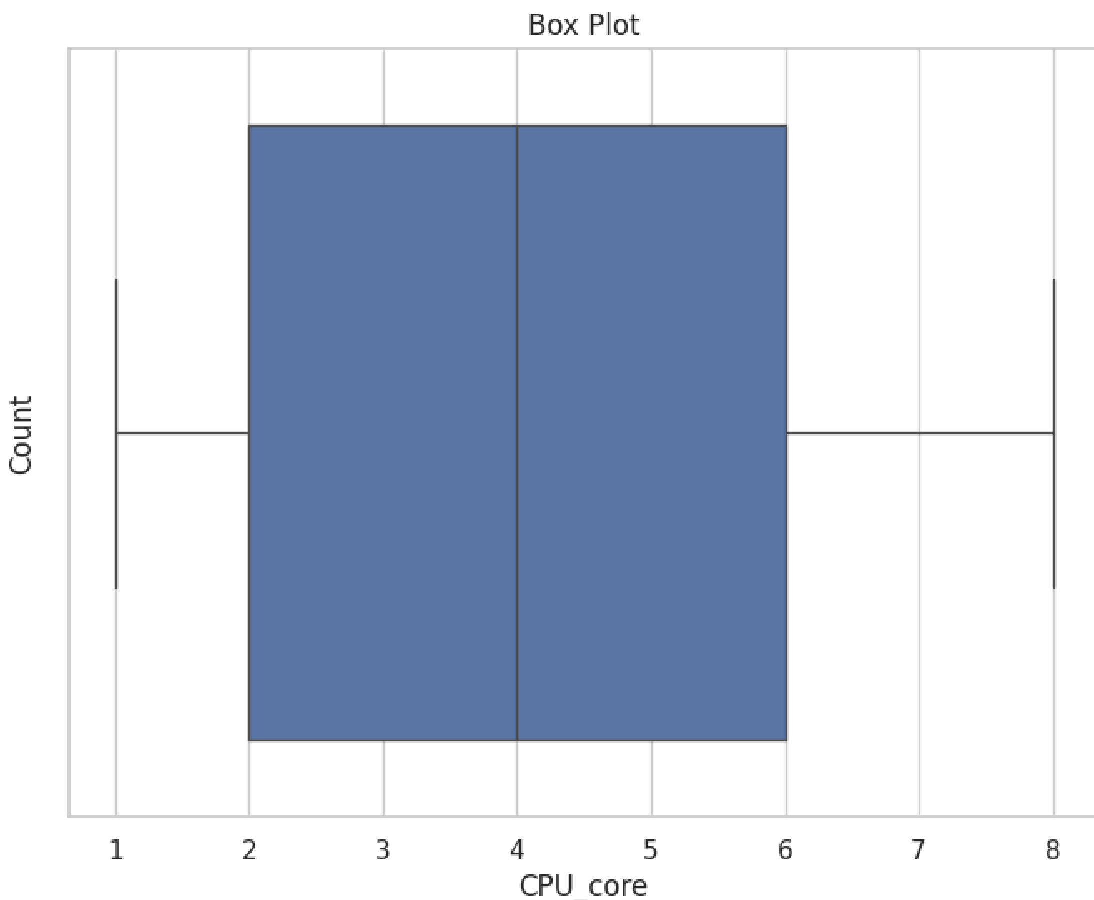
## 23 Outlier Detection

[321]:
```
for column in df_merged.columns:
  plt.figure(figsize=(8, 6))
  sns.boxplot(x=column, data=df_Normalize)
  plt.xlabel(column)
  plt.ylabel('Count')
  plt.title('Box Plot')
  plt.show()
```

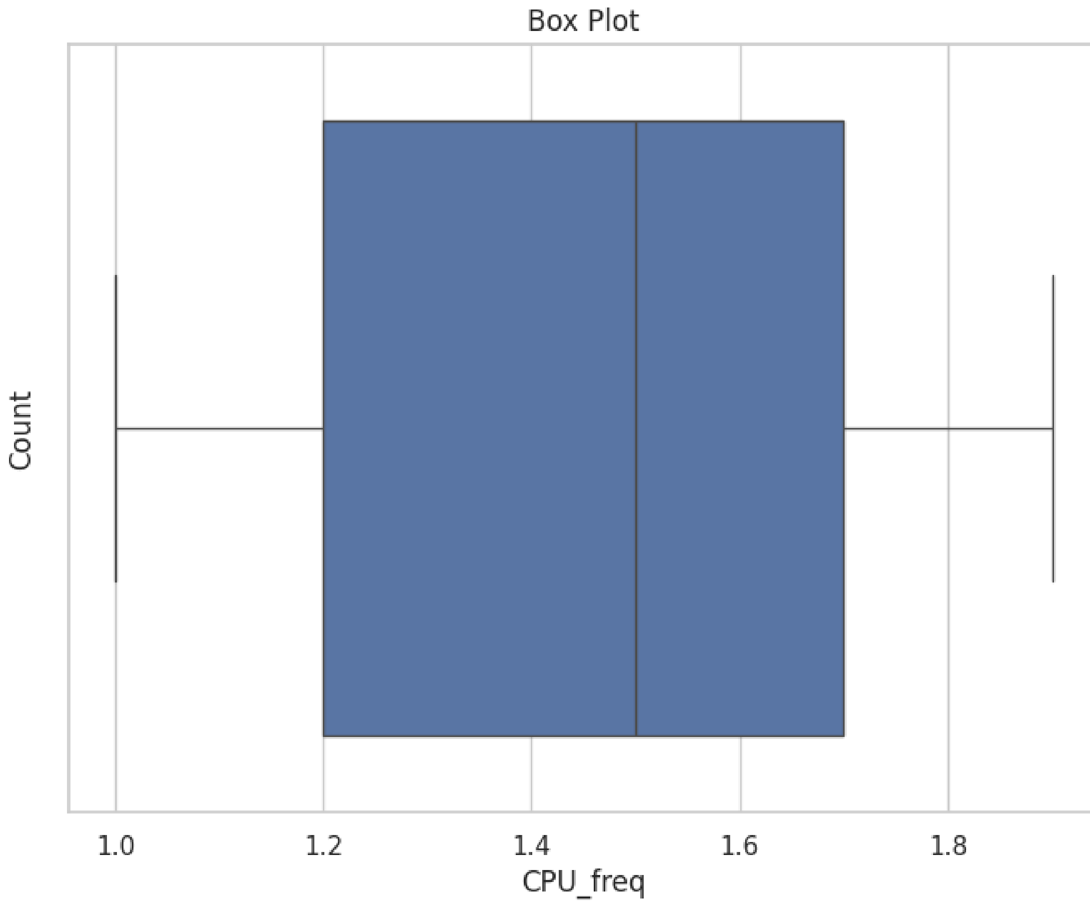


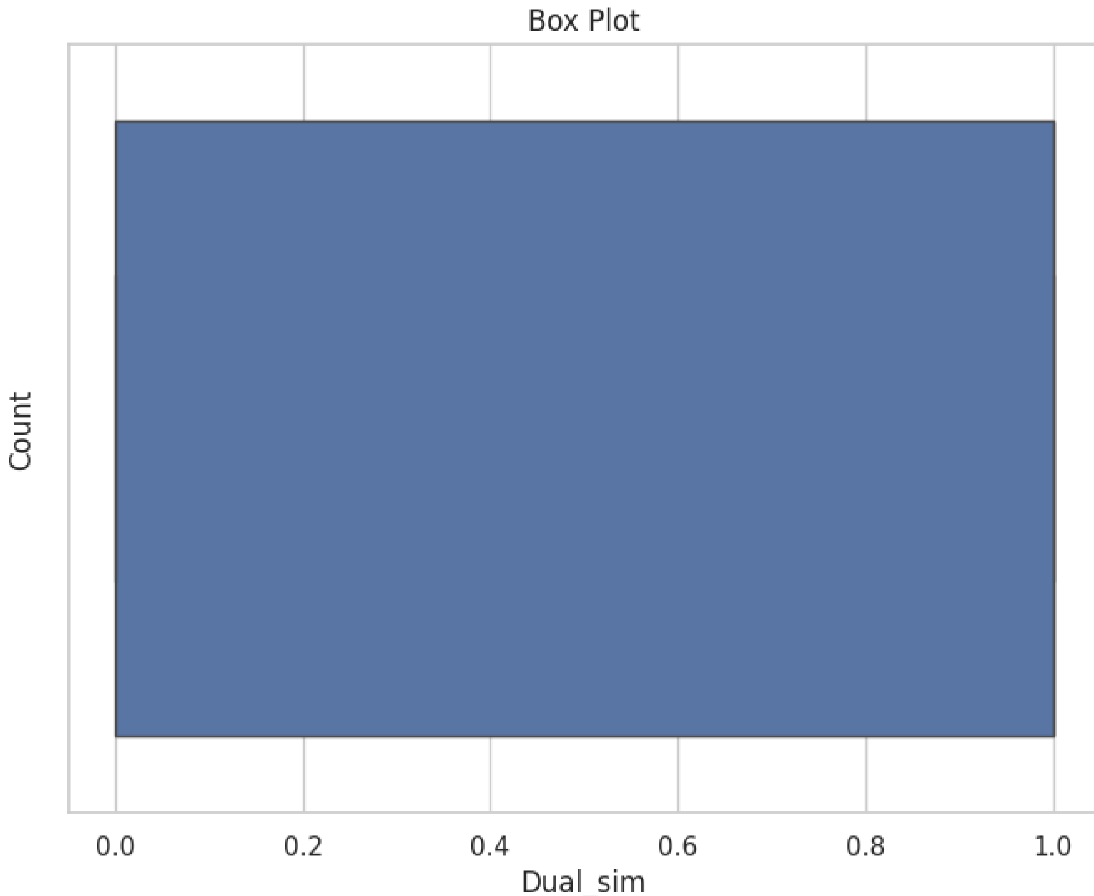

Box Plot
Count
100
120
140
160
180
200
220
240
Weight(gm)

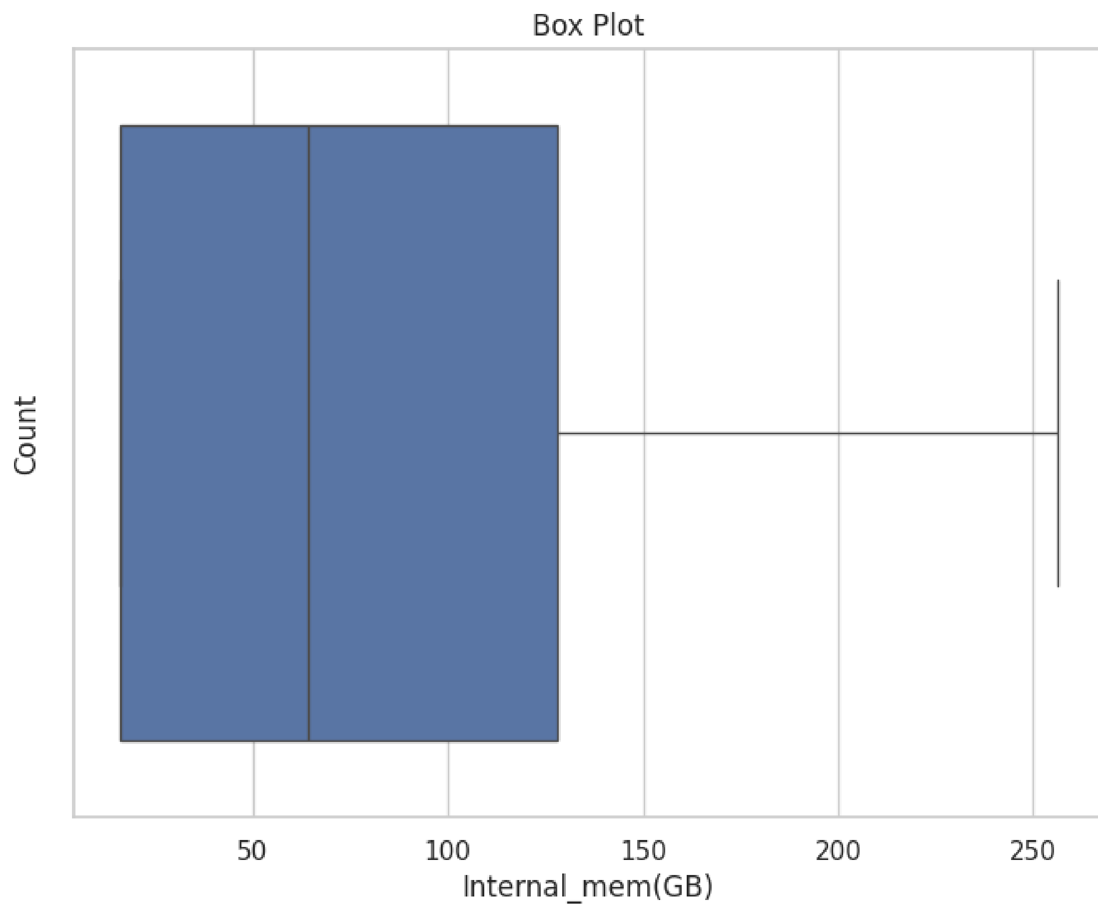

Box Plot
Count
100
200
300
400
500
600
700
800
PPI

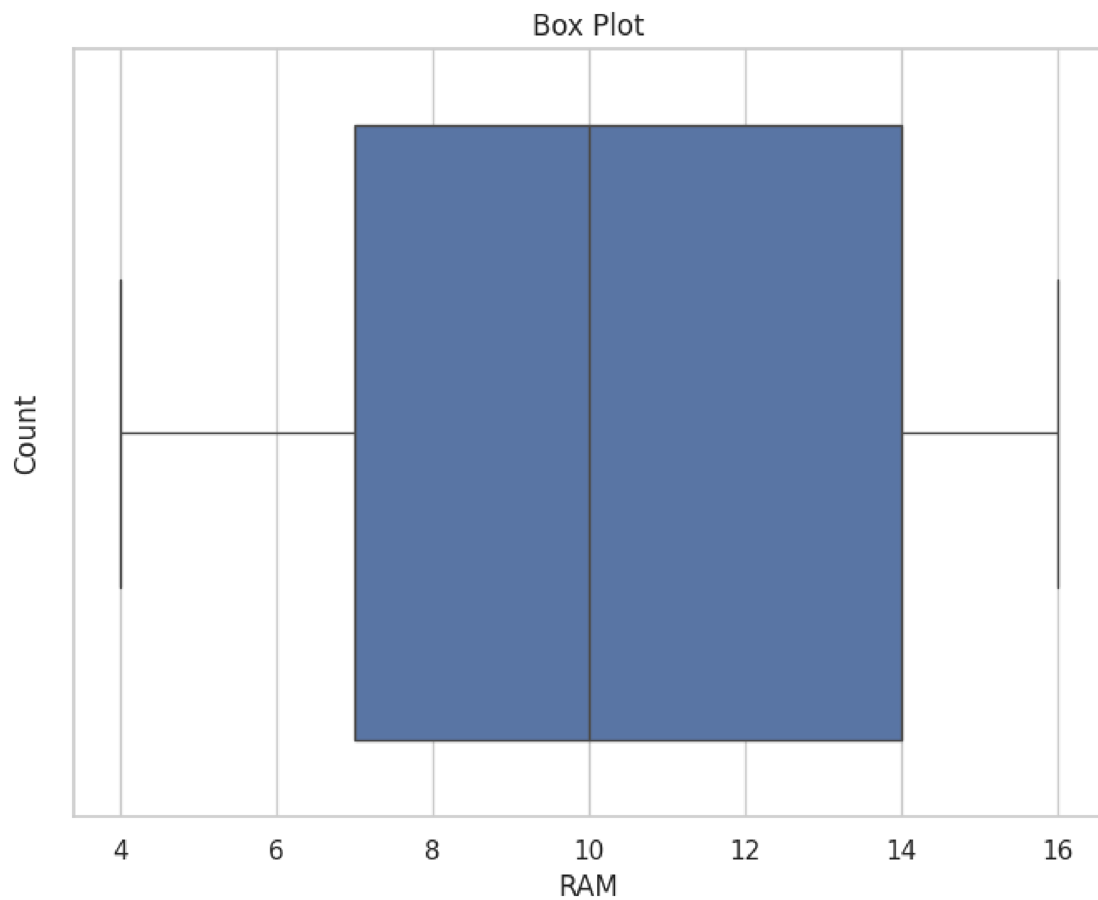


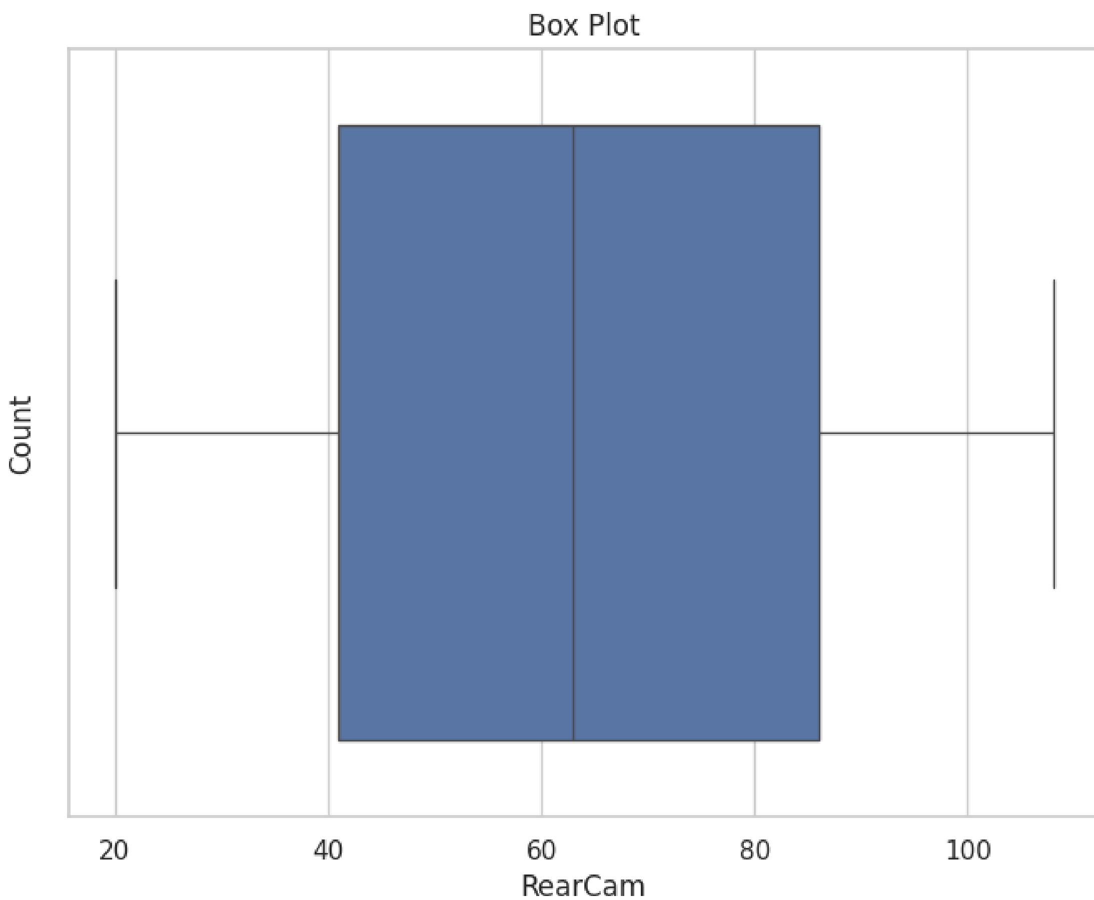
Box Plot
Count
1
2
3
4
5
6
7
8
CPU_core

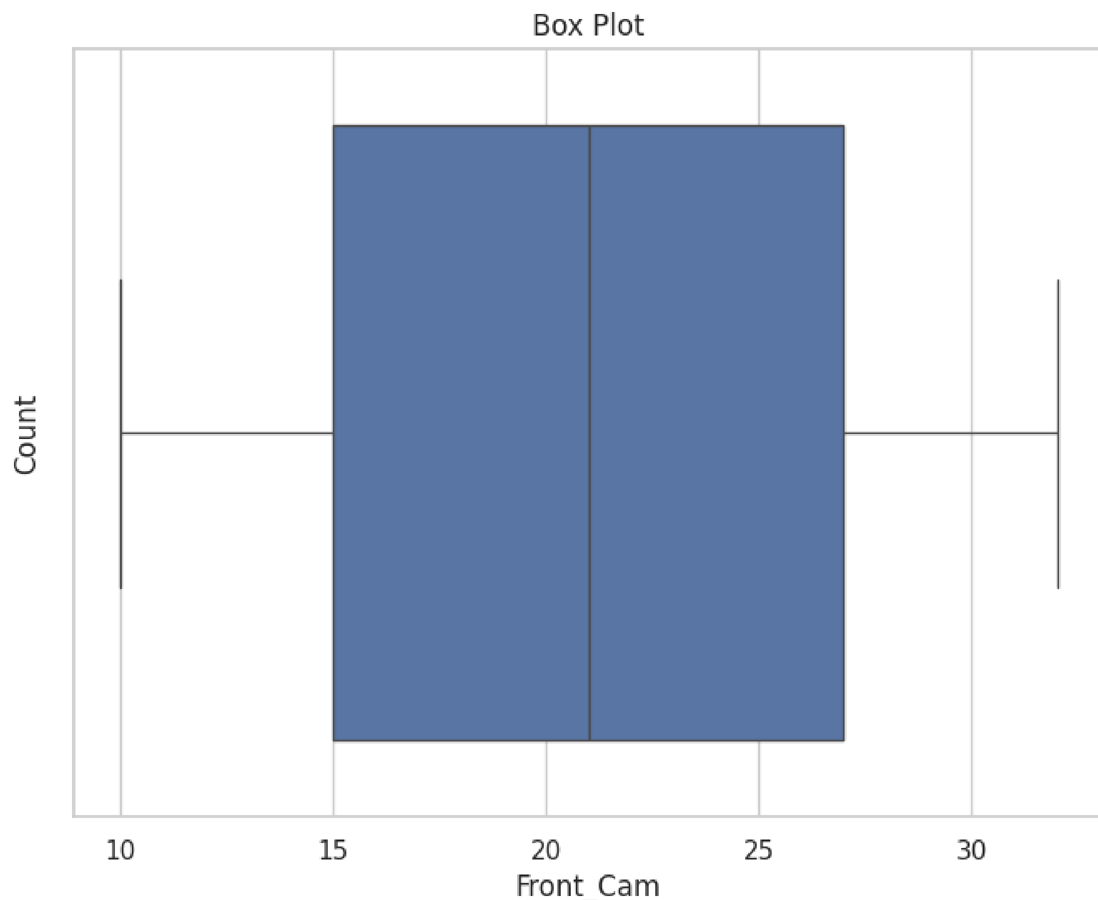

Box Plot
Count
1.0
1.2
1.4
1.6
1.8
CPU_freq

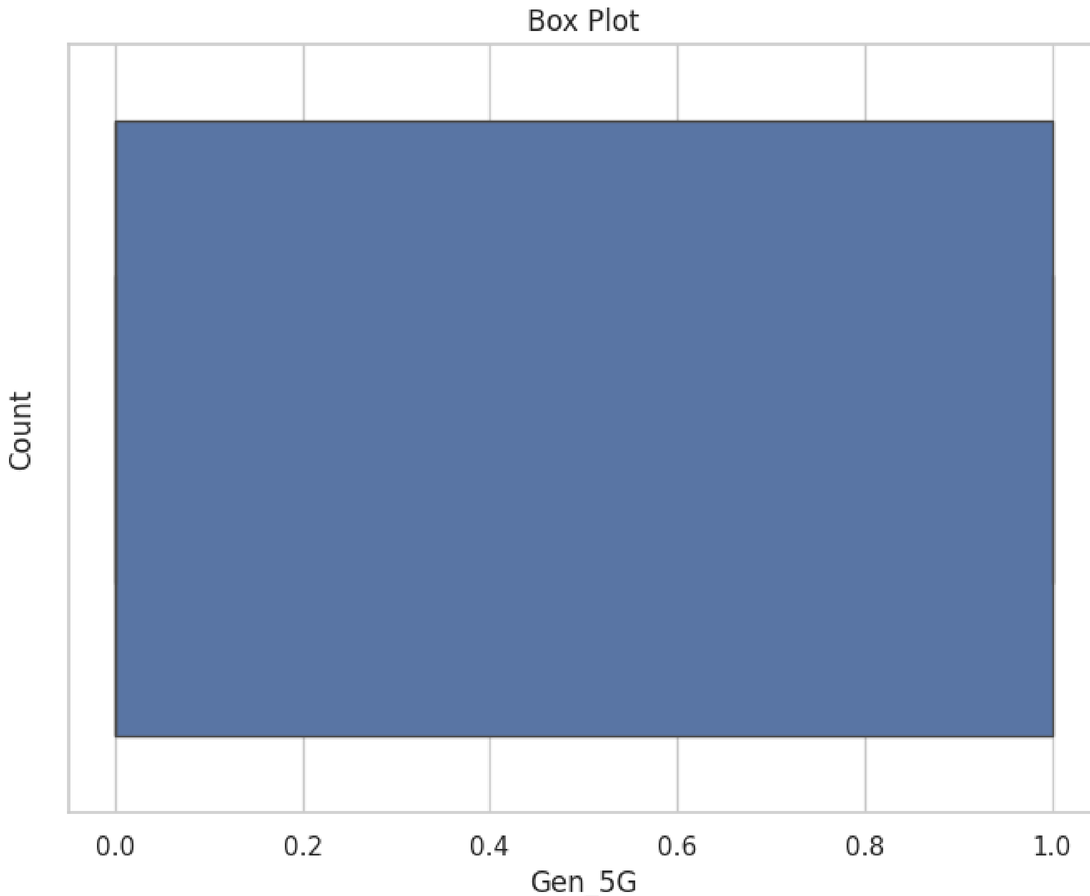

Box Plot
Count
0.0
0.2
0.4
0.6
0.8
1.0
Dual_sim

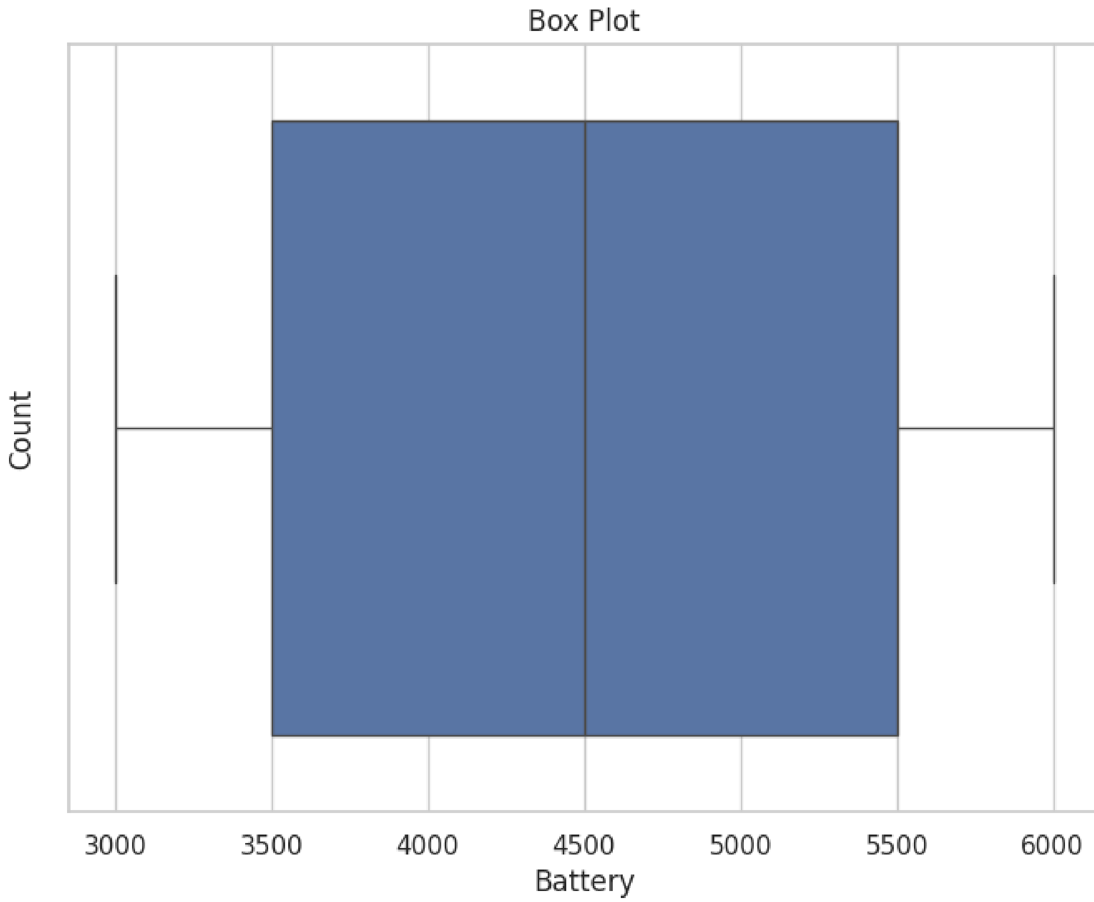

Box Plot
Count
50
100
150
200
250
Internal_mem(GB)

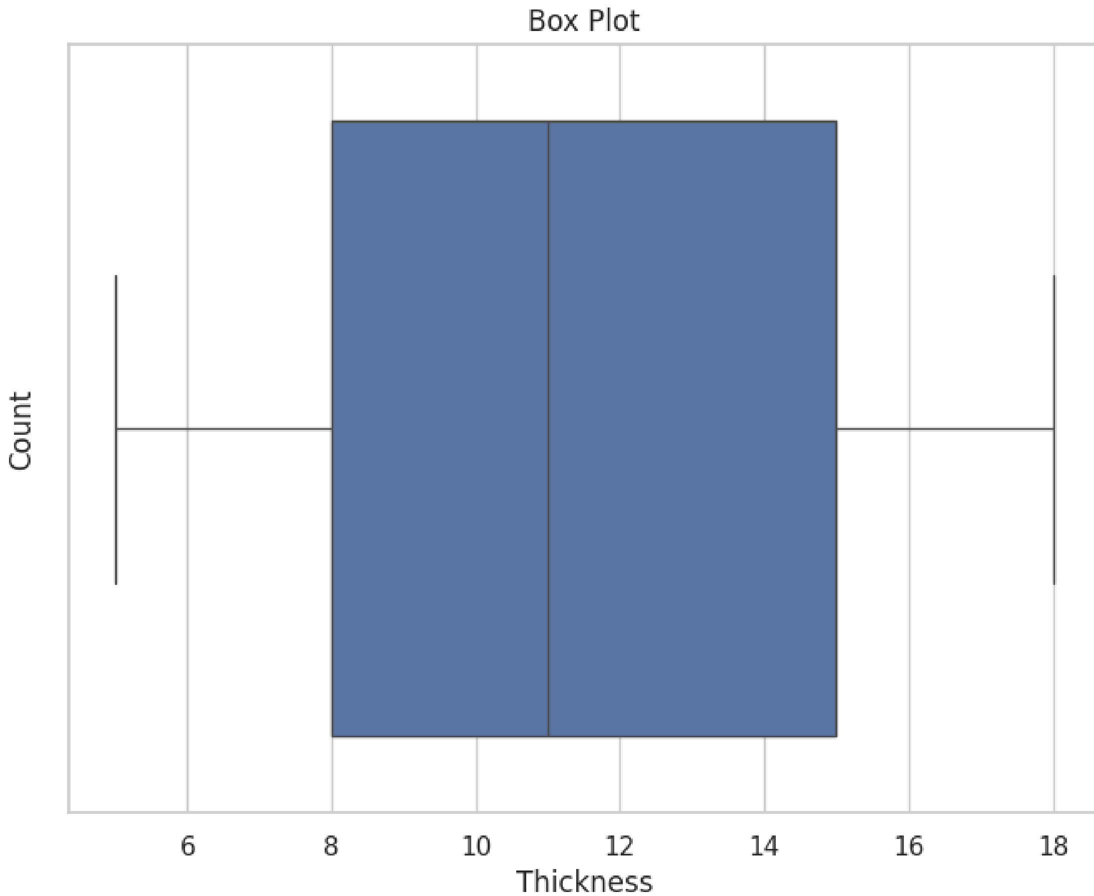

Box Plot
Count
4
6
8
10
12
14
16
RAM

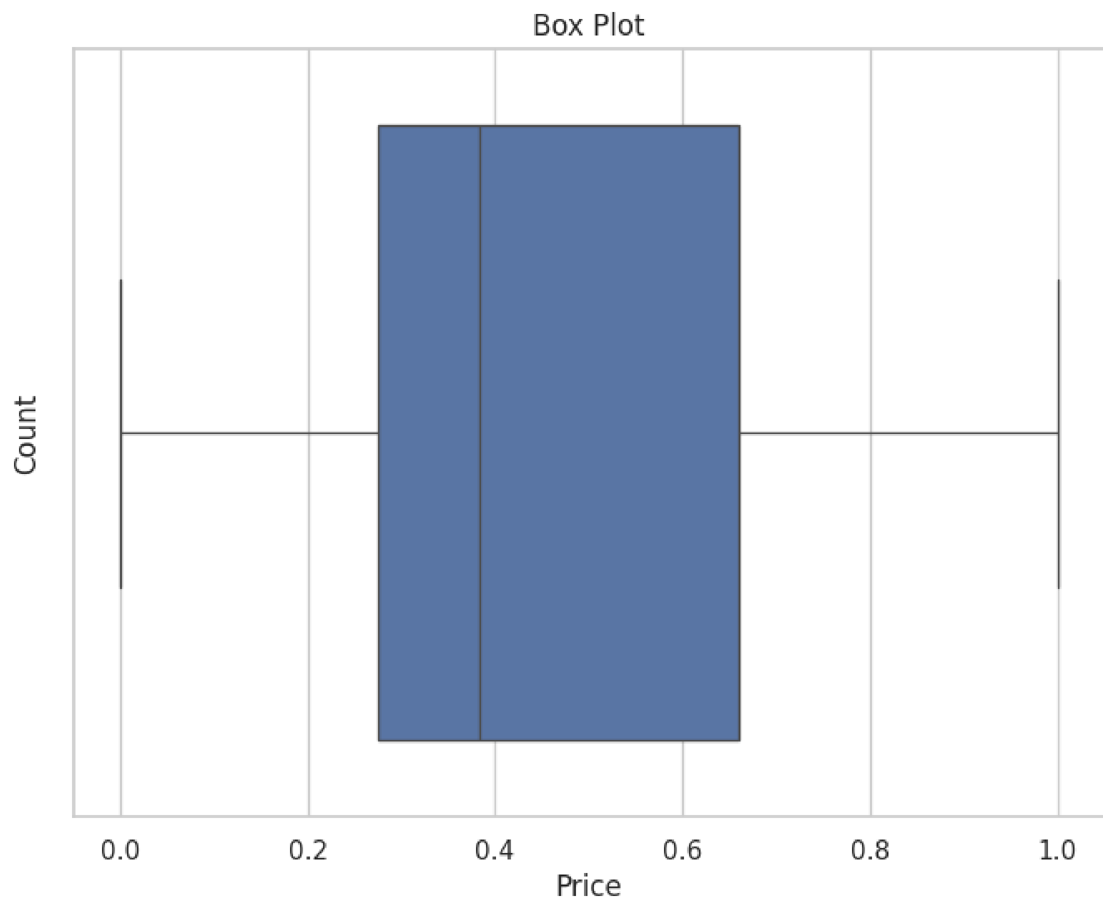

Box Plot
Count
20
40
60
80
100
RearCam


Box Plot
Count
10
15
20
25
30
Front_Cam

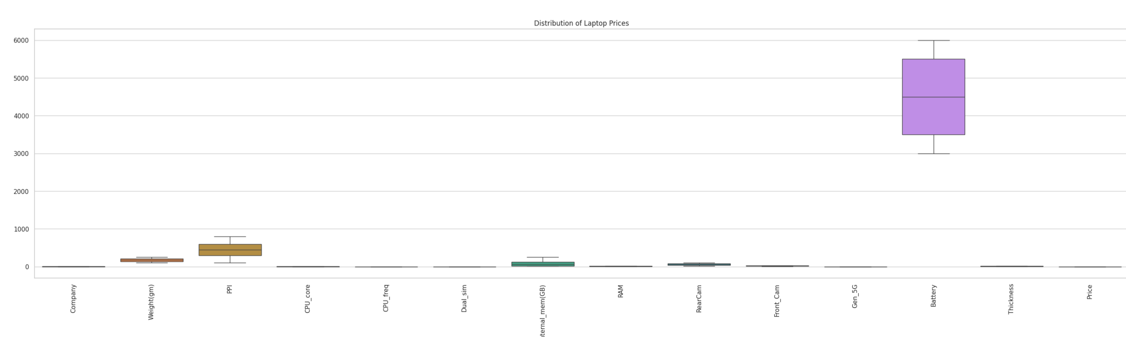

Box Plot
Count
0.0
0.2
0.4
0.6
0.8
1.0
Gen_5G


Box Plot
Count
3000
3500
4000
4500
5000
5500
6000
Battery


Box Plot
Count
6
8
10
12
14
16
18
Thickness




[322]:
```
plt.figure(figsize=(35, 8))
sns.boxplot(data=df_Normalize)
plt.title('Distribution of Laptop Prices')
plt.xticks(rotation='vertical')
plt.show()
```



[323]:
```
sns.boxplot(data=df_Normalize, y='Price')
plt.title('Distribution of Prices')
plt.show()
```


[324]:
```
max_weight = df_merged['Weight(gm)'].max()
min_weight = df_merged['Weight(gm)'].min()

print(f"Maximum Weight: {max_weight}")
print(f"Minimum Weight: {min_weight}")
```

```
Maximum Weight: 250.0
Minimum Weight: 100.0
```

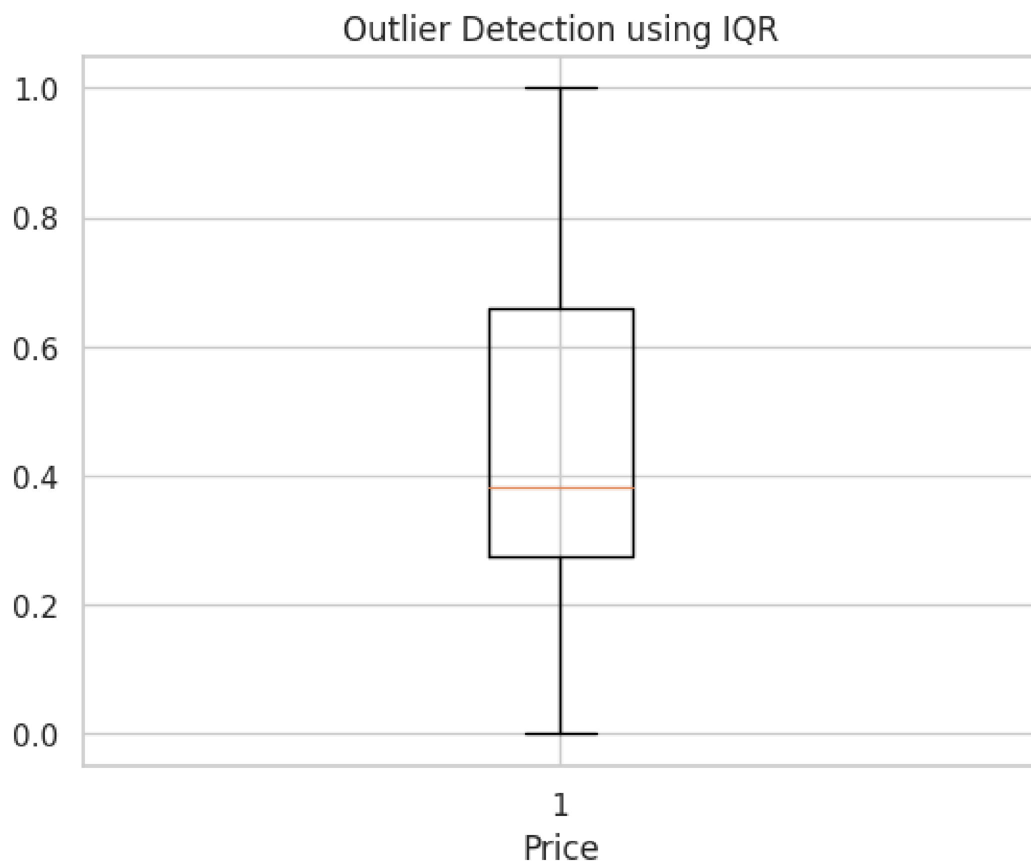
## 24 Outlair detection for Price (target Column) using IQR Method

[325]:
```
columns_with_outliers = ['Price']

def remove_outliers_iqr(df, columns):
    for column in columns:
        Q1 = df[column].quantile(0.25)
        Q3 = df[column].quantile(0.75)
```

```python
        IQR = Q3 - Q1

        lower_bound = Q1 - 1.5 * IQR
        upper_bound = Q3 + 1.5 * IQR

        df = df[(df[column] >= lower_bound) & (df[column] <= upper_bound)]

    return df

IQRout_dataset = remove_outliers_iqr(df_Normalize, columns_with_outliers)
```

[326]:
```python
import pandas as pd
import matplotlib.pyplot as plt

p_column = df_Normalize['Price']
Q1 = p_column.quantile(0.25)
Q3 = p_column.quantile(0.75)
IQR = Q3 - Q1

lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR
outliers = df_merged[(p_column < lower_bound) | (p_column > upper_bound)]
# Display the outliers
print("Outliers:")
print(outliers['Price'])

plt.boxplot(p_column)
plt.xlabel('Price')
plt.title('Outlier Detection using IQR')
plt.show()
```

```
Outliers:
Series([], Name: Price, dtype: float64)
```




## 25 Removing Outliars using Z__score method by Setting threshold Value

[327]:
```
from scipy.stats import zscore
z_scores = zscore(df_merged)
abs_z_scores = np.abs(z_scores)
threshold = 2.5
df_no_outliers2 = df_Normalize[(abs_z_scores < threshold).all(axis=1)]
df_no_outliers2
```

[327]:
```
      Company  Weight(gm)  PPI  CPU_core  CPU_freq  Dual_sim  \
0           9       180.0  312         1       1.5         0
1           2       160.0  362         1       1.6         0
2           1       160.0  241         1       1.0         0
3           6       210.0  555         4       1.2         1
4          11       100.0  607         8       1.8         1
…        …          …   …       …        …        …
1495        3       220.0  627         3       1.6         0
```

```
1496        0       150.0  461          2       1.3          1
1497       10       210.0  466          4       1.4          0
1498        3       100.0  742          2       1.7          1
1499       12       220.0  677          4       1.5          0

      Internal_mem(GB)  RAM  RearCam  Front_Cam  Gen_5G  Battery  Thickness  \
0                 16.0    8       77         31     1.0   5000.0         17
1                 64.0    8       51         13     0.0   3000.0         12
2                 16.0   11       84         23     0.0   5000.0         11
3                 32.0    7       91         10     0.0   6000.0          8
4                128.0   12       71         27     0.0   4500.0         11
…                    …    …        …          …       …        …
1495              16.0   11       54         11     1.0   4500.0         15
1496              32.0    4       63         25     0.0   5000.0          6
1497              16.0    7       77         25     0.0   6000.0         13
1498              16.0    6       43         31     0.0   3000.0          5
1499             256.0    5       43         22     1.0   3500.0          6

         Price
0     0.594341
1     0.520853
2     0.685658
3     0.659710
4     0.368775
…          …
1495  0.221961
1496  0.902845
1497  0.396989
1498  0.142859
1499  0.275045

[1500 rows x 14 columns]
```

[328]:
```
df_no_outliers2.shape
```

[328]:
```
(1500, 14)
```

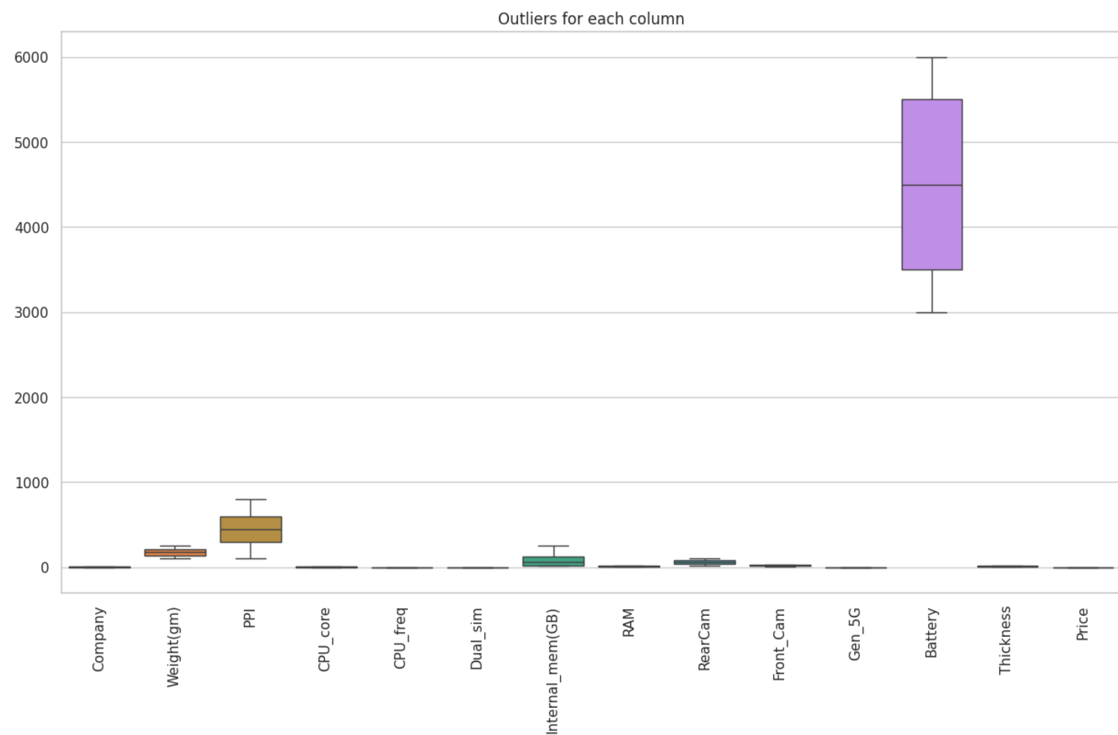
[329]:
```
df_no_outliers2['Company'].value_counts()
```

[329]:
```
2     144
0     128
4     120
9     116
10    116
11    115
12    113
1     110
```

```
8      109
6      108
3      108
5      107
7      106
Name: Company, dtype: int64
```

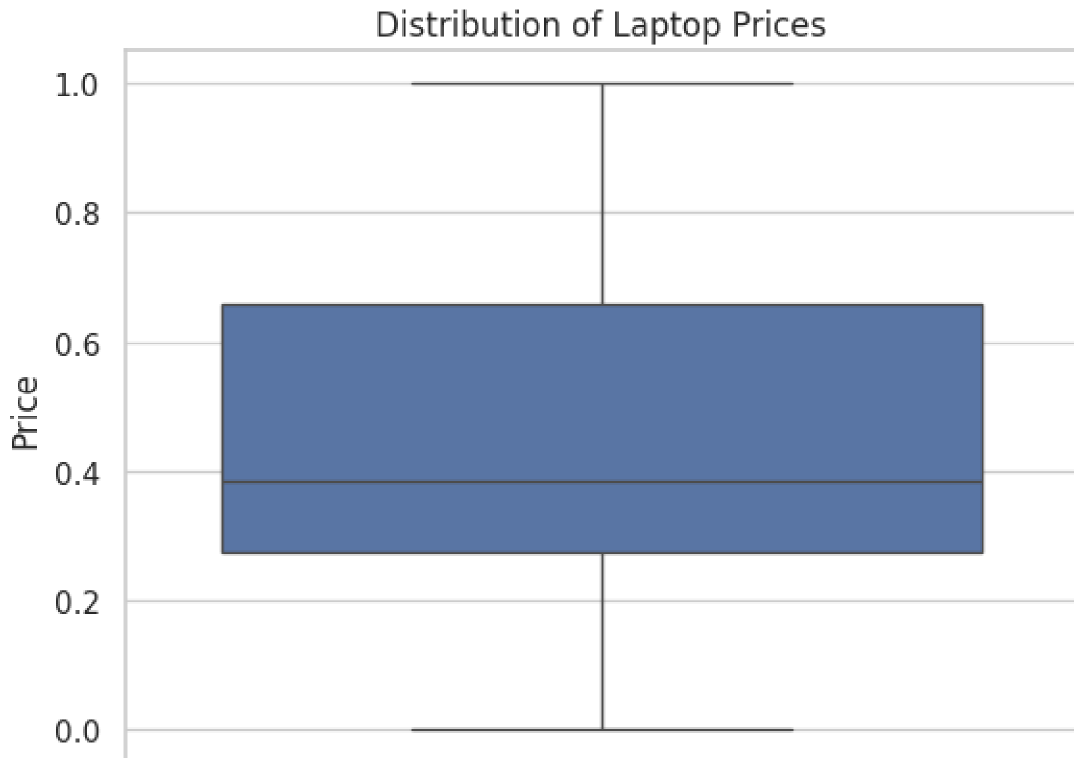
[330]:

```python
plt.figure(figsize=(15, 8))
sns.boxplot(data=df_no_outliers2)
plt.title('Outliers for each column')
plt.xticks(rotation='vertical')
plt.show()
```

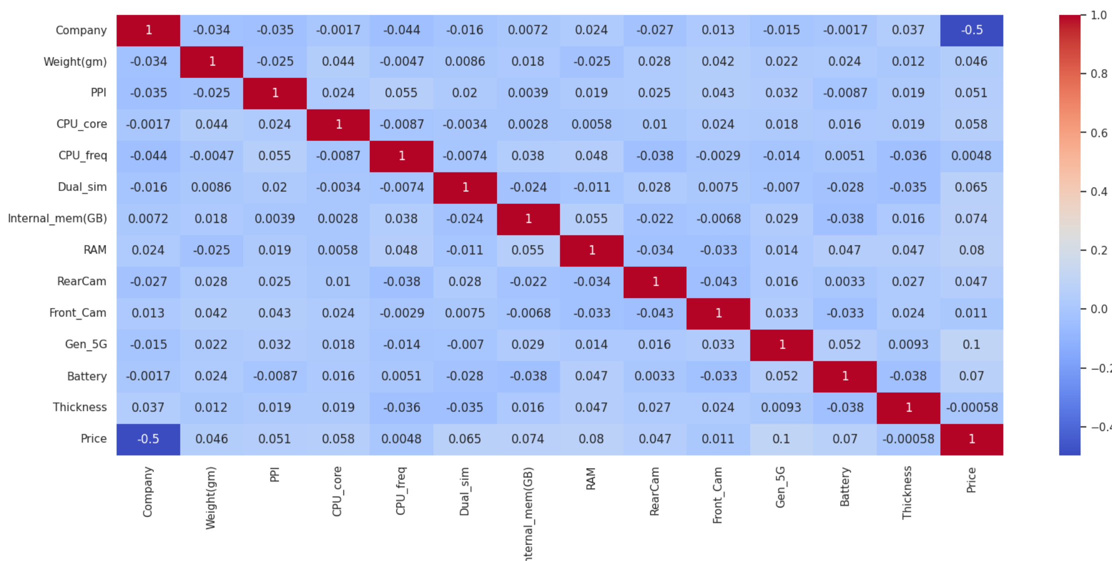



[331]:

```python
sns.boxplot(data=df_no_outliers2, y='Price')
plt.title('Distribution of Laptop Prices')
plt.show()
```

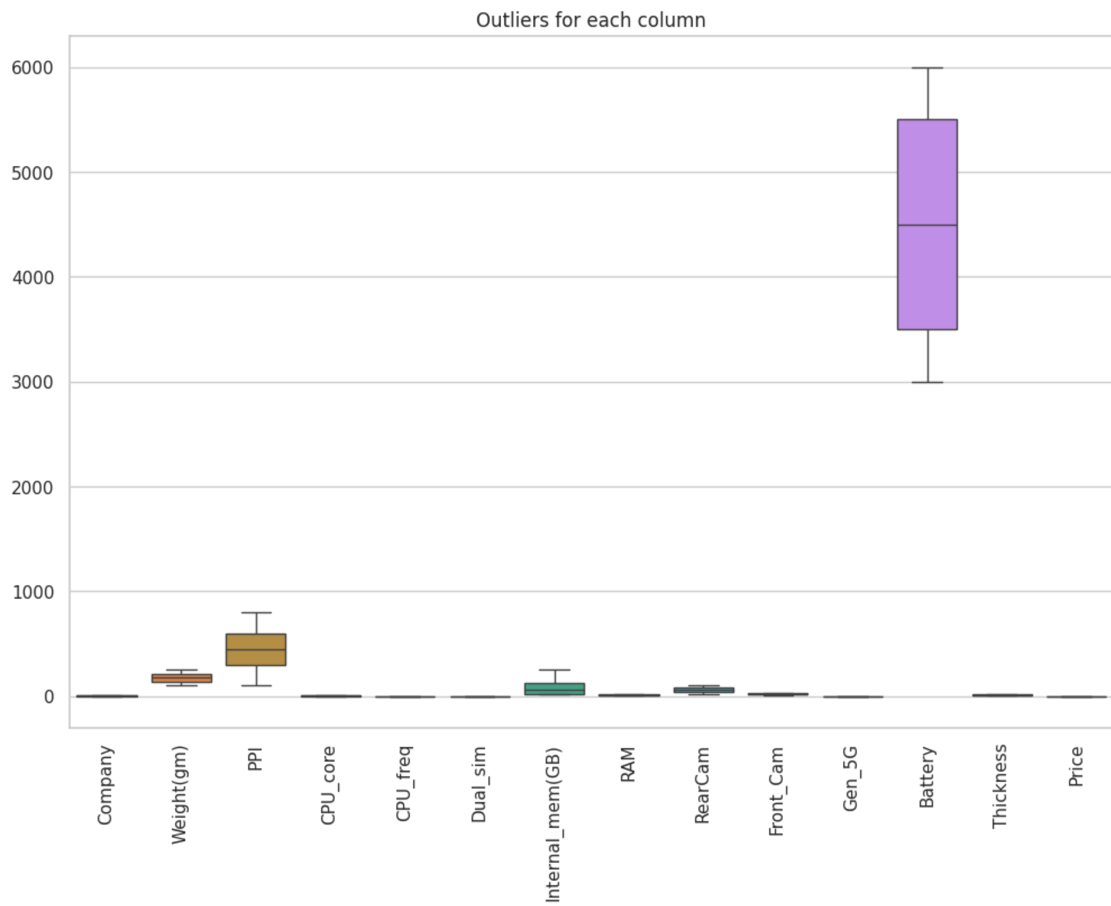



[332]:
```python
plt.figure(figsize=(20, 8))
correlation_matrix = df_no_outliers2.corr()
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
plt.show()
```

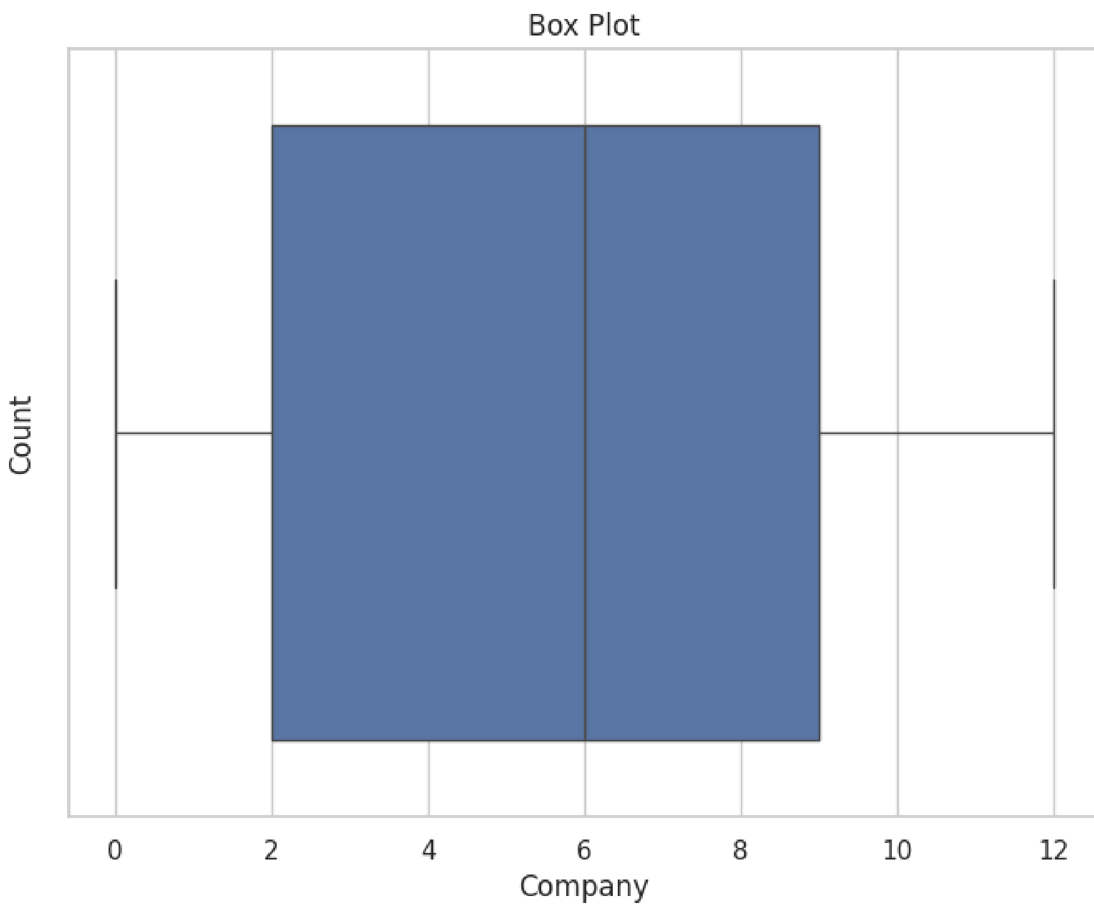


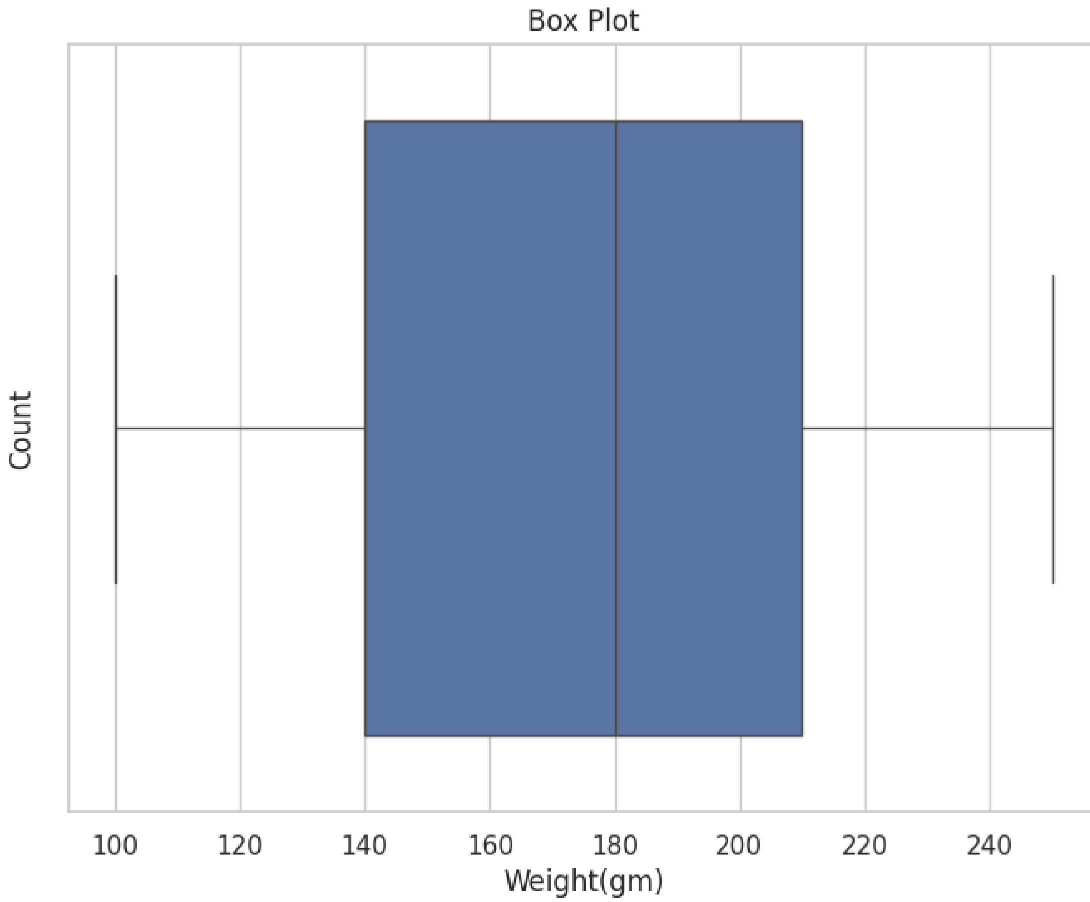
[333]:
```
df_1 = df_merged.copy()
```

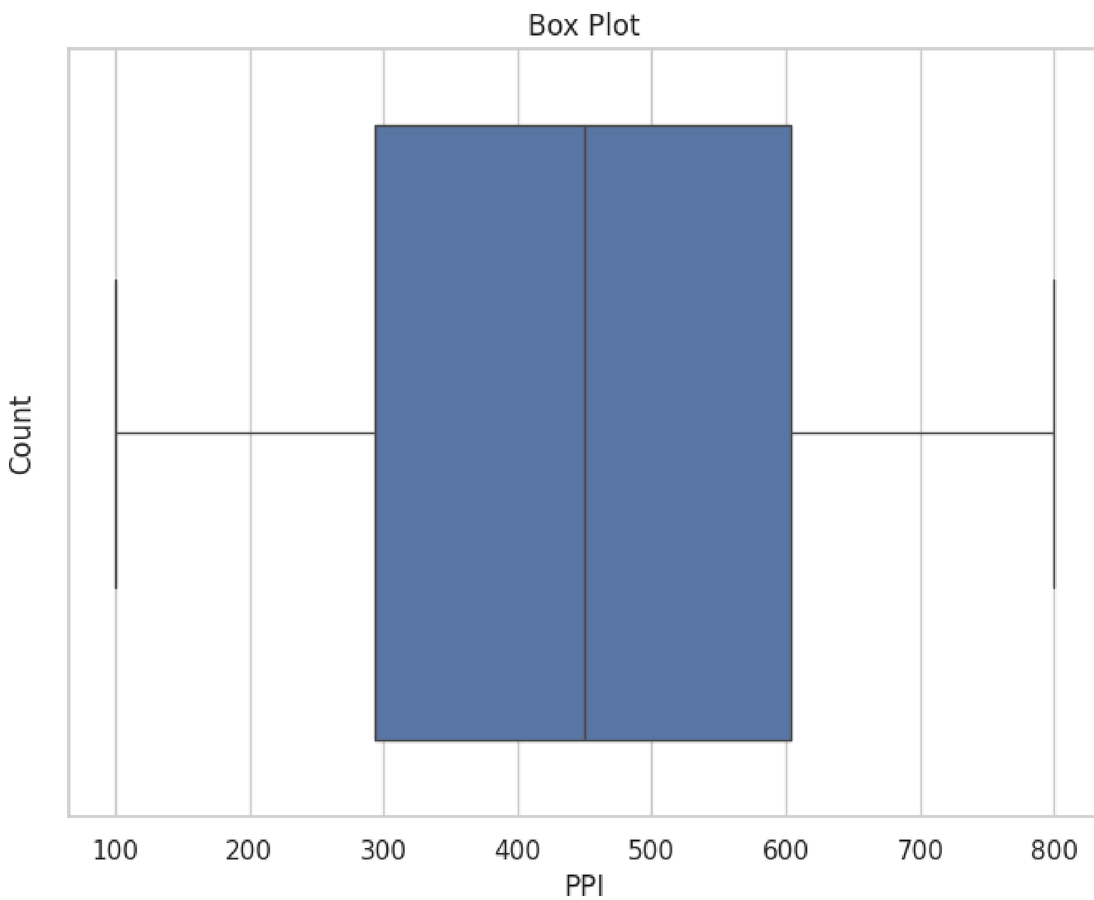
[334]:
```
plt.figure(figsize=(12, 8))
plt.xticks(rotation='vertical')
sns.boxplot(data=df_no_outliers2)
plt.title('Outliers for each column')
plt.show()
```



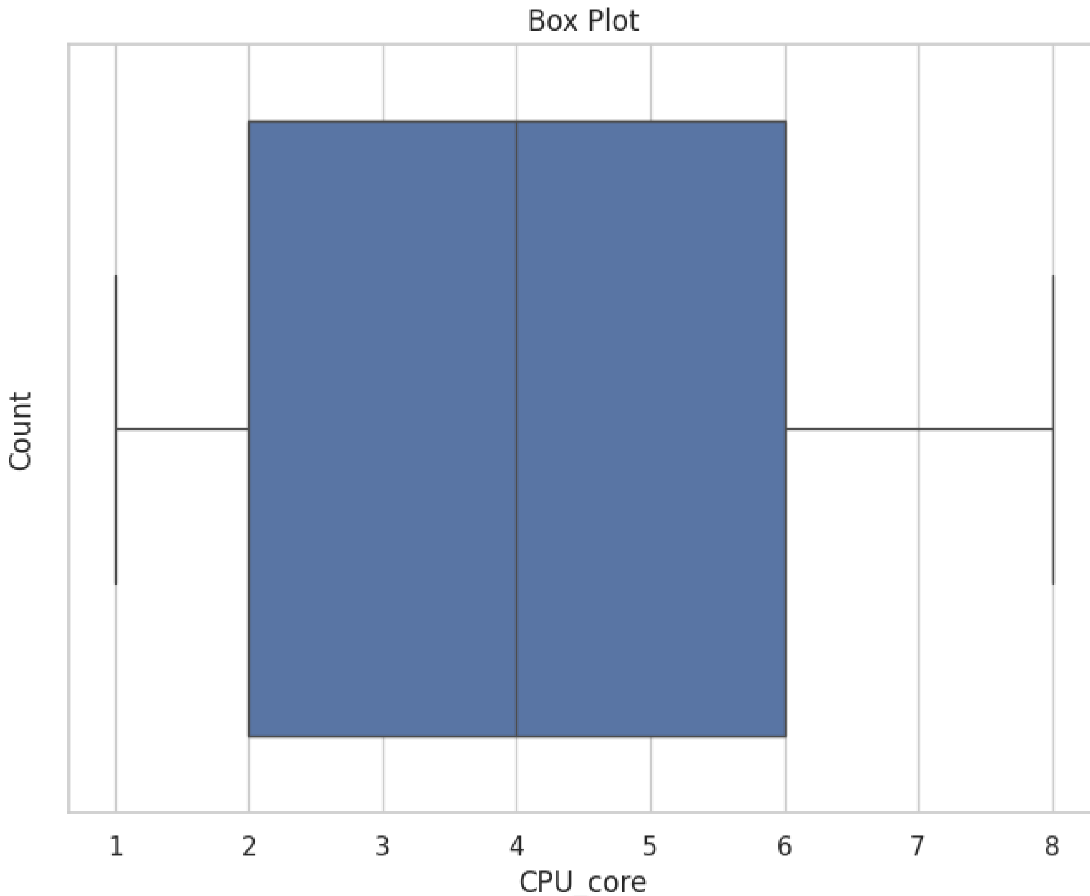

[335]:
```
for column in df_no_outliers2.columns:
  plt.figure(figsize=(8, 6))
  sns.boxplot(x=column, data=df_no_outliers2)
  plt.xlabel(column)
  plt.ylabel('Count')
  plt.title('Box Plot')
  plt.show()
```

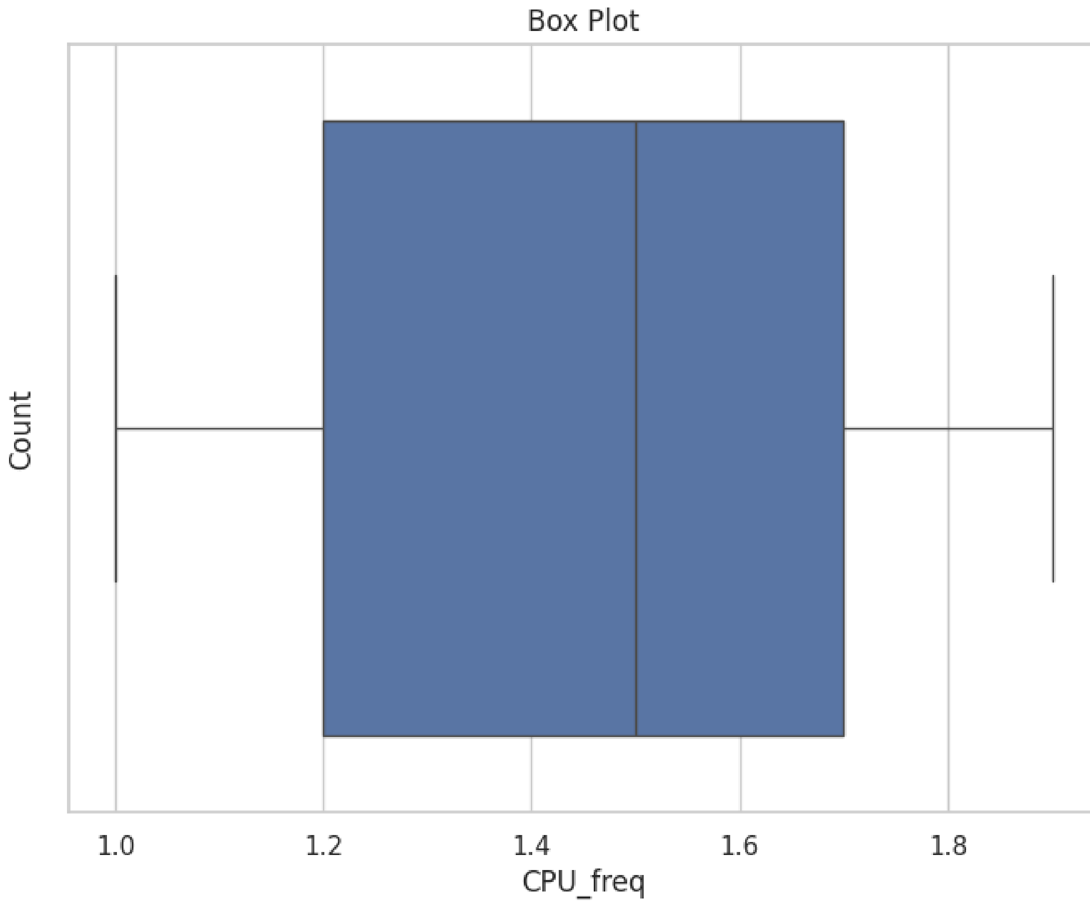

Box Plot
Count
0
2
4
6
8
10
12
Company

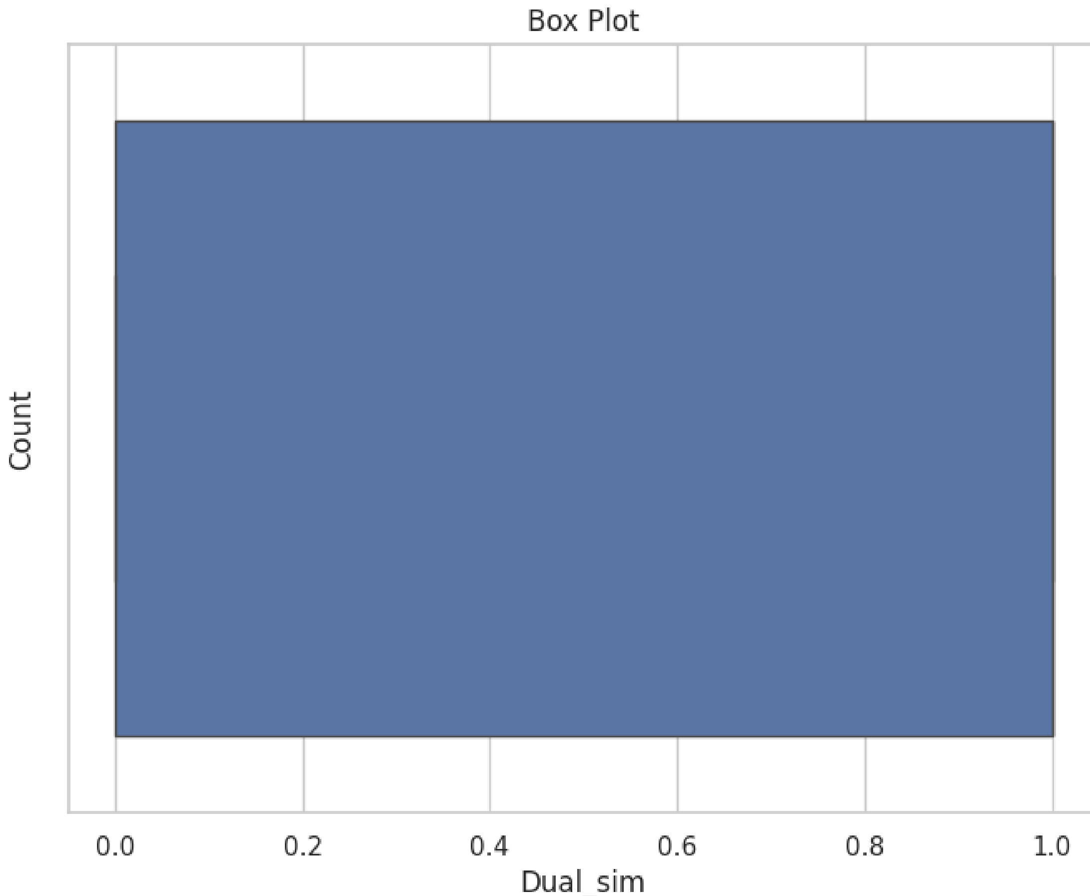

Box Plot
Count
100
120
140
160
180
200
220
240
Weight(gm)

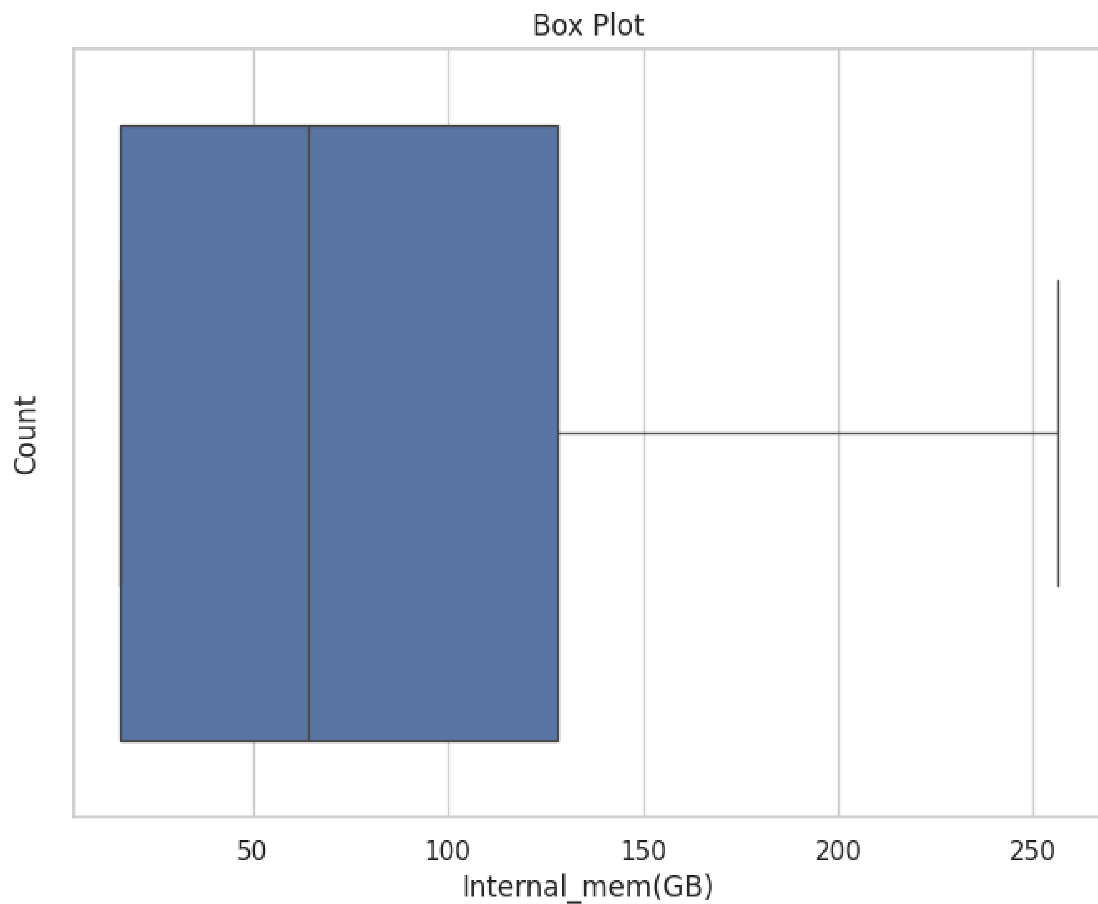


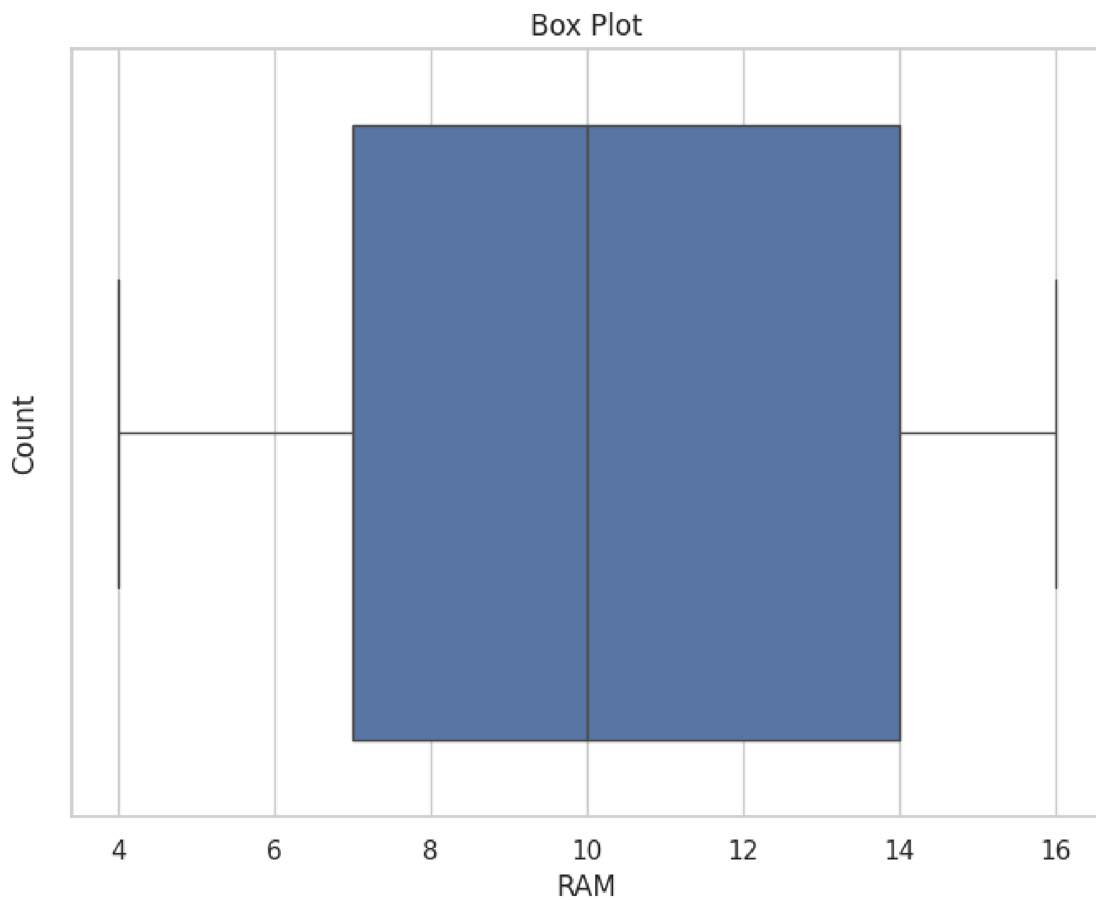
Box Plot
Count
100
200
300
400
500
600
700
800
PPI

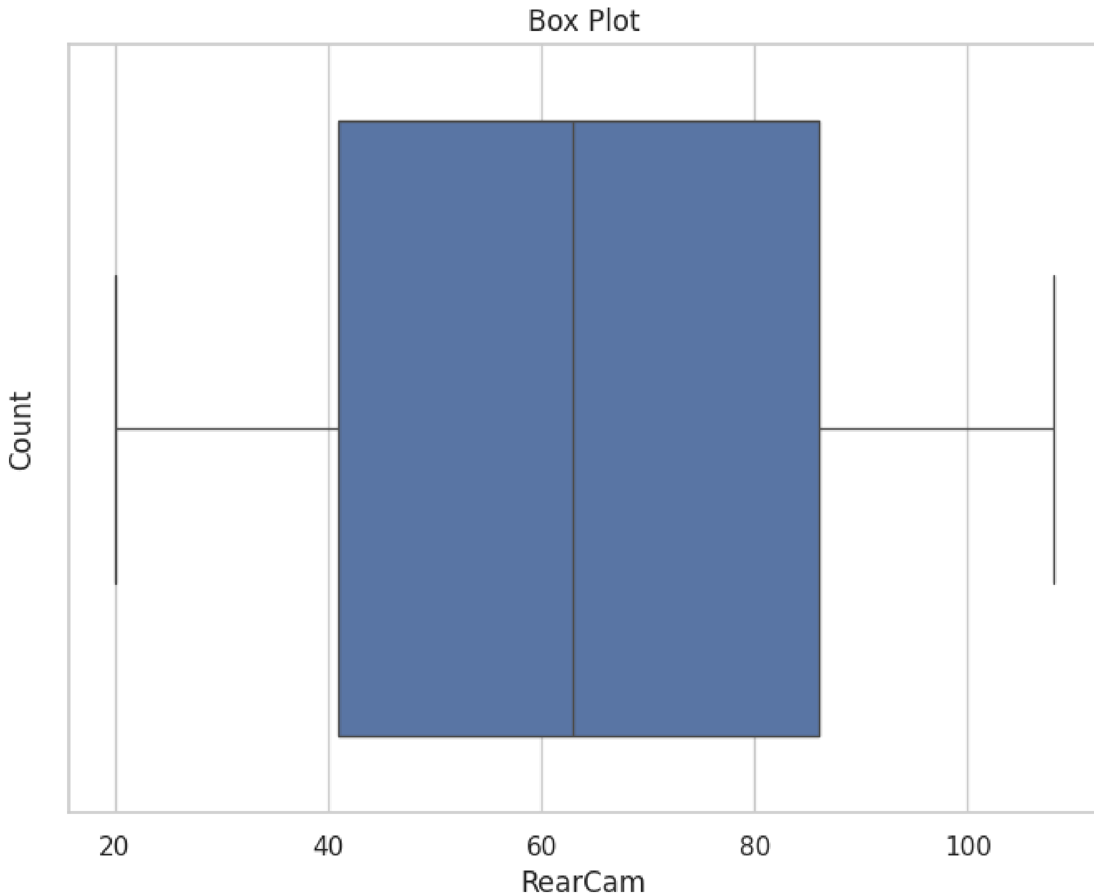

Box Plot
Count
1
2
3
4
5
6
7
8
CPU_core


Box Plot
Count
1.0
1.2
1.4
1.6
1.8
CPU_freq

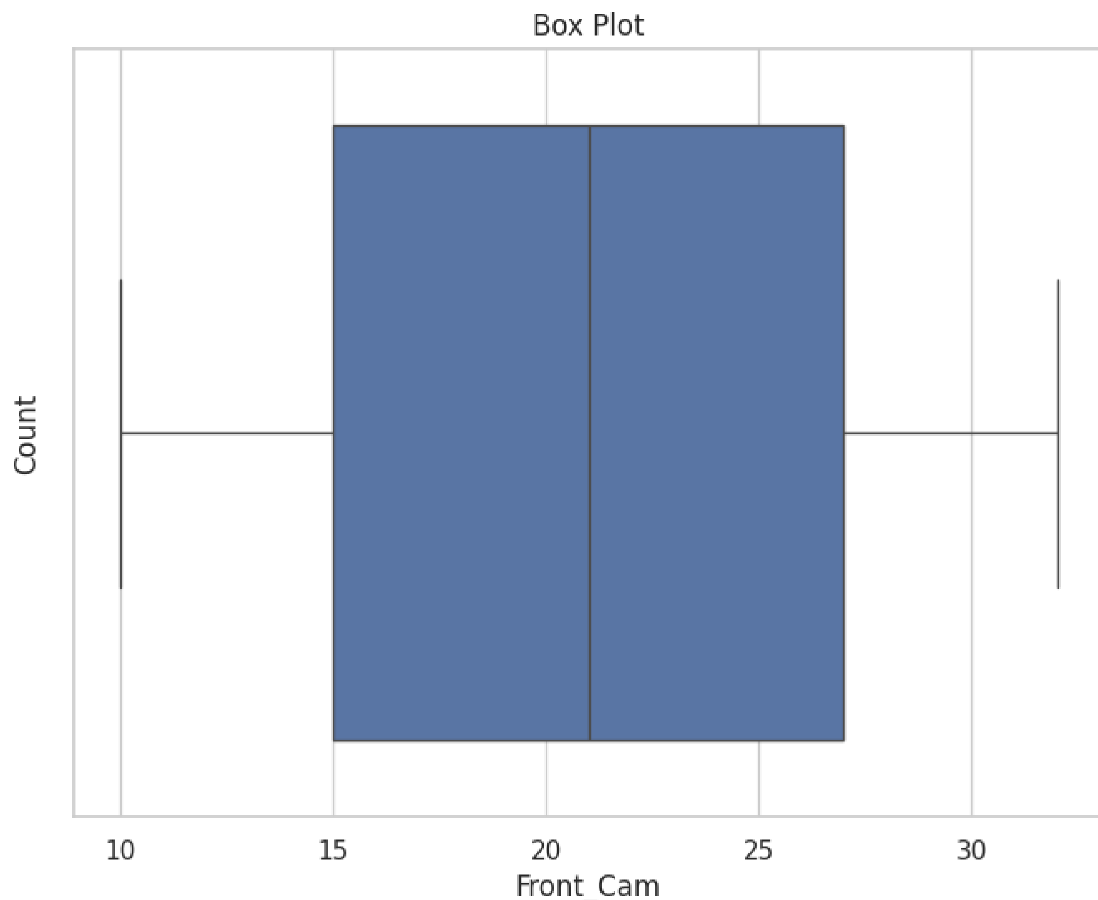

Box Plot
Count
0.0
0.2
0.4
0.6
0.8
1.0
Dual_sim

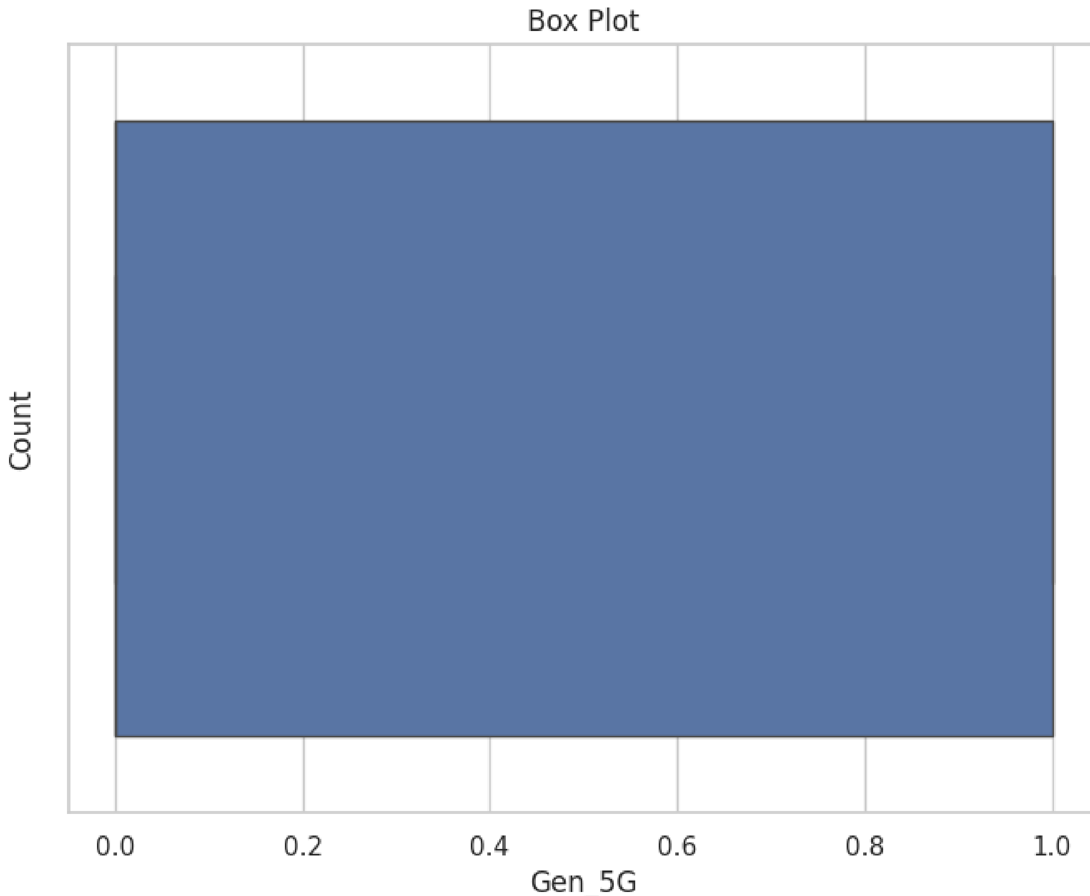

Box Plot
Count
50
100
150
200
250
Internal_mem(GB)

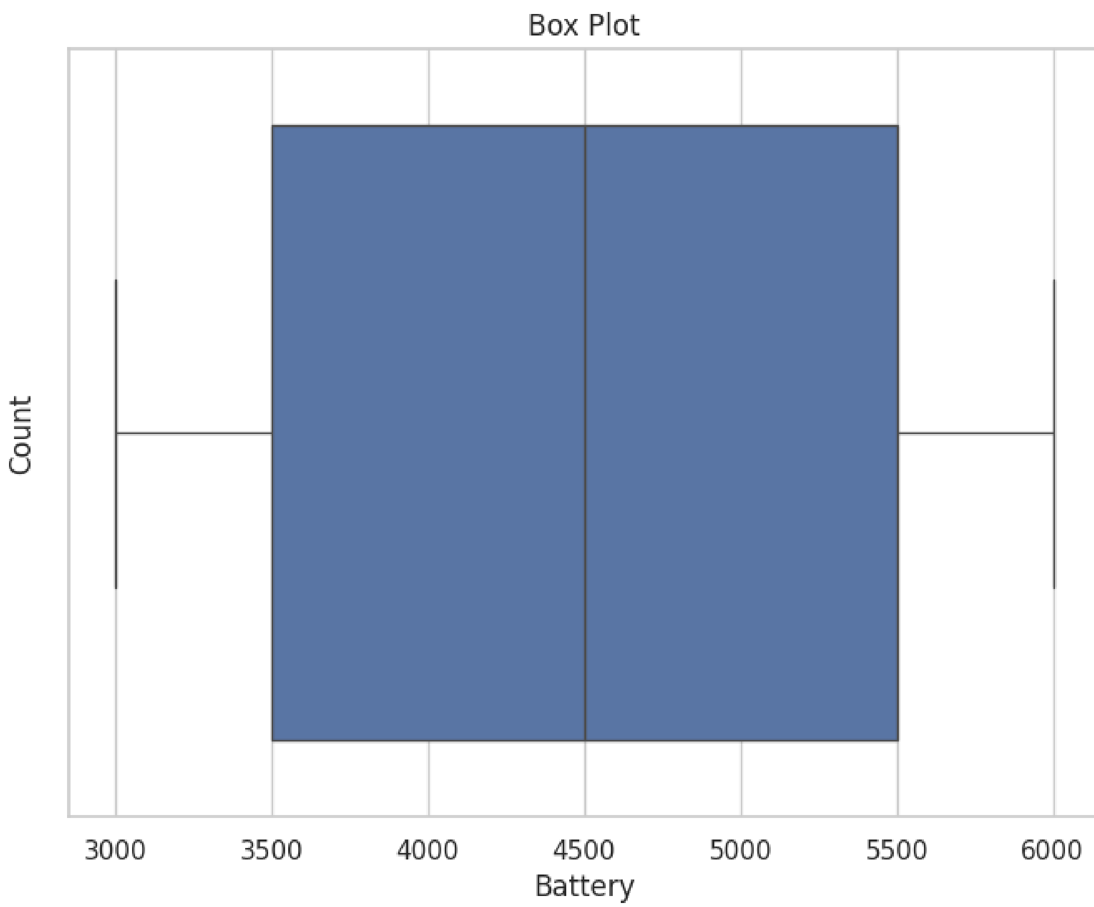

Box Plot
Count
4
6
8
10
12
14
16
RAM

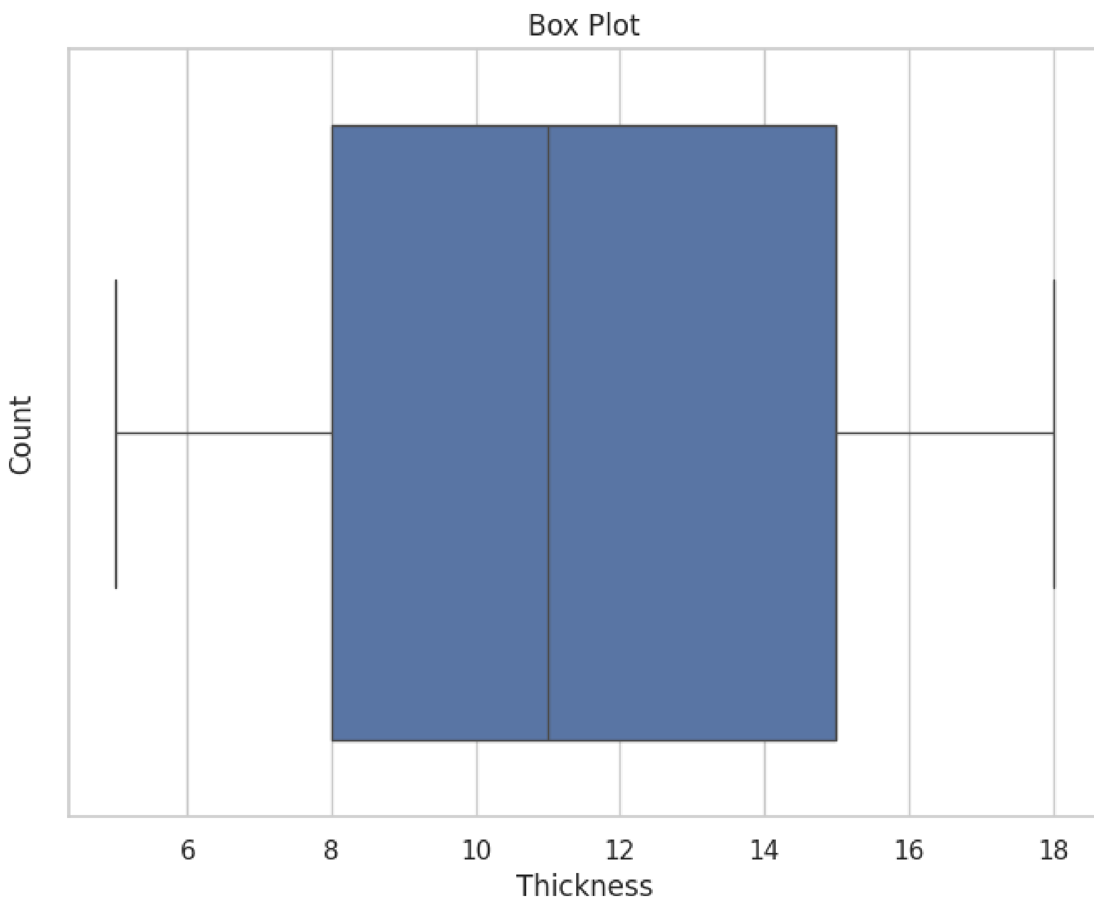


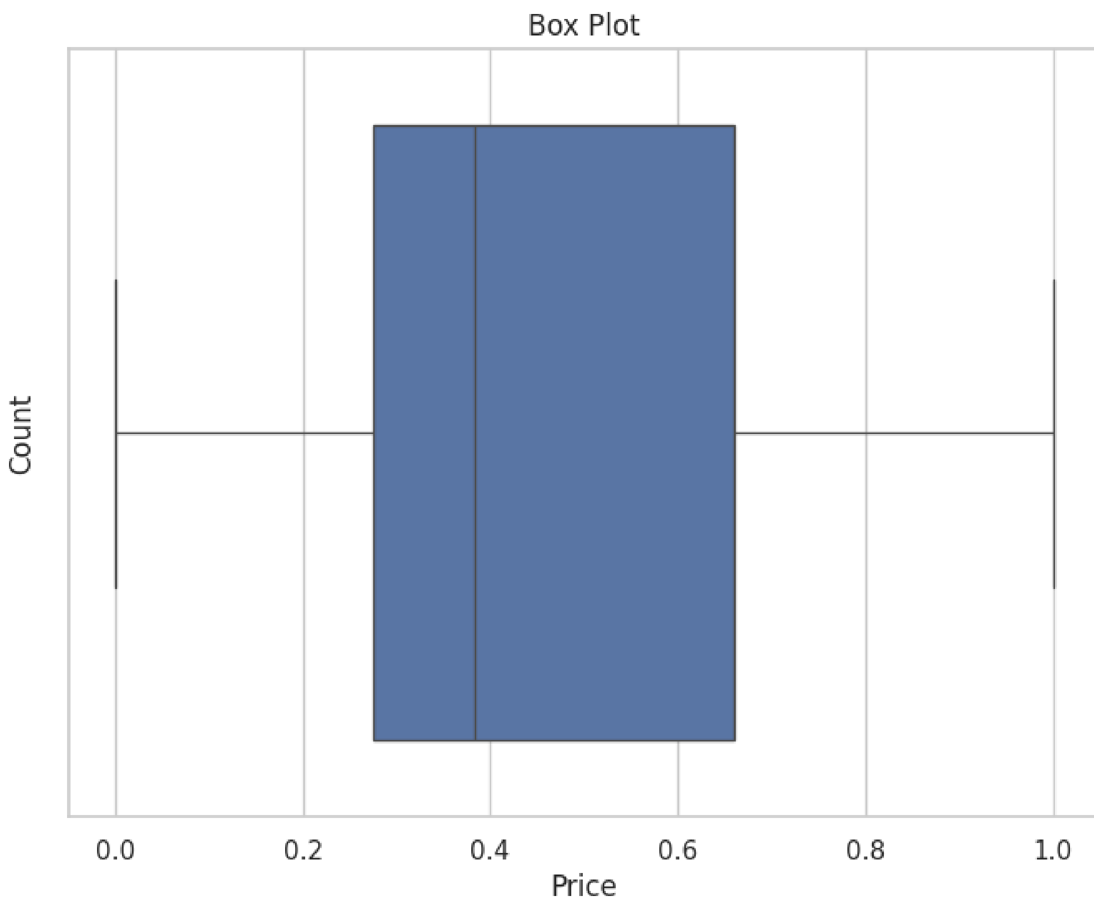
Box Plot
Count
20
40
60
80
100
RearCam


Box Plot
Count
10
15
20
25
30
Front_Cam


Box Plot
Count
0.0
0.2
0.4
0.6
0.8
1.0
Gen_5G


Box Plot
Count
3000
3500
4000
4500
5000
5500
6000
Battery


Box Plot
Count
6
8
10
12
14
16
18
Thickness




[336]:
```
df_no_outliers2.head(n=3)
```

[336]:
```
   Company  Weight(gm)  PPI  CPU_core  CPU_freq  Dual_sim  Internal_mem(GB)  \
0        9       180.0  312         1       1.5         0              16.0
1        2       160.0  362         1       1.6         0              64.0
2        1       160.0  241         1       1.0         0              16.0

   RAM  RearCam  Front_Cam  Gen_5G  Battery  Thickness     Price
0    8       77         31     1.0   5000.0         17  0.594341
1    8       51         13     0.0   3000.0         12  0.520853
2   11       84         23     0.0   5000.0         11  0.685658
```

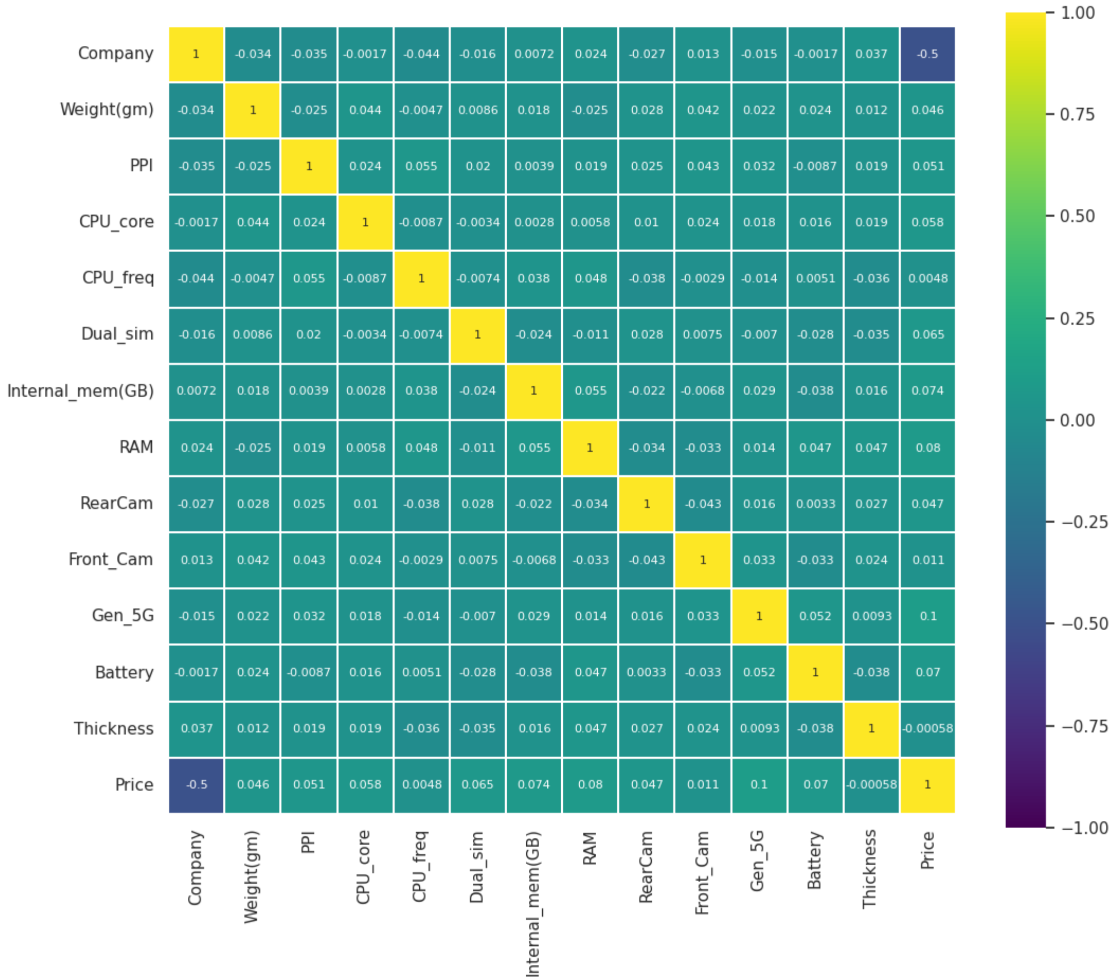
[372]:
```
column_types = df_no_outliers2.dtypes
print(column_types)
```

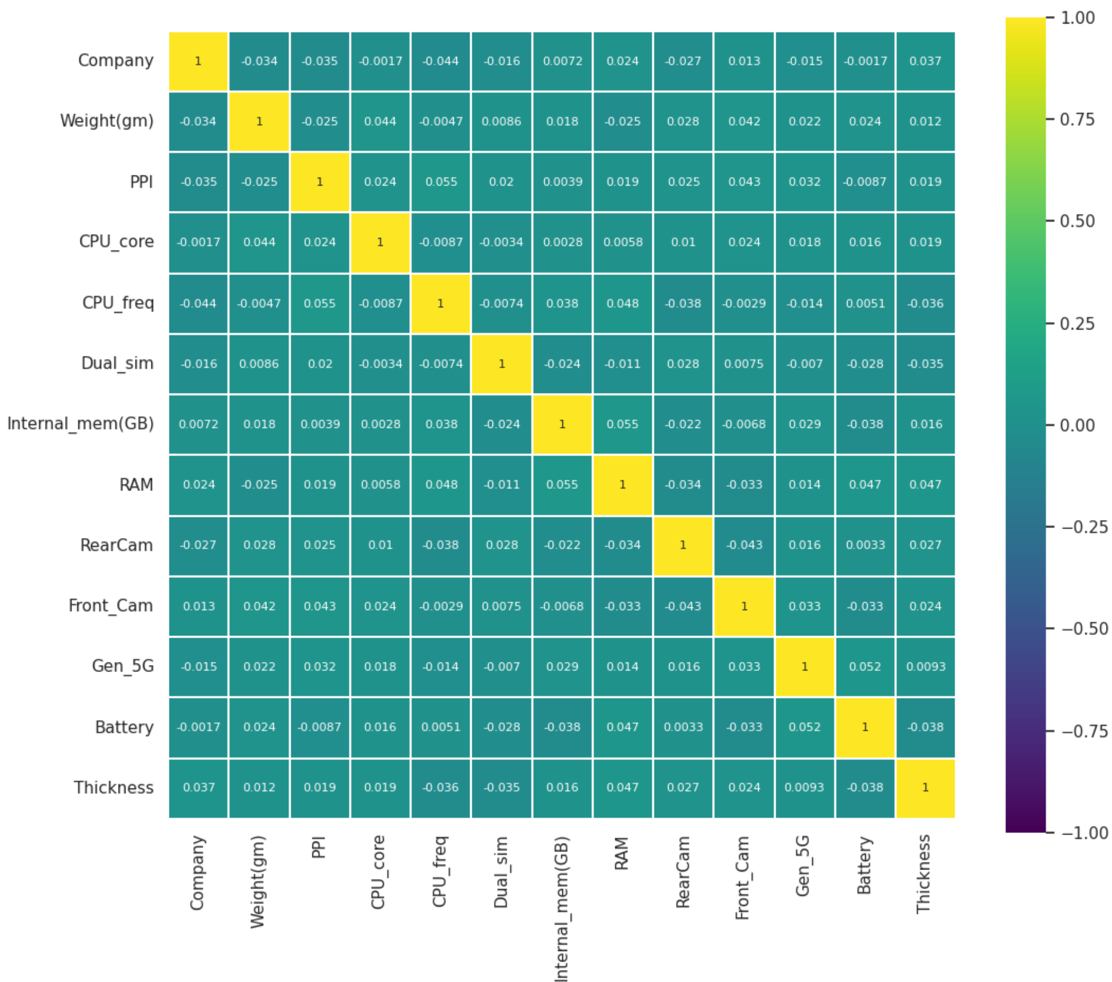
```
Company             category
Weight(gm)          category
PPI                 category
CPU_core            category
```

```
CPU_freq            category
Dual_sim            category
Internal_mem(GB)    category
RAM                 category
RearCam             category
Front_Cam           category
Gen_5G              category
Battery             category
Thickness           category
Price               category
dtype: object
```

[337]:

```python
corr = df_no_outliers2.corr()
plt.figure(figsize=(12, 10))

sns.heatmap(corr[(corr <= 0.5) | (corr >= -0.4)],cmap='viridis', vmax=1.0,␣
 ↪vmin=-1.0, linewidths=0.1,
            annot=True, annot_kws={"size": 8}, square=True);
corr = df_no_outliers2.drop('Price', axis=1).corr()
plt.figure(figsize=(12, 10))

sns.heatmap(corr[(corr <= 0.5) | (corr >= -0.4)],
            cmap='viridis', vmax=1.0, vmin=-1.0, linewidths=0.1,
            annot=True, annot_kws={"size": 8}, square=True);
```


Company
Weight(gm)
PPI
CPU_core
CPU_freq
Dual_sim
Internal_mem(GB)
RAM
RearCam
Front_Cam
Gen_5G
Battery
Thickness
Price
1 -0.034 -0.035 -0.0017 -0.044 -0.016 0.0072 0.024 -0.027 0.013 -0.015 -0.0017 0.037 -0.5
-0.034 1 -0.025 0.044 -0.0047 0.0086 0.018 -0.025 0.028 0.042 0.022 0.024 0.012 0.046
-0.035 -0.025 1 0.024 0.055 0.02 0.0039 0.019 0.025 0.043 0.032 -0.0087 0.019 0.051
-0.0017 0.044 0.024 1 -0.0087 -0.0034 0.0028 0.0058 0.01 0.024 0.018 0.016 0.019 0.058
-0.044 -0.0047 0.055 -0.0087 1 -0.0074 0.038 0.048 -0.038 -0.0029 -0.014 0.0051 -0.036 0.0048
-0.016 0.0086 0.02 -0.0034 -0.0074 1 -0.024 -0.011 0.028 0.0075 -0.007 -0.028 -0.035 0.065
0.0072 0.018 0.0039 0.0028 0.038 -0.024 1 0.055 -0.022 -0.0068 0.029 -0.038 0.016 0.074
0.024 -0.025 0.019 0.0058 0.048 -0.011 0.055 1 -0.034 -0.033 0.014 0.047 0.047 0.08
-0.027 0.028 0.025 0.01 -0.038 0.028 -0.022 -0.034 1 -0.043 0.016 0.0033 0.027 0.047
0.013 0.042 0.043 0.024 -0.0029 0.0075 -0.0068 -0.033 -0.043 1 0.033 -0.033 0.024 0.011
-0.015 0.022 0.032 0.018 -0.014 -0.007 0.029 0.014 0.016 0.033 1 0.052 0.0093 0.1
-0.0017 0.024 -0.0087 0.016 0.0051 -0.028 -0.038 0.047 0.0033 -0.033 0.052 1 -0.038 0.07
0.037 0.012 0.019 0.019 -0.036 -0.035 0.016 0.047 0.027 0.024 0.0093 -0.038 1 -0.00058
-0.5 0.046 0.051 0.058 0.0048 0.065 0.074 0.08 0.047 0.011 0.1 0.07 -0.00058 1
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00




# 26 EDA

[338]:
```
# sns.pairplot(df_no_outliers2,hue="Price")
```

[376]:
```
df_no_outliers2['Company'] = df_no_outliers2['Company'].astype('int')

numeric_columns = ['Weight(gm)', 'PPI', 'CPU_core', 'CPU_freq', 
 ↪'Internal_mem(GB)', 'RAM', 'Dual_sim','RearCam', 'Front_Cam', 'Gen_5G', 
 ↪'Battery', 'Thickness', 'Price']
df_no_outliers2[numeric_columns] = df_no_outliers2[numeric_columns].
 ↪astype('float')

column_types = df_no_outliers2.dtypes
print(column_types)
```

```
Company                    int64
```

```
Weight(gm)          float64
PPI                 float64
CPU_core            float64
CPU_freq            float64
Dual_sim            float64
Internal_mem(GB)    float64
RAM                 float64
RearCam             float64
Front_Cam           float64
Gen_5G              float64
Battery             float64
Thickness           float64
Price               float64
dtype: object
```

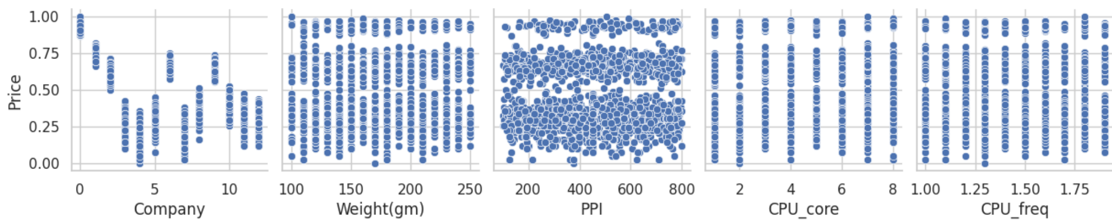
# 27 How mobile Prices are distribution across Companies

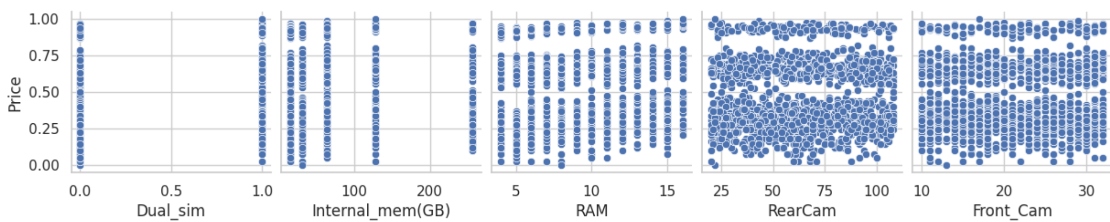
[380]:
```
df_no_outliers2.hist(figsize=(16, 20), bins=50, xlabelsize=6, ylabelsize=6);
```

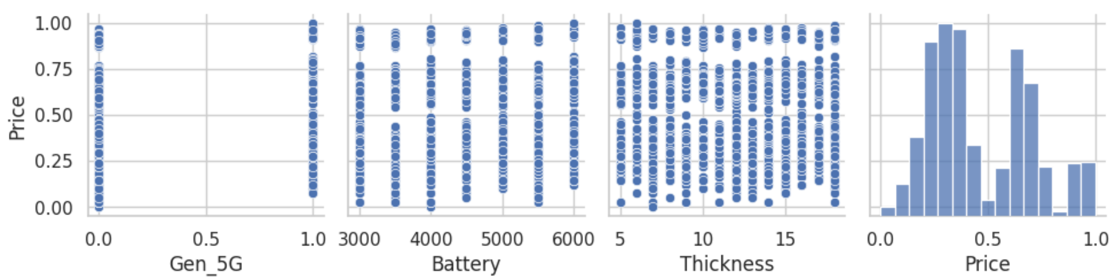

Company
Weight(gm)
PPI
CPU_core
CPU_freq
Dual_sim
Internal_mem(GB)
RAM
RearCam
Front_Cam
Gen_5G
Battery
Thickness
Price

## 28 Pair Plots

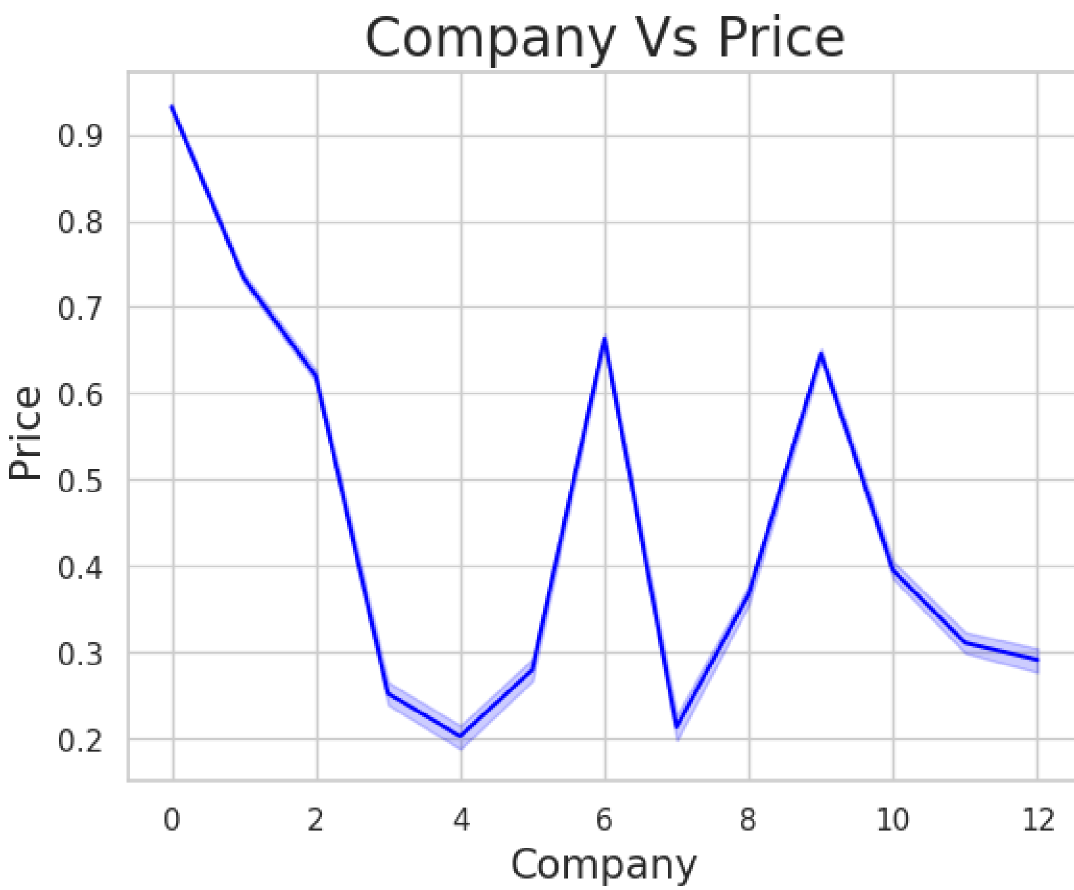
[381]:
```python
for i in range(0, len(df_no_outliers2.columns), 5):
    sns.pairplot(data=df_no_outliers2,
                 x_vars=df_no_outliers2.columns[i:i+5],
                 y_vars=['Price'])
```



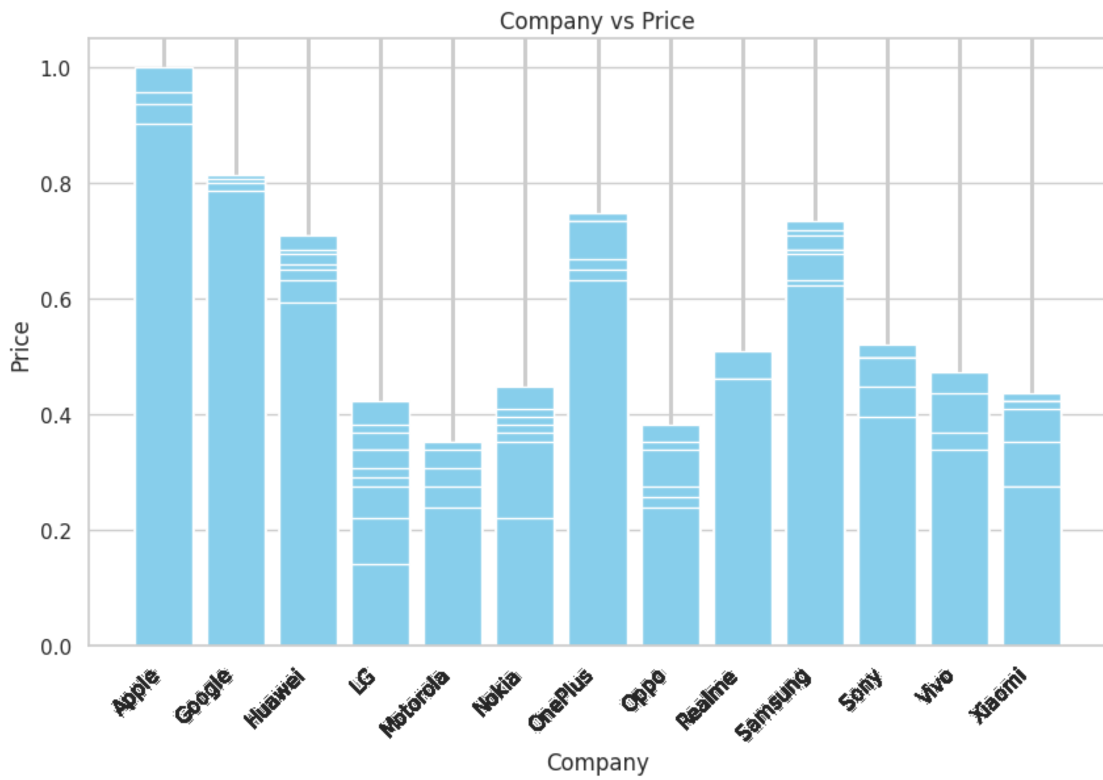




[340]:
```python
sns.lineplot(data=df_no_outliers2,x='Company',y='Price',color='blue')
plt.title('Company Vs Price',fontsize=20)
plt.xlabel('Company',fontsize=15)
plt.ylabel('Price',fontsize=15)
plt.show()
```




[341]:
```
import matplotlib.pyplot as plt
company_encoding = {
    0: 'Apple',
    1: 'Google',
    2: 'Huawei',
    3: 'LG',
    4: 'Motorola',
    5: 'Nokia',
    6: 'OnePlus',
    7: 'Oppo',
    8: 'Realme',
    9: 'Samsung',
    10: 'Sony',
    11: 'Vivo',
    12: 'Xiaomi'
}
plt.figure(figsize=(10, 6))
plt.bar(df_no_outliers2['Company'], df_no_outliers2['Price'], color='skyblue')
```

```
plt.title('Company vs Price')
plt.xlabel('Company')
plt.ylabel('Price')
plt.xticks(df_no_outliers2['Company'], [company_encoding[company] for company␣
 ↪in df_no_outliers2['Company']], rotation=45, ha='right')

plt.show()
```

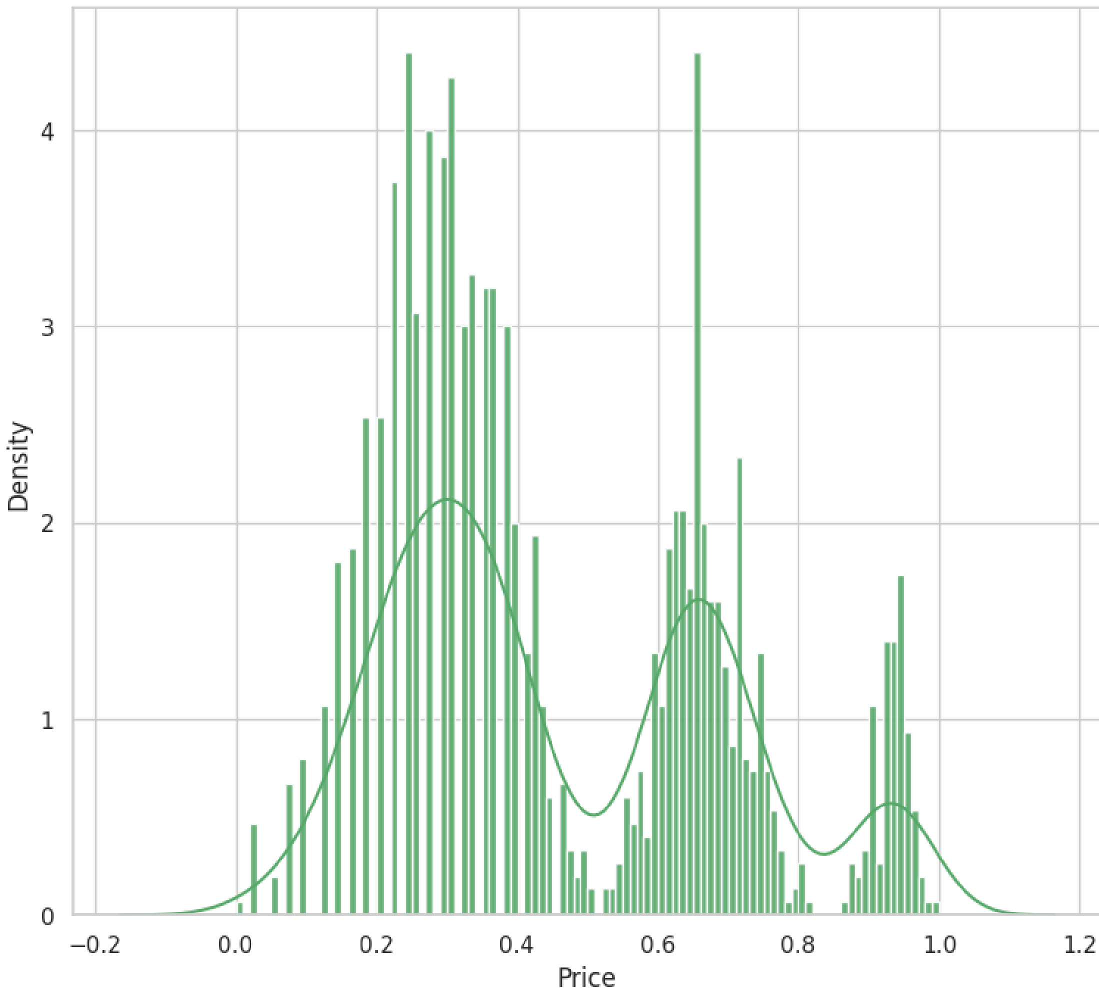



## 29 How the mobile price is distributed

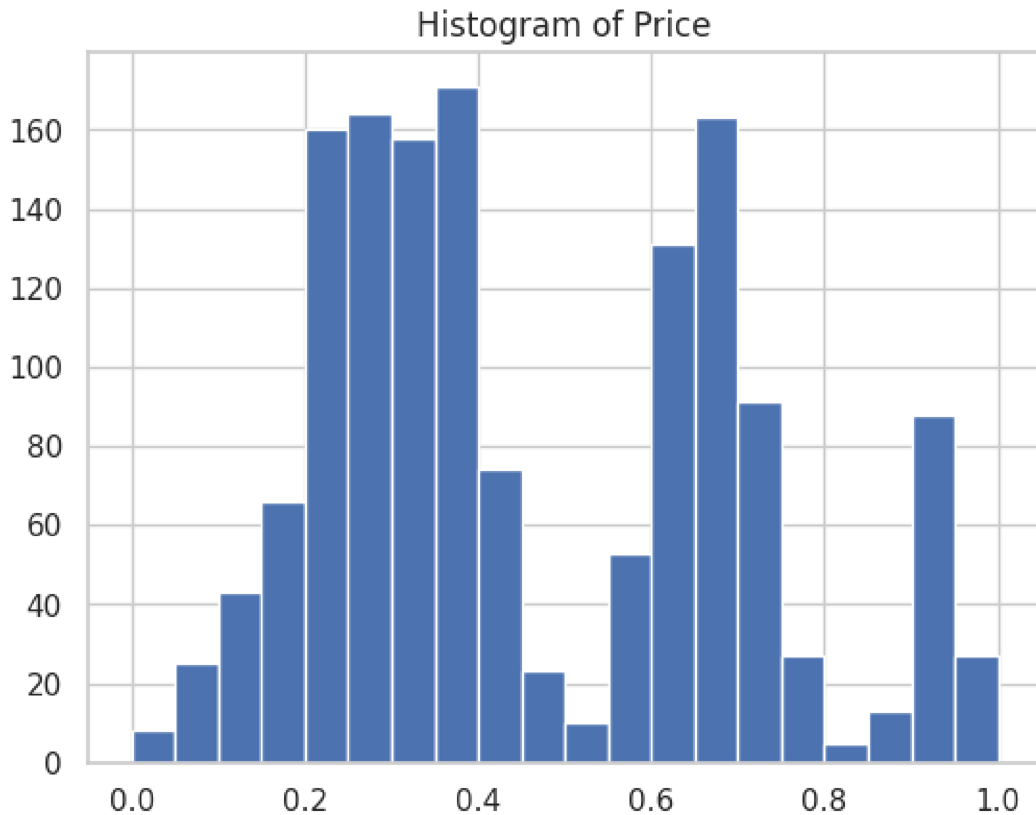
[342]:
```
print(df_no_outliers2['Price'].describe())
plt.figure(figsize=(9, 8))
sns.distplot(df_no_outliers2['Price'], color='g', bins=100, hist_kws={'alpha':␣
 ↪0.9});
```

```
count    1500.000000
mean        0.463338
std         0.236044
min         0.000000
25%         0.275045
50%         0.383050
```

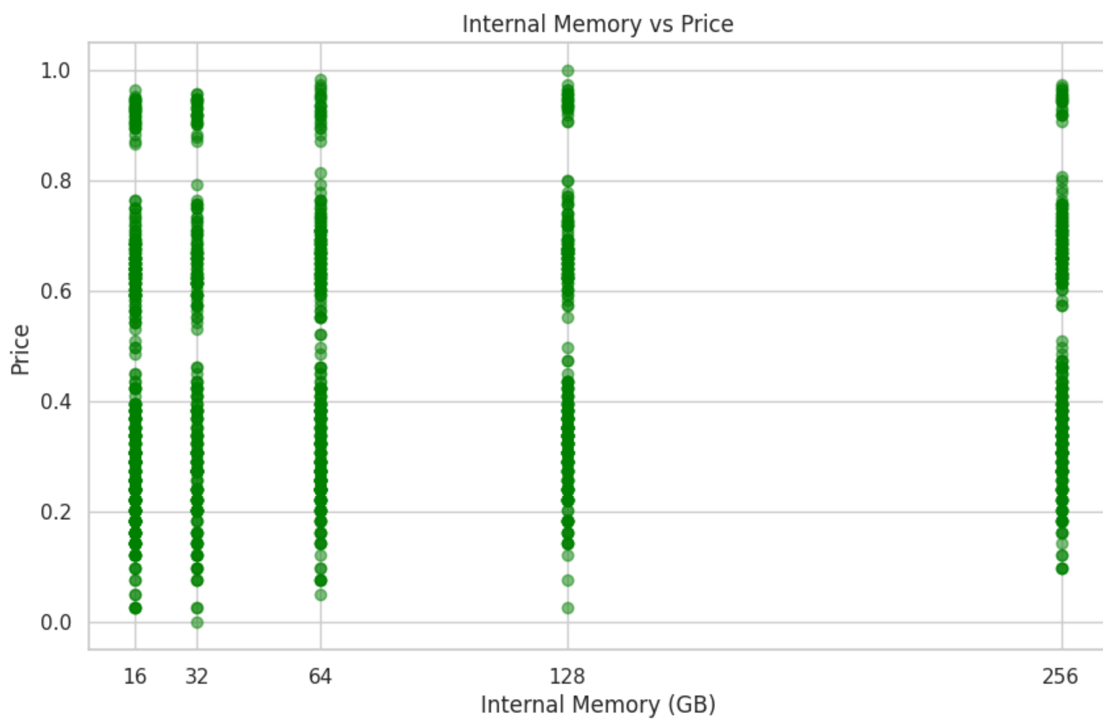
```
75%          0.659710
max          1.000000
Name: Price, dtype: float64
```




[343]:
```
plt.hist(df_no_outliers2['Price'], bins=20)
plt.title('Histogram of Price')
plt.show()
```

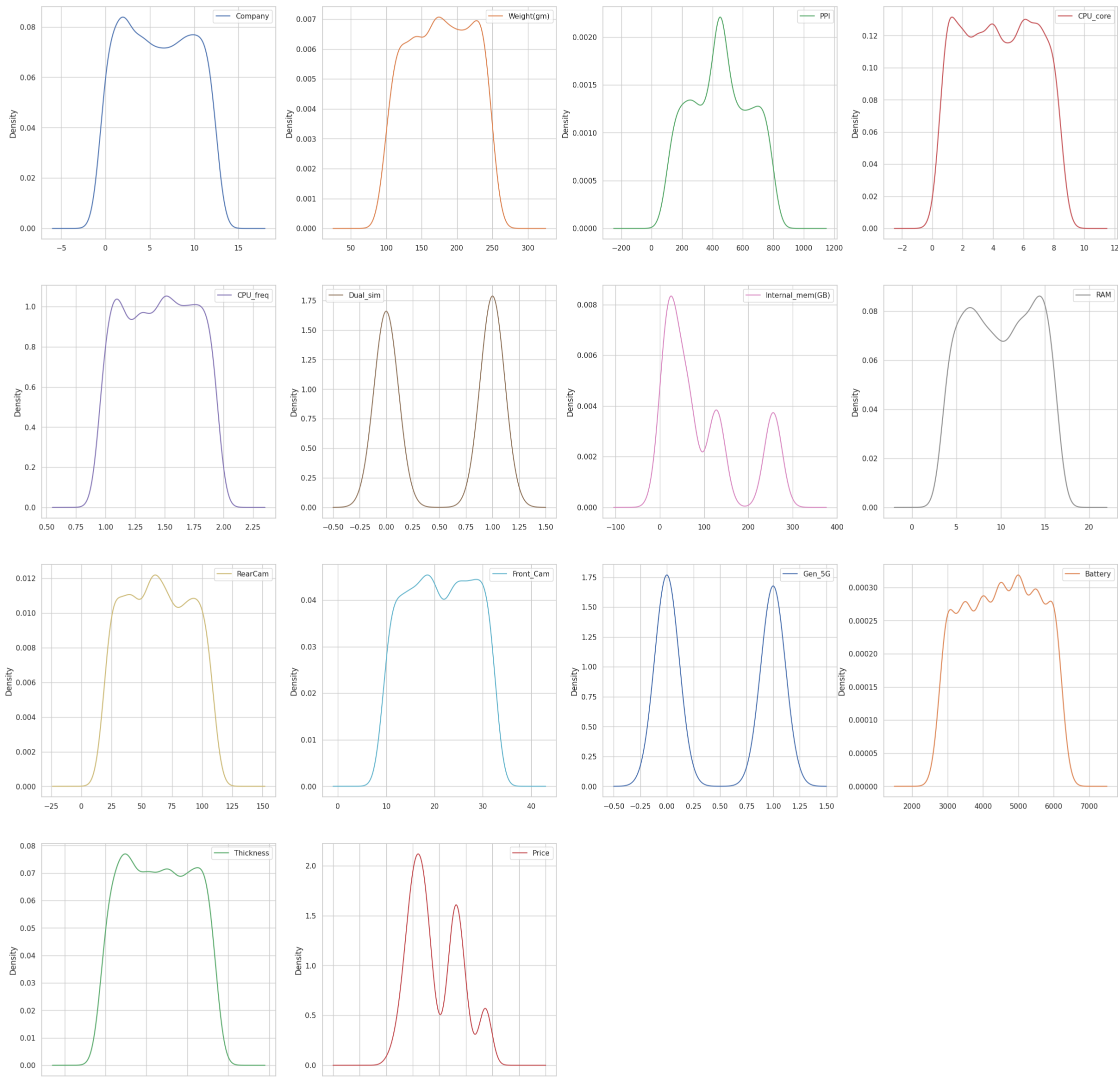



[345]:
```
import matplotlib.pyplot as plt

# Set the figure size
plt.figure(figsize=(10, 6))

# Create a scatter plot
plt.scatter(df_no_outliers2['Internal_mem(GB)'], df_no_outliers2['Price'],␣
 ↪color='green', alpha=0.5)

# Set title and labels
plt.title('Internal Memory vs Price')
plt.xlabel('Internal Memory (GB)')
plt.ylabel('Price')

# Set the x-axis labels based on the internal memory values
plt.xticks(df_no_outliers2['Internal_mem(GB)'].unique())

# Display the plot
plt.show()
```



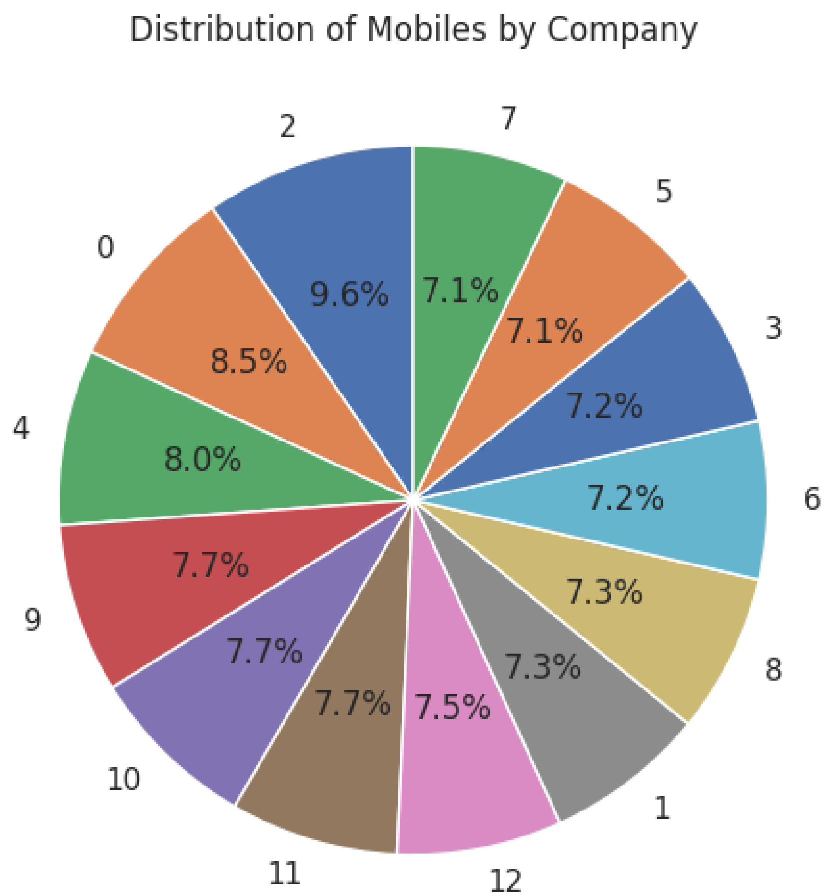

## 30 Ploting the distribution of quantitative features

[346]:
```
import math
quantitative_features = df_no_outliers2.select_dtypes(include=['float64',␣
↪'int64']).columns
num_features = len(quantitative_features)

layout_rows = math.ceil(math.sqrt(num_features))
layout_cols = math.ceil(num_features / layout_rows)

df_no_outliers2[quantitative_features].plot(
    kind='density', subplots=True, layout=(layout_rows, layout_cols),␣
↪sharex=False, figsize=(30, 30)
)
plt.show()
```



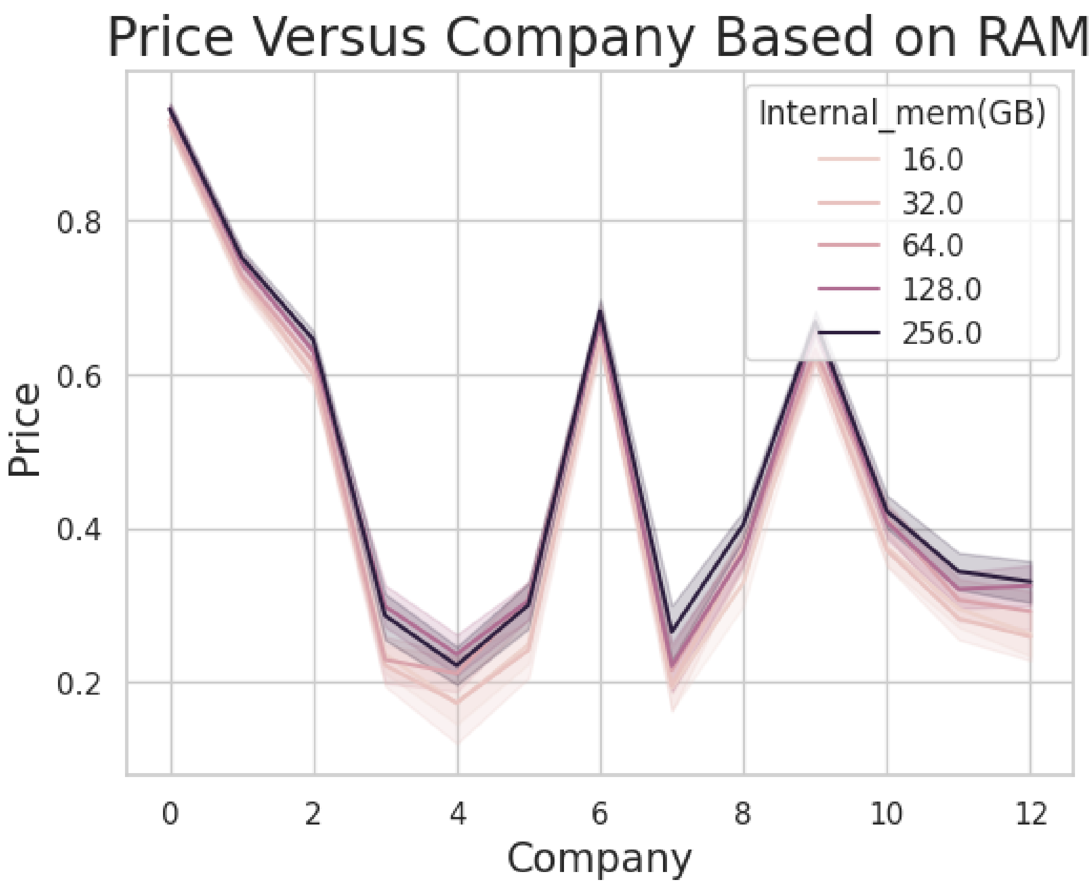

# 31 percentage of mobiles across the companies

[347]:
```
import matplotlib.pyplot as plt
company_counts = df_no_outliers2['Company'].value_counts()
plt.figure(figsize=(10, 6))
plt.pie(company_counts, labels=company_counts.index, autopct='%1.1f%%', startangle=90)
plt.title('Distribution of Mobiles by Company')
plt.show()
```




## 32 comparison of price & companies based on Ram

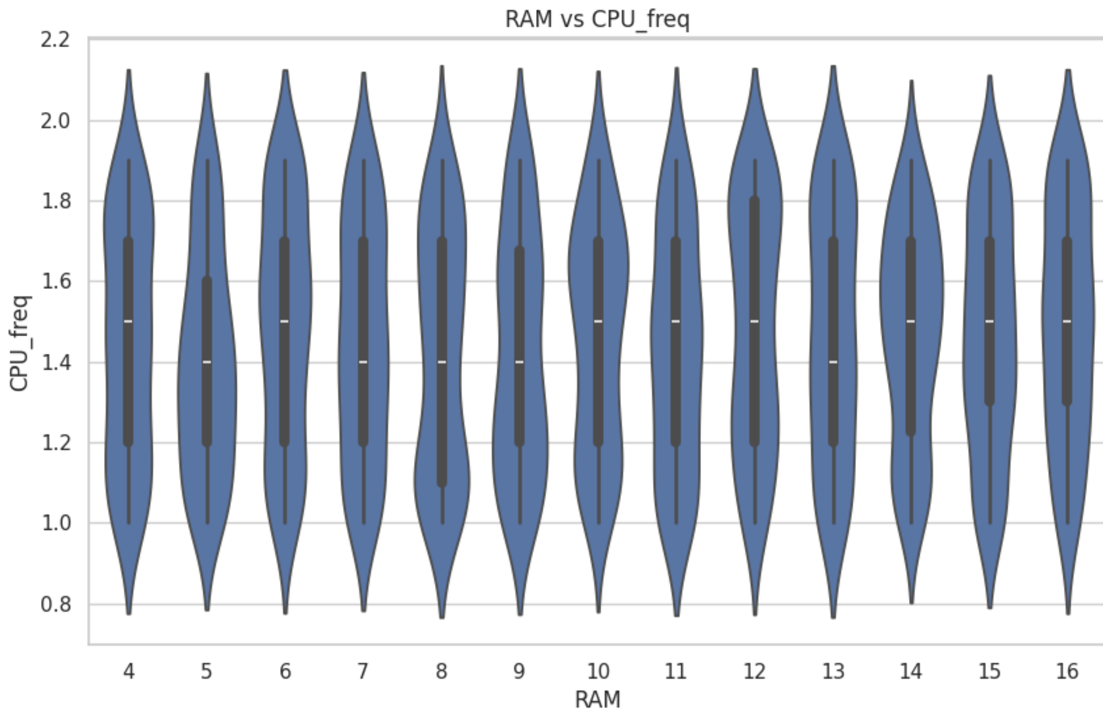
[348]:
```
sns.lineplot(data=df_no_outliers2,x='Company',y='Price',hue='Internal_mem(GB)')
plt.title('Price Versus Company Based on RAM',fontsize=20)
plt.xlabel('Company',fontsize=15)
plt.ylabel('Price',fontsize=15)
plt.show()
```




## 33 Price Comparison by Company and 5G Generation

[349]:
```
sns.barplot(data=df_no_outliers2, x='Company', y='Price', hue='Gen_5G')
plt.title('Price Comparison by Company and 5G Generation')
plt.show()
```


[350]:
```
plt.figure(figsize=(10, 6))
sns.violinplot(x='RAM', y='CPU_freq', data=df_no_outliers2)
plt.xlabel('RAM')
plt.ylabel('CPU_freq')
plt.title('RAM vs CPU_freq')
plt.show()
```




[351]:
```
df_no_outliers2.head()
```

[351]:
```
   Company  Weight(gm)  PPI  CPU_core  CPU_freq  Dual_sim  Internal_mem(GB)  \
0        9       180.0  312         1       1.5         0              16.0
1        2       160.0  362         1       1.6         0              64.0
2        1       160.0  241         1       1.0         0              16.0
3        6       210.0  555         4       1.2         1              32.0
4       11       100.0  607         8       1.8         1             128.0

   RAM  RearCam  Front_Cam  Gen_5G  Battery  Thickness     Price
0    8       77         31     1.0   5000.0         17  0.594341
1    8       51         13     0.0   3000.0         12  0.520853
2   11       84         23     0.0   5000.0         11  0.685658
3    7       91         10     0.0   6000.0          8  0.659710
4   12       71         27     0.0   4500.0         11  0.368775
```

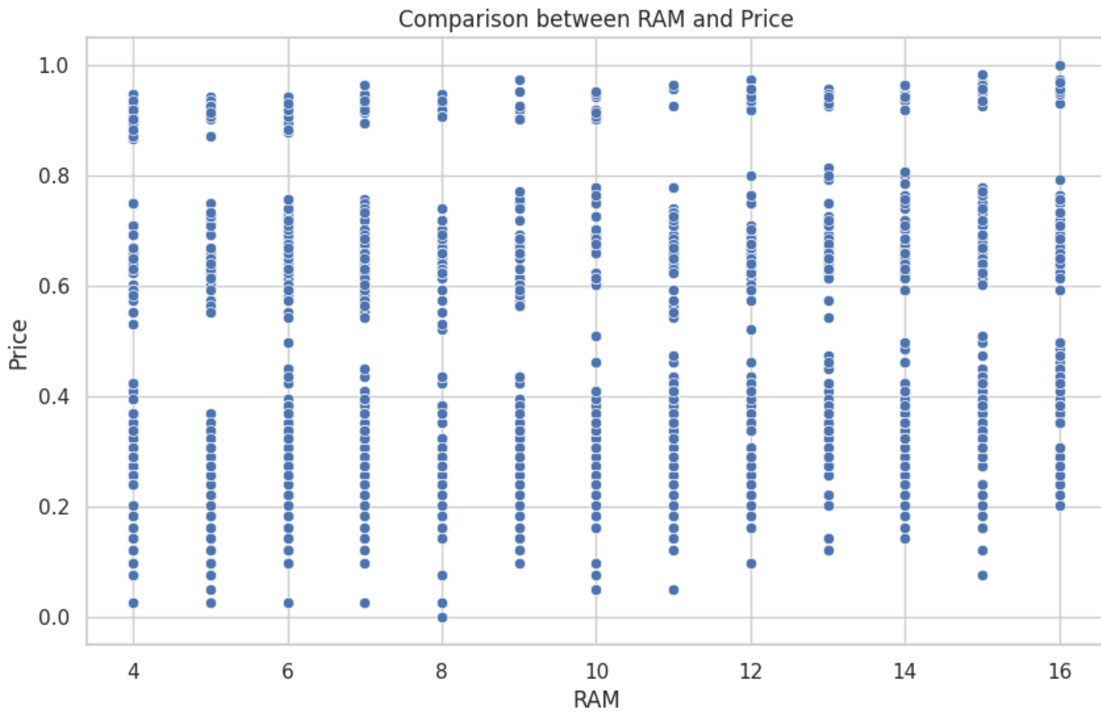
# 34 Price Comparison based on Dual sim feature

[352]:
```
import plotly.express as px

# Assuming df_no_outliers1 is your DataFrame
fig = px.scatter(df_no_outliers2, x="Dual_sim", y="Price")
```

```
# Define custom y-axis tick values and labels
custom_x_ticks = [0, 1]

# Update layout to set custom y-axis ticks
fig.update_layout(
    xaxis=dict(
        tickmode='array',
        tickvals=custom_x_ticks,
    ),
    width=800,
    height=600,
)
fig.show()
```

## 35 comparison of price & Ram

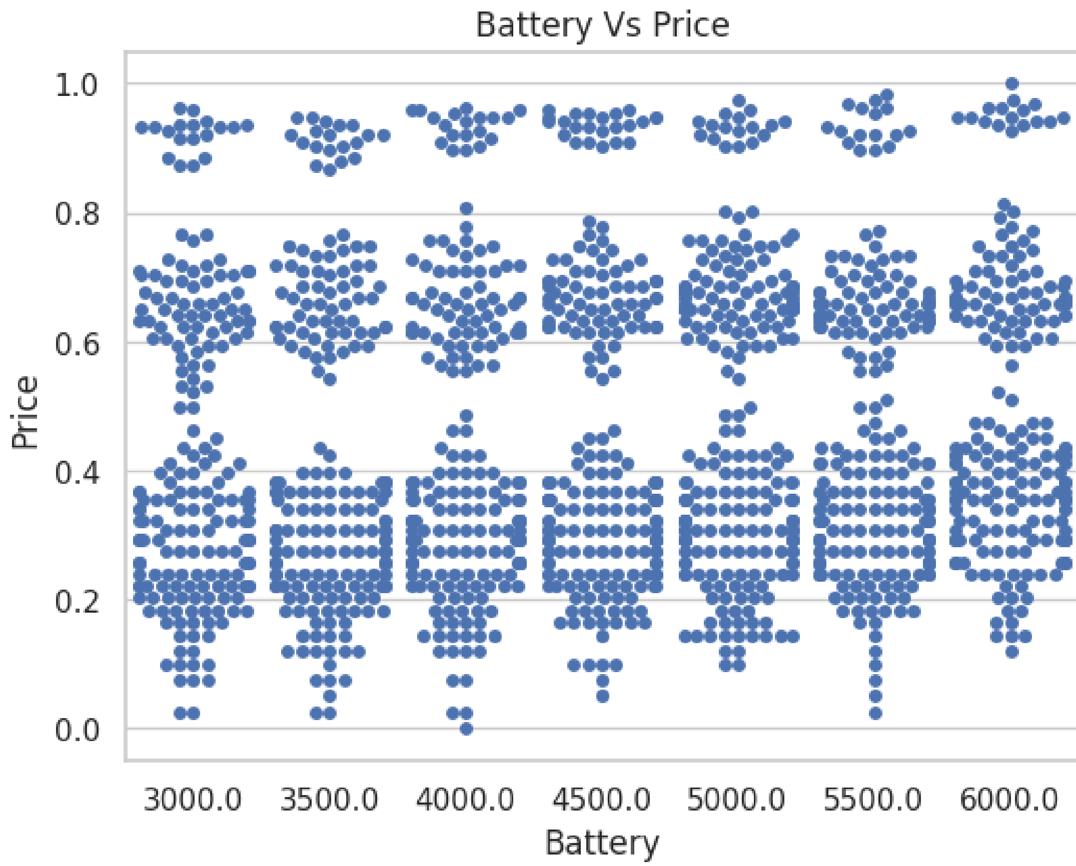
[353]:
```
import matplotlib.pyplot as plt
import seaborn as sns

# Assuming df is your DataFrame
plt.figure(figsize=(10, 6))
sns.scatterplot(x='RAM', y='Price', data=df_no_outliers2)
plt.title('Comparison between RAM and Price')
plt.xlabel('RAM')
plt.ylabel('Price')
plt.grid(True)
plt.show()
```




[354]:
```
from matplotlib import cm

cl = cm.get_cmap('Accent')
tw1 = df_no_outliers2.query('Gen_5G==1 and Dual_sim==1')['Price'].value_counts()
tw2 = df_no_outliers2.query('Gen_5G==0 and Dual_sim==1')['Price'].value_counts()
tw3 = df_no_outliers2.query('Gen_5G==0 and Dual_sim==0')['Price'].value_counts()
tw4 = df_no_outliers2.query('Gen_5G==1 and Dual_sim==0')['Price'].value_counts()

colors = [cl(0), cl(0.2), cl(0.9), cl(0.4)]
twlist = [tw1, tw2, tw3, tw4]
titles = ['Gen_5G==1 and Dual_sim==1', 'Gen_5G==0 and Dual_sim==1', 'Gen_5G==0␣
 ↪and Dual_sim==0', 'Gen_5G==1 and Dual_sim==0']

fig, axis = plt.subplots(4, 1, figsize=(30, 20))
for i in range(4):
    sns.barplot(y=twlist[i], x=twlist[i].index, ax=axis[i], color=colors[i])
    axis[i].set_title(titles[i])
    axis[i].set_xticks(range(len(twlist[i].index)))
    axis[i].set_xticklabels(twlist[i].index, rotation=45, ha='right')

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

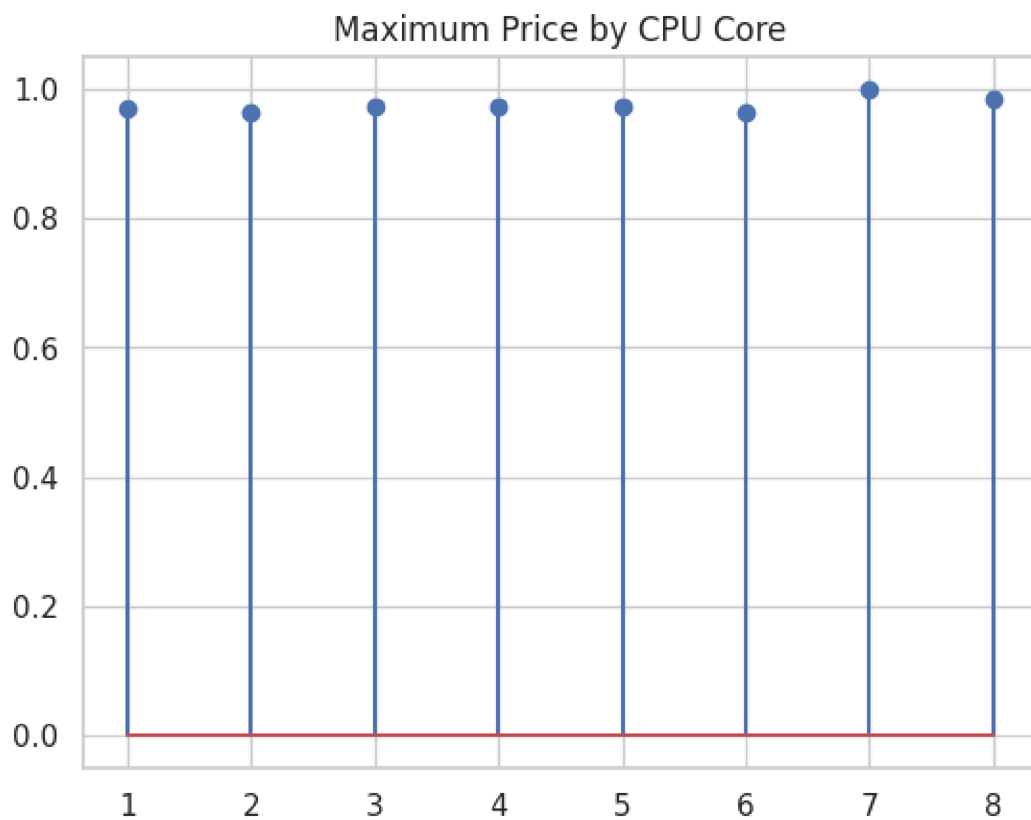

# 36 comparison of price & Battery

[355]:
```
sns.swarmplot(data=df_no_outliers2, x='Battery', y='Price')
plt.title('Battery Vs Price')
plt.show()
```




## 37 comparison of price & cpu_core

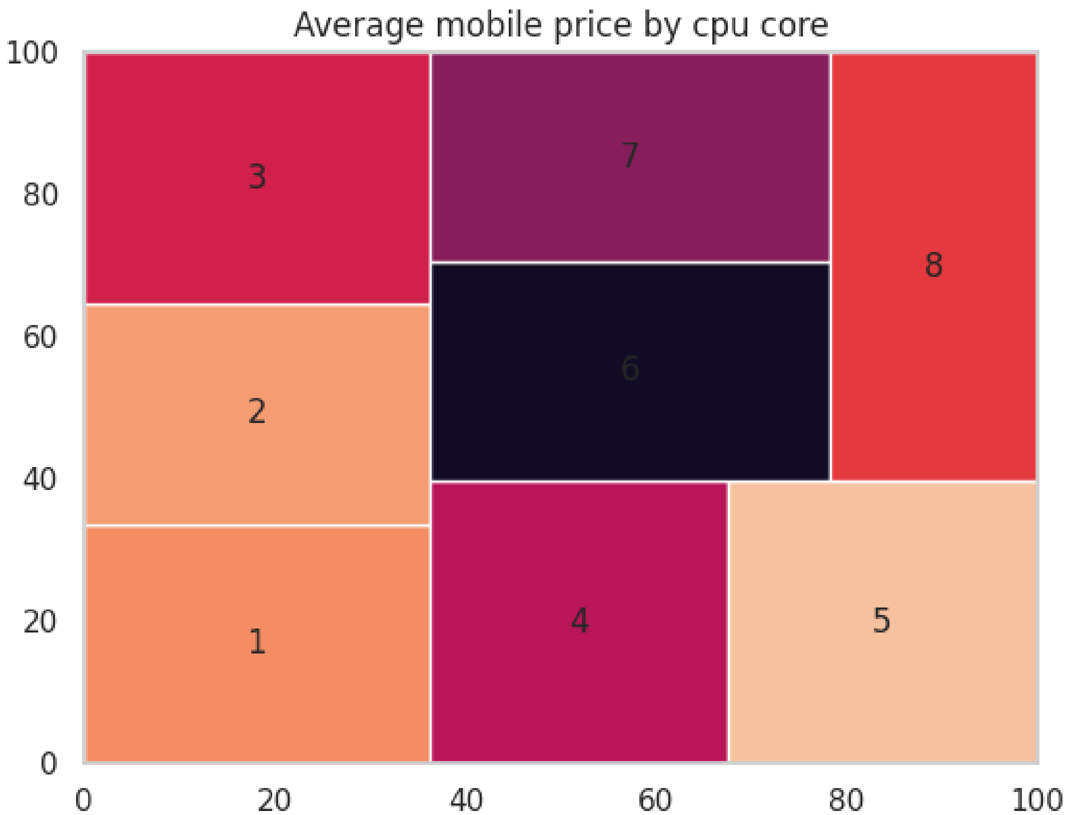
[356]:
```
d_grouped = df_no_outliers2.groupby('CPU_core')[['CPU_core', 'Price']].max()
plt.stem(d_grouped['CPU_core'], d_grouped['Price'])
plt.title('Maximum Price by CPU Core')
plt.show()
```




[357]:
```
pip install squarify
```

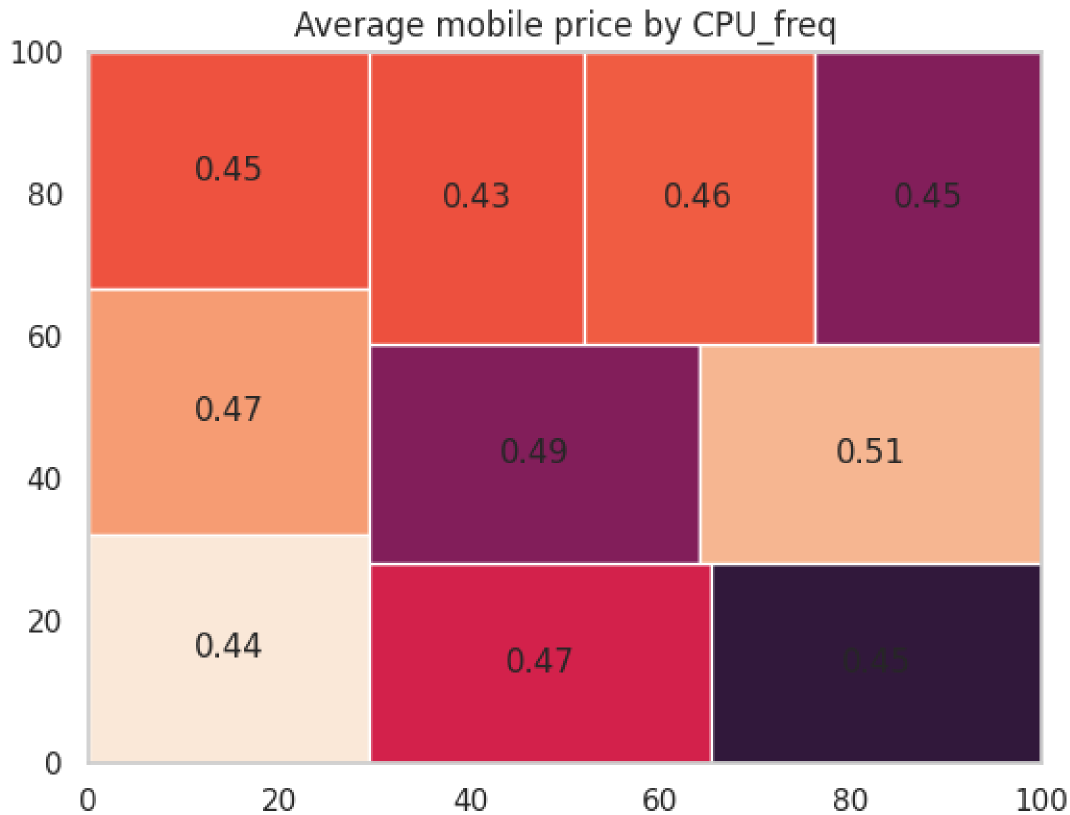
```
Collecting squarify
  Downloading squarify-0.4.3-py3-none-any.whl (4.3 kB)
Installing collected packages: squarify
Successfully installed squarify-0.4.3
```

[358]:
```
import squarify
d1_grouped = df_no_outliers2[['CPU_core', 'Price']].groupby('CPU_core').mean().
  ↪reset_index()
# Creating a treemap
squarify.plot(sizes=d1_grouped['Price'], label=d1_grouped['CPU_core'])
plt.title('Average mobile price by cpu core')
plt.show()
```



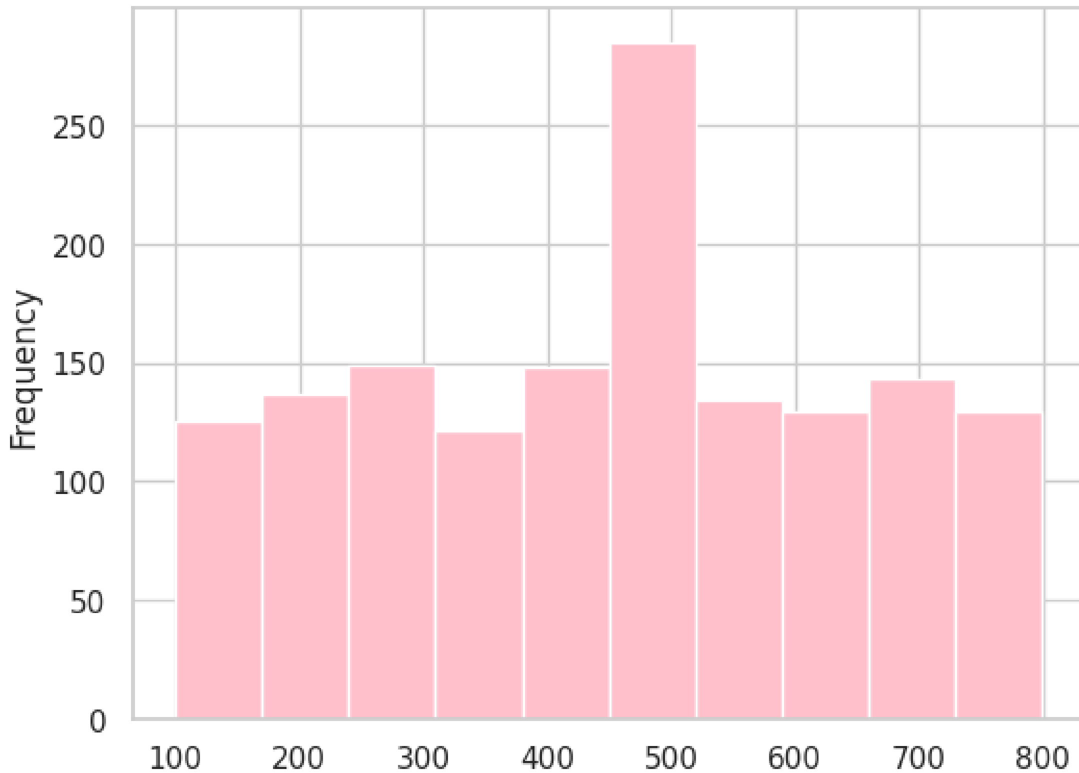

## 38 comparison of price & cpu freq

[359]:
```
import squarify
d1_grouped = df_no_outliers2[['CPU_freq', 'Price']].groupby('CPU_freq').mean().
  ↪reset_index()
# Creating a treemap
squarify.plot(sizes=d1_grouped['Price'], label=[f'{price:.2f}' for freq, price␣
  ↪in zip(d1_grouped['CPU_freq'], d1_grouped['Price'])])
plt.title('Average mobile price by CPU_freq')
plt.show()
```




[360]:
```
df_no_outliers2['PPI'].plot(kind='hist',bins=10, color='pink')
```

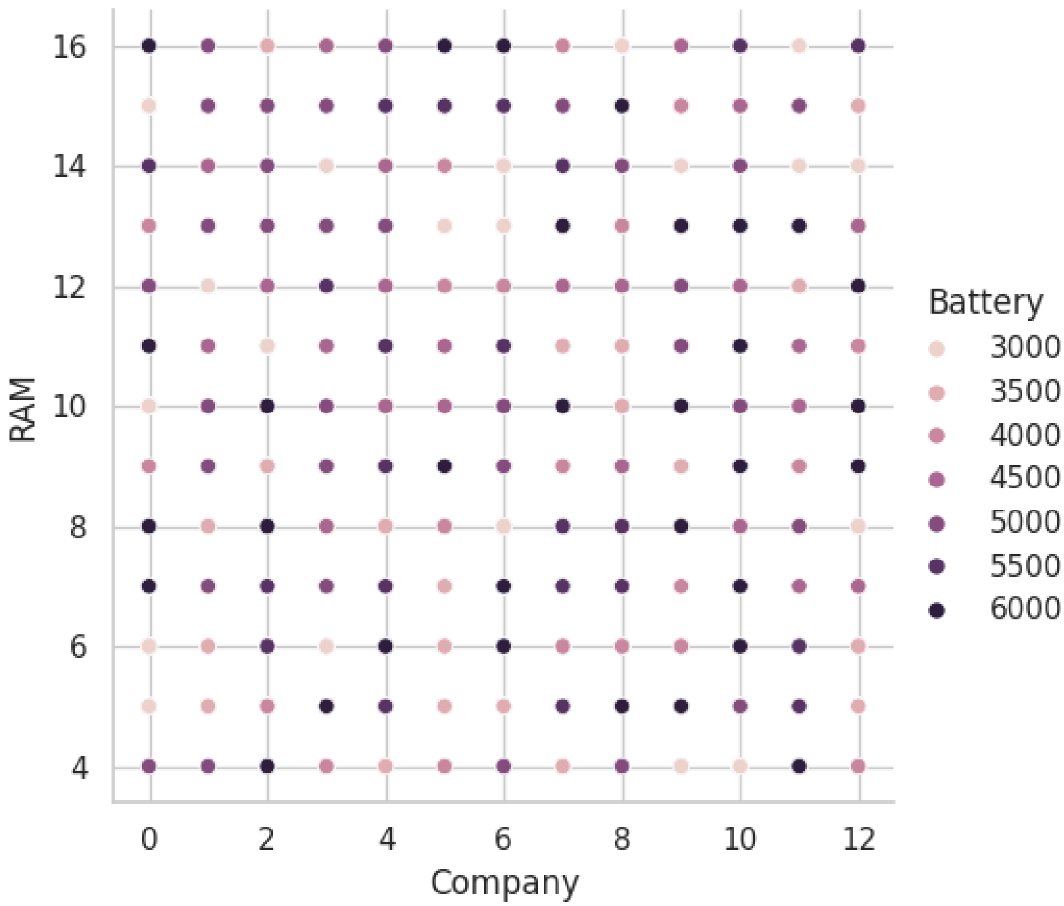
[360]: <Axes: ylabel='Frequency'>




## 39 comparison of Ram & Battery & Company

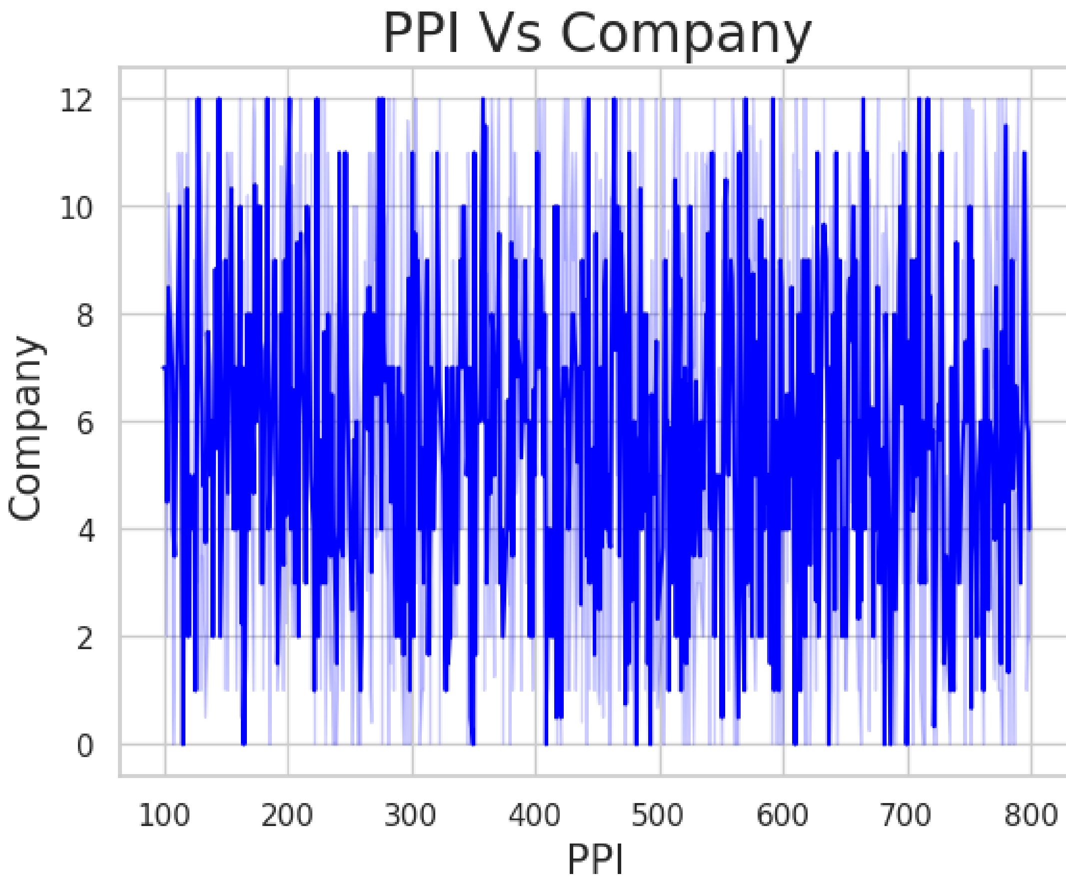
[361]:
```
sns.relplot(x='Company', y='RAM', hue='Battery', data=df_no_outliers2)
```

[361]:
```
<seaborn.axisgrid.FacetGrid at 0x78fec30ec490>
```




## 40 PPI Vs Company

[362]:
```
sns.lineplot(data=df_no_outliers2,x='PPI',y='Company',color='blue')
plt.title('PPI Vs Company',fontsize=20)
plt.xlabel('PPI',fontsize=15)
plt.ylabel('Company',fontsize=15)
plt.show()
```


PPI Vs Company
Company
PPI
0
2
4
6
8
10
12
100
200
300
400
500
600
700
800