```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px

# Load the dataset from the file
data = pd.read_csv('Mobile phone price.csv')
data.head()
```

| | Brand | Model | Storage | RAM | Screen Size (inches) | Camera (MP) | Batt Capac (m |
|---|---|---|---|---|---|---|---|
| 0 | Apple | iPhone 13 Pro | 128 GB | 6 GB | 6.1 | 12 + 12 + | 3 |

```
data.columns
```

```
Index(['Brand', 'Model', 'Storage ', 'RAM ', 'Screen Size (inches)',
       'Camera (MP)', 'Battery Capacity (mAh)', 'Price ($)'],
      dtype='object')
```

```
# Renaming the columns
data = data.rename({'Brand':'brand',
            'Model':'model',
            'Storage ':'storage',
            'RAM ':'ram',
            'Screen Size (inches)':'screen_size',
            'Camera (MP)':'camera',
            'Battery Capacity (mAh)':'battery',
            'Price ($)':'price'},axis=1)

data.head()

```

| | brand | model | storage | ram | screen_size | camera | ba |
|---|---|---|---|---|---|---|---|
| 0 | Apple | iPhone 13 Pro | 128 GB | 6 GB | 6.1 | 12 + 12 + 12 | |

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 407 entries, 0 to 406
```

```
Data columns (total 8 columns):
 #   Column       Non-Null Count  Dtype 
---  ------       --------------  ----- 
 0   brand        407 non-null    object
 1   model        407 non-null    object
 2   storage      407 non-null    object
 3   ram          407 non-null    object
 4   screen_size  407 non-null    object
 5   camera       407 non-null    object
 6   battery      407 non-null    int64 
 7   price        407 non-null    object
dtypes: int64(1), object(7)
memory usage: 25.6+ KB
```

```
# converting the barnd and model to lowercase

data['brand'] = data['brand'].str.lower()
data['model'] = data['model'].str.lower()
```

```
#Removing the 'BG from the storage and ram

data['storage'] = data['storage'].str.replace('GB','')
data['ram'] = data['ram'].str.replace('GB','')
```

```
#Creating a new feature from camera: Number of cameras

data['n_cameras'] = data['camera'].str.count('\\+') + 1
data['n_cameras'].unique()


```

Rosemary Maina
15:35 Today

The maximum number of cameras is 4. So we can create four new features: Camera 1 resolution, Camera 2 resolution, Camera 3 resolution and Camera 4 resolution.

```
array([3, 4, 2, 1])
```

```
data.head()
```

| | brand | model | storage | ram | screen_size | camera | battery | price | n_cameras |
|---|---|---|---|---|---|---|---|---|---|
| 0 | apple | iphone 13 pro | 128 | 6 | 6.1 | 12 + 12 + 12 | 3095 | 999 | 3 |
| 1 | samsung | galaxy s21 ultra | 256 | 12 | 6.8 | 108 + 10 + 10 + 12 | 5000 | 1199 | 4 |
| 2 | oneplus | 9 pro | 128 | 8 | 6.7 | 48 + 50 + 8 + 2 | 4500 | 899 | 4 |
| 3 | xiaomi | redmi note 10 pro | 128 | 6 | 6.67 | 64 + 8 + 5 + 2 | 5020 | 279 | 4 |
| 4 | google | pixel 6 | 128 | 8 | 6.4 | 50 + 12.2 | 4614 | 799 | 2 |

```
# Creating four new feature and removing camera

res1 = []
res2 = []
res3 = []
res4 = []
for x in data['camera']:
    resolutions = x.split('+')
    tam = len(resolutions)

```

```
    if tam == 1:
        res1.append(resolutions[0])
        res2.append('0')
        res3.append('0')
        res4.append('0')

    if tam == 2:
        res1.append(resolutions[0])
        res2.append(resolutions[1])
        res3.append('0')
        res4.append('0')

    if tam == 3:
        res1.append(resolutions[0])
        res2.append(resolutions[1])
        res3.append(resolutions[2])
        res4.append('0')

    if tam == 4:
        res1.append(resolutions[0])
        res2.append(resolutions[1])
        res3.append(resolutions[2])
        res4.append(resolutions[3])

data['res1'] = res1
data['res2'] = res2
data['res3'] = res3
data['res4'] = res4

data = data.drop(columns='camera')
```

```
data.head()
```

| | brand | model | storage | ram | screen_size | battery | price | n_cameras | res1 | res2 | res3 | res4 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | apple | iphone 13 pro | 128 | 6 | 6.1 | 3095 | 999 | 3 | 12 | 12 | 12 | 0 |
| 1 | samsung | galaxy s21 ultra | 256 | 12 | 6.8 | 5000 | 1199 | 4 | 108 | 10 | 10 | 12 |
| 2 | oneplus | 9 pro | 128 | 8 | 6.7 | 4500 | 899 | 4 | 48 | 50 | 8 | 2 |
| 3 | xiaomi | redmi note 10 pro | 128 | 6 | 6.67 | 5020 | 279 | 4 | 64 | 8 | 5 | 2 |
| 4 | google | pixel 6 | 128 | 8 | 6.4 | 4614 | 799 | 2 | 50 | 12.2 | 0 | 0 |

```
# Cleaning data

for x in data:
    print(f' Type of {x} : {data[x].dtype}\n')
```

```
Type of brand : object

Type of model : object

Type of storage : object

Type of ram : object

Type of screen_size : object
```

```
Type of battery : int64

Type of price : object

Type of n_cameras : int64

Type of res1 : object

Type of res2 : object

Type of res3 : object

Type of res4 : object
```

```
data['res3'].unique()

```

```
array([' 12', ' 10 ', ' 8 ', ' 5 ', '0', ' 2 ', ' 16 ', ' 12 ', ' 2',
       ' 13 ', ' 5', ' 13', ' 12MP', ' 2MP', ' 2MP ', ' 12MP ', ' 13MP ',
       ' 8MP', ' 8MP ', ' 5MP ', ' 48MP', ' 5MP', ' 16MP ', ' 10MP ',
       '12', '2', '5', '10', '13', '40', '8', '16'], dtype=object)
```

```
data['res1'] = data['res1'].str.replace('MP','')
data['res2'] = data['res2'].str.replace('MP','')
data['res3'] = data['res3'].str.replace('MP','')
data['res4'] = data['res4'].str.replace('MP','')
data['price'] = data['price'].str.replace('$','')
data['price'] = data['price'].str.replace(',','.')
data.loc[88,'screen_size'] = '6.8'
data.loc[373,'screen_size'] = '7.6'
data.loc[342,'res4'] = 0
data.loc[342,'n_cameras'] = 3
data.loc[292,'res4'] = 0
data.loc[292,'n_cameras'] = 3
data.loc[312,'res4'] = 2
data.loc[312,'n_cameras'] = 4
data.loc[330,'res4'] = 0
data.loc[330,'n_cameras'] = 3
data.loc[361,'res4'] = 8
data.loc[361,'res3'] = 8
data.loc[361,'n_cameras'] = 4
data.loc[367,'res4'] = 0
data.loc[367,'n_cameras'] = 3
data.loc[376,'res4'] = 2
data.loc[376,'n_cameras'] = 4
```

```
# Casting the features to numeric type

for feature in data:
    print(f'Type of {feature}: {data[feature].dtype}')
```

```
Type of brand: object
Type of model: object
Type of storage: object
Type of ram: object
Type of screen_size: object
```

```
Type of battery: int64
Type of price: object
Type of n_cameras: int64
Type of res1: object
Type of res2: object
Type of res3: object
Type of res4: object
```

```
data['storage'] = pd.to_numeric(data['storage'])

data['ram'] = pd.to_numeric(data['ram'])

data['screen_size'] = pd.to_numeric(data['screen_size'])

data['price'] = pd.to_numeric(data['price'])

data['res1'] = pd.to_numeric(data['res1'])

data['res2'] = pd.to_numeric(data['res2'])

data['res3'] = pd.to_numeric(data['res3'])

data['res4'] = pd.to_numeric(data['res4'])
```

```
for feature in data:
    print(f'Type of {feature}: {data[feature].dtype}')
```

```
Type of brand: object
Type of model: object
Type of storage: int64
Type of ram: int64
Type of screen_size: float64
Type of battery: int64
Type of price: float64
Type of n_cameras: int64
Type of res1: float64
Type of res2: float64
Type of res3: int64
Type of res4: float64
```

```
data.head()

```

| | brand | model | storage | ram | screen_size | battery | price | n_cameras | res1 | res2 | res3 | res4 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | apple | iphone 13 pro | 128 | 6 | 6.10 | 3095 | 999.0 | 3 | 12.0 | 12.0 | 12 | 0.0 |
| 1 | samsung | galaxy s21 ultra | 256 | 12 | 6.80 | 5000 | 1199.0 | 4 | 108.0 | 10.0 | 10 | 12.0 |
| 2 | oneplus | 9 pro | 128 | 8 | 6.70 | 4500 | 899.0 | 4 | 48.0 | 50.0 | 8 | 2.0 |
| 3 | xiaomi | redmi note 10 pro | 128 | 6 | 6.67 | 5020 | 279.0 | 4 | 64.0 | 8.0 | 5 | 2.0 |
| 4 | google | pixel 6 | 128 | 8 | 6.40 | 4614 | 799.0 | 2 | 50.0 | 12.2 | 0 | 0.0 |

```
# Missing values and duplicate values

data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 407 entries, 0 to 406
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   brand        407 non-null    object
 1   model        407 non-null    object
 2   storage      407 non-null    int64
 3   ram          407 non-null    int64
 4   screen_size  407 non-null    float64
 5   battery      407 non-null    int64
 6   price        407 non-null    float64
 7   n_cameras    407 non-null    int64
 8   res1         407 non-null    float64
 9   res2         407 non-null    float64
 10  res3         407 non-null    int64
 11  res4         407 non-null    float64
dtypes: float64(5), int64(5), object(2)
memory usage: 38.3+ KB
```

```
data.isna().sum(),data.isna().mean()     #Alternatively, we can use data.isna().sum() for absolute values or data.isna().mean() for percentage values.

```

```
(brand          0
 model          0
 storage        0
 ram            0
 screen_size    0
 battery        0
 price          0
 n_cameras      0
 res1           0
 res2           0
 res3           0
 res4           0
 dtype: int64,
 brand          0.0
 model          0.0
 storage        0.0
 ram            0.0
 screen_size    0.0
 battery        0.0
 price          0.0
 n_cameras      0.0
 res1           0.0
 res2           0.0
 res3           0.0
 res4           0.0
 dtype: float64)
```

```
#49 rows of our data are duplicates, and that's 12% of all our data
```

```
absolute = data.duplicated().sum()

relative = data.duplicated().mean()*100
```

```
print(f'Duplicated:\n\ndata(#): {absolute}\n\nRelative: {round(relative,2)} %')
```

```
Duplicated:

data(#): 49

Relative: 12.04 %
```

```
# Removing duplicates.

dup = data[data.duplicated()]

data_without_dup = data.drop_duplicates()

data_without_dup.reset_index()
```

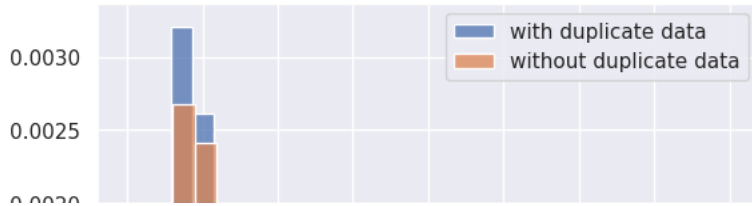
| | index | brand | model | storage | ram | screen_size | battery | price | n_cameras | res1 | res2 | res3 | res4 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 0 | apple | iphone 13 pro | 128 | 6 | 6.10 | 3095 | 999.0 | 3 | 12.0 | 12.0 | 12 | 0.0 |
| **1** | 1 | samsung | galaxy s21 ultra | 256 | 12 | 6.80 | 5000 | 1199.0 | 4 | 108.0 | 10.0 | 10 | 12.0 |
| **2** | 2 | oneplus | 9 pro | 128 | 8 | 6.70 | 4500 | 899.0 | 4 | 48.0 | 50.0 | 8 | 2.0 |
| **3** | 3 | xiaomi | redmi note 10 pro | 128 | 6 | 6.67 | 5020 | 279.0 | 4 | 64.0 | 8.0 | 5 | 2.0 |
| **4** | 4 | google | pixel 6 | 128 | 8 | 6.40 | 4614 | 799.0 | 2 | 50.0 | 12.2 | 0 | 0.0 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **353** | 401 | huawei | p30 lite | 128 | 4 | 6.15 | 3340 | 329.0 | 3 | 48.0 | 8.0 | 2 | 0.0 |
| **354** | 402 | samsung | galaxy note20 5g | 128 | 8 | 6.70 | 4300 | 1049.0 | 3 | 12.0 | 64.0 | 12 | 0.0 |
| **355** | 403 | xiaomi | mi 10 lite 5g | 128 | 6 | 6.57 | 4160 | 349.0 | 4 | 48.0 | 8.0 | 2 | 2.0 |
| **356** | 404 | apple | iphone 12 pro max | 128 | 6 | 6.70 | 3687 | 1099.0 | 3 | 12.0 | 12.0 | 12 | 0.0 |
| **357** | 405 | oppo | reno3 | 128 | 8 | 6.40 | 4025 | 429.0 | 4 | 48.0 | 13.0 | 8 | 2.0 |

358 rows × 13 columns

```
# Here you can see all duplicate data
dup
```

| | brand | model | storage | ram | screen_size | battery | price | n_cameras | res1 | res2 | res3 | res4 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 45 | apple | iphone 12 mini | 64 | 4 | 5.40 | 2227 | 699.0 | 2 | 12.0 | 12.0 | 0 | 0.0 |
| 61 | xiaomi | poco m3 pro 5g | 64 | 4 | 6.50 | 5000 | 199.0 | 3 | 48.0 | 2.0 | 2 | 0.0 |
| 77 | apple | iphone 13 | 128 | 4 | 6.10 | 2815 | 799.0 | 2 | 12.0 | 12.0 | 0 | 0.0 |
| 78 | samsung | galaxy s21 | 128 | 8 | 6.20 | 4000 | 799.0 | 3 | 64.0 | 12.0 | 12 | 0.0 |
| 132 | nokia | xr20 | 128 | 6 | 6.67 | 4630 | 549.0 | 2 | 48.0 | 13.0 | 0 | 0.0 |
| 133 | samsung | galaxy a52s 5g | 128 | 6 | 6.50 | 4500 | 449.0 | 4 | 64.0 | 12.0 | 5 | 5.0 |
| 156 | vivo | y21s | 128 | 4 | 6.51 | 5000 | 179.0 | 2 | 50.0 | 2.0 | 0 | 0.0 |
| 160 | vivo | v21e | 128 | 8 | 6.44 | 4000 | 369.0 | 2 | 64.0 | 8.0 | 0 | 0.0 |
| 164 | xiaomi | redmi note 10s | 128 | 6 | 6.43 | 5000 | 229.0 | 4 | 64.0 | 8.0 | 2 | 2.0 |
| 165 | oppo | a74 5g | 128 | 6 | 6.50 | 5000 | 299.0 | 3 | 48.0 | 2.0 | 2 | 0.0 |
| 167 | samsung | galaxy m52 5g | 128 | 6 | 6.70 | 5000 | 449.0 | 4 | 64.0 | 12.0 | 5 | 5.0 |
| 170 | motorola | moto g stylus 5g | 128 | 5 | 6.80 | 5000 | 399.0 | 3 | 48.0 | 8.0 | 5 | 0.0 |
| 174 | xiaomi | poco x3 pro | 128 | 6 | 6.67 | 5160 | 249.0 | 4 | 48.0 | 8.0 | 2 | 2.0 |
| 195 | oppo | a74 5g | 128 | 6 | 6.50 | 5000 | 299.0 | 3 | 48.0 | 2.0 | 2 | 0.0 |
| 211 | realme | c25s | 128 | 4 | 6.50 | 6000 | 159.0 | 3 | 13.0 | 2.0 | 2 | 0.0 |
| 221 | vivo | y12s | 32 | 3 | 6.51 | 5000 | 149.0 | 2 | 13.0 | 2.0 | 0 | 0.0 |
| 229 | xiaomi | redmi note 10 pro max | 128 | 8 | 6.67 | 5020 | 329.0 | 4 | 108.0 | 8.0 | 5 | 2.0 |
| 230 | samsung | galaxy a52 5g | 128 | 6 | 6.50 | 4500 | 449.0 | 4 | 64.0 | 12.0 | 5 | 5.0 |
| 240 | nokia | c20 plus | 32 | 3 | 6.50 | 4950 | 99.0 | 2 | 8.0 | 2.0 | 0 | 0.0 |
| 246 | xiaomi | poco x3 pro | 128 | 6 | 6.67 | 5160 | 249.0 | 4 | 48.0 | 8.0 | 2 | 2.0 |
| 248 | oppo | a16 | 32 | 3 | 6.52 | 5000 | 149.0 | 3 | 13.0 | 2.0 | 2 | 0.0 |

```
# The difference of price distribution with duplicate data and without duplicate data

sns.histplot(data=data,x='price',label='with duplicate data', stat='density')
sns.histplot(data=data_without_dup,x='price',label='without duplicate data',stat='density')
plt.legend();
```




```
data.shape , data_without_dup.shape
```

```
((407, 12), (358, 12))
```

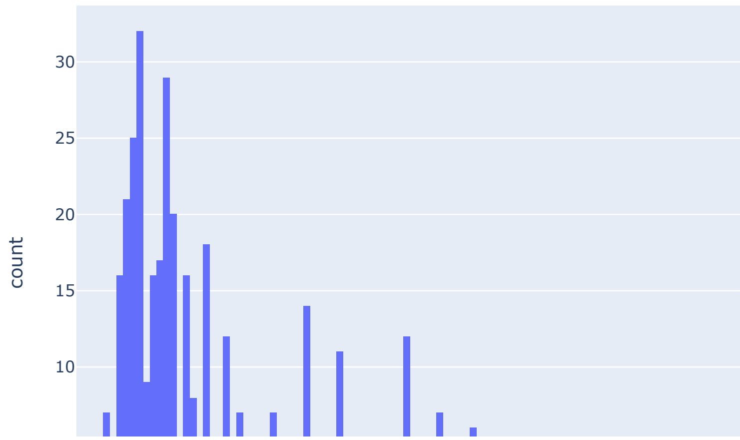
```
407 - 358
```

```
49
```


```
# EDA
# I'll start with describe method
# We see that the minimum price is a mistake. A cell phone never costs 1 dollar

data_without_dup.describe().T
```

| | count | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| **storage** | 358.0 | 125.050279 | 67.913050 | 32.000 | 64.00 | 128.0 | 128.0 | 512.0 |
| **ram** | 358.0 | 5.910615 | 2.510002 | 2.000 | 4.00 | 6.0 | 8.0 | 16.0 |
| **screen_size** | 358.0 | 6.481508 | 0.302918 | 4.500 | 6.44 | 6.5 | 6.6 | 7.6 |
| **battery** | 358.0 | 4695.363128 | 780.972153 | 1821.000 | 4300.00 | 5000.0 | 5000.0 | 7000.0 |
| **price** | 358.0 | 401.675131 | 302.959522 | 1.199 | 199.00 | 284.0 | 466.5 | 1999.0 |
| **n_cameras** | 358.0 | 3.134078 | 0.755121 | 1.000 | 3.00 | 3.0 | 4.0 | 4.0 |
| **res1** | 358.0 | 43.616201 | 24.942903 | 8.000 | 13.00 | 48.0 | 64.0 | 108.0 |
| **res2** | 358.0 | 9.218436 | 10.493717 | 0.000 | 2.00 | 8.0 | 12.0 | 64.0 |
| **res3** | 358.0 | 3.737430 | 5.098283 | 0.000 | 2.00 | 2.0 | 5.0 | 48.0 |
| **res4** | 358.0 | 0.972905 | 1.762691 | 0.000 | 0.00 | 0.0 | 2.0 | 12.0 |

```
# Let's see the price distribution with plotly

# The data set has three cell phones priced between 0 and 19 dollars. This is an error and we will remove these rows

px.histogram(data_without_dup,x='price',nbins=100)
```




```
index = data_without_dup.query('price < 20').index
data_without_dup = data_without_dup.drop(index)
data_without_dup.shape
```

```
(355, 12)
```

```
# The most expensive cell phone
#We can see the 10 most expensive cell phones and the most expensive cell phone is galaxy z fold2 5g from Samsung costing $1999.
#Samsung accounts for 60% of the most expensive phones in the top 10
#Huawei corresponds to 20%
#The others corresponds to 30%


data_without_dup.sort_values(by='price',ascending=False).head(10)
```

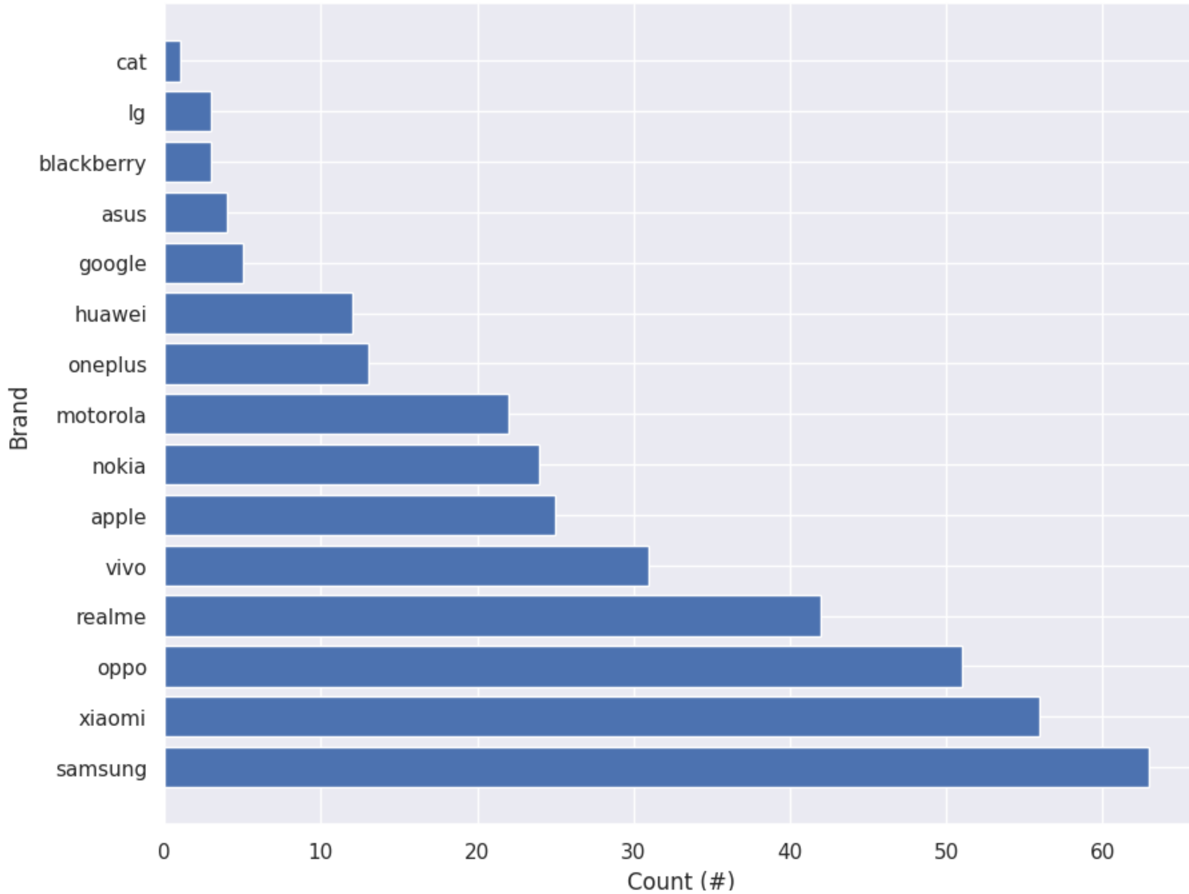
| | brand | model | storage | ram | screen_size | battery | price | n_cameras | res1 | res2 | res3 | res4 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **373** | samsung | galaxy z fold2 5g | 256 | 12 | 7.60 | 4500 | 1999.0 | 3 | 12.0 | 12.0 | 12 | 0.0 |
| **367** | samsung | galaxy s20 ultra 5g | 512 | 16 | 6.90 | 5000 | 1399.0 | 3 | 108.0 | 48.0 | 12 | 0.0 |
| **361** | huawei | p40 pro+ | 512 | 8 | 6.58 | 4200 | 1399.0 | 4 | 50.0 | 40.0 | 8 | 8.0 |
| **57** | apple | iphone 13 pro max | 256 | 6 | 6.70 | 4352 | 1299.0 | 3 | 12.0 | 12.0 | 12 | 0.0 |
| **288** | samsung | galaxy note 20 ultra | 256 | 12 | 6.90 | 4500 | 1299.0 | 3 | 108.0 | 12.0 | 12 | 0.0 |
| **309** | samsung | galaxy s21 ultra 5g | 256 | 12 | 6.80 | 5000 | 1199.0 | 4 | 108.0 | 10.0 | 10 | 12.0 |
| **392** | samsung | galaxy s20 ultra 5g | 128 | 12 | 6.90 | 5000 | 1199.0 | 4 | 108.0 | 48.0 | 12 | 0.3 |
| **1** | samsung | galaxy s21 ultra | 256 | 12 | 6.80 | 5000 | 1199.0 | 4 | 108.0 | 10.0 | 10 | 12.0 |
| **9** | vivo | x70 pro+ | 256 | 12 | 6.78 | 4500 | 1199.0 | 4 | 50.0 | 48.0 | 12 | 8.0 |
| **292** | huawei | mate 40 pro | 256 | 8 | 6.76 | 4400 | 1199.0 | 3 | 50.0 | 20.0 | 12 | 0.0 |

```
# The most frequent brand
#Samsung accounts for 17.75% of the entire dataset and is the most frequent brand.
```

```
#The second most frequent brand is Xiaomi which corresponds to 15.77%
#Third is Oppo with 14.37%


most_frequent = data_without_dup.groupby('brand').size().sort_values(ascending=False)

total_of_mobiles = 355

for brand,quant in most_frequent.items():
    print(f"{brand.capitalize()} has {quant} mobiles and corresponds to {round(quant/total_of_mobiles * 100,2)}% of the entire dataset\n")
```

```
Samsung has 63 mobiles and corresponds to 17.75% of the entire dataset

Xiaomi has 56 mobiles and corresponds to 15.77% of the entire dataset

Oppo has 51 mobiles and corresponds to 14.37% of the entire dataset

Realme has 42 mobiles and corresponds to 11.83% of the entire dataset

Vivo has 31 mobiles and corresponds to 8.73% of the entire dataset

Apple has 25 mobiles and corresponds to 7.04% of the entire dataset

Nokia has 24 mobiles and corresponds to 6.76% of the entire dataset

Motorola has 22 mobiles and corresponds to 6.2% of the entire dataset

Oneplus has 13 mobiles and corresponds to 3.66% of the entire dataset

Huawei has 12 mobiles and corresponds to 3.38% of the entire dataset

Google has 5 mobiles and corresponds to 1.41% of the entire dataset

Asus has 4 mobiles and corresponds to 1.13% of the entire dataset

Blackberry has 3 mobiles and corresponds to 0.85% of the entire dataset

Lg has 3 mobiles and corresponds to 0.85% of the entire dataset

Cat has 1 mobiles and corresponds to 0.28% of the entire dataset
```

```
#fig ,ax = plt.subplots(1,1,constrained_layout=True,figsize=(20,10))
plt.figure(figsize=(10,8))
ex = most_frequent.keys()
ey = most_frequent.values

plt.barh(y=ex,width=ey)
plt.xlabel('Count (#)',fontsize=12)
plt.ylabel('Brand',fontsize=12);


#ax[0].barh(y=ex,width=ey)
#ax[0].set_xlabel('Count (#)',fontsize=12)
#ax[0].set_ylabel('Brand',fontsize=12)

#ax[1].plot(ey,ex)
#ax[1].set_xlabel('Count (#)',fontsize=12)
```




```
#Which is the most expensive and cheapest brand?
#The most expensive brand is Asus and the cheapest is Realme
#Perhaps it would be more interesting to consider only brands with more cell phones. But we can leave that for later.


```

```
costs = data_without_dup.groupby('brand')['price'].mean().sort_values(ascending=False)

for brand,price in costs.items():
    print(f"On average {brand.capitalize()} costs ${round(price,2)}\n")
```

```
On average Asus costs $874.0

On average Huawei costs $783.17

On average Apple costs $783.0

On average Google costs $699.0

On average Oneplus costs $664.38

On average Lg costs $615.67
```

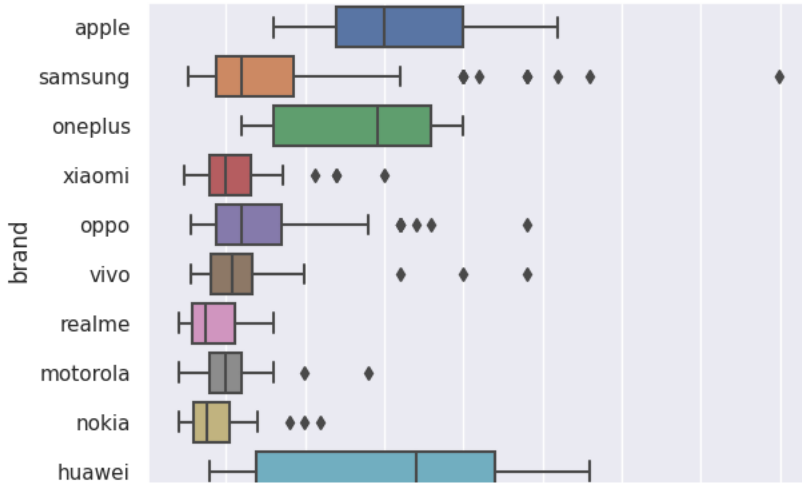
```
On average Blackberry costs $499.0

On average Samsung costs $470.13

On average Oppo costs $387.43

On average Vivo costs $337.39

On average Cat costs $299.0

On average Xiaomi costs $275.96

On average Motorola costs $272.64

On average Nokia costs $230.25

On average Realme costs $208.05
```

```
#The most expensive and cheapest cell phone for the top 10 most frequent brands

top10 = most_frequent.head(10)
print('To remember, the top10 brands are: \n')
for brand in top10.keys():
    print(brand,'\n')
```

```
To remember, the top10 brands are:

samsung

xiaomi

oppo

realme

vivo

apple

nokia

motorola

oneplus

huawei
```

```
#We will start with the distribution of prices for each top10 brand

top10 = data_without_dup.query(f'brand == {top10.keys().tolist()}')

sns.boxplot(data=top10,x='price',y='brand')
```

```
<Axes: xlabel='price', ylabel='brand'>
```




```
1 print('The expensive cell phones of each brand')
2 top10.groupby('brand')[['model','price']].max().sort_values(by='price',ascending=False)
```

```
The expensive cell phones of each brand
```

| brand | model | price |
|---|---|---|
| samsung | galaxy z fold2 5g | 1999.0 |
| huawei | y7p | 1399.0 |
| apple | iphone xs max | 1299.0 |
| oppo | reno6 z 5g | 1199.0 |
| vivo | y72 5g | 1199.0 |
| oneplus | nord n10 5g | 999.0 |
| xiaomi | redmi note 9s | 749.0 |
| motorola | moto g9 power lite | 699.0 |
| nokia | xr20 | 549.0 |
| realme | narzo 50i | 399.0 |

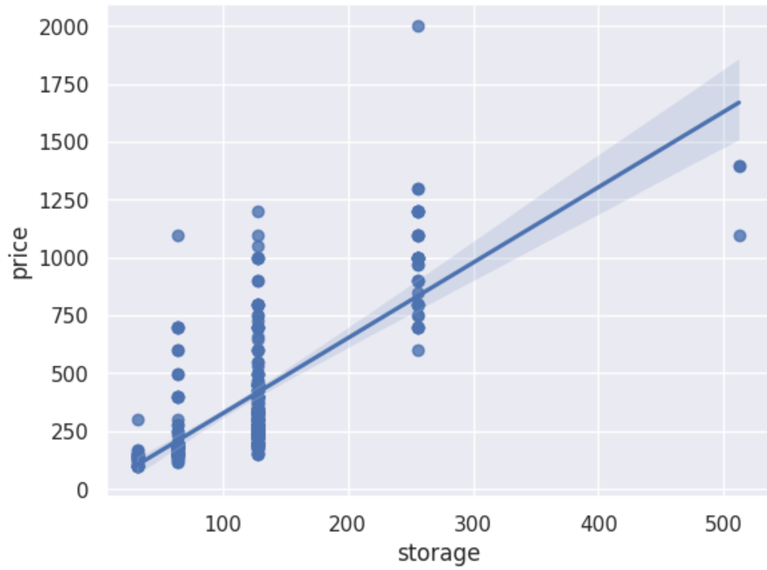
```
1 print('The cheapest cell phones of each brand')
2 top10.groupby('brand')[['model','price']].min().sort_values(by='price',ascending=False)
```

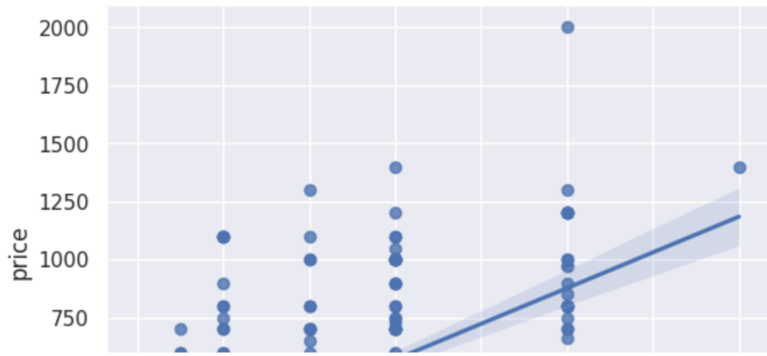
The cheapest cell phones of each brand

| | model | price |
|---|---|---|
| **brand** | | |
| **apple** | iphone 11 | 399.0 |
| **oneplus** | 7 pro | 299.0 |
| **huawei** | mate 30 pro 5g | 199.0 |
| **oppo** | a12 | 139.0 |
| **vivo** | v20 se | 139.0 |

```
#What are the features that have some correlation with the price?
#First strategy: Plot each feature with price.
#Second strategy: Calculate the correlation coefficient to measure a linear correlation.
#Most features have a linear correlation with price. However, we also observe linear correlation between features, for example: Storage and Ram have 0.68 correlation and so on.
#We can also calculate the VIF (variance inflation factor) to measure the degree of multicollinearity.
#Correlation of features with price:
#storage: 0.729
#res3: 0.632
#res2: 0.631
#ram: 0.630
#res4: 0.202
#res1: 0.127
#screen_size: 0.082
#n_cameras: 0.056
#battery: -0.409
```

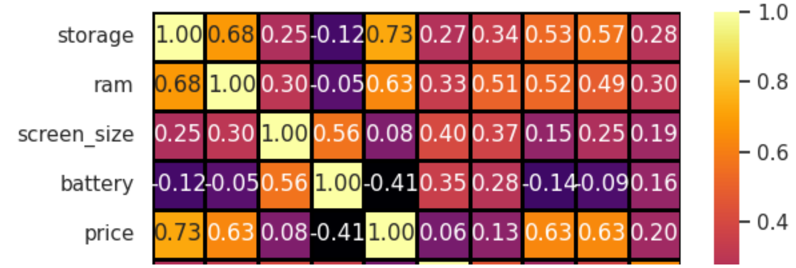
```
for feature in data_without_dup:
    if feature in ['brand','model','price']:
        continue
    sns.regplot(y=data_without_dup['price'],x=data_without_dup[feature])
    plt.show()
```




```
1 correlation = data_without_dup.corr()
2
3 sns.heatmap(correlation,annot=True,fmt='.2f',linecolor='black', linewidths=2, cmap='inferno')
```

```
<Axes: >
```




```
#More Questions and new features
#Our dataset has some brands from different continents and countries, for example:

#Apple - United States - North America

#Samsung - South Korea - Asia

#Xiaomi - China - Asia

#etc...

#Is there any difference about country or continent? If yes, what are the differences? Are price and other variables affected by country or continent?

#To answer these questions we need to add two new features: Country and Continente. So let's go!
```

```
print('The brands are: \n')
for brands in data_without_dup['brand'].unique():
    print(brands.capitalize(),'\n')
```

```
The brands are:

Apple

Samsung

Oneplus

Xiaomi

Google

Oppo

Vivo

Realme

Motorola

Nokia

Lg

Asus

Blackberry
```

```
Cat

Huawei
```

```
data_without_dup.reset_index(inplace=True)
```

```
data_without_dup[['country','continent']] = np.nan

for index,brand in enumerate(data_without_dup['brand']):

    if brand in ['apple','cat','google', 'motorola']:
        data_without_dup.loc[index,'country'] = 'united states'
        data_without_dup.loc[index,'continent'] = 'north america'

    elif brand in ['blackberry']:
        data_without_dup.loc[index,'country'] = 'canada'
        data_without_dup.loc[index,'continent'] = 'north america'

    elif brand in ['nokia']:
        data_without_dup.loc[index,'country'] = 'finland'
        data_without_dup.loc[index,'continent'] = 'europa'

    elif brand in ['samsung','lg']:
        data_without_dup.loc[index,'country'] = 'south korean'
        data_without_dup.loc[index,'continent'] = 'asia'

    else:
        data_without_dup.loc[index,'country'] = 'china'
        data_without_dup.loc[index,'continent'] = 'asia'
```

```
data_without_dup.head(10)
```

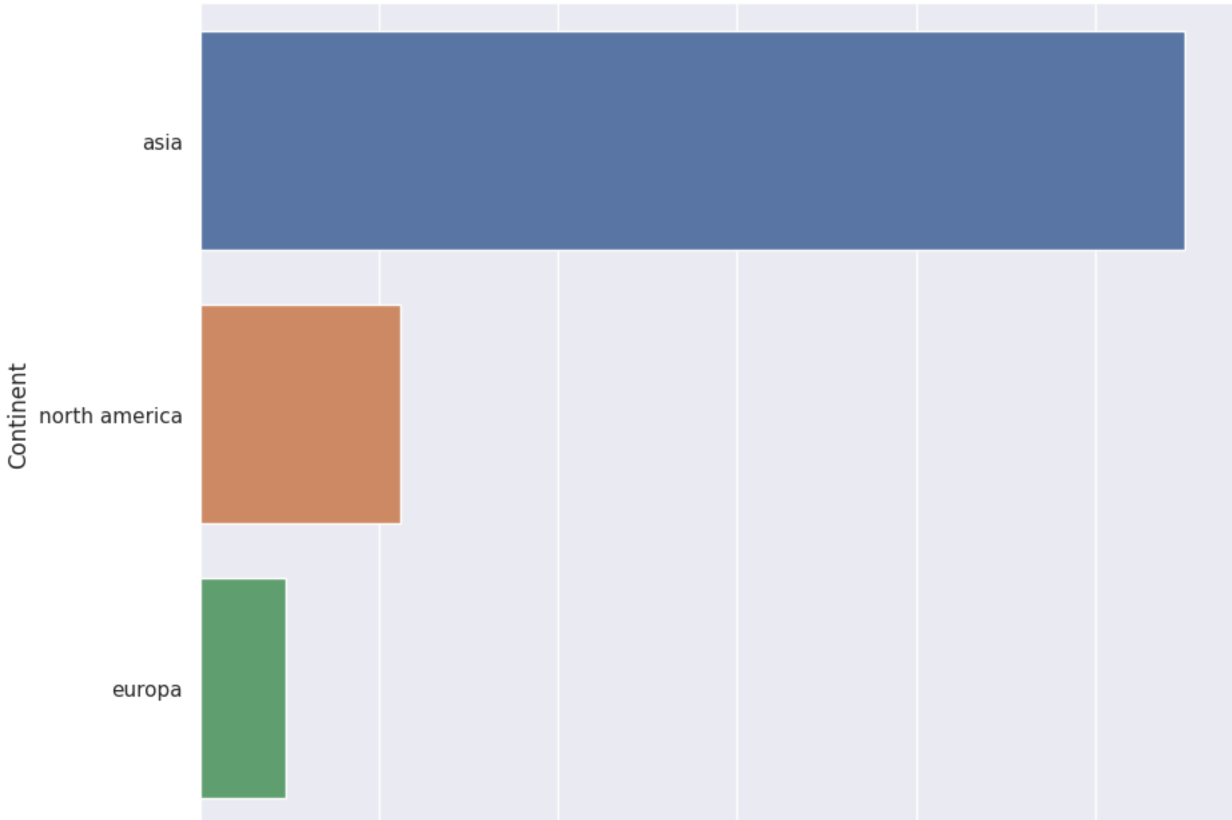
| | index | brand | model | storage | ram | screen_size | battery | price | n_cameras | res1 | res2 | res3 | res4 | country | continent |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 0 | apple | iphone 13 pro | 128 | 6 | 6.10 | 3095 | 999.0 | 3 | 12.0 | 12.0 | 12 | 0.0 | united states | north america |
| **1** | 1 | samsung | galaxy s21 ultra | 256 | 12 | 6.80 | 5000 | 1199.0 | 4 | 108.0 | 10.0 | 10 | 12.0 | south korean | asia |
| **2** | 2 | oneplus | 9 pro | 128 | 8 | 6.70 | 4500 | 899.0 | 4 | 48.0 | 50.0 | 8 | 2.0 | china | asia |
| **3** | 3 | xiaomi | redmi note 10 pro | 128 | 6 | 6.67 | 5020 | 279.0 | 4 | 64.0 | 8.0 | 5 | 2.0 | china | asia |
| **4** | 4 | google | pixel 6 | 128 | 8 | 6.40 | 4614 | 799.0 | 2 | 50.0 | 12.2 | 0 | 0.0 | united states | north america |
| **5** | 5 | apple | iphone 13 | 128 | 4 | 6.10 | 2815 | 799.0 | 2 | 12.0 | 12.0 | 0 | 0.0 | united states | north america |
| **6** | 6 | samsung | galaxy z flip3 | 256 | 8 | 6.70 | 3300 | 999.0 | 2 | 12.0 | 12.0 | 0 | 0.0 | south korean | asia |
| **7** | 7 | xiaomi | poco x3 pro | 128 | 6 | 6.67 | 5160 | 249.0 | 4 | 48.0 | 8.0 | 2 | 2.0 | china | asia |
| **8** | 8 | oppo | reno6 pro+ 5g | 128 | 8 | 6.55 | 4500 | 699.0 | 4 | 50.0 | 13.0 | 16 | 2.0 | china | asia |
| **9** | 9 | vivo | x70 pro+ | 256 | 12 | 6.78 | 4500 | 1199.0 | 4 | 50.0 | 48.0 | 12 | 8.0 | china | asia |

```
#Let's do a basic exploration on Contry and Continent features

# 1. Continent Statistics:

# 77.46% of cell phones are from Asia
# 15.77% of cell phones are from North america
# 6.76% of cell phones are from Europa
# 2. Country Statistics:

# 58.87% of cell phones are from China
# 18.59% of cell phones are from South korean
# 14.93% of cell phones are from United states
# 6.76% of cell phones are from Finland
# 0.85% of cell phones are from Canada
# Samsung is the most frequent brand, however Chinese brands together dominate our dataset.

# On average/median, North American cell phones are more expensive than Asian cell phones. And US cell phone prices are more dispersed than Asian ones.
```

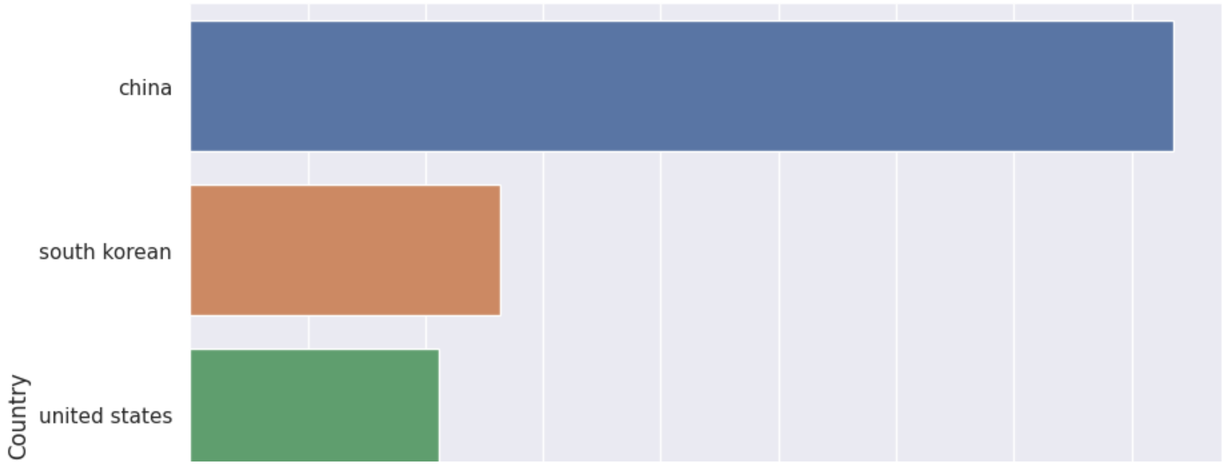

```
most_frequent_country = data_without_dup.groupby('country').size().sort_values(ascending=False)
most_frequent_continent = data_without_dup.groupby('continent').size().sort_values(ascending=False)

total_of_mobiles = 355

for continent,quant in most_frequent_continent.items():
    print(f'{round(quant/total_of_mobiles*100,2)}%  ({quant}) of cell phones are from {continent.capitalize()}')

print()
for country,quant in most_frequent_country.items():
    print(f'{round(quant/total_of_mobiles*100,2)}%  ({quant}) of cell phones are from {country.capitalize()}')
```

```
77.46%  (275) of cell phones are from Asia
15.77%  (56) of cell phones are from North america
6.76%  (24) of cell phones are from Europa

58.87%  (209) of cell phones are from China
18.59%  (66) of cell phones are from South korean
14.93%  (53) of cell phones are from United states
6.76%  (24) of cell phones are from Finland
0.85%  (3) of cell phones are from Canada
```

```
plt.figure(figsize=(10,8))
sns.barplot(x=most_frequent_continent.values, y=most_frequent_continent.keys())

plt.ylabel('Continent',fontsize=12)
plt.xlabel('#',fontsize=12);
```

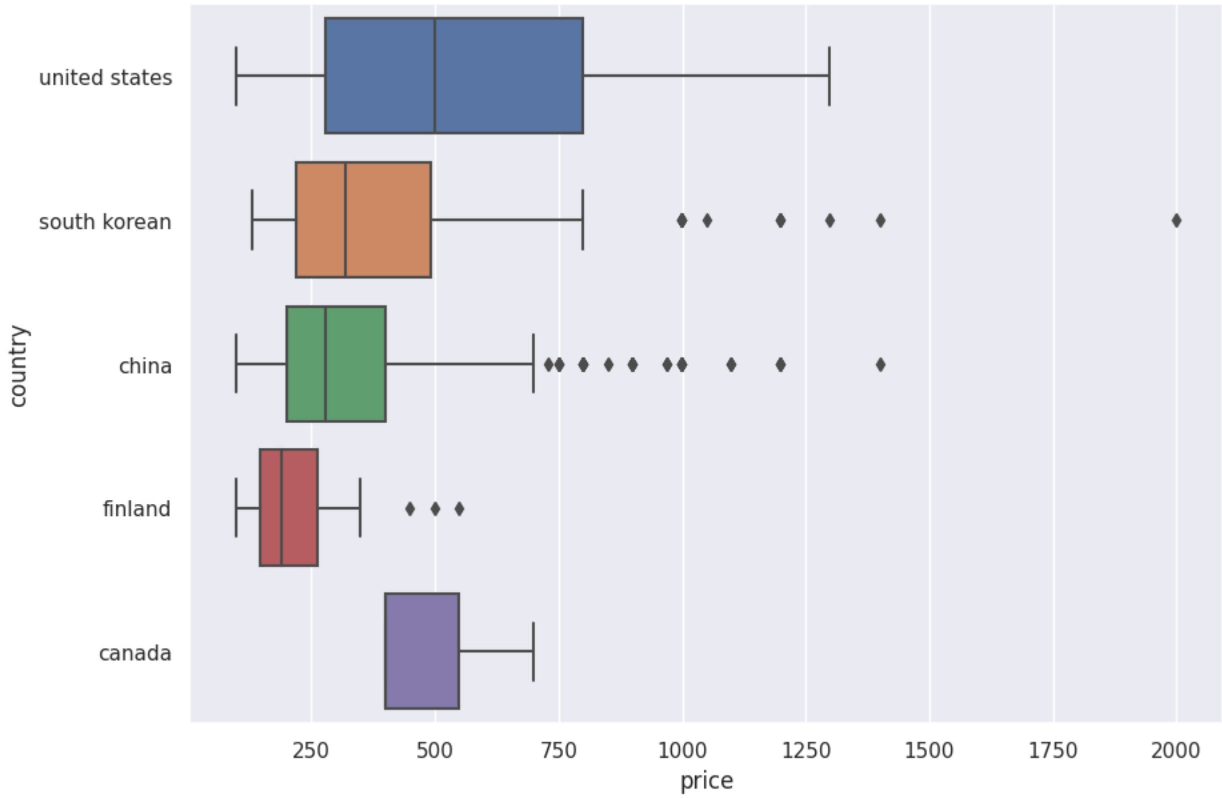



```
plt.figure(figsize=(10,8))
sns.barplot(x=most_frequent_country.values, y=most_frequent_country.keys())

plt.ylabel('Country',fontsize=12)
plt.xlabel('#',fontsize=12);
```



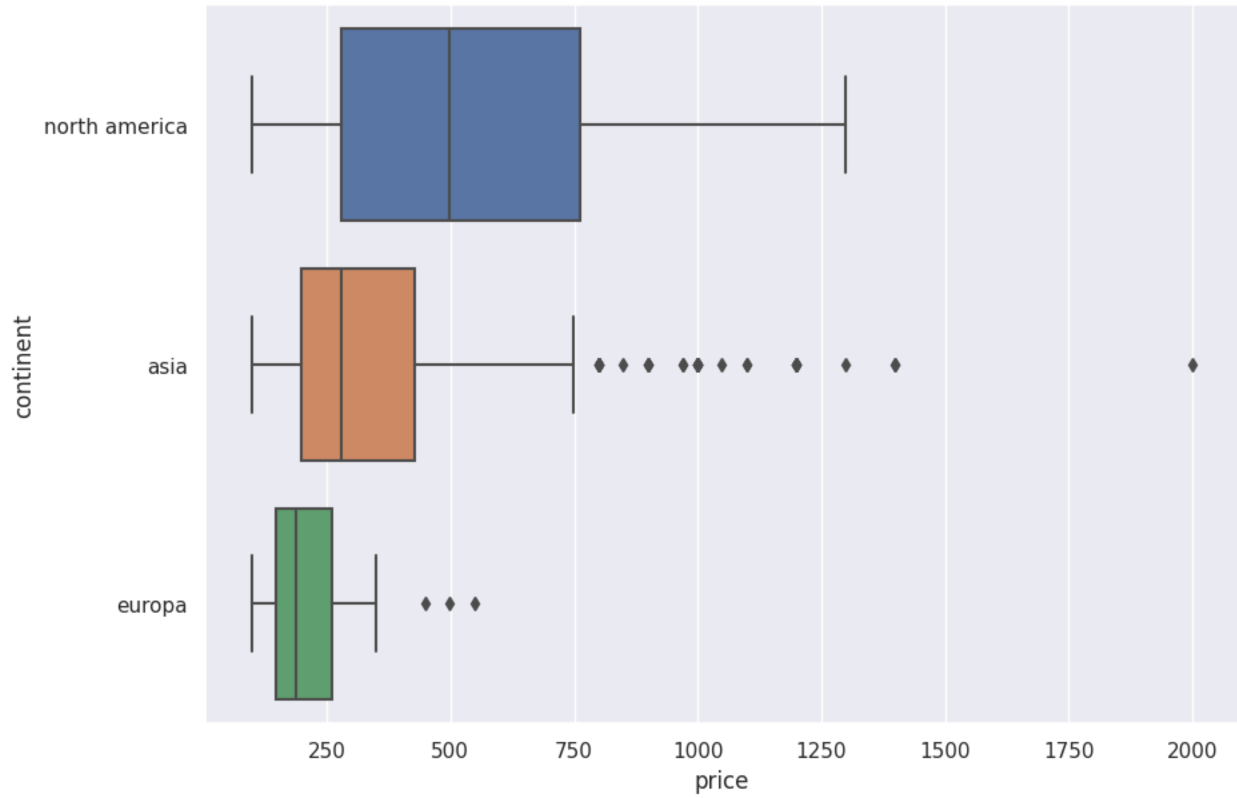

```
1 plt.figure(figsize=(10,7))
2 sns.boxplot(data=data_without_dup,x='price',y='country')
```

```
<Axes: xlabel='price', ylabel='country'>
```



```
plt.figure(figsize=(10,7))
sns.boxplot(data=data_without_dup,x='price',y='continent')
```

<Axes: xlabel='price', ylabel='continent'>




```
statistics_price = data_without_dup.groupby('continent')['price'].agg(['mean','median','std']).sort_values(by='mean',ascending=False)

statistics_price['Coefficient_of_variation'] = statistics_price['std'] / statistics_price['mean']

statistics_price
```

| continent | mean | median | std | Coefficient_of_variation |
|---|---|---|---|---|
| north america | 551.142857 | 499.0 | 310.224050 | 0.562874 |
| asia | 390.567273 | 279.0 | 299.983610 | 0.768072 |
| europa | 230.250000 | 189.0 | 122.521072 | 0.532122 |

```
# What are the differences between North American cell phones and Asian cell phones

# The strategy for analyzing this is to calculate the base statistic for each feature for each continent. We observed, on average, that Asian cell phones have better values than North A
```

```
# Let's calculate the total resolution (res1 + res2 + res3 + res4) to simplify the analysis

data_without_dup['total_resolution'] = data_without_dup['res1'] + data_without_dup['res2'] + data_without_dup['res3'] + data_without_dup['res4']
data_without_dup.head()
```

| | index | brand | model | storage | ram | screen_size | battery | price | n_cameras | res1 | res2 | res3 | res4 | country | continent | total_resolution |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 0 | apple | iphone 13 pro | 128 | 6 | 6.10 | 3095 | 999.0 | 3 | 12.0 | 12.0 | 12 | 0.0 | united states | north america | 36.0 |
| **1** | 1 | samsung | galaxy s21 ultra | 256 | 12 | 6.80 | 5000 | 1199.0 | 4 | 108.0 | 10.0 | 10 | 12.0 | south korean | asia | 140.0 |
| **2** | 2 | oneplus | 9 pro | 128 | 8 | 6.70 | 4500 | 899.0 | 4 | 48.0 | 50.0 | 8 | 2.0 | china | asia | 108.0 |

```
# Mean and standard deviation for multiple features
data_without_dup.groupby('continent')[['storage','ram','screen_size','battery','n_cameras','total_resolution']].agg(['mean','std','median'])
```

| | storage | | | ram | | | screen_size | | | battery | | | n_cameras | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | mean | std | median | mean | std | median | mean | std | median | mean | std | median | mean | std |
| continent | | | | | | | | | | | | | | |
| **asia** | 130.094545 | 65.238293 | 128.0 | 6.316364 | 2.497792 | 6.0 | 6.541855 | 0.133856 | 6.51 | 4868.981818 | 582.627966 | 5000.0 | 3.287273 | 0.67 |
| **europa** | 72.000000 | 39.191836 | 64.0 | 3.791667 | 1.473805 | 4.0 | 6.523333 | 0.202585 | 6.50 | 4500.000000 | 690.078760 | 4500.0 | 2.833333 | 0.81 |
| **north** | 118.285714 | 77.887965 | 128.0 | 4.571429 | 1.693379 | 4.0 | 6.162500 | 0.600113 | 6.40 | 3919.107143 | 1133.006069 | 3984.5 | 2.500000 | 0.73 |

```
# Is there any difference between Asian phones?

#The strategy is the same as in the previous analysis.

# We can see that South Korean cell phones are a little more expensive than Chinese ones. The two countries have similar cell phones, however, the number of cameras and the battery are
```

```
asia = data_without_dup.query('continent == "asia"')
```

```
asia.groupby('country')[['storage','ram','screen_size','battery','n_cameras','total_resolution','price']].agg(['mean','std'])
```

| | storage | | ram | | screen_size | | battery | | n_cameras | | total_resolution | | price |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | mean | std | mean | std | mean | std | mean | std | mean | std | mean | std | mean |
| country | | | | | | | | | | | | | |
| **china** | 129.377990 | 62.071421 | 6.397129 | 2.445599 | 6.530191 | 0.104251 | 4838.133971 | 533.563052 | 3.220096 | 0.685971 | 59.215311 | 29.058074 | 363.3540 |
| **south** | 132.363636 | 74.865137 | 6.060606 | 2.659548 | 6.578788 | 0.197301 | 4966.666667 | 712.165351 | 3.500000 | 0.613941 | 70.292424 | 32.544938 | 476.7424 |

```
# EDA Conclusion
# We saw that Samsung has the most expensive cell phone, and Samsung makes up (proportionally) 60% of the most expensive top 10 brands.

# Samsung is also the most frequent brand in our dataset, accounting for 17.75% of all data.

# The most expensive brand is Asus (on average 874 dollars) and Realme the cheapest (on average 208 dollars). Asus only has a four cell phones in our dataset, so it might be interesting
```

```
# We saw that most features have some linear correlation with price, however, some features are correlated with others and this may indicate multicollinearity. We can measure this with

# Continent Statistics:
# 77.46% of cell phones are from Asia
# 15.77% of cell phones are from North America
# 6.76% of cell phones are from Europa
# Country Statistics:
# 58.87% of cell phones are from China
# 18.59% of cell phones are from South korean
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# Samsung is the most frequent brand, however Chinese brands together dominate our dataset.

# On average/median, North American cell phones are more expensive than Asian cell phones. And US cell phone prices are more dispersed than Asian ones.

# We observed, on average, that Asian cell phones have better values than North American ones.

# We saw that South Korean cell phones are a little more expensive than Chinese ones. The two countries have similar cell phones, however, the number of cameras and the battery are bett
```