In [1]:

```
# This Python 3 environment comes with many helpful analytics libraries installed
# It is defined by the kaggle/python Docker image: https://github.com/kaggle/docke
r-python
# For example, here's several helpful packages to load

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

# Input data files are available in the read-only "../input/" directory
# For example, running this (by clicking run or pressing Shift+Enter) will list al
l files under the input directory

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

# You can write up to 20GB to the current directory (/kaggle/working/) that gets p
reserved as output when you create a version using "Save & Run All"
# You can also write temporary files to /kaggle/temp/, but they won't be saved out
side of the current session
```

```
/kaggle/input/john-tv/SQL data.csv
```

In [2]:

```
data =pd.read_csv('/kaggle/input/john-tv/SQL data.csv')
```

In [3]:

```
data=data.drop(data.columns[0], axis=1)
```

In [4]:

```
data.head()
```

Out[4]:

	description	reviews	Price	discount	Brand	TV_Size	TV_Type	TV_Pixels
0	Amazon Echo Show 10 with Alexa - Charcoal	(1167 Reviews)	$249.99	$80	Amazon Echo	NaN	NaN	NaN
1	Amazon Echo (4th Gen) Smart Home Hub with Alex...	(441 Reviews)	$94.99	$20	Amazon Echo	NaN	NaN	NaN
2	Samsung 55 4K UHD HDR LED Tizen Smart TV (UN55...	(40 Reviews)	$599.99	15.5	Samsung	LED	55.0	4K
3	Samsung 43 4K UHD HDR LED Tizen Smart TV (UN43...	(1015 Reviews)	$399.99	12.2	Samsung	LED	43.0	4K
4	Samsung The Frame 65 4K UHD HDR QLED Tizen Sma...	(418 Reviews)	$2,299.99	$400	Samsung	LED	65.0	4K

In [5]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1642 entries, 0 to 1641
Data columns (total 8 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   description  1642 non-null   object 
 1   reviews      1640 non-null   object 
 2   Price        1622 non-null   object 
 3   discount     1428 non-null   object 
 4   Brand        1642 non-null   object 
 5   TV_Size      1560 non-null   object 
 6   TV_Type      1556 non-null   float64
 7   TV_Pixels    1486 non-null   object 
dtypes: float64(1), object(7)
memory usage: 102.8+ KB
```

In [6]:

```
data.isna().sum()
```

Out[6]:

```
description      0
reviews          2
Price           20
discount       214
Brand            0
TV_Size         82
TV_Type         86
TV_Pixels      156
dtype: int64
```

In [7]:

```
data.isnull().sum(axis=1)
```

Out[7]:

```
0       3
1       3
2       0
3       0
4       0
       ..
1637    0
1638    0
1639    0
1640    3
1641    3
Length: 1642, dtype: int64
```

In [8]:

```
#data = data[data.isnull().sum(axis=1) < 2]
```

In [9]:

```
data.isna().sum()
```

Out[9]:

```
description      0
reviews          2
Price           20
discount       214
Brand            0
TV_Size         82
TV_Type         86
TV_Pixels      156
dtype: int64
```

In [10]:

```
data.discount = data.discount.fillna(0)
```

In [11]:

```
data.TV_Size.unique()
```

Out[11]:

```
array([nan, 'LED', 'OLED', 'QNED', 'LCD'], dtype=object)
```

In [12]:

```
data.TV_Type.unique()
```

Out[12]:

```
array([ nan,  55.,  43.,  65.,  58.,  32.,  50.,  40.,  42.,  70.,
75.,
        77.,  85.,  82.,  48.,  86.,  24.,  98., 100.,  83.,  60.,
22.,
        49.,  19.,  46.,  37.,   7.,   6.])
```

In [13]:

```
data.TV_Pixels.unique()
```

Out[13]:

```
array([nan, '4K', '1080p', '720p', 'Ultra HD'], dtype=object)
```

Handling missing values

In [14]:

```
missing_data = data[data['TV_Size'].isna() | data['TV_Type'].isna() | data['TV_P
ixels'].isna()]
```

In [15]:

```
missing_data.head()
```

Out[15]:

	description	reviews	Price	discount	Brand	TV_Size	TV_Type	TV_Pixels
0	Amazon Echo Show 10 with Alexa - Charcoal	(1167 Reviews)	$249.99	$80	Amazon Echo	NaN	NaN	NaN
1	Amazon Echo (4th Gen) Smart Home Hub with Alex...	(441 Reviews)	$94.99	$20	Amazon Echo	NaN	NaN	NaN
5	Explore Sonyâ■■s full TV lineup.	NaN	NaN	15.5	Sony	NaN	NaN	NaN
27	Amazon Echo Show 10 with Alexa - Glacier White	(1163 Reviews)	$249.99	$35	Amazon Echo	NaN	NaN	NaN
28	Amazon Echo (4th Gen) Smart Home Hub with Alex...	(1209 Reviews)	$94.99	15.5	Amazon Echo	NaN	NaN	NaN

In [16]:

```
missing_data.shape
```

Out[16]:

```
(242, 8)
```

In [17]:

```
missing_data.isna().sum()
```

Out[17]:

```
description      0
reviews          2
Price           14
discount         0
Brand            0
TV_Size         82
TV_Type         86
TV_Pixels      156
dtype: int64
```

In [18]:

```
tv_type_pattern = r'\b(\d+)(?=\s?(?:inch|inches)?)\b'
tv_pixels_pattern = r'(?i)\b\s*(4K|8K|1080p|720p|Ultra\s?HD)\s*\b'
```

In [19]:

```
missing_data.loc[missing_data['TV_Type'].isna(), 'TV_Type'] = missing_data.loc[m
issing_data['TV_Type'].isna(), 'description'].str.extract(tv_type_pattern)
missing_data['TV_Type'] = missing_data['TV_Type'].astype(float)
```

```
/tmp/ipykernel_21/3255014934.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pan
das-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-
copy
  missing_data['TV_Type'] = missing_data['TV_Type'].astype(float)
```

In [20]:

```
missing_tv_pixels = missing_data[missing_data['TV_Pixels'].isna()].copy()
missing_tv_pixels['TV_Pixels'] = missing_tv_pixels['description'].str.extract(tv
_pixels_pattern)
```

In [21]:

```
missing_tv_pixels.dropna(inplace=True)
```

In [22]:

```
missing_data.loc[missing_tv_pixels.index, 'TV_Pixels'] = missing_tv_pixels['TV_P
ixels']
```

In [23]:

```
missing_data.isna().sum()
```

Out[23]:

```
description     0
reviews         2
Price          14
discount        0
Brand           0
TV_Size        82
TV_Type        86
TV_Pixels      76
dtype: int64
```

In [24]:

```
missing_data.dropna(inplace=True)
```

```
/tmp/ipykernel_21/3061999497.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pan
das-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-
copy
  missing_data.dropna(inplace=True)
```

Preprocess the data

In [25]:

```
data['TV_Type'] = data['TV_Type'].combine_first(missing_data['TV_Type'])
```

In [26]:

```
data['TV_Pixels'] = data['TV_Pixels'].combine_first(missing_data['TV_Pixels'])
```

In [27]:

```
data.dropna(inplace=True)
```

In [28]:

```
data['Price'] = data['Price'].str.replace('[\$,]', '', regex=True).astype(float)
```

In [29]:

```
data['discount'] = data['discount'].str.replace('[\$,]', '', regex=True).astype
(float)
```

In [30]:

```
data['reviews'] = data['reviews'].str.replace(r'\D', '').astype(int)
```

```
/tmp/ipykernel_21/2700039186.py:1: FutureWarning: The default value
of regex will change from True to False in a future version.
  data['reviews'] = data['reviews'].str.replace(r'\D', '').astype(i
nt)
```

Visuals

In [31]:

```
pip install matplotlib seaborn
```

```
Requirement already satisfied: matplotlib in /opt/conda/lib/python
3.10/site-packages (3.7.1)
Requirement already satisfied: seaborn in /opt/conda/lib/python3.1
0/site-packages (0.12.2)
Requirement already satisfied: contourpy>=1.0.1 in /opt/conda/lib/p
ython3.10/site-packages (from matplotlib) (1.1.0)
Requirement already satisfied: cycler>=0.10 in /opt/conda/lib/pytho
n3.10/site-packages (from matplotlib) (0.11.0)
Requirement already satisfied: fonttools>=4.22.0 in /opt/conda/lib/
python3.10/site-packages (from matplotlib) (4.40.0)
Requirement already satisfied: kiwisolver>=1.0.1 in /opt/conda/lib/
python3.10/site-packages (from matplotlib) (1.4.4)
Requirement already satisfied: numpy>=1.20 in /opt/conda/lib/python
3.10/site-packages (from matplotlib) (1.23.5)
Requirement already satisfied: packaging>=20.0 in /opt/conda/lib/py
thon3.10/site-packages (from matplotlib) (21.3)
Requirement already satisfied: pillow>=6.2.0 in /opt/conda/lib/pyth
on3.10/site-packages (from matplotlib) (9.5.0)
Requirement already satisfied: pyparsing>=2.3.1 in /opt/conda/lib/p
ython3.10/site-packages (from matplotlib) (3.0.9)
Requirement already satisfied: python-dateutil>=2.7 in /opt/conda/l
ib/python3.10/site-packages (from matplotlib) (2.8.2)
Requirement already satisfied: pandas>=0.25 in /opt/conda/lib/pytho
n3.10/site-packages (from seaborn) (1.5.3)
Requirement already satisfied: pytz>=2020.1 in /opt/conda/lib/pytho
n3.10/site-packages (from pandas>=0.25->seaborn) (2023.3)
Requirement already satisfied: six>=1.5 in /opt/conda/lib/python3.1
0/site-packages (from python-dateutil>=2.7->matplotlib) (1.16.0)
Note: you may need to restart the kernel to use updated packages.
```

In [32]:

```
import seaborn as sns
import matplotlib.pyplot as plt
```

```
/opt/conda/lib/python3.10/site-packages/scipy/__init__.py:146: User
Warning: A NumPy version >=1.16.5 and <1.23.0 is required for this
version of SciPy (detected version 1.23.5
  warnings.warn(f"A NumPy version >={np_minversion} and <{np_maxver
sion}"
```

In [33]:

```
data.dtypes
```

Out[33]:

```
description     object
reviews          int64
Price          float64
discount       float64
Brand           object
TV_Size         object
TV_Type        float64
TV_Pixels       object
dtype: object
```

In [34]:

```
data.head(2)
```

Out[34]:

	description	reviews	Price	discount	Brand	TV_Size	TV_Type	TV_Pixels
2	Samsung 55 4K UHD HDR LED Tizen Smart TV (UN55...	40	599.99	15.5	Samsung	LED	55.0	4K
3	Samsung 43 4K UHD HDR LED Tizen Smart TV (UN43...	1015	399.99	12.2	Samsung	LED	43.0	4K

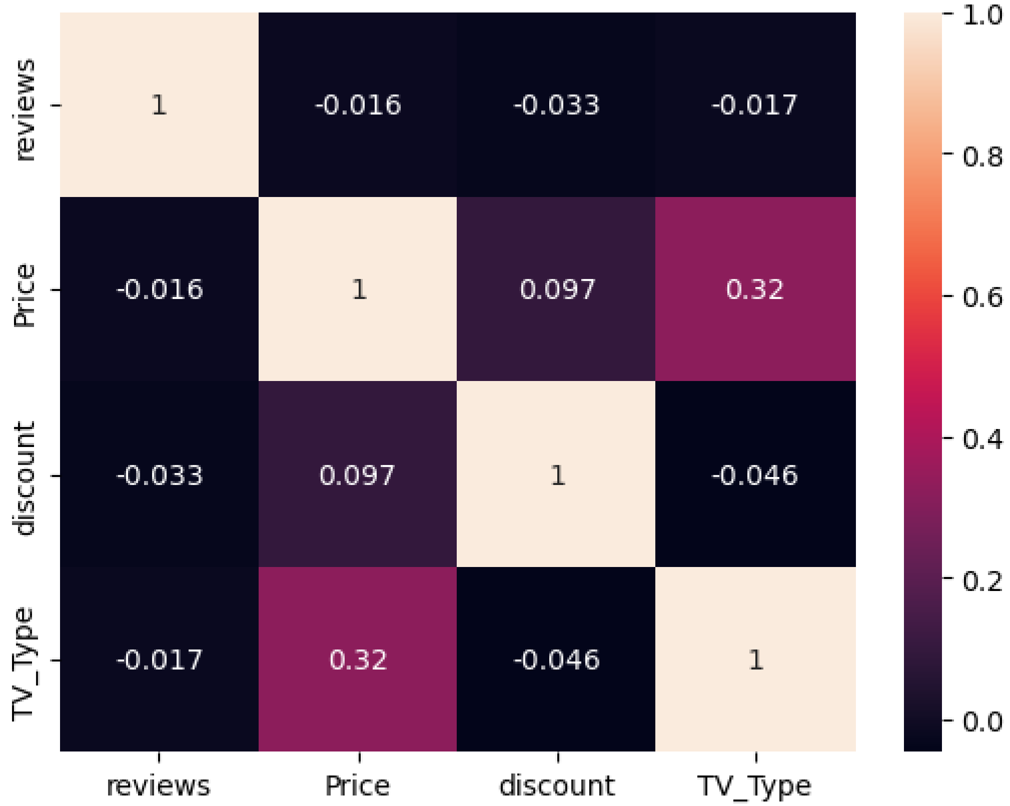
In [35]:

```
data['discount'] = data['discount'].astype(float)
data['TV_Type'] = data['TV_Type'].astype(float)
```

In [36]:

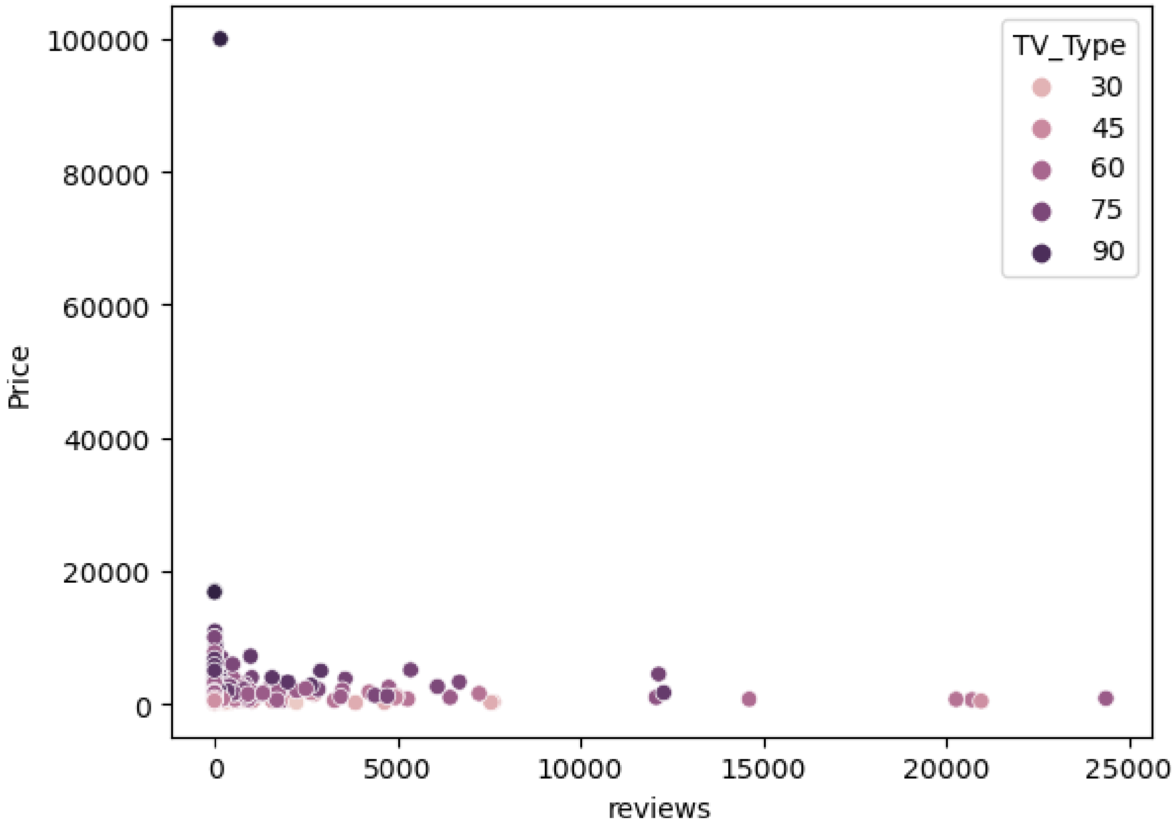
```
sns.heatmap(data.corr(), annot=True)
plt.show()
```

```
/tmp/ipykernel_21/104075714.py:1: FutureWarning: The default value
of numeric_only in DataFrame.corr is deprecated. In a future versio
n, it will default to False. Select only valid columns or specify t
he value of numeric_only to silence this warning.
  sns.heatmap(data.corr(), annot=True)
```



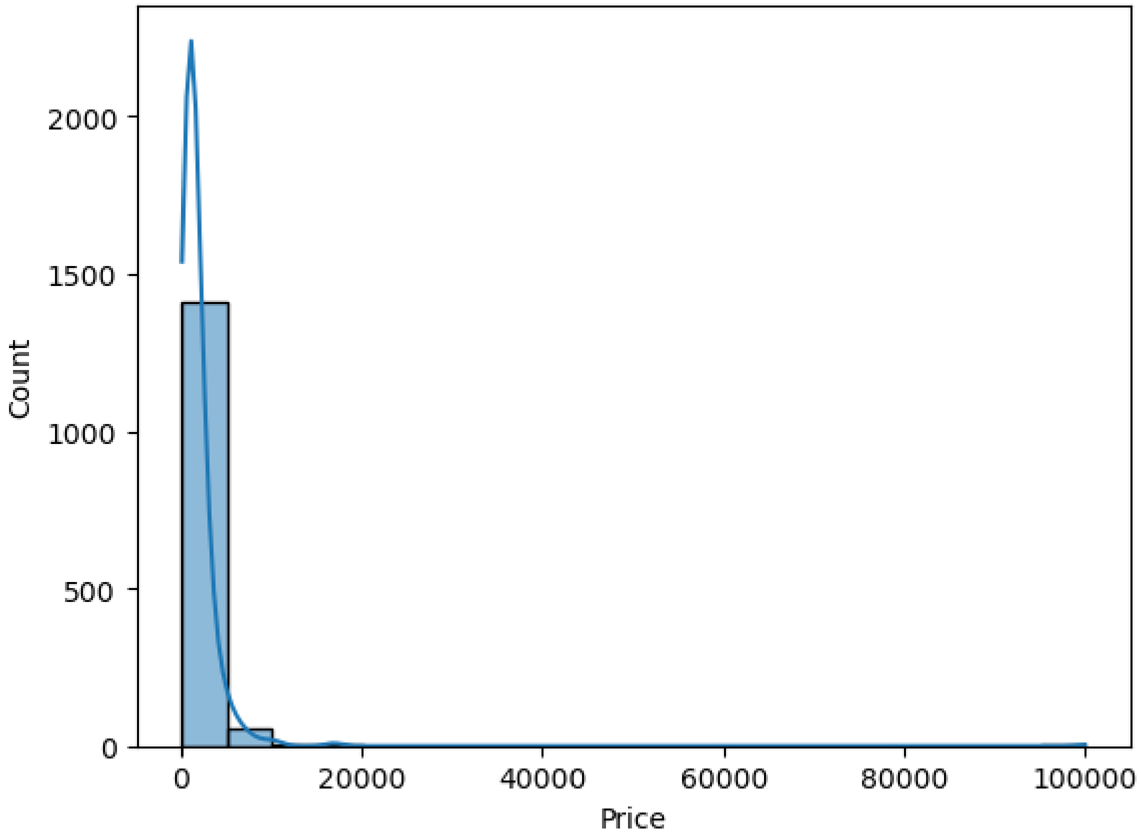
In [37]:

```
sns.scatterplot(x='reviews', y='Price', hue='TV_Type', data=data)
plt.show()
```



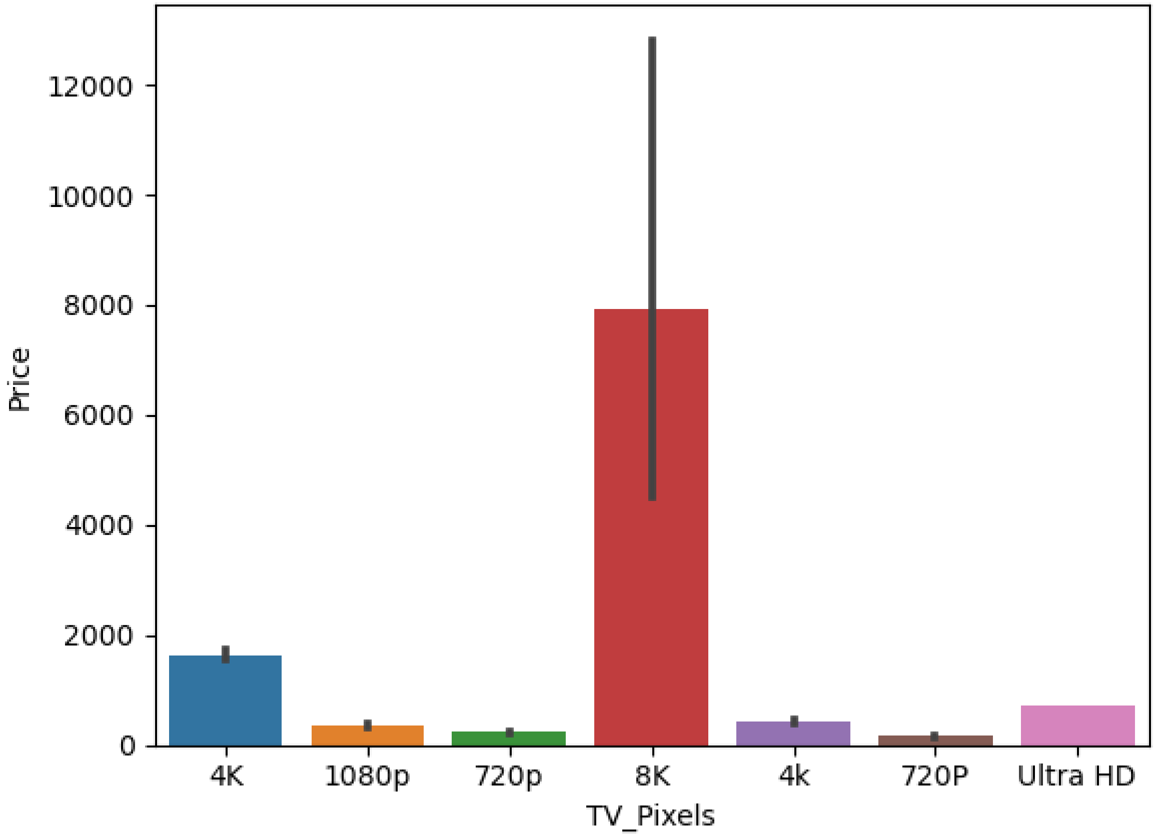
In [38]:

```
sns.histplot(data['Price'], bins=20, kde=True)
plt.show()
```



In [39]:

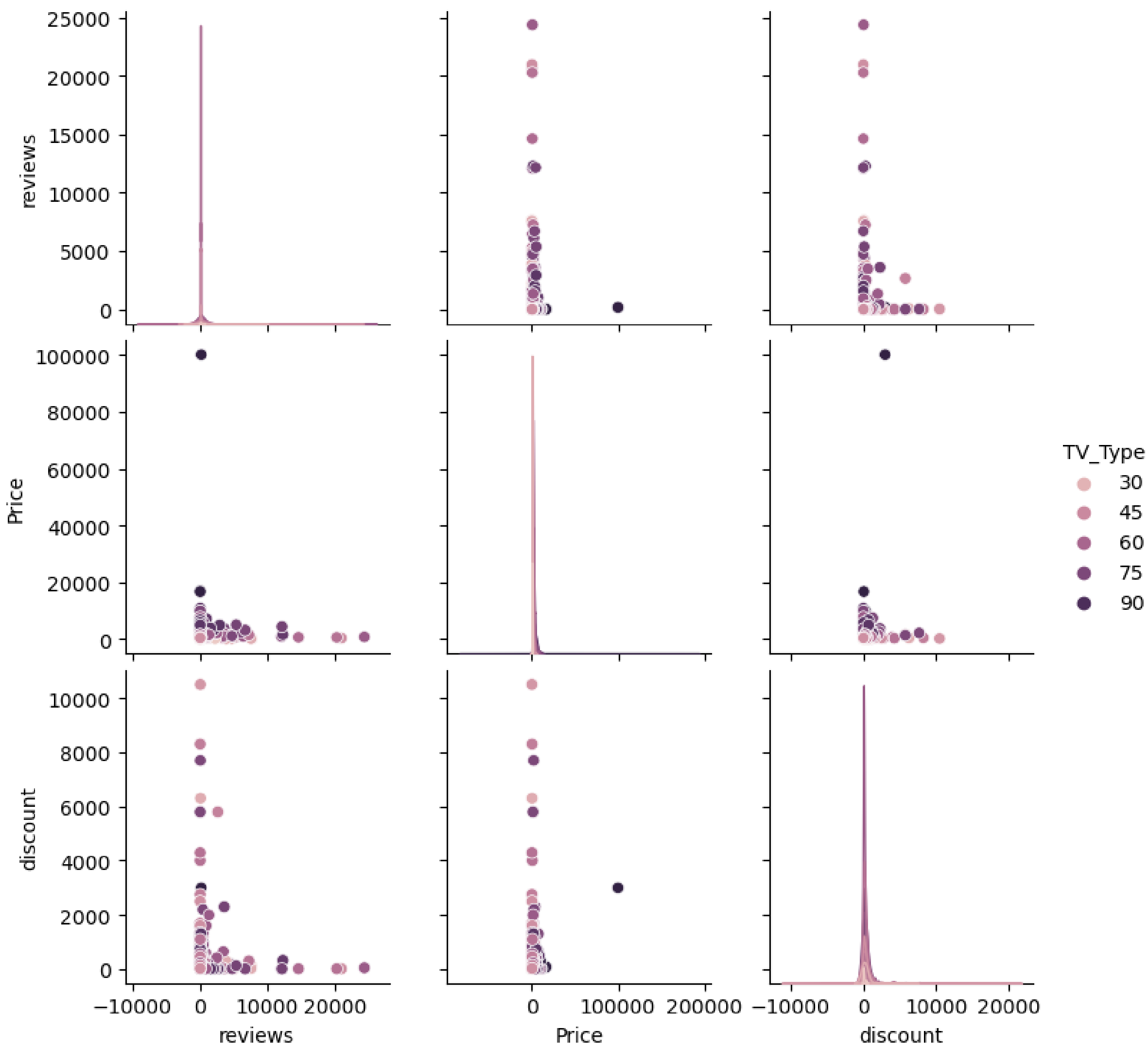
```
sns.barplot(x='TV_Pixels', y='Price', data=data)
plt.show()
```



In [40]:

```
sns.pairplot(data[['reviews', 'Price', 'discount', 'TV_Size', 'TV_Type']], diag_
kind='kde', markers='o', hue='TV_Type')
plt.show()
```

```
/opt/conda/lib/python3.10/site-packages/seaborn/axisgrid.py:118: Us
erWarning: The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```



Removing Outliers

In [41]:

```
rows_above_90k = data[data['Price'] > 90000]
print(rows_above_90k)
```

```
                                          description  reviews  
Price  \
162  Samsung 98 8K UHD HDR QLED Tizen Smart TV (QN9...      161   99
999.99
985  Samsung 98 8K UHD HDR QLED Tizen Smart TV (QN9...      161   99
999.99

     discount                 Brand TV_Size  TV_Type TV_Pixels
162    3000.0  Samsung                  LED     98.0        8K
985    3000.0  Samsung                  LED     98.0        8K
```

In [42]:

```
data = data.drop([162, 985])
```

In [43]:

```
data1 = data[['Price', 'TV_Type']]
```

In [44]:

```
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
```

In [45]:

```
scaler = StandardScaler()
scaled_features = scaler.fit_transform(data1)
```

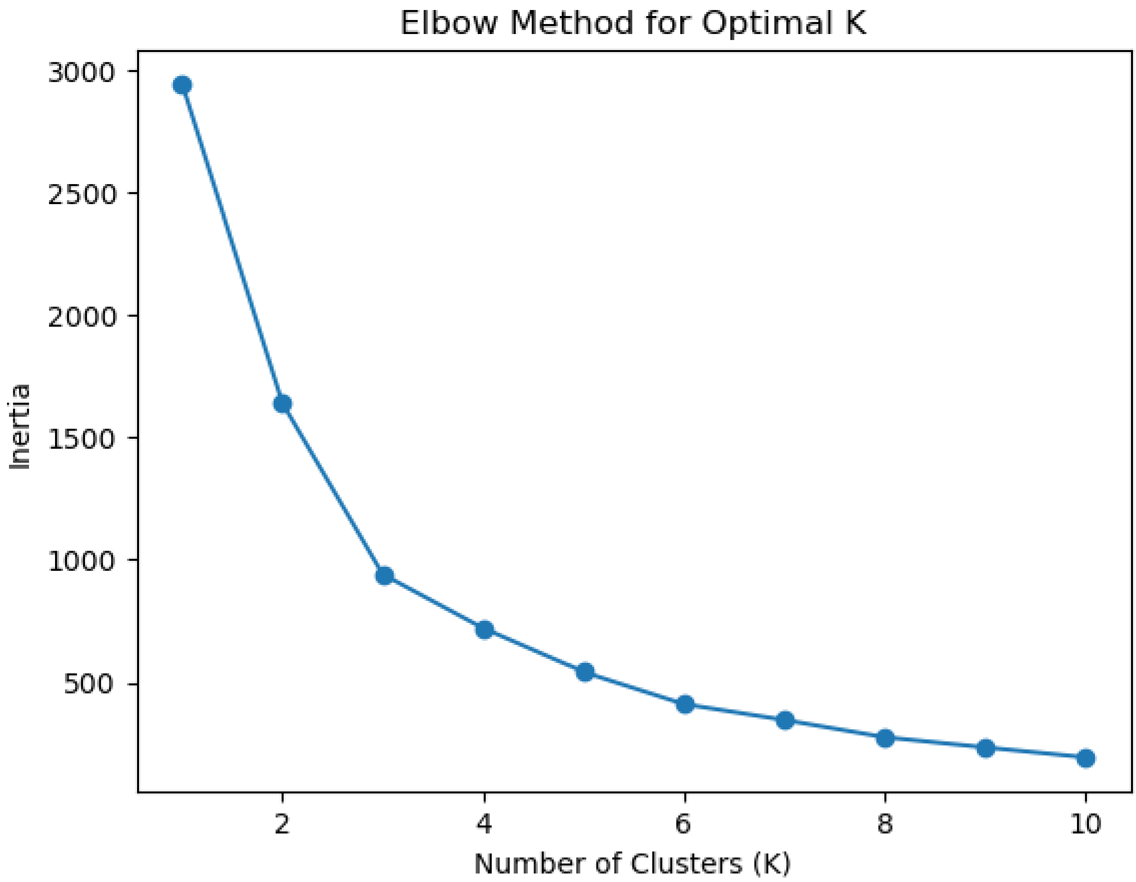
In [46]:

```
# Determine the optimal number of clusters using the elbow method
inertia = []
for k in range(1, 11):
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(scaled_features)
    inertia.append(kmeans.inertia_)

# Plot the elbow curve to find the optimal number of clusters
plt.plot(range(1, 11), inertia, marker='o')
plt.xlabel('Number of Clusters (K)')
plt.ylabel('Inertia')
plt.title('Elbow Method for Optimal K')
plt.show()
```

```
/opt/conda/lib/python3.10/site-packages/sklearn/cluster/_kmeans.py:
870: FutureWarning: The default value of `n_init` will change from
10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppre
ss the warning
  warnings.warn(
/opt/conda/lib/python3.10/site-packages/sklearn/cluster/_kmeans.py:
870: FutureWarning: The default value of `n_init` will change from
10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppre
ss the warning
  warnings.warn(
/opt/conda/lib/python3.10/site-packages/sklearn/cluster/_kmeans.py:
870: FutureWarning: The default value of `n_init` will change from
10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppre
ss the warning
  warnings.warn(
/opt/conda/lib/python3.10/site-packages/sklearn/cluster/_kmeans.py:
870: FutureWarning: The default value of `n_init` will change from
10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppre
ss the warning
  warnings.warn(
/opt/conda/lib/python3.10/site-packages/sklearn/cluster/_kmeans.py:
870: FutureWarning: The default value of `n_init` will change from
10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppre
ss the warning
  warnings.warn(
/opt/conda/lib/python3.10/site-packages/sklearn/cluster/_kmeans.py:
870: FutureWarning: The default value of `n_init` will change from
10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppre
ss the warning
  warnings.warn(
/opt/conda/lib/python3.10/site-packages/sklearn/cluster/_kmeans.py:
870: FutureWarning: The default value of `n_init` will change from
10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppre
ss the warning
  warnings.warn(
/opt/conda/lib/python3.10/site-packages/sklearn/cluster/_kmeans.py:
870: FutureWarning: The default value of `n_init` will change from
10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppre
ss the warning
  warnings.warn(
/opt/conda/lib/python3.10/site-packages/sklearn/cluster/_kmeans.py:
870: FutureWarning: The default value of `n_init` will change from
10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppre
```

```
ss the warning
  warnings.warn(
/opt/conda/lib/python3.10/site-packages/sklearn/cluster/_kmeans.py:
870: FutureWarning: The default value of `n_init` will change from
10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppre
ss the warning
  warnings.warn(
```



In [47]:

```
# From the elbow plot, choose the number of clusters (K) and perform K-means clust
ering
k = 6  # Choose the optimal K from the elbow plot
kmeans = KMeans(n_clusters=k, random_state=42)
kmeans.fit(scaled_features)
```

```
/opt/conda/lib/python3.10/site-packages/sklearn/cluster/_kmeans.py:
870: FutureWarning: The default value of `n_init` will change from
10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppre
ss the warning
  warnings.warn(
```

Out[47]:

```
▾ KMeans
KMeans(n_clusters=6, random_state=42)
```

In [48]:

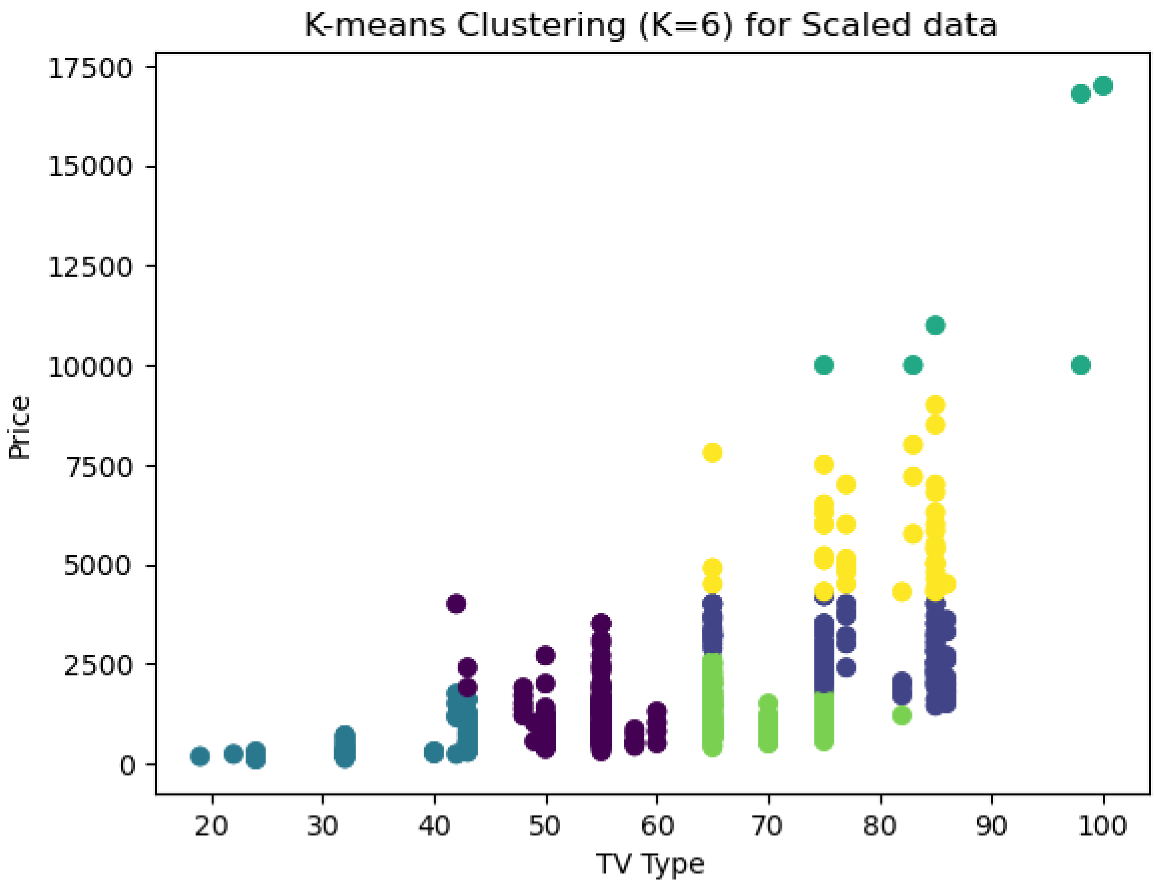
```
data1['Cluster'] = kmeans.labels_
data['Cluster'] = kmeans.labels_
```

```
/tmp/ipykernel_21/4071563275.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pan
das-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-
copy
  data1['Cluster'] = kmeans.labels_
```

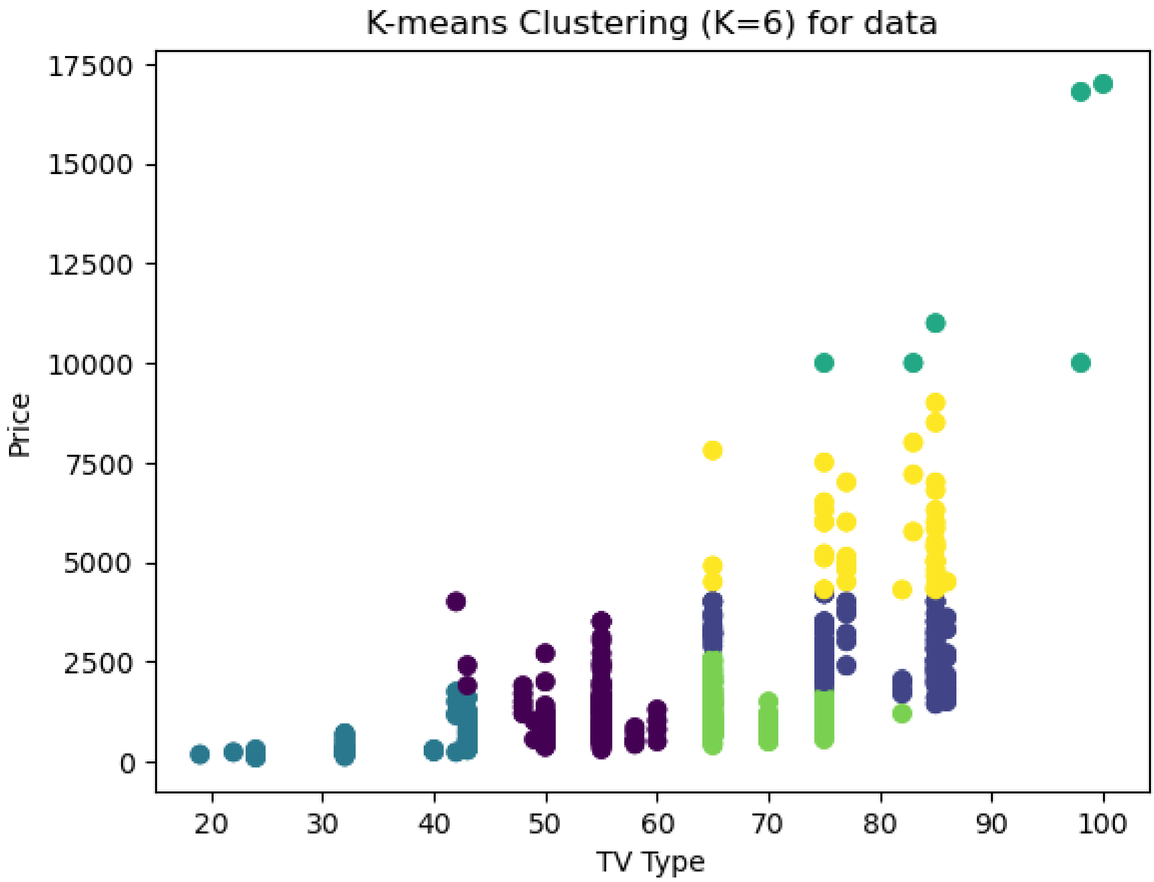
In [49]:

```
plt.scatter(data1['TV_Type'], data1['Price'], c=data1['Cluster'], cmap='viridi
s')
plt.xlabel('TV Type')
plt.ylabel('Price')
plt.title(f'K-means Clustering (K={k}) for Scaled data')
plt.show()
```



In [50]:

```
plt.scatter(data['TV_Type'], data['Price'], c=data['Cluster'], cmap='viridis')
plt.xlabel('TV Type')
plt.ylabel('Price')
plt.title(f'K-means Clustering (K={k}) for data')
plt.show()
```

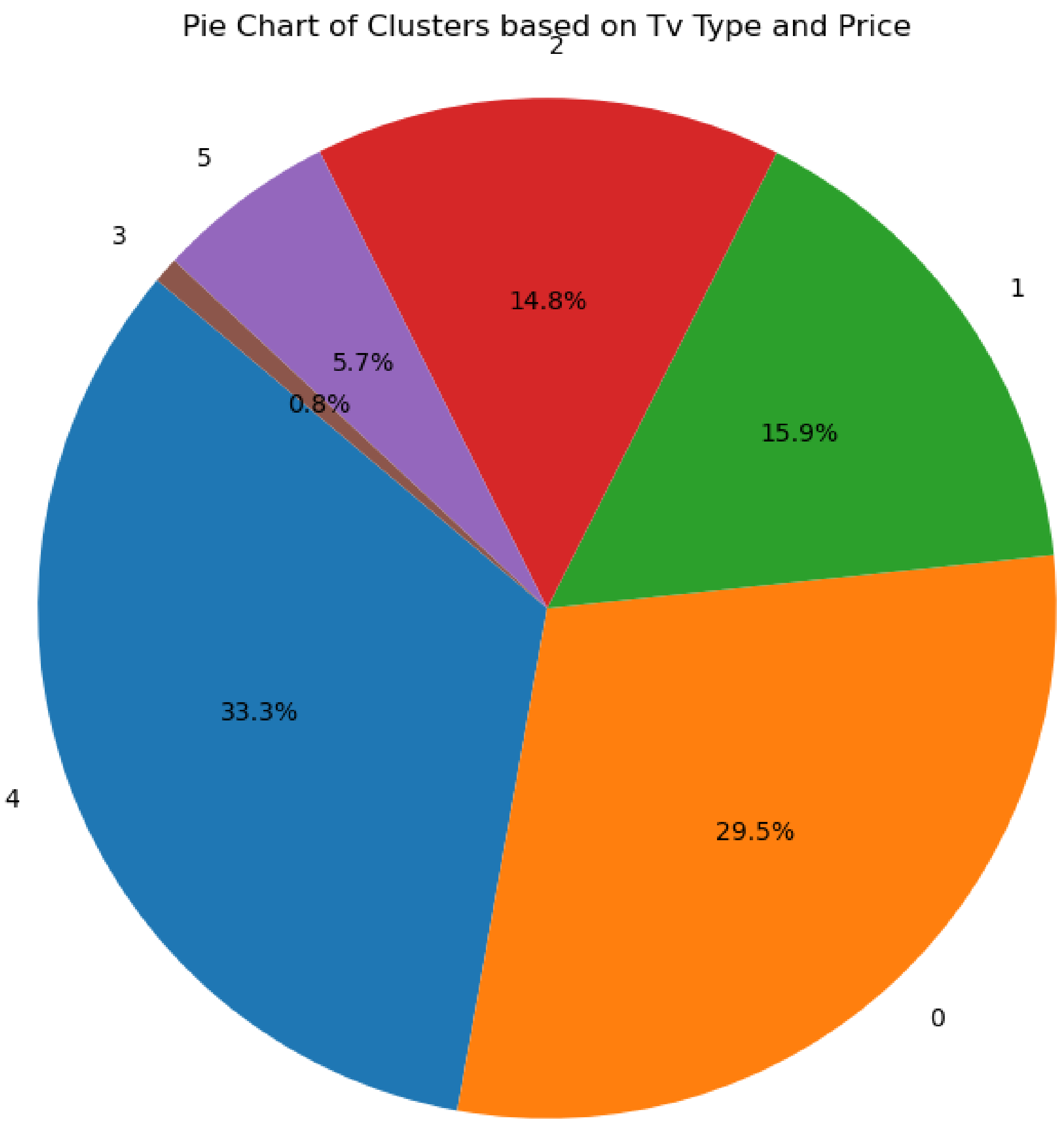


Cluster Depiction

In [51]:

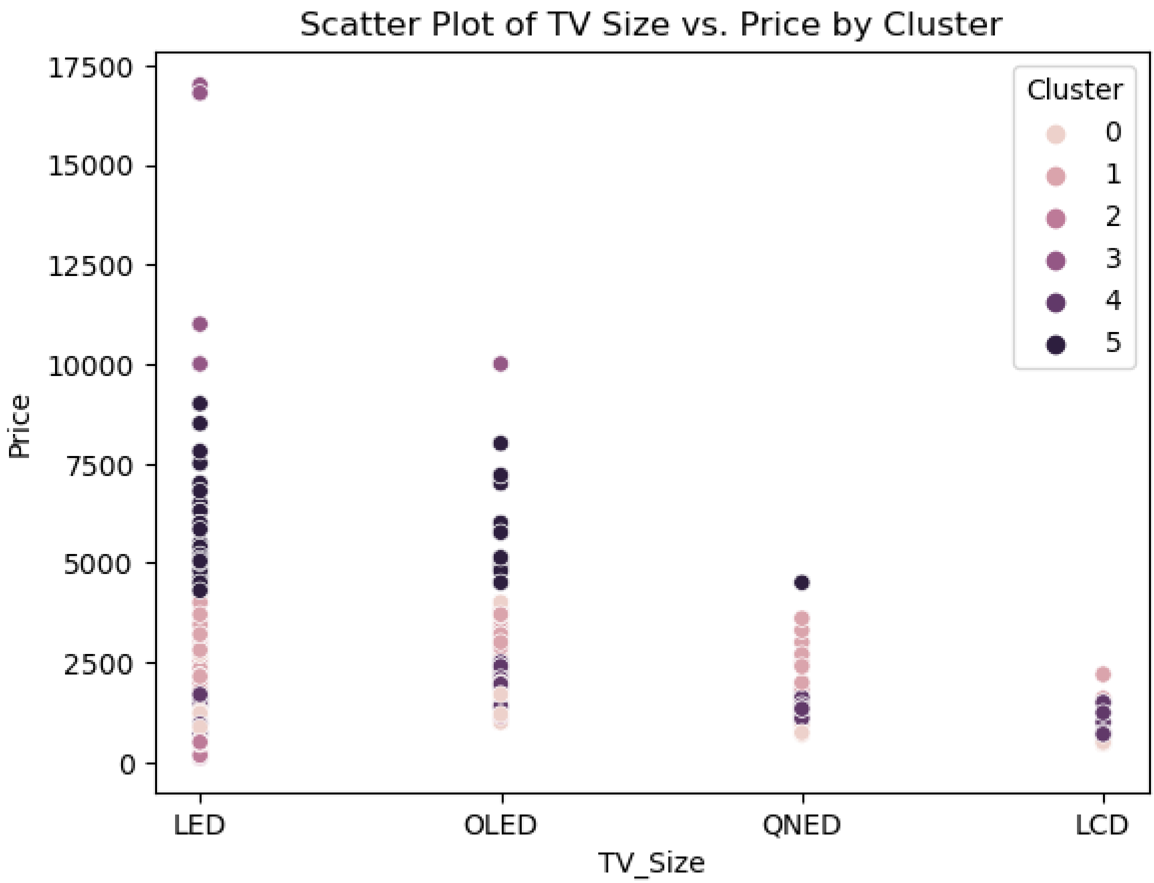
```
count = data['Cluster'].value_counts()

plt.figure(figsize=(8, 8))
plt.pie(count, labels=count.index, autopct='%1.1f%%', startangle=140)
plt.title(f'Pie Chart of Clusters based on Tv Type and Price')
plt.axis('equal')
plt.show()
```



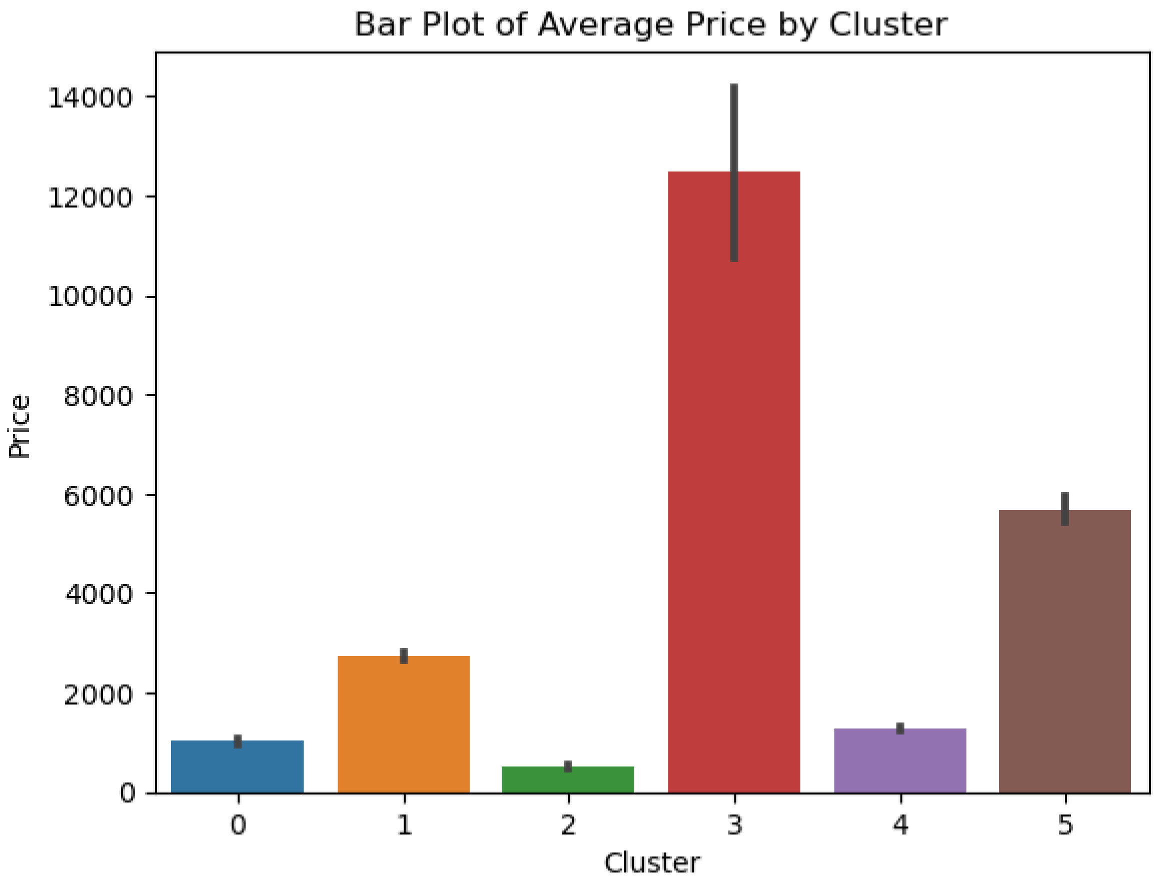
In [52]:

```
sns.scatterplot(data=data, x='TV_Size', y='Price', hue='Cluster')
plt.title('Scatter Plot of TV Size vs. Price by Cluster')
plt.show()
```



In [53]:

```
sns.barplot(data=data, x='Cluster', y='Price')
plt.title('Bar Plot of Average Price by Cluster')
plt.show()
```



In [54]:

```
from sklearn.tree import DecisionTreeRegressor
from sklearn.model_selection import train_test_split
```

In [55]:

```
data.head()
```

Out[55]:

	description	reviews	Price	discount	Brand	TV_Size	TV_Type	TV_Pixels	Clus
2	Samsung 55 4K UHD HDR LED Tizen Smart TV (UN55...	40	599.99	15.5	Samsung	LED	55.0	4K	0
3	Samsung 43 4K UHD HDR LED Tizen Smart TV (UN43...	1015	399.99	12.2	Samsung	LED	43.0	4K	2
4	Samsung The Frame 65 4K UHD HDR QLED Tizen Sma...	418	2299.99	400.0	Samsung	LED	65.0	4K	4
6	Samsung 65 4K UHD HDR LED Tizen Smart TV (UN65...	24374	849.99	50.0	Samsung	LED	65.0	4K	4
7	Samsung 55 4K UHD HDR LED Tizen Smart TV (UN55...	157	699.99	15.5	Samsung	LED	55.0	4K	0

In [56]:

```
data.Brand.unique()
```

Out[56]:

```
array(['Samsung                 ', 'Sony                    ',
       'LG                      ', 'Toshiba                 ',
       'NA                      ', 'Hisense                 ',
       'Amazon fire TV          ', 'Insignia                ',
       'TCL 75                  ', 'VIZIO                   ',
       'Philips 75              ', 'TCL 6Series 65          ',
       'RCA 32                  ', 'JVC 58                  '], dtype=objec
t)
```

In [57]:

```
pixel_map = {
    '4K': 0,
    '1080p': 1,
    '720p': 2,
    '8K': 3,
    '4k': 4,
    '720P': 5,
    'Ultra HD': 6
}
data['TV_Pixels'] = data['TV_Pixels'].map(pixel_map)
```

In [58]:

```
brand_map = {
    'Samsung                ': 0,
    'Sony                   ': 1,
    'LG                     ': 2,
    'Toshiba                ': 3,
    'NA                     ': 4,
    'Hisense                ': 5,
    'Amazon fire TV         ': 6,
    'Insignia               ': 7,
    'TCL 75                 ': 8,
    'VIZIO                  ': 9,
    'Philips 75             ': 10,
    'TCL 6Series 65         ': 11,
    'RCA 32                 ': 12,
    'JVC 58                 ': 13
}

data['Brand'] = data['Brand'].map(brand_map)
```

In [59]:

```
X = data[['TV_Type','TV_Pixels','Brand']]
y = data['Price']
```

In [60]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_
state=42)
```

In [61]:

```
decision_tree = DecisionTreeRegressor(random_state=42)
decision_tree.fit(X_train, y_train)
```

Out[61]:

```
▾ DecisionTreeRegressor
DecisionTreeRegressor(random_state=42)
```

In [62]:

```
y_pred = decision_tree.predict(X_test)
```

In [63]:

```
from sklearn.metrics import r2_score
accuracy = r2_score(y_test, y_pred)
print(accuracy)
```

```
0.8013344372542037
```

type , pixels → 0.7945 type, brand → 0.719 type, brand, pixel → 0.795

Model using Scaled Features

In [64]:

```
X1 = data1[['TV_Type','Cluster']]
y1 = data1['Price']
```

In [65]:

```
X_train1, X_test1, y_train1, y_test1 = train_test_split(X1, y1, test_size=0.2, r
andom_state=42)
```

In [66]:

```
decision_tree1 = DecisionTreeRegressor(random_state=42)
decision_tree1.fit(X_train1, y_train1)
```

Out[66]:

```
▾ DecisionTreeRegressor
DecisionTreeRegressor(random_state=42)
```

In [67]:

```
y_pred1 = decision_tree1.predict(X_test1)
```

In [68]:

```
accuracy = r2_score(y_test1, y_pred1)
print(accuracy)
```

```
0.8817377335279933
```

Perform Cross Validation

In [69]:

```
from sklearn.model_selection import cross_val_score
```

In [70]:

```
cv_scores = cross_val_score(decision_tree, X, y, cv=5)
cv_scores1 = cross_val_score(decision_tree1, X1, y1, cv=5)
```

In [71]:

```
print("Cross-Validation Scores for non clustered data:", cv_scores)
print("Mean Accuracy for non clustered data:", cv_scores.mean())
```

```
Cross-Validation Scores for non clustered data: [0.82442163 0.58753
821 0.69495793 0.79989258 0.6015048 ]
Mean Accuracy for non clustered data: 0.7016630316636171
```

In [72]:

```
print("Cross-Validation Scores for clustered data:", cv_scores1)
print("Mean Accuracy for clustered data:", cv_scores1.mean())
```

```
Cross-Validation Scores for clustered data: [0.90391703 0.84848763
0.80955516 0.90949148 0.85283509]
Mean Accuracy for clustered data: 0.8648572778491521
```

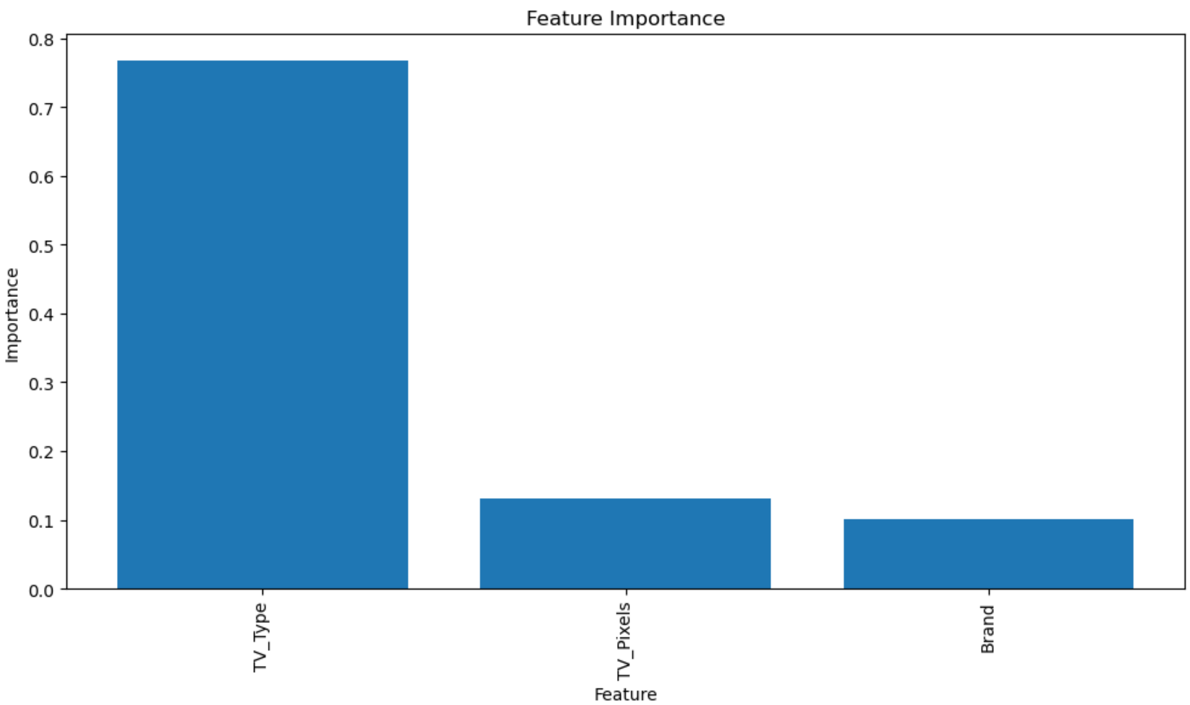
In [73]:

```
feature_importance = decision_tree.feature_importances_

# Create a DataFrame to store the feature importances and their corresponding colu
mn names
importance_df = pd.DataFrame({'Feature': X.columns, 'Importance': feature_import
ance})

# Sort the DataFrame in descending order of feature importance
importance_df = importance_df.sort_values(by='Importance', ascending=False)

# Plot the feature importances using a bar chart
plt.figure(figsize=(10, 6))
plt.bar(importance_df['Feature'], importance_df['Importance'])
plt.xlabel('Feature')
plt.ylabel('Importance')
plt.title('Feature Importance')
plt.xticks(rotation=90)
plt.tight_layout()
plt.show()
```



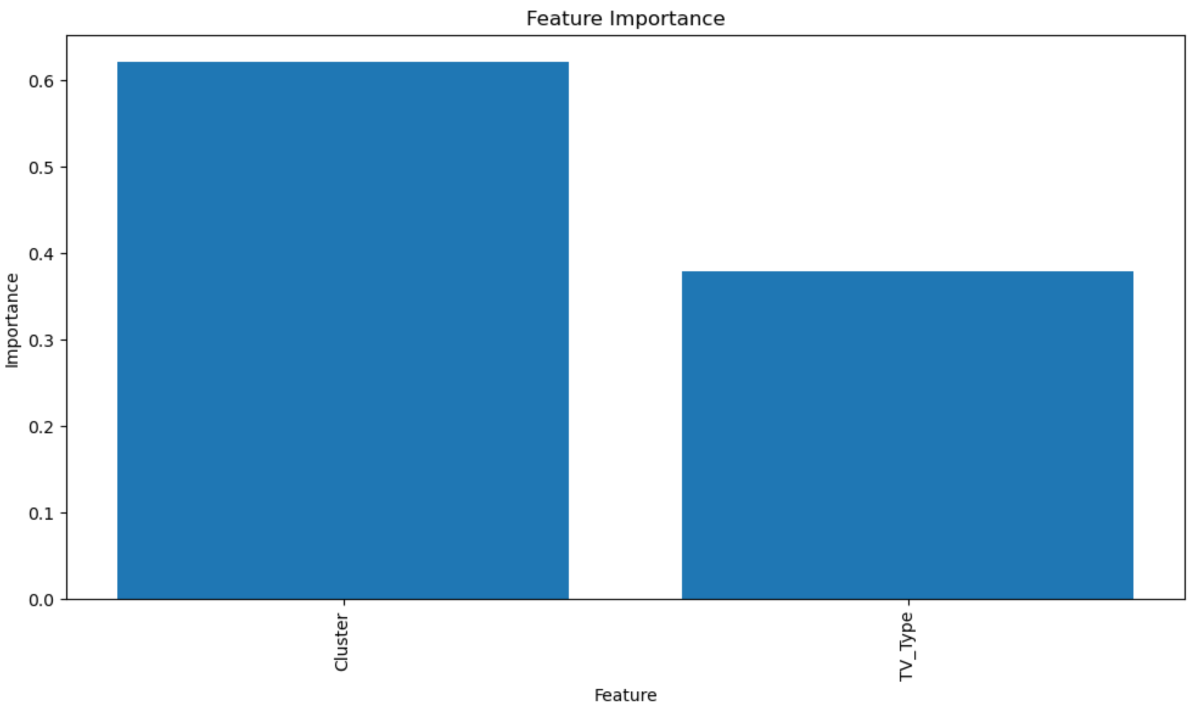
In [74]:

```
feature_importance = decision_tree1.feature_importances_

# Create a DataFrame to store the feature importances and their corresponding colu
mn names
importance_df = pd.DataFrame({'Feature': X1.columns, 'Importance': feature_impor
tance})

# Sort the DataFrame in descending order of feature importance
importance_df = importance_df.sort_values(by='Importance', ascending=False)

# Plot the feature importances using a bar chart
plt.figure(figsize=(10, 6))
plt.bar(importance_df['Feature'], importance_df['Importance'])
plt.xlabel('Feature')
plt.ylabel('Importance')
plt.title('Feature Importance')
plt.xticks(rotation=90)
plt.tight_layout()
plt.show()
```



By Applying Cluster from data1 and applying it to data

In [75]:

```
X12 = data[['TV_Type','TV_Pixels','Brand','Cluster']]
y12 = data['Price']
X_train12, X_test12, y_train12, y_test12 = train_test_split(X12, y12, test_size=
0.2, random_state=42)
decision_tree12 = DecisionTreeRegressor(random_state=42)
decision_tree12.fit(X_train12, y_train12)
y_pred12 = decision_tree12.predict(X_test12)
accuracy = r2_score(y_test12, y_pred12)
print(accuracy)
```

```
0.9061104595068785
```

In [76]:

```
cv_scores12 = cross_val_score(decision_tree12, X12, y12, cv=5)
print(cv_scores12.mean())
```

```
0.8892904955770801
```

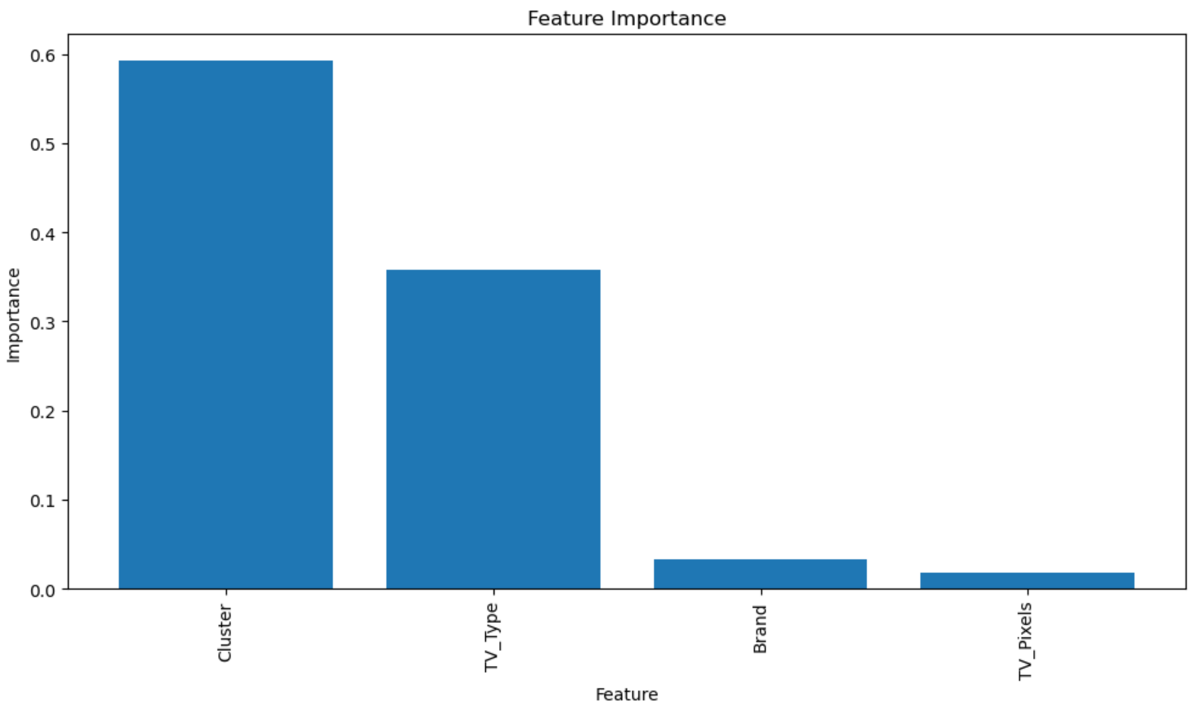
In [77]:

```
feature_importance = decision_tree12.feature_importances_

# Create a DataFrame to store the feature importances and their corresponding colu
mn names
importance_df = pd.DataFrame({'Feature': X12.columns, 'Importance': feature_impo
rtance})

# Sort the DataFrame in descending order of feature importance
importance_df = importance_df.sort_values(by='Importance', ascending=False)

# Plot the feature importances using a bar chart
plt.figure(figsize=(10, 6))
plt.bar(importance_df['Feature'], importance_df['Importance'])
plt.xlabel('Feature')
plt.ylabel('Importance')
plt.title('Feature Importance')
plt.xticks(rotation=90)
plt.tight_layout()
plt.show()
```



This is the best method to predict the Price.

In [78]:

```
import joblib
model_filename = 'decision_tree_model.joblib'
joblib.dump(decision_tree12, model_filename)
```

Out[78]:

```
['decision_tree_model.joblib']
```

Input: 'TV_Type','TV_Pixels','Brand','Cluster' Output: Price model name: ['decision_tree_model.joblib']

For real time purpose, the other model without cluster is suggested, With Input: 'TV_Type','TV_Pixels','Brand' Output:Price model name: prediction.joblib

In [79]:

```
model_filename = 'prediction.joblib'
joblib.dump(decision_tree, model_filename)
```

Out[79]:

```
['prediction.joblib']
```

In [ ]:

```

```