The aim of this data analysis is twofold: first, to develop a model that can accurately forecast property prices in Beijing, China, and secondly, to construct a model that categorizes properties as either underpriced or overpriced relative to their original listing price.

1. Initially, the focus is on cleaning and preprocessing the data, followed by constructing a regression model capable of predicting property prices based on various property features.
2. Moving on to the second phase of the analysis, K-means clustering is utilized to group properties according to their features. Subsequently, each cluster is examined to identify properties that significantly deviate from the cluster's average price, thereby identifying underpriced and overpriced properties.

In [1]:
```
# Loading the necessary libraries
import re
import folium
import numpy as np
import pandas as pd
import seaborn as sns
import lightgbm as lgb
from gower import gower_matrix
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, silhouette_score, r2_score
```

Data Dictionary:

1. url: the url which fetches the data
2. id: the id of transaction
3. Lng: Longitudes
4. Lat: Latitudes
5. Cid: community id
6. tradeTime: the time of transaction
7. DOM: active days on market
8. followers: the number of people following the transaction.
9. totalPrice: the total price
10. price: the average price by square
11. square: the total area of the house
12. livingRoom: the number of living rooms
13. drawingRoom: the number of drawing rooms
14. kitchen: the number of kitchen
15. bathroom: the number of bathrooms
16. floor: the height of the house
17. buildingType: including tower(1) , bungalow(2), combination of plate and tower(3), plate(4).
18. constructionTime: the time of construction
19. renovationCondition: including other(1), rough(2),Simplicity(3), hardcover(4)

20. buildingStructure: including unknow(1), mixed(2), brick and wood(3), brick and concrete(4),steel(5) and steel-concrete composite (6).
21. ladderRatio: the proportion between number of residents on the same floor and number of elevator of ladder. It describes how many ladders a resident have on average.
22. elevator have (1) or not have elevator(0)
23. fiveYearsProperty: if the owner have the property for less than 5 years

In [2]:

```
# Setting the seed and Loading the dataset
np.random.seed(99)
df = pd.read_csv(r'C:\Users\himan\OneDrive\Desktop\Beijing_Housing.csv', encod
df
```

```
C:\Users\himan\AppData\Local\Temp\ipykernel_20144\1512002212.py:3: DtypeWarn
ing: Columns (1,11,12,14) have mixed types. Specify dtype option on import o
r set low_memory=False.
  df = pd.read_csv(r'C:\Users\himan\OneDrive\Desktop\Beijing_Housing.csv', e
ncoding='ISO-8859-1')
```

Out[2]:

	url	id	Lng	Lat	
0	https://bj.lianjia.com/chengjiao/101084782030....	101084782030	116.475489	40.019520	1111(
1	https://bj.lianjia.com/chengjiao/101086012217....	101086012217	116.453917	39.881534	1111(
2	https://bj.lianjia.com/chengjiao/101086041636....	101086041636	116.561978	39.877145	1111(
3	https://bj.lianjia.com/chengjiao/101086406841....	101086406841	116.438010	40.076114	1111(
4	https://bj.lianjia.com/chengjiao/101086920653....	101086920653	116.428392	39.886229	1111(
...	...	...	...	...	
160869	https://bj.lianjia.com/chengjiao/BJYZ92299606....	BJYZ92299606	116.550348	39.755625	1111(
160870	https://bj.lianjia.com/chengjiao/BJYZ92303482....	BJYZ92303482	116.546899	39.755236	1111(
160871	https://bj.lianjia.com/chengjiao/BJYZ92311192....	BJYZ92311192	116.546899	39.755236	1111(
160872	https://bj.lianjia.com/chengjiao/BJYZ92324217....	BJYZ92324217	116.497256	39.804081	1111(
160873	https://bj.lianjia.com/chengjiao/BJYZ92363553....	BJYZ92363553	116.497474	39.810115	1111(

160874 rows × 26 columns

Data Preprocessing:

1. Some columns have been dropped as they aren't important in the analysis.

2. As the total null values in the dataset are only ~1%, those rows have been dropped from the dataset.
3. The column 'floor' had unrecognizable non-numeric characters along with numeric characters. The numeric characters have been extracted and the non-numeric characters deleted.
4. Some other columns that had numbers as strings have been converted to integer types for building the regression model later on.
5. The column 'tradeTime' was in string format. It was converted to a date type and then year, month and day have been extracted as new columns from it as integer types.
6. Some Variables that are categorical, their type has been defined as 'category' for building

In [3]:
```
columnsToDrop = ['url','id','Cid','price']
df = df.drop(columns=columnsToDrop)
nullValuesPercent = round((df.isnull().sum()/len(df))*100,2)
print(f'percentage of null values by column: \n{nullValuesPercent}')
```

```
percentage of null values by column:
Lng                    0.00
Lat                    0.00
tradeTime              0.00
DOM                    0.00
followers              0.00
totalPrice             0.00
square                 0.00
livingRoom             0.00
drawingRoom            0.00
kitchen                0.00
bathRoom               0.00
floor                  0.00
buildingType           0.82
constructionTime       0.00
renovationCondition    0.00
buildingStructure      0.00
ladderRatio            0.00
elevator               0.02
fiveYearsProperty      0.02
subway                 0.02
district               0.00
communityAverage       0.13
dtype: float64
```

In [4]:
```
df.dropna(inplace=True)
df.shape
```

Out[4]:
```
(159376, 22)
```

In [5]:
```
cols = ['tradeTime','livingRoom','drawingRoom','bathRoom','floor','constructio
for col in cols:
    print(f'{col}:{df[col].unique()}')
```

```
tradeTime:['2016-08-09' '2016-07-28' '2016-12-11' ... '2014-06-02' '2014-08-
04'
 '2014-05-01']
livingRoom:[2 3 1 4 5 6 0 7 '3' '1' '4' '2' '7' '5' '0' '6']
drawingRoom:[1 2 0 4 3 '1' '2' '3' '0' '4' '5']
bathRoom:[1 2 3 0 4 5 6 '2' '1' '0' '3' '4' '6' '5']
floor:['Â¸Ã\x9f 26' 'Â¸Ã\x9f 22' 'Ã\x96Ã\x90 4' 'ÂµÃ\x97 21' 'Ã\x96Ã\x90 6'
 'Ã\x96Ã\x90 8' 'Â¸Ã\x9f 6' 'Â¸Ã\x9f 10' 'Ã\x96Ã\x90 23' 'ÂµÃ\x97 11'
 'Â¸Ã\x9f 24' 'ÂµÃ\x8d 23' 'Ã\x96Ã\x90 19' 'Â¸Ã\x9f 18' 'ÂµÃ\x8d 25'
 'Ã\x96Ã\x90 12' 'Ã\x96Ã\x90 14' 'Ã\x96Ã\x90 30' 'Ã\x96Ã\x90 27'
 'Ã\x96Ã\x90 5' 'ÂµÃ\x8d 18' 'ÂµÃ\x97 28' 'Ã\x96Ã\x90 11' 'ÂµÃ\x8d 9'
 'Â¶Â¥ 7' 'Â¶Â¥ 27' 'ÂµÃ\x8d 6' 'Ã\x96Ã\x90 17' 'Â¶Â¥ 6' 'Ã\x96Ã\x90 24'
 'Ã\x96Ã\x90 15' 'ÂµÃ\x97 5' 'Ã\x96Ã\x90 29' 'Â¶Â¥ 19' 'Â¶Â¥ 5'
 'Ã\x96Ã\x90 9' 'ÂµÃ\x8d 22' 'Â¶Â¥ 18' 'ÂµÃ\x8d 16' 'Â¸Ã\x9f 13'
 'Â¸Ã\x9f 9' 'Â¸Ã\x9f 17' 'ÂµÃ\x97 6' 'Ã\x96Ã\x90 28' 'ÂµÃ\x8d 26'
 'ÂµÃ\x97 15' 'Â¸Ã\x9f 16' 'ÂµÃ\x8d 7' 'Ã\x96Ã\x90 13' 'ÂµÃ\x8d 33'
 'ÂµÃ\x97 14' 'Â¸Ã\x9f 15' 'Â¶Â¥ 11' 'Ã\x96Ã\x90 32' 'Â¶Â¥ 16'
 'ÂµÃ\x97 18' 'Â¶Â¥ 17' 'ÂµÃ\x8d 14' 'ÂµÃ\x8d 10' 'ÂµÃ\x97 20'
 'Â¸Ã\x9f 12' 'ÂµÃ\x8d 31' 'ÂµÃ\x97 4' 'ÂµÃ\x97 2' 'ÂµÃ\x8d 30'
 'ÂµÃ\x8d 19' 'ÂµÃ\x8d 12' 'Ã\x96Ã\x90 10' 'Ã\x96Ã\x90 16' 'Â¶Â¥ 20'
 'ÂµÃ\x97 19' 'Ã\x96Ã\x90 31' 'ÂµÃ\x8d 13' 'ÂµÃ\x97 10' 'Â¸Ã\x9f 25'
 'Ã\x96Ã\x90 21' 'Ã\x96Ã\x90 20' 'Â¸Ã\x9f 20' 'ÂµÃ\x8d 21' 'ÂµÃ\x8d 24'
 'Â¶Â¥ 4' 'Â¸Ã\x9f 21' 'Â¸Ã\x9f 7' 'Ã\x96Ã\x90 22' 'Ã\x96Ã\x90 7'
 'ÂµÃ\x97 8' 'Â¶Â¥ 15' 'Ã\x96Ã\x90 18' 'Â¸Ã\x9f 28' 'Â¶Â¥ 14' 'Â¶Â¥ 13'
 'ÂµÃ\x8d 20' 'ÂµÃ\x97 26' 'ÂµÃ\x8d 17' 'Â¶Â¥ 24' 'ÂµÃ\x97 23' 'Â¶Â¥ 21'
 'ÂµÃ\x97 24' 'Â¸Ã\x9f 30' 'Â¸Ã\x9f 11' 'ÂµÃ\x97 25' 'Â¸Ã\x9f 27'
 'ÂµÃ\x97 9' 'ÂµÃ\x8d 11' 'ÂµÃ\x8d 28' 'ÂµÃ\x8d 15' 'Â¶Â¥ 26' 'ÂµÃ\x8d 34'
 'Â¶Â¥ 12' 'Ã\x96Ã\x90 25' 'ÂµÃ\x97 17' 'Â¸Ã\x9f 32' 'Â¸Ã\x9f 8' 'Â¶Â¥ 3'
 'Â¸Ã\x9f 19' 'ÂµÃ\x97 7' 'Â¶Â¥ 28' 'Â¶Â¥ 9' 'Â¸Ã\x9f 31' 'Ã\x96Ã\x90 26'
 'Â¶Â¥ 8' 'ÂµÃ\x97 32' 'Ã\x96Ã\x90 42' 'ÂµÃ\x97 30' 'ÂµÃ\x8d 32'
 'ÂµÃ\x8d 3' 'ÂµÃ\x97 22' 'Â¸Ã\x9f 14' 'Â¸Ã\x9f 23' 'ÂµÃ\x97 27'
 'ÂµÃ\x97 13' 'ÂµÃ\x8d 27' 'Â¶Â¥ 23' 'ÂµÃ\x8d 29' 'Â¶Â¥ 22' 'Â¸Ã\x9f 29'
 'Ã\x96Ã\x90 34' 'ÂµÃ\x97 3' 'Â¶Â¥ 25' 'Â¸Ã\x9f 34' 'Â¶Â¥ 10' 'ÂµÃ\x8d 37'
 'ÂµÃ\x97 16' 'ÂµÃ\x97 12' 'Ã\x8eÂ´Ã\x96Âª 6' 'Â¶Â¥ 32' 'ÂµÃ\x8d 42'
 'Â¶Â¥ 30' 'ÂµÃ\x97 33' 'Â¸Ã\x9f 42' 'ÂµÃ\x8d 8' 'Â¸Ã\x9f 33'
 'Ã\x96Ã\x90 33' 'Â¶Â¥ 2' 'Â¶Â¥ 29' 'ÂµÃ\x97 1' 'ÂµÃ\x97 29'
 'Ã\x8eÂ´Ã\x96Âª 15' 'Â¸Ã\x9f 37' 'ÂµÃ\x8d 36' 'ÂµÃ\x8d 35' 'Â¶Â¥ 34'
 'Â¸Ã\x9f 36' 'Ã\x96Ã\x90 37' 'Ã\x96Ã\x90 35' 'ÂµÃ\x97 31'
 'Ã\x8eÂ´Ã\x96Âª 12' 'Â¶Â¥ 31' 'ÂµÃ\x8d 63' 'Ã\x8eÂ´Ã\x96Âª 21'
 'ÂµÃ\x97 34' 'Ã\x96Ã\x90 57' 'Â¶Â¥ 33' 'Ã\x8eÂ´Ã\x96Âª 11'
 'Ã\x8eÂ´Ã\x96Âª 10' 'Ã\x8eÂ´Ã\x96Âª 8' 'Ã\x8eÂ´Ã\x96Âª 18'
 'Ã\x8eÂ´Ã\x96Âª 7' 'Ã\x8eÂ´Ã\x96Âª 20' 'Ã\x8eÂ´Ã\x96Âª 25'
 'Ã\x8eÂ´Ã\x96Âª 16' 'Ã\x8eÂ´Ã\x96Âª 23' 'Ã\x8eÂ´Ã\x96Âª 14'
 'Ã\x8eÂ´Ã\x96Âª 27' 'Ã\x8eÂ´Ã\x96Âª 28' 'Ã\x8eÂ´Ã\x96Âª 5'
 'Ã\x8eÂ´Ã\x96Âª 22' 'Ã\x8eÂ´Ã\x96Âª 17' 'ÂµÃ\x8d 2' 'Ã\x8eÂ´Ã\x96Âª 4'
 'Ã\x8eÂ´Ã\x96Âª 13' 'Ã\x96Ã\x90 36' 'Ã\x8eÂ´Ã\x96Âª 26'
 'Ã\x8eÂ´Ã\x96Âª 24' 'Ã\x8eÂ´Ã\x96Âª 9' 'Ã\x8eÂ´Ã\x96Âª 30'
 'Ã\x8eÂ´Ã\x96Âª 19' 'Ã\x8eÂ´Ã\x96Âª 31']
constructionTime:['2005' '2004' '2008' '1960' '1997' '2009' '1991' '2001' '1
990' '2011'
 '2000' '1998' '2010' '1996' '1993' '2006' '2002' 'Ã\x8eÂ´Ã\x96Âª' '2012'
 '1989' '2003' '2007' '1994' '1984' '1992' '2014' '1985' '1999' '1979'
 '1981' '1976' '1982' '1975' '1983' '1986' '1995' '1965' '2013' '1988'
 '1987' '2015' '1955' '1980' '1978' '1958' '1970' '1956' '1977' '1964'
 '1963' '1967' '2016' '1974' '1973' '1959' '1954' '1962' '1966' '1957'
 '1972' '1971' '1953' '1968' '1961' '1950' '1952' '1969']
```

In [6]:
```
def extractNumeric(s):
    return re.sub(r'\D','',s)
df['floor'] = df['floor'].apply(extractNumeric)

cols = cols[1:]
for col in cols:
    df[col] = pd.to_numeric(df[col],errors='coerce')

meanConstructionTime = round(df['constructionTime'].mean())
df['constructionTime'].fillna(meanConstructionTime, inplace=True)

df['tradeTime'] = pd.to_datetime(df['tradeTime'])
df['tradeYear'] = df['tradeTime'].dt.year
df['tradeMonth'] = df['tradeTime'].dt.month
df['tradeDay'] = df['tradeTime'].dt.day
df.drop(columns=['tradeTime'], inplace=True)
```

In [7]:
```
catCols = ['buildingType','renovationCondition','buildingStructure','elevator
for col in catCols:
    df[col] = df[col].astype('category')
```

Regression Model:

Light Gradient Boosting Machine (LGBM) is chosen for building the regression model. LGBM is chosen because it is known for its efficiency in training and inference, especially on large datasets. It implements gradient boosting algorithms, which generally train faster than traditional ensemble methods like Random Forest. It also generally outperforms both Random Forest and Linear Regression in terms of predictive accuracy.

The column 'totalPrice' is chosen as the target variable. The dataset is split into training and testing sets. Based on the training results the top 10 important features out of the 23 features are selected. Testing is done once with all the features and then with only the top 10 features. The RMSE in both cases is same ~107. Also the R^2 value in both the cases is ~81%.

In [8]:
```
# Dividing the data into target variable and the independent variables and als
X = df.drop(columns=['totalPrice'])
y = df['totalPrice']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rando
```

In [9]:
```
# Defining the parameters of the lgbm model
params = {'boosting_type': 'dart',
          'objective': 'regression',
          'metric': 'rmse',
          'num_leaves': 31,
          'learning_rate': 0.05,
          'feature_fraction': 0.9,
          'seed': 99}

trainData = lgb.Dataset(X_train, label=y_train, categorical_feature=catCols)
testData = lgb.Dataset(X_test, label=y_test, categorical_feature=catCols, refe
```

In [10]:
```
model = lgb.train(params, trainData, num_boost_round=100, valid_sets=[testData
```

```
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of te
sting was 0.009210 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 1904
[LightGBM] [Info] Number of data points in the train set: 127500, number of
used features: 23
[LightGBM] [Info] Start training from score 409.377336
```

In [11]:
```
# Important Variables in predicting the price in decreasing order
featureImportance = model.feature_importance(importance_type='gain')

featureImportanceDf = pd.DataFrame({'Feature': model.feature_name(), 'Importar

featureImportanceDf = featureImportanceDf.sort_values(by='Importance', ascendi

print(featureImportanceDf)
```

```
                 Feature    Importance
4                 square  6.622094e+10
19      communityAverage  5.334922e+10
20             tradeYear  1.739085e+10
2                    DOM  1.407755e+10
18              district  5.806078e+09
8               bathRoom  1.796832e+09
21            tradeMonth  7.694184e+08
5             livingRoom  5.460086e+08
11      constructionTime  1.325027e+08
0                    Lng  1.298598e+08
1                    Lat  1.247739e+08
14           ladderRatio  7.813243e+07
3              followers  4.208859e+07
15              elevator  1.716025e+07
12  renovationCondition  8.658620e+06
13     buildingStructure  3.162620e+06
10          buildingType  0.000000e+00
16     fiveYearsProperty  0.000000e+00
17                subway  0.000000e+00
9                  floor  0.000000e+00
7                kitchen  0.000000e+00
6            drawingRoom  0.000000e+00
22              tradeDay  0.000000e+00
```

In [12]:
```
# Predicting on the test set using all the features
y_pred = model.predict(X_test, num_iteration=model.best_iteration)

rmse = np.sqrt(mean_squared_error(y_test, y_pred))

r2 = r2_score(y_test, y_pred)

print("RMSE:", rmse)
print("R^2:", r2)
```

```
RMSE: 107.88755984222088
R^2: 0.8144671341774744
```

In [13]:
```
topFeatures = featureImportanceDf.head(10)['Feature'].tolist()
print(f'The 10 most important features are: \n{topFeatures}')
```

```
The 10 most important features are:
['square', 'communityAverage', 'tradeYear', 'DOM', 'district', 'bathRoom',
'tradeMonth', 'livingRoom', 'constructionTime', 'Lng']
```

In [14]:
```
# Predicting on the test set using only the top 10 features
newCatCol = ['district']

X_train_top = X_train[topFeatures]
X_test_top = X_test[topFeatures]

trainDataTop = lgb.Dataset(X_train_top, label=y_train, categorical_feature=new
testDataTop = lgb.Dataset(X_test_top, label=y_test, categorical_feature=newCat

modelTop = lgb.train(params, trainDataTop, num_boost_round=100, valid_sets=[te

y_pred_top = modelTop.predict(X_test_top, num_iteration=modelTop.best_iteratio
```

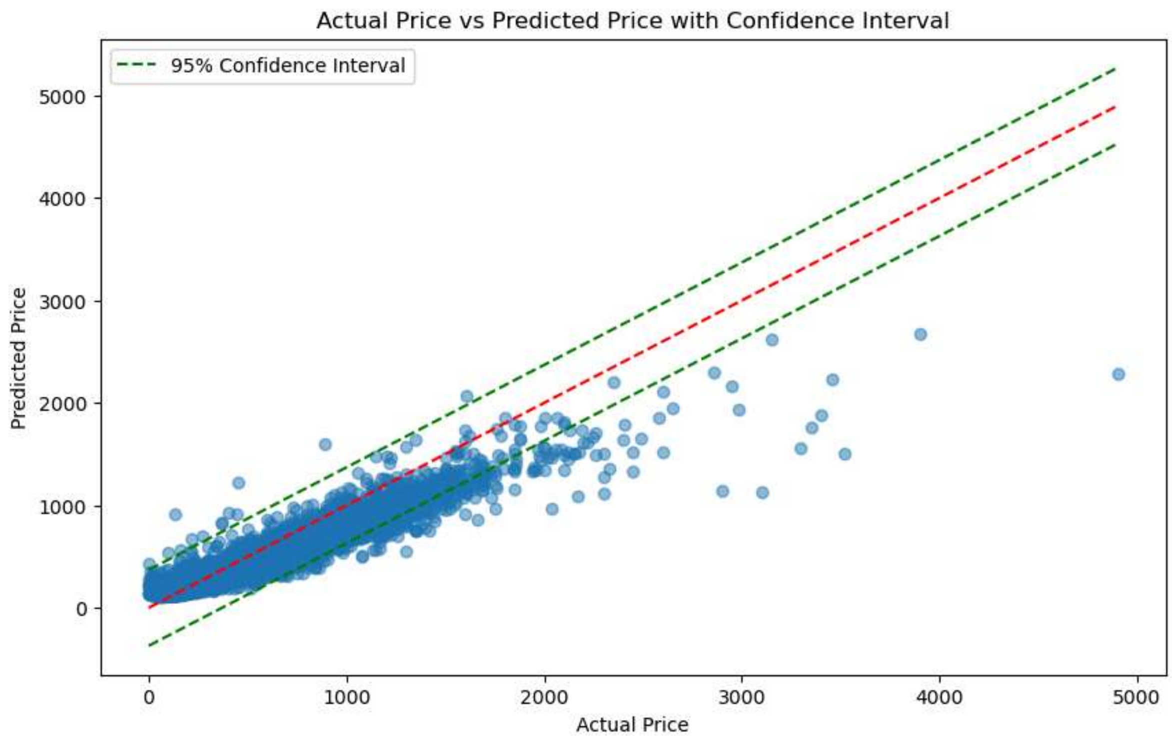
```
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of te
sting was 0.001517 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 1136
[LightGBM] [Info] Number of data points in the train set: 127500, number of
used features: 10
[LightGBM] [Info] Start training from score 409.377336
```

In [15]:
```
rmseTop = np.sqrt(mean_squared_error(y_test, y_pred_top))

r2Top = r2_score(y_test, y_pred_top)

print("RMSE:", rmseTop)
print("R^2:", r2Top)
```

```
RMSE: 107.75417981563106
R^2: 0.8149255944818011
```

Below is a scatter plot showing most of the predicted prices lying within a 95% confidence interval of the actual prices.

In [16]:
```
confidence_interval = 1.96 * np.std(y_pred_top)

plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred_top, alpha=0.5)
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], '--', color=
plt.plot([min(y_test), max(y_test)], [min(y_test) - confidence_interval, max(y
plt.plot([min(y_test), max(y_test)], [min(y_test) + confidence_interval, max(y
plt.title('Actual Price vs Predicted Price with Confidence Interval')
plt.xlabel('Actual Price')
plt.ylabel('Predicted Price')
plt.legend()
plt.show()
```



Classification of Properties as Underpriced or Overpriced.

1. A subset of the dataframe consisting of only the top ten features and the target variable 'totalPrice' is created. This is to reduce the curse of dimensionality while using K-Means. Even though the variable 'Lat': Latitude is not in the top 10 features, it is included becuase it is used later on in the analysis to locate the properties on a map.
2. As the computational speed becomes very slow with a large dataset while using K-Means, so a random sample of 2000 rows is selected to work on.
3. Since the dataset consists of a mix of continuous and categorical variables, it is preprocessed by calculating the Gower's distance of the variables before plugging into the K-Means model.

In [17]:
```
subsetDf = df[topFeatures]
subsetDf['totalPrice'] = df['totalPrice']
subsetDf['Lat'] = df['Lat']
```

```
C:\Users\himan\AppData\Local\Temp\ipykernel_20144\4027769544.py:2: SettingWi
thCopyWarning:
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/pandas-docs/
stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pand
as.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-v
ersus-a-copy)
  subsetDf['totalPrice'] = df['totalPrice']
C:\Users\himan\AppData\Local\Temp\ipykernel_20144\4027769544.py:3: SettingWi
thCopyWarning:
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/pandas-docs/
stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pand
as.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-v
ersus-a-copy)
  subsetDf['Lat'] = df['Lat']
```

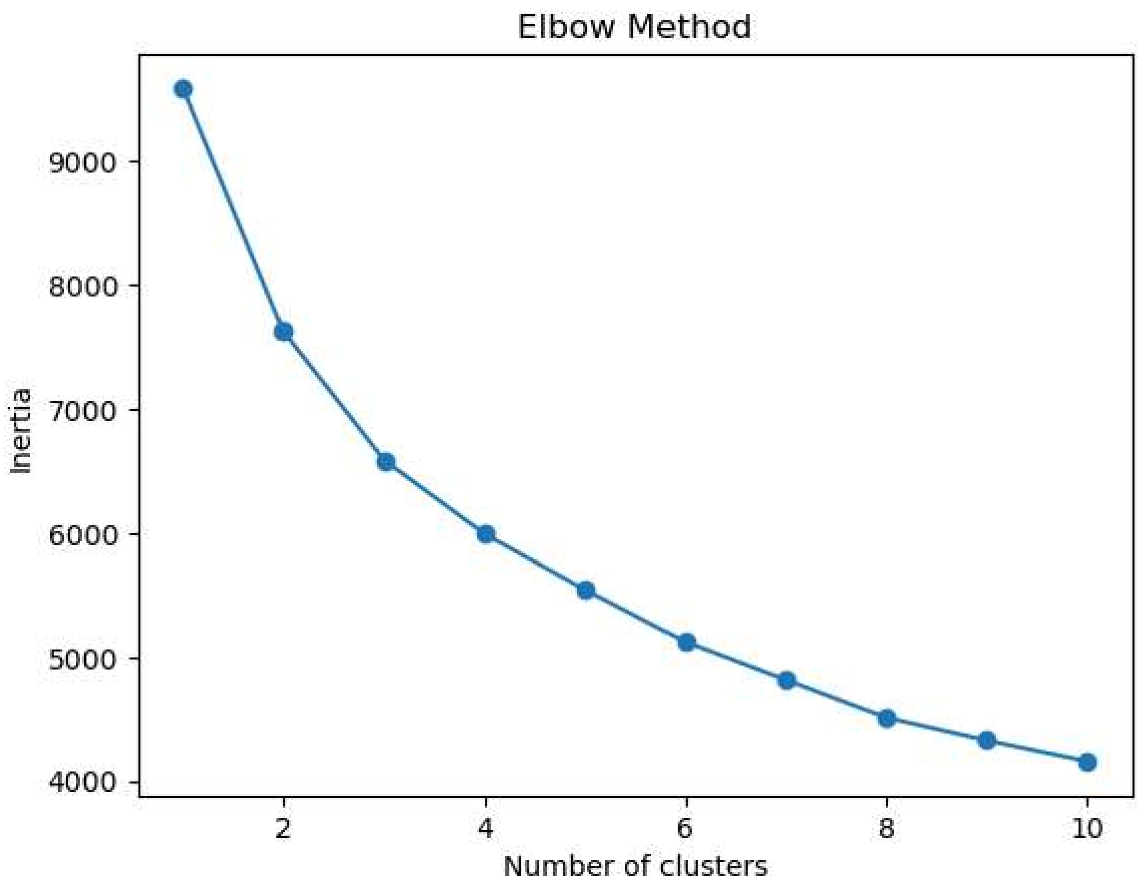
In [18]:
```
# Taking a random sample of 2000
randomSample = subsetDf.sample(n=2000, random_state=78, replace=False)
selectedCols = [col for col in randomSample.columns if col != 'totalPrice']
selectedData = randomSample[selectedCols]

selectedData = selectedData.apply(lambda x: x.astype('category').cat.codes if

# Calculating the gower's distance
distanceMatrix = gower_matrix(selectedData)
```

Number of Clusters:

The ideal number of clusters to be used in K-Means can be decided by different methods. Two methods are used here:

1. The Elbow Method: The idea is to select the value of k at the "elbow" point, as it represents the point where increasing the number of clusters does not significantly decrease the within-cluster sum of squares or the Inertia. Based on the plot the cluster value at the elbow is 3.
2. The Silhouette Score Method: The objective of clustering is to group similar data points together while keeping dissimilar points in different clusters. A high average Silhouette Score indicates that this objective is being achieved effectively. Based on this method the ideal cluster value is 2.

In [19]:
```
inertia = []
for k in range(1, 11):
    kmeans = KMeans(n_clusters=k, random_state=42, n_init=10)
    kmeans.fit(distanceMatrix)
    inertia.append(kmeans.inertia_)

plt.plot(range(1, 11), inertia, marker='o')
plt.xlabel('Number of clusters')
plt.ylabel('Inertia')
plt.title('Elbow Method')
plt.show()
```

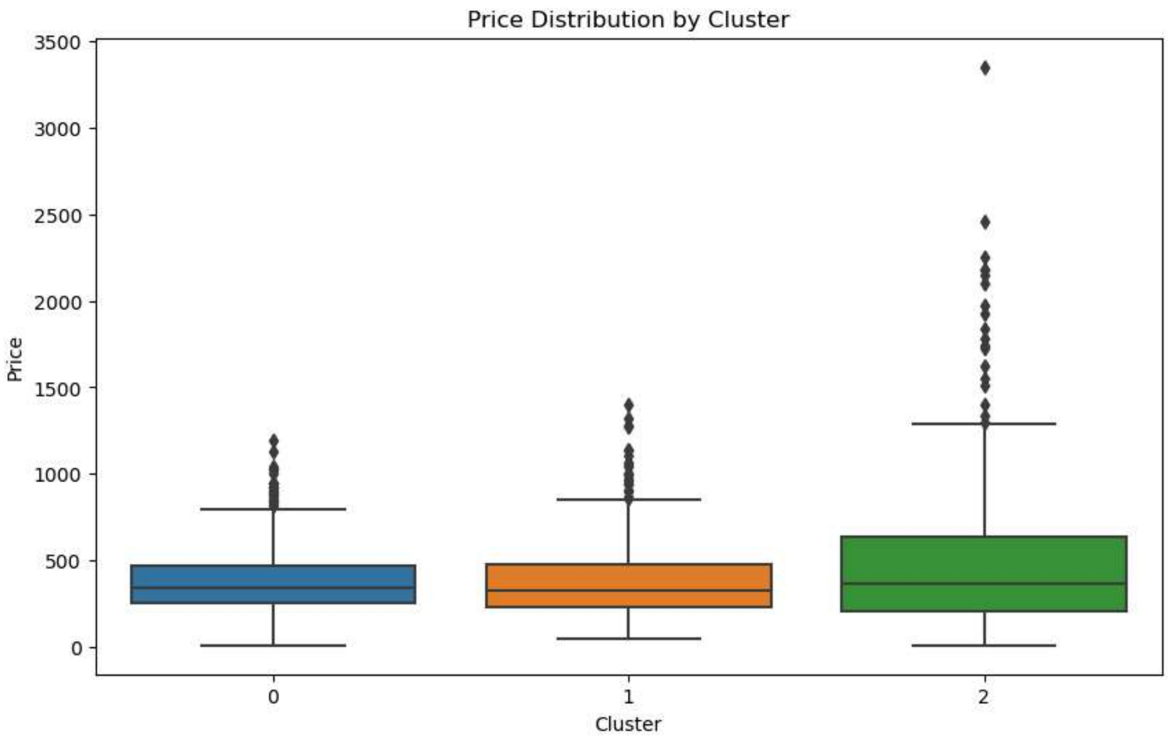


In [20]:
```
silhouetteScores = []
for k in range(2, 11):
    kmeans = KMeans(n_clusters=k, random_state=42, n_init=10)
    kmeans.fit(distanceMatrix)
    score = silhouette_score(distanceMatrix, kmeans.labels_)
    silhouetteScores.append(score)

plt.plot(range(2, 11), silhouetteScores, marker='o')
plt.xlabel('Number of clusters')
plt.ylabel('Silhouette Score')
plt.title('Silhouette Score Method')
plt.show()
```

In [21]:
```
# no. of clusters = 3
kmeans = KMeans(n_clusters=3, n_init=10)
kmeans.fit(distanceMatrix)
cluster_labels = kmeans.labels_
```

The properties are divided among 3 clusters based on the 10 features selected earlier. The following graph and the summary statistics are based on the prices of properties within each cluster.

In [22]:
```
clusterPrices = pd.DataFrame({'Cluster': cluster_labels, 'Price': randomSample

plt.figure(figsize=(10, 6))
sns.boxplot(x='Cluster', y='Price', data=clusterPrices)
plt.title('Price Distribution by Cluster')
plt.xlabel('Cluster')
plt.ylabel('Price')
plt.show()
```



In [23]:
```
clusterSummaryStats = clusterPrices.groupby('Cluster')['Price'].describe()

print("Summary statistics for each cluster:")
print(clusterSummaryStats)
```

```
Summary statistics for each cluster:
         count        mean         std   min     25%    50%    75%     max
Cluster
0        952.0  381.227521  176.919966  11.2  253.00  345.0  472.0  1190.0
1        627.0  380.086284  213.558944  50.0  229.75  330.0  480.0  1400.0
2        421.0  498.329454  428.490219  11.1  205.00  368.0  638.0  3350.0
```

The method of classifying a property as underpriced or overpriced is based on calculating the mean price and standard deviation of each cluster. Any property within a cluster, if its price is more than one standard deviation than the mean, it is classified as overpriced. If its price is less than one standard deviation of the mean price of its cluster, then it is classified as underpriced.

The following table shows the datapoints classified as such. Of the 2000 data points analayzed, 483 or around 1/4th are either underpriced or overpriced.

In [24]:
```
clusterAvgPrice = clusterPrices.groupby('Cluster')['Price'].mean()

clusterPrices['ClusterAvgPrice'] = clusterPrices['Cluster'].map(clusterAvgPri

clusterStd = clusterPrices.groupby('Cluster')['Price'].std()

clusterPrices['ClusterStd'] = clusterPrices['Cluster'].map(clusterStd)

thresholdMultiplier = 1
overpriced = clusterPrices[clusterPrices['Price'] > clusterPrices['ClusterAvgP
underpriced = clusterPrices[clusterPrices['Price'] < clusterPrices['ClusterAvg

overpricedIndices = overpriced.index
underpricedIndices = underpriced.index

overpricedDf = randomSample.loc[overpricedIndices].copy()
underpricedDf = randomSample.loc[underpricedIndices].copy()
overpricedDf = overpricedDf.assign(PricedType='Overpriced')
underpricedDf = underpricedDf.assign(PricedType='Underpriced')

overOrUnderPricedDf = pd.concat([overpricedDf, underpricedDf])

overOrUnderPricedDf
```

Out[24]:

	square	communityAverage	tradeYear	DOM	district	bathRoom	tradeMonth	livingRoo
37042	51.01	119449.0	2016	16.0	10	1	9	
79302	107.30	60013.0	2017	68.0	7	1	8	
60670	107.41	94271.0	2017	43.0	1	1	3	
35429	83.00	75858.0	2016	5.0	8	1	9	
88863	117.47	52197.0	2017	20.0	6	2	11	
...	...	...	...	...	...	...	...	
14148	54.00	46072.0	2016	25.0	7	1	7	
95227	61.89	37661.0	2015	1.0	6	1	3	
118720	37.93	59730.0	2016	1.0	7	1	5	
93145	128.71	38281.0	2011	1.0	6	2	12	
19158	35.50	58959.0	2016	57.0	2	1	9	

483 rows × 13 columns

The following is a street map of Beijing showing the overpriced (in Red) and underpriced (in Green) properties.

In [25]:
```
map = folium.Map(location=[overOrUnderPricedDf ['Lat'].mean(), overOrUnderPri

colors = {'Underpriced': 'green', 'Overpriced': 'red'}

for index, row in overOrUnderPricedDf .iterrows():
    folium.Marker([row['Lat'], row['Lng']], icon=folium.Icon(color=colors[row

map
```

Out[25]: