An indepth analysis on house prices - dataset used(Real estate.csv)

April 1, 2024

[1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.ensemble import RandomForestRegressor
```

[13]:
```
# Load the dataset
data = pd.read_csv("./Dataset/Real estate.csv")
print(data.columns)
```

```
Index(['No', 'X1 transaction date', 'X2 house age',
       'X3 distance to the nearest MRT station',
       'X4 number of convenience stores', 'X5 latitude', 'X6 longitude',
       'Y house price of unit area'],
      dtype='object')
```

[3]:
```
# Display the first few rows of the dataset
print("First few rows of the dataset:")
print(data.head())
```

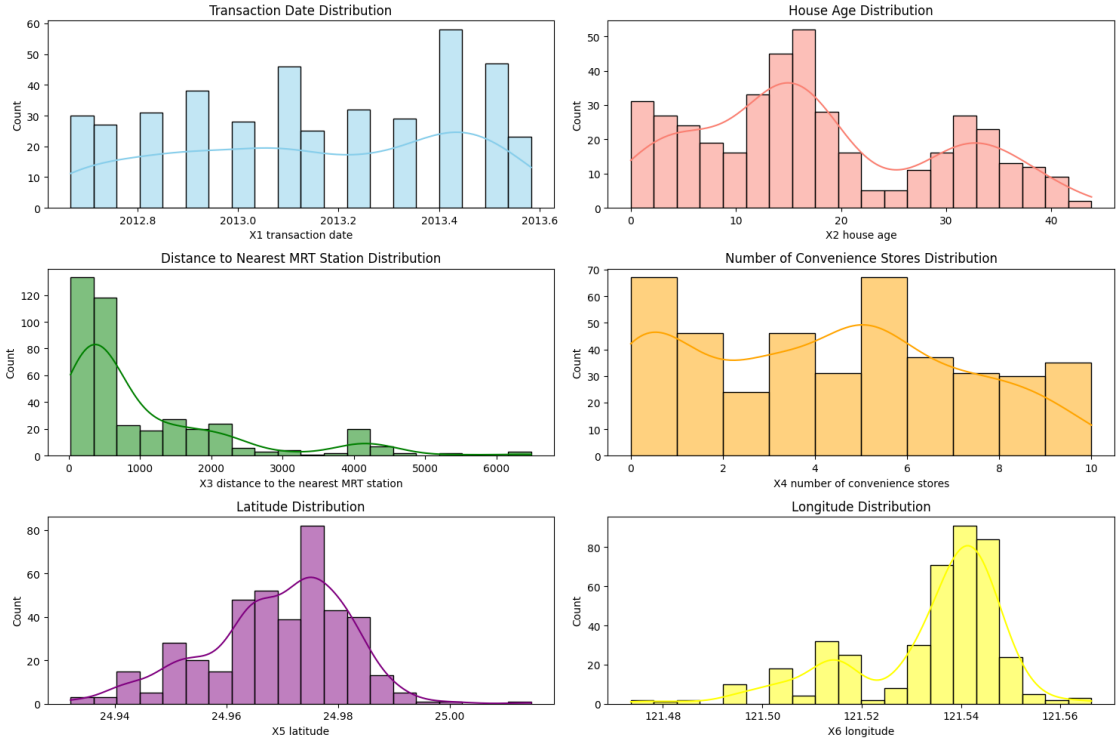
```
First few rows of the dataset:
   No  X1 transaction date  X2 house age  \
0   1             2012.917          32.0
1   2             2012.917          19.5
2   3             2013.583          13.3
3   4             2013.500          13.3
4   5             2012.833           5.0

   X3 distance to the nearest MRT station  X4 number of convenience stores  \
0                                84.87882                               10
1                               306.59470                                9
2                               561.98450                                5
3                               561.98450                                5
4                               390.56840                                5

   X5 latitude  X6 longitude  Y house price of unit area
0     24.98298     121.54024                        37.9
1     24.98034     121.53951                        42.2
2     24.98746     121.54391                        47.3
```

```
3     24.98746     121.54391                        54.8
4     24.97937     121.54245                        43.1
```

[4]:
```
# Summary statistics of numerical columns
print("\nSummary statistics of numerical columns:")
print(data.describe())
```

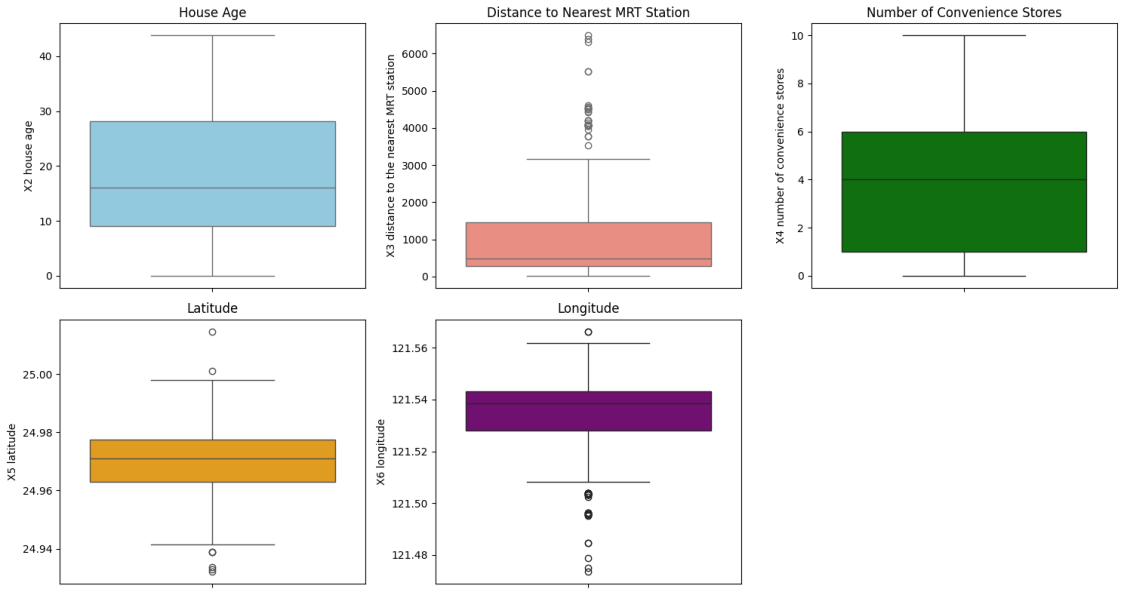
```
Summary statistics of numerical columns:
                No  X1 transaction date  X2 house age  \
count  414.000000           414.000000    414.000000
mean   207.500000          2013.148971     17.712560
std    119.655756             0.281967     11.392485
min      1.000000          2012.667000      0.000000
25%    104.250000          2012.917000      9.025000
50%    207.500000          2013.167000     16.100000
75%    310.750000          2013.417000     28.150000
max    414.000000          2013.583000     43.800000

       X3 distance to the nearest MRT station  \
count                              414.000000
mean                              1083.885689
std                               1262.109595
min                                 23.382840
25%                                289.324800
50%                                492.231300
75%                               1454.279000
max                               6488.021000

       X4 number of convenience stores  X5 latitude  X6 longitude  \
count                       414.000000   414.000000    414.000000
mean                          4.094203    24.969030    121.533361
std                           2.945562     0.012410      0.015347
min                           0.000000    24.932070    121.473530
25%                           1.000000    24.963000    121.528085
50%                           4.000000    24.971100    121.538630
75%                           6.000000    24.977455    121.543305
max                          10.000000    25.014590    121.566270

       Y house price of unit area
count                  414.000000
mean                    37.980193
std                     13.606488
min                      7.600000
25%                     27.700000
50%                     38.450000
75%                     46.600000
max                    117.500000
```

[5]:
```
# Visualize distributions of numerical features
plt.figure(figsize=(15, 10))
plt.subplot(3, 2, 1)
sns.histplot(data['X1 transaction date'], kde=True, bins=20, color='skyblue')
plt.title('Transaction Date Distribution')

plt.subplot(3, 2, 2)
sns.histplot(data['X2 house age'], kde=True, bins=20, color='salmon')
plt.title('House Age Distribution')

plt.subplot(3, 2, 3)
sns.histplot(data['X3 distance to the nearest MRT station'], kde=True, bins=20,␣
↪color='green')
plt.title('Distance to Nearest MRT Station Distribution')

plt.subplot(3, 2, 4)
sns.histplot(data['X4 number of convenience stores'], kde=True, bins=10,␣
↪color='orange')
plt.title('Number of Convenience Stores Distribution')

plt.subplot(3, 2, 5)
sns.histplot(data['X5 latitude'], kde=True, bins=20, color='purple')
plt.title('Latitude Distribution')

plt.subplot(3, 2, 6)
sns.histplot(data['X6 longitude'], kde=True, bins=20, color='yellow')
plt.title('Longitude Distribution')

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



[6]:
```
# Outlier Detection
plt.figure(figsize=(15, 8))
plt.subplot(2, 3, 1)
sns.boxplot(data['X2 house age'], color='skyblue')
plt.title('House Age')

plt.subplot(2, 3, 2)
sns.boxplot(data['X3 distance to the nearest MRT station'], color='salmon')
plt.title('Distance to Nearest MRT Station')

plt.subplot(2, 3, 3)
sns.boxplot(data['X4 number of convenience stores'], color='green')
plt.title('Number of Convenience Stores')

plt.subplot(2, 3, 4)
sns.boxplot(data['X5 latitude'], color='orange')
plt.title('Latitude')

plt.subplot(2, 3, 5)
sns.boxplot(data['X6 longitude'], color='purple')
plt.title('Longitude')

plt.tight_layout()
```

```
plt.show()
```



[7]:
```
# Feature Importance
# Splitting features and target variable
X = data.drop(columns=['No', 'Y house price of unit area'])
Y = data['Y house price of unit area']
```

[8]:
```
# Train Random Forest model to determine feature importances
rf_model = RandomForestRegressor(random_state=42)
rf_model.fit(X, Y)
```

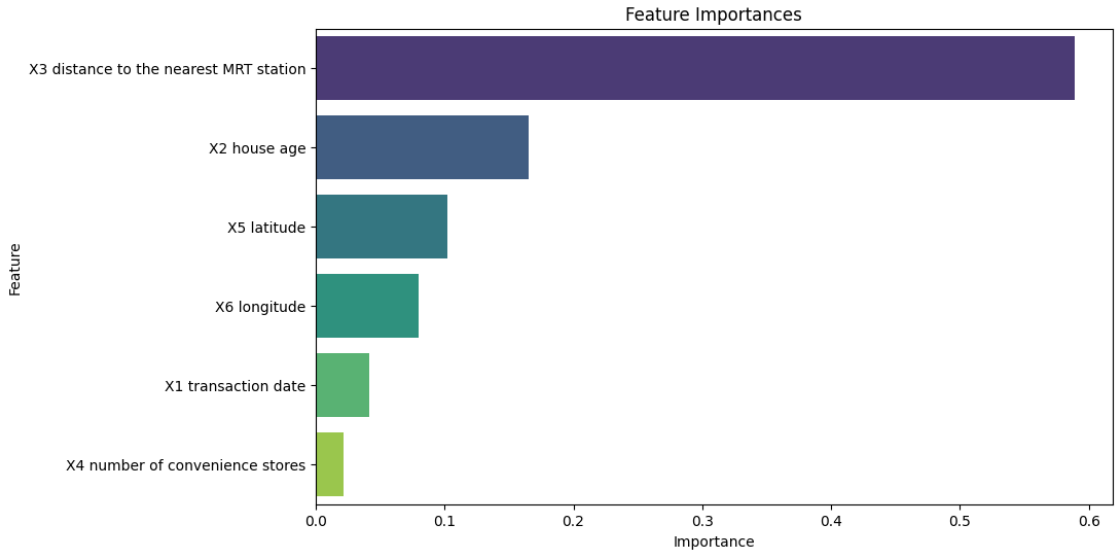
[8]:
```
RandomForestRegressor(random_state=42)
```

[9]:
```
# Visualize feature importances
feature_importances = pd.Series(rf_model.feature_importances_, index=X.columns)
feature_importances_sorted = feature_importances.sort_values(ascending=False)
plt.figure(figsize=(10, 6))
sns.barplot(x=feature_importances_sorted, y=feature_importances_sorted.index,␣
 ↪palette="viridis")
plt.title('Feature Importances')
plt.xlabel('Importance')
plt.ylabel('Feature')
plt.show()
```

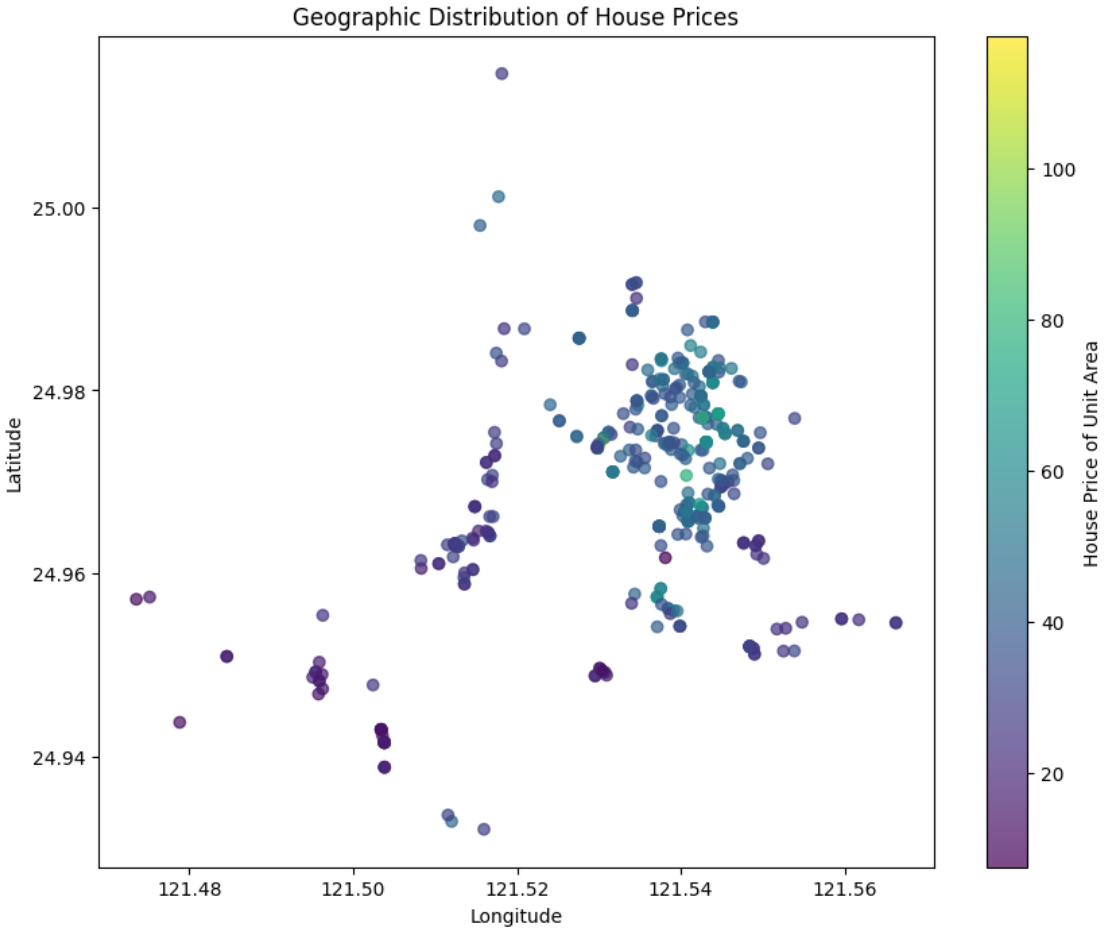
```
<ipython-input-9-eb8a5e906647>:5: FutureWarning:

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

effect.

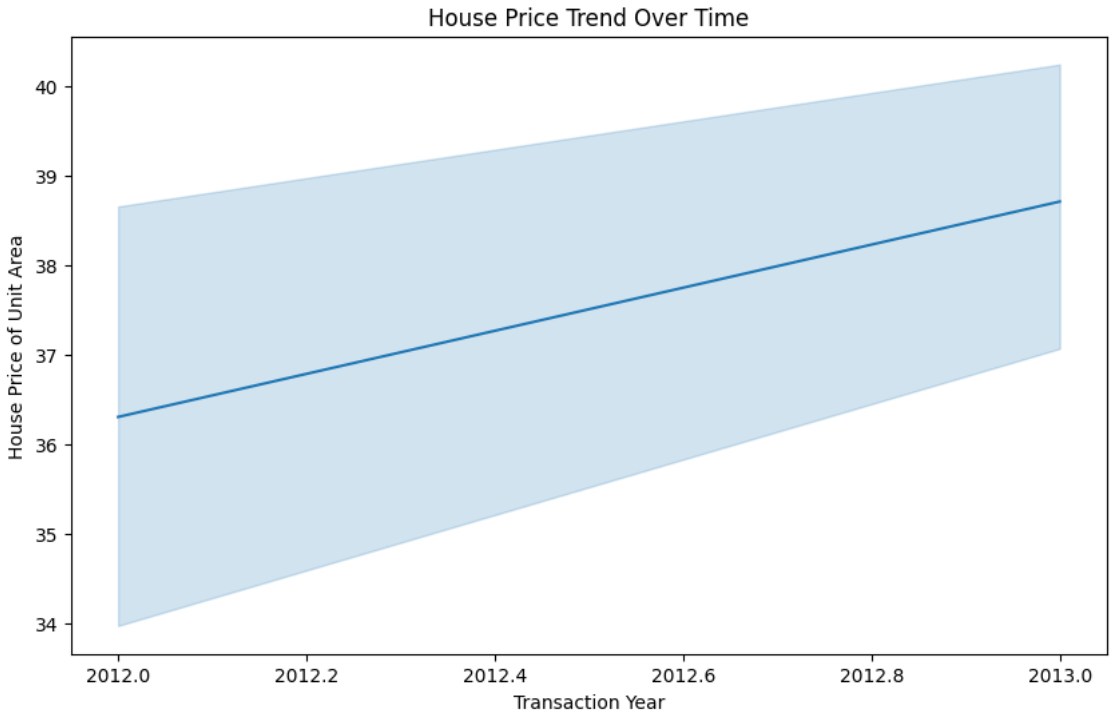
```
  sns.barplot(x=feature_importances_sorted, y=feature_importances_sorted.index,
palette="viridis")
```



[10]:
```
# Geographic Analysis
plt.figure(figsize=(10, 8))
plt.scatter(data['X6 longitude'], data['X5 latitude'], c=data['Y house price of␣
↪unit area'], cmap='viridis', alpha=0.7)
plt.colorbar(label='House Price of Unit Area')
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.title('Geographic Distribution of House Prices')
plt.show()
```

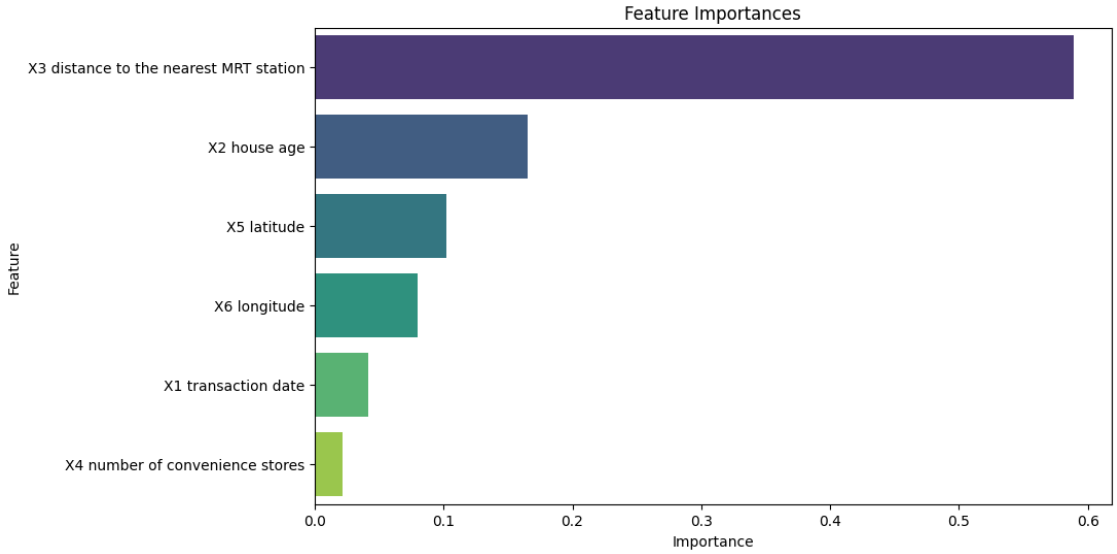


[11]:
```
# Time Series Analysis
data['Transaction Year'] = data['X1 transaction date'].astype(int)
plt.figure(figsize=(10, 6))
sns.lineplot(x='Transaction Year', y='Y house price of unit area', data=data)
plt.title('House Price Trend Over Time')
plt.xlabel('Transaction Year')
plt.ylabel('House Price of Unit Area')
plt.show()
```



[12]:
```
# Correlation with Target Variable
plt.figure(figsize=(10, 6))
sns.barplot(x=feature_importances_sorted, y=feature_importances_sorted.index,␣
 ↪palette="viridis")
plt.title('Feature Importances')
plt.xlabel('Importance')
plt.ylabel('Feature')
plt.show()
```

```
<ipython-input-12-0f70867a8288>:3: FutureWarning:

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

  sns.barplot(x=feature_importances_sorted, y=feature_importances_sorted.index,
palette="viridis")
```


Feature Importances
X3 distance to the nearest MRT station
X2 house age
X5 latitude
X6 longitude
X1 transaction date
X4 number of convenience stores
Feature
0.0
0.1
0.2
0.3
0.4
0.5
0.6
Importance