CISD 43 Final Project

June 9, 2024

0.1 Title here (i.e., House Price Prediction)

[1]:
```
# Edit all the Mardown cells below with the appropriate information
# Run all cells, containing your code
# Save this Jupyter with the outputs of your executed cells
# PS: Save again the notebook with this outcome.
# PSPS: Don't forget to include the dataset in your submission
```

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Course: CISD 43 – BIG DATA (Spring, 2024)

0.1.1 Problem Statement

- This project is about house price predictions. I wasn't very creative, so I just used the sample suggestion of houes prices.
- **Keywords:** House price prediction, real estate

0.1.2 Required packages

- If you are using Jupyter Notebook via Anaconda with `pip` properly configured, the following lines should successfully install the required modules. They are commented out by default as to not attempt to re-install if you were to fully re-run the notebook

[2]:
```
#!pip install pandas
#!pip install numpy
#!pip install matplotlib
#!pip install seaborn
#!pip install sklearn
#!pip install scikitplot
```

0.1.3 Methodology

1. Explan your big data metodology
2. Introduce the topics you used in your project

- Model 1
  - KNN
- Model 2
  - Linear Regression

0.1.4 Your code starts here

[58]:
```python
import pandas as pd, numpy as np, matplotlib.pyplot as plt, seaborn as sns
from sklearn.neighbors import KNeighborsRegressor
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import r2_score, mean_squared_error

import warnings
warnings.filterwarnings("ignore")
%matplotlib inline
sns.set_style("whitegrid")
```

[4]:
```python
df = pd.read_csv("data/house_data.csv")
```

[5]:
```python
# we're immediately just going to scrap any columns with missing valuess
df = df.dropna(0)

# clean up date

df["date"] = pd.to_datetime(df["date"])
df["year"] = df["date"].dt.year
df["month"] = df["date"].dt.month

# Split into X & y - we need to drop id, date, price, zipcode from X
# date is now year/month, id is irrelevant, and i chose to not include the␣
↪categorical data (zipcodes)
X, y = df, df["price"]
X = X.drop(["id", "date", "price", "zipcode"], axis=1)
```

[44]:
```python
# split dataset into train/test, proportioned at 25%
scaler = StandardScaler()
scaled_X = scaler.fit_transform(X)

X_train, X_test, y_train, y_test = train_test_split(scaled_X, y, shuffle =␣
↪True, test_size = 0.25)
```

[7]:
```python
df.head()
```

[7]:
```
           id       date     price  bedrooms  bathrooms  sqft_living  \
0  7129300520 2014-10-13  221900.0         3       1.00         1180
1  6414100192 2014-12-09  538000.0         3       2.25         2570
2  5631500400 2015-02-25  180000.0         2       1.00          770
3  2487200875 2014-12-09  604000.0         4       3.00         1960
4  1954400510 2015-02-18  510000.0         3       2.00         1680

   sqft_lot  floors  waterfront  view  …  sqft_basement  yr_built  \
```

```
0      5650     1.0            0      0  ...              0       1955
1      7242     2.0            0      0  ...            400       1951
2     10000     1.0            0      0  ...              0       1933
3      5000     1.0            0      0  ...            910       1965
4      8080     1.0            0      0  ...              0       1987

   yr_renovated  zipcode      lat     long  sqft_living15  sqft_lot15  year  \
0             0    98178  47.5112 -122.257           1340        5650  2014
1          1991    98125  47.7210 -122.319           1690        7639  2014
2             0    98028  47.7379 -122.233           2720        8062  2015
3             0    98136  47.5208 -122.393           1360        5000  2014
4             0    98074  47.6168 -122.045           1800        7503  2015

   month
0     10
1     12
2      2
3     12
4      2

[5 rows x 23 columns]
```

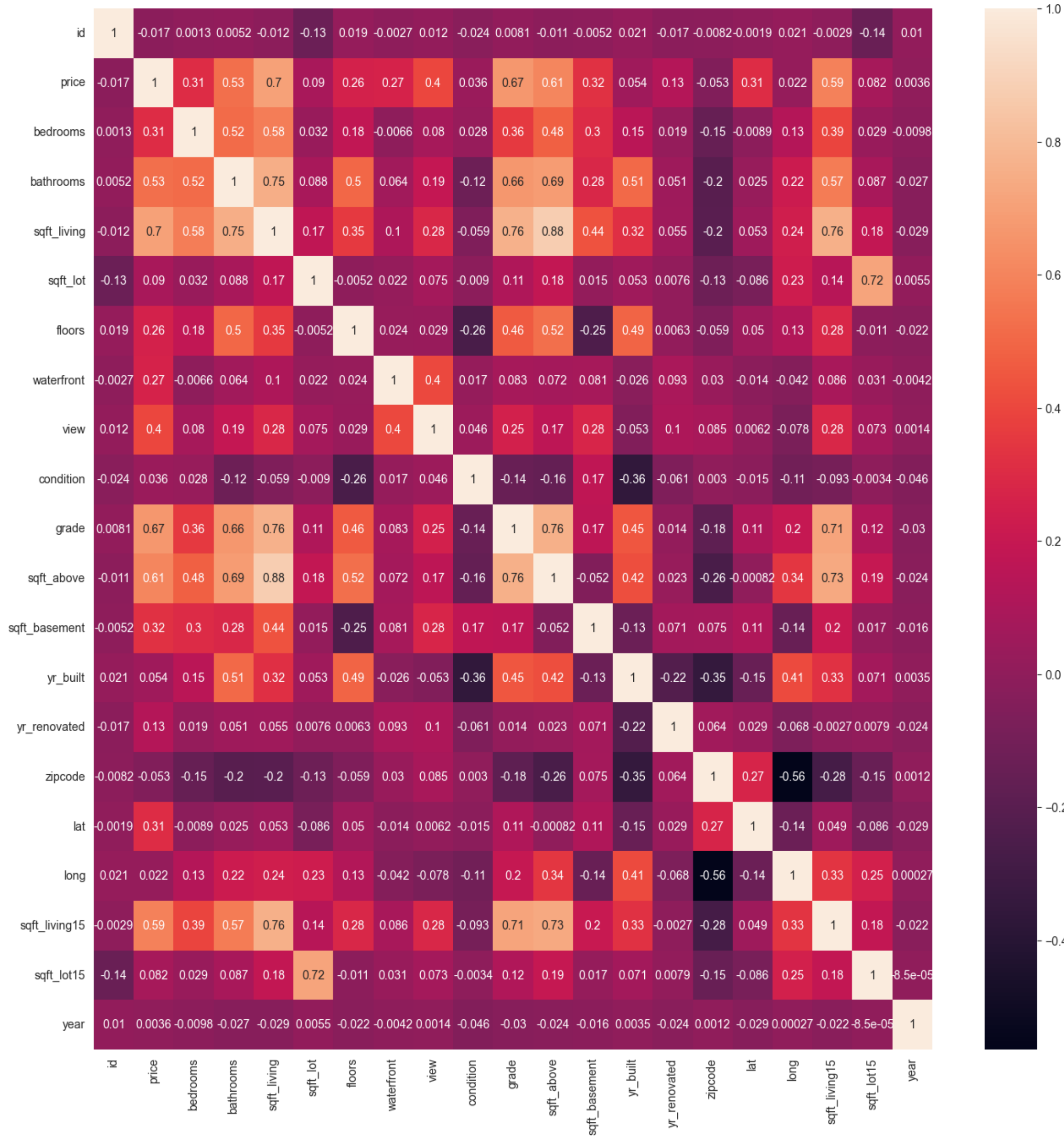
[8]:
```
df.describe()
```

[8]:
```
                 id         price      bedrooms     bathrooms   sqft_living  \
count  2.161300e+04  2.161300e+04  21613.000000  21613.000000  21613.000000
mean   4.580302e+09  5.400881e+05      3.370842      2.114757   2079.899736
std    2.876566e+09  3.671272e+05      0.930062      0.770163    918.440897
min    1.000102e+06  7.500000e+04      0.000000      0.000000    290.000000
25%    2.123049e+09  3.219500e+05      3.000000      1.750000   1427.000000
50%    3.904930e+09  4.500000e+05      3.000000      2.250000   1910.000000
75%    7.308900e+09  6.450000e+05      4.000000      2.500000   2550.000000
max    9.900000e+09  7.700000e+06     33.000000      8.000000  13540.000000

           sqft_lot        floors    waterfront          view     condition  \
count  2.161300e+04  21613.000000  21613.000000  21613.000000  21613.000000
mean   1.510697e+04      1.494309      0.007542      0.234303      3.409430
std    4.142051e+04      0.539989      0.086517      0.766318      0.650743
min    5.200000e+02      1.000000      0.000000      0.000000      1.000000
25%    5.040000e+03      1.000000      0.000000      0.000000      3.000000
50%    7.618000e+03      1.500000      0.000000      0.000000      3.000000
75%    1.068800e+04      2.000000      0.000000      0.000000      4.000000
max    1.651359e+06      3.500000      1.000000      4.000000      5.000000

       ...  sqft_basement      yr_built  yr_renovated       zipcode  \
count  ...   21613.000000  21613.000000  21613.000000  21613.000000
mean   ...     291.509045   1971.005136     84.402258  98077.939805
```

```
std    …     442.575043    29.373411    401.679240     53.505026
min    …       0.000000  1900.000000      0.000000  98001.000000
25%    …       0.000000  1951.000000      0.000000  98033.000000
50%    …       0.000000  1975.000000      0.000000  98065.000000
75%    …     560.000000  1997.000000      0.000000  98118.000000
max    …    4820.000000  2015.000000   2015.000000  98199.000000

                lat          long  sqft_living15     sqft_lot15          year  \
count  21613.000000  21613.000000   21613.000000   21613.000000  21613.000000
mean      47.560053   -122.213896    1986.552492   12768.455652   2014.322954
std        0.138564      0.140828     685.391304   27304.179631      0.467616
min       47.155900   -122.519000     399.000000     651.000000   2014.000000
25%       47.471000   -122.328000    1490.000000    5100.000000   2014.000000
50%       47.571800   -122.230000    1840.000000    7620.000000   2014.000000
75%       47.678000   -122.125000    2360.000000   10083.000000   2015.000000
max       47.777600   -121.315000    6210.000000  871200.000000   2015.000000

              month
count  21613.000000
mean       6.574423
std        3.115308
min        1.000000
25%        4.000000
50%        6.000000
75%        9.000000
max       12.000000

[8 rows x 22 columns]
```

[13]:

```
plt.figure(figsize = (16,16))
sns.heatmap(df.iloc[:,:-1].corr(), annot=True)
plt.show()
```



[41]:
```python
fig = plt.figure(figsize=(16, 16))
labels = list(df.drop(["id", "date", "view", "waterfront", "year", "month",
 ↪"zipcode"], axis=1).columns)
for label in range(len(labels)):
    ax = fig.add_subplot(4,4,label+1)
    ax.plot(df.iloc[:, label], color = "blue", alpha = 0.3)
    ax.set_xlabel(labels[label])
    ax.autoscale(True)
```

[ ]:
```python
# Here is where the ML part starts
```

[45]:
```python
X_train
```

[45]:
```
array([[ 0.67648506,  0.1756067 , -0.04344391, …, -0.04645754,
          1.44790136, -1.46840343],
        [-0.39873715, -0.14900736, -0.23943274, …, -0.27917455,
          1.44790136, -1.14740043],
        [ 1.75170727,  0.1756067 , -0.02166737, …, -0.29184689,
         -0.69065478,  0.77861755],
        …,
        [-0.39873715,  0.50022075, -0.65318696, …, -0.42087774,
```

```
         -0.69065478, -0.18439144],
        [-1.47395936, -1.44746357, -1.39358923, …, -0.27075073,
         -0.69065478,  1.42062355],
        [-1.47395936, -1.44746357, -0.78384618, …, -0.00616973,
         -0.69065478,  0.13661156]])
```

[46]:
```
X_test
```

[46]:
```
array([[-1.47395936, -1.44746357, -0.37009197, …, -0.17098348,
         -0.69065478,  1.09962055],
        [-0.39873715,  0.8248348 ,  0.66647122, …, -0.25888414,
          1.44790136, -1.14740043],
        [-1.47395936, -1.44746357, -1.01249983, …, -0.07612401,
         -0.69065478,  1.09962055],
        …,
        [-1.47395936, -1.44746357, -1.28470655, …, -0.27778279,
          1.44790136, -1.78940643],
        [-0.39873715,  0.1756067 , -0.30476236, …, -0.15190171,
         -0.69065478,  1.09962055],
        [ 0.67648506, -0.14900736, -0.1849914 , …,  0.1037061 ,
         -0.69065478,  0.45761455]])
```

[47]:
```
K = []
scores = []

for i in range(2, 10):
    knn = KNeighborsRegressor(n_neighbors = i)
    knn.fit(X_train, y_train)
    s = knn.score(X_test, y_test)
    print(f"k = {i}: {s}")
    scores.append(s)

print(scores)
```

```
k = 2: 0.7414030057849562
k = 3: 0.766575752224133
k = 4: 0.7742231283592205
k = 5: 0.7812822298714657
k = 6: 0.7844945931859527
k = 7: 0.7878581007483119
k = 8: 0.7894831792276535
k = 9: 0.7904318377078658
[0.7414030057849562, 0.766575752224133, 0.7742231283592205, 0.7812822298714657,
0.7844945931859527, 0.7878581007483119, 0.7894831792276535, 0.7904318377078658]
```

[48]:
```
good_k = np.argmax(scores) + 1

knn = KNeighborsRegressor(n_neighbors = good_k)
```

```
knn.fit(X_train, y_train)
```

[48]: KNeighborsRegressor(n_neighbors=8)

[49]:
```
y_pred = knn.predict(X_test)
```

[50]:
```
r2_score(y_test, y_pred)
```

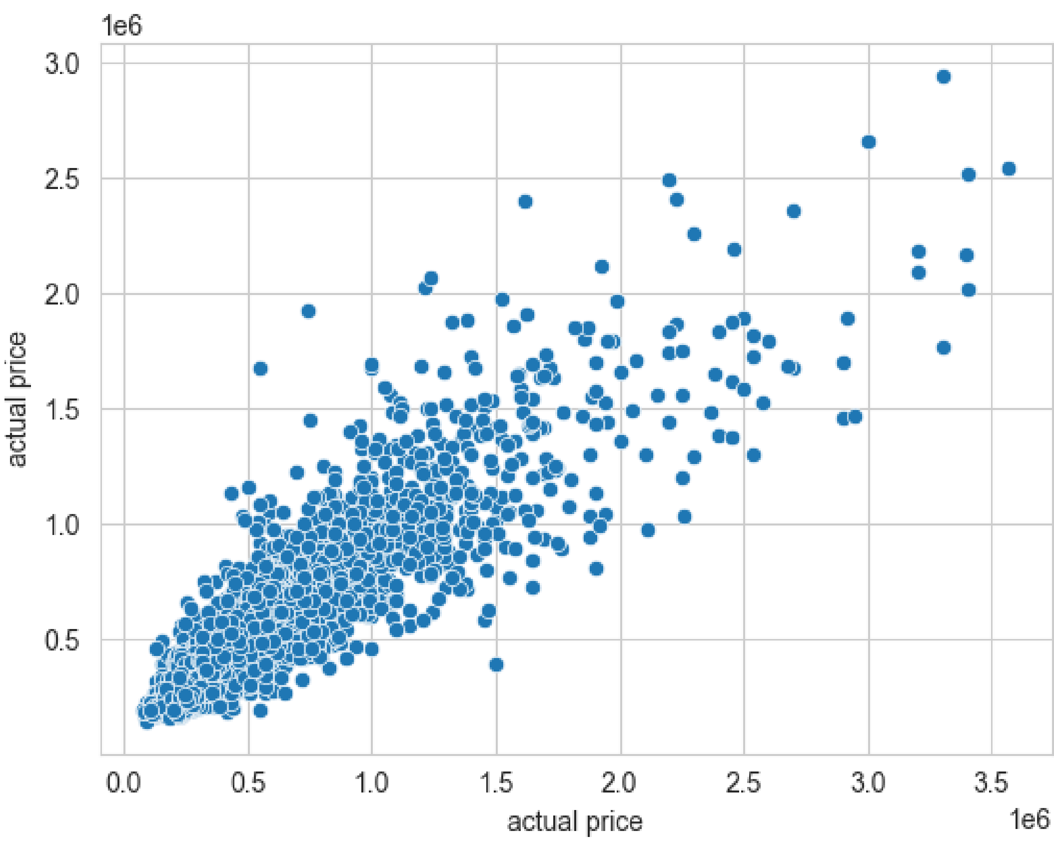
[50]: 0.7894831792276535

[51]:
```
mean_squared_error(y_test, y_pred)
```

[51]: 25681060979.49989

[57]:
```
sns.scatterplot(x = y_test, y = y_pred)
plt.xlabel("actual price")
plt.ylabel("actual price")
```

[57]: Text(0, 0.5, 'actual price')



[67]:
```
reg = LinearRegression()
reg.fit(X_train, y_train)

reg.score(X_test, y_test), reg.coef_
```

[67]:
```
(0.6925495620411505,
 array([-39241.12953713,  34324.78619446,  87410.07508251,   6321.57012566,
         -2571.62511083,  47898.12687306,  38942.01578742,  20425.65307168,
        113778.66497505,  82184.29435247,  27622.24240613, -70742.14923179,
          9304.95451654,  76900.85415064, -18174.16249917,  11997.57351894,
        -10604.10639166,  17626.82769587,   4711.39783398]))
```

[63]:
```
y_pred = reg.predict(X_test)
```

[64]:
```
r2_score(y_test, y_pred)
```

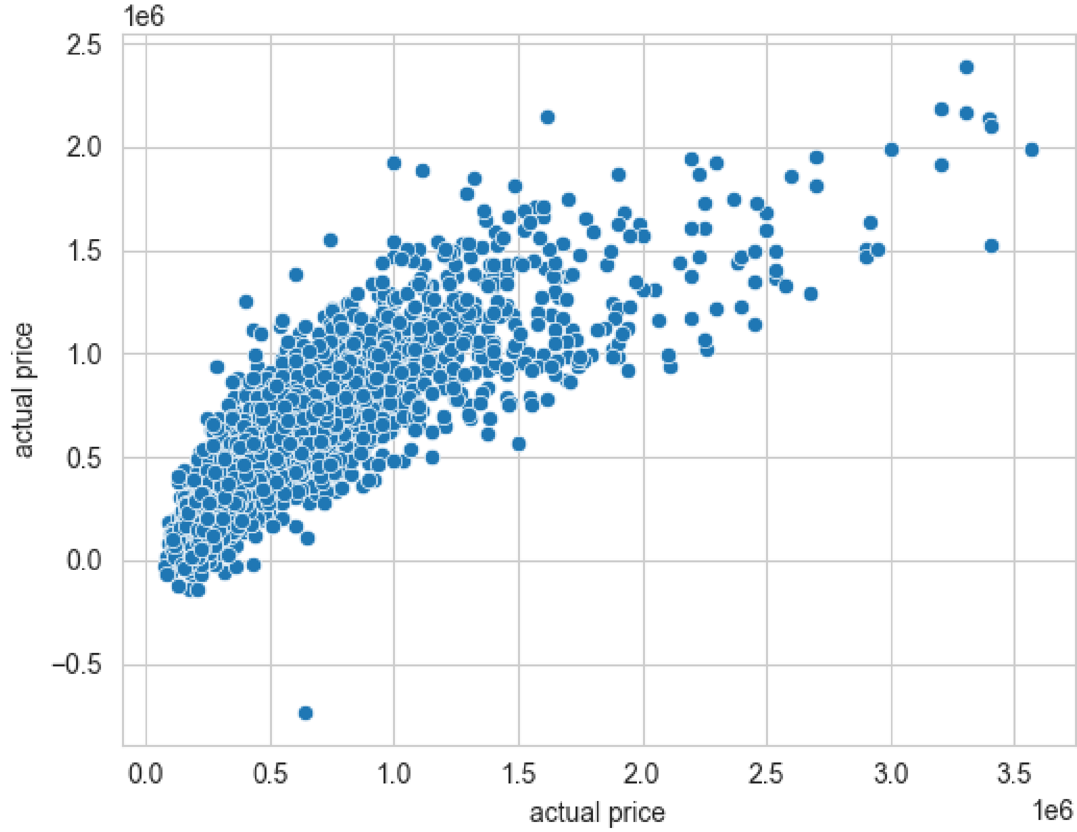
[64]:
```
0.6925495620411505
```

[65]:
```
mean_squared_error(y_test, y_pred)
```

[65]:
```
37506045438.21011
```

[66]:
```
sns.scatterplot(x = y_test, y = y_pred)
plt.xlabel("actual price")
plt.ylabel("actual price")
```

[66]:
```
Text(0, 0.5, 'actual price')
```



0.1.5 Conclusions

[71]:
```
print("""
Overall, KNN was obviously much better - I'm not really surprised. It's␣
  ↪definitely more involved than plain linear regression.

The r2 score was lower for both than I was hoping for - loosely, it means that␣
  ↪the dataset accounted for 78% of the variance (in the KNN regressor), and␣
  ↪then only 69% in the linear regression. This is probably not entirely␣
  ↪accurate, since I'd say house prices are close to 90% at minimum, but who␣
  ↪knows - maybe I know something the real estate market doesn't!

The MSE is abysmal because house prices are so high. Unfortunately, it's not a␣
  ↪very useful metric here - however, it would be remiss to NOT show it,␣
  ↪because it's a staple metric of regression problems.""")
```

```
Overall, KNN was obviously much better - I'm not really surprised. It's
definitely more involved than plain linear regression.
```

```
The r2 score was lower for both than I was hoping for - loosely, it means that
the dataset accounted for 78% of the variance (in the KNN regressor), and then
only 69% in the linear regression. This is probably not entirely accurate, since
I'd say house prices are close to 90% at minimum, but who knows - maybe I know
something the real estate market doesn't!

The MSE is abysmal because house prices are so high. Unfortunately, it's not a
very useful metric here - however, it would be remiss to NOT show it, because
it's a staple metric of regression problems.
```

0.1.6 References

- Academic (if any)
- Online (if any)

[69]:
```
print("""None applicable, I think.""")
```

```
None applicable, I think.
```

0.1.7 Credits

- If you use and/or adapt your code from existing projects, you must provide links and acknowldge the authors. > *This code is based on …. (if any)*

[68]:
```
print("""This code is based on the template that existed here before me, and␣
 ↪also the sklearn docs (that I had to double check a bunch of the exact␣
 ↪packages things were in). I used no other external sources for code help.""")
```

```
This code is based on the template that existed here before me, and also the
sklearn docs (that I had to double check a bunch of the exact packages things
were in). I used no other external sources for code help.
```

[ ]:
```
# End of Project
```