project

June 28, 2020

0.1 EDA

[61]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.linear_model import LinearRegression
#1
df = pd.read_csv('kc_house_data.csv')

# Correlation Plot Heatmap
plt.figure(figsize= (12, 12))
sns.heatmap(df.corr())
df.corr(method='pearson')
```

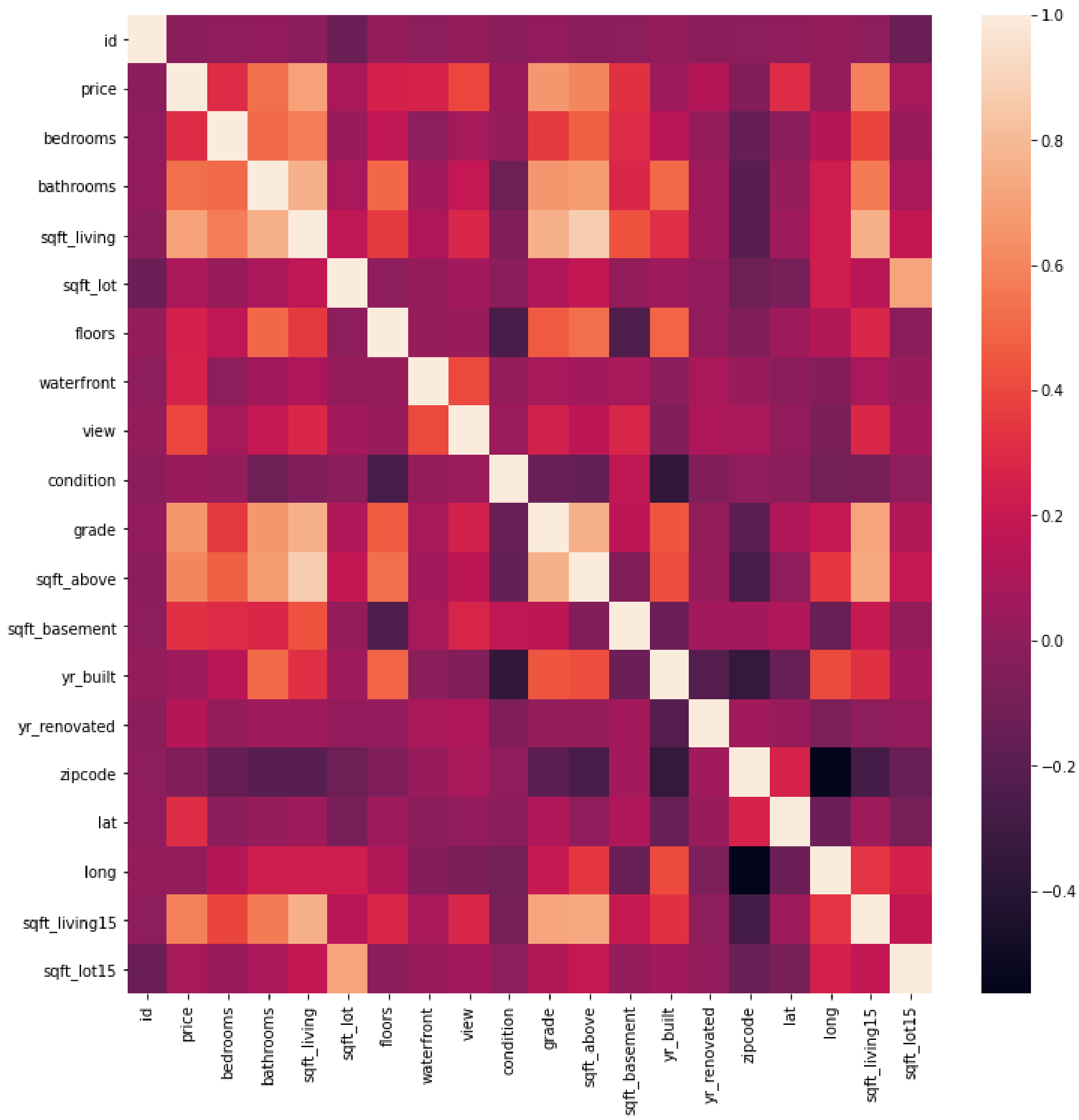
[61]:
```
                     id     price  bedrooms  bathrooms  sqft_living  sqft_lot  \
id             1.000000 -0.016772  0.001150   0.005162    -0.012241 -0.131911
price         -0.016772  1.000000  0.308787   0.525906     0.701917  0.089876
bedrooms       0.001150  0.308787  1.000000   0.514508     0.578212  0.032471
bathrooms      0.005162  0.525906  0.514508   1.000000     0.755758  0.088373
sqft_living   -0.012241  0.701917  0.578212   0.755758     1.000000  0.173453
sqft_lot      -0.131911  0.089876  0.032471   0.088373     0.173453  1.000000
floors         0.018608  0.256804  0.177944   0.502582     0.353953 -0.004814
waterfront    -0.002727  0.266398 -0.006834   0.063744     0.103854  0.021632
view           0.011536  0.397370  0.080008   0.188386     0.284709  0.074900
condition     -0.023803  0.036056  0.026496  -0.126479    -0.059445 -0.008830
grade          0.008188  0.667951  0.356563   0.665838     0.762779  0.114731
sqft_above    -0.010799  0.605368  0.479386   0.686668     0.876448  0.184139
sqft_basement -0.005193  0.323799  0.302808   0.283440     0.435130  0.015418
yr_built       0.021617  0.053953  0.155670   0.507173     0.318152  0.052946
yr_renovated  -0.016925  0.126424  0.018389   0.050544     0.055308  0.007686
zipcode       -0.008211 -0.053402 -0.154092  -0.204786    -0.199802 -0.129586
lat           -0.001798  0.306692 -0.009951   0.024280     0.052155 -0.085514
long           0.020672  0.022036  0.132054   0.224903     0.241214  0.230227
```

sqft_living15	-0.002701	0.585241	0.393406	0.569884	0.756402	0.144763
sqft_lot15	-0.138557	0.082845	0.030690	0.088303	0.184342	0.718204

	floors	waterfront	view	condition	grade	\
id	0.018608	-0.002727	0.011536	-0.023803	0.008188	
price	0.256804	0.266398	0.397370	0.036056	0.667951	
bedrooms	0.177944	-0.006834	0.080008	0.026496	0.356563	
bathrooms	0.502582	0.063744	0.188386	-0.126479	0.665838	
sqft_living	0.353953	0.103854	0.284709	-0.059445	0.762779	
sqft_lot	-0.004814	0.021632	0.074900	-0.008830	0.114731	
floors	1.000000	0.023755	0.028814	-0.264075	0.458794	
waterfront	0.023755	1.000000	0.401971	0.016611	0.082888	
view	0.028814	0.401971	1.000000	0.045999	0.251728	
condition	-0.264075	0.016611	0.045999	1.000000	-0.146896	
grade	0.458794	0.082888	0.251728	-0.146896	1.000000	
sqft_above	0.523989	0.072109	0.167609	-0.158904	0.756073	
sqft_basement	-0.245715	0.080559	0.277078	0.173849	0.168220	
yr_built	0.489193	-0.026153	-0.053636	-0.361592	0.447865	
yr_renovated	0.006427	0.092873	0.103951	-0.060788	0.014261	
zipcode	-0.059541	0.030272	0.084622	0.002888	-0.185771	
lat	0.049239	-0.014306	0.005871	-0.015102	0.113575	
long	0.125943	-0.041904	-0.078107	-0.105877	0.200341	
sqft_living15	0.280102	0.086507	0.280681	-0.093072	0.713867	
sqft_lot15	-0.010722	0.030781	0.072904	-0.003126	0.120981	

	sqft_above	sqft_basement	yr_built	yr_renovated	zipcode	\
id	-0.010799	-0.005193	0.021617	-0.016925	-0.008211	
price	0.605368	0.323799	0.053953	0.126424	-0.053402	
bedrooms	0.479386	0.302808	0.155670	0.018389	-0.154092	
bathrooms	0.686668	0.283440	0.507173	0.050544	-0.204786	
sqft_living	0.876448	0.435130	0.318152	0.055308	-0.199802	
sqft_lot	0.184139	0.015418	0.052946	0.007686	-0.129586	
floors	0.523989	-0.245715	0.489193	0.006427	-0.059541	
waterfront	0.072109	0.080559	-0.026153	0.092873	0.030272	
view	0.167609	0.277078	-0.053636	0.103951	0.084622	
condition	-0.158904	0.173849	-0.361592	-0.060788	0.002888	
grade	0.756073	0.168220	0.447865	0.014261	-0.185771	
sqft_above	1.000000	-0.052156	0.424037	0.023251	-0.261570	
sqft_basement	-0.052156	1.000000	-0.133064	0.071233	0.074725	
yr_built	0.424037	-0.133064	1.000000	-0.224907	-0.347210	
yr_renovated	0.023251	0.071233	-0.224907	1.000000	0.064325	
zipcode	-0.261570	0.074725	-0.347210	0.064325	1.000000	
lat	-0.001199	0.110414	-0.148370	0.029350	0.266742	
long	0.344842	-0.144546	0.409993	-0.068321	-0.564259	
sqft_living15	0.731767	0.200443	0.326377	-0.002695	-0.279299	
sqft_lot15	0.195077	0.017550	0.070777	0.007944	-0.147294	

	lat	long	sqft_living15	sqft_lot15
id	-0.001798	0.020672	-0.002701	-0.138557
price	0.306692	0.022036	0.585241	0.082845
bedrooms	-0.009951	0.132054	0.393406	0.030690
bathrooms	0.024280	0.224903	0.569884	0.088303
sqft_living	0.052155	0.241214	0.756402	0.184342
sqft_lot	-0.085514	0.230227	0.144763	0.718204
floors	0.049239	0.125943	0.280102	-0.010722
waterfront	-0.014306	-0.041904	0.086507	0.030781
view	0.005871	-0.078107	0.280681	0.072904
condition	-0.015102	-0.105877	-0.093072	-0.003126
grade	0.113575	0.200341	0.713867	0.120981
sqft_above	-0.001199	0.344842	0.731767	0.195077
sqft_basement	0.110414	-0.144546	0.200443	0.017550
yr_built	-0.148370	0.409993	0.326377	0.070777
yr_renovated	0.029350	-0.068321	-0.002695	0.007944
zipcode	0.266742	-0.564259	-0.279299	-0.147294
lat	1.000000	-0.135371	0.048679	-0.086139
long	-0.135371	1.000000	0.335626	0.255586
sqft_living15	0.048679	0.335626	1.000000	0.183515
sqft_lot15	-0.086139	0.255586	0.183515	1.000000

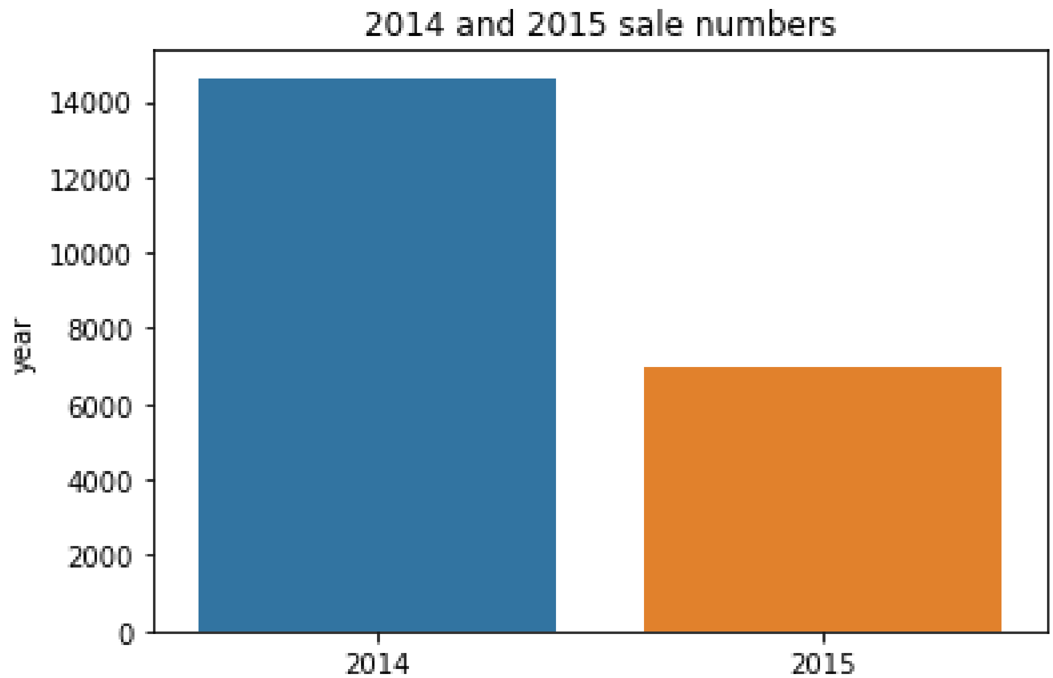


Most Positive: Sqft, Bedrooms, Bathrooms Most Negative: Zipcode, Lat, Long

(2). Sale numbers Vs. (years,months) and Sale prices correlation Vs. (years,months)

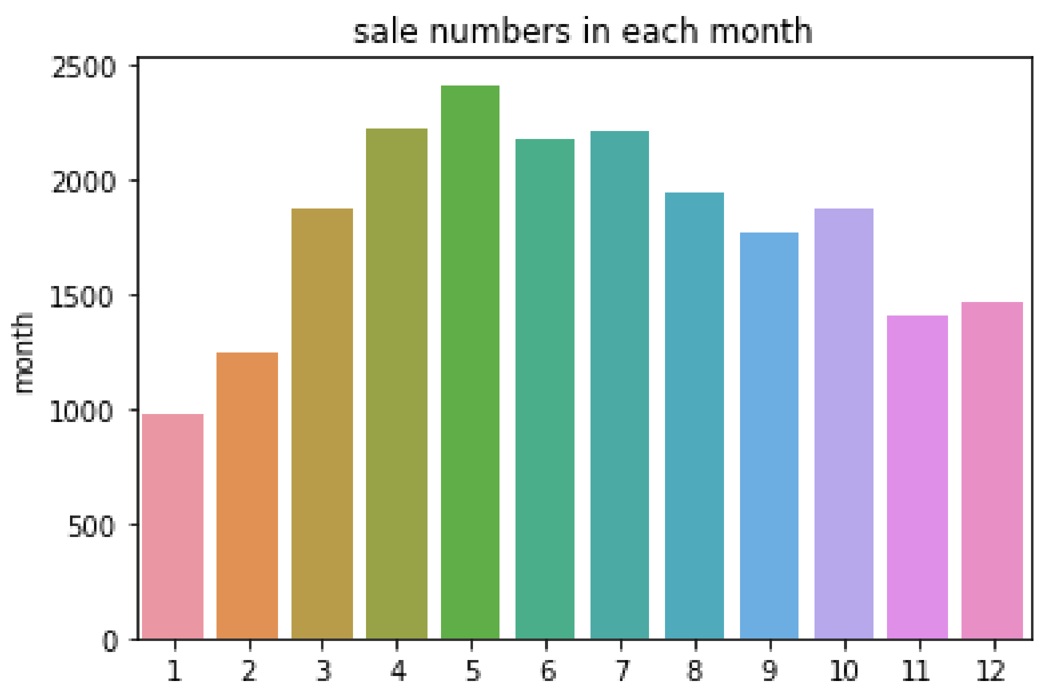
[62]:
```
df['month'] = pd.DatetimeIndex(df['date']).month
df['year'] = pd.DatetimeIndex(df['date']).year
month = df['month'].value_counts()
year = df['year'].value_counts()
sns.barplot(year.index.tolist(),year)
plt.title("2014 and 2015 sale numbers")
```

[62]:
```
Text(0.5, 1.0, '2014 and 2015 sale numbers')
```



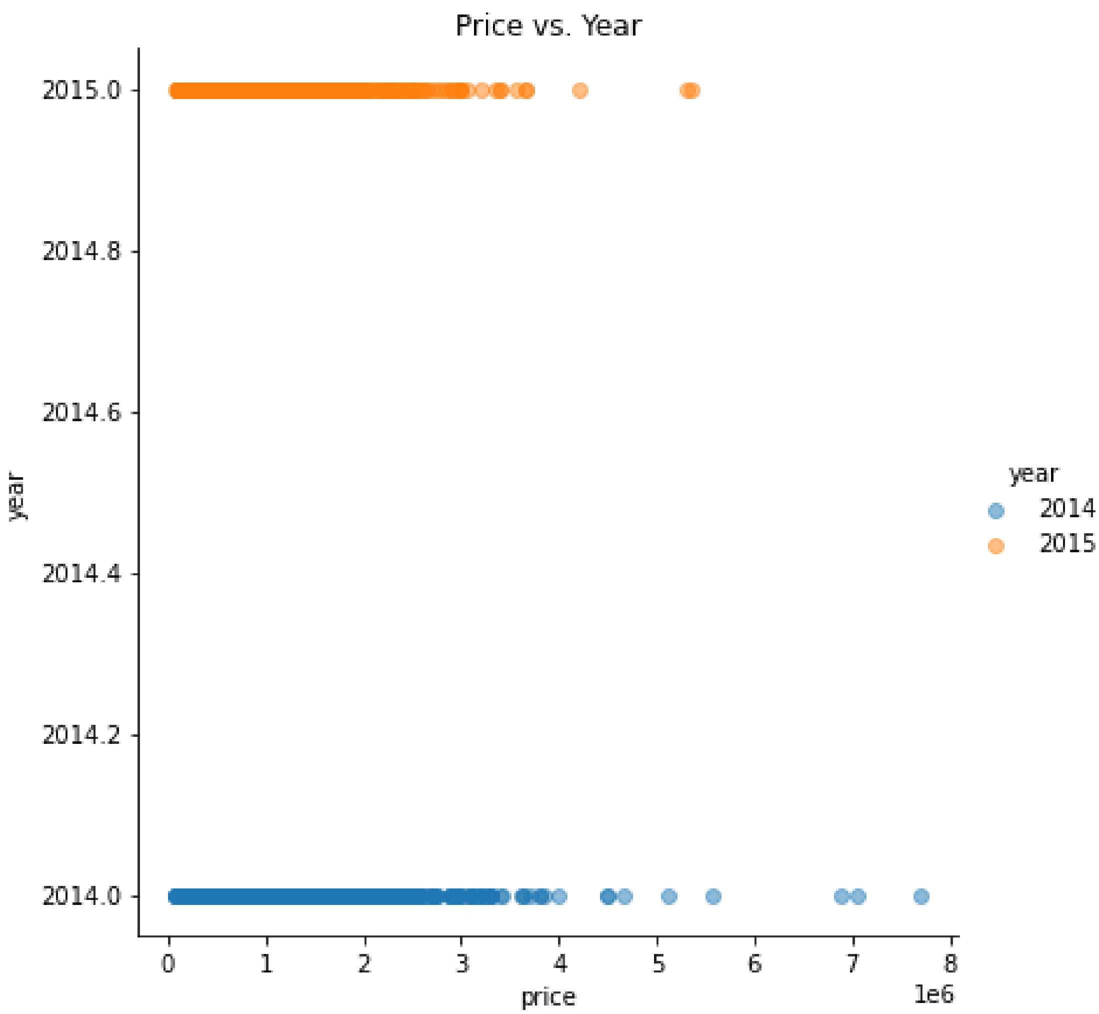

```
[63]: sns.barplot(month.index.tolist(),month)
      plt.title("sale numbers in each month")
```

```
[63]: Text(0.5, 1.0, 'sale numbers in each month')
```



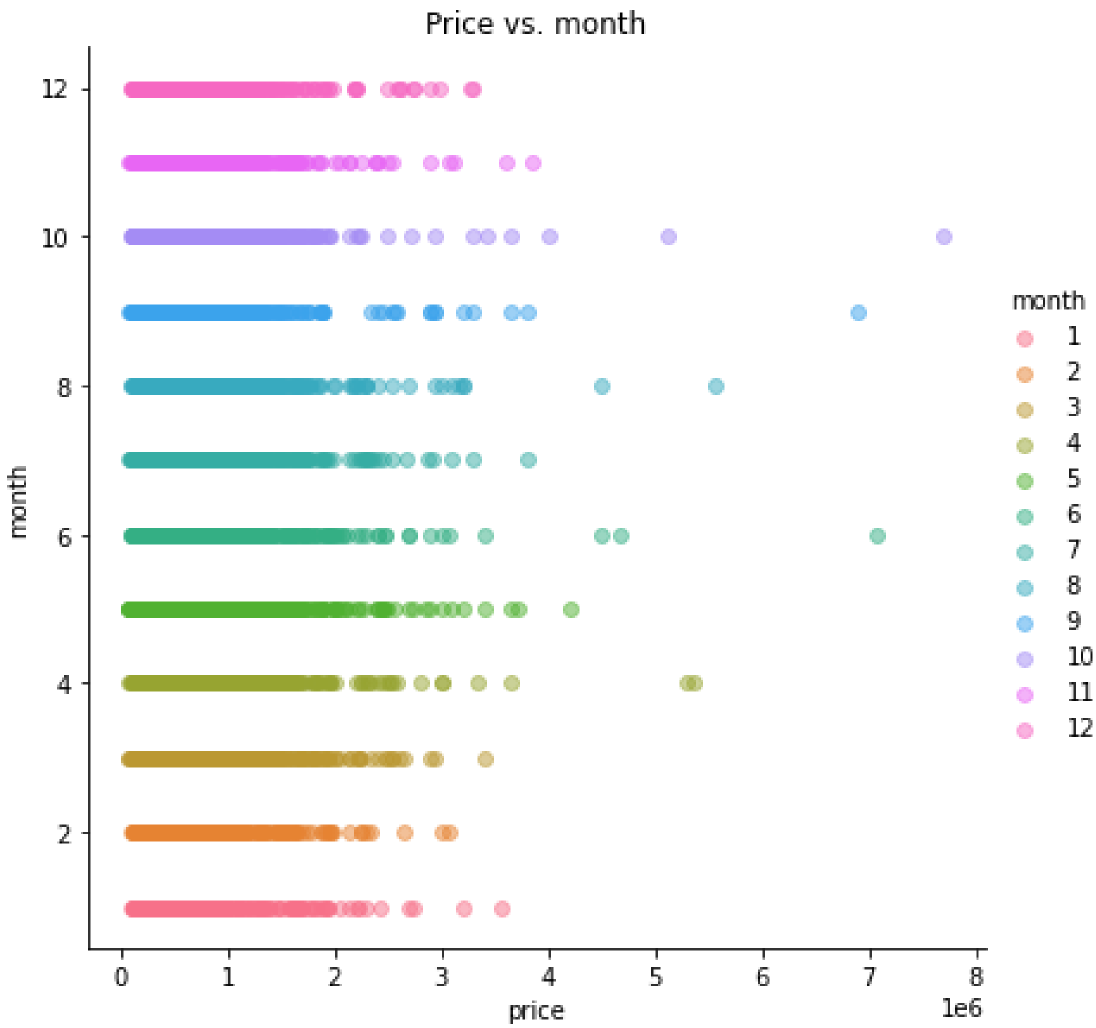
[64]:
```
g=sns.FacetGrid(df,hue='year',height=6)
g.map(plt.scatter,'price','year',alpha=0.5)
g.add_legend()
plt.title("Price vs. Year")
```

[64]: Text(0.5, 1.0, 'Price vs. Year')



[65]:
```
g=sns.FacetGrid(df,hue='month',height=6)
g.map(plt.scatter,'price','month',alpha=0.5)
g.add_legend()
plt.title("Price vs. month")
```

[65]: Text(0.5, 1.0, 'Price vs. month')



[66]:
```
print("Price correlation with year: ",df['price'].corr(df['year']))
print("Price correlation with month: ",df['price'].corr(df['month']))
```

```
Price correlation with year:  0.003727139624315499
Price correlation with month:  -0.009928289245273971
```

[67]:
```
#3 from sklearn.linear_model import LinearRegression
fig, (ax, box, sq, yr) = plt.subplots(4, figsize=(10,10))
plt.subplots_adjust(hspace = .5)
# Price
ax = sns.violinplot(ax = ax, x = df['price'])
print(np.percentile(df['price'], [25, 50, 75]))
ax.set(xlabel = 'Price')

#'bedrooms', 'bathrooms', 'floors', 'condition'
```

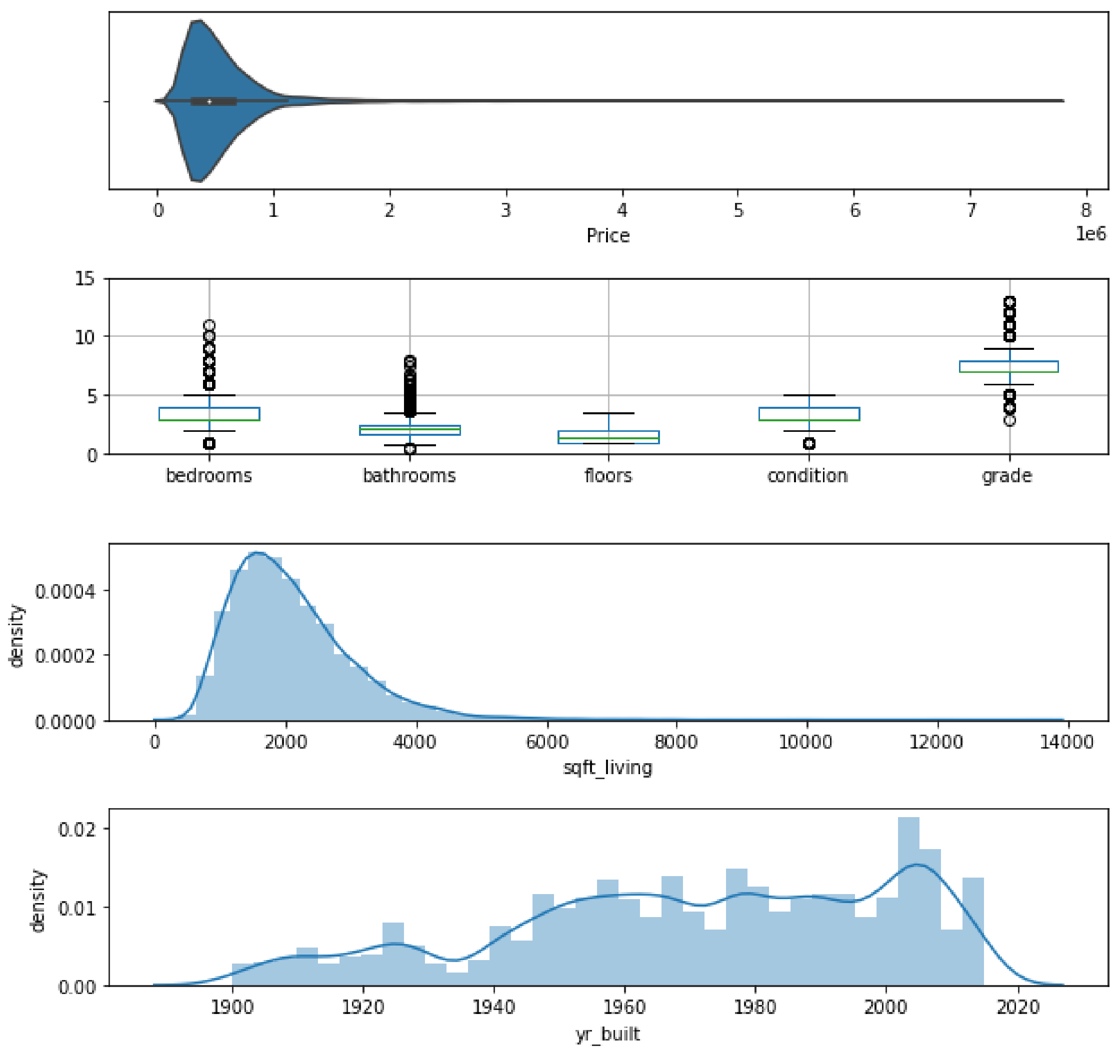
```
box = df.boxplot(ax = box, column = ['bedrooms', 'bathrooms', 'floors',␣
↪'condition', 'grade'])
box.set_ylim([0,15])

# Square feet living room
sq = sns.distplot(df.sqft_living, ax = sq)
sq.set(ylabel = 'density')

# Year built
yr = sns.distplot(df.yr_built, ax = yr)
yr.set(ylabel = 'density')
```

```
[322000. 450000. 645000.]
```

[67]: `[Text(0, 0.5, 'density')]`



1 The first graph shows the distribution of prices in a violin plot. We can tell the 25-75% quartile is between $322,000 and $645,000 2 The second plot shows the box plots of bedrooms, bathrooms, floors, condition, grade. The medians are: Bedrooms ~ 3 Bathrooms ~ 2.5 Floors ~ 2 Condition ~ 3 Grade ~ 7 3 The third plot shows the distribution of square foot in living room. This plot is skewed with the most being ~1800 sqft 4 The last plot is the distribution of houses built over time. There has been a recent phase of construction in the 2000s, which means many houses are newly built and in decent condition.

(4). Create the scoring function for 'Grade' with accuracy:70%

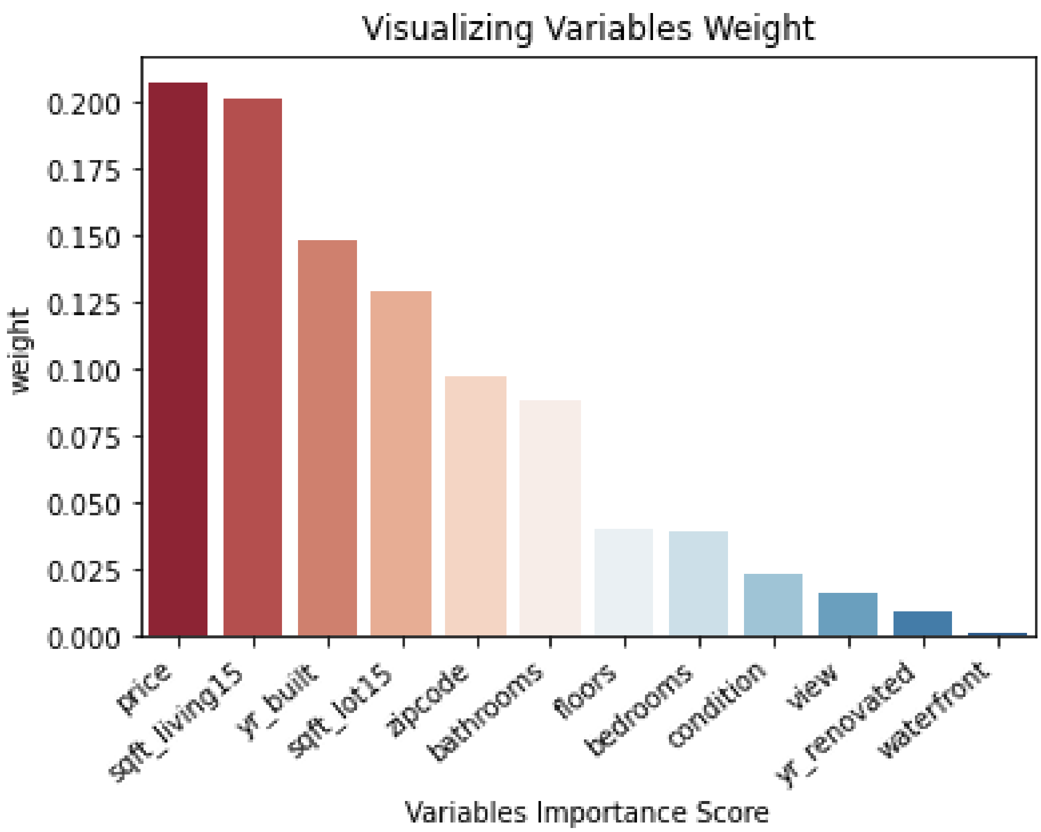
[68]:
```
X=df[['price','bedrooms','bathrooms','sqft_living15','sqft_lot15','floors','waterfront',"condi
      "yr_renovated"]]
y=df['grade']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3)
```

[69]:
```
clf = RandomForestClassifier(n_estimators=100)
clf.fit(X_train,y_train)
y_predit=clf.predict(X_test)
```

[70]:
```
variables = pd.Series(clf.feature_importances_,index=X.columns).
 ↪sort_values(ascending=False)
variables
```

[70]:
```
price            0.207003
sqft_living15    0.200625
yr_built         0.148349
sqft_lot15       0.129360
zipcode          0.097564
bathrooms        0.088222
floors           0.039792
bedrooms         0.039237
condition        0.023602
view             0.015830
yr_renovated     0.009228
waterfront       0.001188
dtype: float64
```

[71]:
```
ax=sns.barplot(x=variables.index, y=variables,palette=sns.color_palette("RdBu",␣
 ↪12))
ax.set_xticklabels(ax.get_xticklabels(), rotation=40, ha="right")
# Add labels to your graph
plt.xlabel('Variables Importance Score')
plt.ylabel('weight')
plt.title("Visualizing Variables Weight")
plt.show()
```



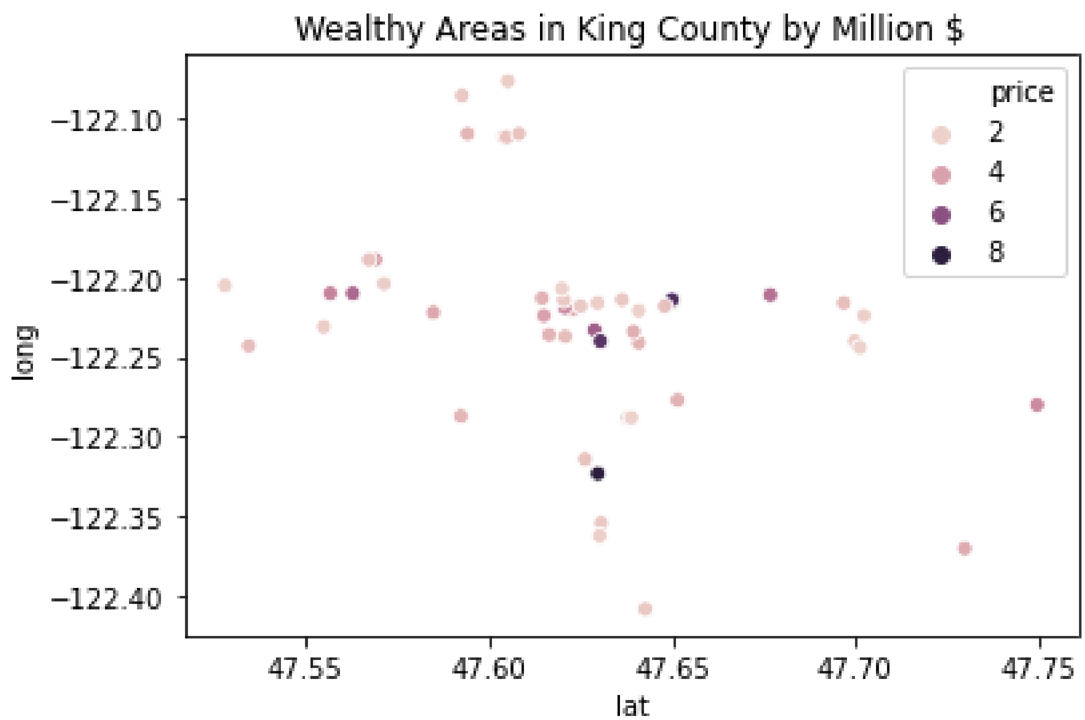
[72]:
```
print("Scoring function accuracy:",metrics.accuracy_score(y_test, y_predit))
```

```
Scoring function accuracy: 0.6978395061728395
```

[73]:
```
#5
import seaborn as sns

wealthy = df.loc[df['price'] >= 3000000]

plt.title("Wealthy Areas in King County by Million $")
ax = sns.scatterplot(x=wealthy.lat, y=wealthy.long, hue=wealthy.price)
```



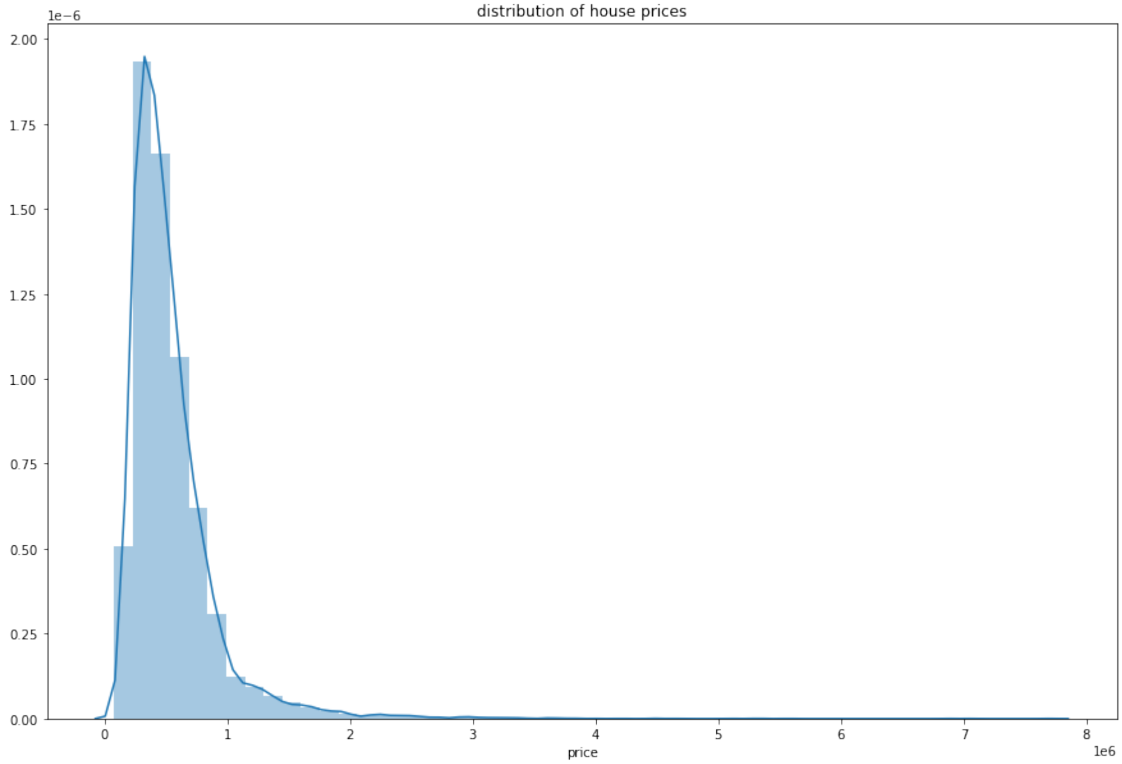
0.2 Modeling

0.2.1 Linear Regression

[74]:
```
X=df[['bedrooms','bathrooms','sqft_living15','grade','sqft_lot15','floors','waterfront',"condi
      "yr_renovated"]]
y=df['price']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3)
```

[75]:
```
plt.figure(figsize=(15,10))
plt.tight_layout()
sns.distplot(df['price'])
plt.title("distribution of house prices")
```

[75]: Text(0.5, 1.0, 'distribution of house prices')



[76]:
```
reg = LinearRegression()
reg.fit(X_train,y_train)
coeff_df = pd.DataFrame(reg.coef_, X.columns, columns=['Coefficient'])
coeff_df
```

[76]:

	Coefficient
bedrooms	-5450.988933
bathrooms	117738.326770
sqft_living15	87.593633
grade	155061.065637
sqft_lot15	-0.254915
floors	19202.780808
waterfront	626799.808457
condition	21715.815162
yr_built	-4159.997373
zipcode	52.681775
view	44875.705945
yr_renovated	12.653962

[77]:
```
y_predit = reg.predict(X_test)
accurate_rate=1-np.mean(np.abs(y_predit-y_test)/y_test)
print("Accuracy: ",accurate_rate)
```

```
Accuracy:  0.6919052903203426
```

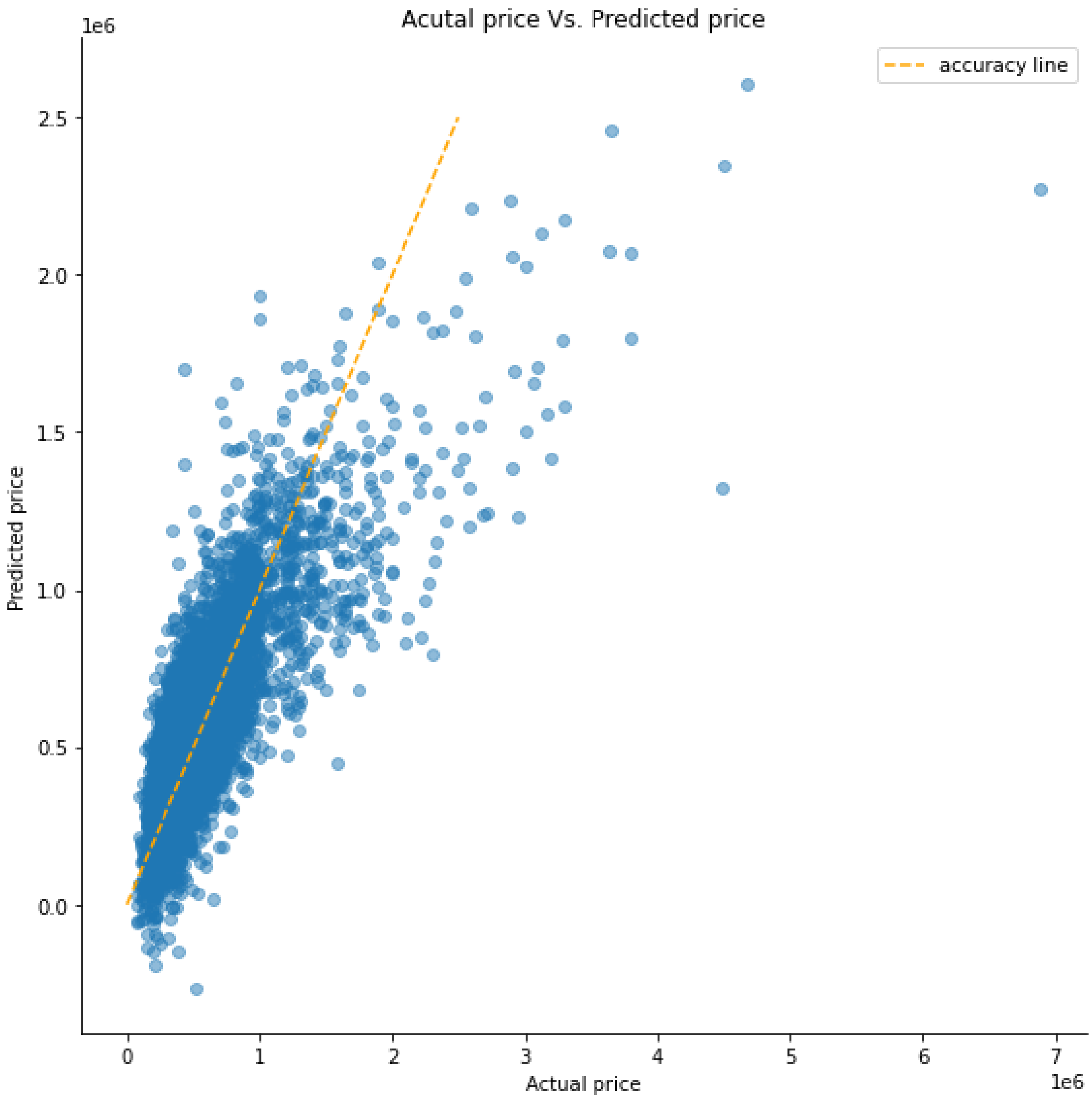
[78]:
```python
result = pd.DataFrame({'Actual price': y_test, 'Predicted price': y_predit})
result.head(8)
```

[78]:

	Actual price	Predicted price
15923	279000.0	410862.181731
760	565000.0	558983.663389
21541	530000.0	443872.010897
6091	302000.0	359798.502064
6271	435000.0	708855.350446
11170	525000.0	436397.003055
20655	310000.0	280622.271501
763	374950.0	373464.988084

[79]:
```python
g = sns.FacetGrid(result,height=8)
g.map(plt.scatter,'Actual price','Predicted price',alpha=0.5)
plt.plot([0,2500000],[0,2500000],ls='--',color='orange',label='accuracy line')
plt.title("Acutal price Vs. Predicted price")
plt.legend()
print("Model accuracy: ",accurate_rate)
```

```
Model accuracy:  0.6919052903203426
```



Linear regression is a model to find possible W, in "Y= XW+error" which has minimum Mean squared error(MSE). This linear regression model accuracy rate is around 66%.

0.2.2 Random Forest Model

[80]:
```
X=df[['bedrooms','bathrooms','sqft_living15','grade','sqft_lot15','floors','waterfront',"condi
      "yr_renovated"]]
y=df['price']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3)
clf = RandomForestRegressor(n_estimators=100)
clf.fit(X_train,y_train)
y_predit=clf.predict(X_test)
```

[81]:

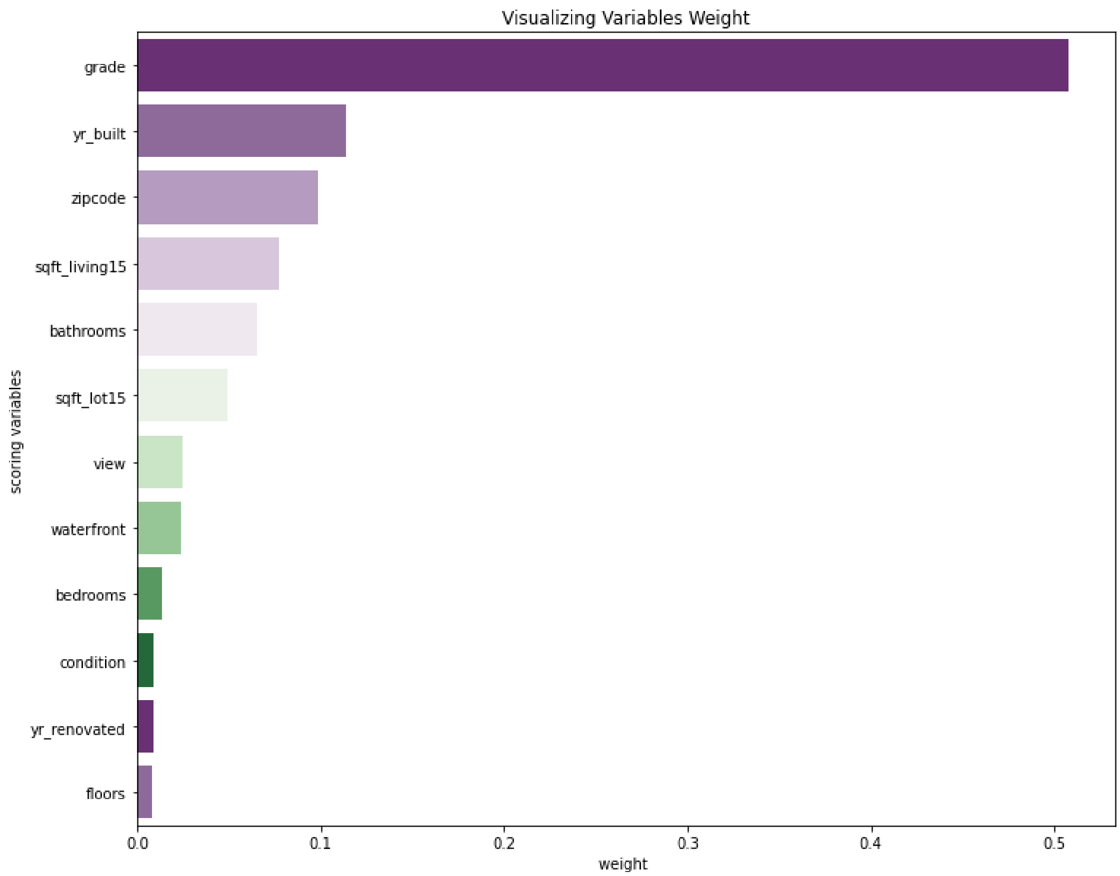
```
variables = pd.Series(clf.feature_importances_,index=X.columns).
 ↪sort_values(ascending=False)
variables
```

[81]:

```
grade            0.507429
yr_built         0.113978
zipcode          0.098742
sqft_living15    0.077054
bathrooms        0.065604
sqft_lot15       0.049521
view             0.024773
waterfront       0.024266
bedrooms         0.013208
condition        0.009076
yr_renovated     0.008426
floors           0.007922
dtype: float64
```

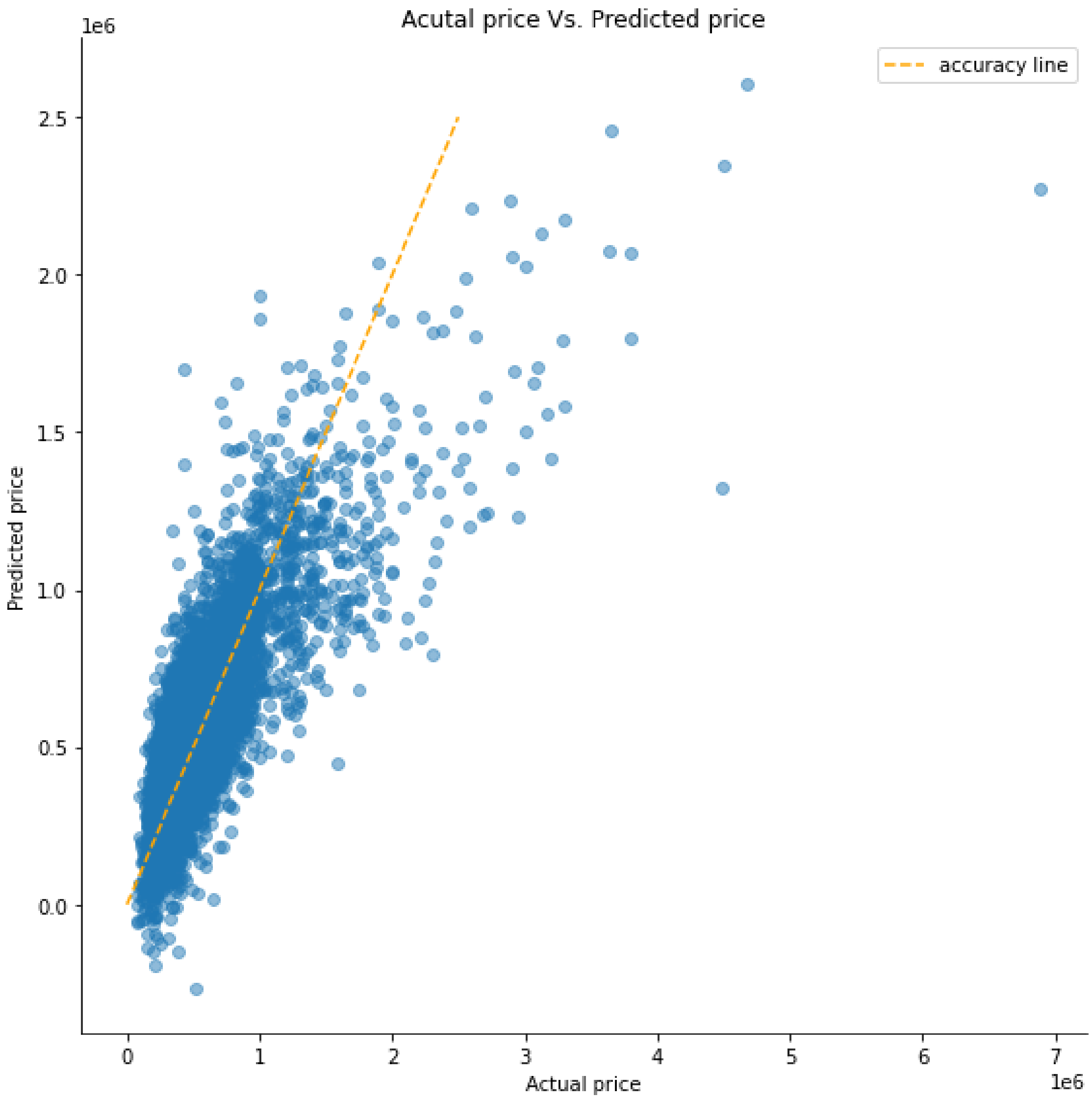
[82]:

```
ax=sns.barplot(x=variables, y=variables.index,palette=sns.color_palette("PRGn",␣
 ↪10))
ax.figure.set_size_inches(12,10)
# Add labels to your graph
plt.xlabel('weight ')
plt.ylabel('scoring variables')
plt.title("Visualizing Variables Weight")
plt.show()
```



[83]:
```
g = sns.FacetGrid(result,height=8)
g.map(plt.scatter,'Actual price','Predicted price',alpha=0.5)
plt.plot([0,2500000],[0,2500000],ls='--',color='orange',label='accuracy line')
plt.title("Acutal price Vs. Predicted price")
plt.legend()
print("Model accuracy: ",accurate_rate)
```

```
Model accuracy:  0.6919052903203426
```



[84]:
```
accurate_rate=1-np.mean(np.abs(y_predit-y_test)/y_test)
print("Random Forest accuracy:",accurate_rate)
```

```
Random Forest accuracy: 0.8261395691303726
```

Random forest regression is to select random samples and build decision trees for each sample. Then, Perform a vote for each predicted result and select the prediction result with the most votes as the final prediction. The Random forest model has accuracy rate around 81%.

0.2.3 K Nearest Neighbors

[85]:
```
from sklearn import neighbors
X=df[['bedrooms','bathrooms','floors','grade','sqft_living15','waterfront',"condition","yr_bui
      "yr_renovated"]]
y=df['price']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3)

model = neighbors.KNeighborsRegressor(n_neighbors=10)
model.fit(X_train, y_train)
preds = model.predict(X_test)
```

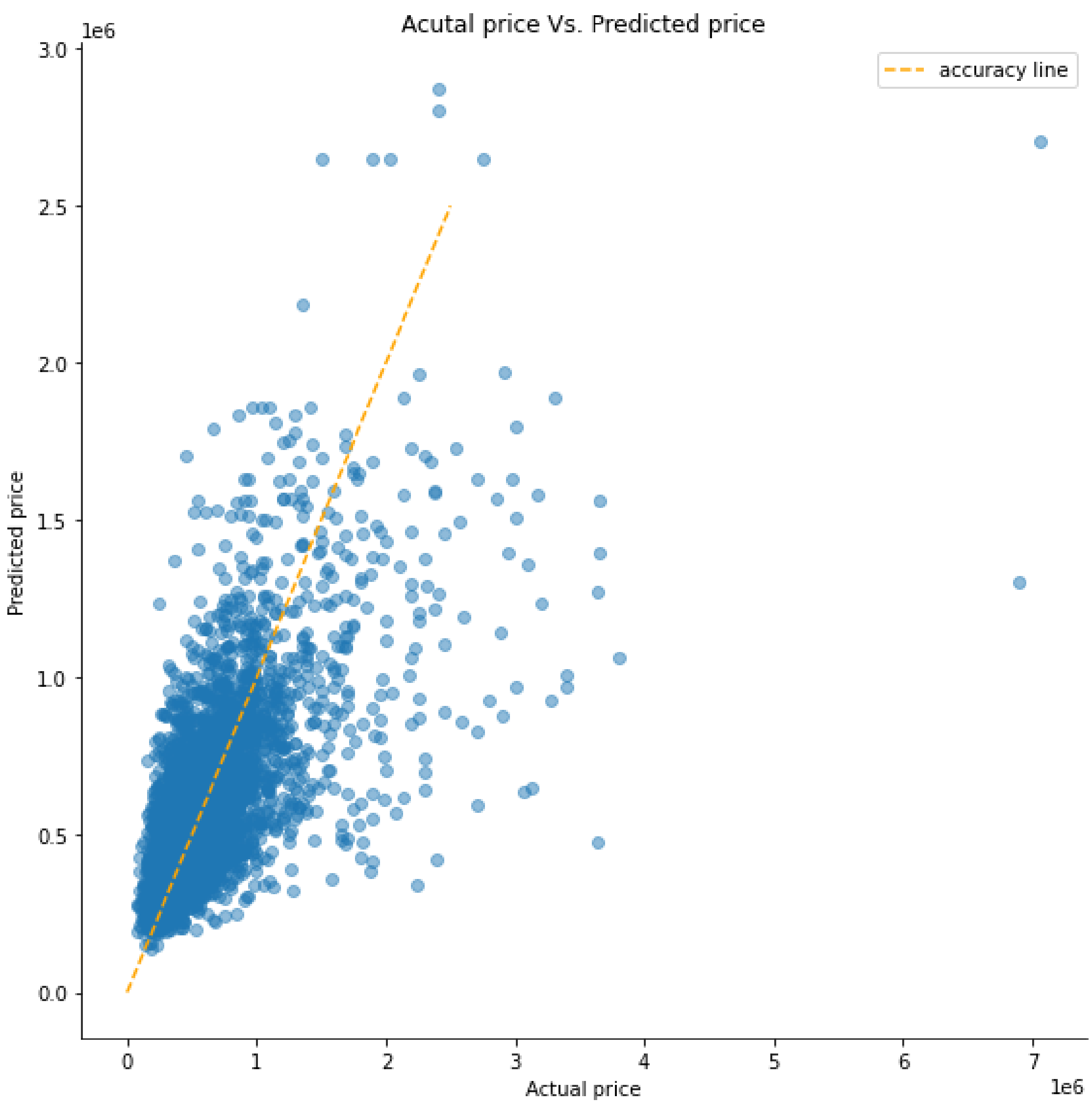
[86]:
```
result = pd.DataFrame({'Actual price': y_test, 'Predicted price': preds})
result.head(8)
```

[86]:

	Actual price	Predicted price
6025	300000.0	351050.0
6357	264950.0	364545.0
1908	400000.0	521080.0
8163	470500.0	343140.0
18756	315000.0	393145.0
5837	616000.0	247950.0
10008	291600.0	410350.0
8642	249000.0	241128.0

[87]:
```
g = sns.FacetGrid(result,height=8)
g.map(plt.scatter,'Actual price','Predicted price',alpha=0.5)
plt.plot([0,2500000],[0,2500000],ls='--',color='orange',label='accuracy line')
plt.title("Acutal price Vs. Predicted price")
plt.legend()
```

[87]: <matplotlib.legend.Legend at 0x28b31bbeb88>



[88]:
```
print('Nearest Neighbors Accuracy: ', model.score(X_test, y_test))
```

```
Nearest Neighbors Accuracy:  0.46316299843696496
```

KNN works by finding the distances between a query and all the examples in the data, selecting the specified number examples (K) closest to the query, then votes for the most frequent label (in the case of classification) or averages the labels (in the case of regression).

This method is not the best because it yielded a ~45% accuracy.

[89]:
```
KNN works by finding the distances between a query and all the examples in the␣
↪data, selecting the specified number examples (K) closest to the query, then␣
↪votes for the most frequent label (in the case of classification) or␣
↪averages the labels (in the case of regression).
```

```
This method is not the best because it yielded a ~45% accuracy.
```

```
      File "<ipython-input-89-bf6d3144be4b>", line 1
    KNN works by finding the distances between a query and all the examples␣
↪in the data, selecting the specified number examples (K) closest to the query,␣
↪then votes for the most frequent label (in the case of classification) or␣
↪averages the labels (in the case of regression).
              ^
SyntaxError: invalid syntax
```

Random forest regression is to select random samples and build decision trees for each sample. Then, Perform a vote for each predicted result and select the prediction result with the most votes as the final prediction. The Random forest model has accuracy rate around 81%.

0.2.4 K Nearest Neighbors

[ ]:
```python
from sklearn import neighbors
X=df[['bedrooms','bathrooms','floors','grade','sqft_living15','waterfront',"condition","yr_bui
      "yr_renovated"]]
y=df['price']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3)

model = neighbors.KNeighborsRegressor(n_neighbors=10)
model.fit(X_train, y_train)
preds = model.predict(X_test)
```

[ ]:
```python
result = pd.DataFrame({'Actual price': y_test, 'Predicted price': preds})
result.head(8)
```

[ ]:
```python
g = sns.FacetGrid(result,height=8)
g.map(plt.scatter,'Actual price','Predicted price',alpha=0.5)
plt.plot([0,2500000],[0,2500000],ls='--',color='orange',label='accuracy line')
plt.title("Acutal price Vs. Predicted price")
plt.legend()
```

[ ]:
```python
print('Nearest Neighbors Accuracy: ', model.score(X_test, y_test))
```

KNN works by finding the distances between a query and all the examples in the data, selecting the specified number examples (K) closest to the query, then votes for the most frequent label (in the case of classification) or averages the labels (in the case of regression).

This method is not the best because it yielded a ~45% accuracy.

[46]:
```
KNN works by finding the distances between a query and all the examples in the␣
↪data, selecting the specified number examples (K) closest to the query, then␣
↪votes for the most frequent label (in the case of classification) or␣
↪averages the labels (in the case of regression).

This method is not the best because it yielded a ~45% accuracy.
```

```
Random Forest accuracy: 0.8081079949703387
```

Random forest regression is to select random samples and build decision trees for each sample. Then, Perform a vote for each predicted result and select the prediction result with the most votes as the final prediction. The Random forest model has accuracy rate around 81%.

0.2.5 K Nearest Neighbors

[96]:
```
from sklearn import neighbors
X=df[['bedrooms','bathrooms','floors','grade','sqft_living15','waterfront',"condition","yr_bui
      "yr_renovated"]]
y=df['price']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3)

model = neighbors.KNeighborsRegressor(n_neighbors=10)
model.fit(X_train, y_train)
preds = model.predict(X_test)
```

```
Nearest Neighbors Accuracy:  0.4579753111121226
```

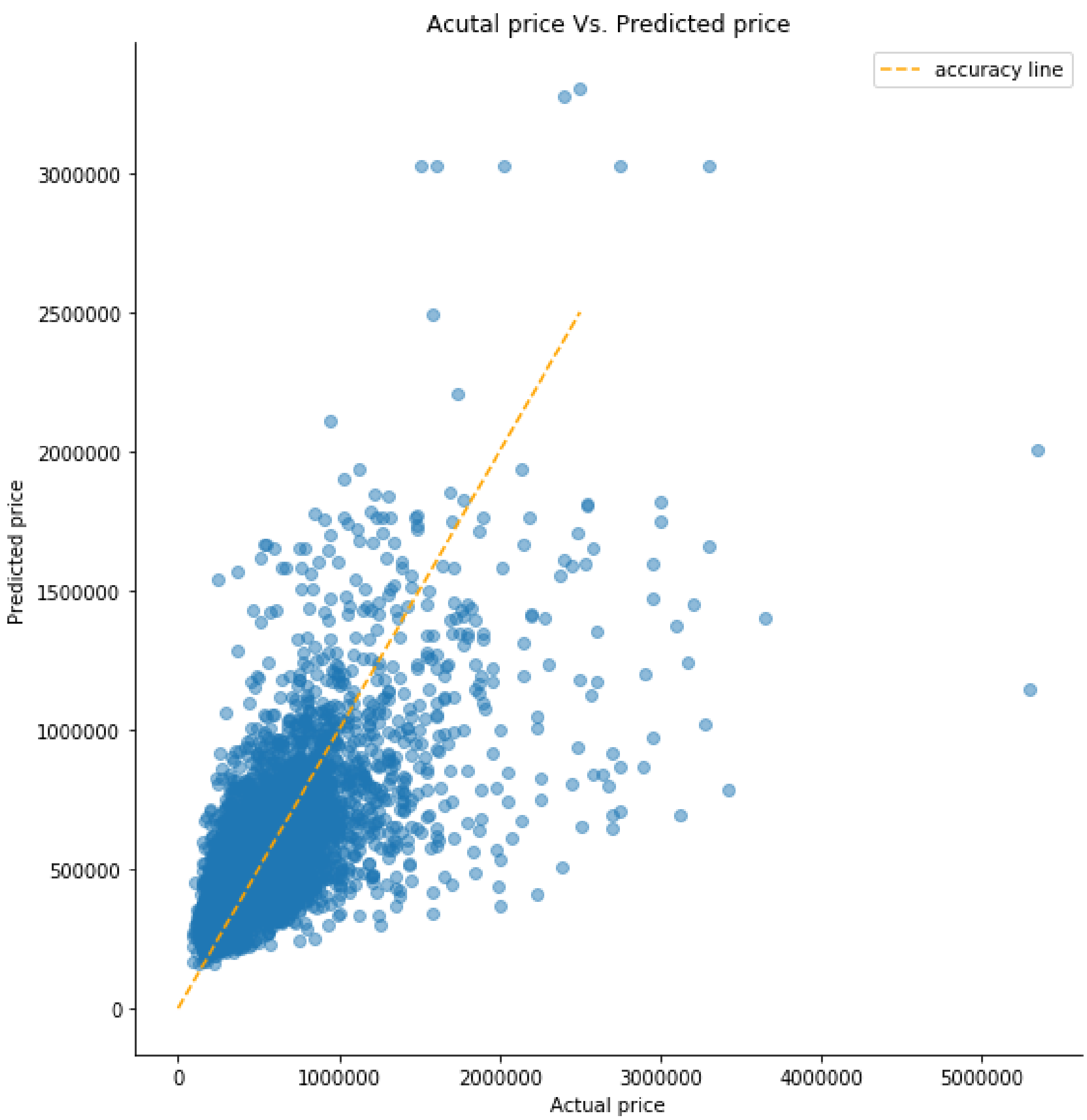
[98]:
```
result = pd.DataFrame({'Actual price': y_test, 'Predicted price': preds})
result.head(8)
```

[98]:

	Actual price	Predicted price
16790	1650000.0	1110250.0
15822	1160000.0	1506890.0
18857	245000.0	399985.0
3027	770000.0	580400.0
11445	390000.0	339100.0
12103	599000.0	774355.0
20975	910000.0	711174.5
7508	450000.0	463150.0

[99]:
```
g = sns.FacetGrid(result,height=8)
g.map(plt.scatter,'Actual price','Predicted price',alpha=0.5)
plt.plot([0,2500000],[0,2500000],ls='--',color='orange',label='accuracy line')
plt.title("Acutal price Vs. Predicted price")
plt.legend()
```

[99]:
```
<matplotlib.legend.Legend at 0x7f9ac8cbbd90>
```



[97]:
```
print('Nearest Neighbors Accuracy: ', model.score(X_test, y_test))
```

```
Nearest Neighbors Accuracy:  0.4579753111121226
```

KNN works by finding the distances between a query and all the examples in the data, selecting the specified number examples (K) closest to the query, then votes for the most frequent label (in the case of classification) or averages the labels (in the case of regression).

This method is not the best because it yielded a ~45% accuracy.