```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings("ignore")

from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error

from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso
from sklearn.linear_model import ElasticNet
from sklearn.ensemble import RandomForestRegressor
from sklearn.svm import SVR
from xgboost import XGBRegressor
from sklearn.preprocessing import PolynomialFeatures
```

```
house = pd.read_csv('/content/data.csv')
house.head(20)
```

	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	conditi
0	2014-05-02 00:00:00	313000.0	3.0	1.50	1340	7912	1.5	0	0	
1	2014-05-02 00:00:00	2384000.0	5.0	2.50	3650	9050	2.0	0	4	
2	2014-05-02 00:00:00	342000.0	3.0	2.00	1930	11947	1.0	0	0	
3	2014-05-02 00:00:00	420000.0	3.0	2.25	2000	8030	1.0	0	0	

```
house.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4600 entries, 0 to 4599
Data columns (total 18 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   date           4600 non-null   object 
 1   price          4600 non-null   float64
 2   bedrooms       4600 non-null   float64
 3   bathrooms      4600 non-null   float64
 4   sqft_living    4600 non-null   int64  
 5   sqft_lot       4600 non-null   int64  
 6   floors         4600 non-null   float64
 7   waterfront     4600 non-null   int64  
 8   view           4600 non-null   int64  
 9   condition      4600 non-null   int64  
 10  sqft_above     4600 non-null   int64  
 11  sqft_basement  4600 non-null   int64  
 12  yr_built       4600 non-null   int64  
 13  yr_renovated   4600 non-null   int64  
 14  street         4600 non-null   object 
 15  city           4600 non-null   object 
 16  statezip       4600 non-null   object 
 17  country        4600 non-null   object 
dtypes: float64(4), int64(9), object(5)
memory usage: 647.0+ KB
```

11 05-02 1400000.0 4.0 2.50 2920 4000 1.5 0 0

```
house.nunique(axis = 0)
```

```
date              70
price           1741
bedrooms          10
bathrooms         26
sqft_living      566
sqft_lot        3113
floors             6
waterfront         2
view               5
condition          5
sqft_above       511
sqft_basement    207
yr_built         115
yr_renovated      60
street          4525
city              44
statezip          77
country            1
dtype: int64
```

17 05-02 367500.0 4.0 3.00 3110 7231 2.0 0 0

```
house.isnull().sum()
```

```
date             0
price            0
bedrooms         0
bathrooms        0
sqft_living      0
sqft_lot         0
floors           0
waterfront       0
view             0
condition        0
sqft_above       0
sqft_basement    0
yr_built         0
yr_renovated     0
street           0
city             0
statezip         0
```

```
country          0
dtype: int64
```

```
house.columns
```

```
Index(['date', 'price', 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot',
       'floors', 'waterfront', 'view', 'condition', 'sqft_above',
       'sqft_basement', 'yr_built', 'yr_renovated', 'street', 'city',
       'statezip', 'country'],
      dtype='object')
```

```
house.describe().T
```

	count	mean	std	min	25%	50%
price	4600.0	551962.988473	563834.702547	0.0	322875.00	460943.461539
bedrooms	4600.0	3.400870	0.908848	0.0	3.00	3.000000
bathrooms	4600.0	2.160815	0.783781	0.0	1.75	2.250000
sqft_living	4600.0	2139.346957	963.206916	370.0	1460.00	1980.000000
sqft_lot	4600.0	14852.516087	35884.436145	638.0	5000.75	7683.000000
floors	4600.0	1.512065	0.538288	1.0	1.00	1.500000
waterfront	4600.0	0.007174	0.084404	0.0	0.00	0.000000
view	4600.0	0.240652	0.778405	0.0	0.00	0.000000
condition	4600.0	3.451739	0.677230	1.0	3.00	3.000000
sqft_above	4600.0	1827.265435	862.168977	370.0	1190.00	1590.000000
sqft_basement	4600.0	312.081522	464.137228	0.0	0.00	0.000000
yr_built	4600.0	1970.786304	29.731848	1900.0	1951.00	1976.000000
yr_renovated	4600.0	808.608261	979.414536	0.0	0.00	0.000000

```
house['date'] = pd.to_datetime(house['date'])
```

```
house['date'].dt.year
```

```
0       2014
1       2014
2       2014
3       2014
4       2014
        ...
4595    2014
4596    2014
4597    2014
4598    2014
4599    2014
Name: date, Length: 4600, dtype: int64
```

```
house['year'] = house['date'].dt.year
house.head()
```

	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	v
0	2014-05-02	313000.0	3.0	1.50	1340	7912	1.5	0	
1	2014-05-02	2384000.0	5.0	2.50	3650	9050	2.0	0	
2	2014-05-02	342000.0	3.0	2.00	1930	11947	1.0	0	
3	2014-05-02	420000.0	3.0	2.25	2000	8030	1.0	0	
4	2014-05-02	550000.0	4.0	2.50	1940	10500	1.0	0	

```
(house['price'] == 0).sum(0)
```

```
49
```

```
house[house['price'] == 0].shape
```

```
(49, 19)
```

```
house['price'].replace(0, np.nan, inplace = True)
house.isnull().sum()
```

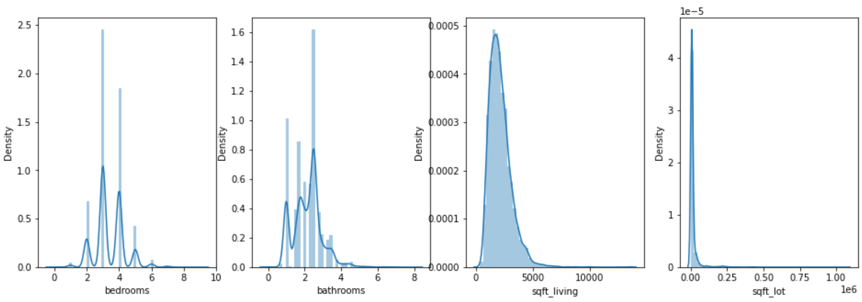
```
date              0
price            49
bedrooms          0
bathrooms         0
sqft_living       0
sqft_lot          0
floors            0
waterfront        0
view              0
condition         0
sqft_above        0
sqft_basement     0
yr_built          0
yr_renovated      0
street            0
city              0
statezip          0
country           0
year              0
dtype: int64
```

```
house['price'].fillna(value = house['price'].mean(), inplace = True)
house.isnull().sum().sum()
```

```
0
```

```
house1 = house.drop(['date', 'street', 'statezip', 'country', 'city'], axis = 1)
```

```
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
plt.figure(figsize = (16, 5))
plt.subplot(1,4,1)
sns.distplot(house1['bedrooms'])
plt.subplot(1,4,2)
sns.distplot(house1['bathrooms'])
plt.subplot(1,4,3)
sns.distplot(house1['sqft_living'])
plt.subplot(1,4,4)
sns.distplot(house1['sqft_lot'])
plt.show()
```




```
def replace_outliers_with_nan_iqr(house1, feature, inplace = False):
    desired_feature = house1[feature]

    q1, q3 = desired_feature.quantile([0.25, 0.75])
    iqr = q3 - q1
    upper_bound = q3 + 1.5 * iqr
    lower_bound = q1 - 1.5 * iqr
    indices = (desired_feature[(desired_feature > upper_bound) | (desired_feature < lower_bound)]).index
    if not inplace:
```

```
        return desired_feature.replace(desired_feature[indices].values, np.nan)
    return desired_feature.replace(desired_feature[indices].values, np.nan, inplace=True)
```

```
replace_outliers_with_nan_iqr(house1, 'price', inplace = True)
house1.price.isnull().sum()
```

```
249
```

```
house1.fillna(value = house1['price'].mean(), inplace = True)
house1.isnull().sum().sum()
```

```
0
```

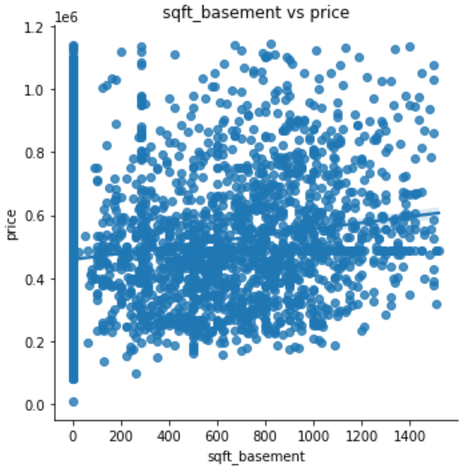
```
replace_outliers_with_nan_iqr(house1, 'sqft_basement', inplace = True)
```

```
house1['sqft_basement'].fillna(value = house1['sqft_basement'].mean(), inplace = True)
house1.isnull().sum().sum()
```

```
0
```

```
ax = sns.lmplot(data = house1, x = 'sqft_basement', y = 'price')
ax.set(title = 'sqft_basement vs price')
```

```
<seaborn.axisgrid.FacetGrid at 0x7f8b04f16a90>
```



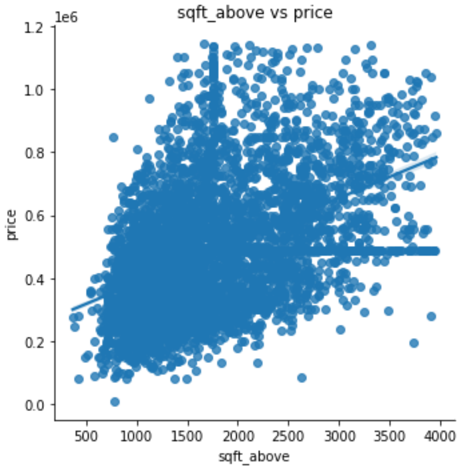

```
replace_outliers_with_nan_iqr(house1, 'sqft_above', inplace = True)
```

```
house1['sqft_above'].fillna(value = house1['sqft_above'].mean(), inplace = True)
house1.isnull().sum().sum()
```

```
0
```

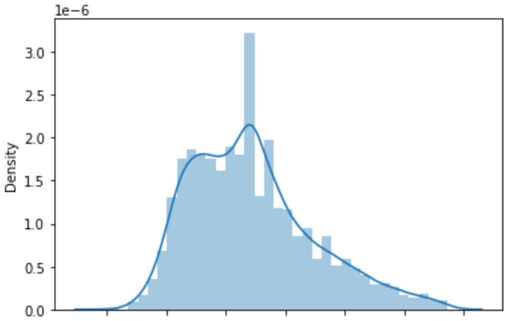
```
ax = sns.lmplot(data = house1, x = 'sqft_above', y = 'price')
ax.set(title = 'sqft_above vs price')
```

```
<seaborn.axisgrid.FacetGrid at 0x7f8b02c40220>
```

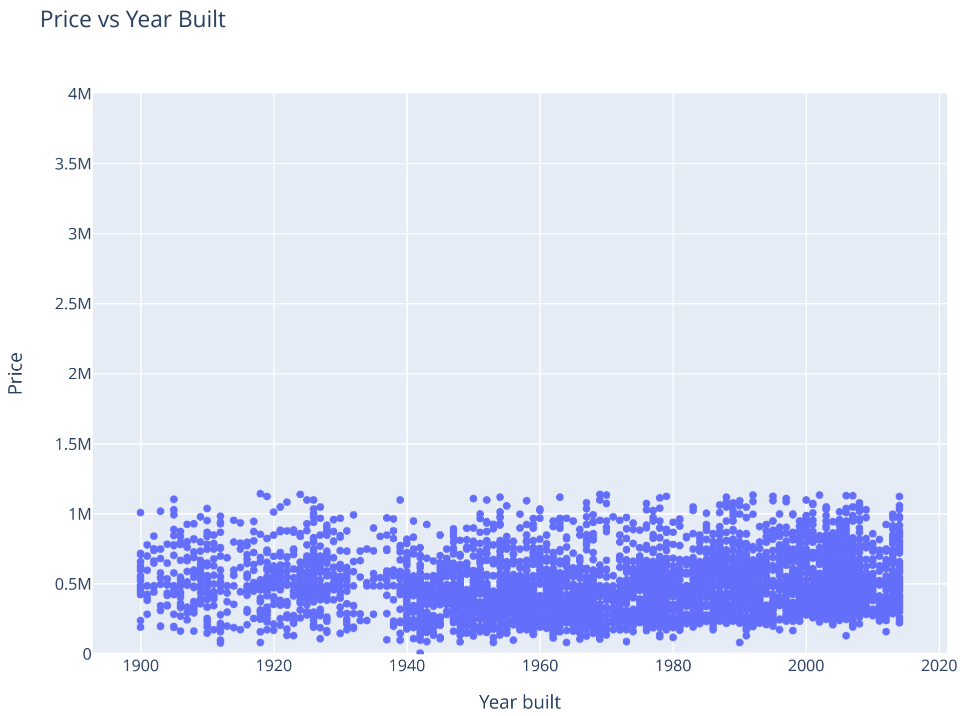



```
sns.distplot(house1['price'])
```

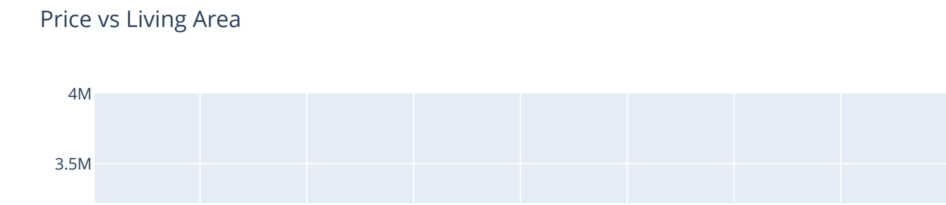
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8afe5860a0>
```




```
import plotly.express as px

year_trend = pd.concat([house1['price'], house1['yr_built']], axis = 1)
fig = px.scatter(house1, x = 'yr_built', y = 'price', title = 'Price vs Year Built', labels = dict(price = "Price ", yr_built = "Year bui
fig.update_layout(yaxis_range = [0 , 4000000], width = 800, height = 600)
fig.show()
```

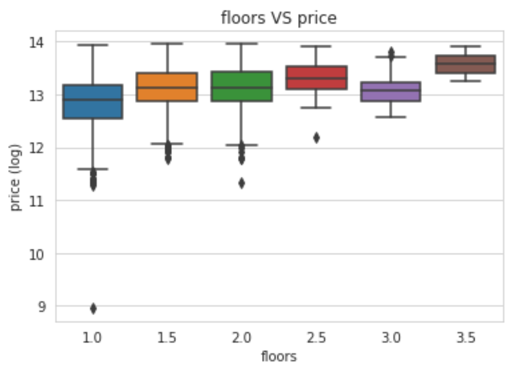



```
sqft_trend = pd.concat([house1['price'], house1['sqft_living']], axis = 1)
fig = px.scatter(house1, x = 'sqft_living', y = 'price', title = 'Price vs Living Area', labels = dict(price = "Price ", sqft_living = "S
fig.update_layout(yaxis_range = [0 , 4000000], xaxis_range = [0 , 8000], width = 800, height = 600)
fig.show()
```

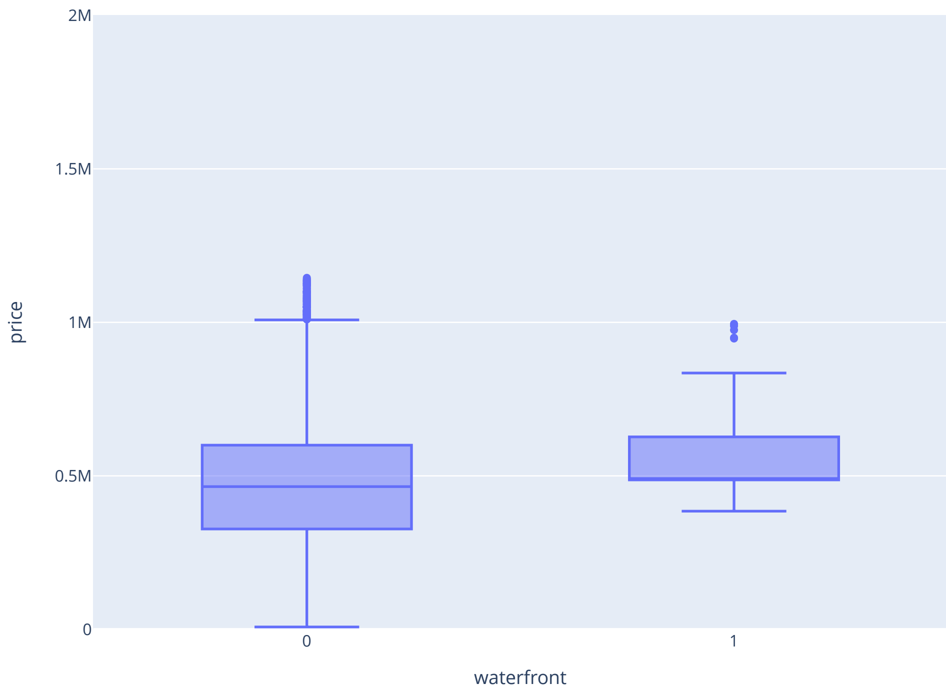



```
def draw_boxplot(feature):
    sns.set_style('whitegrid')
    ax = sns.boxplot(x = house1[feature], y = np.log(house1['price']))
    ax.set_ylabel('price (log)')
    ax.set(title = f'{feature} VS price')
```

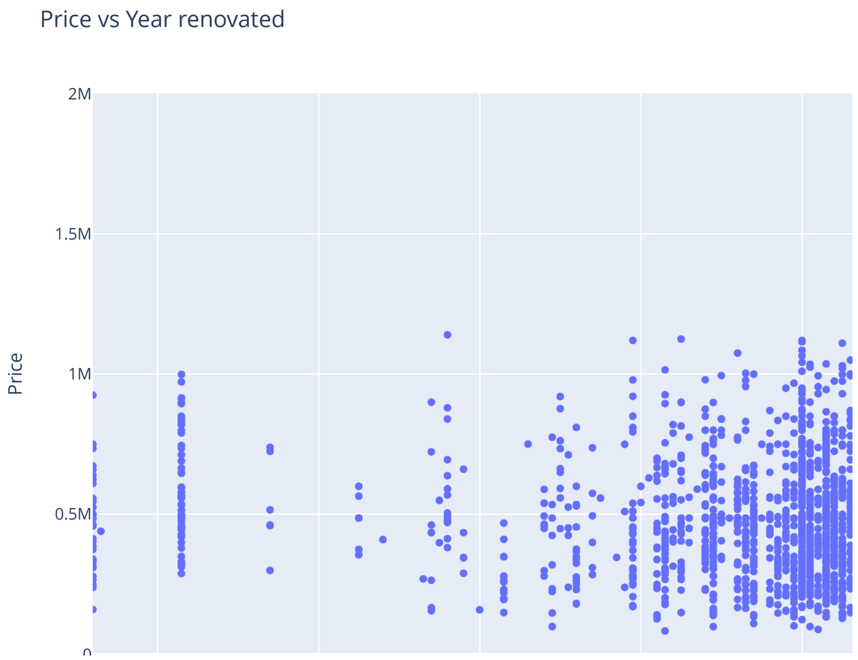
```
draw_boxplot('floors')
```




```
fig = px.box(house1, y = "price", x = "waterfront",)
fig.update_layout(yaxis_range = [0 , 2000000], width = 800, height = 600)
fig.show()
```




```
year_ren_trend = pd.concat([house1['price'], house1['yr_renovated']], axis = 1)
fig = px.scatter(house1, x = 'yr_renovated', y = 'price', title = 'Price vs Year renovated', labels = dict(price = "Price ", yr_renovatec
fig.update_layout(yaxis_range=[0 , 2000000], xaxis_range = [1912 , 2018], width = 800, height = 600)
fig.show()
```




```
house1.isnull()
```

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	sqft_above	sqft_basement	yr_built	y
0	False	False	False	False	False	False	False	False	False	False	False	False	
1	False	False	False	False	False	False	False	False	False	False	False	False	
2	False	False	False	False	False	False	False	False	False	False	False	False	
3	False	False	False	False	False	False	False	False	False	False	False	False	
4	False	False	False	False	False	False	False	False	False	False	False	False	
...	...	...	...	...	...	...	...	...	...	...	...	...	
4595	False	False	False	False	False	False	False	False	False	False	False	False	
4596	False	False	False	False	False	False	False	False	False	False	False	False	
4597	False	False	False	False	False	False	False	False	False	False	False	False	
4598	False	False	False	False	False	False	False	False	False	False	False	False	
4599	False	False	False	False	False	False	False	False	False	False	False	False	

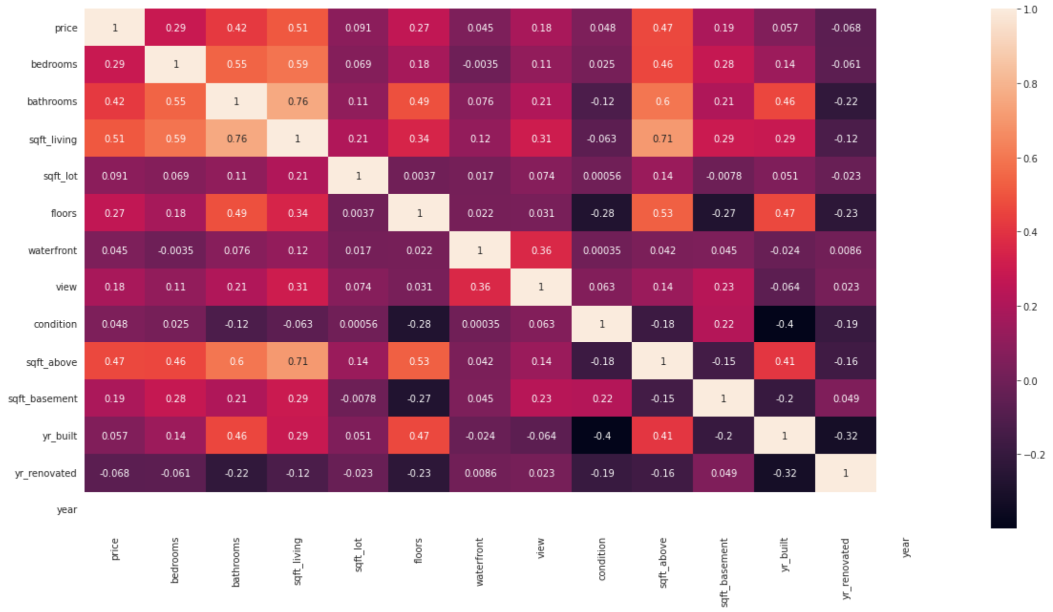
4600 rows × 14 columns

```
house1.corr()
```

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	c
price	1.000000	0.291655	0.422480	0.510498	0.091087	0.266329	0.045479	0.181319	
bedrooms	0.291655	1.000000	0.545920	0.594884	0.068819	0.177895	-0.003483	0.111028	
bathrooms	0.422480	0.545920	1.000000	0.761154	0.107837	0.486428	0.076232	0.211960	-
sqft_living	0.510498	0.594884	0.761154	1.000000	0.210538	0.344850	0.117616	0.311009	-
sqft_lot	0.091087	0.068819	0.107837	0.210538	1.000000	0.003750	0.017241	0.073907	
floors	0.266329	0.177895	0.486428	0.344850	0.003750	1.000000	0.022024	0.031211	-
waterfront	0.045479	-0.003483	0.076232	0.117616	0.017241	0.022024	1.000000	0.360935	
view	0.181319	0.111028	0.211960	0.311009	0.073907	0.031211	0.360935	1.000000	
condition	0.048298	0.025080	-0.119994	-0.062826	0.000558	-0.275013	0.000352	0.063077	
sqft_above	0.468932	0.460774	0.597445	0.706465	0.137959	0.532653	0.042397	0.139097	-
sqft_basement	0.191012	0.280241	0.205283	0.294995	-0.007777	-0.274430	0.045447	0.232825	
yr_built	0.056706	0.142461	0.463498	0.287775	0.050706	0.467481	-0.023563	-0.064465	-
yr_renovated	-0.068266	-0.061082	-0.215886	-0.122817	-0.022730	-0.233996	0.008625	0.022967	-
year	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	

```
plt.figure(figsize = (20, 10))
sns.heatmap(house1.corr(), annot = True)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8b0263de80>
```



```
x = house1.drop('price', axis = 1)
y = house1['price']
```

```
from sklearn.feature_selection import mutual_info_regression

def get_mi_score(x, y):
    mi = mutual_info_regression(x, y, random_state = 10)
    mi = pd.Series(mi, index = x.columns).sort_values(ascending = False)
    return mi
```

```
mi_score = get_mi_score(x, y)
mi_score
```

```
sqft_living      0.312164
sqft_above       0.223771
bathrooms        0.177888
yr_built         0.085256
sqft_lot         0.082656
view             0.067964
bedrooms         0.067502
floors           0.056619
sqft_basement    0.054973
condition        0.012651
waterfront       0.008716
yr_renovated     0.000000
year             0.000000
dtype: float64
```

```
x.drop(['yr_renovated', 'condition', 'waterfront'], axis = 1, inplace = True)
```

```
from sklearn.model_selection import train_test_split, cross_val_score

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.3, random_state = 20)
```

```
from sklearn import preprocessing

scaler = preprocessing.MinMaxScaler()
house1 = pd.DataFrame(scaler.fit_transform(house1[['price']]))
house1.columns = ['price']
```

```
def rmse_cv(model):
    rmse = np.sqrt(-cross_val_score(model, x, y, scoring = "neg_mean_squared_error", cv = 5)).mean()
    return rmse


def evaluation(y, predictions):
    mae = mean_absolute_error(y, predictions)
    mse = mean_squared_error(y, predictions)
    rmse = np.sqrt(mean_squared_error(y, predictions))
    r_squared = r2_score(y, predictions)
    return mae, mse, rmse, r_squared
```

```
models = pd.DataFrame(columns = ["Model","MAE","MSE","RMSE","R2 Score","RMSE (Cross-Validation)"])
```

```
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error

from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso
from sklearn.linear_model import ElasticNet
from sklearn.ensemble import RandomForestRegressor
from sklearn.svm import SVR
from xgboost import XGBRegressor
from sklearn.preprocessing import PolynomialFeatures

lin_reg = LinearRegression()
lin_reg.fit(x_train, y_train)
predictions = lin_reg.predict(x_test)

mae, mse, rmse, r_squared = evaluation(y_test, predictions)
print("MAE:", mae)
print("MSE:", mse)
print("RMSE:", rmse)
print("R2 Score:", r_squared)
print("-"*30)
rmse_cross_val = rmse_cv(lin_reg)
print("RMSE Cross-Validation:", rmse_cross_val)

new_row = {"Model": "LinearRegression","MAE": mae, "MSE": mse, "RMSE": rmse, "R2 Score": r_squared, "RMSE (Cross-Validation)": rmse_cross
models = models.append(new_row, ignore_index = True)
```

```
MAE: 133741.6262676969
MSE: 28620196949.513638
RMSE: 169175.0482474104
R2 Score: 0.3373454456548026
------------------------------
RMSE Cross-Validation: 168732.31562741447
```

```
ridge = Ridge()
ridge.fit(x_train, y_train)
predictions = ridge.predict(x_test)

mae, mse, rmse, r_squared = evaluation(y_test, predictions)
print("MAE:", mae)
print("MSE:", mse)
print("RMSE:", rmse)
print("R2 Score:", r_squared)
print("-"*30)
rmse_cross_val = rmse_cv(ridge)
print("RMSE Cross-Validation:", rmse_cross_val)

new_row = {"Model": "Ridge","MAE": mae, "MSE": mse, "RMSE": rmse, "R2 Score": r_squared, "RMSE (Cross-Validation)": rmse_cross_val}
models = models.append(new_row, ignore_index = True)
```

```
MAE: 133742.36818533868
MSE: 28619790095.889595
RMSE: 169173.8457796878
R2 Score: 0.337354865695042
------------------------------
RMSE Cross-Validation: 168731.9923854514
```

```
lasso = Lasso()
lasso.fit(x_train, y_train)
predictions = lasso.predict(x_test)

mae, mse, rmse, r_squared = evaluation(y_test, predictions)
print("MAE:", mae)
print("MSE:", mse)
print("RMSE:", rmse)
print("R2 Score:", r_squared)
```

```
print("-"*30)
rmse_cross_val = rmse_cv(lasso)
print("RMSE Cross-Validation:", rmse_cross_val)

new_row = {"Model": "Lasso","MAE": mae, "MSE": mse, "RMSE": rmse, "R2 Score": r_squared, "RMSE (Cross-Validation)": rmse_cross_val}
models = models.append(new_row, ignore_index = True)
```

```
MAE: 133741.7466540965
MSE: 28620159639.520885
RMSE: 169174.93797699732
R2 Score: 0.33734630950757993
------------------------------
RMSE Cross-Validation: 168732.25893166117
```

```
elastic_net = ElasticNet()
elastic_net.fit(x_train, y_train)
predictions = elastic_net.predict(x_test)

mae, mse, rmse, r_squared = evaluation(y_test, predictions)
print("MAE:", mae)
print("MSE:", mse)
print("RMSE:", rmse)
print("R2 Score:", r_squared)
print("-"*30)
rmse_cross_val = rmse_cv(elastic_net)
print("RMSE Cross-Validation:", rmse_cross_val)

new_row = {"Model": "ElasticNet","MAE": mae, "MSE": mse, "RMSE": rmse, "R2 Score": r_squared, "RMSE (Cross-Validation)": rmse_cross_val}
models = models.append(new_row, ignore_index = True)
```

```
MAE: 135116.32522043382
MSE: 28794144177.48552
RMSE: 169688.37372514806
R2 Score: 0.3333179778133122
------------------------------
RMSE Cross-Validation: 169662.33946817095
```

```
svr = SVR(C = 400000)
svr.fit(x_train, y_train)
predictions = svr.predict(x_test)

mae, mse, rmse, r_squared = evaluation(y_test, predictions)
print("MAE:", mae)
print("MSE:", mse)
print("RMSE:", rmse)
print("R2 Score:", r_squared)
print("-"*30)
rmse_cross_val = rmse_cv(svr)
print("RMSE Cross-Validation:", rmse_cross_val)

new_row = {"Model": "SVR","MAE": mae, "MSE": mse, "RMSE": rmse, "R2 Score": r_squared, "RMSE (Cross-Validation)": rmse_cross_val}
models = models.append(new_row, ignore_index = True)
```

```
MAE: 137450.28746358078
MSE: 30808389459.81173
RMSE: 175523.18781235637
R2 Score: 0.28668137317162146
------------------------------
RMSE Cross-Validation: 173486.95233496005
```

```
random_forest = RandomForestRegressor(n_estimators = 100)
random_forest.fit(x_train, y_train)
predictions = random_forest.predict(x_test)

mae, mse, rmse, r_squared = evaluation(y_test, predictions)
print("MAE:", mae)
print("MSE:", mse)
print("RMSE:", rmse)
print("R2 Score:", r_squared)
print("-"*30)
rmse_cross_val = rmse_cv(random_forest)
print("RMSE Cross-Validation:", rmse_cross_val)

new_row = {"Model": "RandomForestRegressor","MAE": mae, "MSE": mse, "RMSE": rmse, "R2 Score": r_squared, "RMSE (Cross-Validation)": rmse_
models = models.append(new_row, ignore_index = True)
```

```
MAE: 125372.40173601688
MSE: 26443904895.131
RMSE: 162615.81994114534
R2 Score: 0.3877339822524317
------------------------------
RMSE Cross-Validation: 158460.13650611366
```

```
xgb = XGBRegressor(n_estimators = 1000, learning_rate = 0.01)
xgb.fit(x_train, y_train)
predictions = xgb.predict(x_test)

mae, mse, rmse, r_squared = evaluation(y_test, predictions)
print("MAE:", mae)
print("MSE:", mse)
print("RMSE:", rmse)
print("R2 Score:", r_squared)
print("-"*30)
rmse_cross_val = rmse_cv(xgb)
print("RMSE Cross-Validation:", rmse_cross_val)

new_row = {"Model": "XGBRegressor","MAE": mae, "MSE": mse, "RMSE": rmse, "R2 Score": r_squared, "RMSE (Cross-Validation)": rmse_cross_val
models = models.append(new_row, ignore_index = True)
```

```
[15:55:25] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of reg:squarederror.
MAE: 125042.5312612655
MSE: 25542924413.34506
RMSE: 159821.53926597335
R2 Score: 0.408594733863777
------------------------------
[15:55:27] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of reg:squarederror.
[15:55:29] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of reg:squarederror.
[15:55:31] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of reg:squarederror.
[15:55:34] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of reg:squarederror.
[15:55:36] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of reg:squarederror.
RMSE Cross-Validation: 155091.75429007187
```

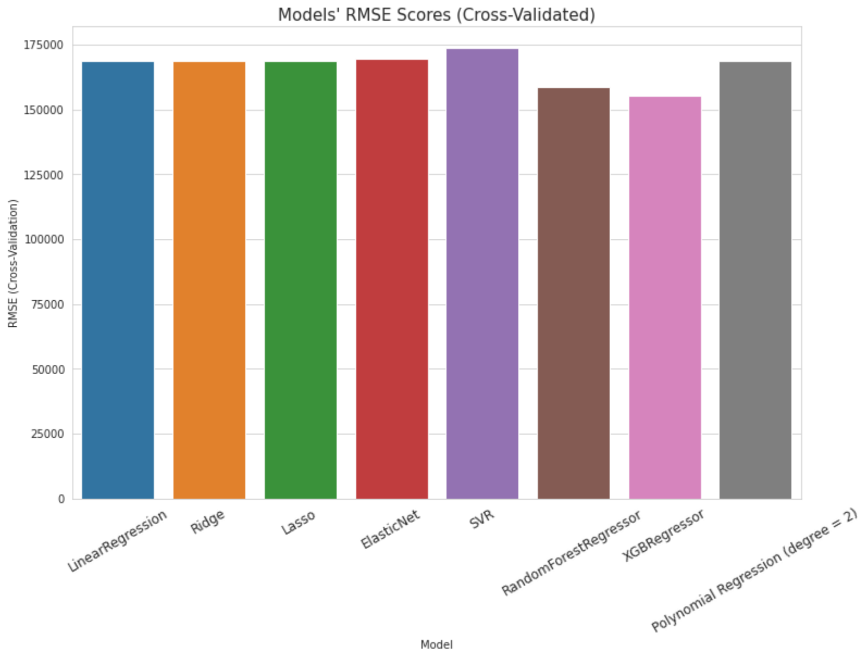
```
poly_reg = PolynomialFeatures(degree = 2)
x_train_2d = poly_reg.fit_transform(x_train)
x_test_2d = poly_reg.transform(x_test)

lin_reg = LinearRegression()
lin_reg.fit(x_train_2d, y_train)
predictions = lin_reg.predict(x_test_2d)

mae, mse, rmse, r_squared = evaluation(y_test, predictions)
print("MAE:", mae)
print("MSE:", mse)
print("RMSE:", rmse)
print("R2 Score:", r_squared)
print("-"*30)
rmse_cross_val = rmse_cv(lin_reg)
print("RMSE Cross-Validation:", rmse_cross_val)

new_row = {"Model": "Polynomial Regression (degree = 2)","MAE": mae, "MSE": mse, "RMSE": rmse, "R2 Score": r_squared, "RMSE (Cross-Valida
models = models.append(new_row, ignore_index = True)
```

```
MAE: 131496.8999323232
MSE: 29908367582.969944
RMSE: 172940.3584562318
R2 Score: 0.30751992982975984
------------------------------
RMSE Cross-Validation: 168732.31562741447
```

```
models.sort_values(by = "RMSE (Cross-Validation)")
```

	Model	MAE	MSE	RMSE	R2 Score	RMSE (Valid
6	XGBRegressor	125042.531261	2.554292e+10	159821.539266	0.408595	155091.
5	RandomForestRegressor	125372.401736	2.644390e+10	162615.819941	0.387734	158460.
1	Ridge	133742.368185	2.861979e+10	169173.845780	0.337355	168731.
2	Lasso	133741.746654	2.862016e+10	169174.937977	0.337346	168732.
0	LinearRegression	133741.626268	2.862020e+10	169175.048247	0.337345	168732.
7	Polynomial Regression (degree = 2)	131496.899932	2.990837e+10	172940.358456	0.307520	168732.
3	ElasticNet	135116.325220	2.879414e+10	169688.373725	0.333318	169662

```
plt.figure(figsize = (12, 8))
sns.barplot(x = models["Model"], y = models["RMSE (Cross-Validation)"])
plt.title("Models' RMSE Scores (Cross-Validated)", size = 15)
plt.xticks(rotation = 30, size = 12)
plt.show()
```


Models' RMSE Scores (Cross-Validated)
RMSE (Cross-Validation)
175000
150000
125000
100000
75000
50000
25000
0
LinearRegression
Ridge
Lasso
ElasticNet
SVR
RandomForestRegressor
XGBRegressor
Polynomial Regression (degree = 2)
Model