Housing Prices in King County

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Overview

This notebook contains a regression analysis of the cost of King County real estate. Utilizing the CRISP-DM framework, linear regression models, and statistical techniques, I created and refined a model that describes the cost of real estate in King County in relation to a list of independent variables.

My data, methodology, and derived conclusions are detailed in the body of this document.

Business Problem

To gain an edge in the industry, a Seattle-based real estate company wants to automate their initial appraisal process. Developing an algorithm to accurately appraise the value of a house without physically inspecting the property can be an invaluable advantage in the fast paced real estate market of a rapidly expanding city. Using county data and multiple linear regression I created a model the company can use to predict real estate values.

Data

The data utilized in this model describes houses sold in 2014 and 2015.

The data is summarized below.

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
sns.set_style('darkgrid')
%matplotlib inline
```

In [2]:
```
df = pd.read_csv('data/kc_house_data.csv')
df.head()
```

Out[2]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfr
0	7129300520	10/13/2014	221900.0	3	1.00	1180	5650	1.0	N
1	6414100192	12/9/2014	538000.0	3	2.25	2570	7242	2.0	
2	5631500400	2/25/2015	180000.0	2	1.00	770	10000	1.0	
3	2487200875	12/9/2014	604000.0	4	3.00	1960	5000	1.0	
4	1954400510	2/18/2015	510000.0	3	2.00	1680	8080	1.0	

5 rows × 21 columns

In [3]:
```
# Data Summary
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   id             21597 non-null  int64  
 1   date           21597 non-null  object 
 2   price          21597 non-null  float64
 3   bedrooms       21597 non-null  int64  
 4   bathrooms      21597 non-null  float64
 5   sqft_living    21597 non-null  int64  
 6   sqft_lot       21597 non-null  int64  
 7   floors         21597 non-null  float64
 8   waterfront     19221 non-null  float64
 9   view           21534 non-null  float64
 10  condition      21597 non-null  int64  
 11  grade          21597 non-null  int64  
 12  sqft_above     21597 non-null  int64  
 13  sqft_basement  21597 non-null  object 
 14  yr_built       21597 non-null  int64  
 15  yr_renovated   17755 non-null  float64
 16  zipcode        21597 non-null  int64  
 17  lat            21597 non-null  float64
 18  long           21597 non-null  float64
 19  sqft_living15  21597 non-null  int64  
 20  sqft_lot15     21597 non-null  int64  
dtypes: float64(8), int64(11), object(2)
memory usage: 3.5+ MB
```

In [4]:
```
# Exploration of Values
for column in df.columns:
    print(column, '\n')
    print(df[column].value_counts())
    print('________')
```

```
id 

795000620     3
1825069031    2
2019200220    2
7129304540    2
1781500435    2
             ..
7812801125    1
4364700875    1
3021059276    1
880000205     1
1777500160    1
Name: id, Length: 21420, dtype: int64
________
date 

6/23/2014    142
6/25/2014    131
6/26/2014    131
7/8/2014     127
4/27/2015    126
            ... 
2/15/2015      1
8/3/2014       1
1/17/2015      1
1/10/2015      1
```

```
5/24/2015      1
Name: date, Length: 372, dtype: int64
________
price

350000.0    172
450000.0    172
550000.0    159
500000.0    152
425000.0    150
           ...
870515.0      1
336950.0      1
386100.0      1
176250.0      1
884744.0      1
Name: price, Length: 3622, dtype: int64
________
bedrooms

3     9824
4     6882
2     2760
5     1601
6      272
1      196
7       38
8       13
9        6
10       3
11       1
33       1
Name: bedrooms, dtype: int64
________
bathrooms

2.50    5377
1.00    3851
1.75    3048
2.25    2047
2.00    1930
1.50    1445
2.75    1185
3.00     753
3.50     731
3.25     589
3.75     155
4.00     136
4.50     100
4.25      79
0.75      71
4.75      23
5.00      21
5.25      13
5.50      10
1.25       9
6.00       6
5.75       4
0.50       4
8.00       2
6.25       2
6.75       2
6.50       2
7.50       1
7.75       1
```

```
Name: bathrooms, dtype: int64
________
sqft_living

1300    138
1400    135
1440    133
1660    129
1010    129
       ...
4970      1
2905      1
2793      1
4810      1
1975      1
Name: sqft_living, Length: 1034, dtype: int64
________
sqft_lot

5000      358
6000      290
4000      251
7200      220
7500      119
         ...
1448        1
38884       1
17313       1
35752       1
315374      1
Name: sqft_lot, Length: 9776, dtype: int64
________
floors

1.0    10673
2.0     8235
1.5     1910
3.0      611
2.5      161
3.5        7
Name: floors, dtype: int64
________
waterfront

0.0    19075
1.0      146
Name: waterfront, dtype: int64
________
view

0.0    19422
2.0      957
3.0      508
1.0      330
4.0      317
Name: view, dtype: int64
________
condition

3    14020
4     5677
5     1701
2      170
1       29
Name: condition, dtype: int64
```

```
_________
grade

7     8974
8     6065
9     2615
6     2038
10    1134
11     399
5      242
12      89
4       27
13      13
3        1
Name: grade, dtype: int64
_________
sqft_above

1300    212
1010    210
1200    206
1220    192
1140    184
       ...
2601      1
440       1
2473      1
2441      1
1975      1
Name: sqft_above, Length: 942, dtype: int64
_________
sqft_basement

0.0       12826
?           454
600.0       217
500.0       209
700.0       208
          ...
2180.0        1
3480.0        1
2400.0        1
2050.0        1
1770.0        1
Name: sqft_basement, Length: 304, dtype: int64
_________
yr_built

2014    559
2006    453
2005    450
2004    433
2003    420
       ...
1933     30
1901     29
1902     27
1935     24
1934     21
Name: yr_built, Length: 116, dtype: int64
_________
yr_renovated

0.0       17011
2014.0       73
```

```
2003.0       31
2013.0       31
2007.0       30
           ...
1946.0        1
1959.0        1
1971.0        1
1951.0        1
1954.0        1
Name: yr_renovated, Length: 70, dtype: int64
________
zipcode

98103    602
98038    589
98115    583
98052    574
98117    553
        ...
98102    104
98010    100
98024     80
98148     57
98039     50
Name: zipcode, Length: 70, dtype: int64
________
lat

47.6624    17
47.5491    17
47.5322    17
47.6846    17
47.6711    16
           ..
47.2785     1
47.4162     1
47.3870     1
47.2313     1
47.2715     1
Name: lat, Length: 5033, dtype: int64
________
long

-122.290    115
-122.300    111
-122.362    104
-122.291    100
-122.372     99
           ...
-121.403      1
-121.804      1
-121.726      1
-121.895      1
-121.893      1
Name: long, Length: 751, dtype: int64
________
sqft_living15

1540    197
1440    195
1560    192
1500    180
1460    169
       ...
4890      1
```

```
2873      1
952       1
3193      1
2049      1
Name: sqft_living15, Length: 777, dtype: int64
________
sqft_lot15

5000      427
4000      356
6000      288
7200      210
4800      145
         ...
11036       1
8989        1
871200      1
809         1
6147        1
Name: sqft_lot15, Length: 8682, dtype: int64
________
```

Data Preprocessing

To begin, columns we are not interested in will be dropped. We are not concerned with the date the house was sold or if the house has been viewed.

Additionally, because all of our data ranges over only two years, we will count multiple sales of the same house independently, and therefore can drop the house ID. The rational behind this is that houses constantly on the market may hint at some underlining issue that may or may not be described numerically by our data so we will leave each sale in our analysis to obtain the broadest picture.

In [5]:
```
df.drop(columns = ['id', 'date', 'view'], inplace = True)
```

Observing the data types and value counts in our data exploration above it can be seen that basement square footage is stored as a string. most values can be expressed as floats, so we will change data types to be treated as a continuous variable. unknown values (stored as '?') will be changed to 0.0

In [6]:
```
df['sqft_basement'].replace('?','0.0', inplace = True)
df['sqft_basement'] = df['sqft_basement'].astype('float')
```

Now that all of our data is in a usable format, we can create our first baseline model

Baseline Model

To keep as much data as possible in all future models, we will not drop missing values from our data until just before creating a new model

In [7]:
```
baseline_data = df.dropna()
baseline_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 15809 entries, 1 to 21596
Data columns (total 18 columns):
 #   Column         Non-Null Count  Dtype
```

```
 ---  ------         --------------  -----
 0    price          15809 non-null  float64
 1    bedrooms       15809 non-null  int64
 2    bathrooms      15809 non-null  float64
 3    sqft_living    15809 non-null  int64
 4    sqft_lot       15809 non-null  int64
 5    floors         15809 non-null  float64
 6    waterfront     15809 non-null  float64
 7    condition      15809 non-null  int64
 8    grade          15809 non-null  int64
 9    sqft_above     15809 non-null  int64
 10   sqft_basement  15809 non-null  float64
 11   yr_built       15809 non-null  int64
 12   yr_renovated   15809 non-null  float64
 13   zipcode        15809 non-null  int64
 14   lat            15809 non-null  float64
 15   long           15809 non-null  float64
 16   sqft_living15  15809 non-null  int64
 17   sqft_lot15     15809 non-null  int64
dtypes: float64(8), int64(10)
memory usage: 2.3 MB
```

In [8]:
```
import statsmodels.api as sm
```

In [9]:
```
baseline_predictors = baseline_data.drop('price', axis=1)
model = sm.OLS(baseline_data['price'], sm.add_constant(baseline_predictors)).fit
model.summary()
```

Out[9]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.694
Model:	OLS	**Adj. R-squared:**	0.693
Method:	Least Squares	**F-statistic:**	2103.
Date:	Sat, 16 Jan 2021	**Prob (F-statistic):**	0.00
Time:	13:32:41	**Log-Likelihood:**	-2.1594e+05
No. Observations:	15809	**AIC:**	4.319e+05
Df Residuals:	15791	**BIC:**	4.320e+05
Df Model:	17		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-2.373e+06	3.51e+06	-0.675	0.499	-9.26e+06	4.51e+06
bedrooms	-4.066e+04	2249.400	-18.074	0.000	-4.51e+04	-3.62e+04
bathrooms	4.608e+04	3924.315	11.743	0.000	3.84e+04	5.38e+04
sqft_living	157.4150	21.879	7.195	0.000	114.530	200.300
sqft_lot	0.1354	0.057	2.371	0.018	0.023	0.247
floors	5905.1578	4336.868	1.362	0.173	-2595.600	1.44e+04
waterfront	7.917e+05	1.92e+04	41.132	0.000	7.54e+05	8.29e+05
condition	2.762e+04	2829.941	9.759	0.000	2.21e+04	3.32e+04
grade	9.804e+04	2603.022	37.663	0.000	9.29e+04	1.03e+05

sqft_above	35.3500	21.823	1.620	0.105	-7.425	78.125
sqft_basement	14.4558	21.658	0.667	0.504	-27.997	56.908
yr_built	-2821.6048	87.044	-32.416	0.000	-2992.221	-2650.988
yr_renovated	21.8909	4.438	4.932	0.000	13.191	30.590
zipcode	-496.6853	39.529	-12.565	0.000	-574.167	-419.204
lat	5.813e+05	1.28e+04	45.244	0.000	5.56e+05	6.07e+05
long	-2.313e+05	1.58e+04	-14.639	0.000	-2.62e+05	-2e+05
sqft_living15	27.9778	4.128	6.778	0.000	19.887	36.069
sqft_lot15	-0.3309	0.086	-3.847	0.000	-0.500	-0.162

Omnibus:	13670.728	**Durbin-Watson:**	1.972
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1430940.355
Skew:	3.652	**Prob(JB):**	0.00
Kurtosis:	49.032	**Cond. No.**	2.15e+08

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.15e+08. This might indicate that there are strong multicollinearity or other numerical problems.

Model Tuning/ Reitteration

Statistically Insignificant Variables/Collinearity

To achieve a better fit, the model can be tuned. Setting alpha to 0.05, we can determine which variables are not statistically significant and can be dropped. Additionally, examining the collinearity of the independent variables can give clues on what variables to drop to improve our R-squared value in the next itteration. The table below shows the correlation between the independent variables.

In [10]:

```
lin_test=baseline_predictors.corr().abs().stack().reset_index().sort_values(0, a
# zip the variable name columns (Which were only named level_0 and level_1 by de
lin_test['pairs'] = list(zip(lin_test.level_0, lin_test.level_1))
# set index to pairs
lin_test.set_index(['pairs'], inplace = True)
#d rop level columns
lin_test.drop(columns=['level_1', 'level_0'], inplace = True)
# rename correlation column as cc rather than 0
lin_test.columns = ['cc']
# drop duplicates. This could be dangerous if you have variables perfectly corre
# for the sake of exercise, kept it in.
lin_test.drop_duplicates(inplace=True)
lin_test.head(15)
```

Out[10]:

cc

pairs	cc
pairs	
(bedrooms, bedrooms)	1.000000
(sqft_above, sqft_living)	0.876023
(grade, sqft_living)	0.764699
(grade, sqft_above)	0.758407
(sqft_living, sqft_living15)	0.756818
(sqft_living, bathrooms)	0.754361
(sqft_above, sqft_living15)	0.732934
(sqft_lot, sqft_lot15)	0.719935
(sqft_living15, grade)	0.717371
(sqft_above, bathrooms)	0.686171
(grade, bathrooms)	0.665321
(sqft_living, bedrooms)	0.573750
(bathrooms, sqft_living15)	0.570180
(zipcode, long)	0.562116
(sqft_above, floors)	0.529702

To start, variables with a P-value above our threshhold (alpha) are dropped. Additionally, some variables with high collinearity are dropped.

In [11]:
```
to_drop = ['floors', 'sqft_above', 'sqft_basement','sqft_lot', 'sqft_lot15', 'sq

df.drop(to_drop, axis=1, inplace=True)
df.head()
```

Out[11]:

	price	bedrooms	bathrooms	sqft_living	waterfront	condition	grade	yr_built	yr_renovat
0	221900.0	3	1.00	1180	NaN	3	7	1955	(
1	538000.0	3	2.25	2570	0.0	3	7	1951	199
2	180000.0	2	1.00	770	0.0	3	6	1933	N
3	604000.0	4	3.00	1960	0.0	5	7	1965	(
4	510000.0	3	2.00	1680	0.0	3	8	1987	(

In [12]:
```
model_2_data = df.dropna()
model_2_predictors = model_2_data.drop('price', axis=1)
model = sm.OLS(model_2_data['price'], sm.add_constant(model_2_predictors)).fit()
model.summary()
```

Out[12]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.692
Model:	OLS	**Adj. R-squared:**	0.692

Method:	Least Squares	**F-statistic:**	3224.
Date:	Sat, 16 Jan 2021	**Prob (F-statistic):**	0.00
Time:	13:32:41	**Log-Likelihood:**	-2.1598e+05
No. Observations:	15809	**AIC:**	4.320e+05
Df Residuals:	15797	**BIC:**	4.321e+05
Df Model:	11		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	2.651e+06	3.36e+06	0.790	0.430	-3.93e+06	9.23e+06
bedrooms	-4.074e+04	2244.302	-18.154	0.000	-4.51e+04	-3.63e+04
bathrooms	4.565e+04	3783.151	12.068	0.000	3.82e+04	5.31e+04
sqft_living	194.4893	3.662	53.114	0.000	187.312	201.667
waterfront	7.928e+05	1.93e+04	41.112	0.000	7.55e+05	8.31e+05
condition	2.453e+04	2810.180	8.728	0.000	1.9e+04	3e+04
grade	1.071e+05	2407.087	44.478	0.000	1.02e+05	1.12e+05
yr_built	-2791.2713	84.465	-33.046	0.000	-2956.832	-2625.710
yr_renovated	20.4666	4.438	4.611	0.000	11.767	29.166
zipcode	-516.7809	39.280	-13.156	0.000	-593.774	-439.788
lat	5.81e+05	1.28e+04	45.511	0.000	5.56e+05	6.06e+05
long	-2.06e+05	1.5e+04	-13.746	0.000	-2.35e+05	-1.77e+05

Omnibus:	13471.346	**Durbin-Watson:**	1.969
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1339076.232
Skew:	3.580	**Prob(JB):**	0.00
Kurtosis:	47.515	**Cond. No.**	1.99e+08

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.99e+08. This might indicate that there are
strong multicollinearity or other numerical problems.

We will not drop any more full columns, so we can commit to dropping rows with missing data.

In [13]:
```
df.dropna(inplace = True)
```

Categorical Variables

Next, we'll recheck the values of our columns to see if any variables are categorical.

In [14]:
```
# Exploration of Values
for column in df.columns:
    print(column, '\n')
    print(df[column].value_counts())
    print('________')
```

```
price 

350000.0    130
450000.0    121
500000.0    115
550000.0    113
425000.0    111
           ... 
959750.0      1
503500.0      1
927000.0      1
648475.0      1
311300.0      1
Name: price, Length: 3042, dtype: int64
________
bedrooms 

3     7143
4     5094
2     2007
5     1186
6      194
1      141
7       23
8       10
9        6
10       3
11       1
33       1
Name: bedrooms, dtype: int64
________
bathrooms 

2.50    4013
1.00    2769
1.75    2235
2.25    1494
2.00    1398
1.50    1064
2.75     853
3.50     544
3.00     544
3.25     432
3.75     104
4.00     100
4.50      75
4.25      62
0.75      50
4.75      17
5.00      14
5.25      11
5.50       8
6.00       6
1.25       6
0.50       3
8.00       2
5.75       2
7.75       1
```

```
7.50       1
6.75       1
Name: bathrooms, dtype: int64
________
sqft_living

1820    102
1440    100
1400     98
1300     95
1320     94
       ...
1794      1
1802      1
1834      1
5960      1
1715      1
Name: sqft_living, Length: 913, dtype: int64
________
waterfront

0.0    15688
1.0      121
Name: waterfront, dtype: int64
________
condition

3    10252
4     4151
5     1256
2      131
1       19
Name: condition, dtype: int64
________
grade

7     6562
8     4444
9     1927
6     1488
10     835
11     291
5      167
12      67
4       16
13      11
3        1
Name: grade, dtype: int64
________
yr_built

2014    401
2006    335
2005    328
2007    310
2004    307
       ...
1901     22
1933     18
1902     18
1934     15
1935     14
Name: yr_built, Length: 116, dtype: int64
________
yr_renovated
```

```
0.0       15157
2014.0       64
2013.0       29
2005.0       27
2000.0       25
          ...
1974.0        1
1959.0        1
1934.0        1
1944.0        1
1976.0        1
Name: yr_renovated, Length: 70, dtype: int64
________
zipcode

98038    439
98103    426
98052    416
98115    409
98042    409
        ...
98010     70
98102     65
98024     59
98148     42
98039     36
Name: zipcode, Length: 70, dtype: int64
________
lat

47.6955    14
47.6846    14
47.6647    13
47.6711    13
47.6624    13
           ..
47.7697     1
47.4195     1
47.3227     1
47.1903     1
47.2051     1
Name: lat, Length: 4754, dtype: int64
________
long

-122.290    86
-122.300    78
-122.365    78
-122.288    77
-122.357    75
            ..
-121.822     1
-121.739     1
-122.475     1
-121.833     1
-121.676     1
Name: long, Length: 729, dtype: int64
________
```

Condition, grade, and zipcode columns can likely be treated as categorical variables, so will be converted to dummy variables.

In [15]:
```
categoricals = ['condition', 'grade', 'zipcode']
```

```
condition_cat = pd.get_dummies(df['condition'], prefix = 'condition', drop_first
grade_cat = pd.get_dummies(df['grade'], prefix = 'grade', drop_first=True)
zipcode_cat = pd.get_dummies(df['zipcode'], prefix = 'zipcode', drop_first = Tru
df = df.drop(columns = categoricals)
df = pd.concat([df, condition_cat, grade_cat, zipcode_cat], axis=1)
```

additionally, the 'yr_renovated' column will be converted to a categorical 'renovated' column

In [16]:
```
df['renovated'] = df['yr_renovated'].map(lambda x: 0 if x == 0 else 1)
df.drop(columns=['yr_renovated'], inplace = True)
df.head()
```

Out[16]:

	price	bedrooms	bathrooms	sqft_living	waterfront	yr_built	lat	long	conditior
1	538000.0	3	2.25	2570	0.0	1951	47.7210	-122.319	
3	604000.0	4	3.00	1960	0.0	1965	47.5208	-122.393	
4	510000.0	3	2.00	1680	0.0	1987	47.6168	-122.045	
5	1230000.0	4	4.50	5420	0.0	2001	47.6561	-122.005	
6	257500.0	3	2.25	1715	0.0	1995	47.3097	-122.327	

5 rows × 92 columns

Future models in this notebook will be created with Scikit Learn

In [17]:
```
from sklearn.linear_model import LinearRegression
```

In [18]:
```
lin_reg_3 = LinearRegression()
y = df['price']
X = df.drop(['price'], axis = 1)
lin_reg_3.fit(X, y)
print('R-Squared: ', lin_reg_3.score(X, y))
```

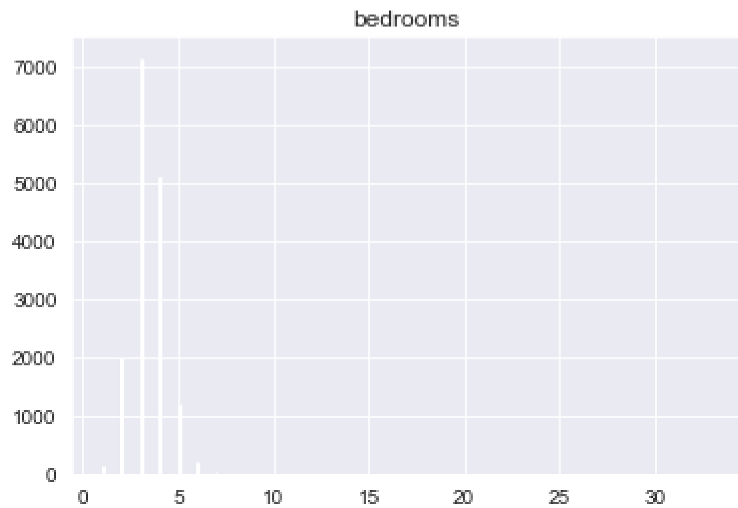
```
R-Squared:  0.8241407664576075
```

Normalization/Log Transformations

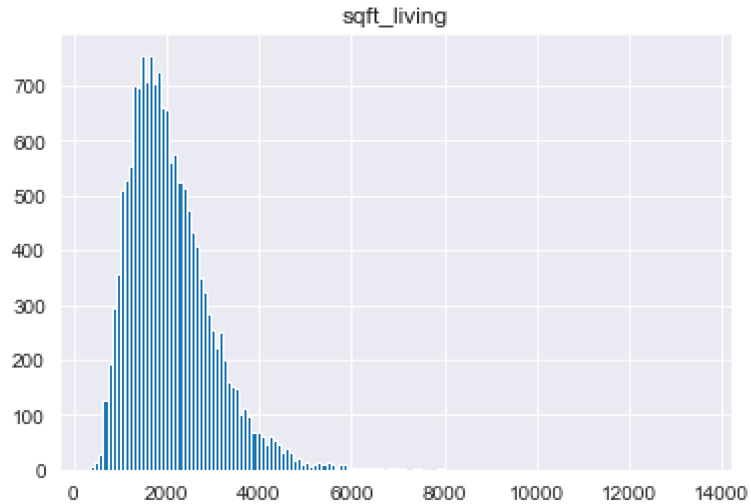
Using histograms, continuous variables are checked for normality and outliers

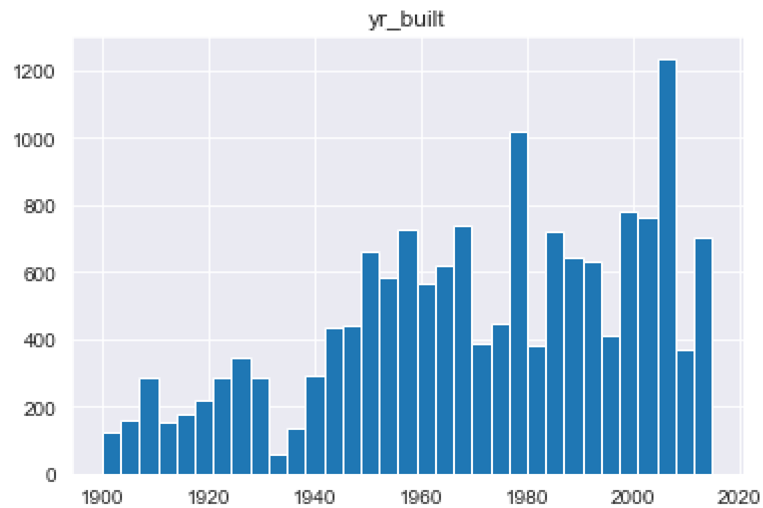
In [19]:
```
continuous = ['price', 'bedrooms','bathrooms', 'sqft_living', 'yr_built', 'lat',
for var in continuous:
    df[var].hist(bins='auto')
    plt.title(var)
    plt.show()
```

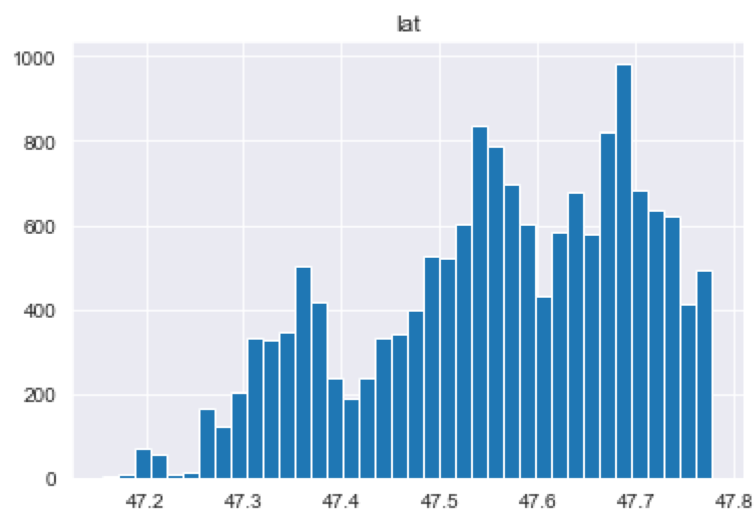

price
800
600
400
200
0
0
1
2
3
4
5
6
7
8
1e6

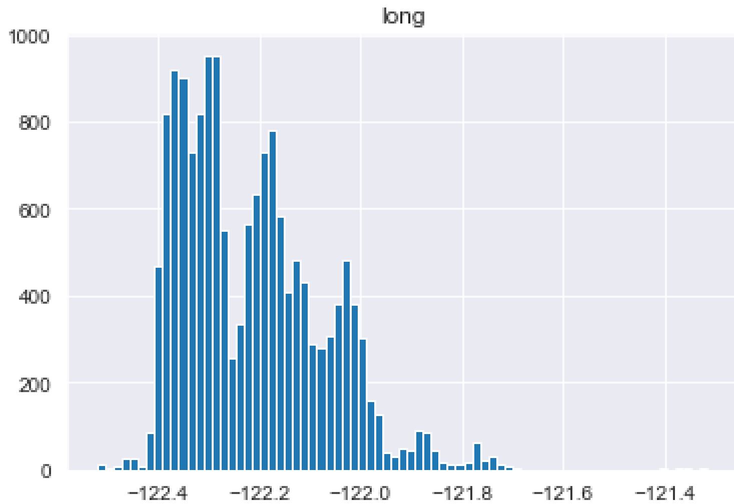

bedrooms
7000
6000
5000
4000
3000
2000
1000
0
0
5
10
15
20
25
30


bathrooms
4000
3500
3000
2500
2000
1500
1000
500
0
1
2
3
4
5
6
7
8


sqft_living
700
600
500
400
300
200
100
0
0
2000
4000
6000
8000
10000
12000
14000

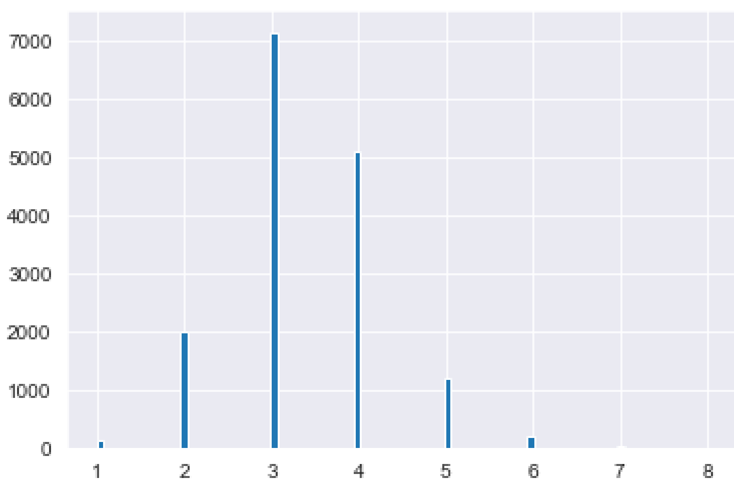

yr_built
1200
1000
800
600
400
200
0
1900
1920
1940
1960
1980
2000
2020


lat
1000
800
600
400
200
0
47.2
47.3
47.4
47.5
47.6
47.7
47.8



In [20]:
```
# Bedroom outliers
df.drop(df.loc[df['bedrooms'] > 8].index, inplace=True)
df['bedrooms'].hist(bins = 'auto')
```

Out[20]: <AxesSubplot:>



In [21]:
```
# Log Transformations
df['log_long'] = df['long'].map(lambda x: np.log(x*-1))
df.drop('long', axis = 1, inplace = True)
df['log_lat'] = df['lat'].map(lambda x: np.log(x))
df.drop('lat', axis = 1, inplace = True)
df['log_yr_built'] = df['yr_built'].map(lambda x: np.log(x))
df.drop('yr_built', axis = 1, inplace = True)
df['log_sqft_living'] = df['sqft_living'].map(lambda x: np.log(x))
df.drop('sqft_living', axis = 1, inplace = True)
df['log_bed'] = df['bedrooms'].map(lambda x: np.log(x))
df.drop('bedrooms', axis = 1, inplace = True)
df['log_price'] = df['price'].map(lambda x: np.log(x))
df.drop('price', axis = 1, inplace = True)
```

In [22]:
```
df.head()
```

Out[22]:

	bathrooms	waterfront	condition_2	condition_3	condition_4	condition_5	grade_4	grade_5	g
1	2.25	0.0	0	1	0	0	0	0	
3	3.00	0.0	0	0	0	1	0	0	

	bathrooms	waterfront	condition_2	condition_3	condition_4	condition_5	grade_4	grade_5	g
4	2.00	0.0	0	1	0	0	0	0	
5	4.50	0.0	0	1	0	0	0	0	
6	2.25	0.0	0	1	0	0	0	0	

5 rows × 92 columns

In [23]:
```
lin_reg_4 = LinearRegression()
y = df['log_price'].map(lambda x: np.log(x))
X = df.drop(['log_price'], axis = 1)
lin_reg_4.fit(X, y)
print('R-Squared: ', lin_reg_4.score(X, y))
```

```
R-Squared:  0.8666057935678042
```

With a model that represents 86% of the variation of data, We can move forward to model evaluation.

Model Evaluation

Using Scikitlearn to randomly split the data into a train group and a test group, the model can be evaluated for accuracy

In [24]:
```
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error as mse
```

In [25]:
```
X = df.drop('log_price', axis = 1)
y = df['log_price']
```

In [26]:
```
X_train, X_test, y_train, y_test = train_test_split(X,y)
```

In [27]:
```
linreg = LinearRegression()
linreg.fit(X_train, y_train)
y_hat_train = linreg.predict(X_train)
y_hat_test = linreg.predict(X_test)
print('R-Squared: ', linreg.score(X_train, y_train))
```

```
R-Squared:  0.8694121573436995
```

In [28]:
```
train_mse = mse(y_train, y_hat_train)
test_mse = mse(y_test, y_hat_test)
print('Train MSE: ', train_mse)
print('Test MSE: ', test_mse)
```

```
Train MSE:  0.03597150394098349
Test MSE:  0.03731187808602213
```

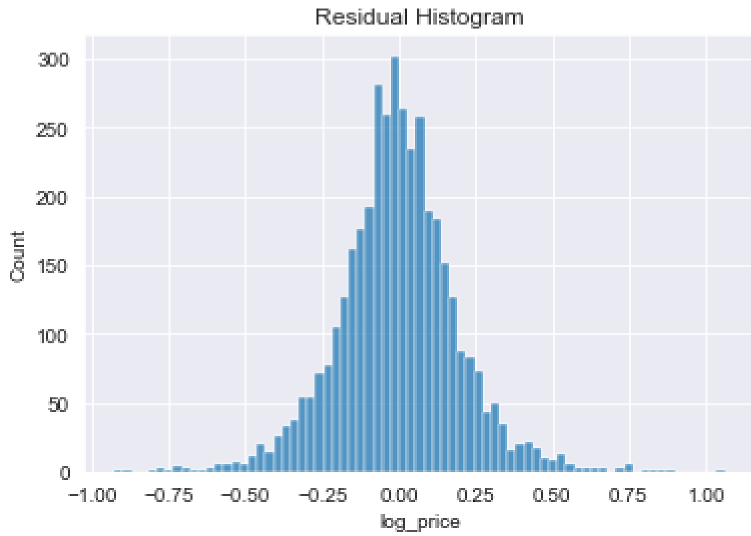
The mean squared error of the test data is actually lower than the mean squared error of the training data. This is a good sign that our model is properly fitted.

Lastly, the distribution of residuals will be analyzed.

In [29]:
```
residuals = y_test - linreg.predict(X_test)
```

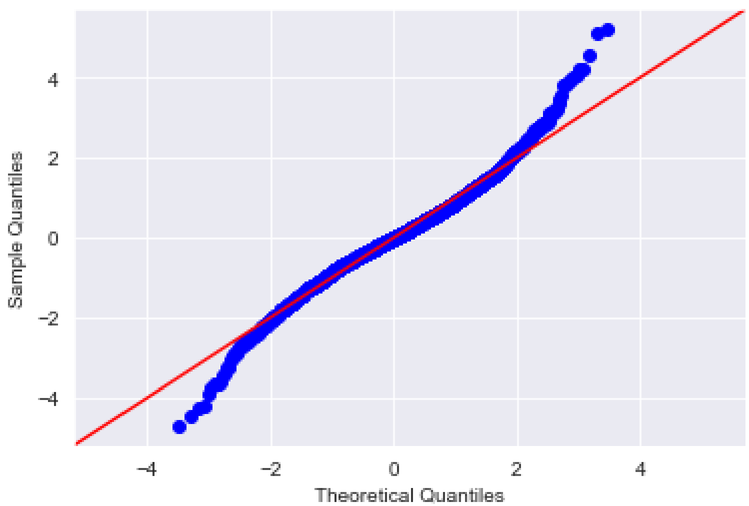
In [30]:
```
sns.histplot(residuals);
```

```
plt.title('Residual Histogram');
```



In [31]:

```
import scipy.stats as stats
model = sm.OLS(y_test, sm.add_constant(X_test)).fit()
sm_residuals = model.resid
fig = sm.graphics.qqplot(sm_residuals, dist=stats.norm, line='45', fit=True)
```



The residuals of the model are not perfectly normal. this may cause some issues with price predictions at the upper and lower levels of our distribution.

Deployment

Using the pickle module, we can store our model and use it in a leaner notebook or .py file to predict the value of a house in King County.

In [32]:

```
import pickle
with open('deployment/regression_model.pickle', 'wb') as f:
    pickle.dump(linreg, f)
```

In [33]:

```
house_df = pd.DataFrame(np.zeros((1, len(X.columns))), columns = X.columns)
with open('deployment/house_data.pickle', 'wb') as f:
    pickle.dump(house_df, f)
```

Using our regression model and a datadrame template to be filled out and fed to the model, I created house_price_prediction.py which can be run from the terminal to predict real estate prices in King County

Conclusions

After cleaning and normalizing data on real estate prices in King County, A multiple linear regression model was created that captures 86% of our data's variance.

The dataset is suitably linear, and its residuals follow a near-normal distribution, but there is some hteroscedasticity in the data that suggests some inaccuracy.

This model was exported to `house_price_prediction.py` so it can be used in the backend of a prediction software for a real estate company to automate the initial appraisal of houses in King County.

Future Work

- Create GUI that takes data and delivers a price estimate.
- Explore using multiple models for different locations to achieve higher accuracy
- Modify function to accept an address as an input rather than taking zipcode, latitude, and longitude separately