Uncovering the Housing Market's Secrets: Multiple Linear Regression Analysis

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Overview

This data science project uses multiple linear regression analysis techniques to build a reliable, statistically significant model for predicting housing prices in Kings County, Seattle. The data will contain home sale prices from May 2014 to May 2015, from King County's government records. The stakeholder is KCHA, Kings County Housing authority, a public agency that provides affordable housing options and services to low-income families, individuals, and seniors in King County. Their particular concern is providing homes for a family of five or more people. This project will help them to make data-driven well-informed decisions on making future services and polices.

Business Problem

Who is King County Housing Authority?

The KCHA is a public agency that provides affordable housing options and services to low-income families, individuals, and seniors in King County. They aim to help improve the quality of life for residents in the area by providing safe, decent, and affordable housing options, as well as supportive services and programs.

What are their headaches?

- The metropolitan area has a severe shortage of affordable housing, and KCHA is working to address this issue, possibly due to the concentration of large corporate campuses in the Seattle area.
- However, the presence of these high-earning populations and corporate campuses makes it challenging to acquire new affordable housing units, requiring extreme precise mathematical precision.
- The housing market in Seattle is experiencing significant turbulence:
    - Housing prices have seen a sharp increase following the pandemic.
    - Rising interest rates are driving up mortgage rates.
    - The potential for an economic recession adds to the uncertain outlook of the housing market.
    - The presence of nearby tech campuses and potential for tech lay-offs further complicates the situation.
- KCHA asked to provide a housing price prediction model that can accomodate a family of any size.

Why do they need this project?

- A multi-linear regression model can provide valuable insights into the factors that influence housing prices, helping KCHA make more informed decisions about acquiring new affordable housing units.
- The model can help KCHA understand the impact of changes in the housing market and make more accurate predictions about future trends, informing their strategic planning and decision-making.
- By providing valuable insights and predictions about the housing market, the model can help KCHA address the challenges they face in providing affordable housing in the metropolitan Seattle area.

Data Understanding

Import Packages

In [1]:
```
# Import basic packages
import numpy as np
import pandas as pd

# Import visualization pacakages
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

# Import math
import math

# Import scipy
from scipy import stats

# Import statsmodels
import statsmodels.api as sm
from statsmodels.formula.api import ols
from statsmodels.stats.outliers_influence import variance_inflation_factor
from statsmodels.graphics.gofplots import qqplot

# Import sklearn
from sklearn.linear_model import LinearRegression
from sklearn.feature_selection import RFE
from sklearn.preprocessing import StandardScaler, OneHotEncoder, OrdinalEnc
from sklearn.model_selection import train_test_split
import sklearn.metrics as metrics

# Import warnings
import warnings
warnings.filterwarnings("ignore", category= FutureWarning)
warnings.filterwarnings("ignore", category=DeprecationWarning)

# Import miscellaneous packages
from IPython.display import Markdown
```

Data 1: Home Sales Prices of King County in 2021 and 2022

This data was gathered from King County's official government website [https://kingcounty.gov/ (https://kingcounty.gov/)](https://kingcounty.gov/). This is our primary dataset and it contains detailed information about features of the houses sold.

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

Out[2]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront
0	7399300360	5/24/2022	675000.0	4	1.0	1180	7140	1.0	NO
1	8910500230	12/13/2021	920000.0	5	2.5	2770	6703	1.0	NO
2	1180000275	9/29/2021	311000.0	6	2.0	2880	6156	1.0	NO
3	1604601802	12/14/2021	775000.0	3	3.0	2160	1400	2.0	NO
4	8562780790	8/24/2021	592500.0	2	2.0	1120	758	2.0	NO

5 rows × 25 columns

Column Names and Descriptions for King County Data Set

- `id` - Unique identifier for a house
- `date` - Date house was sold
- `price` - Sale price (prediction target)
- `bedrooms` - Number of bedrooms
- `bathrooms` - Number of bathrooms
- `sqft_living` - Square footage of living space in the home
- `sqft_lot` - Square footage of the lot
- `floors` - Number of floors (levels) in house
- `waterfront` - Whether the house is on a waterfront
  - Includes Duwamish, Elliott Bay, Puget Sound, Lake Union, Ship Canal, Lake Washington, Lake Sammamish, other lake, and river/slough waterfronts
- `greenbelt` - Whether the house is adjacent to a green belt
- `nuisance` - Whether the house has traffic noise or other recorded nuisances
- `view` - Quality of view from house

    - Includes views of Mt. Rainier, Olympics, Cascades, Territorial, Seattle Skyline, Puget Sound, Lake Washington, Lake Sammamish, small lake / river / creek, and other
- `condition` - How good the overall condition of the house is. Related to maintenance of house.
    - See the [King County Assessor Website (https://info.kingcounty.gov/assessor/esales/Glossary.aspx?type=r)](https://info.kingcounty.gov/assessor/esales/Glossary.aspx?type=r) for further explanation of each condition code
- `grade` - Overall grade of the house. Related to the construction and design of the house.
    - See the [King County Assessor Website (https://info.kingcounty.gov/assessor/esales/Glossary.aspx?type=r)](https://info.kingcounty.gov/assessor/esales/Glossary.aspx?type=r) for further explanation of each building grade code
- `heat_source` - Heat source for the house
- `sewer_system` - Sewer system for the house
- `sqft_above` - Square footage of house apart from basement
- `sqft_basement` - Square footage of the basement
- `sqft_garage` - Square footage of garage space
- `sqft_patio` - Square footage of outdoor porch or deck space
- `yr_built` - Year when house was built
- `yr_renovated` - Year when house was renovated
- `address` - The street address
- `lat` - Latitude coordinate
- `long` - Longitude coordinate

Most fields were pulled from the [King County Assessor Data Download (https://info.kingcounty.gov/assessor/DataDownload/default.aspx)](https://info.kingcounty.gov/assessor/DataDownload/default.aspx).

The `address` , `lat` , and `long` fields have been retrieved using a third-party [geocoding API (https://docs.mapbox.com/api/search/geocoding/)](https://docs.mapbox.com/api/search/geocoding/). In some cases due to missing or incorrectly-entered data from the King County Assessor, this API returned locations outside of King County, WA. If you plan to use the `address` , `lat` , or `long` fields in your modeling, consider identifying outliers prior to including the values in your model.

Data 2: Reported Incidents in King County up to 2019

This data was gathered from King County's official government website [https://kingcounty.gov/ (https://kingcounty.gov/)](https://kingcounty.gov/). This is our supporting dataset and it contains detailed information about reported incidents in King County all the way to 2019. This information can be useful in creating new columns that tell how many incidents occurred in different regions.

In [3]:
```
# Read Data
df_incident = pd.read_csv('data/KCSO_Incident_Dataset__Historic_to_2019.csv
df_incident.head()
```

Out[3]:

	case_number	incident_datetime	incident_type	FCR	address_1	city	state	zip	created_
0	C19046940	12/09/2019 09:02:00 AM	Other	503	1 Block AVE & YESLER WAY	SEATTLE	WA	98104	12/12/20 06:19: F
1	C19046039	12/02/2019 06:01:00 PM	Other	162	19700 Block 635TH PL NE	BARING	WA	98224	12/05/20 05:15: F
2	C19026684	07/14/2019 01:29:00 AM	Vehicle Recovery	311	1 Block PL S & DES MOINES MEMORIAL DR S	BURIEN	WA	98168	07/15/20 05:45: A
3	C19043968	11/16/2019 10:07:00 PM	Traffic	404	RAINIER AVE N & RENTON AVE S	SKYWAY	WA	98178	11/19/20 04:30: F
4	C19042199	11/04/2019 07:18:00 AM	Property Crime	313	1 Block PL S & DES MOINES MEMORIAL DR S	BURIEN	WA	98168	11/05/20 04:35: F

Data 3: Reported Offenses in King County from 2020

This data was gathered from King County's official government website [https://kingcounty.gov/ (https://kingcounty.gov/)](https://kingcounty.gov/). This is our supporting dataset and it contains detailed information about reported offenses in King County since 2020. This information can be useful in creating new columns that tell how many offenses occurred in different regions.

In [4]:
```python
# Read data
df_offense = pd.read_csv("data/KCSO_Offense_Reports__2020_to_Present.csv")
df_offense.head()
```

Out[4]:

	case_number	incident_datetime	nibrs_code	nibrs_code_name	block_address	
0	C21034525	10/29/2021 11:21:00 AM	120	Robbery	14900 Block 4TH AVE SW	BUI
1	C21034462	10/28/2021 08:10:00 PM	290	Destruction/Damage/Vandalism of Property	17600 Block 152ND PL SE	REN
2	C21034548	10/29/2021 12:30:00 AM	240	Motor Vehicle Theft	100 Block SW 112TH ST	SEAT
3	C21034576	10/28/2021 05:00:00 PM	13B	Simple Assault	14400 Block 162ND AVE SE	REN
4	C22012227	04/12/2022 08:36:00 PM	13B	Simple Assault	2800 Block NE 200TH ST	SHOREI

Data 4: Population, City, County by Zipcode

This data was gathered from King County's official government website [https://kingcounty.gov/ (https://kingcounty.gov/)](https://kingcounty.gov/). This is our supporting dataset and it contains a conversion table for zipcode, population and city.

In [5]:
```python
# Read data
df_county = pd.read_csv("data/kc_zipcode.csv")
df_county.head()
```

Out[5]:

	zip	population	city	county
0	99301	81583	Pasco	Franklin
1	98052	71940	Redmond	King
2	98012	70009	Bothell	Snohomish
3	98682	63768	Vancouver	Clark
4	98208	58211	Everett	Snohomish

We will extract zipcode from 'address' attribute of 'df' and make conversion by accessing 'df_county'.

In [6]:
```
# Change attribute's name, and dtype.
df_county['zipcode'] = df_county['zip']
df_county['zipcode'] = df_county['zipcode'].astype(str)
df_county = df_county[['population', 'city', 'county', 'zipcode']]
df_county.head()
```

Out[6]:

	population	city	county	zipcode
0	81583	Pasco	Franklin	99301
1	71940	Redmond	King	98052
2	70009	Bothell	Snohomish	98012
3	63768	Vancouver	Clark	98682
4	58211	Everett	Snohomish	98208

Data Preparation

In this step, we will explore data and clean them so they are ready for multi-regressional analysis.

Dealing with Missing Values

We will thoroughly survey each column for missing values, and fill them after analyzing each attribute's distribution.

In [7]:
```
# Display all missing values.
display(df.info(), df.isna().any())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30155 entries, 0 to 30154
Data columns (total 25 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   id             30155 non-null  int64
 1   date           30155 non-null  object
 2   price          30155 non-null  float64
 3   bedrooms       30155 non-null  int64
 4   bathrooms      30155 non-null  float64
 5   sqft_living    30155 non-null  int64
 6   sqft_lot       30155 non-null  int64
 7   floors         30155 non-null  float64
 8   waterfront     30155 non-null  object
 9   greenbelt      30155 non-null  object
 10  nuisance       30155 non-null  object
 11  view           30155 non-null  object
 12  condition      30155 non-null  object
 13  grade          30155 non-null  object
 14  heat_source    30123 non-null  object
 15  sewer_system   30141 non-null  object
 16  sqft_above     30155 non-null  int64
 17  sqft_basement  30155 non-null  int64
 18  sqft_garage    30155 non-null  int64
 19  sqft_patio     30155 non-null  int64
 20  yr_built       30155 non-null  int64
 21  yr_renovated   30155 non-null  int64
 22  address        30155 non-null  object
 23  lat            30155 non-null  float64
 24  long           30155 non-null  float64
dtypes: float64(5), int64(10), object(10)
memory usage: 5.8+ MB

None
```

```
id               False
date             False
price            False
bedrooms         False
bathrooms        False
sqft_living      False
sqft_lot         False
floors           False
waterfront       False
greenbelt        False
nuisance         False
view             False
condition        False
grade            False
heat_source       True
sewer_system      True
sqft_above       False
sqft_basement    False
sqft_garage      False
sqft_patio       False
yr_built         False
yr_renovated     False
address          False
lat              False
long             False
dtype: bool
```

In [8]:

```
# Study the nature of the attribute 'heat_source'
display(df.heat_source.unique(), df.heat_source.value_counts(), df.heat_sou
```

```
array(['Gas', 'Oil', 'Electricity', 'Gas/Solar', 'Electricity/Solar',
       'Other', nan, 'Oil/Solar'], dtype=object)

Gas                  20583
Electricity           6465
Oil                   2899
Gas/Solar               93
Electricity/Solar       59
Other                   20
Oil/Solar                4
Name: heat_source, dtype: int64

32
```

The distribution is extremely unimodal so it will be filled with the mode.

In [9]:

```
# Fill missing values
df['heat_source'] = df['heat_source'].fillna('Gas')
```

In [10]:
```
# Study distribution of 'sewer_system'
display(df.sewer_system.unique(), df.sewer_system.value_counts(), df.sewer_
```

```
array(['PUBLIC', 'PRIVATE', 'PRIVATE RESTRICTED', nan,
       'PUBLIC RESTRICTED'], dtype=object)
```

```
PUBLIC                25777
PRIVATE                4355
PRIVATE RESTRICTED        6
PUBLIC RESTRICTED         3
Name: sewer_system, dtype: int64
```

```
14
```

This is an even more extreme unimodal distribution. Fill-in with 'PUBLIC'.

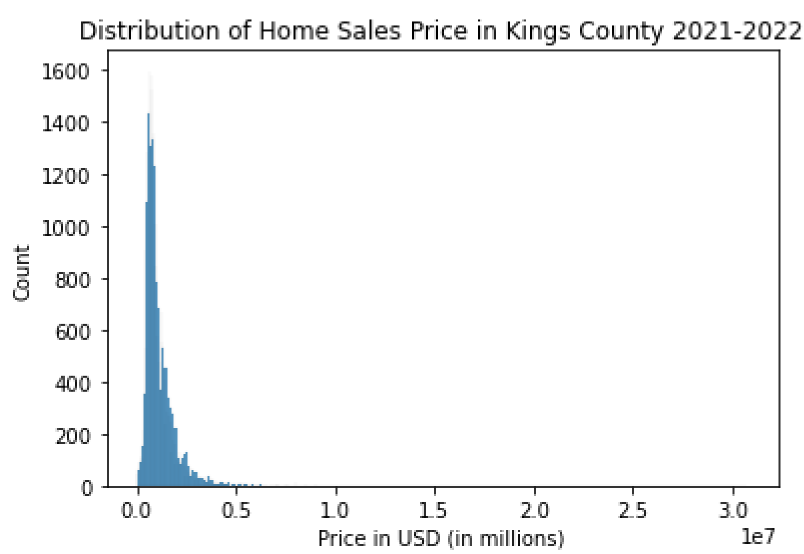
In [11]:
```
# Fill-in missing values
df['sewer_system'] = df['sewer_system'].fillna('PUBLIC')
```

Dropping Outliers

Since we are predicting on 'price', we will study deeper into its distribution and check for potential outliers that are better removed.

```
In [12]: print('1st percentile:      ', round(df.price.quantile(0.01)))
         print('2nd percentile:      ', round(df.price.quantile(0.02)))
         print('3rd percentile:      ', round(df.price.quantile(0.03)))
         print('4th percentile:      ', round(df.price.quantile(0.04)))
         print('5th percentile:      ', round(df.price.quantile(0.05)), '\n')
         print('average:             ', round(df.price.mean()))
         print('median:              ', round(df.price.median()))
         print('maximum:             ', round(df.price.max()))
         print('std. dev.:           ', round(df.price.std()), '\n')
         print('95th percentile:     ', round(df.price.quantile(0.95)))
         print('96th percentile:     ', round(df.price.quantile(0.96)))
         print('97th percentile:     ', round(df.price.quantile(0.97)))
         print('98th percentile:     ', round(df.price.quantile(0.98)))
         print('99th percentile:     ', round(df.price.quantile(0.99)))
         print('99.5th percentile:   ', round(df.price.quantile(0.995)))

         sns.histplot(df.price)
         plt.title("Distribution of Home Sales Price in Kings County 2021-2022")
         plt.xlabel("Price in USD (in millions)")
         plt.show()
```

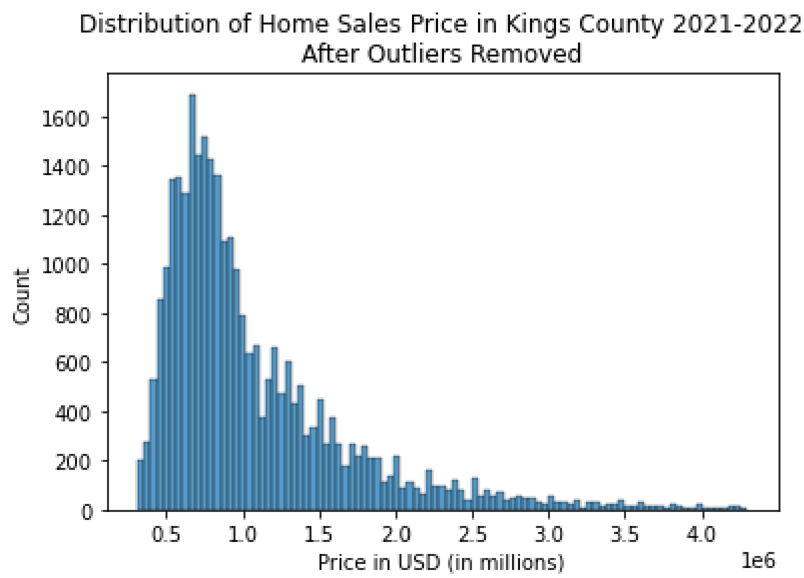
```
1st percentile:       200000.0
2nd percentile:       308264.0
3rd percentile:       370000.0
4th percentile:       400000.0
5th percentile:       425000.0

average:              1108536.0
median:               860000.0
maximum:              30750000.0
std. dev.:            896386.0

95th percentile:      2500000.0
96th percentile:      2700000.0
97th percentile:      2976900.0
98th percentile:      3450000.0
99th percentile:      4300000.0
99.5th percentile:    5658970.0
```

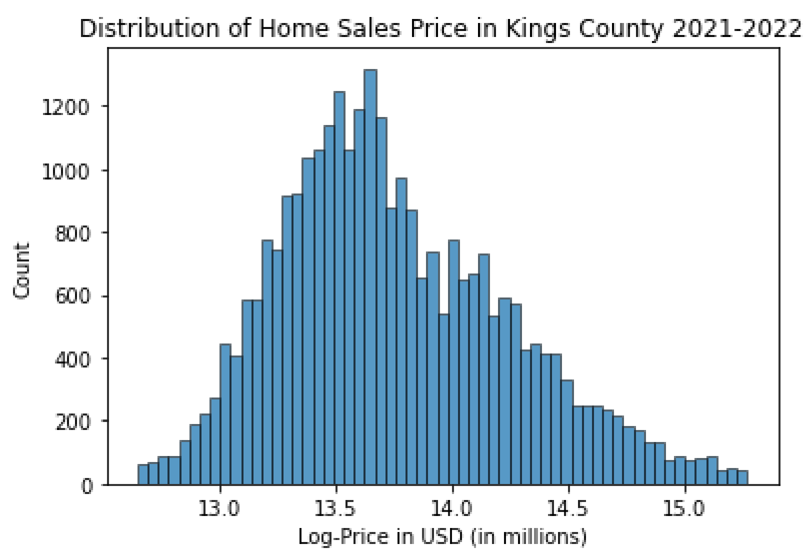


The distribution of the data is right-skewed, but it follows a normal distribution if the extreme values are removed. The presence of these extreme values is greatly distorting the distribution of the data, so we will remove them. The upper outliers are far more extreme than the lower outliers, so we will exclude them from the analysis by setting a threshold at the 99th percentile. The lower outliers are also meaningless for our study since they represent the cheapest homes that only hold minimal value for property contractors. The prices of these homes reflect the value of the lot rather than the value of the property itself. Therefore, we will exclude the lower outliers from our analysis as well at a threshold of 2nd percentile.

In [13]:

```
# Remove outliers
df = df.loc[(df['price'] < df['price'].quantile(0.99)) &
            (df['price'] > df['price'].quantile(0.02))]

# Show distribution of price after removing outliers
sns.histplot(df.price)
plt.title("Distribution of Home Sales Price in Kings County 2021-2022\nAfte
plt.xlabel("Price in USD (in millions)")
plt.show()

# Check distribution of price after log-transformation for reference.
df['log_price'] = np.log(df['price'])
sns.histplot(df.log_price)
plt.title("Distribution of Home Sales Price in Kings County 2021-2022")
plt.xlabel("Log-Price in USD (in millions)")
plt.show()
df.drop('log_price', axis=1, inplace=True)
```





We have flattened the distribution into a more normal looking shape. The log-transformation histogram show us we can employ this transformation in the future.

Creating New Column 1: zipcode, city, population, county

We will create new columns that can be meaningfully interpreted.

In [14]:
```
# See address attribute
display(df.address.head(), df.address[0])
```

```
0    2102 Southeast 21st Court, Renton, Washington ...
1    11231 Greenwood Avenue North, Seattle, Washing...
2    8504 South 113th Street, Seattle, Washington 9...
3    4079 Letitia Avenue South, Seattle, Washington...
4    2193 Northwest Talus Drive, Issaquah, Washingt...
Name: address, dtype: object

'2102 Southeast 21st Court, Renton, Washington 98055, United States'
```

It's in string format so we will extract this and create a new attribute 'zipcode' to hold the value.

In [15]:

```
# Extract zipcodes and and create a new column to store them
df['last_25'] = df['address'].str[-20:]
df['zipcode'] = df['last_25'].str.extract(r'([0-9]{5})')
df.drop('last_25', axis=1, inplace=True)
df['zipcode'] = df['address'].str[-20:-15]
df['zipcode'].unique()
```

```
Out[15]: array(['98055', '98133', '98178', '98118', '98027', '98166', '98030',
       '98023', '98019', '98144', '98031', '68106', '98092', '98103',
       '98006', '98136', '98007', '98038', '98057', '98077', '98126',
       '98053', '98107', '98008', '98155', '98168', '98199', '98004',
       '98045', '98052', '98011', '98002', '98033', '98116', '08360',
       '98198', '98125', '98001', '62859', '98112', '98034', '98059',
       '98005', '98040', '98014', '98106', '98029', '98122', '98003',
       '98117', '98042', '98119', '98065', '98022', '98072', '98039',
       '98058', '98056', '98108', '98115', '98074', '98105', '98024',
       '07087', '98146', '11704', '68123', '98102', '52405', '02066',
       '80501', '91343', '19131', '98028', '98188', '55417', '98177',
       '98075', '98010', '98148', '53158', '98047', '15120', '98109',
       '98032', '97210', '98070', '11105', '91730', '68410', '58490',
       '68048', '62703', '68601', '61108', '96816', '47060', '98288',
       '48503', '55901', '11703', '98051', '63653', '63601', '46554',
       '80401', '07111', '34601', '02916', '07103', '97221', '85296',
       '43211', '68133', '55382', '84790', '45831', '29582', '47714',
       '96064', '08752', '52040', '69154', '98354', '90605', '98272',
       '33054', '61104', '75050', '91910', '52241', '07712', '68132',
       '63624', '45856', '92879', '68651', '11510', '68972', '49090',
       '98296', '58261', '11106', '79339', '53142', '68502', '93033',
       '80631', '34698', '97214', '64503', '25177', '98271', '43210',
       '98050', '08008', '48336', '46403', '68307', '78216', '52732',
       '46929', '58558', '63090', '61244', '45403', '19129', '55112',
       '61201', '68632', '59102', '07719', '98387', '47805', '46312',
       '63640', '07063', '02568', '56464', '11762', '49858', '58102',
       '54002', '78257', '07107', '62896', '85040', '55929', '33147',
       '63014', '54751', '87507', '64124', '07006', '60088', '55406',
       '53095', '55404', '15301', '55407', '83712', '08054', '70584',
       '98251', '98223', '11204', '50325', '15010', '55912', '99701',
       '98338', '02790', '56549', '98224', '56472', '53081', '72751',
       '56387', '45044', '16001', '97201', '66503', '58203', '19139',
       '07504', '19104', '29405', '02134', '84115', '02852', '58104',
       '83687', '68654', '11501', '11772', '66102', '53208', '62205',
       '66109', '16601', '07079', '66104', '11731', '94403', '47575',
       '15223', '68628', '50161', '61933', '64641', '76205', '98372',
       '11706', '99504', '89108', '53213', '33619', '79423', '54007',
       '62204', '12546', '68862', '98663', '85207', '99202', '64119',
       '58801', '61264', '53214', '44714', '68347', '80904', '85295',
       '85705', '68788', '47546', '59405', '32609', '50644', '56560',
       '95822', '60155', '73064', '33138', '58059', '07513', '17922',
       '64156', '52172', '11363', '55411', '02341', '17702', '68455',
       '64649', '58042', '56364', '46032', '99705', '45659', '11980',
       '21702', '15064', '01541', '93041', '58270', '68660', '10011',
       '99403', '47265', '34116', '56027', '18052', '46151', '02149',
       '55117', '10550', '94607', '13205', '49051', '55063', '58018',
       '59501', '54736', '98422', '84104', '95205', '95240', '58212',
       '80238', '07031', '08260', '68652', '55369', '18960', '11373',
       '19146', '08096', '67846', '94530', '02645', '63301', '33179',
       '08204', '11717', '11370', '68504', '68305', '34208', '56537',
       '68970', '64116', '62281', '97006', '68031', '17111', '99203',
       '52590', '55021', '92250', '68826', '55412', '68354', '55379',
       '90063', '56303', '58504', '07650', '58503', '45039', '99223',
       '55356', '80210', '47272', '55734', '67801', '68643', '60411',
       '50237', '97459', '49783', '11369', '99501', '58572', '62401',
       '98270', '93523', '08520', '11360', '53215', '84403', '11215',
```

```
       '56251', '73118', '65049', '94122', '85210', '34470'], dtype=objec
t)
```

In [16]:
```
# Merge dataframes so that 'df' now has added column values for df_county.c
df = pd.merge(df, df_county, on='zipcode')
df.head()
```

Out[16]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront
0	7399300360	5/24/2022	675000.0	4	1.0	1180	7140	1.0	NO
1	3340401570	3/2/2022	750000.0	3	2.0	1830	7969	1.0	NO
2	7399301200	3/29/2022	728000.0	4	2.0	2170	7520	1.0	NO
3	9899200050	3/24/2022	565000.0	4	2.0	1400	10364	1.5	NO
4	6673070070	12/28/2021	645000.0	3	2.0	1520	8250	1.0	NO

5 rows × 29 columns

In [17]:
```
# Check values for attribute 'county'
display(df.county.value_counts(), df.county.isna().sum(), len(df))
```

```
King         27695
Pierce          28
Snohomish       20
Spokane          3
Clark            2
Asotin           1
Name: county, dtype: int64

0

27749
```

In [18]:
```
# Drop all data points outside King County
df = df.loc[df['county'] == 'King']
display(df.head(), len(df))
```

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront
0	7399300360	5/24/2022	675000.0	4	1.0	1180	7140	1.0	NO
1	3340401570	3/2/2022	750000.0	3	2.0	1830	7969	1.0	NO
2	7399301200	3/29/2022	728000.0	4	2.0	2170	7520	1.0	NO
3	9899200050	3/24/2022	565000.0	4	2.0	1400	10364	1.5	NO
4	6673070070	12/28/2021	645000.0	3	2.0	1520	8250	1.0	NO

5 rows × 29 columns

```
27695
```

New Column 2: zip_incident

We will create a new column 'zip_incident' that displays number of reported incidents in a certain zipcode.

In [19]:
```
# Create 'zip_incident'
df_incident['zipcode'] = df_incident['zip']
df_incident.drop('zip', axis=1, inplace=True)

dict_incident = dict(df_incident.zipcode.value_counts())

df['zip_incident'] = df['zipcode'].apply(lambda x: dict_incident[x] if x in
```

New Column 3: zip_offense

We will create a new column 'zip_offense' that displays number of reported offenses in a certain zipcode.

In [20]:
```
# Create 'zip_offense'
df_offense['zipcode'] = df_offense['zip']
df_offense.drop('zip', axis=1, inplace=True)

dict_offense = dict(df_offense.zipcode.value_counts())

df['zip_offense'] = df['zipcode'].apply(lambda x: dict_offense[x] if x in d
```

New Colum 4: age

We will create a new column 'age' that displays the house age at the time of the sale.

In [21]:
```
# Change date's dtype to datetime, keep only the year, then change to integ
df['date'] = pd.to_datetime(df['date']).dt.year
df.date = df.date.astype(int)

# Compute age of the house
df['age'] = df['date'] - df['yr_built']

# For any negative value, change the year to 0
df.loc[df['age'] < 0, 'age'] = 0
```

Negative values of 1 are not dropped because they were homes built in 2022.

New Colum 5: min_dist

We will create a new column that tracks the minimum distance to important headquarters in King County.

In [22]:
```python
def haversine(lat, long):
    # Latitude and longitude coordinates of the headquarters
    amazon = (47.6062, -122.3321)
    microsoft = (47.6395, -122.1282)
    starbucks = (47.5906, -122.3331)
    boeing = (47.5301, -122.0326)
    costco = (47.8107, -122.3774)


    # List of coordinates of the headquarters
    coordinates = [amazon, microsoft, starbucks, boeing, costco]

    R = 6371  # radius of the earth in kilometers
    distances = []

    # Compute distances to all headquarters
    for c in coordinates:
        dlat = math.radians(c[0] - lat)
        dlon = math.radians(c[1] - long)
        a = math.sin(dlat/2) * math.sin(dlat/2) + math.cos(math.radians(lat
            * math.cos(math.radians(c[0])) * math.sin(dlon/2) * math.sin(dl
        c = 2 * math.atan2(math.sqrt(a), math.sqrt(1-a))
        distance = R * c
        distances.append(distance)

    # Return the minimum distance
    return min(distances)

df['min_dist'] = df.apply(lambda row: haversine(row['lat'], row['long']), a
```

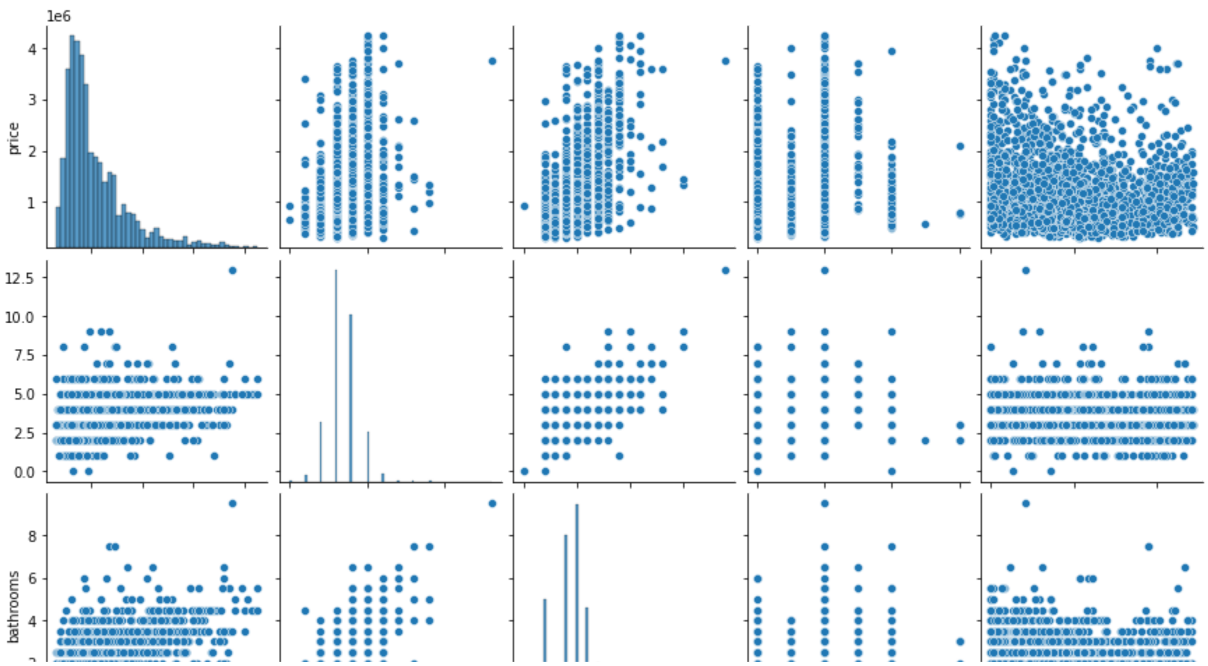
Before moving on, check for missing values again after data cleaning.

In [23]:
```python
df.isna().any()
```

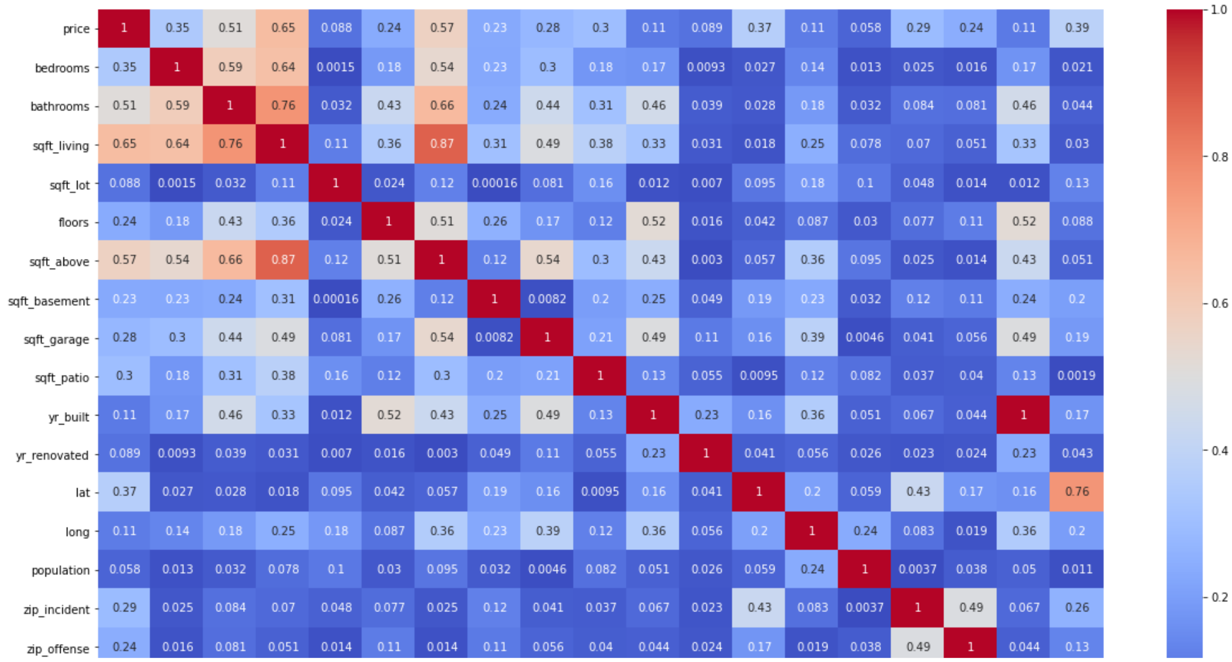
Out[23]:
```
id                 False
date               False
price              False
bedrooms           False
bathrooms          False
sqft_living        False
sqft_lot           False
floors             False
waterfront         False
greenbelt          False
nuisance           False
view               False
condition          False
grade              False
heat_source        False
sewer_system       False
sqft_above         False
sqft_basement      False
sqft_garage        False
```

We are ready to create the baseline model. Before doing that, we will create pairplots and correlation heatmaps to gain insights for future modeling.

In [24]:
```
sample_df = df.sample(n=3000, random_state=817)

pairplot_columns1 = ['price', 'bedrooms', 'bathrooms', 'floors', 'age']
pairplot_columns2 = ['price', 'sqft_living', 'sqft_lot', 'sqft_above',
                     'sqft_basement', 'sqft_garage', 'sqft_patio']
pairplot_columns3 = ['price', 'min_dist', 'zip_incident', 'zip_offense', 'p


sns.pairplot(sample_df[pairplot_columns1])
plt.show()

sns.pairplot(sample_df[pairplot_columns2])
plt.show()

sns.pairplot(sample_df[pairplot_columns3])
plt.show()
```



In [25]:
```python
corr = abs(df.drop(['id', 'date'], axis=1).corr())
fig, ax = plt.subplots(figsize=(20,12))
sns.heatmap(corr, annot=True, cmap='coolwarm')
plt.show()
```



Pre-work for Ordinal Values

We will use OrdinalEncoder() later when creating multi-linear regression model.

In [26]:
```python
# Divide predictor columns to three groups based on their features
numeric_columns = ['bedrooms', 'bathrooms', 'floors', 'sqft_living', 'sqft_
                   'sqft_basement', 'sqft_garage', 'sqft_patio', 'zip_incid
                   'zip_offense', 'age', 'min_dist']
ordinal_columns = ['condition', 'grade', 'view']
nominal_columns = ['waterfront', 'greenbelt', 'nuisance', 'heat_source',
                   'sewer_system','zipcode', 'city']
```

Let's clean ordinal columns so that they are ready for ordinal encoding.

In [27]:
```
# Display information about ordinal columns
display(df[ordinal_columns].info(), df[ordinal_columns].isna().any())
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 27695 entries, 0 to 27738
Data columns (total 3 columns):
 #   Column     Non-Null Count  Dtype 
---  ------     --------------  ----- 
 0   condition  27695 non-null  object
 1   grade      27695 non-null  object
 2   view       27695 non-null  object
dtypes: object(3)
memory usage: 865.5+ KB
```

```
None
```

```
condition    False
grade        False
view         False
dtype: bool
```

There are no missing values to fill. We will now change ordinal columns' category to dtype category and then assign the order of magnitude to each category.

In [28]:
```python
# Change data type
df['condition'] = df['condition'].astype('category')
df['grade'] = df['grade'].astype('category')
df['view'] = df['view'].astype('category')

# Display ordinal columns so that order can be arranged
display(df.condition, df.grade, df.view)
```

```
0             Good
1          Average
2          Average
3             Good
4          Average
           ...
27690      Average
27691      Average
27725    Very Good
27726    Very Good
27738      Average
Name: condition, Length: 27695, dtype: category
Categories (5, object): ['Average', 'Fair', 'Good', 'Poor', 'Very Good']
```

```
0            7 Average
1            7 Average
2            7 Average
3        6 Low Average
4               8 Good
             ...
27690        7 Average
27691           8 Good
27725         9 Better
27726    6 Low Average
27738    6 Low Average
Name: grade, Length: 27695, dtype: category
Categories (13, object): ['1 Cabin', '10 Very Good', '11 Excellent', '12
Luxury', ..., '6 Low Average', '7 Average', '8 Good', '9 Better']
```

```
0             NONE
1             NONE
2             NONE
3             NONE
4             NONE
           ...
27690         NONE
27691    EXCELLENT
27725         GOOD
27726         NONE
27738         NONE
Name: view, Length: 27695, dtype: category
Categories (5, object): ['AVERAGE', 'EXCELLENT', 'FAIR', 'GOOD', 'NONE']
```

In [29]:
```
# Assign the order for each category
df['condition'] = df['condition'].cat.reorder_categories(['Poor', 'Fair', '
df['grade'] = df['grade'].cat.reorder_categories(['1 Cabin', '2 Substandard
                                                  '5 Fair', '6 Low Average'
                                                  '9 Better', '10 Very Good
                                                  '13 Mansion'])
df['view'] = df['view'].cat.reorder_categories(['NONE', 'FAIR', 'AVERAGE',
```

In [30]:
```
# Assign the order for each category to a corresponding list for future ord
condition_list = df.condition.cat.categories.tolist()
grade_list = df.grade.cat.categories.tolist()
view_list = df.view.cat.categories.tolist()
```

Pre-work for Nominal Values

Now that pre-work for ordinal encoding is done, we will do the same for nominal encoding.

In [31]:
```
# Change data type for nominal categorical data
df['zipcode'] = df['zipcode'].astype('category')
df['city'] = df['city'].astype('category')
```

Evaluation/Modeling

We will now start making multi-linear regression models for price prediction. We will explore different possibilities and finish by choosing the best model.

In [32]:
```
# Create a list 'results' that store r-squared and rmse of different regres
results = []
```

Baseline: Most Correlated Varaibles

Based on the correlation heatmap, two most correlated variables to the price are 'sqft_living' and 'sqft_above'. We will start our regression models with a baseline model that uses these two as predictor variables for the target variable 'price'.

In [33]:
```
# Define Predictor variable X and target variable y
X = df[['sqft_living', 'sqft_above']]
y = df['price']
```

In [34]:
```
# Train test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, ra
```

In [35]:
```
# Fit / Transform the numeric data
ss = StandardScaler()
X_train_scaled = ss.fit_transform(X_train)
X_test_scaled = ss.transform(X_test)

X_train_scaled = pd.DataFrame(X_train_scaled,
                              columns=X_train.columns,
                              index=X_train.index)
X_test_scaled = pd.DataFrame(X_test_scaled,
                             columns=X_test.columns,
                             index=X_test.index)

X_train_final = X_train_scaled
X_test_final = X_test_scaled
```

In [36]:
```
# Fit the model, predict, evaluate
baseline = LinearRegression()
baseline.fit(X_train_final, y_train)
y_hat = baseline.predict(X_test_final)
residual = y_test-y_hat

r2 = metrics.r2_score(y_test, y_hat)
rmse = metrics.mean_squared_error(y_test, y_hat, squared=False)
result_baseline = [r2, rmse]
results.append(result_baseline)

print('R^2:   ', r2)
print('RMSE: ', rmse)
```

```
R^2:   0.42557063181769383
RMSE:  476488.2144957241
```

RMSE is still high, and only 42% of the variation in target variable is explained by our model. We will work to increase these numbers.

First Model: Newly Created Variables

We will only put newly created variables into the first model, to see their impacts only on the target variable.

In [37]:
```
# Define predictor variable and target variable
X = df[['zip_incident', 'zip_offense', 'age', 'min_dist']]
y = df['price']
```

In [38]:
```
# Tran test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, ra
```

```
In [39]: # Fit / transform numeric data
ss = StandardScaler()
X_train_scaled = ss.fit_transform(X_train)
X_test_scaled = ss.transform(X_test)

X_train_scaled = pd.DataFrame(X_train_scaled,
                              columns=X_train.columns,
                              index=X_train.index)
X_test_scaled = pd.DataFrame(X_test_scaled,
                             columns=X_test.columns,
                             index=X_test.index)

X_train_final = X_train_scaled
X_test_final = X_test_scaled
```

```
In [40]: # Fit / predict / evaluate
model_1 = LinearRegression()
model_1.fit(X_train_final, y_train)
y_hat = model_1.predict(X_test_final)
residual = y_test-y_hat

r2 = metrics.r2_score(y_test, y_hat)
rmse = metrics.mean_squared_error(y_test, y_hat, squared=False)
result_model_1 = [r2, rmse]
results.append(result_model_1)

print('R^2:   ', r2)
print('RMSE: ', rmse)
```

```
R^2:   0.23319379901140724
RMSE:  550524.5031316202
```

Their impacts are meaningful, but not strong enough by themselves.

Second Model: All Numerical Variables

In this model we will include all numeric data to see the maximum level which it can predict the target variable with numeric predictors only.

```
In [41]: # Define predictor variables and target variable
X = df[numeric_columns]
y = df['price']
```

```
In [42]: # Train test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, ra
```

In [43]:
```
# Fit / transform numeric data
ss = StandardScaler()
X_train_scaled = ss.fit_transform(X_train)
X_test_scaled = ss.transform(X_test)

X_train_scaled = pd.DataFrame(X_train_scaled,
                              columns=X_train.columns,
                              index=X_train.index)
X_test_scaled = pd.DataFrame(X_test_scaled,
                             columns=X_test.columns,
                             index=X_test.index)

X_train_final = X_train_scaled
X_test_final = X_test_scaled
```

In [44]:
```
# Fit / predict /evaluate
model_2 = LinearRegression()
model_2.fit(X_train_final, y_train)
y_hat = model_2.predict(X_test_final)
residual = y_test-y_hat

r2 = metrics.r2_score(y_test, y_hat)
rmse = metrics.mean_squared_error(y_test, y_hat, squared=False)
result_model_2 = [r2, rmse]
results.append(result_model_2)

display(r2, rmse)
```

```
0.6161450190214732
```

```
389508.9451005957
```

Our studies have progressed much. Now let's introduce nominal varaibles and ordinal variables separately, and eventually add them all together.

Third Model: Nominal Variables

In this model, we will try to predict target variable with the help of nominal variable only.

In [45]:
```
# For reference purpose only
numeric_columns = ['bedrooms', 'bathrooms', 'floors', 'sqft_living', 'sqft_
                   'sqft_basement', 'sqft_garage', 'sqft_patio', 'zip_incid
                   'zip_offense', 'age', 'min_dist']
ordinal_columns = ['condition', 'grade', 'view']
nominal_columns = ['waterfront', 'greenbelt', 'nuisance', 'heat_source', 's
```

In [46]:
```
# Define predictor variables and target variable
X = df[nominal_columns]
y = y
```

In [47]:
```
# Train test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, ra
```

In [48]:
```
# Use OneHotEncoder
X_train_nominal = X_train[nominal_columns]
X_test_nominal = X_test[nominal_columns]

ohe = OneHotEncoder(sparse=False , handle_unknown='ignore')
X_train_ohe = ohe.fit_transform(X_train_nominal)
X_test_ohe = ohe.transform(X_test_nominal)

X_train_ohe  = pd.DataFrame(X_train_ohe, columns=ohe.get_feature_names())
X_test_ohe = pd.DataFrame(X_test_ohe, columns = ohe.get_feature_names())

X_train_final = X_train_ohe
X_test_final = X_test_ohe
```

In [49]:
```
# Fit and Predict
model_3 = LinearRegression()
model_3.fit(X_train_final, y_train)
y_hat = model_3.predict(X_test_final)
residual = y_test-y_hat

r2 = metrics.r2_score(y_test, y_hat)
rmse = metrics.mean_squared_error(y_test, y_hat, squared=False)
result_model_3 = [r2, rmse]
results.append(result_model_3)

print('R^2:  ', r2)
print('RMSE: ', rmse)
```

```
R^2:   0.046905004227658864
RMSE:  613764.7470465882
```

Nominal variables aren't as powerful as expected.

Fourth Model: Ordinal Variables

Now we will evaluate the impact of ordinal predictor variables on the target variable.

In [50]:
```
# Define predictor variables and target variable
X = df[ordinal_columns]
y = df['price']
```

In [51]:
```
# Train test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, ra
```

In [52]:
```
# Process ordinal data
oe = OrdinalEncoder(categories = [condition_list, grade_list, view_list])

X_train_oe = oe.fit_transform(X_train)
X_test_oe = oe.transform(X_test)

X_train_oe = pd.DataFrame(X_train_oe, columns=X_train.columns)
X_test_oe = pd.DataFrame(X_test_oe, columns=X_test.columns)

X_train_final = X_train_oe
X_test_final = X_test_oe
```

In [53]:
```
# Fit / transform / predict
model_4 = LinearRegression()
model_4.fit(X_train_final, y_train)
y_hat = model_4.predict(X_test_final)
residual = y_test - y_hat

r2 = metrics.r2_score(y_test, y_hat)
rmse = metrics.mean_squared_error(y_test, y_hat, squared=False)
result_model_4 = [r2, rmse]
results.append(result_model_4)

print('R^2:  ', r2)
print('RMSE: ', rmse)
```

```
R^2:   0.42748099991875543
RMSE:  475695.23104822653
```

We have much stronger results with this model than we did with nominal data only.

Fifth Model

This time we will use all columns of different data types together for the first time.

In [54]:
```
# List and organize all the predictor variables
numeric_columns = ['bedrooms', 'floors', 'sqft_living', 'sqft_lot',
                   'sqft_basement', 'sqft_garage', 'sqft_patio', 'zip_incid
                   'zip_offense', 'age', 'min_dist']
ordinal_columns = ['condition', 'grade', 'view']
nominal_columns = ['waterfront', 'greenbelt', 'nuisance', 'heat_source',
                   'sewer_system']

predictor_columns = numeric_columns + ordinal_columns + nominal_columns
```

In [55]:
```
# Define predictor variables and target variable
X = df[predictor_columns]
y = df['price']
```

In [56]:
```
# Train test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, ra
```

In [57]:
```
# Process numerical data
ss = StandardScaler()
X_train_scaled = ss.fit_transform(X_train[numeric_columns])
X_test_scaled = ss.transform(X_test[numeric_columns])

X_train_scaled = pd.DataFrame(X_train_scaled,
                              columns=X_train[numeric_columns].columns,
                              index=X_train.index)
X_test_scaled = pd.DataFrame(X_test_scaled,
                             columns=X_test[numeric_columns].columns,
                             index=X_test.index)
```

In [58]:
```
# Process ordinal data
oe = OrdinalEncoder(categories = [condition_list, grade_list, view_list])

X_train_oe = oe.fit_transform(X_train[ordinal_columns])
X_test_oe = oe.transform(X_test[ordinal_columns])

X_train_oe = pd.DataFrame(X_train_oe, columns=X_train[ordinal_columns].colu
X_test_oe = pd.DataFrame(X_test_oe, columns=X_test[ordinal_columns].columns
```

In [59]:
```
# Process nominal data
ohe = OneHotEncoder(sparse=False , handle_unknown='ignore')
X_train_ohe = ohe.fit_transform(X_train[nominal_columns])
X_test_ohe = ohe.transform(X_test[nominal_columns])

X_train_ohe  = pd.DataFrame(X_train_ohe, columns = ohe.get_feature_names())
X_test_ohe = pd.DataFrame(X_test_ohe, columns = ohe.get_feature_names())
```

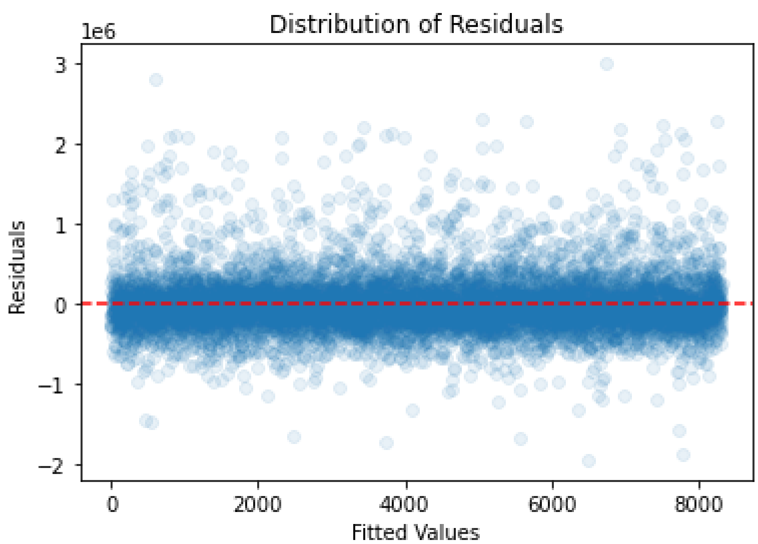
In [60]:
```
# Concatenate all the processed data
X_train_scaled.index = X_train.index
X_train_oe.index = X_train.index
X_train_ohe.index = X_train.index
X_train_final = pd.concat([X_train_scaled, X_train_oe, X_train_ohe], axis=1

X_test_scaled.index = X_test.index
X_test_oe.index = X_test.index
X_test_ohe.index = X_test.index
X_test_final = pd.concat([X_test_scaled, X_test_oe, X_test_ohe], axis=1)
```

In [61]:
```
# Fit / Predict / Results
model_5 = LinearRegression()
model_5.fit(X_train_final, y_train)
y_hat = model_5.predict(X_test_final)
residual = y_test - y_hat

r2 = metrics.r2_score(y_test, y_hat)
rmse = metrics.mean_squared_error(y_test, y_hat, squared=False)
result_model_5= [r2, rmse]
results.append(result_model_5)

print('R^2:  ', r2)
print('RMSE: ', rmse)
```

```
R^2:   0.6553421256465599
RMSE:  369086.3195849872
```

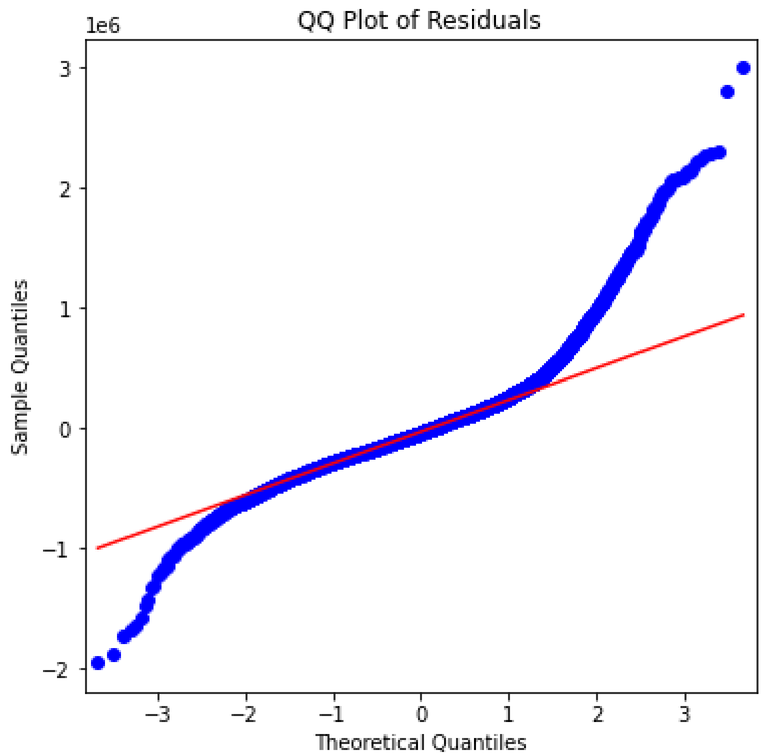
We are happier with improved R^2 but we will go for higher by possible transformation or introduction of new variables.

In [62]:
```
# Draw residual plot
fig, ax = plt.subplots()
ax.scatter(x=range(y_hat.shape[0]),y=residual, alpha=0.1)
ax.axhline(y=0, color='red', linestyle='--')
plt.title("Distribution of Residuals")
plt.xlabel("Fitted Values")
plt.ylabel("Residuals")
plt.show()
```



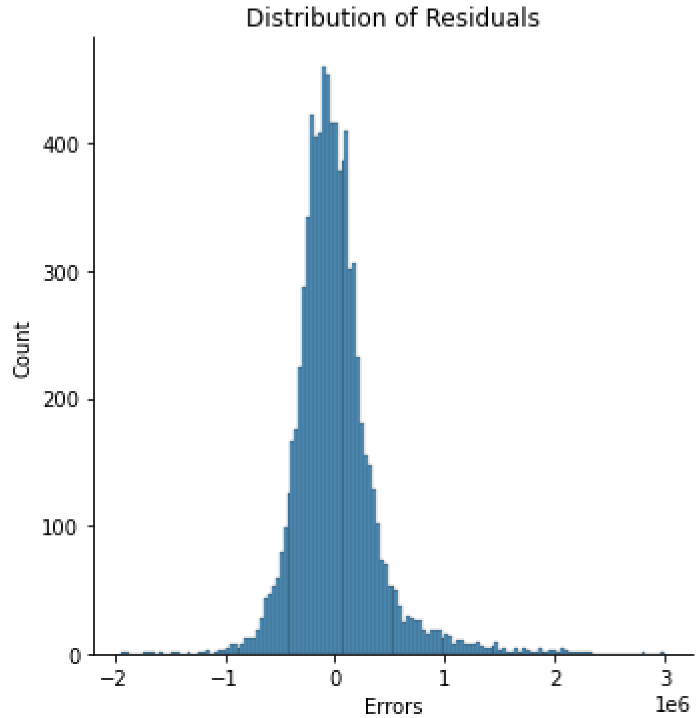
Consistent distribution of residuals is one of the assumptions of linear regression and it's clearly present with our fifth model.

In [63]:
```
fig, ax = plt.subplots(figsize=(6, 6))
qqplot(np.array(residual), line='q', ax=ax)
plt.title('QQ Plot of Residuals')
plt.show()
```



The distribution of residuals isn't strictly normal. However, it's closer to normal shape than before.

In [64]:
```
sns.displot(residual)
plt.title("Distribution of Residuals")
plt.xlabel("Errors")
plt.show()
```



Sixth Model

In this model, we will log-transform the target variable, to see if this can result in a more accurate prediction model.

In [65]:
```
# Log-transform target variable
df['log_price'] = np.log(df['price'])
```

In [66]:
```
# Display variables of our interest
numeric_columns = ['bedrooms', 'floors', 'sqft_living', 'sqft_lot',
                   'sqft_basement', 'sqft_patio', 'zip_incident', 'age', 'm
ordinal_columns = ['condition', 'grade', 'view']
nominal_columns = ['waterfront', 'greenbelt', 'nuisance', 'heat_source',
                   'sewer_system']

predictor_columns = numeric_columns + ordinal_columns + nominal_columns
```

In [67]:
```
# Define predictor and target variables
X = df[predictor_columns]
y = df['log_price']
```

In [68]:
```
# Train test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, ra
```

In [69]:
```
# Process numeric train
ss = StandardScaler()
X_train_scaled = ss.fit_transform(X_train[numeric_columns])
X_test_scaled = ss.transform(X_test[numeric_columns])

X_train_scaled = pd.DataFrame(X_train_scaled,
                              columns=X_train[numeric_columns].columns,
                              index=X_train.index)
X_test_scaled = pd.DataFrame(X_test_scaled,
                             columns=X_test[numeric_columns].columns,
                             index=X_test.index)
```

In [70]:
```
# Process ordinal train
oe = OrdinalEncoder(categories = [condition_list, grade_list, view_list])

X_train_oe = oe.fit_transform(X_train[ordinal_columns])
X_test_oe = oe.transform(X_test[ordinal_columns])

X_train_oe = pd.DataFrame(X_train_oe, columns=X_train[ordinal_columns].colu
X_test_oe = pd.DataFrame(X_test_oe, columns=X_test[ordinal_columns].columns
```

In [71]:
```
# Concatenate the processed trains
X_train_scaled.index = X_train.index
X_train_oe.index = X_train.index
X_train_final = pd.concat([X_train_scaled, X_train_oe], axis=1)

X_test_scaled.index = X_test.index
X_test_oe.index = X_test.index
X_test_final = pd.concat([X_test_scaled, X_test_oe], axis=1)

X_train_final = pd.concat([X_train_scaled, X_train_oe], axis=1)
X_test_final = pd.concat([X_test_scaled, X_test_oe], axis=1)
```

In [72]:
```
# Fit / Predict / Results
model_6 = LinearRegression()
model_6.fit(X_train_final, y_train)
y_hat = model_6.predict(X_test_final)
residual = y_test - y_hat

r2 = metrics.r2_score(y_test, y_hat)
rmse = metrics.mean_squared_error(np.exp(y_test), np.exp(y_hat), squared=Fa
result_model_6 = [r2, rmse]
results.append(result_model_6)

print('R^2:  ', r2)
print('RMSE: ', rmse)
```

```
R^2:   0.6950602984195035
RMSE:  485840.57251121226
```

After obtaining the best result so far, we will now proceed to check the assumptions of linear regression for reference. Since we have an R-squared value of 0.7, we can assume that there is a strong linear relationship between the dependent and independent variables. Additionally, we know that the samples contained in the data are independent of one another. We will now check for no muliti-collinearity, normality of residuals and homoskedasticity.

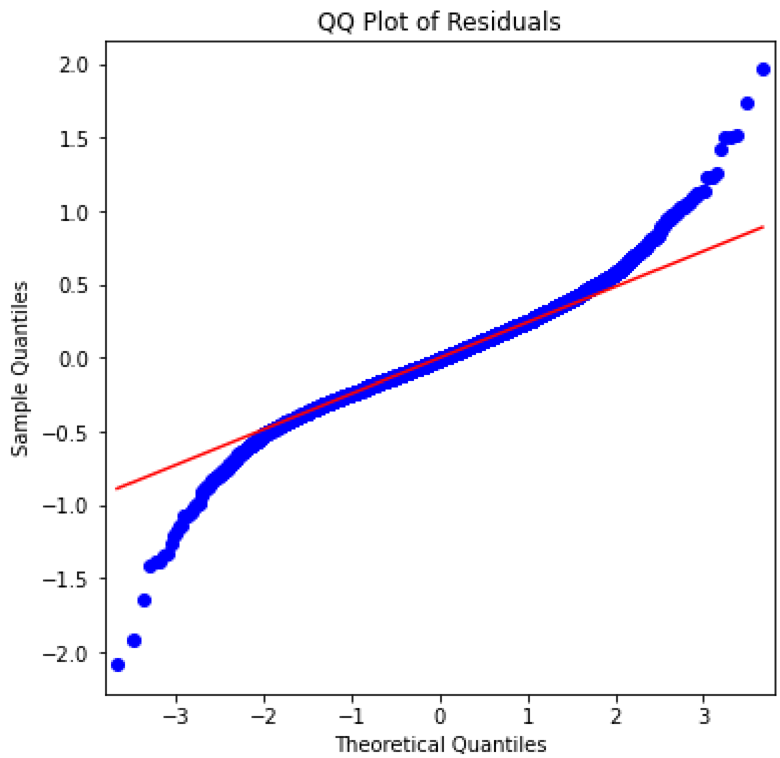
In [73]:
```
# Create vif dataframe
vif = pd.DataFrame()
vif["VIF Factor"] = [variance_inflation_factor(X_train_final.values, i) for
vif["features"] = X_train_final.columns
vif.sort_values('VIF Factor', ascending=False)
```

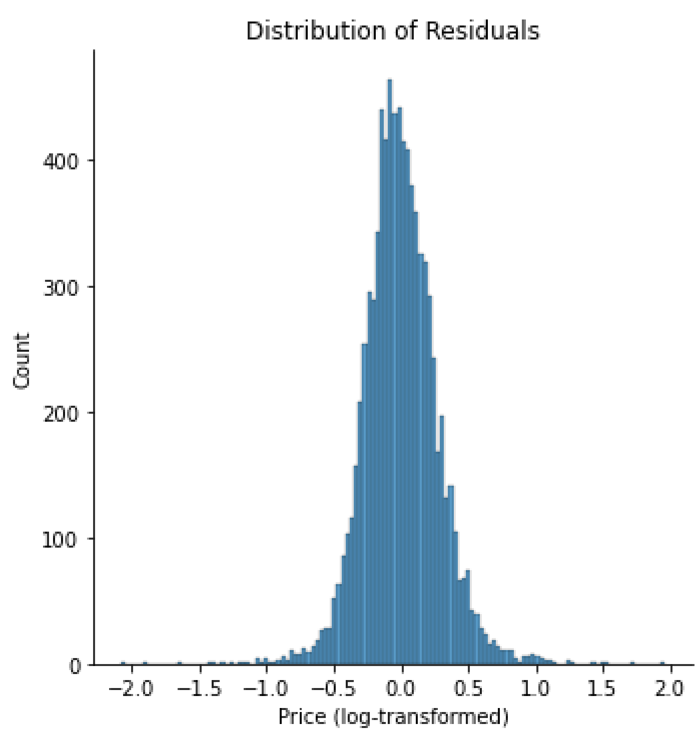
Out[73]:

	VIF Factor	features
10	13.868745	grade
9	13.546238	condition
2	2.739769	sqft_living
0	1.813139	bedrooms
7	1.802022	age
1	1.747221	floors
4	1.536408	sqft_basement
11	1.312958	view
5	1.246250	sqft_patio
8	1.226261	min_dist
6	1.092761	zip_incident
3	1.075326	sqft_lot

'grade' and 'condition' higher variance inflation factor but not high enough to discredit the model. Other variables have satisfying variance inflation factor. There is no multi-collinearity among predictor variables.

In [74]:
```
fig, ax = plt.subplots(figsize=(6, 6))
qqplot(np.array(residual), line='q', ax=ax)
plt.title('QQ Plot of Residuals')
plt.show()

sns.displot(residual)
plt.title("Distribution of Residuals")
plt.xlabel("Price (log-transformed)")
plt.show()
```

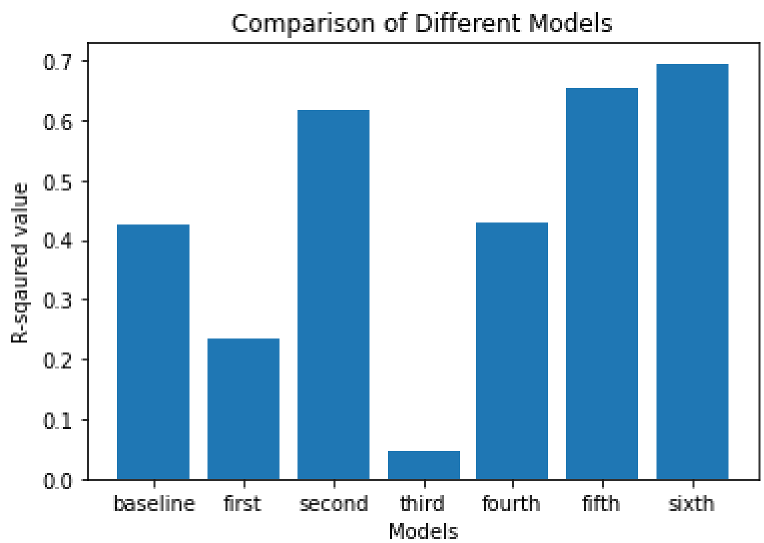




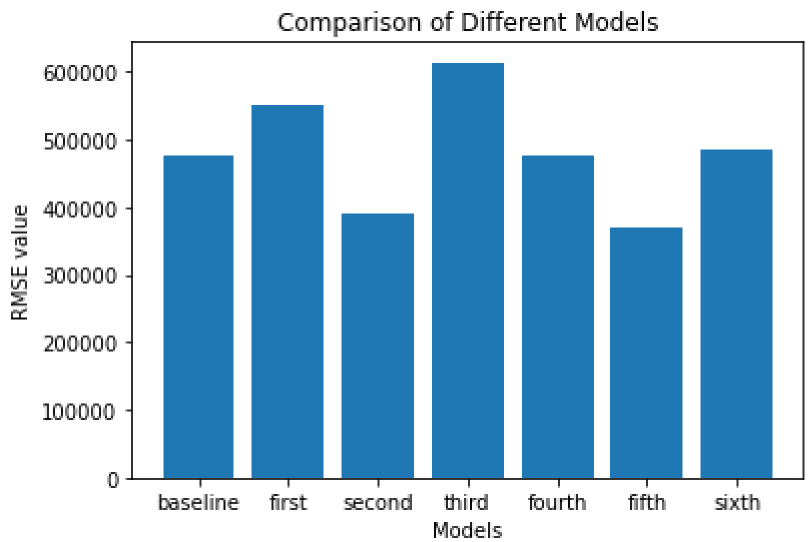
Final Model

We will create results of our models into bar graphs for comparison.

In [75]:
```
# Define the x-coordinates, heights and colors of the bars
x = ['baseline', 'first', 'second', 'third', 'fourth', 'fifth', 'sixth']
heights = [result[0] for result in results]

# Create an axis object and plot the bar chart
fig, ax = plt.subplots()
ax.bar(x, heights)

# Plot
ax.set_xlabel('Models')
ax.set_ylabel('R-sqaured value')
ax.set_title('Comparison of Different Models')
plt.show()
```



In [76]:
```
# Define the x-coordinates and heights of the bars
x = ['baseline', 'first', 'second', 'third', 'fourth', 'fifth', 'sixth']
heights = [result[1] for result in results]

# Create an axis object and plot the bar chart
fig, ax = plt.subplots()
ax.bar(x, heights)

# Plot
ax.set_xlabel('Models')
ax.set_ylabel('RMSE value')
ax.set_title('Comparison of Different Models')
plt.show()
```



The last two models are by far the best, I will choose the fifth as the final model. While slightly less impressive in accuracy of prediction, the fifth model compensates for it by providing way less errors associated with its prediction.

Conclusion

We have developed a model for predicting housing prices in King County, and have seen a significant improvement in prediction accuracy from 42% to 70%. While this is a notable improvement, we acknowledge that the model can be further enhanced by incorporating additional datasets and introducing new predictor variables. With continued refinement, it is possible to achieve even higher levels of accuracy. I remain committed to this effort, and will provide updates on any further improvements that are made to the model.