Keras Regression Code Along Project

Let's now apply our knowledge to a more realistic data set. Here we will also focus on feature engineering and cleaning our data!

The Data

We will be using data from a Kaggle data set:

https://www.kaggle.com/harlfoxem/housesalesprediction

Feature Columns

- id - Unique ID for each home sold
- date - Date of the home sale
- price - Price of each home sold
- bedrooms - Number of bedrooms
- bathrooms - Number of bathrooms, where .5 accounts for a room with a toilet but no shower
- sqft_living - Square footage of the apartments interior living space
- sqft_lot - Square footage of the land space
- floors - Number of floors
- waterfront - A dummy variable for whether the apartment was overlooking the waterfront or not
- view - An index from 0 to 4 of how good the view of the property was
- condition - An index from 1 to 5 on the condition of the apartment,
- grade - An index from 1 to 13, where 1-3 falls short of building construction and design, 7 has an average level of construction and design, and 11-13 have a high quality level of construction and design.
- sqft_above - The square footage of the interior housing space that is above ground level
- sqft_basement - The square footage of the interior housing space that is below ground level
- yr_built - The year the house was initially built
- yr_renovated - The year of the house's last renovation
- zipcode - What zipcode area the house is in
- lat - Lattitude
- long - Longitude
- sqft_living15 - The square footage of interior housing living space for the nearest 15 neighbors
- sqft_lot15 - The square footage of the land lots of the nearest 15 neighbors

In [3]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [4]:
```python
df = pd.read_csv('kc_house_data.csv')
```

Exploratory Data Analysis

In [5]:
```python
df.isnull() #To check if there is any missing data
```

Out[5]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_above	sqft_basement	yr_bu
0	False	False	False	False	False	False	False	False	False	False	...	False	False	False	Fals
1	False	False	False	False	False	False	False	False	False	False	...	False	False	False	Fals
2	False	False	False	False	False	False	False	False	False	False	...	False	False	False	Fals
3	False	False	False	False	False	False	False	False	False	False	...	False	False	False	Fals
4	False	False	False	False	False	False	False	False	False	False	...	False	False	False	Fals
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
21592	False	False	False	False	False	False	False	False	False	False	...	False	False	False	Fals
21593	False	False	False	False	False	False	False	False	False	False	...	False	False	False	Fals
21594	False	False	False	False	False	False	False	False	False	False	...	False	False	False	Fals
21595	False	False	False	False	False	False	False	False	False	False	...	False	False	False	Fals
21596	False	False	False	False	False	False	False	False	False	False	...	False	False	False	Fals

21597 rows × 21 columns

In [6]:
```
df.isnull().sum() #Not missing will return 0, missing will return 1
```

Out[6]:
```
id               0
date             0
price            0
bedrooms         0
bathrooms        0
sqft_living      0
sqft_lot         0
floors           0
waterfront       0
view             0
condition        0
grade            0
sqft_above       0
sqft_basement    0
yr_built         0
yr_renovated     0
zipcode          0
lat              0
long             0
sqft_living15    0
sqft_lot15       0
dtype: int64
```

In [7]:
```
df.describe().transpose()
```

Out[7]:

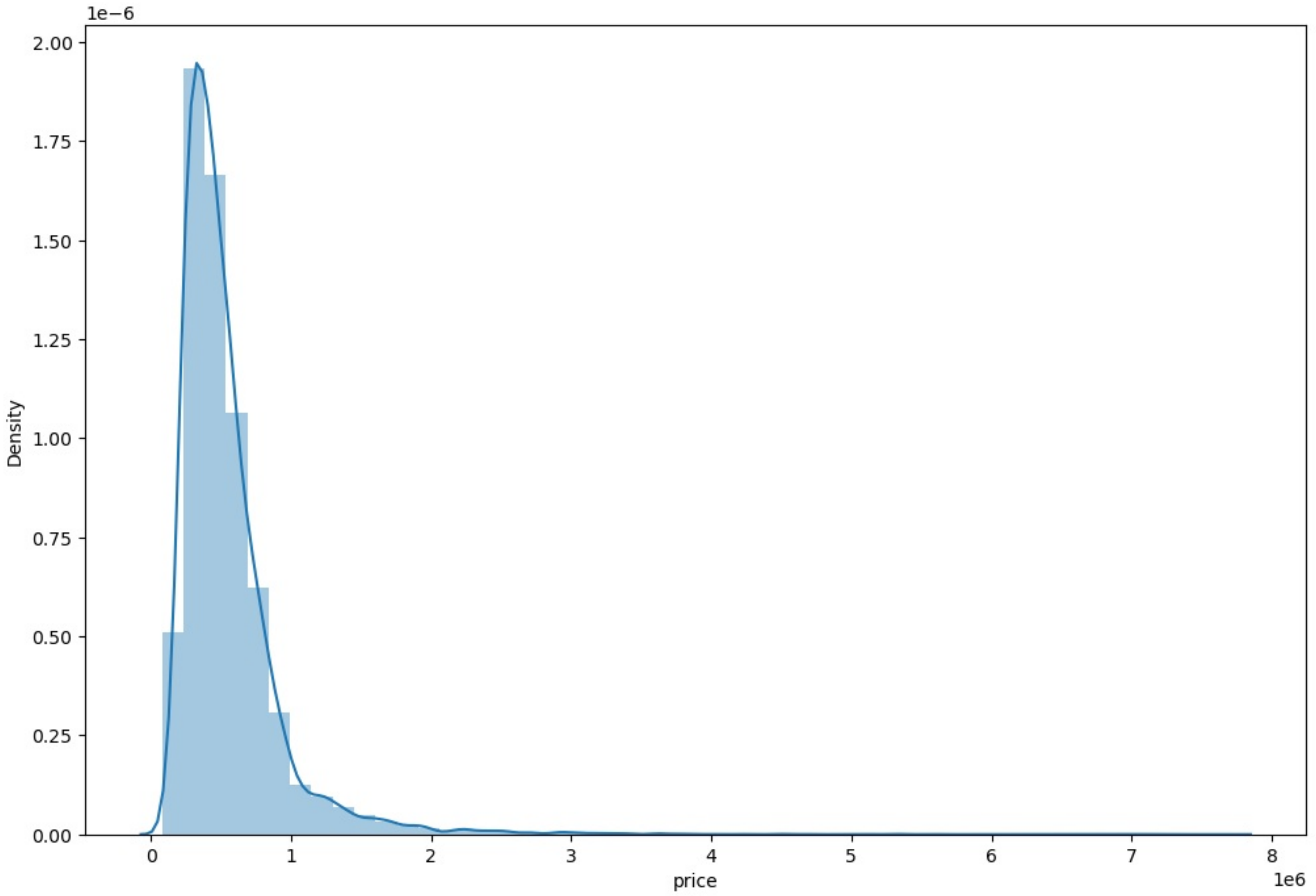
	count	mean	std	min	25%	50%	75%	max
id	21597.0	4.580474e+09	2.876736e+09	1.000102e+06	2.123049e+09	3.904930e+09	7.308900e+09	9.900000e+09
price	21597.0	5.402966e+05	3.673681e+05	7.800000e+04	3.220000e+05	4.500000e+05	6.450000e+05	7.700000e+06
bedrooms	21597.0	3.373200e+00	9.262989e-01	1.000000e+00	3.000000e+00	3.000000e+00	4.000000e+00	3.300000e+01
bathrooms	21597.0	2.115826e+00	7.689843e-01	5.000000e-01	1.750000e+00	2.250000e+00	2.500000e+00	8.000000e+00
sqft_living	21597.0	2.080322e+03	9.181061e+02	3.700000e+02	1.430000e+03	1.910000e+03	2.550000e+03	1.354000e+04
sqft_lot	21597.0	1.509941e+04	4.141264e+04	5.200000e+02	5.040000e+03	7.618000e+03	1.068500e+04	1.651359e+06
floors	21597.0	1.494096e+00	5.396828e-01	1.000000e+00	1.000000e+00	1.500000e+00	2.000000e+00	3.500000e+00
waterfront	21597.0	7.547345e-03	8.654900e-02	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	1.000000e+00
view	21597.0	2.342918e-01	7.663898e-01	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	4.000000e+00
condition	21597.0	3.409825e+00	6.505456e-01	1.000000e+00	3.000000e+00	3.000000e+00	4.000000e+00	5.000000e+00
grade	21597.0	7.657915e+00	1.173200e+00	3.000000e+00	7.000000e+00	7.000000e+00	8.000000e+00	1.300000e+01
sqft_above	21597.0	1.788597e+03	8.277598e+02	3.700000e+02	1.190000e+03	1.560000e+03	2.210000e+03	9.410000e+03
sqft_basement	21597.0	2.917250e+02	4.426678e+02	0.000000e+00	0.000000e+00	0.000000e+00	5.600000e+02	4.820000e+03
yr_built	21597.0	1.971000e+03	2.937523e+01	1.900000e+03	1.951000e+03	1.975000e+03	1.997000e+03	2.015000e+03
yr_renovated	21597.0	8.446479e+01	4.018214e+02	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	2.015000e+03
zipcode	21597.0	9.807795e+04	5.351307e+01	9.800100e+04	9.803300e+04	9.806500e+04	9.811800e+04	9.819900e+04
lat	21597.0	4.756009e+01	1.385518e-01	4.715590e+01	4.747110e+01	4.757180e+01	4.767800e+01	4.777760e+01
long	21597.0	-1.222140e+02	1.407235e-01	-1.225190e+02	-1.223280e+02	-1.222310e+02	-1.221250e+02	-1.213150e+02
sqft_living15	21597.0	1.986620e+03	6.852305e+02	3.990000e+02	1.490000e+03	1.840000e+03	2.360000e+03	6.210000e+03
sqft_lot15	21597.0	1.275828e+04	2.727444e+04	6.510000e+02	5.100000e+03	7.620000e+03	1.008300e+04	8.712000e+05

In [8]:
```
plt.figure(figsize=(12,8))
sns.distplot(df['price'])
```

```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a deprec
ated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure
-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[8]:

```
<AxesSubplot:xlabel='price', ylabel='Density'>
```



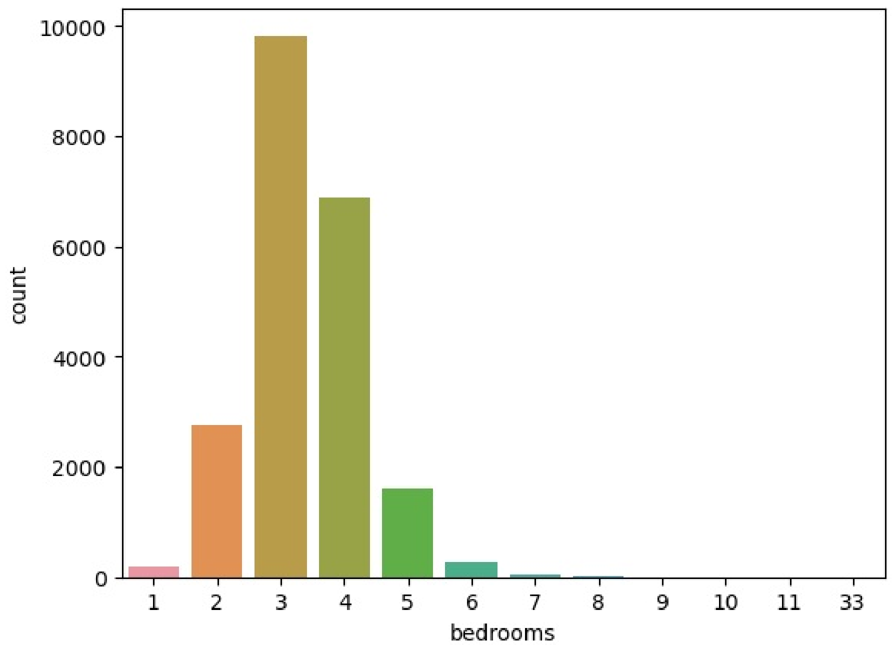
In [9]:

```python
sns.countplot(df['bedrooms']) #They show 33 because there is one with that
```

```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variabl
e as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other
arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[9]:

```
<AxesSubplot:xlabel='bedrooms', ylabel='count'>
```



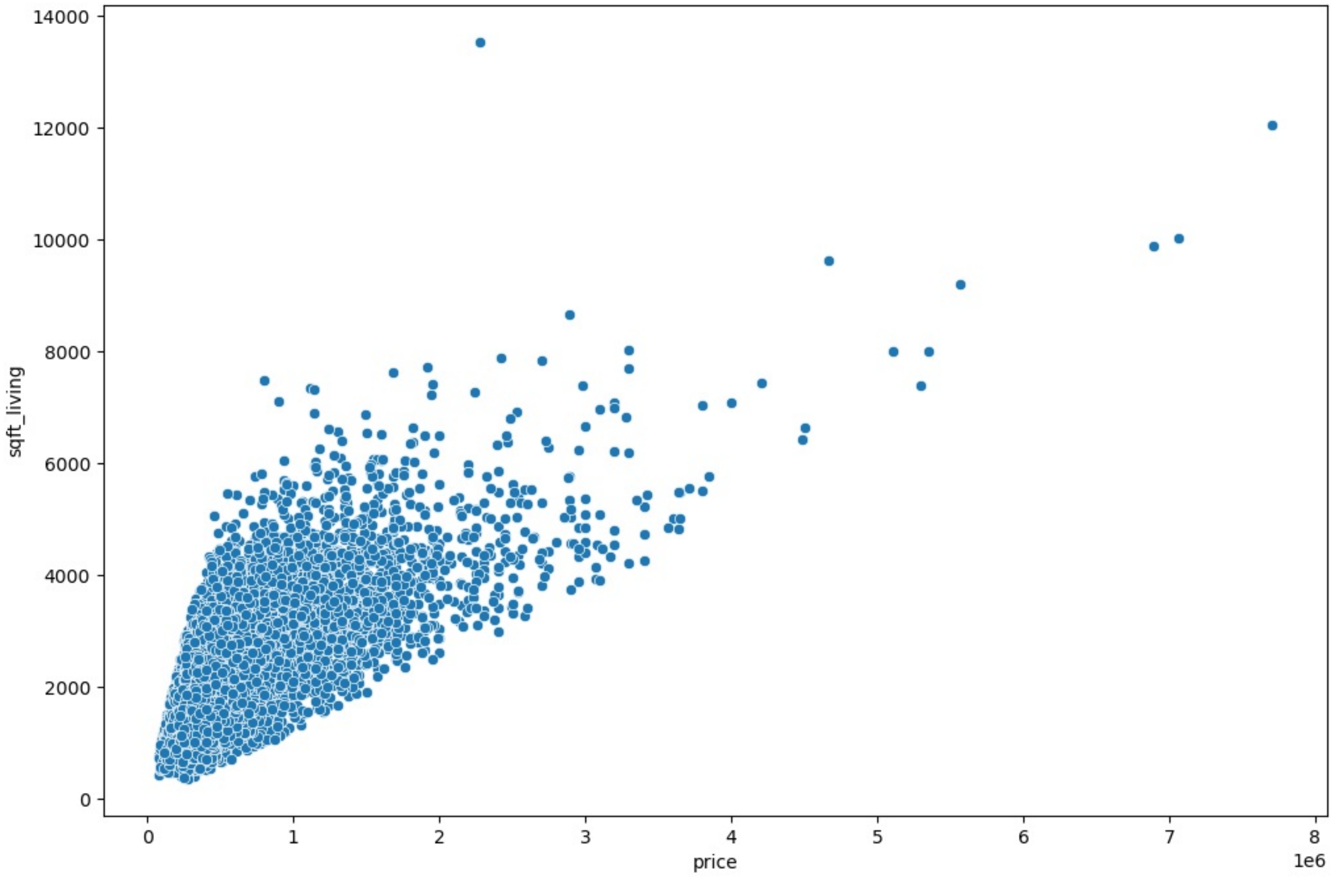
In [10]:

```python
#Let's check what is correlated with what
df.corr()['price'].sort_values() #Sqft living is well correlated with price
```

Out[10]:
```
zipcode         -0.053402
id              -0.016772
long             0.022036
condition        0.036056
yr_built         0.053953
sqft_lot15       0.082845
sqft_lot         0.089876
yr_renovated     0.126424
floors           0.256804
waterfront       0.266398
lat              0.306692
bedrooms         0.308787
sqft_basement    0.323799
view             0.397370
bathrooms        0.525906
sqft_living15    0.585241
sqft_above       0.605368
grade            0.667951
sqft_living      0.701917
price            1.000000
Name: price, dtype: float64
```

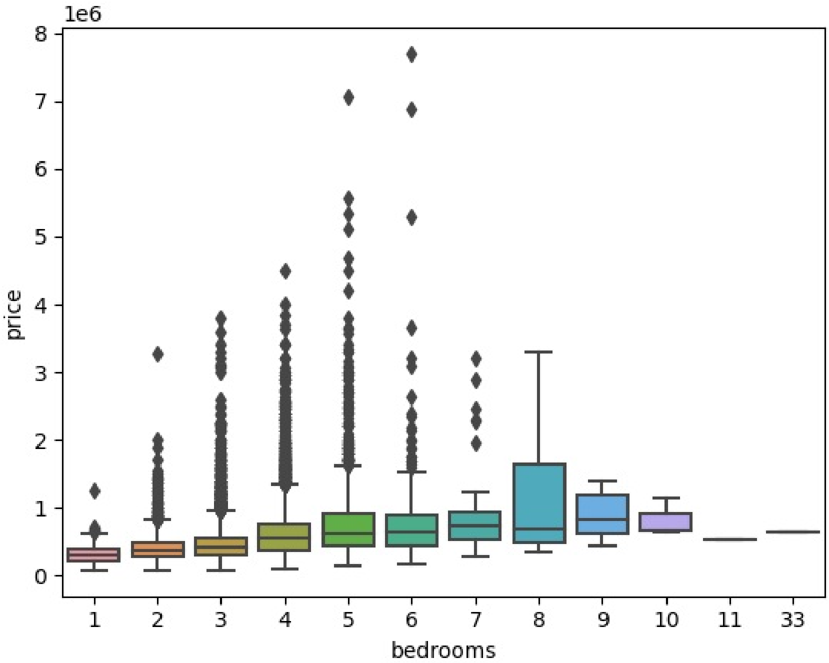
In [11]:
```
plt.figure(figsize=(12,8))
sns.scatterplot(x='price',y='sqft_living',data=df) #To check how correlated they are
```

Out[11]:
```
<AxesSubplot:xlabel='price', ylabel='sqft_living'>
```



In [12]:
```
sns.boxplot(x='bedrooms',y='price',data=df)  #Let's check the distribution
```

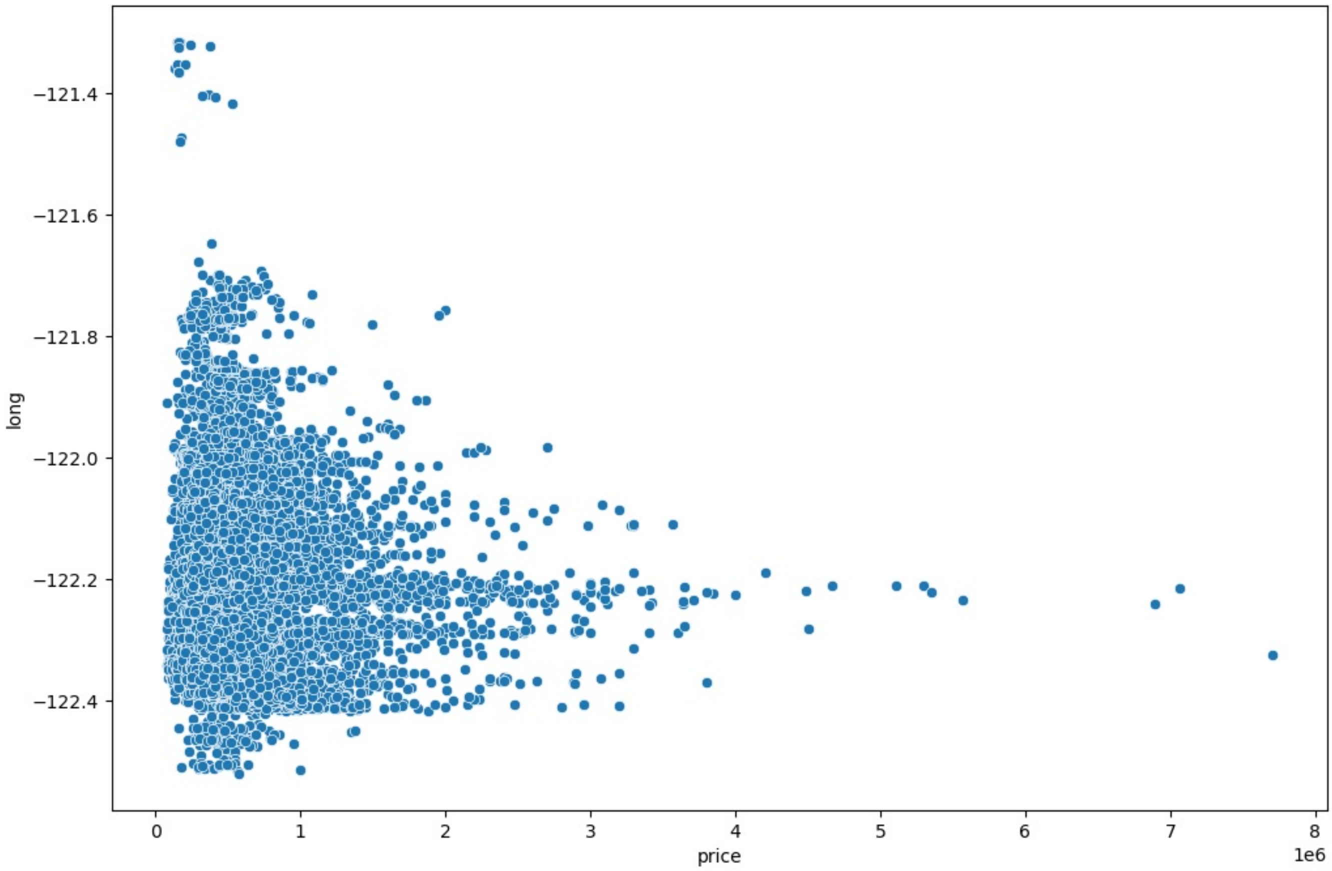
Out[12]:
```
<AxesSubplot:xlabel='bedrooms', ylabel='price'>
```



Geographical Properties

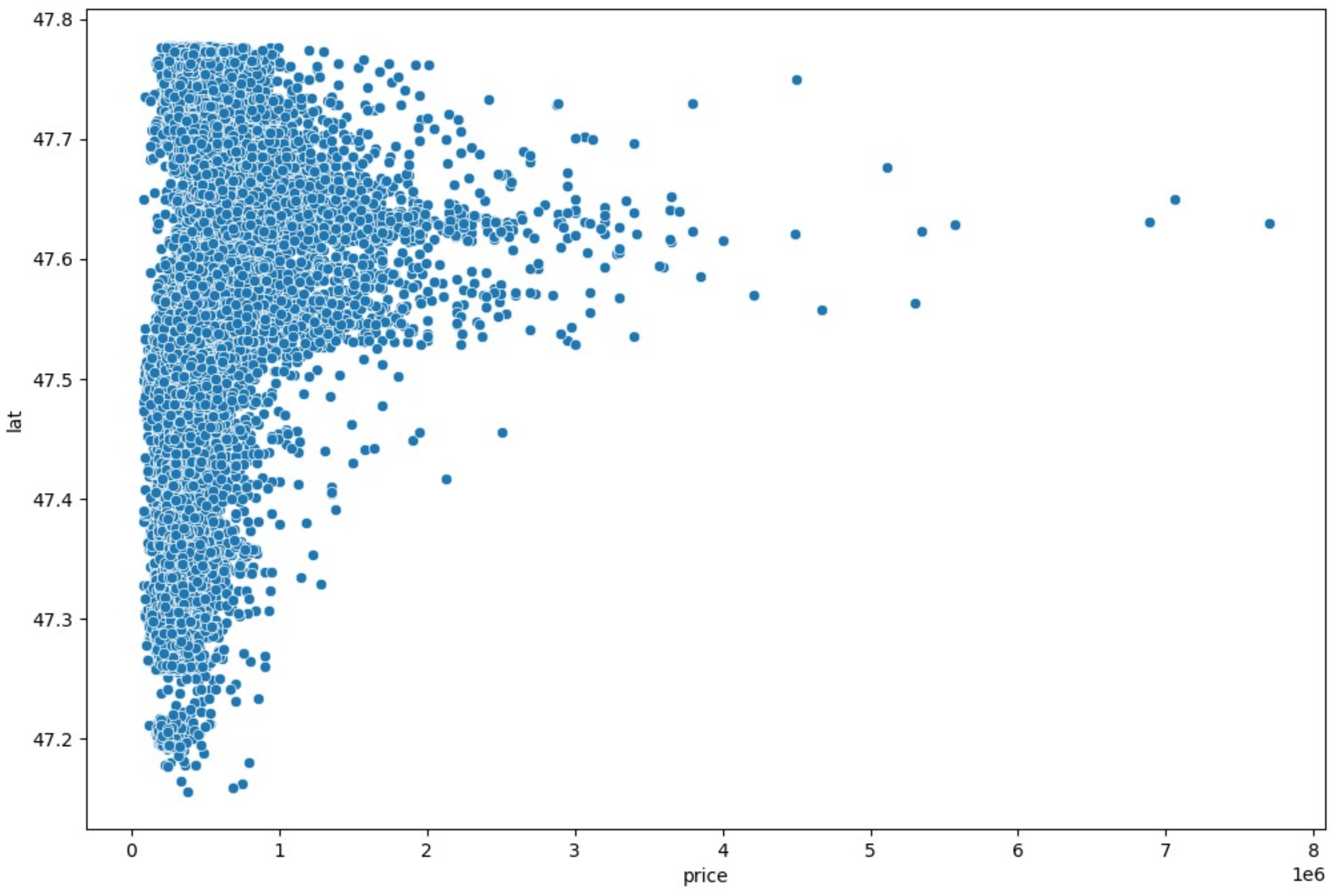
In [13]:
```
plt.figure(figsize=(12,8))
sns.scatterplot(x='price',y='long',data=df)
```

Out[13]:
```
<AxesSubplot:xlabel='price', ylabel='long'>
```



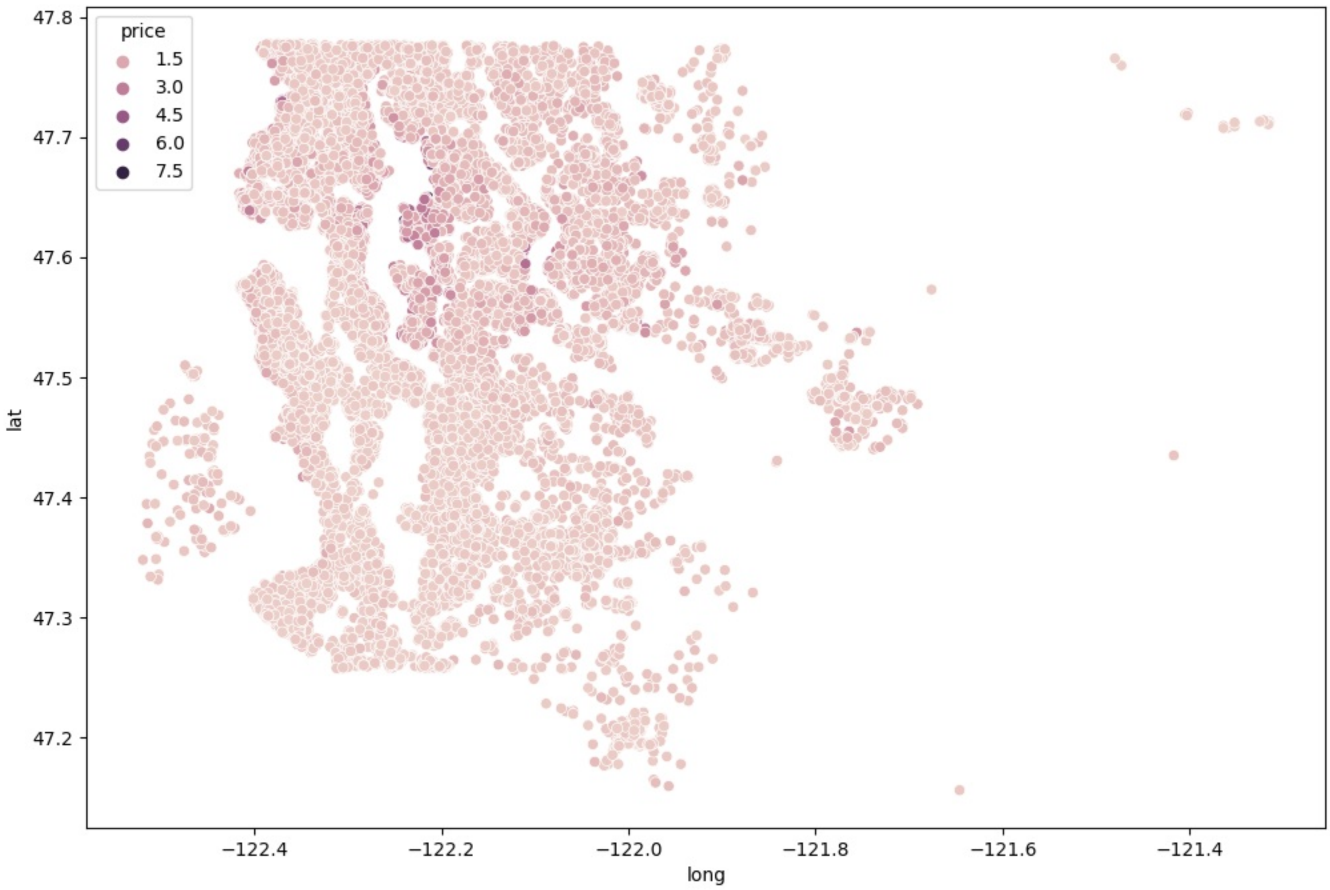
In [14]:
```
plt.figure(figsize=(12,8))
sns.scatterplot(x='price',y='lat',data=df)
#It looks like there is a particular combination zone of long and lat that tends
# to be an expensive area, Check the real life map of these
```

Out[14]: <AxesSubplot:xlabel='price', ylabel='lat'>



In [15]:
```
plt.figure(figsize=(12,8))
sns.scatterplot(x='long',y='lat',data=df,hue='price') #Matches with King County Seattle
```

Out[15]:
```
<AxesSubplot:xlabel='long', ylabel='lat'>
```



In [16]:

```
#Let's see if we can clean this and makei it more prominent
df.sort_values('price',ascending=False).head(20)
#A cut off at 3 million would be nice as our distribution plot above
# showed that there was not main houses at those points
```

Out[16]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_above	sqft_ba
7245	6762700020	10/13/2014	7700000.0	6	8.00	12050	27600	2.5	0	3	...	13	8570	
3910	9808700762	6/11/2014	7060000.0	5	4.50	10040	37325	2.0	1	2	...	11	7680	
9245	9208900037	9/19/2014	6890000.0	6	7.75	9890	31374	2.0	0	4	...	13	8860	
4407	2470100110	8/4/2014	5570000.0	5	5.75	9200	35069	2.0	0	0	...	13	6200	
1446	8907500070	4/13/2015	5350000.0	5	5.00	8000	23985	2.0	0	4	...	12	6720	
1313	7558700030	4/13/2015	5300000.0	6	6.00	7390	24829	2.0	1	4	...	12	5000	
1162	1247600105	10/20/2014	5110000.0	5	5.25	8010	45517	2.0	1	4	...	12	5990	
8085	1924059029	6/17/2014	4670000.0	5	6.75	9640	13068	1.0	1	4	...	12	4820	
2624	7738500731	8/15/2014	4500000.0	5	5.50	6640	40014	2.0	1	4	...	12	6350	
8629	3835500195	6/18/2014	4490000.0	4	3.00	6430	27517	2.0	0	0	...	12	6430	
12358	6065300370	5/6/2015	4210000.0	5	6.00	7440	21540	2.0	0	0	...	12	5550	
4145	6447300265	10/14/2014	4000000.0	4	5.50	7080	16573	2.0	0	0	...	12	5760	
2083	8106100105	11/14/2014	3850000.0	4	4.25	5770	21300	2.0	1	4	...	11	5770	
7028	853200010	7/1/2014	3800000.0	5	5.50	7050	42840	1.0	0	2	...	13	4320	
19002	2303900100	9/11/2014	3800000.0	3	4.25	5510	35000	2.0	0	4	...	13	4910	
16288	7397300170	5/30/2014	3710000.0	4	3.50	5550	28078	2.0	0	2	...	12	3350	
18467	4389201095	5/11/2015	3650000.0	5	3.75	5020	8694	2.0	0	1	...	12	3970	
6502	4217402115	4/21/2015	3650000.0	6	4.75	5480	19401	1.5	1	4	...	11	3910	
15241	2425049063	9/11/2014	3640000.0	4	3.25	4830	22257	2.0	1	4	...	11	4830	
19133	3625049042	10/11/2014	3640000.0	5	6.00	5490	19897	2.0	0	0	...	12	5490	

20 rows × 21 columns

In [17]:

```
len(df)*(0.01) #We originally have 21597 houses and 1% of it is 215.97
```

Out[17]:

```
215.97
```

In [18]:

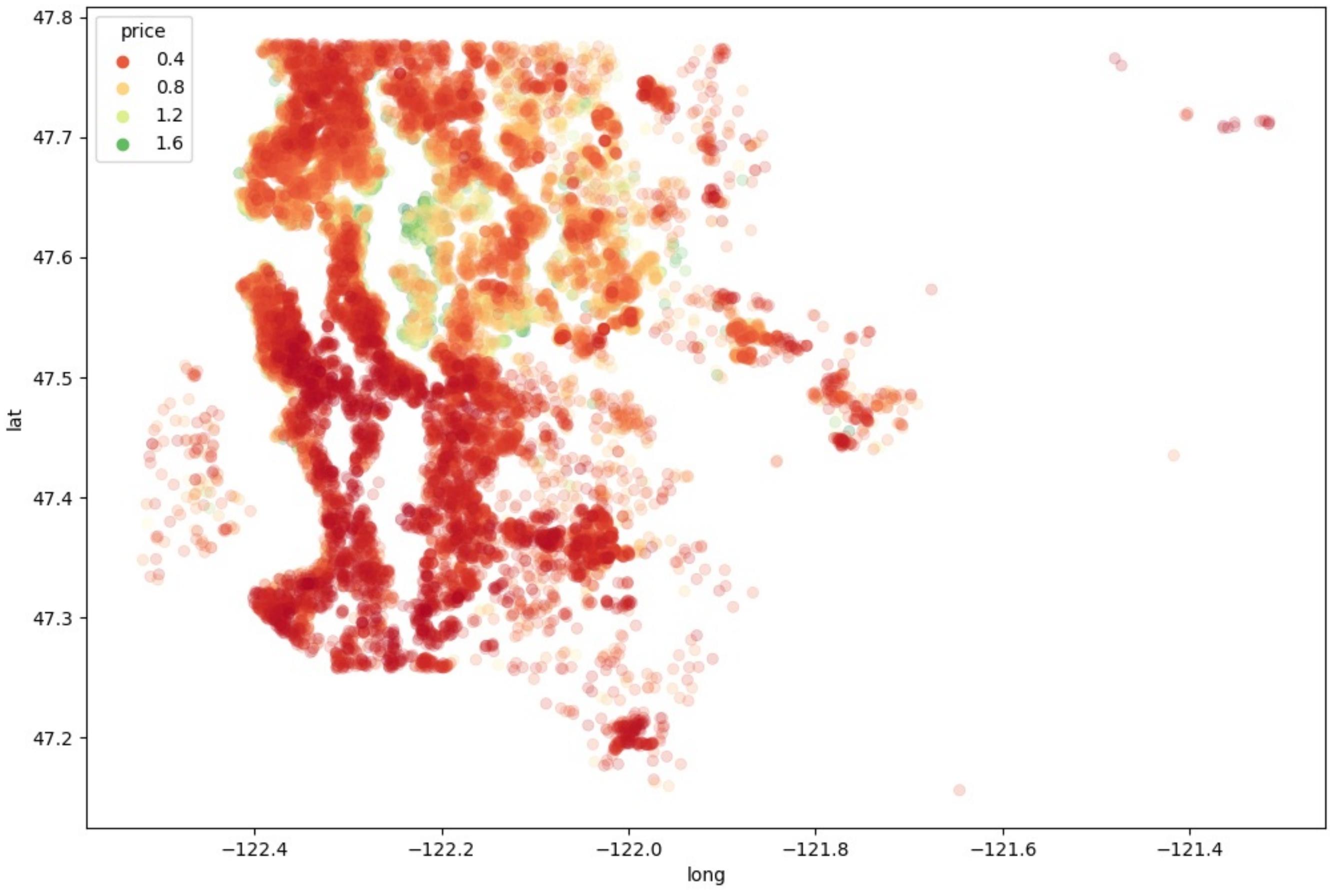
```
non_top_1_perc = df.sort_values('price',ascending=False).iloc[216:]
#So this is us trying to grab everything after the top 216 houses (Top 1%)
# because we want a more bold graph and some very expensive outlier houses
```

In [19]:

```
plt.figure(figsize=(12,8))
sns.scatterplot(x='long',y='lat',
                data=non_top_1_perc,hue='price', #Same code as above data just changed
                palette='RdYlGn',edgecolor=None,alpha=0.2)
```

Out[19]:

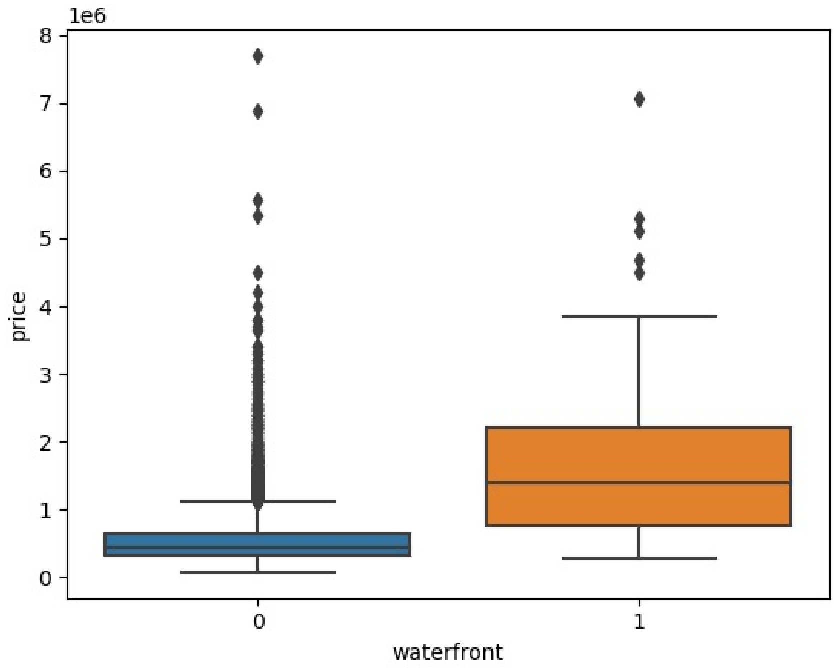
```
<AxesSubplot:xlabel='long', ylabel='lat'>
```



Other Features

In [20]:
```
sns.boxplot(x='waterfront',y='price',data=df) #Looks like waterfront properties are more expensive
```

Out[20]:
```
<AxesSubplot:xlabel='waterfront', ylabel='price'>
```



Working with Feature Data

In [21]:
```
df.head()
```

Out[21]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_above	sqft_baseme
0	7129300520	10/13/2014	221900.0	3	1.00	1180	5650	1.0	0	0	...	7	1180	
1	6414100192	12/9/2014	538000.0	3	2.25	2570	7242	2.0	0	0	...	7	2170	4
2	5631500400	2/25/2015	180000.0	2	1.00	770	10000	1.0	0	0	...	6	770	
3	2487200875	12/9/2014	604000.0	4	3.00	1960	5000	1.0	0	0	...	7	1050	9
4	1954400510	2/18/2015	510000.0	3	2.00	1680	8080	1.0	0	0	...	8	1680	

5 rows × 21 columns

In [22]:
```
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     21597 non-null  int64  
 9   view           21597 non-null  int64  
 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  int64  
 14  yr_built       21597 non-null  int64  
 15  yr_renovated   21597 non-null  int64  
 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(5), int64(15), object(1)
memory usage: 3.5+ MB
```

In [23]:
```
df = df.drop('id',axis=1) #We want to drop id as it isn't relevant to our analysis
```

In [24]:
```
df.head()
```

Out[24]:

	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	sqft_above	sqft_basement	y
0	10/13/2014	221900.0	3	1.00	1180	5650	1.0	0	0	3	7	1180	0	
1	12/9/2014	538000.0	3	2.25	2570	7242	2.0	0	0	3	7	2170	400	
2	2/25/2015	180000.0	2	1.00	770	10000	1.0	0	0	3	6	770	0	
3	12/9/2014	604000.0	4	3.00	1960	5000	1.0	0	0	5	7	1050	910	
4	2/18/2015	510000.0	3	2.00	1680	8080	1.0	0	0	3	8	1680	0	

Feature Engineering from Date

In [25]:
```
df['date'] = pd.to_datetime(df['date']) #As it was a string before
```

In [26]:
```
df['date']
```

Out[26]:
```
0       2014-10-13
1       2014-12-09
2       2015-02-25
3       2014-12-09
4       2015-02-18
           ...
21592   2014-05-21
21593   2015-02-23
21594   2014-06-23
21595   2015-01-16
21596   2014-10-15
Name: date, Length: 21597, dtype: datetime64[ns]
```

In [27]:
```
df['month'] = df['date'].apply(lambda date:date.month)
```

In [28]:
```
df['year'] = df['date'].apply(lambda date:date.year)
```

In [29]:
```
df.head()
```

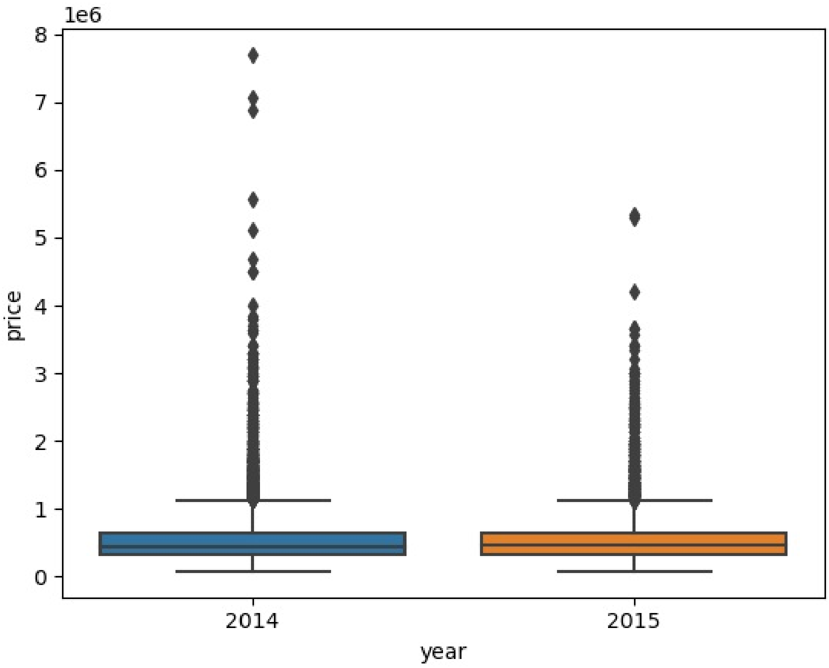
Out[29]:

	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	...	sqft_basement	yr_built	yr_renovated
0	2014-10-13	221900.0	3	1.00	1180	5650	1.0	0	0	3	...	0	1955	0
1	2014-12-09	538000.0	3	2.25	2570	7242	2.0	0	0	3	...	400	1951	1991
2	2015-02-25	180000.0	2	1.00	770	10000	1.0	0	0	3	...	0	1933	0
3	2014-12-09	604000.0	4	3.00	1960	5000	1.0	0	0	5	...	910	1965	0
4	2015-02-18	510000.0	3	2.00	1680	8080	1.0	0	0	3	...	0	1987	0

5 rows × 22 columns

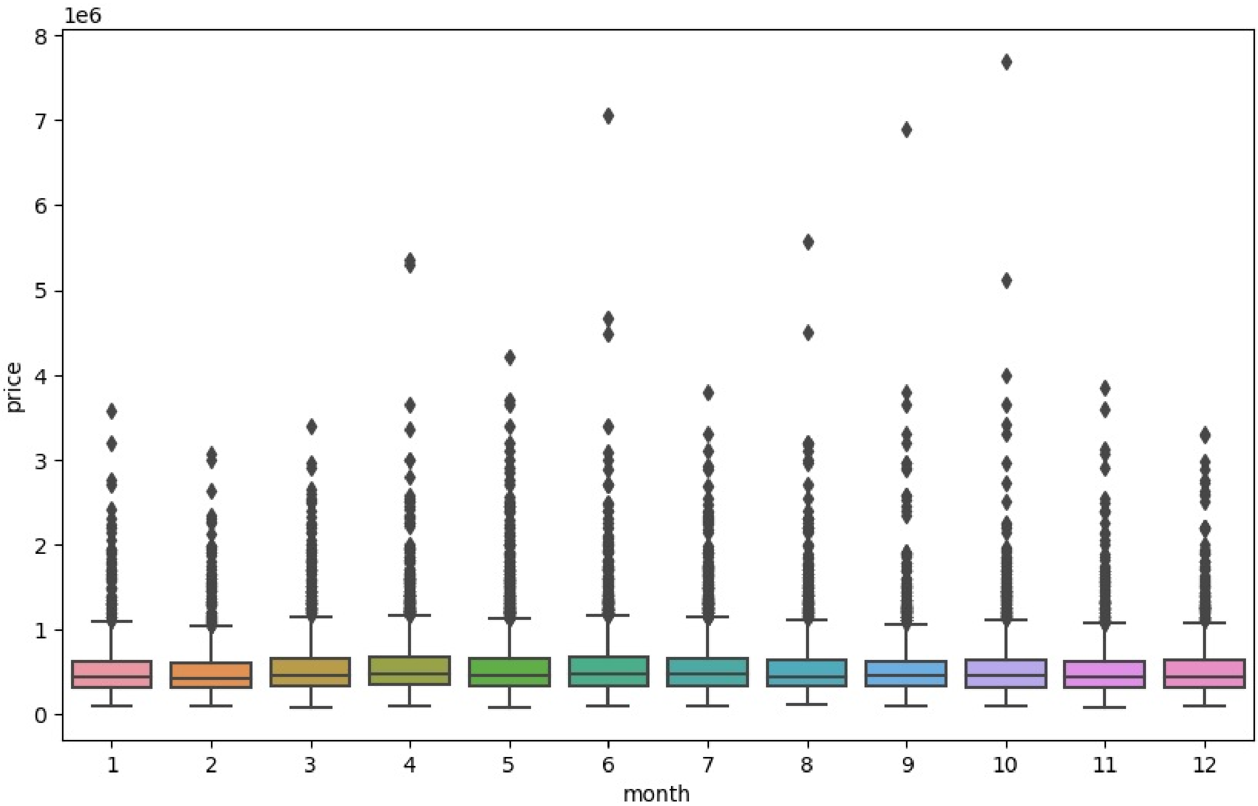
In [30]:
```
sns.boxplot(x='year',y='price',data=df)
```

Out[30]:
```
<AxesSubplot:xlabel='year', ylabel='price'>
```



In [31]:
```
plt.figure(figsize=(10,6))
sns.boxplot(x='month',y='price',data=df)
```

Out[31]:
```
<AxesSubplot:xlabel='month', ylabel='price'>
```

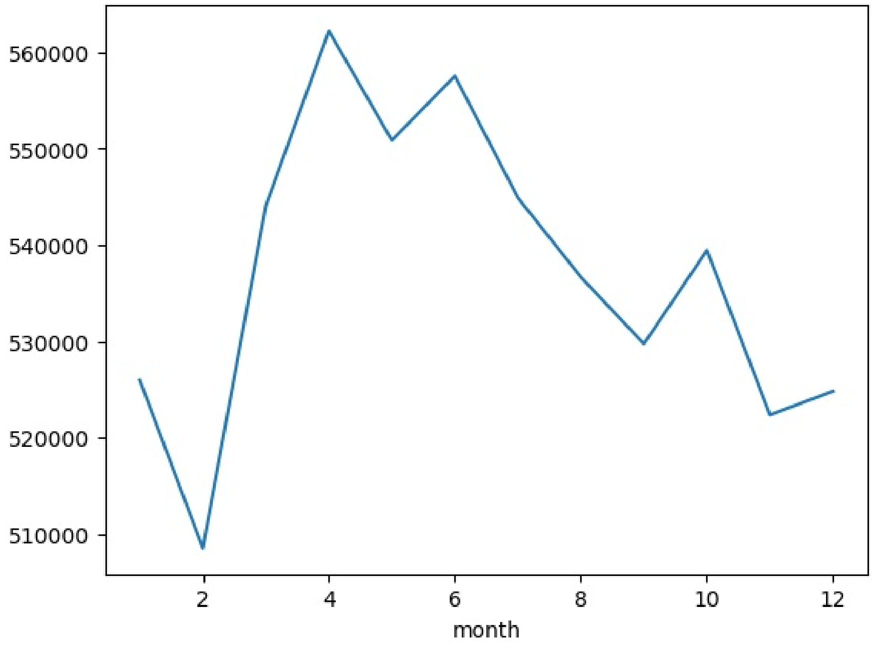


In [32]:
```
df.groupby('month').mean()['price']
```

Out[32]:
```
month
1     525963.251534
2     508520.051323
3     544057.683200
4     562215.615074
5     550849.746893
6     557534.318182
7     544892.161013
8     536655.212481
9     529723.517787
10    539439.447228
11    522359.903478
12    524799.902041
Name: price, dtype: float64
```

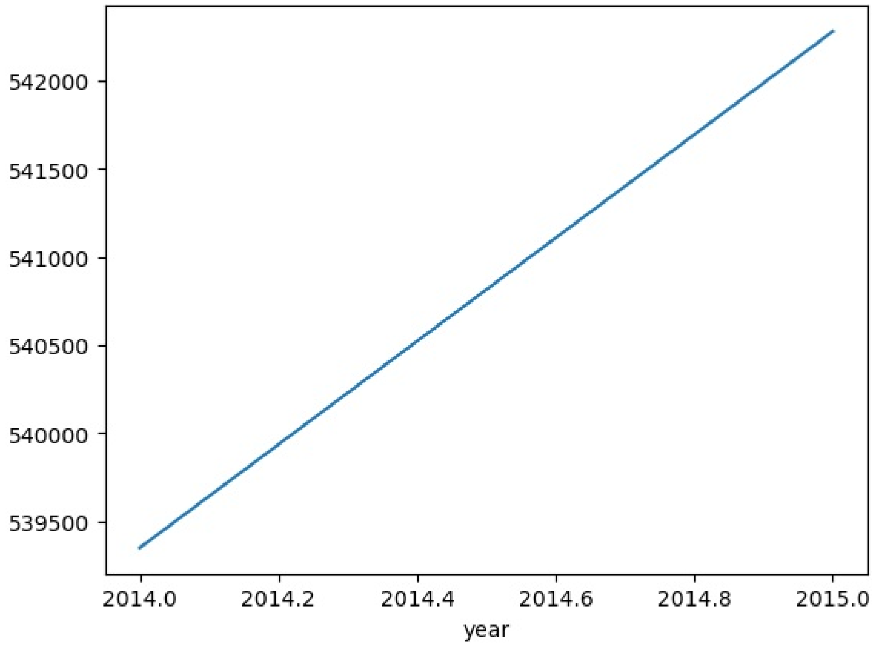
In [33]:
```
df.groupby('month').mean()['price'].plot() #Range is not that big ngl
```

Out[33]:
```
<AxesSubplot:xlabel='month'>
```



In [34]:
```python
df.groupby('year').mean()['price'].plot()
```

Out[34]:
```
<AxesSubplot:xlabel='year'>
```



In [35]:
```python
df = df.drop('date',axis=1) #Let's drop the og date
```

In [36]:
```python
df.columns #Check columns
```

Out[36]:
```
Index(['price', 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors',
       'waterfront', 'view', 'condition', 'grade', 'sqft_above',
       'sqft_basement', 'yr_built', 'yr_renovated', 'zipcode', 'lat', 'long',
       'sqft_living15', 'sqft_lot15', 'month', 'year'],
      dtype='object')
```

In [37]:
```python
df.head() #Let's analyze zipcode and maybe drop it as python can believe is some sort of continous number
```

Out[37]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	...	sqft_basement	yr_built	yr_renovated
0	221900.0	3	1.00	1180	5650	1.0	0	0	3	7	...	0	1955	0
1	538000.0	3	2.25	2570	7242	2.0	0	0	3	7	...	400	1951	1991
2	180000.0	2	1.00	770	10000	1.0	0	0	3	6	...	0	1933	0
3	604000.0	4	3.00	1960	5000	1.0	0	0	5	7	...	910	1965	0
4	510000.0	3	2.00	1680	8080	1.0	0	0	3	8	...	0	1987	0

5 rows × 21 columns

In [38]:
```python
# https://i.pinimg.com/originals/4a/ab/31/4aab31ce95d5b8474fd2cc063f334178.jpg
```

```
# May be worth considering to remove this or feature engineer categories from it
df['zipcode'].value_counts() #We have 70 categories of zipcodes which is too much
```

Out[38]:
```
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
```

In [39]:
```
df = df.drop('zipcode',axis=1)
```

In [40]:
```
df.head()
```

Out[40]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	sqft_above	sqft_basement	yr_built	yr_re
0	221900.0	3	1.00	1180	5650	1.0	0	0	3	7	1180	0	1955	
1	538000.0	3	2.25	2570	7242	2.0	0	0	3	7	2170	400	1951	
2	180000.0	2	1.00	770	10000	1.0	0	0	3	6	770	0	1933	
3	604000.0	4	3.00	1960	5000	1.0	0	0	5	7	1050	910	1965	
4	510000.0	3	2.00	1680	8080	1.0	0	0	3	8	1680	0	1987	

In [41]:
```
# could make sense due to scaling, higher should correlate to more value
df['yr_renovated'].value_counts() #The more recent the renovation most of the time the higher price
```

Out[41]:
```
0       20683
2014       91
2013       37
2003       36
2005       35
        ...
1951        1
1959        1
1948        1
1954        1
1944        1
Name: yr_renovated, Length: 70, dtype: int64
```

In [42]:
```
df['sqft_basement'].value_counts() #No basement less value #Let's keep both as continous relevant factors
```

Out[42]:
```
0      13110
600      221
700      218
500      214
800      206
       ...
518        1
374        1
784        1
906        1
248        1
Name: sqft_basement, Length: 306, dtype: int64
```

Scaling and Train Test Split

In [43]:
```
X = df.drop('price',axis=1)
y = df['price']  # To split our data
```

In [44]:
```
from sklearn.model_selection import train_test_split
```

In [45]:
```
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.3,random_state=101)
```

Scaling

In [46]:
```
from sklearn.preprocessing import MinMaxScaler
```

In [47]:
```
scaler = MinMaxScaler()
```

In [48]:
```
X_train= scaler.fit_transform(X_train)
```

In [49]:
```
X_test = scaler.transform(X_test) #We do not want to assume so don't fit
```

In [50]:
```
X_train.shape # 19 neurons in our layer
```

Out[50]: (15117, 19)

In [51]:
```
X_test.shape
```

Out[51]: (6480, 19)

Creating a Model

In [52]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Activation
from tensorflow.keras.optimizers import Adam
```

In [53]:
```
model = Sequential()

model.add(Dense(19,activation='relu')) #Rectified Linear Unit
model.add(Dense(19,activation='relu'))
model.add(Dense(19,activation='relu'))
model.add(Dense(19,activation='relu'))
model.add(Dense(1))

model.compile(optimizer='adam',loss='mse')
```

Training the Model

In [54]:
```
model.fit(x=X_train,y=y_train.values,
          validation_data=(X_test,y_test.values), #
          batch_size=128,epochs=400)
```

```
Epoch 1/400
119/119 [==============================] - 2s 5ms/step - loss: 430242267136.0000 - val_loss: 418925707264.0000
Epoch 2/400
119/119 [==============================] - 0s 3ms/step - loss: 429207552000.0000 - val_loss: 415250382848.0000
Epoch 3/400
119/119 [==============================] - 0s 3ms/step - loss: 413973250048.0000 - val_loss: 379979497472.0000
Epoch 4/400
119/119 [==============================] - 0s 3ms/step - loss: 338258329600.0000 - val_loss: 256669401088.0000
Epoch 5/400
119/119 [==============================] - 0s 3ms/step - loss: 185565184000.0000 - val_loss: 115349110784.0000
Epoch 6/400
119/119 [==============================] - 0s 2ms/step - loss: 103814193152.0000 - val_loss: 94800297984.0000
Epoch 7/400
119/119 [==============================] - 0s 2ms/step - loss: 97183318016.0000 - val_loss: 93176545280.0000
Epoch 8/400
119/119 [==============================] - 0s 3ms/step - loss: 95438127104.0000 - val_loss: 91537285120.0000
Epoch 9/400
119/119 [==============================] - 0s 3ms/step - loss: 93659357184.0000 - val_loss: 90027761664.0000
Epoch 10/400
119/119 [==============================] - 0s 3ms/step - loss: 91943272448.0000 - val_loss: 88164696064.0000
Epoch 11/400
119/119 [==============================] - 0s 3ms/step - loss: 90063372288.0000 - val_loss: 86418563072.0000
Epoch 12/400
119/119 [==============================] - 0s 4ms/step - loss: 88148000768.0000 - val_loss: 84669112320.0000
Epoch 13/400
119/119 [==============================] - 0s 4ms/step - loss: 86207045632.0000 - val_loss: 82596118528.0000
Epoch 14/400
119/119 [==============================] - 0s 4ms/step - loss: 84128227328.0000 - val_loss: 80557023232.0000
Epoch 15/400
119/119 [==============================] - 1s 5ms/step - loss: 82016993280.0000 - val_loss: 78484103168.0000
Epoch 16/400
119/119 [==============================] - 1s 5ms/step - loss: 79727943680.0000 - val_loss: 76374859776.0000
Epoch 17/400
119/119 [==============================] - 1s 5ms/step - loss: 77422592000.0000 - val_loss: 74097467392.0000
Epoch 18/400
119/119 [==============================] - 1s 4ms/step - loss: 74939129856.0000 - val_loss: 71570161664.0000
Epoch 19/400
119/119 [==============================] - 0s 4ms/step - loss: 72408203264.0000 - val_loss: 69160468480.0000
Epoch 20/400
119/119 [==============================] - 1s 4ms/step - loss: 69878489088.0000 - val_loss: 66580205568.0000
Epoch 21/400
119/119 [==============================] - 0s 4ms/step - loss: 67311730688.0000 - val_loss: 64170012672.0000
Epoch 22/400
119/119 [==============================] - 0s 4ms/step - loss: 64792952832.0000 - val_loss: 61763063808.0000
Epoch 23/400
119/119 [==============================] - 0s 4ms/step - loss: 62326906880.0000 - val_loss: 59486789632.0000
Epoch 24/400
119/119 [==============================] - 0s 3ms/step - loss: 60017192960.0000 - val_loss: 57248374784.0000
Epoch 25/400
119/119 [==============================] - 0s 3ms/step - loss: 57881006080.0000 - val_loss: 55437094912.0000
Epoch 26/400
119/119 [==============================] - 0s 3ms/step - loss: 56038879232.0000 - val_loss: 53689593856.0000
Epoch 27/400
119/119 [==============================] - 0s 3ms/step - loss: 54398914560.0000 - val_loss: 52244930560.0000
Epoch 28/400
```

```
119/119 [==============================] - 0s 3ms/step - loss: 53059571712.0000 - val_loss: 51082842112.0000
Epoch 29/400
119/119 [==============================] - 0s 3ms/step - loss: 51898142720.0000 - val_loss: 50037440512.0000
Epoch 30/400
119/119 [==============================] - 0s 3ms/step - loss: 50958786560.0000 - val_loss: 49130749952.0000
Epoch 31/400
119/119 [==============================] - 0s 3ms/step - loss: 50044944384.0000 - val_loss: 48368476160.0000
Epoch 32/400
119/119 [==============================] - 0s 3ms/step - loss: 49252798464.0000 - val_loss: 47669030912.0000
Epoch 33/400
119/119 [==============================] - 0s 3ms/step - loss: 48596791296.0000 - val_loss: 47006715904.0000
Epoch 34/400
119/119 [==============================] - 0s 2ms/step - loss: 47950811136.0000 - val_loss: 46402502656.0000
Epoch 35/400
119/119 [==============================] - 0s 3ms/step - loss: 47341318144.0000 - val_loss: 45841776640.0000
Epoch 36/400
119/119 [==============================] - 0s 3ms/step - loss: 46795997184.0000 - val_loss: 45333651456.0000
Epoch 37/400
119/119 [==============================] - 0s 2ms/step - loss: 46308687872.0000 - val_loss: 44834824192.0000
Epoch 38/400
119/119 [==============================] - 0s 2ms/step - loss: 45797900288.0000 - val_loss: 44439613440.0000
Epoch 39/400
119/119 [==============================] - 0s 3ms/step - loss: 45321768960.0000 - val_loss: 43969081344.0000
Epoch 40/400
119/119 [==============================] - 0s 3ms/step - loss: 44883623936.0000 - val_loss: 43531313152.0000
Epoch 41/400
119/119 [==============================] - 0s 2ms/step - loss: 44465823744.0000 - val_loss: 43124183040.0000
Epoch 42/400
119/119 [==============================] - 0s 3ms/step - loss: 44073005056.0000 - val_loss: 42785484800.0000
Epoch 43/400
119/119 [==============================] - 0s 2ms/step - loss: 43745382400.0000 - val_loss: 42349518848.0000
Epoch 44/400
119/119 [==============================] - 0s 2ms/step - loss: 43345780736.0000 - val_loss: 42003984384.0000
Epoch 45/400
119/119 [==============================] - 0s 2ms/step - loss: 43002023936.0000 - val_loss: 41742823424.0000
Epoch 46/400
119/119 [==============================] - 0s 3ms/step - loss: 42740813824.0000 - val_loss: 41383272448.0000
Epoch 47/400
119/119 [==============================] - 0s 3ms/step - loss: 42373017600.0000 - val_loss: 41044680704.0000
Epoch 48/400
119/119 [==============================] - 0s 3ms/step - loss: 42030465024.0000 - val_loss: 40747855872.0000
Epoch 49/400
119/119 [==============================] - 0s 2ms/step - loss: 41765634048.0000 - val_loss: 40473321472.0000
Epoch 50/400
119/119 [==============================] - 0s 2ms/step - loss: 41497927680.0000 - val_loss: 40177528832.0000
Epoch 51/400
119/119 [==============================] - 0s 3ms/step - loss: 41157976064.0000 - val_loss: 39932338176.0000
Epoch 52/400
119/119 [==============================] - 0s 3ms/step - loss: 40906047488.0000 - val_loss: 39613988864.0000
Epoch 53/400
119/119 [==============================] - 0s 3ms/step - loss: 40628039680.0000 - val_loss: 39359156224.0000
Epoch 54/400
119/119 [==============================] - 0s 3ms/step - loss: 40357842944.0000 - val_loss: 39136604160.0000
Epoch 55/400
119/119 [==============================] - 0s 3ms/step - loss: 40064053248.0000 - val_loss: 38896697344.0000
Epoch 56/400
119/119 [==============================] - 0s 3ms/step - loss: 39901523968.0000 - val_loss: 38590533632.0000
Epoch 57/400
119/119 [==============================] - 0s 3ms/step - loss: 39584174080.0000 - val_loss: 38355218432.0000
Epoch 58/400
119/119 [==============================] - 0s 3ms/step - loss: 39385964544.0000 - val_loss: 38115876864.0000
Epoch 59/400
119/119 [==============================] - 0s 3ms/step - loss: 39131480064.0000 - val_loss: 37864701952.0000
Epoch 60/400
119/119 [==============================] - 0s 3ms/step - loss: 38896295936.0000 - val_loss: 37606891520.0000
Epoch 61/400
119/119 [==============================] - 0s 3ms/step - loss: 38639087616.0000 - val_loss: 37360668672.0000
Epoch 62/400
119/119 [==============================] - 0s 3ms/step - loss: 38420348928.0000 - val_loss: 37140987904.0000
Epoch 63/400
119/119 [==============================] - 0s 3ms/step - loss: 38211854336.0000 - val_loss: 36947619840.0000
Epoch 64/400
119/119 [==============================] - 0s 3ms/step - loss: 38025162752.0000 - val_loss: 36717092864.0000
Epoch 65/400
119/119 [==============================] - 0s 3ms/step - loss: 37842989056.0000 - val_loss: 36519444480.0000
Epoch 66/400
119/119 [==============================] - 0s 3ms/step - loss: 37641887744.0000 - val_loss: 36351430656.0000
Epoch 67/400
119/119 [==============================] - 0s 3ms/step - loss: 37453946880.0000 - val_loss: 36154454016.0000
Epoch 68/400
119/119 [==============================] - 0s 3ms/step - loss: 37289013248.0000 - val_loss: 36003049472.0000
Epoch 69/400
119/119 [==============================] - 0s 3ms/step - loss: 37138255872.0000 - val_loss: 35831558144.0000
Epoch 70/400
119/119 [==============================] - 0s 2ms/step - loss: 37042737152.0000 - val_loss: 35699261440.0000
Epoch 71/400
119/119 [==============================] - 0s 3ms/step - loss: 36852359168.0000 - val_loss: 35506573312.0000
Epoch 72/400
119/119 [==============================] - 0s 3ms/step - loss: 36665294848.0000 - val_loss: 35408420864.0000
```

```
Epoch 73/400
119/119 [==============================] - 0s 2ms/step - loss: 36541530112.0000 - val_loss: 35218849792.0000
Epoch 74/400
119/119 [==============================] - 0s 2ms/step - loss: 36397699072.0000 - val_loss: 35084517376.0000
Epoch 75/400
119/119 [==============================] - 0s 2ms/step - loss: 36297543680.0000 - val_loss: 34993766400.0000
Epoch 76/400
119/119 [==============================] - 0s 2ms/step - loss: 36134711296.0000 - val_loss: 34984976384.0000
Epoch 77/400
119/119 [==============================] - 0s 2ms/step - loss: 36045979648.0000 - val_loss: 34741952512.0000
Epoch 78/400
119/119 [==============================] - 0s 3ms/step - loss: 35930116096.0000 - val_loss: 34614419456.0000
Epoch 79/400
119/119 [==============================] - 0s 3ms/step - loss: 35798106112.0000 - val_loss: 34501120000.0000
Epoch 80/400
119/119 [==============================] - 0s 3ms/step - loss: 35703300096.0000 - val_loss: 34438524928.0000
Epoch 81/400
119/119 [==============================] - 0s 3ms/step - loss: 35592081408.0000 - val_loss: 34324948992.0000
Epoch 82/400
119/119 [==============================] - 0s 2ms/step - loss: 35490422784.0000 - val_loss: 34215956480.0000
Epoch 83/400
119/119 [==============================] - 0s 3ms/step - loss: 35390136320.0000 - val_loss: 34238210048.0000
Epoch 84/400
119/119 [==============================] - 0s 3ms/step - loss: 35333799936.0000 - val_loss: 34048929792.0000
Epoch 85/400
119/119 [==============================] - 0s 2ms/step - loss: 35244445696.0000 - val_loss: 33962262528.0000
Epoch 86/400
119/119 [==============================] - 0s 2ms/step - loss: 35165814784.0000 - val_loss: 33859512320.0000
Epoch 87/400
119/119 [==============================] - 0s 2ms/step - loss: 35041357824.0000 - val_loss: 33777125376.0000
Epoch 88/400
119/119 [==============================] - 0s 2ms/step - loss: 34995261440.0000 - val_loss: 33703479296.0000
Epoch 89/400
119/119 [==============================] - 0s 2ms/step - loss: 34911248384.0000 - val_loss: 33670215680.0000
Epoch 90/400
119/119 [==============================] - 0s 2ms/step - loss: 34843004928.0000 - val_loss: 33553246208.0000
Epoch 91/400
119/119 [==============================] - 0s 2ms/step - loss: 34740027392.0000 - val_loss: 33470871552.0000
Epoch 92/400
119/119 [==============================] - 0s 3ms/step - loss: 34665295872.0000 - val_loss: 33390032896.0000
Epoch 93/400
119/119 [==============================] - 0s 2ms/step - loss: 34608443392.0000 - val_loss: 33318737920.0000
Epoch 94/400
119/119 [==============================] - 0s 3ms/step - loss: 34527494144.0000 - val_loss: 33238624256.0000
Epoch 95/400
119/119 [==============================] - 0s 2ms/step - loss: 34447204352.0000 - val_loss: 33228244992.0000
Epoch 96/400
119/119 [==============================] - 0s 3ms/step - loss: 34416140288.0000 - val_loss: 33099905024.0000
Epoch 97/400
119/119 [==============================] - 0s 2ms/step - loss: 34347646976.0000 - val_loss: 33041514496.0000
Epoch 98/400
119/119 [==============================] - 0s 3ms/step - loss: 34267883520.0000 - val_loss: 33045334016.0000
Epoch 99/400
119/119 [==============================] - 0s 2ms/step - loss: 34230865920.0000 - val_loss: 32913944576.0000
Epoch 100/400
119/119 [==============================] - 0s 3ms/step - loss: 34175311872.0000 - val_loss: 32848060416.0000
Epoch 101/400
119/119 [==============================] - 0s 2ms/step - loss: 34136674304.0000 - val_loss: 32780466176.0000
Epoch 102/400
119/119 [==============================] - 0s 2ms/step - loss: 34087313408.0000 - val_loss: 32813797376.0000
Epoch 103/400
119/119 [==============================] - 0s 2ms/step - loss: 33983496192.0000 - val_loss: 32708986880.0000
Epoch 104/400
119/119 [==============================] - 0s 2ms/step - loss: 33954684928.0000 - val_loss: 32776323072.0000
Epoch 105/400
119/119 [==============================] - 0s 2ms/step - loss: 33880465408.0000 - val_loss: 32588216320.0000
Epoch 106/400
119/119 [==============================] - 0s 3ms/step - loss: 33882761216.0000 - val_loss: 32515672064.0000
Epoch 107/400
119/119 [==============================] - 0s 3ms/step - loss: 33818769408.0000 - val_loss: 32444391424.0000
Epoch 108/400
119/119 [==============================] - 0s 3ms/step - loss: 33758834688.0000 - val_loss: 32508284928.0000
Epoch 109/400
119/119 [==============================] - 0s 3ms/step - loss: 33725071360.0000 - val_loss: 32371423232.0000
Epoch 110/400
119/119 [==============================] - 0s 3ms/step - loss: 33662095360.0000 - val_loss: 32285898752.0000
Epoch 111/400
119/119 [==============================] - 0s 3ms/step - loss: 33599825920.0000 - val_loss: 32289802240.0000
Epoch 112/400
119/119 [==============================] - 0s 3ms/step - loss: 33612599296.0000 - val_loss: 32209788928.0000
Epoch 113/400
119/119 [==============================] - 0s 3ms/step - loss: 33551065088.0000 - val_loss: 32138536960.0000
Epoch 114/400
119/119 [==============================] - 0s 3ms/step - loss: 33504268288.0000 - val_loss: 32096860160.0000
Epoch 115/400
119/119 [==============================] - 0s 3ms/step - loss: 33454977024.0000 - val_loss: 32043710464.0000
Epoch 116/400
119/119 [==============================] - 0s 3ms/step - loss: 33387114496.0000 - val_loss: 32016447488.0000
Epoch 117/400
```

```
119/119 [==============================] - 0s 2ms/step - loss: 33332324352.0000 - val_loss: 31946860544.0000
Epoch 118/400
119/119 [==============================] - 0s 3ms/step - loss: 33320740864.0000 - val_loss: 31968749568.0000
Epoch 119/400
119/119 [==============================] - 0s 3ms/step - loss: 33298718720.0000 - val_loss: 31866263552.0000
Epoch 120/400
119/119 [==============================] - 1s 5ms/step - loss: 33302556672.0000 - val_loss: 31824990208.0000
Epoch 121/400
119/119 [==============================] - 1s 5ms/step - loss: 33199077376.0000 - val_loss: 31759876096.0000
Epoch 122/400
119/119 [==============================] - 1s 5ms/step - loss: 33205094400.0000 - val_loss: 31761035264.0000
Epoch 123/400
119/119 [==============================] - 1s 4ms/step - loss: 33134610432.0000 - val_loss: 31675062272.0000
Epoch 124/400
119/119 [==============================] - 0s 3ms/step - loss: 33093611520.0000 - val_loss: 31609450496.0000
Epoch 125/400
119/119 [==============================] - 0s 3ms/step - loss: 33072070656.0000 - val_loss: 31624990720.0000
Epoch 126/400
119/119 [==============================] - 0s 3ms/step - loss: 33081942016.0000 - val_loss: 31523268608.0000
Epoch 127/400
119/119 [==============================] - 0s 2ms/step - loss: 32993624064.0000 - val_loss: 31548153856.0000
Epoch 128/400
119/119 [==============================] - 0s 3ms/step - loss: 32966201344.0000 - val_loss: 31465312256.0000
Epoch 129/400
119/119 [==============================] - 0s 2ms/step - loss: 32922343424.0000 - val_loss: 31535454208.0000
Epoch 130/400
119/119 [==============================] - 0s 3ms/step - loss: 32913991680.0000 - val_loss: 31438319616.0000
Epoch 131/400
119/119 [==============================] - 0s 2ms/step - loss: 32883390464.0000 - val_loss: 31344199680.0000
Epoch 132/400
119/119 [==============================] - 0s 3ms/step - loss: 32840841216.0000 - val_loss: 31290116096.0000
Epoch 133/400
119/119 [==============================] - 0s 3ms/step - loss: 32830988288.0000 - val_loss: 31309535232.0000
Epoch 134/400
119/119 [==============================] - 0s 2ms/step - loss: 32784140288.0000 - val_loss: 31302215680.0000
Epoch 135/400
119/119 [==============================] - 0s 2ms/step - loss: 32757921792.0000 - val_loss: 31214331904.0000
Epoch 136/400
119/119 [==============================] - 0s 2ms/step - loss: 32688973824.0000 - val_loss: 31120879616.0000
Epoch 137/400
119/119 [==============================] - 0s 2ms/step - loss: 32665051136.0000 - val_loss: 31117244416.0000
Epoch 138/400
119/119 [==============================] - 0s 2ms/step - loss: 32646664192.0000 - val_loss: 31127359488.0000
Epoch 139/400
119/119 [==============================] - 0s 2ms/step - loss: 32573814784.0000 - val_loss: 31159990272.0000
Epoch 140/400
119/119 [==============================] - 0s 2ms/step - loss: 32624158720.0000 - val_loss: 30981844992.0000
Epoch 141/400
119/119 [==============================] - 0s 2ms/step - loss: 32552431616.0000 - val_loss: 30945882112.0000
Epoch 142/400
119/119 [==============================] - 0s 2ms/step - loss: 32542990336.0000 - val_loss: 30896920576.0000
Epoch 143/400
119/119 [==============================] - 0s 2ms/step - loss: 32502378496.0000 - val_loss: 30923749376.0000
Epoch 144/400
119/119 [==============================] - 0s 2ms/step - loss: 32508620800.0000 - val_loss: 30865752064.0000
Epoch 145/400
119/119 [==============================] - 0s 2ms/step - loss: 32478648320.0000 - val_loss: 30839834624.0000
Epoch 146/400
119/119 [==============================] - 0s 3ms/step - loss: 32436852736.0000 - val_loss: 30882193408.0000
Epoch 147/400
119/119 [==============================] - 0s 2ms/step - loss: 32425715712.0000 - val_loss: 30743787520.0000
Epoch 148/400
119/119 [==============================] - 0s 2ms/step - loss: 32392632320.0000 - val_loss: 30709676032.0000
Epoch 149/400
119/119 [==============================] - 0s 2ms/step - loss: 32362465280.0000 - val_loss: 30678616064.0000
Epoch 150/400
119/119 [==============================] - 0s 2ms/step - loss: 32372371456.0000 - val_loss: 30632654848.0000
Epoch 151/400
119/119 [==============================] - 0s 2ms/step - loss: 32285800448.0000 - val_loss: 30622695424.0000
Epoch 152/400
119/119 [==============================] - 0s 2ms/step - loss: 32286758912.0000 - val_loss: 30570391552.0000
Epoch 153/400
119/119 [==============================] - 0s 3ms/step - loss: 32270626816.0000 - val_loss: 30559944704.0000
Epoch 154/400
119/119 [==============================] - 0s 3ms/step - loss: 32286294016.0000 - val_loss: 30546137088.0000
Epoch 155/400
119/119 [==============================] - 0s 3ms/step - loss: 32182376448.0000 - val_loss: 30519830528.0000
Epoch 156/400
119/119 [==============================] - 0s 3ms/step - loss: 32177825792.0000 - val_loss: 30488434688.0000
Epoch 157/400
119/119 [==============================] - 0s 3ms/step - loss: 32153155584.0000 - val_loss: 30453813248.0000
Epoch 158/400
119/119 [==============================] - 0s 3ms/step - loss: 32141006848.0000 - val_loss: 30409838592.0000
Epoch 159/400
119/119 [==============================] - 0s 3ms/step - loss: 32233404416.0000 - val_loss: 30485413888.0000
Epoch 160/400
119/119 [==============================] - 0s 3ms/step - loss: 32088610816.0000 - val_loss: 30361038848.0000
Epoch 161/400
119/119 [==============================] - 0s 3ms/step - loss: 32068999168.0000 - val_loss: 30379292672.0000
```

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Epoch 162/400
119/119 [==============================] - 0s 3ms/step - loss: 32041205760.0000 - val_loss: 30324006912.0000
Epoch 163/400
119/119 [==============================] - 0s 3ms/step - loss: 32026638336.0000 - val_loss: 30297493504.0000
Epoch 164/400
119/119 [==============================] - 0s 3ms/step - loss: 31984599040.0000 - val_loss: 30352130048.0000
Epoch 165/400
119/119 [==============================] - 0s 3ms/step - loss: 32052492288.0000 - val_loss: 30215782400.0000
Epoch 166/400
119/119 [==============================] - 0s 2ms/step - loss: 31958079488.0000 - val_loss: 30369388544.0000
Epoch 167/400
119/119 [==============================] - 0s 3ms/step - loss: 31995123712.0000 - val_loss: 30190548992.0000
Epoch 168/400
119/119 [==============================] - 0s 3ms/step - loss: 31905662976.0000 - val_loss: 30272794624.0000
Epoch 169/400
119/119 [==============================] - 0s 3ms/step - loss: 31912048640.0000 - val_loss: 30127155200.0000
Epoch 170/400
119/119 [==============================] - 0s 2ms/step - loss: 31872350208.0000 - val_loss: 30094827520.0000
Epoch 171/400
119/119 [==============================] - 0s 2ms/step - loss: 31866691584.0000 - val_loss: 30096852992.0000
Epoch 172/400
119/119 [==============================] - 0s 2ms/step - loss: 31840716800.0000 - val_loss: 30122196992.0000
Epoch 173/400
119/119 [==============================] - 0s 3ms/step - loss: 31832244224.0000 - val_loss: 30080051200.0000
Epoch 174/400
119/119 [==============================] - 0s 2ms/step - loss: 31831187456.0000 - val_loss: 30015406080.0000
Epoch 175/400
119/119 [==============================] - 0s 2ms/step - loss: 31806007296.0000 - val_loss: 29988370432.0000
Epoch 176/400
119/119 [==============================] - 0s 2ms/step - loss: 31792605184.0000 - val_loss: 29963433984.0000
Epoch 177/400
119/119 [==============================] - 0s 2ms/step - loss: 31808532480.0000 - val_loss: 29932701696.0000
Epoch 178/400
119/119 [==============================] - 0s 2ms/step - loss: 31762749440.0000 - val_loss: 29928337408.0000
Epoch 179/400
119/119 [==============================] - 0s 2ms/step - loss: 31720192000.0000 - val_loss: 29890361344.0000
Epoch 180/400
119/119 [==============================] - 0s 2ms/step - loss: 31698247680.0000 - val_loss: 29877411840.0000
Epoch 181/400
119/119 [==============================] - 0s 2ms/step - loss: 31691356160.0000 - val_loss: 29838182400.0000
Epoch 182/400
119/119 [==============================] - 0s 3ms/step - loss: 31651299328.0000 - val_loss: 29932484608.0000
Epoch 183/400
119/119 [==============================] - 0s 2ms/step - loss: 31699322880.0000 - val_loss: 29807740928.0000
Epoch 184/400
119/119 [==============================] - 0s 2ms/step - loss: 31651012608.0000 - val_loss: 29849026560.0000
Epoch 185/400
119/119 [==============================] - 0s 2ms/step - loss: 31588993024.0000 - val_loss: 30113996800.0000
Epoch 186/400
119/119 [==============================] - 0s 3ms/step - loss: 31622498304.0000 - val_loss: 29762400256.0000
Epoch 187/400
119/119 [==============================] - 0s 2ms/step - loss: 31622225920.0000 - val_loss: 29769648128.0000
Epoch 188/400
119/119 [==============================] - 0s 2ms/step - loss: 31606005760.0000 - val_loss: 29743714304.0000
Epoch 189/400
119/119 [==============================] - 0s 2ms/step - loss: 31562377216.0000 - val_loss: 29672060928.0000
Epoch 190/400
119/119 [==============================] - 0s 3ms/step - loss: 31523842048.0000 - val_loss: 29699858432.0000
Epoch 191/400
119/119 [==============================] - 0s 2ms/step - loss: 31519019008.0000 - val_loss: 29648656384.0000
Epoch 192/400
119/119 [==============================] - 0s 2ms/step - loss: 31499341824.0000 - val_loss: 29650857984.0000
Epoch 193/400
119/119 [==============================] - 0s 3ms/step - loss: 31527954432.0000 - val_loss: 29605328896.0000
Epoch 194/400
119/119 [==============================] - 0s 3ms/step - loss: 31462969344.0000 - val_loss: 29591814144.0000
Epoch 195/400
119/119 [==============================] - 0s 2ms/step - loss: 31458732032.0000 - val_loss: 29568600064.0000
Epoch 196/400
119/119 [==============================] - 0s 3ms/step - loss: 31502802944.0000 - val_loss: 29561241600.0000
Epoch 197/400
119/119 [==============================] - 0s 3ms/step - loss: 31393310720.0000 - val_loss: 29580306432.0000
Epoch 198/400
119/119 [==============================] - 0s 3ms/step - loss: 31453954048.0000 - val_loss: 29516658688.0000
Epoch 199/400
119/119 [==============================] - 0s 3ms/step - loss: 31398985728.0000 - val_loss: 29564766208.0000
Epoch 200/400
119/119 [==============================] - 0s 4ms/step - loss: 31389036544.0000 - val_loss: 29489942528.0000
Epoch 201/400
119/119 [==============================] - 1s 5ms/step - loss: 31371694080.0000 - val_loss: 29504825344.0000
Epoch 202/400
119/119 [==============================] - 1s 4ms/step - loss: 31336282112.0000 - val_loss: 29447063552.0000
Epoch 203/400
119/119 [==============================] - 1s 5ms/step - loss: 31334512640.0000 - val_loss: 29440522240.0000
Epoch 204/400
119/119 [==============================] - 1s 6ms/step - loss: 31316049920.0000 - val_loss: 29487988736.0000
Epoch 205/400
119/119 [==============================] - 1s 6ms/step - loss: 31330148352.0000 - val_loss: 29419040768.0000
Epoch 206/400
```

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119/119 [==============================] - 1s 5ms/step - loss: 31322765312.0000 - val_loss: 29444657152.0000
Epoch 207/400
119/119 [==============================] - 1s 5ms/step - loss: 31278243840.0000 - val_loss: 29377521664.0000
Epoch 208/400
119/119 [==============================] - 1s 5ms/step - loss: 31303958528.0000 - val_loss: 29345490944.0000
Epoch 209/400
119/119 [==============================] - 1s 4ms/step - loss: 31251736576.0000 - val_loss: 29357766656.0000
Epoch 210/400
119/119 [==============================] - 1s 4ms/step - loss: 31262160896.0000 - val_loss: 29361164288.0000
Epoch 211/400
119/119 [==============================] - 1s 5ms/step - loss: 31215667200.0000 - val_loss: 29299722240.0000
Epoch 212/400
119/119 [==============================] - 1s 5ms/step - loss: 31228856320.0000 - val_loss: 29261215744.0000
Epoch 213/400
119/119 [==============================] - 1s 5ms/step - loss: 31225122816.0000 - val_loss: 29243072512.0000
Epoch 214/400
119/119 [==============================] - 1s 5ms/step - loss: 31228878848.0000 - val_loss: 29202987008.0000
Epoch 215/400
119/119 [==============================] - 1s 5ms/step - loss: 31175141376.0000 - val_loss: 29258153984.0000
Epoch 216/400
119/119 [==============================] - 0s 4ms/step - loss: 31156291584.0000 - val_loss: 29236717568.0000
Epoch 217/400
119/119 [==============================] - 0s 4ms/step - loss: 31150340096.0000 - val_loss: 29267894272.0000
Epoch 218/400
119/119 [==============================] - 0s 3ms/step - loss: 31088001024.0000 - val_loss: 29225910272.0000
Epoch 219/400
119/119 [==============================] - 0s 2ms/step - loss: 31181268992.0000 - val_loss: 29142192128.0000
Epoch 220/400
119/119 [==============================] - 0s 2ms/step - loss: 31104385024.0000 - val_loss: 29167943680.0000
Epoch 221/400
119/119 [==============================] - 0s 2ms/step - loss: 31079749632.0000 - val_loss: 29113583616.0000
Epoch 222/400
119/119 [==============================] - 0s 3ms/step - loss: 31068522496.0000 - val_loss: 29200887808.0000
Epoch 223/400
119/119 [==============================] - 0s 2ms/step - loss: 31049068544.0000 - val_loss: 29087285248.0000
Epoch 224/400
119/119 [==============================] - 0s 3ms/step - loss: 31095187456.0000 - val_loss: 29121318912.0000
Epoch 225/400
119/119 [==============================] - 0s 2ms/step - loss: 31023759360.0000 - val_loss: 29089142784.0000
Epoch 226/400
119/119 [==============================] - 0s 3ms/step - loss: 31062077440.0000 - val_loss: 29039812608.0000
Epoch 227/400
119/119 [==============================] - 0s 2ms/step - loss: 31094906880.0000 - val_loss: 29044965376.0000
Epoch 228/400
119/119 [==============================] - 0s 2ms/step - loss: 31009099776.0000 - val_loss: 29016678400.0000
Epoch 229/400
119/119 [==============================] - 0s 2ms/step - loss: 31010506752.0000 - val_loss: 29065275392.0000
Epoch 230/400
119/119 [==============================] - 0s 2ms/step - loss: 30959405056.0000 - val_loss: 29008701440.0000
Epoch 231/400
119/119 [==============================] - 0s 2ms/step - loss: 30975907840.0000 - val_loss: 28961034240.0000
Epoch 232/400
119/119 [==============================] - 0s 3ms/step - loss: 30969595904.0000 - val_loss: 28931983360.0000
Epoch 233/400
119/119 [==============================] - 0s 2ms/step - loss: 30941825024.0000 - val_loss: 28997597184.0000
Epoch 234/400
119/119 [==============================] - 0s 2ms/step - loss: 30935367680.0000 - val_loss: 28916070400.0000
Epoch 235/400
119/119 [==============================] - 0s 2ms/step - loss: 30949201920.0000 - val_loss: 28908738560.0000
Epoch 236/400
119/119 [==============================] - 0s 3ms/step - loss: 30965962752.0000 - val_loss: 28891197440.0000
Epoch 237/400
119/119 [==============================] - 0s 3ms/step - loss: 30880090112.0000 - val_loss: 28939798528.0000
Epoch 238/400
119/119 [==============================] - 0s 3ms/step - loss: 30865842176.0000 - val_loss: 28887461888.0000
Epoch 239/400
119/119 [==============================] - 0s 2ms/step - loss: 30883633152.0000 - val_loss: 28828594176.0000
Epoch 240/400
119/119 [==============================] - 0s 2ms/step - loss: 30890096640.0000 - val_loss: 28813150208.0000
Epoch 241/400
119/119 [==============================] - 0s 2ms/step - loss: 30849335296.0000 - val_loss: 28809105408.0000
Epoch 242/400
119/119 [==============================] - 0s 3ms/step - loss: 30877329408.0000 - val_loss: 28791805952.0000
Epoch 243/400
119/119 [==============================] - 0s 3ms/step - loss: 30842355712.0000 - val_loss: 28850655232.0000
Epoch 244/400
119/119 [==============================] - 0s 3ms/step - loss: 30829195264.0000 - val_loss: 28784869376.0000
Epoch 245/400
119/119 [==============================] - 0s 3ms/step - loss: 30813743104.0000 - val_loss: 28750977024.0000
Epoch 246/400
119/119 [==============================] - 0s 3ms/step - loss: 30803003392.0000 - val_loss: 28757903360.0000
Epoch 247/400
119/119 [==============================] - 0s 3ms/step - loss: 30772692992.0000 - val_loss: 28716290048.0000
Epoch 248/400
119/119 [==============================] - 0s 3ms/step - loss: 30778568704.0000 - val_loss: 28709961728.0000
Epoch 249/400
119/119 [==============================] - 0s 3ms/step - loss: 30801321984.0000 - val_loss: 28715282432.0000
Epoch 250/400
119/119 [==============================] - 0s 3ms/step - loss: 30718697472.0000 - val_loss: 28828379136.0000
```

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Epoch 251/400
119/119 [==============================] - 0s 3ms/step - loss: 30824525824.0000 - val_loss: 28759156736.0000
Epoch 252/400
119/119 [==============================] - 0s 3ms/step - loss: 30712006656.0000 - val_loss: 28772974592.0000
Epoch 253/400
119/119 [==============================] - 0s 3ms/step - loss: 30727235584.0000 - val_loss: 28696438784.0000
Epoch 254/400
119/119 [==============================] - 0s 3ms/step - loss: 30709139456.0000 - val_loss: 28647948288.0000
Epoch 255/400
119/119 [==============================] - 0s 3ms/step - loss: 30735116288.0000 - val_loss: 28614080512.0000
Epoch 256/400
119/119 [==============================] - 0s 3ms/step - loss: 30662150144.0000 - val_loss: 28668880896.0000
Epoch 257/400
119/119 [==============================] - 0s 3ms/step - loss: 30649804800.0000 - val_loss: 28660799488.0000
Epoch 258/400
119/119 [==============================] - 0s 2ms/step - loss: 30669676544.0000 - val_loss: 28600322048.0000
Epoch 259/400
119/119 [==============================] - 0s 3ms/step - loss: 30649636864.0000 - val_loss: 28560502784.0000
Epoch 260/400
119/119 [==============================] - 0s 2ms/step - loss: 30668212224.0000 - val_loss: 28560955392.0000
Epoch 261/400
119/119 [==============================] - 0s 3ms/step - loss: 30652368896.0000 - val_loss: 28582273024.0000
Epoch 262/400
119/119 [==============================] - 0s 3ms/step - loss: 30608412672.0000 - val_loss: 28602662912.0000
Epoch 263/400
119/119 [==============================] - 0s 3ms/step - loss: 30645682176.0000 - val_loss: 28600475648.0000
Epoch 264/400
119/119 [==============================] - 0s 3ms/step - loss: 30582343680.0000 - val_loss: 28606306304.0000
Epoch 265/400
119/119 [==============================] - 0s 3ms/step - loss: 30603552768.0000 - val_loss: 28532899840.0000
Epoch 266/400
119/119 [==============================] - 0s 3ms/step - loss: 30560415744.0000 - val_loss: 28525973504.0000
Epoch 267/400
119/119 [==============================] - 0s 2ms/step - loss: 30563186688.0000 - val_loss: 28522633216.0000
Epoch 268/400
119/119 [==============================] - 0s 2ms/step - loss: 30598047744.0000 - val_loss: 28475574272.0000
Epoch 269/400
119/119 [==============================] - 0s 3ms/step - loss: 30538577920.0000 - val_loss: 28484536320.0000
Epoch 270/400
119/119 [==============================] - 0s 2ms/step - loss: 30520707072.0000 - val_loss: 28440930304.0000
Epoch 271/400
119/119 [==============================] - 0s 2ms/step - loss: 30534219776.0000 - val_loss: 28449757184.0000
Epoch 272/400
119/119 [==============================] - 0s 2ms/step - loss: 30519955456.0000 - val_loss: 28433106944.0000
Epoch 273/400
119/119 [==============================] - 0s 2ms/step - loss: 30480197632.0000 - val_loss: 28578301952.0000
Epoch 274/400
119/119 [==============================] - 0s 2ms/step - loss: 30578098176.0000 - val_loss: 28408758272.0000
Epoch 275/400
119/119 [==============================] - 0s 2ms/step - loss: 30485837824.0000 - val_loss: 28379648000.0000
Epoch 276/400
119/119 [==============================] - 0s 2ms/step - loss: 30504138752.0000 - val_loss: 28381788160.0000
Epoch 277/400
119/119 [==============================] - 0s 3ms/step - loss: 30440509440.0000 - val_loss: 28420132864.0000
Epoch 278/400
119/119 [==============================] - 0s 2ms/step - loss: 30444802048.0000 - val_loss: 28375832576.0000
Epoch 279/400
119/119 [==============================] - 0s 2ms/step - loss: 30434455552.0000 - val_loss: 28464906240.0000
Epoch 280/400
119/119 [==============================] - 0s 2ms/step - loss: 30457524224.0000 - val_loss: 28361914368.0000
Epoch 281/400
119/119 [==============================] - 0s 2ms/step - loss: 30403465216.0000 - val_loss: 28351997952.0000
Epoch 282/400
119/119 [==============================] - 0s 2ms/step - loss: 30410237952.0000 - val_loss: 28336146432.0000
Epoch 283/400
119/119 [==============================] - 0s 2ms/step - loss: 30396282880.0000 - val_loss: 28310913024.0000
Epoch 284/400
119/119 [==============================] - 0s 2ms/step - loss: 30424156160.0000 - val_loss: 28276568064.0000
Epoch 285/400
119/119 [==============================] - 0s 2ms/step - loss: 30387081216.0000 - val_loss: 28263579648.0000
Epoch 286/400
119/119 [==============================] - 0s 2ms/step - loss: 30371909632.0000 - val_loss: 28254439424.0000
Epoch 287/400
119/119 [==============================] - 0s 2ms/step - loss: 30361411584.0000 - val_loss: 28244371456.0000
Epoch 288/400
119/119 [==============================] - 0s 2ms/step - loss: 30328707072.0000 - val_loss: 28290461696.0000
Epoch 289/400
119/119 [==============================] - 0s 2ms/step - loss: 30312267776.0000 - val_loss: 28206446592.0000
Epoch 290/400
119/119 [==============================] - 0s 3ms/step - loss: 30422867968.0000 - val_loss: 28191211520.0000
Epoch 291/400
119/119 [==============================] - 0s 2ms/step - loss: 30302642176.0000 - val_loss: 28163010560.0000
Epoch 292/400
119/119 [==============================] - 0s 2ms/step - loss: 30302056448.0000 - val_loss: 28178237440.0000
Epoch 293/400
119/119 [==============================] - 0s 2ms/step - loss: 30296733696.0000 - val_loss: 28169775104.0000
Epoch 294/400
119/119 [==============================] - 0s 3ms/step - loss: 30259906560.0000 - val_loss: 28178046976.0000
Epoch 295/400
```

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119/119 [==============================] - 0s 3ms/step - loss: 30278596608.0000 - val_loss: 28181901312.0000
Epoch 296/400
119/119 [==============================] - 0s 4ms/step - loss: 30250311680.0000 - val_loss: 28121933824.0000
Epoch 297/400
119/119 [==============================] - 1s 5ms/step - loss: 30271260672.0000 - val_loss: 28111020032.0000
Epoch 298/400
119/119 [==============================] - 1s 5ms/step - loss: 30242019328.0000 - val_loss: 28096161792.0000
Epoch 299/400
119/119 [==============================] - 1s 5ms/step - loss: 30263386112.0000 - val_loss: 28139450368.0000
Epoch 300/400
119/119 [==============================] - 1s 5ms/step - loss: 30230245376.0000 - val_loss: 28153333760.0000
Epoch 301/400
119/119 [==============================] - 1s 5ms/step - loss: 30224277504.0000 - val_loss: 28154370048.0000
Epoch 302/400
119/119 [==============================] - 0s 4ms/step - loss: 30242979840.0000 - val_loss: 28056698880.0000
Epoch 303/400
119/119 [==============================] - 0s 3ms/step - loss: 30223568896.0000 - val_loss: 28044423168.0000
Epoch 304/400
119/119 [==============================] - 0s 4ms/step - loss: 30166280192.0000 - val_loss: 28005570560.0000
Epoch 305/400
119/119 [==============================] - 1s 4ms/step - loss: 30226008064.0000 - val_loss: 28028895232.0000
Epoch 306/400
119/119 [==============================] - 0s 3ms/step - loss: 30252056576.0000 - val_loss: 28050008064.0000
Epoch 307/400
119/119 [==============================] - 0s 3ms/step - loss: 30154555392.0000 - val_loss: 28029681664.0000
Epoch 308/400
119/119 [==============================] - 0s 3ms/step - loss: 30132742144.0000 - val_loss: 27964051456.0000
Epoch 309/400
119/119 [==============================] - 0s 3ms/step - loss: 30132189184.0000 - val_loss: 27959298048.0000
Epoch 310/400
119/119 [==============================] - 0s 3ms/step - loss: 30098305024.0000 - val_loss: 28032161792.0000
Epoch 311/400
119/119 [==============================] - 0s 3ms/step - loss: 30152189952.0000 - val_loss: 27949869056.0000
Epoch 312/400
119/119 [==============================] - 0s 3ms/step - loss: 30112305152.0000 - val_loss: 27959066624.0000
Epoch 313/400
119/119 [==============================] - 0s 3ms/step - loss: 30112413696.0000 - val_loss: 27933915136.0000
Epoch 314/400
119/119 [==============================] - 0s 3ms/step - loss: 30081277952.0000 - val_loss: 28001839104.0000
Epoch 315/400
119/119 [==============================] - 0s 4ms/step - loss: 30068387840.0000 - val_loss: 28096581632.0000
Epoch 316/400
119/119 [==============================] - 0s 3ms/step - loss: 30062835712.0000 - val_loss: 27872000000.0000
Epoch 317/400
119/119 [==============================] - 0s 3ms/step - loss: 30065344512.0000 - val_loss: 27848396800.0000
Epoch 318/400
119/119 [==============================] - 0s 3ms/step - loss: 30039910400.0000 - val_loss: 27868698624.0000
Epoch 319/400
119/119 [==============================] - 0s 3ms/step - loss: 30045067264.0000 - val_loss: 27835324416.0000
Epoch 320/400
119/119 [==============================] - 0s 3ms/step - loss: 30021857280.0000 - val_loss: 27808393216.0000
Epoch 321/400
119/119 [==============================] - 0s 4ms/step - loss: 30022311936.0000 - val_loss: 27790028800.0000
Epoch 322/400
119/119 [==============================] - 0s 3ms/step - loss: 30003054592.0000 - val_loss: 27871549440.0000
Epoch 323/400
119/119 [==============================] - 0s 3ms/step - loss: 29988990976.0000 - val_loss: 27762706432.0000
Epoch 324/400
119/119 [==============================] - 0s 3ms/step - loss: 29984479232.0000 - val_loss: 27785209856.0000
Epoch 325/400
119/119 [==============================] - 0s 3ms/step - loss: 30004699136.0000 - val_loss: 27767275520.0000
Epoch 326/400
119/119 [==============================] - 0s 3ms/step - loss: 29992468480.0000 - val_loss: 27729100800.0000
Epoch 327/400
119/119 [==============================] - 0s 3ms/step - loss: 29965064192.0000 - val_loss: 27719979008.0000
Epoch 328/400
119/119 [==============================] - 0s 2ms/step - loss: 29992331264.0000 - val_loss: 27742353408.0000
Epoch 329/400
119/119 [==============================] - 0s 3ms/step - loss: 29951045632.0000 - val_loss: 27734636544.0000
Epoch 330/400
119/119 [==============================] - 0s 3ms/step - loss: 29906624512.0000 - val_loss: 27742275584.0000
Epoch 331/400
119/119 [==============================] - 0s 3ms/step - loss: 29949360128.0000 - val_loss: 27727413248.0000
Epoch 332/400
119/119 [==============================] - 0s 3ms/step - loss: 29918715904.0000 - val_loss: 27836510208.0000
Epoch 333/400
119/119 [==============================] - 0s 3ms/step - loss: 29899067392.0000 - val_loss: 27665616896.0000
Epoch 334/400
119/119 [==============================] - 0s 3ms/step - loss: 29869744128.0000 - val_loss: 27672887296.0000
Epoch 335/400
119/119 [==============================] - 0s 3ms/step - loss: 29863102464.0000 - val_loss: 27693987840.0000
Epoch 336/400
119/119 [==============================] - 1s 4ms/step - loss: 29897957376.0000 - val_loss: 27636770816.0000
Epoch 337/400
119/119 [==============================] - 0s 4ms/step - loss: 29841391616.0000 - val_loss: 27618234368.0000
Epoch 338/400
119/119 [==============================] - 0s 3ms/step - loss: 29836138496.0000 - val_loss: 27717066752.0000
Epoch 339/400
119/119 [==============================] - 0s 3ms/step - loss: 29838194688.0000 - val_loss: 27637942272.0000
```

```
Epoch 340/400
119/119 [==============================] - 0s 3ms/step - loss: 29858324480.0000 - val_loss: 27702880256.0000
Epoch 341/400
119/119 [==============================] - 0s 3ms/step - loss: 29809772544.0000 - val_loss: 27583078400.0000
Epoch 342/400
119/119 [==============================] - 0s 3ms/step - loss: 29803118592.0000 - val_loss: 27602673664.0000
Epoch 343/400
119/119 [==============================] - 0s 3ms/step - loss: 29777635328.0000 - val_loss: 27590457344.0000
Epoch 344/400
119/119 [==============================] - 0s 3ms/step - loss: 29798862848.0000 - val_loss: 27558529024.0000
Epoch 345/400
119/119 [==============================] - 0s 3ms/step - loss: 29746028544.0000 - val_loss: 27582535680.0000
Epoch 346/400
119/119 [==============================] - 0s 3ms/step - loss: 29762019328.0000 - val_loss: 27643658240.0000
Epoch 347/400
119/119 [==============================] - 0s 3ms/step - loss: 29772795904.0000 - val_loss: 27574362112.0000
Epoch 348/400
119/119 [==============================] - 0s 3ms/step - loss: 29763606528.0000 - val_loss: 27535024128.0000
Epoch 349/400
119/119 [==============================] - 0s 2ms/step - loss: 29745063936.0000 - val_loss: 27539777536.0000
Epoch 350/400
119/119 [==============================] - 0s 3ms/step - loss: 29737000960.0000 - val_loss: 27527294976.0000
Epoch 351/400
119/119 [==============================] - 0s 2ms/step - loss: 29725212672.0000 - val_loss: 27566868480.0000
Epoch 352/400
119/119 [==============================] - 0s 3ms/step - loss: 29798584320.0000 - val_loss: 27467759616.0000
Epoch 353/400
119/119 [==============================] - 0s 3ms/step - loss: 29742002176.0000 - val_loss: 27448891392.0000
Epoch 354/400
119/119 [==============================] - 0s 2ms/step - loss: 29696755712.0000 - val_loss: 27477764096.0000
Epoch 355/400
119/119 [==============================] - 0s 2ms/step - loss: 29709185024.0000 - val_loss: 27416604672.0000
Epoch 356/400
119/119 [==============================] - 0s 3ms/step - loss: 29680977920.0000 - val_loss: 27451092992.0000
Epoch 357/400
119/119 [==============================] - 0s 3ms/step - loss: 29670936576.0000 - val_loss: 27426699264.0000
Epoch 358/400
119/119 [==============================] - 0s 3ms/step - loss: 29674027008.0000 - val_loss: 27432161280.0000
Epoch 359/400
119/119 [==============================] - 0s 2ms/step - loss: 29647382528.0000 - val_loss: 27372937216.0000
Epoch 360/400
119/119 [==============================] - 0s 3ms/step - loss: 29628123136.0000 - val_loss: 27401574400.0000
Epoch 361/400
119/119 [==============================] - 0s 3ms/step - loss: 29615347712.0000 - val_loss: 27446636544.0000
Epoch 362/400
119/119 [==============================] - 0s 3ms/step - loss: 29596520448.0000 - val_loss: 27413774336.0000
Epoch 363/400
119/119 [==============================] - 0s 3ms/step - loss: 29602062336.0000 - val_loss: 27407638528.0000
Epoch 364/400
119/119 [==============================] - 0s 3ms/step - loss: 29605619712.0000 - val_loss: 27309438976.0000
Epoch 365/400
119/119 [==============================] - 0s 2ms/step - loss: 29561042944.0000 - val_loss: 27340052480.0000
Epoch 366/400
119/119 [==============================] - 0s 3ms/step - loss: 29607366656.0000 - val_loss: 27282960384.0000
Epoch 367/400
119/119 [==============================] - 0s 3ms/step - loss: 29587961856.0000 - val_loss: 27329232896.0000
Epoch 368/400
119/119 [==============================] - 0s 3ms/step - loss: 29562589184.0000 - val_loss: 27382677504.0000
Epoch 369/400
119/119 [==============================] - 0s 3ms/step - loss: 29543340032.0000 - val_loss: 27303872512.0000
Epoch 370/400
119/119 [==============================] - 0s 3ms/step - loss: 29547302912.0000 - val_loss: 27260663808.0000
Epoch 371/400
119/119 [==============================] - 0s 3ms/step - loss: 29541906432.0000 - val_loss: 27270717440.0000
Epoch 372/400
119/119 [==============================] - 0s 3ms/step - loss: 29599086592.0000 - val_loss: 27260524544.0000
Epoch 373/400
119/119 [==============================] - 0s 3ms/step - loss: 29529686016.0000 - val_loss: 27224453120.0000
Epoch 374/400
119/119 [==============================] - 0s 2ms/step - loss: 29503473664.0000 - val_loss: 27311183872.0000
Epoch 375/400
119/119 [==============================] - 0s 3ms/step - loss: 29512626176.0000 - val_loss: 27235534848.0000
Epoch 376/400
119/119 [==============================] - 0s 3ms/step - loss: 29453330432.0000 - val_loss: 27183861760.0000
Epoch 377/400
119/119 [==============================] - 0s 3ms/step - loss: 29521297408.0000 - val_loss: 27224324096.0000
Epoch 378/400
119/119 [==============================] - 0s 3ms/step - loss: 29467959296.0000 - val_loss: 27188262912.0000
Epoch 379/400
119/119 [==============================] - 0s 3ms/step - loss: 29446182912.0000 - val_loss: 27170744320.0000
Epoch 380/400
119/119 [==============================] - 0s 3ms/step - loss: 29432285184.0000 - val_loss: 27182317568.0000
Epoch 381/400
119/119 [==============================] - 0s 3ms/step - loss: 29435297792.0000 - val_loss: 27150034944.0000
Epoch 382/400
119/119 [==============================] - 0s 3ms/step - loss: 29423640576.0000 - val_loss: 27178117120.0000
Epoch 383/400
119/119 [==============================] - 0s 3ms/step - loss: 29450397696.0000 - val_loss: 27160487936.0000
Epoch 384/400
```

```
119/119 [==============================] - 0s 3ms/step - loss: 29362563072.0000 - val_loss: 27116795904.0000
Epoch 385/400
119/119 [==============================] - 0s 3ms/step - loss: 29377925120.0000 - val_loss: 27113519104.0000
Epoch 386/400
119/119 [==============================] - 0s 3ms/step - loss: 29380218880.0000 - val_loss: 27099475968.0000
Epoch 387/400
119/119 [==============================] - 0s 3ms/step - loss: 29343066112.0000 - val_loss: 27134148608.0000
Epoch 388/400
119/119 [==============================] - 0s 3ms/step - loss: 29322774528.0000 - val_loss: 27096033280.0000
Epoch 389/400
119/119 [==============================] - 0s 3ms/step - loss: 29307181056.0000 - val_loss: 27047086080.0000
Epoch 390/400
119/119 [==============================] - 0s 3ms/step - loss: 29324800000.0000 - val_loss: 27070154752.0000
Epoch 391/400
119/119 [==============================] - 0s 3ms/step - loss: 29290424320.0000 - val_loss: 27082493952.0000
Epoch 392/400
119/119 [==============================] - 0s 3ms/step - loss: 29314265088.0000 - val_loss: 27068016640.0000
Epoch 393/400
119/119 [==============================] - 0s 3ms/step - loss: 29284495360.0000 - val_loss: 27102044160.0000
Epoch 394/400
119/119 [==============================] - 0s 3ms/step - loss: 29237956608.0000 - val_loss: 26993715200.0000
Epoch 395/400
119/119 [==============================] - 0s 3ms/step - loss: 29218430976.0000 - val_loss: 27034957824.0000
Epoch 396/400
119/119 [==============================] - 0s 3ms/step - loss: 29198929920.0000 - val_loss: 26949095424.0000
Epoch 397/400
119/119 [==============================] - 0s 3ms/step - loss: 29226872832.0000 - val_loss: 26982731776.0000
Epoch 398/400
119/119 [==============================] - 0s 3ms/step - loss: 29182328832.0000 - val_loss: 27063306240.0000
Epoch 399/400
119/119 [==============================] - 0s 2ms/step - loss: 29202814976.0000 - val_loss: 26900543488.0000
Epoch 400/400
119/119 [==============================] - 0s 3ms/step - loss: 29188495360.0000 - val_loss: 26922991616.0000
```

Out[54]:

```
<keras.callbacks.History at 0x25b35e62c10>
```

In [55]:

```python
pd.DataFrame(model.history.history)
```

Out[55]:

	loss	val_loss
0	4.302423e+11	4.189257e+11
1	4.292076e+11	4.152504e+11
2	4.139733e+11	3.799795e+11
3	3.382583e+11	2.566694e+11
4	1.855652e+11	1.153491e+11
...	...	...
395	2.919893e+10	2.694910e+10
396	2.922687e+10	2.698273e+10
397	2.918233e+10	2.706331e+10
398	2.920281e+10	2.690054e+10
399	2.918850e+10	2.692299e+10

400 rows × 2 columns

In [56]:

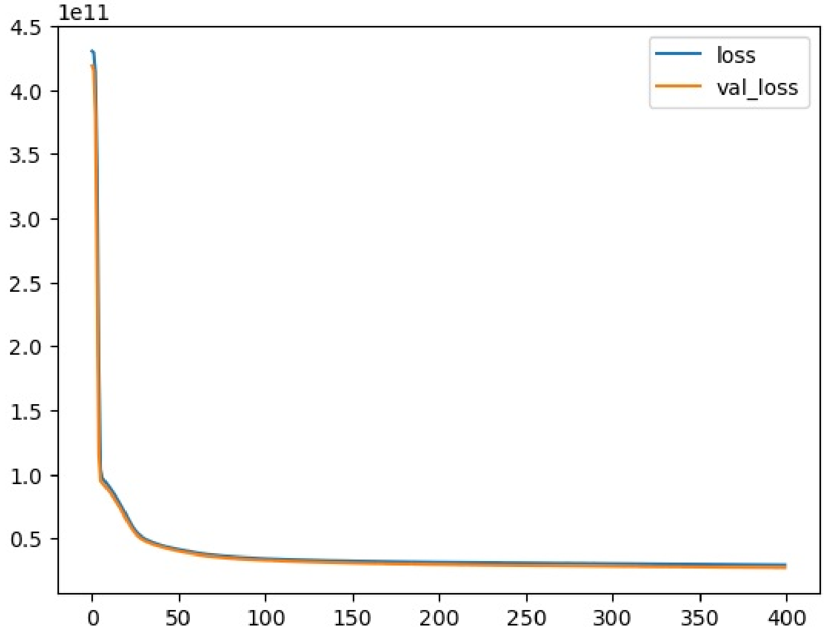
```python
losses = pd.DataFrame(model.history.history)
```

In [57]:

```python
losses.plot() #No overfitting as it goes down together and follow each other
```

Out[57]:

```
<AxesSubplot:>
```



Evaluation on Test Data

https://scikit-learn.org/stable/modules/model_evaluation.html#regression-metrics

In [58]:
```
from sklearn.metrics import mean_squared_error,mean_absolute_error,explained_variance_score
```

Predicting on Brand New Data

In [59]:
```
X_test
```

Out[59]:
```
array([[0.1       , 0.08      , 0.04239917, ..., 0.00887725, 0.63636364,
        0.        ],
       [0.3       , 0.36      , 0.17269907, ..., 0.00993734, 0.81818182,
        0.        ],
       [0.2       , 0.24      , 0.12512927, ..., 0.00547073, 0.90909091,
        0.        ],
       ...,
       [0.1       , 0.08      , 0.05584281, ..., 0.00506255, 1.        ,
        0.        ],
       [0.3       , 0.2       , 0.22233713, ..., 0.00774485, 0.09090909,
        1.        ],
       [0.3       , 0.32      , 0.27611169, ..., 0.0196531 , 0.45454545,
        0.        ]])
```

In [60]:
```
predictions = model.predict(X_test)
```

```
203/203 [==============================] - 0s 1ms/step
```

In [61]:
```
mean_absolute_error(y_test,predictions)
```

Out[61]:
```
101212.89623300057
```

In [62]:
```
np.sqrt(mean_squared_error(y_test,predictions))
```

Out[62]: 164082.25835461583

In [63]:
```
explained_variance_score(y_test,predictions)
```

Out[63]: 0.7972356195420334

In [64]:
```
df['price'].mean() #Compared to MAE it means we are off by 20% - it is not great
```

Out[64]: 540296.5735055795

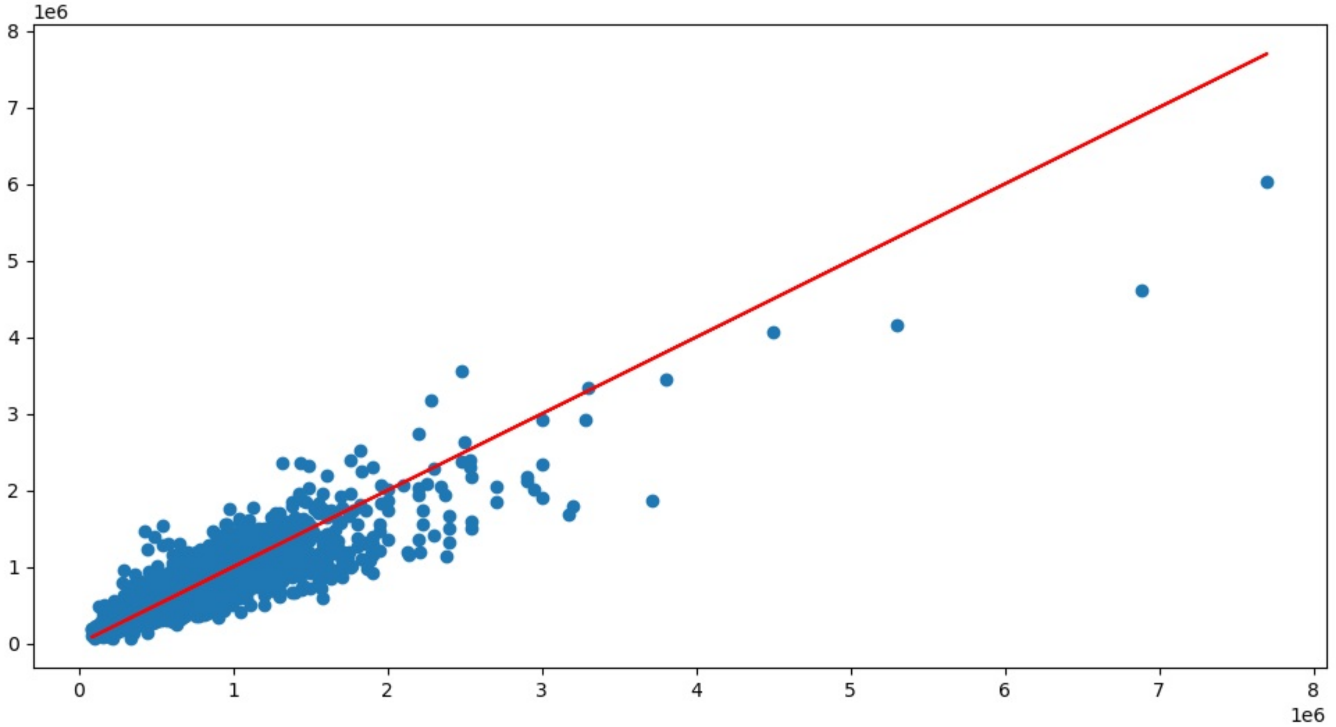
In [65]:
```
df['price'].median()
```

Out[65]: 450000.0

In [66]:
```
# Our predictions
plt.figure(figsize=(12,6))
plt.scatter(y_test,predictions) #So we aren't good at predicting very expensive houses

# Perfect predictions
plt.plot(y_test,y_test,'r')
```

Out[66]: [<matplotlib.lines.Line2D at 0x25b3827d8b0>]

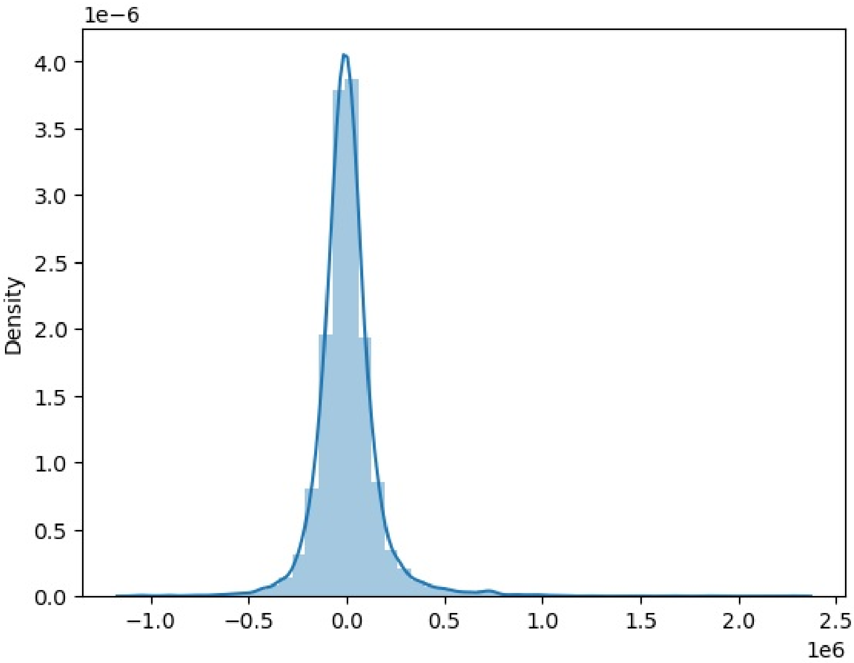


In [67]:
```
errors = y_test.values.reshape(6480, 1) - predictions
```

In [68]:
```
sns.distplot(errors) #We don't really have to do this tbh
```

```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a deprec
ated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure
-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[68]: <AxesSubplot:ylabel='Density'>



Predicting on a brand new house

In [72]:
```
single_house = df.drop('price',axis=1).iloc[0]
```

In [74]:
```
single_house = scaler.transform(single_house.values.reshape(-1, 19))
```

```
---------------------------------------------------------------------------
AttributeError                            Traceback (most recent call last)
~\AppData\Local\Temp\ipykernel_37016\3757999802.py in <module>
----> 1 single_house.values.reshape(-1, 19)

AttributeError: 'numpy.ndarray' object has no attribute 'values'
```

In [75]:
```
single_house
```

Out[75]:
```
array([[0.2       , 0.08      , 0.08376422, 0.00310751, 0.        ,
        0.        , 0.        , 0.5       , 0.4       , 0.10785619,
        0.        , 0.47826087, 0.        , 0.57149751, 0.21760797,
        0.16193426, 0.00582059, 0.81818182, 0.        ]])
```

In [76]:
```
model.predict(single_house)
```

```
1/1 [==============================] - 0s 24ms/step
```

Out[76]:
```
array([[280027.66]], dtype=float32)
```

In [77]:
```
df.iloc[0]
```

Out[77]:
```
price             221900.0000
bedrooms               3.0000
bathrooms              1.0000
sqft_living         1180.0000
sqft_lot            5650.0000
floors                 1.0000
waterfront             0.0000
view                   0.0000
condition              3.0000
grade                  7.0000
sqft_above          1180.0000
sqft_basement          0.0000
yr_built            1955.0000
yr_renovated           0.0000
lat                   47.5112
long                -122.2570
sqft_living15       1340.0000
sqft_lot15          5650.0000
month                 10.0000
year                2014.0000
Name: 0, dtype: float64
```

In [78]:
```
df.head(1)
```

Out[78]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	sqft_above	sqft_basement	yr_built	yr_re
0	221900.0	3	1.0	1180	5650	1.0	0	0	3	7	1180	0	1955	

In [ ]: