Exploratory Data Analysis

```
In [7]: import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        import seaborn as sns
In [2]: df = pd.read_csv('./data/DATA/kc_house_data.csv')
In [3]: df.isnull().sum()
Out[3]: id
                         0
        date
                         0
        price
        bedrooms
        bathrooms
        sqft_living
        sqft_lot
        floors
                         0
        waterfront
        view
        condition
        grade
        sqft_above
        sqft_basement
                         0
        yr_built
                         0
        yr_renovated
        zipcode
                         0
        lat
                         0
        long
                         0
        sqft_living15
        sqft_lot15
                         0
        dtype: int64
In [7]: df.describe().transpose()
```

Out[7]:		count	mean	std	min	25%	
	id	21597.0	4.580474e+09	2.876736e+09	1.000102e+06	2.123049e+09	3.
	price	21597.0	5.402966e+05	3.673681e+05	7.800000e+04	3.220000e+05	4.
	bedrooms	21597.0	3.373200e+00	9.262989e-01	1.000000e+00	3.000000e+00	3.
	bathrooms	21597.0	2.115826e+00	7.689843e-01	5.000000e-01	1.750000e+00	2.
	sqft_living	21597.0	2.080322e+03	9.181061e+02	3.700000e+02	1.430000e+03	1.
	sqft_lot	21597.0	1.509941e+04	4.141264e+04	5.200000e+02	5.040000e+03	7.
	floors	21597.0	1.494096e+00	5.396828e-01	1.000000e+00	1.000000e+00	1.
	waterfront	21597.0	7.547345e-03	8.654900e-02	0.000000e+00	0.000000e+00	0.
	view	21597.0	2.342918e-01	7.663898e-01	0.000000e+00	0.000000e+00	0.
	condition	21597.0	3.409825e+00	6.505456e-01	1.000000e+00	3.000000e+00	3.
	grade	21597.0	7.657915e+00	1.173200e+00	3.000000e+00	7.000000e+00	7.
	sqft_above	21597.0	1.788597e+03	8.277598e+02	3.700000e+02	1.190000e+03	1.
	sqft_basement	21597.0	2.917250e+02	4.426678e+02	0.000000e+00	0.000000e+00	0.
	yr_built	21597.0	1.971000e+03	2.937523e+01	1.900000e+03	1.951000e+03	1.
	yr_renovated	21597.0	8.446479e+01	4.018214e+02	0.000000e+00	0.000000e+00	0.
	zipcode	21597.0	9.807795e+04	5.351307e+01	9.800100e+04	9.803300e+04	9.

In [9]: plt.figure(figsize=(10,6))
sns.distplot(df['price'])

4.756009e+01 1.385518e-01

1.986620e+03 6.852305e+02

1.275828e+04 2.727444e+04

long 21597.0 -1.222140e+02 1.407235e-01

4.715590e+01

3.990000e+02

6.510000e+02

4.747110e+01

1.490000e+03

5.100000e+03

-1.225190e+02 -1.223280e+02 -1.

4.

1.

7.

C:\Users\AMIT_MERUGU\AppData\Local\Temp\1\ipykernel_39744\4141105712.py:2: UserWa
rning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

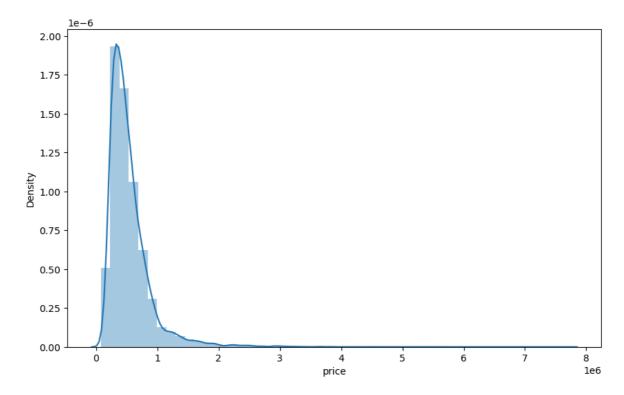
sns.distplot(df['price'])

Out[9]: <Axes: xlabel='price', ylabel='Density'>

lat 21597.0

sqft_living15 21597.0

sqft_lot15 21597.0



In [8]: #The above chart shows most of the house prices fall under \$2M;

In [81]: sns.countplot(df['bedrooms'])

```
Traceback (most recent call last)
KeyboardInterrupt
~\AppData\Local\Temp\1\ipykernel_18900\2996807382.py in ?()
---> 1 sns.countplot(df['bedrooms'])
C:\learnings\Lib\site-packages\seaborn\categorical.py in ?(data, x, y, hue, orde
r, hue_order, orient, color, palette, saturation, fill, hue_norm, stat, width, do
dge, gap, log_scale, native_scale, formatter, legend, ax, **kwargs)
                p.plot_data[count_axis] /= len(p.plot_data) / denom
   2672
   2673
            aggregator = EstimateAggregator("sum", errorbar=None)
  2674
-> 2675
          p.plot bars(
   2676
                aggregator=aggregator,
   2677
                dodge=dodge,
                width=width,
   2678
C:\learnings\Lib\site-packages\seaborn\categorical.py in ?(self, aggregator, dodg
e, gap, width, fill, color, capsize, err_kws, plot_kws)
  1276
  1277
                    ax = self._get_axes(sub_vars)
   1278
  1279
                    agg_data = sub_data if sub_data.empty else (
-> 1280
                        sub data
  1281
                        .groupby(self.orient)
  1282
                        .apply(aggregator, agg_var, **groupby_apply_include_group
s(False))
  1283
                        .reset_index()
C:\learnings\Lib\site-packages\pandas\core\groupby\groupby.py in ?(self, func, in
clude_groups, *args, **kwargs)
  1815
               else:
   1816
                   f = func
  1817
               if not include groups:
  1818
-> 1819
                    return self._python_apply_general(f, self._obj_with_exclusion
s)
  1820
                # ignore SettingWithCopy here in case the user mutates
  1821
   1822
                with option context("mode.chained_assignment", None):
C:\learnings\Lib\site-packages\pandas\core\groupby\groupby.py in ?(self, f, data,
not_indexed_same, is_transform, is_agg)
               values, mutated = self._grouper.apply_groupwise(f, data, self.axi
  1885
s)
  1886
                if not indexed same is None:
  1887
                    not indexed same = mutated
   1888
-> 1889
                return self._wrap_applied_output(
  1890
                    data.
   1891
                    values,
   1892
                    not indexed same,
C:\learnings\Lib\site-packages\pandas\core\groupby\generic.py in ?(self, data, va
lues, not_indexed_same, is_transform)
  1616
                        result = self._insert_inaxis_grouper(result)
   1617
                        return result
   1618
                else:
                    # values are Series
   1619
-> 1620
                    return self._wrap_applied_output_series(
```

```
1621
                        values.
  1622
                        not_indexed_same,
  1623
                        first_not_none,
C:\learnings\Lib\site-packages\pandas\core\groupby\generic.py in ?(self, values,
not_indexed_same, first_not_none, key_index, is_transform)
  1648
  1649
               # Combine values
  1650
  1651
                # vstack+constructor is faster than concat and handles MI-columns
                stacked_values = np.vstack([np.asarray(v) for v in values])
-> 1652
  1653
  1654
                if self.axis == 0:
  1655
                    index = key_index
C:\learnings\Lib\site-packages\pandas\core\generic.py in ?(self, name)
  6292
               if (
  6293
                    name not in self._internal_names_set
  6294
                    and name not in self. metadata
  6295
                    and name not in self._accessors
-> 6296
                    and self._info_axis._can_hold_identifiers_and_holds_name(nam
e)
               ):
  6297
   6298
                    return self[name]
  6299
                return object.__getattribute__(self, name)
C:\learnings\Lib\site-packages\pandas\core\generic.py in ?(self)
--> 667
            @final
   668
            @property
   669
            def info axis(self) -> Index:
                return getattr(self, self._info_axis_name)
   670
KeyboardInterrupt:
Error in callback <function _draw_all_if_interactive at 0x000001AFA753AA20> (for
post execute), with arguments args (),kwargs {}:
KeyboardInterrupt
Error in callback <function flush_figures at 0x000001AFB203CF40> (for post_execut
e), with arguments args (), kwargs {}:
```

KeyboardInterrupt

```
In [11]: df.describe()
```

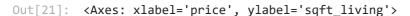
```
Out[11]:
                          id
                                     price
                                              bedrooms
                                                           bathrooms
                                                                        sqft_living
                                                                                        sqf
          count 2.159700e+04 2.159700e+04 21597.000000 21597.000000 21597.000000 2.15970000
          mean 4.580474e+09 5.402966e+05
                                               3.373200
                                                             2.115826
                                                                       2080.321850 1.5099416
            std 2.876736e+09 3.673681e+05
                                               0.926299
                                                             0.768984
                                                                        918.106125 4.141264
           min 1.000102e+06 7.800000e+04
                                                1.000000
                                                             0.500000
                                                                        370.000000 5.2000006
           25% 2.123049e+09 3.220000e+05
                                               3.000000
                                                             1.750000
                                                                       1430.000000 5.0400006
           50% 3.904930e+09 4.500000e+05
                                               3.000000
                                                             2.250000
                                                                       1910.000000 7.6180000
           75% 7.308900e+09 6.450000e+05
                                               4.000000
                                                             2.500000
                                                                       2550.000000 1.0685006
           max 9.900000e+09 7.700000e+06
                                              33.000000
                                                             8.000000 13540.000000 1.6513596
In [13]: df.corr()['price'].sort values()
        ValueError
                                                   Traceback (most recent call last)
        Cell In[13], line 1
        ----> 1 df.corr()['price'].sort_values()
        File C:\learnings\Lib\site-packages\pandas\core\frame.py:11049, in DataFrame.corr
        (self, method, min periods, numeric only)
          11047 cols = data.columns
          11048 idx = cols.copy()
        > 11049 mat = data.to_numpy(dtype=float, na_value=np.nan, copy=False)
          11051 if method == "pearson":
                    correl = libalgos.nancorr(mat, minp=min_periods)
        File C:\learnings\Lib\site-packages\pandas\core\frame.py:1993, in DataFrame.to_nu
        mpy(self, dtype, copy, na_value)
           1991 if dtype is not None:
           1992
                   dtype = np.dtype(dtype)
        -> 1993 result = self._mgr.as_array(dtype=dtype, copy=copy, na_value=na_value)
           1994 if result.dtype is not dtype:
                    result = np.asarray(result, dtype=dtype)
        File C:\learnings\Lib\site-packages\pandas\core\internals\managers.py:1694, in Bl
        ockManager.as array(self, dtype, copy, na_value)
           1692
                        arr.flags.writeable = False
           1693 else:
        -> 1694
                  arr = self._interleave(dtype=dtype, na_value=na_value)
                    # The underlying data was copied within interleave, so no need
                    # to further copy if copy=True or setting na_value
           1696
           1698 if na value is lib.no default:
        File C:\learnings\Lib\site-packages\pandas\core\internals\managers.py:1753, in Bl
        ockManager._interleave(self, dtype, na_value)
           1751
                    else:
           1752
                        arr = blk.get_values(dtype)
        -> 1753
                    result[rl.indexer] = arr
           1754
                    itemmask[rl.indexer] = 1
           1756 if not itemmask.all():
        ValueError: could not convert string to float: '10/13/2014'
```

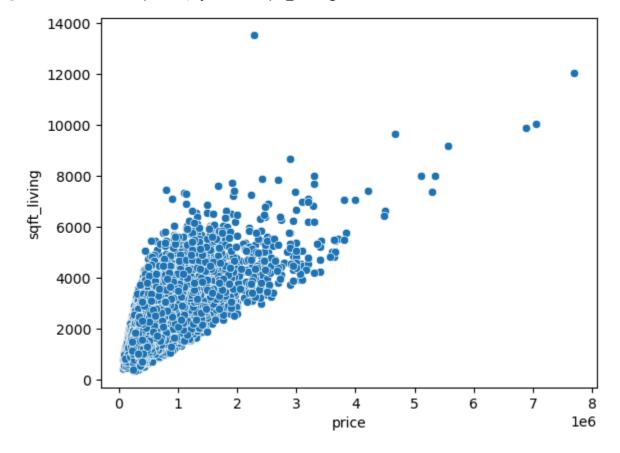
```
In [57]: print(df['price'].dtype)
        float64
In [59]: # Try to convert the column to numeric, and find rows where this fails
          non_numeric = df[pd.to_numeric(df['price'], errors='coerce').isnull()]
          print(non_numeric)
        Empty DataFrame
        Columns: [id, date, price, bedrooms, bathrooms, sqft_living, sqft_lot, floors, wa
        terfront, view, condition, grade, sqft_above, sqft_basement, yr_built, yr_renovat
        ed, zipcode, lat, long, sqft_living15, sqft_lot15]
        Index: []
        [0 rows x 21 columns]
In [61]: print(df['price'].head(10))
        0
              221900.0
              538000.0
        1
        2
              180000.0
        3
              604000.0
        4
              510000.0
        5
             1230000.0
        6
              257500.0
        7
              291850.0
        8
              229500.0
        9
              323000.0
        Name: price, dtype: float64
In [71]: df.head()
        AttributeError
                                                    Traceback (most recent call last)
        Cell In[71], line 1
        ---> 1 df.head()
        AttributeError: 'NoneType' object has no attribute 'head'
In [15]: df = df.drop('date', axis=1)
In [17]:
         df.head()
Out[17]:
                     id
                                  bedrooms bathrooms sqft_living sqft_lot floors waterfront
                            price
          0 7129300520 221900.0
                                          3
                                                   1.00
                                                              1180
                                                                      5650
                                                                               1.0
                                                                                            (
          1 6414100192 538000.0
                                                   2.25
                                                              2570
                                                                      7242
                                                                               2.0
                                                                                            (
          2 5631500400 180000.0
                                          2
                                                   1.00
                                                               770
                                                                     10000
                                                                               1.0
                                                                                            (
          3 2487200875 604000.0
                                                   3.00
                                                              1960
                                                                      5000
                                                                               1.0
                                                                                            (
            1954400510 510000.0
                                          3
                                                   2.00
                                                              1680
                                                                      8080
                                                                               1.0
                                                                                            (
In [19]:
         df.corr()['price'].sort_values()
```

```
Out[19]: 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
                           0.308787
          bedrooms
          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
                           1.000000
          price
          Name: price, dtype: float64
```

In [107... #sqft_living has very high correlation to the price; Let's explore what are the

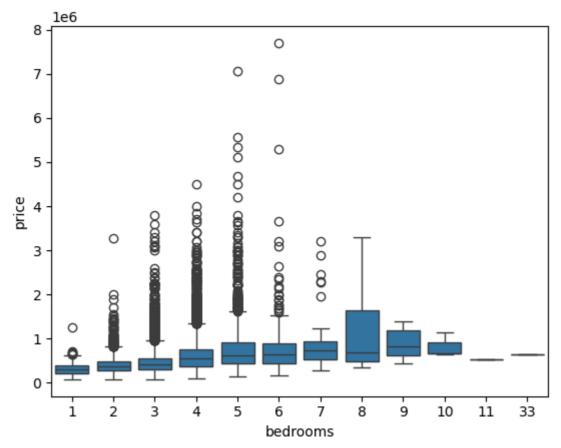
In [21]: sns.scatterplot(x='price', y='sqft_living', data=df)



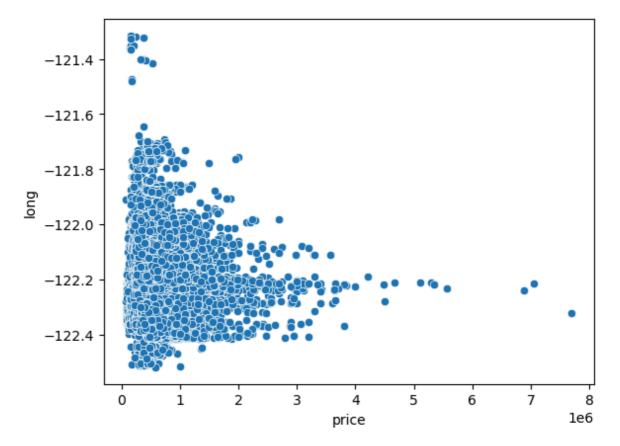


```
In [23]: sns.boxplot(x='bedrooms', y='price', data=df)
```

Out[23]: <Axes: xlabel='bedrooms', ylabel='price'>

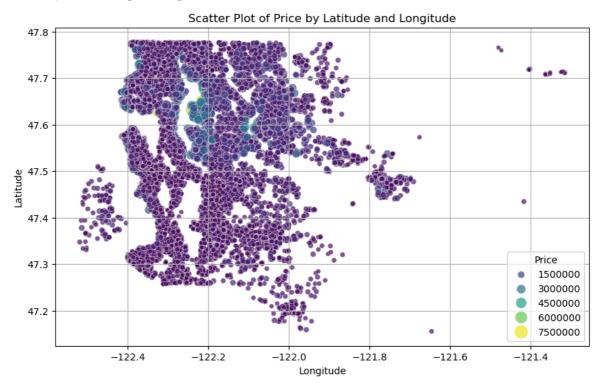


file:///C:/work/issue/house-price-predictions-using-deep-learning.html



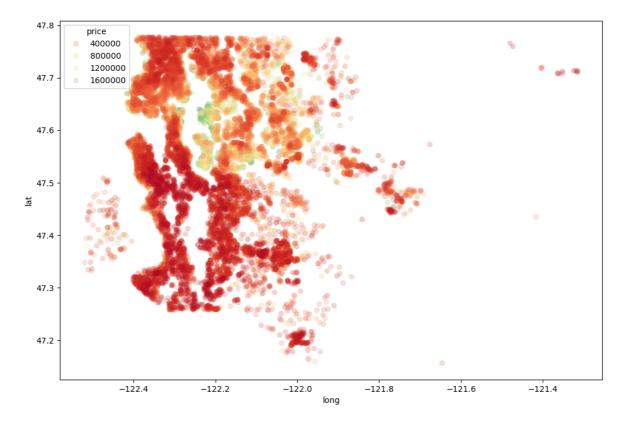
```
In [117... plt.figure(figsize=(10, 6))
    sns.scatterplot(data=df, x='long', y='lat', hue='price',palette='viridis', size=
    plt.title('Scatter Plot of Price by Latitude and Longitude')
    plt.xlabel('Longitude')
    plt.ylabel('Latitude')
    plt.grid()
    plt.legend(title='Price')
```

Out[117... <matplotlib.legend.Legend at 0x1afc5254da0>



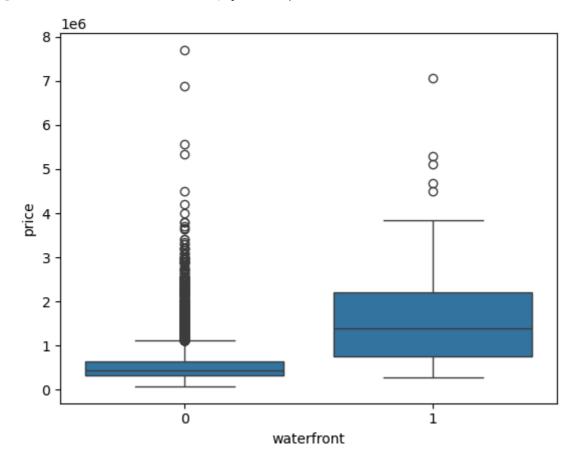
In [31]: df.sort_values('price', ascending=False).head(20)

Out[31]:		id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	wate			
	7245	6762700020	7700000.0	6	8.00	12050	27600	2.5				
	3910	9808700762	7060000.0	5	4.50	10040	37325	2.0				
	9245	9208900037	6890000.0	6	7.75	9890	31374	2.0				
	4407	2470100110	5570000.0	5	5.75	9200	35069	2.0				
	1446	8907500070	5350000.0	5	5.00	8000	23985	2.0				
	1313	7558700030	5300000.0	6	6.00	7390	24829	2.0				
	1162	1247600105	5110000.0	5	5.25	8010	45517	2.0				
	8085	1924059029	4670000.0	5	6.75	9640	13068	1.0				
	2624	7738500731	4500000.0	5	5.50	6640	40014	2.0				
	8629	3835500195	4490000.0	4	3.00	6430	27517	2.0				
	12358	6065300370	4210000.0	5	6.00	7440	21540	2.0				
	4145	6447300265	4000000.0	4	5.50	7080	16573	2.0				
	2083	8106100105	3850000.0	4	4.25	5770	21300	2.0				
	7028	853200010	3800000.0	5	5.50	7050	42840	1.0				
	19002	2303900100	3800000.0	3	4.25	5510	35000	2.0				
	16288	7397300170	3710000.0	4	3.50	5550	28078	2.0				
	18467	4389201095	3650000.0	5	3.75	5020	8694	2.0				
	6502	4217402115	3650000.0	6	4.75	5480	19401	1.5				
	15241	2425049063	3640000.0	4	3.25	4830	22257	2.0				
	19133	3625049042	3640000.0	5	6.00	5490	19897	2.0				
	4								•			
In [35]:	len(df)*0.01										
Out[35]:												
In [37]:	<pre># let's drop bottom 1% which are not densed non_top_1_perc = df.sort_values('price', ascending=False).iloc[216:]</pre>											
In [43]:	<pre>plt.figure(figsize=(12,8)) sns.scatterplot(x='long', y='lat', data=non_top_1_perc, edgecolor=None, alpha=0.</pre>											
Out[43]:	<axes:< th=""><th>xlabel='lor</th><th>ng', ylabel</th><th>='lat'></th><th></th><th></th><th></th><th></th><th></th></axes:<>	xlabel='lor	ng', ylabel	='lat'>								



In [45]: sns.boxplot(x='waterfront', y='price', data=df)

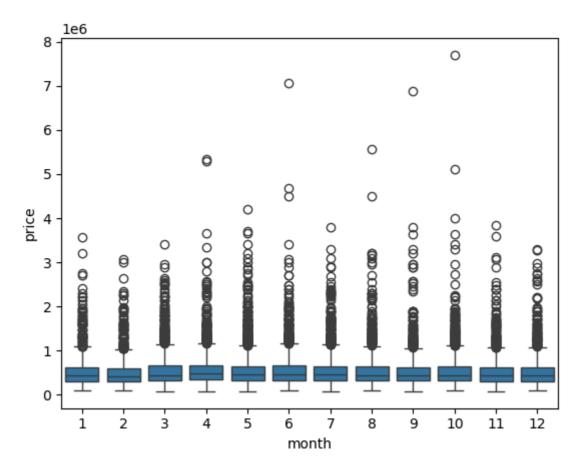
Out[45]: <Axes: xlabel='waterfront', ylabel='price'>



In [47]: #The above chart show if you are on waterfront; you house is more likely expensi
In [49]: df.head()

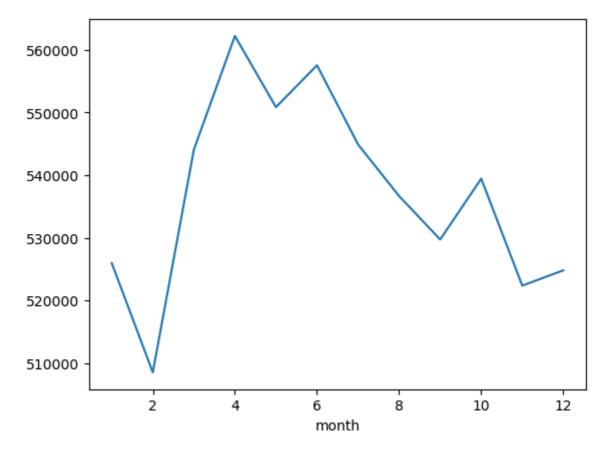
```
Out[49]:
                     id
                            price bedrooms bathrooms sqft_living sqft_lot floors waterfront
          0 7129300520 221900.0
                                           3
                                                    1.00
                                                              1180
                                                                       5650
                                                                                1.0
                                                                                             (
          1 6414100192 538000.0
                                           3
                                                    2.25
                                                              2570
                                                                       7242
                                                                                2.0
                                                                                             (
            5631500400 180000.0
                                           2
                                                    1.00
                                                               770
                                                                      10000
                                                                                1.0
                                                                                             (
             2487200875 604000.0
                                                    3.00
                                                              1960
                                                                       5000
                                                                                1.0
                                                                                             (
             1954400510 510000.0
                                           3
                                                    2.00
                                                              1680
                                                                       8080
                                                                                1.0
                                                                                             (
In [53]:
         #Let's remove the not used features from the dataset; for example id is not used
         df = pd.read_csv('./data/DATA/kc_house_data.csv')
 In [8]:
         df.head()
 In [9]:
 Out[9]:
                     id
                               date
                                        price bedrooms bathrooms sqft_living sqft_lot floors
          0 7129300520 10/13/2014 221900.0
                                                      3
                                                               1.00
                                                                          1180
                                                                                   5650
                                                                                           1.0
          1 6414100192
                          12/9/2014 538000.0
                                                      3
                                                               2.25
                                                                          2570
                                                                                   7242
                                                                                           2.0
                          2/25/2015 180000.0
                                                      2
                                                                                  10000
          2 5631500400
                                                               1.00
                                                                           770
                                                                                           1.0
                                                                3.00
                                                                                   5000
          3 2487200875
                          12/9/2014 604000.0
                                                                          1960
                                                                                           1.0
                                                                          1680
                          2/18/2015 510000.0
                                                      3
                                                               2.00
                                                                                   8080
            1954400510
                                                                                           1.0
         df = df.drop('id', axis=1)
In [10]:
In [11]: df['date']
Out[11]: 0
                   10/13/2014
          1
                    12/9/2014
          2
                    2/25/2015
          3
                    12/9/2014
          4
                    2/18/2015
          21592
                    5/21/2014
          21593
                    2/23/2015
          21594
                    6/23/2014
          21595
                    1/16/2015
          21596
                   10/15/2014
          Name: date, Length: 21597, dtype: object
In [12]: df['date'] = pd.to_datetime(df['date'])
In [13]: df['date']
```

```
Out[13]: 0
                  2014-10-13
          1
                  2014-12-09
                  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 [14]: df['year'] = df['date'].apply(lambda date: date.year)
          df['month'] = df['date'].apply(lambda date: date.month)
         df.head()
In [15]:
Out[15]:
              date
                       price
                             bedrooms bathrooms sqft_living sqft_lot floors waterfront
             2014-
                    221900.0
                                      3
                                               1.00
                                                          1180
                                                                   5650
                                                                           1.0
                                                                                         0
             10-13
             2014-
                    538000.0
                                      3
                                               2.25
                                                          2570
                                                                  7242
                                                                           2.0
             12-09
             2015-
                                                                                         0
          2
                    180000.0
                                      2
                                               1.00
                                                           770
                                                                  10000
                                                                           1.0
             02-25
             2014-
                    604000.0
                                               3.00
                                                          1960
                                                                   5000
                                                                           1.0
             12-09
             2015-
                                                                                         0
                    510000.0
                                      3
                                               2.00
                                                          1680
                                                                   0808
                                                                           1.0
             02-18
          #Let's explore if months column have impact on house prices
In [77]:
          sns.boxplot(x='month', y='price', data=df)
Out[16]: <Axes: xlabel='month', ylabel='price'>
```

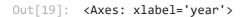


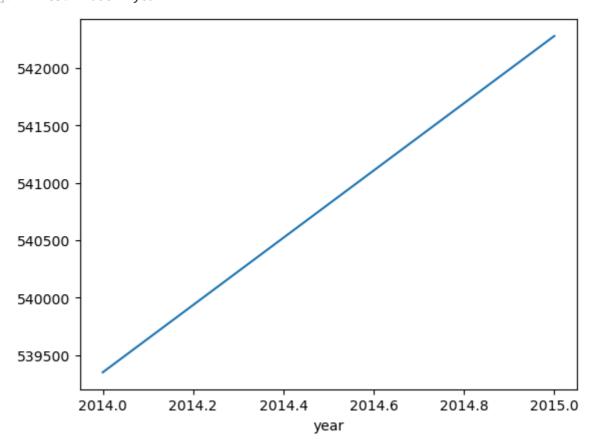
```
In [17]:
         df.groupby('month').mean()['price']
Out[17]:
          month
          1
                525963.251534
          2
                508520.051323
          3
                544057.683200
          4
                562215.615074
          5
                550849.746893
          6
                557534.318182
          7
                544892.161013
          8
                536655.212481
          9
                529723.517787
          10
                539439.447228
          11
                522359.903478
                524799.902041
          Name: price, dtype: float64
In [18]:
         df.groupby('month').mean()['price'].plot()
```

Out[18]: <Axes: xlabel='month'>



In [85]: #Looks like some difference in price particularly in months from mar to jun; cou
In [19]: df.groupby('year').mean()['price'].plot()





```
df = df.drop('date', axis=1)
In [20]:
         df.head()
In [21]:
Out[21]:
                price bedrooms bathrooms sqft_living sqft_lot floors waterfront view
                                                                                          conc
          0 221900.0
                                        1.00
                                                                                       0
                               3
                                                  1180
                                                           5650
                                                                    1.0
                                                                                 0
          1 538000.0
                               3
                                        2.25
                                                  2570
                                                           7242
                                                                    2.0
                                                                                 0
                                                                                       0
          2 180000.0
                                                                                 0
                               2
                                        1.00
                                                   770
                                                          10000
                                                                    1.0
                                                                                       0
          3 604000.0
                               4
                                        3.00
                                                  1960
                                                           5000
                                                                    1.0
                                                                                 0
                                                                                       0
                                                           8080
                                                                                 0
                                                                                       0
            510000.0
                               3
                                        2.00
                                                  1680
                                                                    1.0
         df['zipcode'].value_counts()
In [22]:
Out[22]: zipcode
          98103
                   602
          98038
                   589
          98115
                   583
          98052
                   574
          98117
                   553
                   . . .
          98102
                   104
          98010
                   100
          98024
                   80
          98148
                    57
                    50
          98039
          Name: count, Length: 70, dtype: int64
In [95]: #Looks like we have 70 unique zipcodes
In [23]:
         df = df.drop('zipcode', axis=1)
In [24]: df['yr_renovated'].value_counts()
Out[24]: yr_renovated
                  20683
          2014
                     91
          2013
                      37
          2003
                      36
          2005
                      35
          1951
                      1
          1959
                      1
          1948
                      1
          1954
                       1
          1944
          Name: count, Length: 70, dtype: int64
In [25]: df['sqft_basement'].value_counts()
```

```
Out[25]: sqft_basement
          0
                 13110
          600
                   221
          700
                   218
          500
                   214
                   206
          800
          518
                     1
          374
                     1
          784
                     1
          906
          248
                     1
          Name: count, Length: 306, dtype: int64
```

Data Processing and Creating a Model

```
In [26]: X = df.drop('price', axis=1)
         y = df['price'].values
In [27]: from sklearn.model_selection import train_test_split
In [28]: X_train, X_test, y_train, y_test = train_test_split( X, y, test_size=0.3, random
In [29]: from sklearn.preprocessing import MinMaxScaler
In [30]: scaler = MinMaxScaler()
In [31]: X_train = scaler.fit_transform(X_train)
In [32]: X_test = scaler.transform(X_test)
In [33]: from tensorflow.keras.models import Sequential
         from tensorflow.keras.layers import Dense
In [34]: X_train.shape
Out[34]: (15117, 19)
In [35]: #Looks like we have 19 incoming features; we can have 19 neurons in our model
In [36]: model = Sequential()
In [37]: model.add(Dense(19, activation='relu'))
         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')
In [39]: #we are training with X train and Y train as we are going we are testing with our
         model.fit(x=X_train, y= y_train, validation_data=(X_test, y_test), batch_size=12
```

```
Epoch 1/400
- val_loss: 418869116928.0000
Epoch 2/400
- val loss: 412023783424.0000
Epoch 3/400
- val_loss: 351211945984.0000
Epoch 4/400
- val loss: 182568239104.0000
Epoch 5/400
- val_loss: 96513089536.0000
Epoch 6/400
val loss: 93865385984.0000
Epoch 7/400
119/119 [=============] - 1s 7ms/step - loss: 95982641152.0000 -
val loss: 92092260352.0000
Epoch 8/400
val loss: 90259668992.0000
Epoch 9/400
val loss: 88486961152.0000
Epoch 10/400
val loss: 86527778816.0000
Epoch 11/400
val_loss: 84556652544.0000
Epoch 12/400
val loss: 82518138880.0000
Epoch 13/400
val loss: 80397647872.0000
Epoch 14/400
val loss: 78200586240.0000
Epoch 15/400
val loss: 75886772224.0000
Epoch 16/400
val loss: 73466527744.0000
Epoch 17/400
val loss: 70919774208.0000
Epoch 18/400
val loss: 68452839424.0000
Epoch 19/400
val loss: 65737445376.0000
Epoch 20/400
val loss: 63151091712.0000
```

```
Epoch 21/400
val_loss: 60591603712.0000
Epoch 22/400
val loss: 58286465024.0000
Epoch 23/400
val_loss: 56192286720.0000
Epoch 24/400
val loss: 54369271808.0000
Epoch 25/400
val loss: 52908310528.0000
Epoch 26/400
val loss: 51597168640.0000
Epoch 27/400
val loss: 50562203648.0000
Epoch 28/400
val loss: 49722724352.0000
Epoch 29/400
val loss: 48927887360.0000
Epoch 30/400
val loss: 48401408000.0000
Epoch 31/400
val_loss: 47686627328.0000
Epoch 32/400
val loss: 47198801920.0000
Epoch 33/400
val loss: 46709616640.0000
Epoch 34/400
val loss: 46209531904.0000
Epoch 35/400
val loss: 45769699328.0000
Epoch 36/400
val loss: 45325733888.0000
Epoch 37/400
val loss: 44977508352.0000
Epoch 38/400
val loss: 44487622656.0000
Epoch 39/400
val loss: 44100378624.0000
Epoch 40/400
val loss: 43615334400.0000
```

```
Epoch 41/400
val_loss: 43222396928.0000
Epoch 42/400
val loss: 42852786176.0000
Epoch 43/400
val_loss: 42462482432.0000
Epoch 44/400
- val loss: 42173083648.0000
Epoch 45/400
- val_loss: 41695920128.0000
Epoch 46/400
val loss: 41479053312.0000
Epoch 47/400
val loss: 40987467776.0000
Epoch 48/400
val loss: 40736378880.0000
Epoch 49/400
val loss: 40427692032.0000
Epoch 50/400
val loss: 40087703552.0000
Epoch 51/400
val_loss: 39831789568.0000
Epoch 52/400
val loss: 39624749056.0000
Epoch 53/400
val loss: 39361155072.0000
Epoch 54/400
val loss: 39144529920.0000
Epoch 55/400
val loss: 38899802112.0000
Epoch 56/400
val loss: 38647287808.0000
Epoch 57/400
val loss: 38396284928.0000
Epoch 58/400
- val loss: 38117515264.0000
Epoch 59/400
- val loss: 37948841984.0000
Epoch 60/400
val loss: 37583585280.0000
```

```
Epoch 61/400
val_loss: 37331521536.0000
Epoch 62/400
val loss: 37118603264.0000
Epoch 63/400
val_loss: 36913582080.0000
Epoch 64/400
- val loss: 36738891776.0000
Epoch 65/400
- val loss: 36593623040.0000
Epoch 66/400
val loss: 36476366848.0000
Epoch 67/400
val loss: 36251181056.0000
Epoch 68/400
val loss: 36083511296.0000
Epoch 69/400
val_loss: 35928285184.0000
Epoch 70/400
val loss: 35884253184.0000
Epoch 71/400
val_loss: 35636834304.0000
Epoch 72/400
val loss: 35464351744.0000
Epoch 73/400
val loss: 35330916352.0000
Epoch 74/400
val loss: 35185799168.0000
Epoch 75/400
val loss: 35101319168.0000
Epoch 76/400
val loss: 34920103936.0000
Epoch 77/400
val loss: 34828750848.0000
Epoch 78/400
val loss: 34689495040.0000
Epoch 79/400
- val loss: 34616602624.0000
Epoch 80/400
val loss: 34601730048.0000
```

```
Epoch 81/400
val_loss: 34369662976.0000
Epoch 82/400
- val loss: 34279559168.0000
Epoch 83/400
val_loss: 34223200256.0000
Epoch 84/400
val loss: 34079336448.0000
Epoch 85/400
val loss: 34049181696.0000
Epoch 86/400
val loss: 33895854080.0000
Epoch 87/400
val loss: 33825898496.0000
Epoch 88/400
val loss: 33750310912.0000
Epoch 89/400
val_loss: 33658281984.0000
Epoch 90/400
val loss: 33648007168.0000
Epoch 91/400
val_loss: 33563062272.0000
Epoch 92/400
val loss: 33501816832.0000
Epoch 93/400
val loss: 33405841408.0000
Epoch 94/400
val loss: 33329440768.0000
Epoch 95/400
val loss: 33286666240.0000
Epoch 96/400
val loss: 33219815424.0000
Epoch 97/400
val loss: 33173817344.0000
Epoch 98/400
val loss: 33087862784.0000
Epoch 99/400
val loss: 33048485888.0000
Epoch 100/400
val loss: 32969052160.0000
```

```
Epoch 101/400
val_loss: 32923283456.0000
Epoch 102/400
val loss: 33011257344.0000
Epoch 103/400
val_loss: 32806787072.0000
Epoch 104/400
val loss: 33127395328.0000
Epoch 105/400
119/119 [=============] - 1s 5ms/step - loss: 34005448704.0000 -
val loss: 32687581184.0000
Epoch 106/400
val loss: 32766820352.0000
Epoch 107/400
val loss: 32611862528.0000
Epoch 108/400
val loss: 32539115520.0000
Epoch 109/400
val loss: 32475908096.0000
Epoch 110/400
val loss: 32427218944.0000
Epoch 111/400
val_loss: 32375156736.0000
Epoch 112/400
val loss: 32364267520.0000
Epoch 113/400
val loss: 32275073024.0000
Epoch 114/400
val loss: 32298866688.0000
Epoch 115/400
val loss: 32177739776.0000
Epoch 116/400
val loss: 32253571072.0000
Epoch 117/400
val loss: 32078161920.0000
Epoch 118/400
val loss: 32014864384.0000
Epoch 119/400
val loss: 32053067776.0000
Epoch 120/400
val loss: 31931230208.0000
```

```
Epoch 121/400
val_loss: 31966662656.0000
Epoch 122/400
val loss: 31855583232.0000
Epoch 123/400
val_loss: 31797803008.0000
Epoch 124/400
val loss: 31806201856.0000
Epoch 125/400
val loss: 31703242752.0000
Epoch 126/400
val loss: 31633391616.0000
Epoch 127/400
val loss: 31680096256.0000
Epoch 128/400
val loss: 31558150144.0000
Epoch 129/400
- val_loss: 31597058048.0000
Epoch 130/400
- val loss: 31483781120.0000
Epoch 131/400
- val_loss: 31509493760.0000
Epoch 132/400
119/119 [============= ] - 3s 24ms/step - loss: 32833609728.0000
- val loss: 31528603648.0000
Epoch 133/400
val loss: 31368142848.0000
Epoch 134/400
val loss: 31342374912.0000
Epoch 135/400
- val loss: 31298865152.0000
Epoch 136/400
val loss: 31271712768.0000
Epoch 137/400
val loss: 31233558528.0000
Epoch 138/400
val loss: 31194402816.0000
Epoch 139/400
val loss: 31164375040.0000
Epoch 140/400
val loss: 31168419840.0000
```

```
Epoch 141/400
val_loss: 31093952512.0000
Epoch 142/400
val loss: 31065694208.0000
Epoch 143/400
val_loss: 31029762048.0000
Epoch 144/400
val loss: 31008284672.0000
Epoch 145/400
val loss: 31051726848.0000
Epoch 146/400
val loss: 30952833024.0000
Epoch 147/400
val loss: 30922160128.0000
Epoch 148/400
val loss: 30899970048.0000
Epoch 149/400
val loss: 30882324480.0000
Epoch 150/400
val loss: 30835156992.0000
Epoch 151/400
val_loss: 30778908672.0000
Epoch 152/400
val loss: 30762668032.0000
Epoch 153/400
val loss: 30743654400.0000
Epoch 154/400
val loss: 30723096576.0000
Epoch 155/400
val loss: 30745303040.0000
Epoch 156/400
val loss: 30652637184.0000
Epoch 157/400
val loss: 30664161280.0000
Epoch 158/400
val loss: 30629085184.0000
Epoch 159/400
val loss: 30579183616.0000
Epoch 160/400
val loss: 30545199104.0000
```

```
Epoch 161/400
val_loss: 30514358272.0000
Epoch 162/400
val loss: 30463551488.0000
Epoch 163/400
val_loss: 30449987584.0000
Epoch 164/400
val loss: 30452506624.0000
Epoch 165/400
val loss: 30383149056.0000
Epoch 166/400
val loss: 30450315264.0000
Epoch 167/400
val loss: 30341931008.0000
Epoch 168/400
val loss: 30309199872.0000
Epoch 169/400
val loss: 30284001280.0000
Epoch 170/400
val loss: 30313629696.0000
Epoch 171/400
val_loss: 30287165440.0000
Epoch 172/400
val loss: 30212847616.0000
Epoch 173/400
val loss: 30189543424.0000
Epoch 174/400
val loss: 30175961088.0000
Epoch 175/400
val loss: 30158286848.0000
Epoch 176/400
val loss: 30131431424.0000
Epoch 177/400
val loss: 30113859584.0000
Epoch 178/400
val loss: 30100174848.0000
Epoch 179/400
val loss: 30218889216.0000
Epoch 180/400
val loss: 30049886208.0000
```

```
Epoch 181/400
val_loss: 30083086336.0000
Epoch 182/400
val loss: 30039097344.0000
Epoch 183/400
val_loss: 29969352704.0000
Epoch 184/400
val loss: 29941870592.0000
Epoch 185/400
119/119 [============] - 1s 4ms/step - loss: 31606951936.0000 -
val loss: 29919055872.0000
Epoch 186/400
val loss: 29895421952.0000
Epoch 187/400
val loss: 29914818560.0000
Epoch 188/400
val loss: 29822705664.0000
Epoch 189/400
val loss: 29827422208.0000
Epoch 190/400
val loss: 29801164800.0000
Epoch 191/400
val_loss: 29818882048.0000
Epoch 192/400
val loss: 29741703168.0000
Epoch 193/400
val loss: 29800855552.0000
Epoch 194/400
val loss: 29706520576.0000
Epoch 195/400
val loss: 29695719424.0000
Epoch 196/400
val loss: 29680687104.0000
Epoch 197/400
val loss: 29719535616.0000
Epoch 198/400
val loss: 29691645952.0000
Epoch 199/400
val loss: 29609238528.0000
Epoch 200/400
val loss: 29564549120.0000
```

```
Epoch 201/400
val_loss: 29594306560.0000
Epoch 202/400
val loss: 29554597888.0000
Epoch 203/400
val_loss: 29528922112.0000
Epoch 204/400
val loss: 29529380864.0000
Epoch 205/400
val loss: 29553391616.0000
Epoch 206/400
val loss: 29636616192.0000
Epoch 207/400
val loss: 29466533888.0000
Epoch 208/400
val loss: 29496162304.0000
Epoch 209/400
val loss: 29430577152.0000
Epoch 210/400
val loss: 29413314560.0000
Epoch 211/400
val_loss: 29381892096.0000
Epoch 212/400
val loss: 29530583040.0000
Epoch 213/400
val loss: 29354981376.0000
Epoch 214/400
val loss: 29355716608.0000
Epoch 215/400
val loss: 29305536512.0000
Epoch 216/400
val loss: 29309642752.0000
Epoch 217/400
val loss: 29286580224.0000
Epoch 218/400
val loss: 29294034944.0000
Epoch 219/400
val loss: 29249888256.0000
Epoch 220/400
val loss: 29247606784.0000
```

```
Epoch 221/400
val_loss: 29334720512.0000
Epoch 222/400
val loss: 29198997504.0000
Epoch 223/400
val_loss: 29191364608.0000
Epoch 224/400
val loss: 29183692800.0000
Epoch 225/400
119/119 [============= ] - 1s 5ms/step - loss: 30911199232.0000 -
val loss: 29144514560.0000
Epoch 226/400
val loss: 29151963136.0000
Epoch 227/400
val loss: 29139625984.0000
Epoch 228/400
val loss: 29148968960.0000
Epoch 229/400
val_loss: 29110351872.0000
Epoch 230/400
val loss: 29099855872.0000
Epoch 231/400
val_loss: 29053091840.0000
Epoch 232/400
val loss: 29030682624.0000
Epoch 233/400
val loss: 29023682560.0000
Epoch 234/400
val loss: 28983613440.0000
Epoch 235/400
val loss: 28968429568.0000
Epoch 236/400
val loss: 28962312192.0000
Epoch 237/400
val loss: 28989222912.0000
Epoch 238/400
val loss: 28941160448.0000
Epoch 239/400
val loss: 28908890112.0000
Epoch 240/400
val loss: 28902471680.0000
```

```
Epoch 241/400
val_loss: 28898885632.0000
Epoch 242/400
val loss: 28924588032.0000
Epoch 243/400
val_loss: 28870033408.0000
Epoch 244/400
val loss: 28894676992.0000
Epoch 245/400
val loss: 28850401280.0000
Epoch 246/400
val loss: 28903368704.0000
Epoch 247/400
val loss: 28814772224.0000
Epoch 248/400
val loss: 28898070528.0000
Epoch 249/400
val loss: 28829743104.0000
Epoch 250/400
val loss: 28758986752.0000
Epoch 251/400
val_loss: 28775962624.0000
Epoch 252/400
val loss: 28746268672.0000
Epoch 253/400
val loss: 28802617344.0000
Epoch 254/400
val loss: 28736919552.0000
Epoch 255/400
val loss: 28883173376.0000
Epoch 256/400
val loss: 28713762816.0000
Epoch 257/400
val loss: 28700708864.0000
Epoch 258/400
val loss: 28650997760.0000
Epoch 259/400
val loss: 28653819904.0000
Epoch 260/400
val loss: 28644521984.0000
```

```
Epoch 261/400
val_loss: 28643407872.0000
Epoch 262/400
val loss: 28613142528.0000
Epoch 263/400
val_loss: 28611221504.0000
Epoch 264/400
val loss: 28564111360.0000
Epoch 265/400
val loss: 28565032960.0000
Epoch 266/400
val loss: 28729270272.0000
Epoch 267/400
val loss: 28609914880.0000
Epoch 268/400
val loss: 28547471360.0000
Epoch 269/400
val loss: 28604811264.0000
Epoch 270/400
val loss: 28499828736.0000
Epoch 271/400
val_loss: 28462821376.0000
Epoch 272/400
val loss: 28568539136.0000
Epoch 273/400
val loss: 28604723200.0000
Epoch 274/400
val loss: 28450680832.0000
Epoch 275/400
val loss: 28477775872.0000
Epoch 276/400
val loss: 28442464256.0000
Epoch 277/400
val loss: 28439975936.0000
Epoch 278/400
val loss: 28365785088.0000
Epoch 279/400
val loss: 28331008000.0000
Epoch 280/400
val loss: 28344576000.0000
```

```
Epoch 281/400
val_loss: 28292040704.0000
Epoch 282/400
val loss: 28341043200.0000
Epoch 283/400
val_loss: 28379758592.0000
Epoch 284/400
val loss: 28279928832.0000
Epoch 285/400
119/119 [============] - 1s 5ms/step - loss: 30257784832.0000 -
val loss: 28263133184.0000
Epoch 286/400
val loss: 28313931776.0000
Epoch 287/400
val loss: 28339144704.0000
Epoch 288/400
val loss: 28227037184.0000
Epoch 289/400
val loss: 28204845056.0000
Epoch 290/400
val loss: 28191942656.0000
Epoch 291/400
val_loss: 28288851968.0000
Epoch 292/400
val loss: 28158351360.0000
Epoch 293/400
val loss: 28219623424.0000
Epoch 294/400
val loss: 28272214016.0000
Epoch 295/400
val loss: 28137664512.0000
Epoch 296/400
val loss: 28168501248.0000
Epoch 297/400
val loss: 28128397312.0000
Epoch 298/400
val loss: 28087060480.0000
Epoch 299/400
val loss: 28209532928.0000
Epoch 300/400
val loss: 28169113600.0000
```

```
Epoch 301/400
val_loss: 28060504064.0000
Epoch 302/400
val loss: 28018849792.0000
Epoch 303/400
val_loss: 28018819072.0000
Epoch 304/400
val loss: 28054644736.0000
Epoch 305/400
119/119 [============= ] - 0s 4ms/step - loss: 30050330624.0000 -
val loss: 28002387968.0000
Epoch 306/400
val loss: 27977652224.0000
Epoch 307/400
val loss: 27955832832.0000
Epoch 308/400
val loss: 27929036800.0000
Epoch 309/400
val_loss: 27971868672.0000
Epoch 310/400
val loss: 27897147392.0000
Epoch 311/400
val_loss: 27892289536.0000
Epoch 312/400
val loss: 27900581888.0000
Epoch 313/400
val loss: 27888994304.0000
Epoch 314/400
val loss: 27835164672.0000
Epoch 315/400
val loss: 27839469568.0000
Epoch 316/400
val loss: 27851188224.0000
Epoch 317/400
val loss: 27913805824.0000
Epoch 318/400
val loss: 27856889856.0000
Epoch 319/400
val loss: 27778834432.0000
Epoch 320/400
val loss: 27796140032.0000
```

```
Epoch 321/400
val_loss: 27744749568.0000
Epoch 322/400
val loss: 27730112512.0000
Epoch 323/400
val_loss: 27708731392.0000
Epoch 324/400
val loss: 27685570560.0000
Epoch 325/400
119/119 [============] - Os 4ms/step - loss: 29812836352.0000 -
val loss: 27713470464.0000
Epoch 326/400
val loss: 27707422720.0000
Epoch 327/400
val loss: 27619162112.0000
Epoch 328/400
val loss: 27659737088.0000
Epoch 329/400
val_loss: 27620218880.0000
Epoch 330/400
val loss: 27621541888.0000
Epoch 331/400
val_loss: 27610017792.0000
Epoch 332/400
val loss: 27645659136.0000
Epoch 333/400
val loss: 27615612928.0000
Epoch 334/400
val loss: 27560069120.0000
Epoch 335/400
val loss: 27543631872.0000
Epoch 336/400
val loss: 27664838656.0000
Epoch 337/400
val loss: 27570425856.0000
Epoch 338/400
val loss: 27524079616.0000
Epoch 339/400
val loss: 27459876864.0000
Epoch 340/400
val loss: 27461003264.0000
```

```
Epoch 341/400
val_loss: 27445792768.0000
Epoch 342/400
val loss: 27415463936.0000
Epoch 343/400
val_loss: 27420489728.0000
Epoch 344/400
val loss: 27404521472.0000
Epoch 345/400
val loss: 27397533696.0000
Epoch 346/400
val loss: 27385352192.0000
Epoch 347/400
val loss: 27425802240.0000
Epoch 348/400
val loss: 27323510784.0000
Epoch 349/400
val_loss: 27323801600.0000
Epoch 350/400
val loss: 27300016128.0000
Epoch 351/400
val_loss: 27296124928.0000
Epoch 352/400
val loss: 27268374528.0000
Epoch 353/400
val loss: 27259545600.0000
Epoch 354/400
val loss: 27261282304.0000
Epoch 355/400
val loss: 27280281600.0000
Epoch 356/400
val loss: 27243053056.0000
Epoch 357/400
val loss: 27214211072.0000
Epoch 358/400
val loss: 27314202624.0000
Epoch 359/400
val loss: 27199569920.0000
Epoch 360/400
val loss: 27185453056.0000
```

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Epoch 361/400
val_loss: 27145857024.0000
Epoch 362/400
val loss: 27163344896.0000
Epoch 363/400
val_loss: 27215624192.0000
Epoch 364/400
val loss: 27180982272.0000
Epoch 365/400
119/119 [=============] - 1s 4ms/step - loss: 29369016320.0000 -
val loss: 27100227584.0000
Epoch 366/400
val loss: 27067555840.0000
Epoch 367/400
val loss: 27114795008.0000
Epoch 368/400
val loss: 27076849664.0000
Epoch 369/400
val_loss: 27021608960.0000
Epoch 370/400
val loss: 27087237120.0000
Epoch 371/400
val_loss: 27009830912.0000
Epoch 372/400
val loss: 27032248320.0000
Epoch 373/400
val loss: 26993924096.0000
Epoch 374/400
val loss: 26943868928.0000
Epoch 375/400
val loss: 26957867008.0000
Epoch 376/400
val loss: 26956025856.0000
Epoch 377/400
val loss: 26926837760.0000
Epoch 378/400
val loss: 26899798016.0000
Epoch 379/400
val loss: 26891044864.0000
Epoch 380/400
val loss: 26906265600.0000
```

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Epoch 381/400
val_loss: 27044317184.0000
Epoch 382/400
val loss: 26889832448.0000
Epoch 383/400
val_loss: 26876710912.0000
Epoch 384/400
val loss: 26849505280.0000
Epoch 385/400
val loss: 26845274112.0000
Epoch 386/400
val loss: 26792908800.0000
Epoch 387/400
val loss: 26814840832.0000
Epoch 388/400
val loss: 26800984064.0000
Epoch 389/400
val loss: 26847027200.0000
Epoch 390/400
val loss: 26800373760.0000
Epoch 391/400
val_loss: 26792017920.0000
Epoch 392/400
val loss: 26773809152.0000
Epoch 393/400
val loss: 26767071232.0000
Epoch 394/400
val loss: 26721871872.0000
Epoch 395/400
val loss: 26721095680.0000
Epoch 396/400
val loss: 26786631680.0000
Epoch 397/400
val loss: 26691946496.0000
Epoch 398/400
val loss: 26672660480.0000
Epoch 399/400
val loss: 26731476992.0000
Epoch 400/400
val loss: 26709970944.0000
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Out[39]: <keras.callbacks.History at 0x115ac7155e0>

Model Evaluation and Predictions

In [41]: # we can get histrory of those Losses
model.history.history

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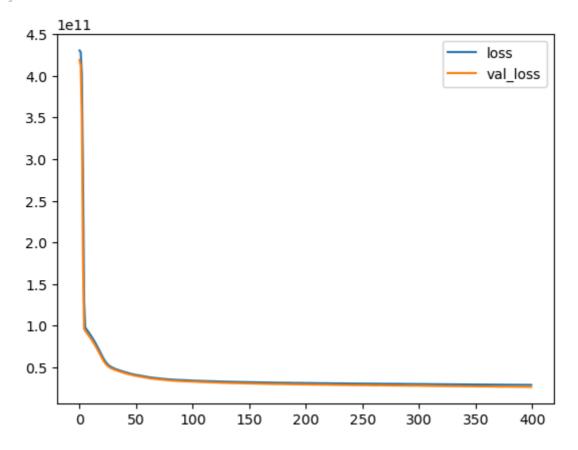
27744749568.0. 27730112512.0, 27708731392.0, 27685570560.0, 27713470464.0, 27707422720.0, 27619162112.0, 27659737088.0, 27620218880.0, 27621541888.0, 27610017792.0, 27645659136.0. 27615612928.0, 27560069120.0, 27543631872.0, 27664838656.0, 27570425856.0, 27524079616.0, 27459876864.0, 27461003264.0, 27445792768.0, 27415463936.0, 27420489728.0, 27404521472.0, 27397533696.0. 27385352192.0, 27425802240.0, 27323510784.0, 27323801600.0, 27300016128.0, 27296124928.0, 27268374528.0, 27259545600.0, 27261282304.0, 27280281600.0, 27243053056.0, 27214211072.0, 27314202624.0, 27199569920.0, 27185453056.0, 27145857024.0, 27163344896.0, 27215624192.0, 27180982272.0, 27100227584.0, 27067555840.0, 27114795008.0, 27076849664.0, 27021608960.0, 27087237120.0, 27009830912.0, 27032248320.0, 26993924096.0, 26943868928.0, 26957867008.0, 26956025856.0, 26926837760.0, 26899798016.0, 26891044864.0, 26906265600.0,

```
27044317184.0,
26889832448.0,
26876710912.0,
26849505280.0,
26845274112.0,
26792908800.0,
26814840832.0,
26800984064.0,
26847027200.0,
26800373760.0,
26792017920.0,
26773809152.0,
26767071232.0,
26721871872.0,
26721095680.0,
26786631680.0,
26691946496.0,
26672660480.0,
26731476992.0,
26709970944.0]}
```

In [42]: # since we requested validation it will provide the validation losses too; in t
In order to see if i'm overfitting the model
losses = pd.DataFrame(model.history.history)

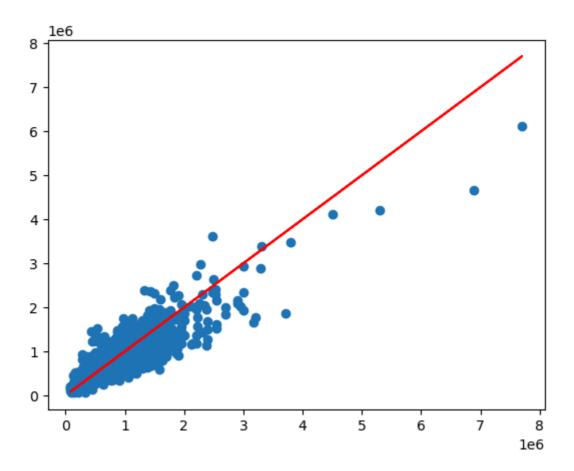
In [43]: losses.plot()

Out[43]: <Axes: >



In [45]: #There is decrease in training loss and validation loss and are aligned
In [46]: from sklearn.metrics import mean_squared_error, mean_absolute_error, explained_v

```
In [47]: predictions = model.predict(X_test)
        203/203 [========== ] - 1s 2ms/step
In [49]: np.sqrt(mean_squared_error(y_test, predictions))
Out[49]: 163431.8572873087
In [50]: mean_absolute_error(y_test, predictions)
Out[50]: 100860.74822832273
In [51]: df['price'].describe()
                 2.159700e+04
Out[51]: count
         mean
                5.402966e+05
                3.673681e+05
         std
         min
                 7.800000e+04
         25%
                3.220000e+05
                4.500000e+05
         50%
         75%
                6.450000e+05
         max
                  7.700000e+06
         Name: price, dtype: float64
In [52]: 5.402966e+05
Out[52]: 540296.6
In [53]: # The average house price is around 540296.6 and our mean absolute error is arou
In [55]: #Best possible score is 1.0, lower values are worse.
         explained_variance_score(y_test, predictions)
Out[55]: 0.7991671867223884
In [57]: plt.scatter(y test, predictions)
         plt.plot(y_test, y_test, 'r')
Out[57]: [<matplotlib.lines.Line2D at 0x115b2ebf370>]
```



In [58]: #In the above the red line represent the best or prefect predicition line. we ar

In [59]: # It is worth retrain our model

In [60]:	df								
Out[60]:		price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view
	0	221900.0	3	1.00	1180	5650	1.0	0	0
	1	538000.0	3	2.25	2570	7242	2.0	0	0
	2	180000.0	2	1.00	770	10000	1.0	0	0
	3	604000.0	4	3.00	1960	5000	1.0	0	0
	4	510000.0	3	2.00	1680	8080	1.0	0	0
	•••								
	21592	360000.0	3	2.50	1530	1131	3.0	0	0
	21593	400000.0	4	2.50	2310	5813	2.0	0	0
	21594	402101.0	2	0.75	1020	1350	2.0	0	0
	21595	400000.0	3	2.50	1600	2388	2.0	0	0
	21596	325000.0	2	0.75	1020	1076	2.0	0	0

21597 rows × 20 columns

```
In [66]: # The below are the only features of new house in the market
          single_house = df.drop('price', axis=1).iloc[0]
In [68]: single_house = scaler.transform(single_house.values.reshape(-1,19))
         C:\learnings\envs\deeplearning\lib\site-packages\sklearn\base.py:450: UserWarnin
         g: X does not have valid feature names, but MinMaxScaler was fitted with feature
         names
           warnings.warn(
In [69]: model.predict(single_house)
         1/1 [======] - 0s 28ms/step
Out[69]: array([[284654.5]], dtype=float32)
In [70]: df.head()
Out[70]:
                price bedrooms bathrooms sqft_living sqft_lot floors waterfront view
                                                                                        conc
          0 221900.0
                                        1.00
                                                  1180
                                                          5650
                                                                                0
                               3
                                                                   1.0
                                                                                      0
             538000.0
                                        2.25
                                                          7242
                               3
                                                  2570
                                                                   2.0
                                                                                0
                                                                                      0
          2 180000.0
                               2
                                        1.00
                                                          10000
                                                                                0
                                                                                      0
                                                   770
                                                                   1.0
          3 604000.0
                               4
                                        3.00
                                                  1960
                                                          5000
                                                                   1.0
                                                                                0
                                                                                      0
            510000.0
                                                  1680
                                                          8080
                                                                                0
                                                                                      0
                               3
                                        2.00
                                                                   1.0
In [72]:
          # The predicted price is 284654.5 vs the true price the house sold at 221900.0;
          #maybe that is causing the difference in price predictions
In [73]: #Let's train our model with dense data set by removing the rows whose house price
In [101...
          df filtered = df[df['price'] <= 800000]</pre>
In [102...
          from sklearn.model_selection import train_test_split
In [103...
          X = df filtered.drop('price', axis=1)
          y = df_filtered['price'].values
          X_train, X_test, y_train, y_test = train_test_split( X, y, test_size=0.3, random
In [104...
In [105...
          from sklearn.preprocessing import MinMaxScaler
In [106...
          scaler = MinMaxScaler()
In [107...
          X train = scaler.fit transform(X train)
In [108...
          X test = scaler.transform(X test)
In [109...
          from tensorflow.keras.models import Sequential
          from tensorflow.keras.layers import Dense
```

```
Epoch 1/400
- val_loss: 215550246912.0000
Epoch 2/400
- val loss: 214020440064.0000
Epoch 3/400
- val_loss: 198722846720.0000
Epoch 4/400
- val loss: 139741446144.0000
Epoch 5/400
val loss: 48124514304.0000
Epoch 6/400
103/103 [============== ] - 1s 10ms/step - loss: 27254722560.0000
- val loss: 18281572352.0000
Epoch 7/400
103/103 [============] - 1s 6ms/step - loss: 17573953536.0000 -
val loss: 17602738176.0000
Epoch 8/400
val loss: 17449564160.0000
Epoch 9/400
val loss: 17286397952.0000
Epoch 10/400
val loss: 17122380800.0000
Epoch 11/400
val_loss: 16955503616.0000
Epoch 12/400
val loss: 16783939584.0000
Epoch 13/400
val loss: 16617796608.0000
Epoch 14/400
val loss: 16436444160.0000
Epoch 15/400
val loss: 16264392704.0000
Epoch 16/400
103/103 [============= ] - 1s 7ms/step - loss: 15951632384.0000 -
val loss: 16085978112.0000
Epoch 17/400
val loss: 15906924544.0000
Epoch 18/400
val loss: 15726090240.0000
Epoch 19/400
val loss: 15539074048.0000
Epoch 20/400
val_loss: 15350710272.0000
```

```
Epoch 21/400
val_loss: 15157758976.0000
Epoch 22/400
val loss: 14973270016.0000
Epoch 23/400
val_loss: 14782533632.0000
Epoch 24/400
val loss: 14593893376.0000
Epoch 25/400
val loss: 14395401216.0000
Epoch 26/400
val loss: 14196056064.0000
Epoch 27/400
103/103 [=============] - 0s 4ms/step - loss: 13853552640.0000 -
val loss: 13996697600.0000
Epoch 28/400
val loss: 13787321344.0000
Epoch 29/400
val_loss: 13584886784.0000
Epoch 30/400
val loss: 13376905216.0000
Epoch 31/400
val_loss: 13173563392.0000
Epoch 32/400
val loss: 12979771392.0000
Epoch 33/400
val loss: 12786670592.0000
Epoch 34/400
val loss: 12590886912.0000
Epoch 35/400
val loss: 12409454592.0000
Epoch 36/400
val loss: 12234571776.0000
Epoch 37/400
val loss: 12083973120.0000
Epoch 38/400
val loss: 11903341568.0000
Epoch 39/400
val loss: 11742703616.0000
Epoch 40/400
val loss: 11585056768.0000
```

```
Epoch 41/400
val_loss: 11449366528.0000
Epoch 42/400
val loss: 11317370880.0000
Epoch 43/400
val_loss: 11181192192.0000
Epoch 44/400
val loss: 11059989504.0000
Epoch 45/400
103/103 [============] - 1s 6ms/step - loss: 10693877760.0000 -
val loss: 10933777408.0000
Epoch 46/400
val loss: 10829475840.0000
Epoch 47/400
val loss: 10751511552.0000
Epoch 48/400
val loss: 10634304512.0000
Epoch 49/400
val_loss: 10556211200.0000
Epoch 50/400
val loss: 10470886400.0000
Epoch 51/400
val_loss: 10406519808.0000
Epoch 52/400
val loss: 10350864384.0000
Epoch 53/400
103/103 [============ ] - 0s 4ms/step - loss: 9970607104.0000 -
val loss: 10284964864.0000
Epoch 54/400
103/103 [============ ] - 0s 4ms/step - loss: 9881254912.0000 -
val loss: 10241559552.0000
Epoch 55/400
val loss: 10197325824.0000
Epoch 56/400
103/103 [============ ] - 0s 4ms/step - loss: 9786087424.0000 -
val loss: 10155897856.0000
Epoch 57/400
val loss: 10133726208.0000
Epoch 58/400
103/103 [============ ] - 1s 5ms/step - loss: 9705323520.0000 -
val loss: 10088614912.0000
Epoch 59/400
103/103 [============ ] - 0s 5ms/step - loss: 9672042496.0000 -
val loss: 10060905472.0000
Epoch 60/400
103/103 [============= ] - 1s 5ms/step - loss: 9653363712.0000 -
val loss: 10036908032.0000
```

```
Epoch 61/400
103/103 [============= ] - 0s 4ms/step - loss: 9618857984.0000 -
val_loss: 10017472512.0000
Epoch 62/400
103/103 [============ ] - 0s 4ms/step - loss: 9587422208.0000 -
val loss: 9989187584.0000
Epoch 63/400
val_loss: 9972257792.0000
Epoch 64/400
103/103 [============ ] - 0s 4ms/step - loss: 9542812672.0000 -
val loss: 9952494592.0000
Epoch 65/400
103/103 [============] - 0s 5ms/step - loss: 9526823936.0000 -
val loss: 9938455552.0000
Epoch 66/400
103/103 [=============== ] - 0s 5ms/step - loss: 9506157568.0000 -
val loss: 9933092864.0000
Epoch 67/400
103/103 [============] - 0s 4ms/step - loss: 9486940160.0000 -
val loss: 9908346880.0000
Epoch 68/400
103/103 [============ ] - 0s 4ms/step - loss: 9484725248.0000 -
val loss: 9894448128.0000
Epoch 69/400
103/103 [============== ] - 0s 5ms/step - loss: 9455128576.0000 -
val loss: 9874071552.0000
Epoch 70/400
103/103 [============ ] - 0s 4ms/step - loss: 9445681152.0000 -
val loss: 9865547776.0000
Epoch 71/400
103/103 [============ ] - 0s 5ms/step - loss: 9451170816.0000 -
val_loss: 9853997056.0000
Epoch 72/400
103/103 [============ ] - 1s 5ms/step - loss: 9423310848.0000 -
val loss: 9856588800.0000
Epoch 73/400
103/103 [============ ] - 1s 6ms/step - loss: 9408557056.0000 -
val loss: 9842800640.0000
Epoch 74/400
103/103 [============ ] - 1s 7ms/step - loss: 9390089216.0000 -
val loss: 9882070016.0000
Epoch 75/400
val loss: 9813881856.0000
Epoch 76/400
103/103 [=============] - 1s 7ms/step - loss: 9371114496.0000 -
val loss: 9819660288.0000
Epoch 77/400
val loss: 9793823744.0000
Epoch 78/400
103/103 [============ ] - 0s 4ms/step - loss: 9352450048.0000 -
val loss: 9819743232.0000
Epoch 79/400
103/103 [============ ] - 0s 4ms/step - loss: 9382492160.0000 -
val loss: 9780751360.0000
Epoch 80/400
103/103 [============= ] - 0s 4ms/step - loss: 9339479040.0000 -
val_loss: 9779832832.0000
```

```
Epoch 81/400
103/103 [============= ] - 0s 4ms/step - loss: 9335874560.0000 -
val_loss: 9762881536.0000
Epoch 82/400
103/103 [============ ] - 0s 4ms/step - loss: 9323252736.0000 -
val loss: 9758262272.0000
Epoch 83/400
val_loss: 9752030208.0000
Epoch 84/400
103/103 [============ ] - 0s 4ms/step - loss: 9305906176.0000 -
val loss: 9742988288.0000
Epoch 85/400
103/103 [============] - 0s 4ms/step - loss: 9303303168.0000 -
val_loss: 9748124672.0000
Epoch 86/400
103/103 [=============== ] - 0s 4ms/step - loss: 9307427840.0000 -
val loss: 9729794048.0000
Epoch 87/400
103/103 [============] - 0s 4ms/step - loss: 9292771328.0000 -
val loss: 9719183360.0000
Epoch 88/400
103/103 [============ ] - 0s 4ms/step - loss: 9277209600.0000 -
val loss: 9717869568.0000
Epoch 89/400
103/103 [============= ] - 0s 4ms/step - loss: 9268679680.0000 -
val_loss: 9707320320.0000
Epoch 90/400
103/103 [============] - 0s 4ms/step - loss: 9264993280.0000 -
val loss: 9708069888.0000
Epoch 91/400
103/103 [=========== ] - 0s 4ms/step - loss: 9302106112.0000 -
val_loss: 9704574976.0000
Epoch 92/400
103/103 [============ ] - 0s 4ms/step - loss: 9260627968.0000 -
val loss: 9693840384.0000
Epoch 93/400
103/103 [============ ] - 0s 4ms/step - loss: 9257176064.0000 -
val loss: 9683342336.0000
Epoch 94/400
103/103 [=========== ] - 0s 4ms/step - loss: 9242689536.0000 -
val loss: 9677283328.0000
Epoch 95/400
val loss: 9674072064.0000
Epoch 96/400
103/103 [=============] - 0s 4ms/step - loss: 9230620672.0000 -
val loss: 9674661888.0000
Epoch 97/400
val loss: 9679053824.0000
Epoch 98/400
103/103 [============ ] - 0s 5ms/step - loss: 9221523456.0000 -
val loss: 9663847424.0000
Epoch 99/400
103/103 [============ ] - 0s 5ms/step - loss: 9228249088.0000 -
val loss: 9651038208.0000
Epoch 100/400
103/103 [============= ] - 1s 6ms/step - loss: 9212642304.0000 -
val loss: 9649317888.0000
```

```
Epoch 101/400
103/103 [============= ] - 1s 5ms/step - loss: 9203915776.0000 -
val_loss: 9646581760.0000
Epoch 102/400
103/103 [============ ] - 1s 5ms/step - loss: 9202284544.0000 -
val loss: 9639828480.0000
Epoch 103/400
val_loss: 9631724544.0000
Epoch 104/400
103/103 [============ ] - 1s 5ms/step - loss: 9190572032.0000 -
val loss: 9639880704.0000
Epoch 105/400
103/103 [============] - 1s 5ms/step - loss: 9190301696.0000 -
val loss: 9621969920.0000
Epoch 106/400
103/103 [=============== ] - 0s 5ms/step - loss: 9184321536.0000 -
val loss: 9618310144.0000
Epoch 107/400
103/103 [============ ] - 0s 5ms/step - loss: 9181173760.0000 -
val loss: 9621405696.0000
Epoch 108/400
103/103 [============ ] - 1s 5ms/step - loss: 9182439424.0000 -
val loss: 9623371776.0000
Epoch 109/400
103/103 [============== ] - 1s 6ms/step - loss: 9175397376.0000 -
val_loss: 9610269696.0000
Epoch 110/400
103/103 [============ ] - 1s 5ms/step - loss: 9172884480.0000 -
val loss: 9617423360.0000
Epoch 111/400
103/103 [============== ] - 1s 5ms/step - loss: 9166979072.0000 -
val_loss: 9602691072.0000
Epoch 112/400
103/103 [============ ] - 0s 5ms/step - loss: 9165888512.0000 -
val loss: 9618353152.0000
Epoch 113/400
103/103 [============ ] - 1s 5ms/step - loss: 9172747264.0000 -
val loss: 9589904384.0000
Epoch 114/400
103/103 [============ ] - 1s 6ms/step - loss: 9148555264.0000 -
val loss: 9592683520.0000
Epoch 115/400
val loss: 9589231616.0000
Epoch 116/400
103/103 [=============] - 1s 5ms/step - loss: 9152131072.0000 -
val loss: 9575997440.0000
Epoch 117/400
val loss: 9573953536.0000
Epoch 118/400
103/103 [============ ] - 0s 4ms/step - loss: 9139298304.0000 -
val loss: 9619775488.0000
Epoch 119/400
103/103 [============ ] - 0s 4ms/step - loss: 9146176512.0000 -
val loss: 9575929856.0000
Epoch 120/400
103/103 [============= ] - 0s 4ms/step - loss: 9132161024.0000 -
val_loss: 9570162688.0000
```

```
Epoch 121/400
103/103 [============ ] - 0s 4ms/step - loss: 9126681600.0000 -
val_loss: 9560169472.0000
Epoch 122/400
103/103 [============ ] - 0s 4ms/step - loss: 9122847744.0000 -
val loss: 9557026816.0000
Epoch 123/400
103/103 [============== ] - 0s 5ms/step - loss: 9121398784.0000 -
val_loss: 9552622592.0000
Epoch 124/400
103/103 [============ ] - 0s 4ms/step - loss: 9119618048.0000 -
val loss: 9549628416.0000
Epoch 125/400
103/103 [============] - 0s 5ms/step - loss: 9113339904.0000 -
val loss: 9549422592.0000
Epoch 126/400
103/103 [=============== ] - 0s 5ms/step - loss: 9119768576.0000 -
val loss: 9545600000.0000
Epoch 127/400
val loss: 9561622528.0000
Epoch 128/400
val loss: 9544435712.0000
Epoch 129/400
103/103 [============= ] - 1s 6ms/step - loss: 9117988864.0000 -
val_loss: 9538914304.0000
Epoch 130/400
103/103 [============ ] - 1s 5ms/step - loss: 9099036672.0000 -
val loss: 9533627392.0000
Epoch 131/400
103/103 [============ ] - 0s 5ms/step - loss: 9099218944.0000 -
val_loss: 9530715136.0000
Epoch 132/400
103/103 [============ ] - 1s 5ms/step - loss: 9092357120.0000 -
val loss: 9525598208.0000
Epoch 133/400
103/103 [============ ] - 1s 5ms/step - loss: 9093794816.0000 -
val loss: 9522783232.0000
Epoch 134/400
103/103 [============ ] - 1s 5ms/step - loss: 9108135936.0000 -
val loss: 9519257600.0000
Epoch 135/400
val loss: 9515893760.0000
Epoch 136/400
103/103 [=============] - 1s 5ms/step - loss: 9100367872.0000 -
val loss: 9531736064.0000
Epoch 137/400
val loss: 9512062976.0000
Epoch 138/400
103/103 [============ ] - 1s 5ms/step - loss: 9080737792.0000 -
val loss: 9509595136.0000
Epoch 139/400
103/103 [============ ] - 1s 5ms/step - loss: 9081311232.0000 -
val loss: 9512019968.0000
Epoch 140/400
103/103 [============= ] - 1s 6ms/step - loss: 9076729856.0000 -
val_loss: 9528796160.0000
```

```
Epoch 141/400
103/103 [============= ] - 1s 7ms/step - loss: 9079942144.0000 -
val_loss: 9502411776.0000
Epoch 142/400
103/103 [============ ] - 1s 5ms/step - loss: 9071255552.0000 -
val loss: 9509685248.0000
Epoch 143/400
val_loss: 9502273536.0000
Epoch 144/400
103/103 [============ ] - 1s 7ms/step - loss: 9066256384.0000 -
val loss: 9504361472.0000
Epoch 145/400
103/103 [============] - 1s 6ms/step - loss: 9064376320.0000 -
val loss: 9499304960.0000
Epoch 146/400
103/103 [=============== ] - 1s 5ms/step - loss: 9066318848.0000 -
val loss: 9498353664.0000
Epoch 147/400
103/103 [============] - 0s 5ms/step - loss: 9059019776.0000 -
val loss: 9490802688.0000
Epoch 148/400
103/103 [============ ] - 0s 4ms/step - loss: 9074212864.0000 -
val loss: 9495243776.0000
Epoch 149/400
103/103 [============= ] - 0s 4ms/step - loss: 9075404800.0000 -
val_loss: 9486939136.0000
Epoch 150/400
103/103 [============ ] - 1s 6ms/step - loss: 9070092288.0000 -
val loss: 9494324224.0000
Epoch 151/400
103/103 [============== ] - 1s 5ms/step - loss: 9055919104.0000 -
val_loss: 9491878912.0000
Epoch 152/400
103/103 [============ ] - 0s 4ms/step - loss: 9056482304.0000 -
val loss: 9482101760.0000
Epoch 153/400
103/103 [=========== ] - 0s 4ms/step - loss: 9059257344.0000 -
val loss: 9484234752.0000
Epoch 154/400
103/103 [============ ] - 1s 5ms/step - loss: 9051720704.0000 -
val loss: 9480678400.0000
Epoch 155/400
val loss: 9477970944.0000
Epoch 156/400
103/103 [=============] - 1s 5ms/step - loss: 9048220672.0000 -
val loss: 9483529216.0000
Epoch 157/400
val loss: 9483783168.0000
Epoch 158/400
103/103 [============ ] - 1s 5ms/step - loss: 9075862528.0000 -
val loss: 9491139584.0000
Epoch 159/400
103/103 [============ ] - 1s 5ms/step - loss: 9063933952.0000 -
val loss: 9473239040.0000
Epoch 160/400
103/103 [============= ] - 0s 4ms/step - loss: 9042425856.0000 -
val_loss: 9466715136.0000
```

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Epoch 161/400
103/103 [============= ] - 0s 5ms/step - loss: 9039409152.0000 -
val_loss: 9486031872.0000
Epoch 162/400
103/103 [============ ] - 1s 6ms/step - loss: 9045139456.0000 -
val loss: 9463535616.0000
Epoch 163/400
val_loss: 9487178752.0000
Epoch 164/400
103/103 [============ ] - 0s 5ms/step - loss: 9064738816.0000 -
val loss: 9481888768.0000
Epoch 165/400
103/103 [============] - 0s 5ms/step - loss: 9034462208.0000 -
val loss: 9462336512.0000
Epoch 166/400
103/103 [============== ] - 1s 6ms/step - loss: 9034741760.0000 -
val loss: 9475880960.0000
Epoch 167/400
103/103 [============ ] - 0s 5ms/step - loss: 9041201152.0000 -
val loss: 9467130880.0000
Epoch 168/400
103/103 [============] - 0s 4ms/step - loss: 9029352448.0000 -
val loss: 9459018752.0000
Epoch 169/400
103/103 [============= ] - 0s 4ms/step - loss: 9037729792.0000 -
val_loss: 9462218752.0000
Epoch 170/400
103/103 [============ ] - 0s 4ms/step - loss: 9031410688.0000 -
val loss: 9459013632.0000
Epoch 171/400
103/103 [=========== ] - 0s 4ms/step - loss: 9028019200.0000 -
val_loss: 9463420928.0000
Epoch 172/400
103/103 [============ ] - 0s 4ms/step - loss: 9048627200.0000 -
val loss: 9469117440.0000
Epoch 173/400
103/103 [=========== ] - 0s 4ms/step - loss: 9029657600.0000 -
val loss: 9476563968.0000
Epoch 174/400
103/103 [============ ] - 0s 4ms/step - loss: 9048854528.0000 -
val loss: 9470761984.0000
Epoch 175/400
val loss: 9464505344.0000
Epoch 176/400
103/103 [=============] - 0s 4ms/step - loss: 9030988800.0000 -
val loss: 9459013632.0000
Epoch 177/400
val loss: 9450598400.0000
Epoch 178/400
103/103 [============ ] - 0s 4ms/step - loss: 9030301696.0000 -
val loss: 9448315904.0000
Epoch 179/400
103/103 [============ ] - 0s 5ms/step - loss: 9020691456.0000 -
val loss: 9461201920.0000
Epoch 180/400
103/103 [============= ] - 1s 6ms/step - loss: 9023173632.0000 -
val loss: 9449737216.0000
```

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Epoch 181/400
103/103 [============= ] - 1s 6ms/step - loss: 9020770304.0000 -
val_loss: 9464857600.0000
Epoch 182/400
103/103 [============ ] - 1s 7ms/step - loss: 9027088384.0000 -
val loss: 9456933888.0000
Epoch 183/400
val_loss: 9447401472.0000
Epoch 184/400
103/103 [============ ] - 1s 5ms/step - loss: 9024186368.0000 -
val loss: 9446866944.0000
Epoch 185/400
103/103 [============] - 1s 5ms/step - loss: 9023870976.0000 -
val loss: 9442555904.0000
Epoch 186/400
103/103 [=============== ] - 0s 5ms/step - loss: 9025731584.0000 -
val loss: 9440955392.0000
Epoch 187/400
103/103 [============ ] - 0s 4ms/step - loss: 9016060928.0000 -
val loss: 9440373760.0000
Epoch 188/400
103/103 [============ ] - 0s 4ms/step - loss: 9016930304.0000 -
val loss: 9441611776.0000
Epoch 189/400
103/103 [============= ] - 0s 5ms/step - loss: 9019457536.0000 -
val loss: 9444140032.0000
Epoch 190/400
103/103 [============ ] - 0s 4ms/step - loss: 9021031424.0000 -
val loss: 9468077056.0000
Epoch 191/400
103/103 [=========== ] - 0s 4ms/step - loss: 9027156992.0000 -
val_loss: 9442548736.0000
Epoch 192/400
103/103 [============ ] - 0s 4ms/step - loss: 9015966720.0000 -
val loss: 9439410176.0000
Epoch 193/400
103/103 [============ ] - 0s 4ms/step - loss: 9023788032.0000 -
val loss: 9449389056.0000
Epoch 194/400
103/103 [============ ] - 1s 5ms/step - loss: 9022461952.0000 -
val loss: 9436761088.0000
Epoch 195/400
val loss: 9441625088.0000
Epoch 196/400
103/103 [=============] - 1s 8ms/step - loss: 9016512512.0000 -
val loss: 9435691008.0000
Epoch 197/400
val loss: 9457235968.0000
Epoch 198/400
103/103 [============ ] - 1s 8ms/step - loss: 9029602304.0000 -
val loss: 9433825280.0000
Epoch 199/400
103/103 [============ ] - 1s 7ms/step - loss: 9023109120.0000 -
val loss: 9431761920.0000
Epoch 200/400
103/103 [============= ] - 1s 6ms/step - loss: 9008960512.0000 -
val_loss: 9435796480.0000
```

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Epoch 201/400
103/103 [============= ] - 0s 5ms/step - loss: 9014844416.0000 -
val_loss: 9437110272.0000
Epoch 202/400
103/103 [============ ] - 0s 5ms/step - loss: 9022753792.0000 -
val loss: 9431292928.0000
Epoch 203/400
val_loss: 9432268800.0000
Epoch 204/400
103/103 [============ ] - 0s 4ms/step - loss: 9008572416.0000 -
val loss: 9431459840.0000
Epoch 205/400
103/103 [============] - 0s 4ms/step - loss: 9036261376.0000 -
val loss: 9455281152.0000
Epoch 206/400
103/103 [=============== ] - 0s 4ms/step - loss: 9030364160.0000 -
val loss: 9427061760.0000
Epoch 207/400
103/103 [============ ] - 0s 4ms/step - loss: 9012513792.0000 -
val loss: 9426505728.0000
Epoch 208/400
103/103 [============ ] - 1s 5ms/step - loss: 9006887936.0000 -
val loss: 9429901312.0000
Epoch 209/400
103/103 [============= ] - 0s 4ms/step - loss: 9005924352.0000 -
val_loss: 9428683776.0000
Epoch 210/400
103/103 [============ ] - 0s 4ms/step - loss: 9008665600.0000 -
val loss: 9435710464.0000
Epoch 211/400
val_loss: 9434354688.0000
Epoch 212/400
103/103 [============ ] - 0s 4ms/step - loss: 9007378432.0000 -
val loss: 9433713664.0000
Epoch 213/400
103/103 [============ ] - 0s 4ms/step - loss: 9029595136.0000 -
val loss: 9446959104.0000
Epoch 214/400
103/103 [============ ] - 0s 4ms/step - loss: 9009811456.0000 -
val loss: 9425084416.0000
Epoch 215/400
val loss: 9435254784.0000
Epoch 216/400
103/103 [=============] - 0s 4ms/step - loss: 9004785664.0000 -
val loss: 9439216640.0000
Epoch 217/400
val loss: 9430566912.0000
Epoch 218/400
103/103 [============ ] - 1s 6ms/step - loss: 9015189504.0000 -
val loss: 9425994752.0000
Epoch 219/400
103/103 [============ ] - 1s 5ms/step - loss: 9002964992.0000 -
val loss: 9428593664.0000
Epoch 220/400
103/103 [============= ] - 1s 5ms/step - loss: 9007156224.0000 -
val loss: 9424994304.0000
```

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Epoch 221/400
103/103 [============= ] - 1s 7ms/step - loss: 9002190848.0000 -
val_loss: 9436689408.0000
Epoch 222/400
103/103 [============ ] - 1s 5ms/step - loss: 9012633600.0000 -
val loss: 9420602368.0000
Epoch 223/400
val_loss: 9423614976.0000
Epoch 224/400
103/103 [============ ] - 1s 6ms/step - loss: 9004661760.0000 -
val loss: 9426170880.0000
Epoch 225/400
103/103 [============ ] - 1s 5ms/step - loss: 9004234752.0000 -
val loss: 9426665472.0000
Epoch 226/400
103/103 [=============== ] - 0s 4ms/step - loss: 9012054016.0000 -
val loss: 9435649024.0000
Epoch 227/400
103/103 [============ ] - 0s 4ms/step - loss: 9004923904.0000 -
val loss: 9425124352.0000
Epoch 228/400
103/103 [============ ] - 1s 5ms/step - loss: 9002823680.0000 -
val loss: 9421573120.0000
Epoch 229/400
103/103 [============== ] - 1s 5ms/step - loss: 9005064192.0000 -
val_loss: 9423504384.0000
Epoch 230/400
103/103 [============ ] - 1s 6ms/step - loss: 8997383168.0000 -
val loss: 9417934848.0000
Epoch 231/400
val_loss: 9416572928.0000
Epoch 232/400
103/103 [============ ] - 1s 6ms/step - loss: 9003675648.0000 -
val loss: 9415260160.0000
Epoch 233/400
103/103 [============ ] - 0s 4ms/step - loss: 9000064000.0000 -
val loss: 9425581056.0000
Epoch 234/400
103/103 [============ ] - 0s 4ms/step - loss: 8998776832.0000 -
val loss: 9423207424.0000
Epoch 235/400
val loss: 9415308288.0000
Epoch 236/400
103/103 [=============] - 1s 7ms/step - loss: 9000054784.0000 -
val loss: 9428114432.0000
Epoch 237/400
val loss: 9418624000.0000
Epoch 238/400
103/103 [============ ] - 1s 5ms/step - loss: 8997869568.0000 -
val loss: 9424515072.0000
Epoch 239/400
103/103 [============ ] - 0s 5ms/step - loss: 8997921792.0000 -
val loss: 9412982784.0000
Epoch 240/400
103/103 [============= ] - 0s 4ms/step - loss: 8998887424.0000 -
val_loss: 9412125696.0000
```

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Epoch 241/400
103/103 [============= ] - 0s 4ms/step - loss: 8997568512.0000 -
val_loss: 9407963136.0000
Epoch 242/400
103/103 [============ ] - 0s 4ms/step - loss: 8988012544.0000 -
val loss: 9405456384.0000
Epoch 243/400
val_loss: 9427266560.0000
Epoch 244/400
103/103 [============ ] - 0s 4ms/step - loss: 8991452160.0000 -
val loss: 9405952000.0000
Epoch 245/400
103/103 [============] - 0s 4ms/step - loss: 9032634368.0000 -
val loss: 9405109248.0000
Epoch 246/400
103/103 [============== ] - 0s 4ms/step - loss: 9000230912.0000 -
val loss: 9405128704.0000
Epoch 247/400
103/103 [============] - 0s 4ms/step - loss: 9007395840.0000 -
val loss: 9413111808.0000
Epoch 248/400
103/103 [============ ] - 0s 5ms/step - loss: 8985669632.0000 -
val loss: 9396877312.0000
Epoch 249/400
103/103 [============= ] - 1s 5ms/step - loss: 8982625280.0000 -
val_loss: 9398598656.0000
Epoch 250/400
103/103 [============ ] - 1s 5ms/step - loss: 8978345984.0000 -
val loss: 9416583168.0000
Epoch 251/400
103/103 [============== ] - 1s 5ms/step - loss: 8975000576.0000 -
val_loss: 9434961920.0000
Epoch 252/400
103/103 [============ ] - 1s 5ms/step - loss: 9005741056.0000 -
val loss: 9395063808.0000
Epoch 253/400
103/103 [============ ] - 1s 5ms/step - loss: 8980396032.0000 -
val loss: 9405391872.0000
Epoch 254/400
103/103 [============ ] - 1s 7ms/step - loss: 8988619776.0000 -
val loss: 9400785920.0000
Epoch 255/400
val loss: 9396624384.0000
Epoch 256/400
103/103 [=============] - 1s 5ms/step - loss: 8971728896.0000 -
val loss: 9448513536.0000
Epoch 257/400
val loss: 9404995584.0000
Epoch 258/400
103/103 [============ ] - 1s 6ms/step - loss: 8976277504.0000 -
val loss: 9398062080.0000
Epoch 259/400
103/103 [============ ] - 1s 5ms/step - loss: 8971416576.0000 -
val loss: 9393737728.0000
Epoch 260/400
103/103 [============= ] - 0s 5ms/step - loss: 8975159296.0000 -
val_loss: 9392521216.0000
```

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Epoch 261/400
103/103 [============== ] - 0s 5ms/step - loss: 8970063872.0000 -
val_loss: 9391412224.0000
Epoch 262/400
103/103 [============] - 0s 4ms/step - loss: 8973373440.0000 -
val loss: 9399151616.0000
Epoch 263/400
val_loss: 9398810624.0000
Epoch 264/400
103/103 [============ ] - 0s 4ms/step - loss: 8966917120.0000 -
val loss: 9390816256.0000
Epoch 265/400
103/103 [============] - 1s 5ms/step - loss: 8971250688.0000 -
val loss: 9391525888.0000
Epoch 266/400
103/103 [============== ] - 0s 4ms/step - loss: 8972892160.0000 -
val loss: 9403995136.0000
Epoch 267/400
103/103 [============ ] - 0s 4ms/step - loss: 8963145728.0000 -
val loss: 9387299840.0000
Epoch 268/400
103/103 [============ ] - 0s 5ms/step - loss: 8975117312.0000 -
val loss: 9385168896.0000
Epoch 269/400
103/103 [============= ] - 1s 5ms/step - loss: 8967814144.0000 -
val_loss: 9384121344.0000
Epoch 270/400
103/103 [============ ] - 1s 5ms/step - loss: 8965753856.0000 -
val loss: 9380780032.0000
Epoch 271/400
103/103 [=========== ] - 0s 4ms/step - loss: 8963641344.0000 -
val_loss: 9380715520.0000
Epoch 272/400
103/103 [============ ] - 0s 4ms/step - loss: 8967118848.0000 -
val loss: 9395043328.0000
Epoch 273/400
103/103 [============ ] - 0s 5ms/step - loss: 8963197952.0000 -
val loss: 9376774144.0000
Epoch 274/400
103/103 [============ ] - 1s 5ms/step - loss: 8959401984.0000 -
val loss: 9432517632.0000
Epoch 275/400
val loss: 9379503104.0000
Epoch 276/400
103/103 [=============] - 1s 6ms/step - loss: 8955126784.0000 -
val loss: 9384759296.0000
Epoch 277/400
val loss: 9376382976.0000
Epoch 278/400
103/103 [============ ] - 0s 5ms/step - loss: 8957927424.0000 -
val loss: 9374622720.0000
Epoch 279/400
103/103 [============ ] - 1s 6ms/step - loss: 8955975680.0000 -
val loss: 9373376512.0000
Epoch 280/400
103/103 [============= ] - 1s 6ms/step - loss: 8951291904.0000 -
val_loss: 9371564032.0000
```

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Epoch 281/400
103/103 [============= ] - 1s 7ms/step - loss: 8957865984.0000 -
val_loss: 9371403264.0000
Epoch 282/400
103/103 [============ ] - 1s 6ms/step - loss: 8954068992.0000 -
val loss: 9372777472.0000
Epoch 283/400
val_loss: 9377554432.0000
Epoch 284/400
103/103 [============ ] - 0s 4ms/step - loss: 8956790784.0000 -
val loss: 9399219200.0000
Epoch 285/400
103/103 [============] - 1s 6ms/step - loss: 8989202432.0000 -
val loss: 9373498368.0000
Epoch 286/400
103/103 [============== ] - 0s 4ms/step - loss: 8944872448.0000 -
val loss: 9368530944.0000
Epoch 287/400
103/103 [============ ] - 0s 5ms/step - loss: 8949108736.0000 -
val loss: 9362804736.0000
Epoch 288/400
103/103 [============ ] - 1s 5ms/step - loss: 8953800704.0000 -
val loss: 9362421760.0000
Epoch 289/400
103/103 [============= ] - 0s 5ms/step - loss: 8945000448.0000 -
val_loss: 9364730880.0000
Epoch 290/400
103/103 [============ ] - 0s 5ms/step - loss: 8987593728.0000 -
val loss: 9379966976.0000
Epoch 291/400
103/103 [=========== ] - 0s 4ms/step - loss: 8950717440.0000 -
val_loss: 9363623936.0000
Epoch 292/400
103/103 [============ ] - 0s 4ms/step - loss: 8940575744.0000 -
val loss: 9364308992.0000
Epoch 293/400
103/103 [============ ] - 0s 4ms/step - loss: 8943338496.0000 -
val loss: 9363253248.0000
Epoch 294/400
103/103 [=========== ] - 0s 4ms/step - loss: 8939529216.0000 -
val loss: 9363546112.0000
Epoch 295/400
val loss: 9370980352.0000
Epoch 296/400
103/103 [=============] - 0s 4ms/step - loss: 8938117120.0000 -
val loss: 9356313600.0000
Epoch 297/400
val loss: 9354376192.0000
Epoch 298/400
103/103 [============ ] - 0s 5ms/step - loss: 8940860416.0000 -
val loss: 9355655168.0000
Epoch 299/400
103/103 [============ ] - 1s 5ms/step - loss: 8934254592.0000 -
val loss: 9370631168.0000
Epoch 300/400
103/103 [============= ] - 1s 6ms/step - loss: 8965822464.0000 -
val_loss: 9355930624.0000
```

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Epoch 301/400
103/103 [============= ] - 1s 9ms/step - loss: 8933695488.0000 -
val_loss: 9351514112.0000
Epoch 302/400
103/103 [============ ] - 1s 8ms/step - loss: 8941947904.0000 -
val loss: 9350827008.0000
Epoch 303/400
val_loss: 9352075264.0000
Epoch 304/400
103/103 [============ ] - 1s 8ms/step - loss: 8934525952.0000 -
val loss: 9352044544.0000
Epoch 305/400
103/103 [============] - 1s 7ms/step - loss: 8936072192.0000 -
val loss: 9364791296.0000
Epoch 306/400
103/103 [============== ] - 1s 6ms/step - loss: 8931090432.0000 -
val loss: 9357554688.0000
Epoch 307/400
103/103 [============ ] - 1s 7ms/step - loss: 8928943104.0000 -
val loss: 9380848640.0000
Epoch 308/400
103/103 [============ ] - 1s 6ms/step - loss: 8958471168.0000 -
val loss: 9366548480.0000
Epoch 309/400
103/103 [============= ] - 1s 6ms/step - loss: 8928245760.0000 -
val_loss: 9361917952.0000
Epoch 310/400
103/103 [============ ] - 1s 7ms/step - loss: 8932788224.0000 -
val loss: 9355660288.0000
Epoch 311/400
103/103 [============== ] - 1s 6ms/step - loss: 8932144128.0000 -
val_loss: 9355293696.0000
Epoch 312/400
103/103 [============ ] - 1s 5ms/step - loss: 8943639552.0000 -
val loss: 9352451072.0000
Epoch 313/400
103/103 [============ ] - 1s 5ms/step - loss: 8923529216.0000 -
val loss: 9353655296.0000
Epoch 314/400
103/103 [============ ] - 1s 9ms/step - loss: 8930688000.0000 -
val loss: 9378880512.0000
Epoch 315/400
val loss: 9350293504.0000
Epoch 316/400
103/103 [=============] - 1s 7ms/step - loss: 8927791104.0000 -
val loss: 9349706752.0000
Epoch 317/400
val loss: 9356544000.0000
Epoch 318/400
val loss: 9380740096.0000
Epoch 319/400
103/103 [============ ] - 1s 6ms/step - loss: 8942918656.0000 -
val loss: 9358572544.0000
Epoch 320/400
103/103 [============= ] - 1s 6ms/step - loss: 8955345920.0000 -
val_loss: 9367427072.0000
```

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Epoch 321/400
103/103 [============== ] - 1s 5ms/step - loss: 8945882112.0000 -
val_loss: 9354984448.0000
Epoch 322/400
103/103 [============ ] - 1s 5ms/step - loss: 8924007424.0000 -
val loss: 9352968192.0000
Epoch 323/400
103/103 [============== ] - 0s 4ms/step - loss: 8924174336.0000 -
val_loss: 9352316928.0000
Epoch 324/400
103/103 [============ ] - 1s 5ms/step - loss: 8922823680.0000 -
val loss: 9359876096.0000
Epoch 325/400
103/103 [============] - 1s 7ms/step - loss: 8923460608.0000 -
val loss: 9358149632.0000
Epoch 326/400
103/103 [=============== ] - 1s 5ms/step - loss: 8925973504.0000 -
val loss: 9349313536.0000
Epoch 327/400
103/103 [============ ] - 0s 5ms/step - loss: 8921391104.0000 -
val loss: 9352092672.0000
Epoch 328/400
103/103 [============ ] - 0s 5ms/step - loss: 8924656640.0000 -
val loss: 9347722240.0000
Epoch 329/400
103/103 [============= ] - 0s 4ms/step - loss: 8925803520.0000 -
val_loss: 9367800832.0000
Epoch 330/400
103/103 [============ ] - 0s 5ms/step - loss: 8926995456.0000 -
val loss: 9348831232.0000
Epoch 331/400
103/103 [============== ] - 1s 5ms/step - loss: 8916421632.0000 -
val_loss: 9365751808.0000
Epoch 332/400
103/103 [============ ] - 1s 6ms/step - loss: 8943143936.0000 -
val loss: 9345626112.0000
Epoch 333/400
103/103 [============ ] - 1s 5ms/step - loss: 8923011072.0000 -
val loss: 9371463680.0000
Epoch 334/400
103/103 [============ ] - 1s 9ms/step - loss: 8923138048.0000 -
val loss: 9353329664.0000
Epoch 335/400
val loss: 9360454656.0000
Epoch 336/400
103/103 [=============] - 1s 6ms/step - loss: 8920018944.0000 -
val loss: 9357959168.0000
Epoch 337/400
val loss: 9346162688.0000
Epoch 338/400
103/103 [============ ] - 1s 5ms/step - loss: 8914514944.0000 -
val loss: 9364969472.0000
Epoch 339/400
103/103 [============ ] - 0s 5ms/step - loss: 8922196992.0000 -
val loss: 9346830336.0000
Epoch 340/400
103/103 [============= ] - 1s 6ms/step - loss: 8916717568.0000 -
val_loss: 9361034240.0000
```

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Epoch 341/400
103/103 [============= ] - 1s 6ms/step - loss: 8923594752.0000 -
val_loss: 9366494208.0000
Epoch 342/400
val loss: 9346534400.0000
Epoch 343/400
val_loss: 9349727232.0000
Epoch 344/400
103/103 [============ ] - 1s 5ms/step - loss: 8915458048.0000 -
val loss: 9359633408.0000
Epoch 345/400
103/103 [============] - 1s 6ms/step - loss: 8931536896.0000 -
val loss: 9360757760.0000
Epoch 346/400
103/103 [============== ] - 1s 8ms/step - loss: 8960088064.0000 -
val loss: 9339785216.0000
Epoch 347/400
103/103 [============ ] - 1s 6ms/step - loss: 8911749120.0000 -
val loss: 9341774848.0000
Epoch 348/400
103/103 [============ ] - 1s 6ms/step - loss: 8918459392.0000 -
val loss: 9341048832.0000
Epoch 349/400
103/103 [============= ] - 1s 6ms/step - loss: 8910022656.0000 -
val_loss: 9339874304.0000
Epoch 350/400
103/103 [============ ] - 1s 5ms/step - loss: 8914613248.0000 -
val loss: 9345826816.0000
Epoch 351/400
103/103 [============= ] - 1s 5ms/step - loss: 8921073664.0000 -
val_loss: 9335777280.0000
Epoch 352/400
103/103 [============ ] - 1s 5ms/step - loss: 8911104000.0000 -
val loss: 9371783168.0000
Epoch 353/400
103/103 [============ ] - 0s 4ms/step - loss: 8936584192.0000 -
val loss: 9344363520.0000
Epoch 354/400
103/103 [============ ] - 0s 4ms/step - loss: 8909442048.0000 -
val loss: 9344273408.0000
Epoch 355/400
val loss: 9336100864.0000
Epoch 356/400
103/103 [=============] - 0s 5ms/step - loss: 8909010944.0000 -
val loss: 9336557568.0000
Epoch 357/400
val loss: 9339418624.0000
Epoch 358/400
103/103 [============ ] - 1s 5ms/step - loss: 8907449344.0000 -
val loss: 9332233216.0000
Epoch 359/400
103/103 [============ ] - 1s 5ms/step - loss: 8905752576.0000 -
val loss: 9334943744.0000
Epoch 360/400
103/103 [============= ] - 1s 6ms/step - loss: 8916343808.0000 -
val_loss: 9336620032.0000
```

```
Epoch 361/400
103/103 [============== ] - 1s 5ms/step - loss: 8901957632.0000 -
val_loss: 9378954240.0000
Epoch 362/400
103/103 [============ ] - 0s 4ms/step - loss: 8904090624.0000 -
val loss: 9344575488.0000
Epoch 363/400
val_loss: 9365069824.0000
Epoch 364/400
103/103 [============ ] - 1s 6ms/step - loss: 8903693312.0000 -
val loss: 9335979008.0000
Epoch 365/400
103/103 [============] - 1s 5ms/step - loss: 8929960960.0000 -
val loss: 9328819200.0000
Epoch 366/400
103/103 [=============== ] - 1s 5ms/step - loss: 8901479424.0000 -
val loss: 9328842752.0000
Epoch 367/400
103/103 [============ ] - 0s 4ms/step - loss: 8906366976.0000 -
val loss: 9349322752.0000
Epoch 368/400
103/103 [============ ] - 0s 4ms/step - loss: 8927039488.0000 -
val loss: 9342968832.0000
Epoch 369/400
103/103 [============== ] - 0s 5ms/step - loss: 8909598720.0000 -
val_loss: 9326685184.0000
Epoch 370/400
103/103 [============ ] - 0s 4ms/step - loss: 8899941376.0000 -
val loss: 9329618944.0000
Epoch 371/400
103/103 [=========== ] - 0s 4ms/step - loss: 8902604800.0000 -
val_loss: 9326776320.0000
Epoch 372/400
103/103 [============ ] - 0s 4ms/step - loss: 8901771264.0000 -
val loss: 9330321408.0000
Epoch 373/400
103/103 [============ ] - 0s 4ms/step - loss: 8897408000.0000 -
val loss: 9405684736.0000
Epoch 374/400
103/103 [============ ] - 0s 4ms/step - loss: 8987667456.0000 -
val loss: 9327840256.0000
Epoch 375/400
val loss: 9324850176.0000
Epoch 376/400
103/103 [=============] - 0s 5ms/step - loss: 8900105216.0000 -
val loss: 9322845184.0000
Epoch 377/400
val loss: 9347809280.0000
Epoch 378/400
103/103 [=========== ] - 0s 4ms/step - loss: 8905579520.0000 -
val loss: 9326695424.0000
Epoch 379/400
103/103 [============ ] - 0s 5ms/step - loss: 8893748224.0000 -
val loss: 9327867904.0000
Epoch 380/400
103/103 [============= ] - 0s 4ms/step - loss: 8899033088.0000 -
val_loss: 9326750720.0000
```

```
Epoch 381/400
103/103 [============== ] - 1s 5ms/step - loss: 8893746176.0000 -
val_loss: 9326065664.0000
Epoch 382/400
103/103 [============ ] - 1s 5ms/step - loss: 8889329664.0000 -
val loss: 9335960576.0000
Epoch 383/400
val_loss: 9325194240.0000
Epoch 384/400
103/103 [============ ] - 0s 4ms/step - loss: 8900458496.0000 -
val loss: 9322503168.0000
Epoch 385/400
103/103 [============] - 0s 4ms/step - loss: 8905996288.0000 -
val loss: 9318460416.0000
Epoch 386/400
103/103 [=============== ] - 0s 4ms/step - loss: 8896350208.0000 -
val loss: 9321228288.0000
Epoch 387/400
103/103 [============ ] - 0s 4ms/step - loss: 8885038080.0000 -
val loss: 9328977920.0000
Epoch 388/400
103/103 [============ ] - 1s 5ms/step - loss: 8890462208.0000 -
val loss: 9317925888.0000
Epoch 389/400
103/103 [============= ] - 1s 5ms/step - loss: 8909631488.0000 -
val_loss: 9321056256.0000
Epoch 390/400
103/103 [============ ] - 1s 7ms/step - loss: 8882468864.0000 -
val loss: 9330028544.0000
Epoch 391/400
103/103 [============ ] - 1s 7ms/step - loss: 8925999104.0000 -
val_loss: 9320474624.0000
Epoch 392/400
103/103 [============ ] - 1s 6ms/step - loss: 8883670016.0000 -
val loss: 9319557120.0000
Epoch 393/400
103/103 [============ ] - 0s 5ms/step - loss: 8884593664.0000 -
val loss: 9317872640.0000
Epoch 394/400
103/103 [============ ] - 0s 5ms/step - loss: 8881545216.0000 -
val loss: 9323112448.0000
Epoch 395/400
val loss: 9327310848.0000
Epoch 396/400
103/103 [=============] - 1s 5ms/step - loss: 8883865600.0000 -
val loss: 9314510848.0000
Epoch 397/400
val loss: 9313868800.0000
Epoch 398/400
103/103 [============ ] - 1s 5ms/step - loss: 8877390848.0000 -
val loss: 9312937984.0000
Epoch 399/400
103/103 [============ ] - 1s 5ms/step - loss: 8879842304.0000 -
val loss: 9315108864.0000
Epoch 400/400
103/103 [============= ] - 1s 7ms/step - loss: 8919650304.0000 -
val_loss: 9324222464.0000
```

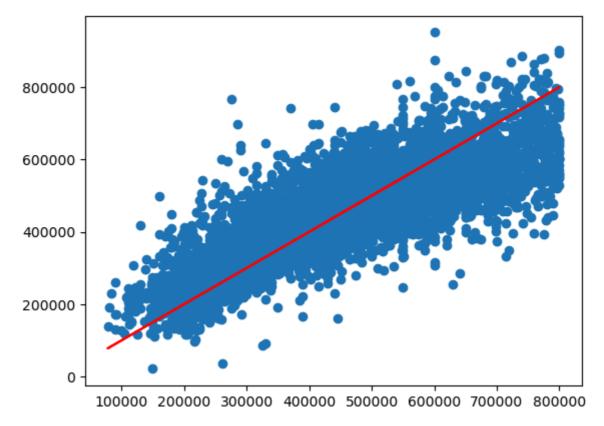
```
Out[113... <keras.callbacks.History at 0x115a9ba9d90>
In [114...
          # since we requested validation it will provide the validation losses too; in t
          # In order to see if i'm overfitting the model
          losses = pd.DataFrame(model.history.history)
In [115...
          losses.plot()
Out[115...
           <Axes: >
              1e11
                                                                          loss
                                                                          val loss
         2.0
         1.5
         1.0
         0.5
         0.0
                0
                        50
                               100
                                       150
                                               200
                                                       250
                                                               300
                                                                       350
                                                                               400
In [116...
          from sklearn.metrics import mean squared error, mean absolute error, explained v
In [117...
          predictions = model.predict(X_test)
         175/175 [=========] - 1s 3ms/step
In [118...
          np.sqrt(mean_squared_error(y_test, predictions))
Out[118...
          96562.01306715109
          mean_absolute_error(y_test, predictions)
In [119...
Out[119...
         74342.13064476506
```

df['price'].describe()

In [120...

```
Out[120...
                    2.159700e+04
           count
           mean
                    5.402966e+05
           std
                    3.673681e+05
                    7.800000e+04
           min
           25%
                    3.220000e+05
           50%
                    4.500000e+05
           75%
                    6.450000e+05
                    7.700000e+06
           max
           Name: price, dtype: float64
          5.402966e+05
In [121...
Out[121...
           540296.6
In [122...
          #Best possible score is 1.0, lower values are worse.
          explained_variance_score(y_test, predictions)
Out[122...
           0.6470470589748937
In [123...
          plt.scatter(y_test, predictions)
          plt.plot(y_test, y_test, 'r')
```

Out[123... [<matplotlib.lines.Line2D at 0x115b4fddaf0>]



```
In [124... # The below are the only features of new house in the market
    single_house = df.drop('price', axis=1).iloc[0]

In [125... single_house = scaler.transform(single_house.values.reshape(-1,19))

C:\learnings\envs\deeplearning\lib\site-packages\sklearn\base.py:450: UserWarnin
    g: X does not have valid feature names, but MinMaxScaler was fitted with feature
    names
    warnings.warn(
```

In [126... model.predict(single_house) 1/1 [======] - 0s 21ms/step Out[126... array([[293580.25]], dtype=float32) In [127... df.head() Out[127... price bedrooms bathrooms sqft_living sqft_lot floors waterfront view 3 0 0 **0** 221900.0 1.00 1180 5650 1.0 **1** 538000.0 2.25 2570 7242 2.0 0 2 **2** 180000.0 1.00 770 10000 1.0 0 0 **3** 604000.0 0 3.00 1960 5000 1.0 0 0 3 1.0 510000.0 2.00 1680 8080 In []: