This Project is for House prices in King County in the USA.Task is to predict the Housing prices using Machine learning alogrithm(linear regression) and Deep learning Keras Tensorflow with Artificial Neutron Network(ANN). source: https://www.kaggle.com/harlfoxem/housesalesprediction. Refer to the meanings of some abbreviations of the feature columns if need be from the above website.

In [1]:

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

In [2]:

```
df=pd.read_csv(r'C:\Users\chumj\Downloads\Housing Prices.csv')
```

EXPLORATORY DATA ANALYSIS

In [3]:

```
df.head(3)
```

Out[3]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_above	sqft_
0	7129300520	10/13/2014	221900.0	3	1.00	1180	5650	1.0	0	0	...	7	1180	
1	6414100192	12/9/2014	538000.0	3	2.25	2570	7242	2.0	0	0	...	7	2170	
2	5631500400	2/25/2015	180000.0	2	1.00	770	10000	1.0	0	0	...	6	770	

3 rows × 21 columns

In [4]:

```
df.info()
```

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

```
dtypes: float64(5), int64(15), object(1)
memory usage: 3.5+ MB
```

In [5]:

```
df.isnull().sum()
```

Out[5]:

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

In [6]:

```
df.describe().transpose()
```

Out[6]:

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

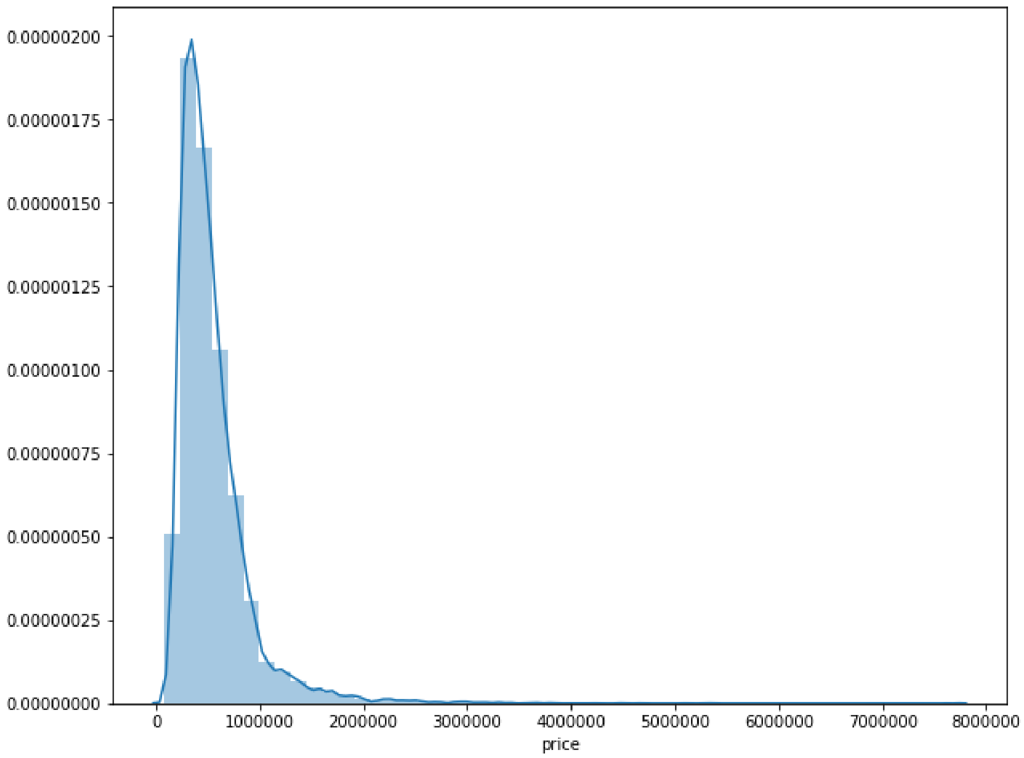
Our main objective is to predictive the Housing Prices.Let's take a look at the Price distribution

In [7]:

```
plt.figure(figsize=(10,8))
sns.distplot(df['price'])
```

Out[7]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1cdf1d8ff08>
```



Correlation with the other features with price.

In [8]:

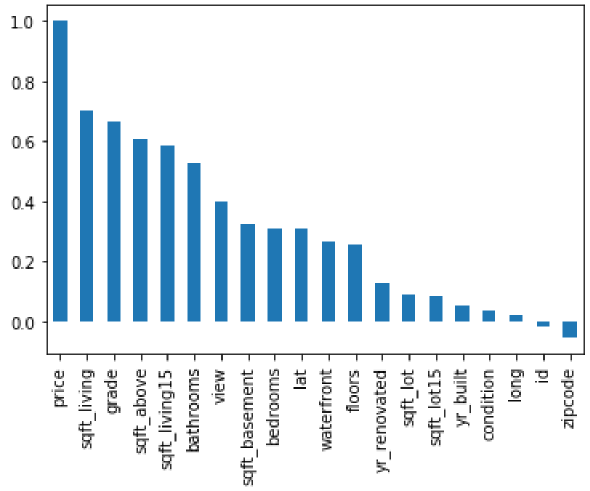
```
df.corr()['price'].sort_values(ascending=False)
```

Out[8]:

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

In [9]:

```
df.corr()['price'].sort_values(ascending=False).plot(kind='bar');
```



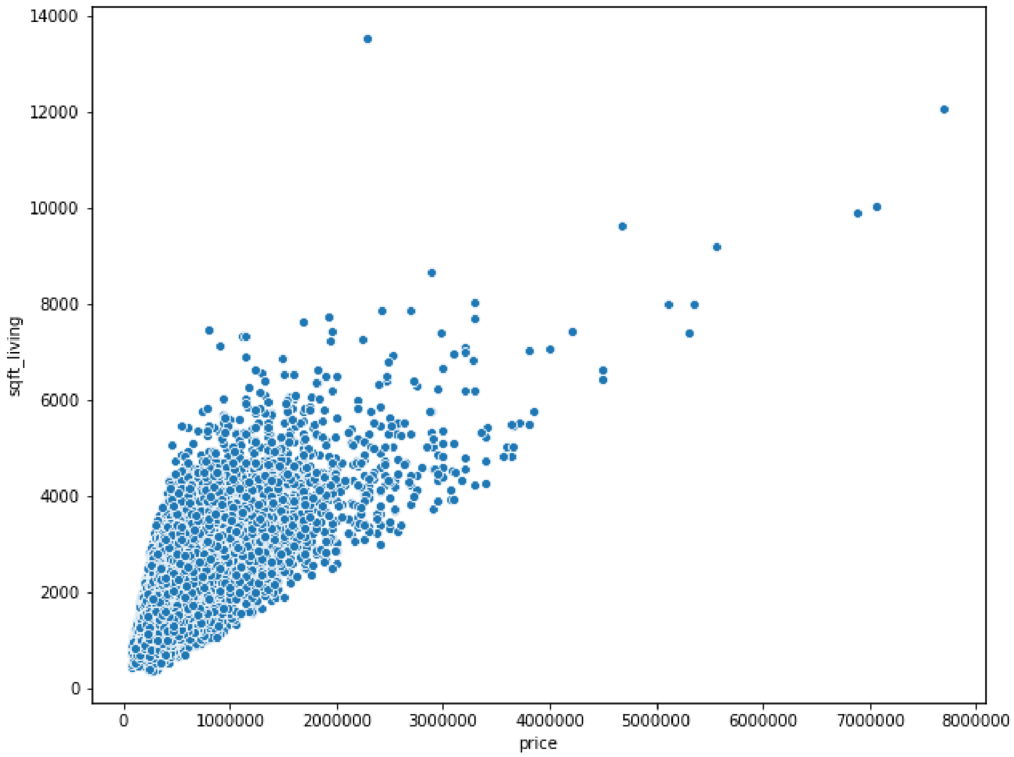
In [10]:

```
#plt.figure(figsize=(15,12))
#sns.heatmap(df.corr(),annot=True);
```

Exploring some important features that have a strong positive correlation with price.

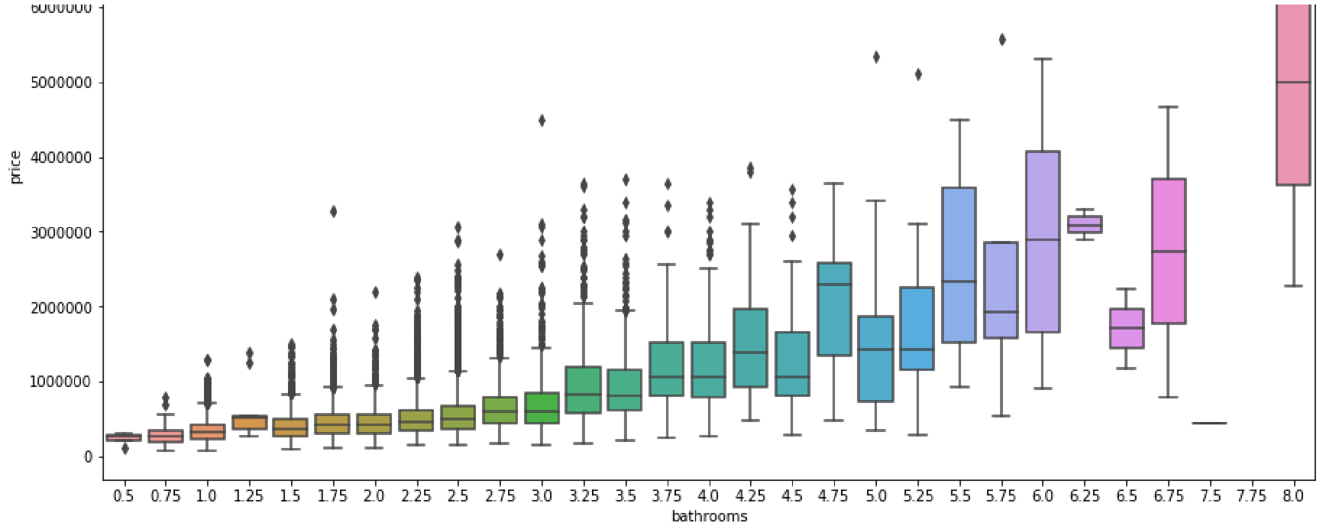
In [11]:

```
plt.figure(figsize=(10,8))
sns.scatterplot(x='price',y='sqft_living',data=df);
```



In [12]:

```
plt.figure(figsize=(15,8))
sns.boxplot(x='bathrooms',y='price',data=df);
```

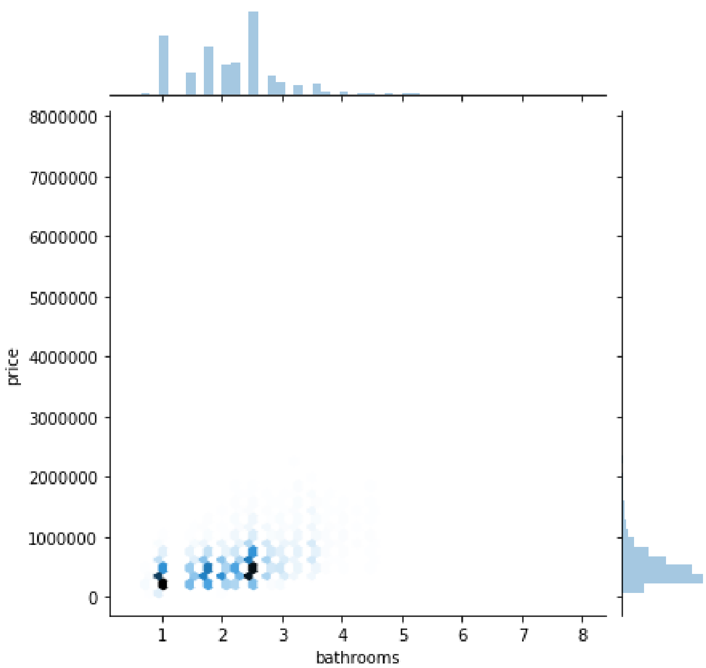


In [13]:

```
sns.jointplot(x='bathrooms',y='price',data=df,kind='hex')
```

Out[13]:

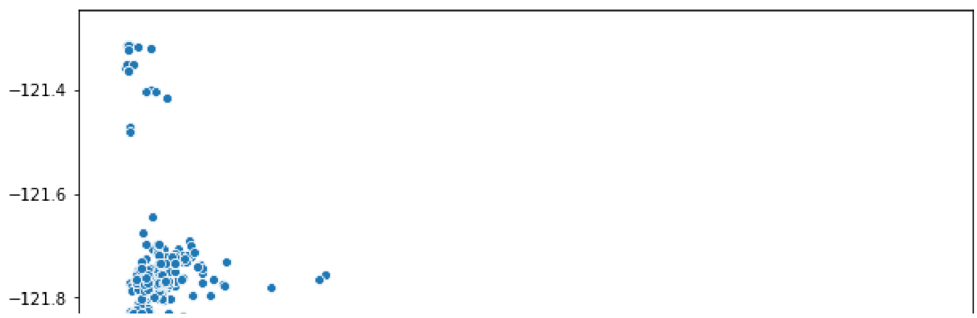
<seaborn.axisgrid.JointGrid at 0x1cdf2d1dd08>

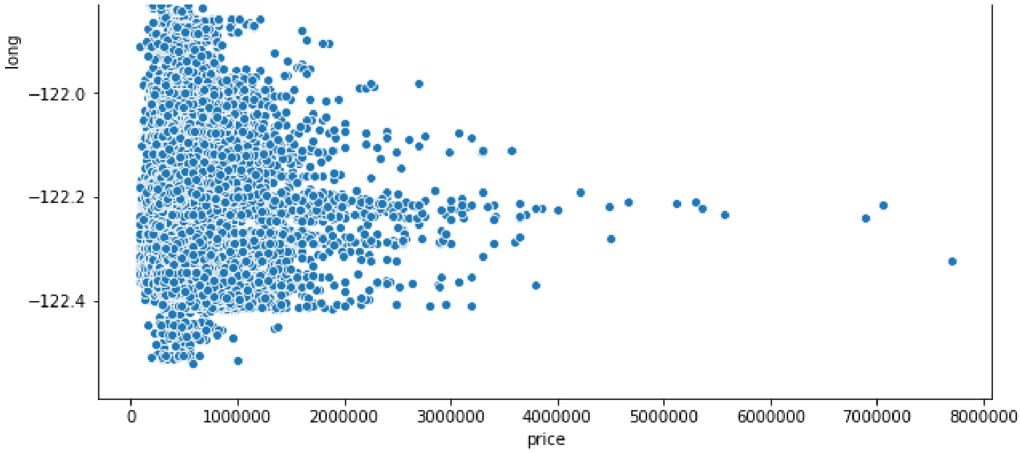


Geography,taking a look at longitude,latitude and waterfront.

In [14]:

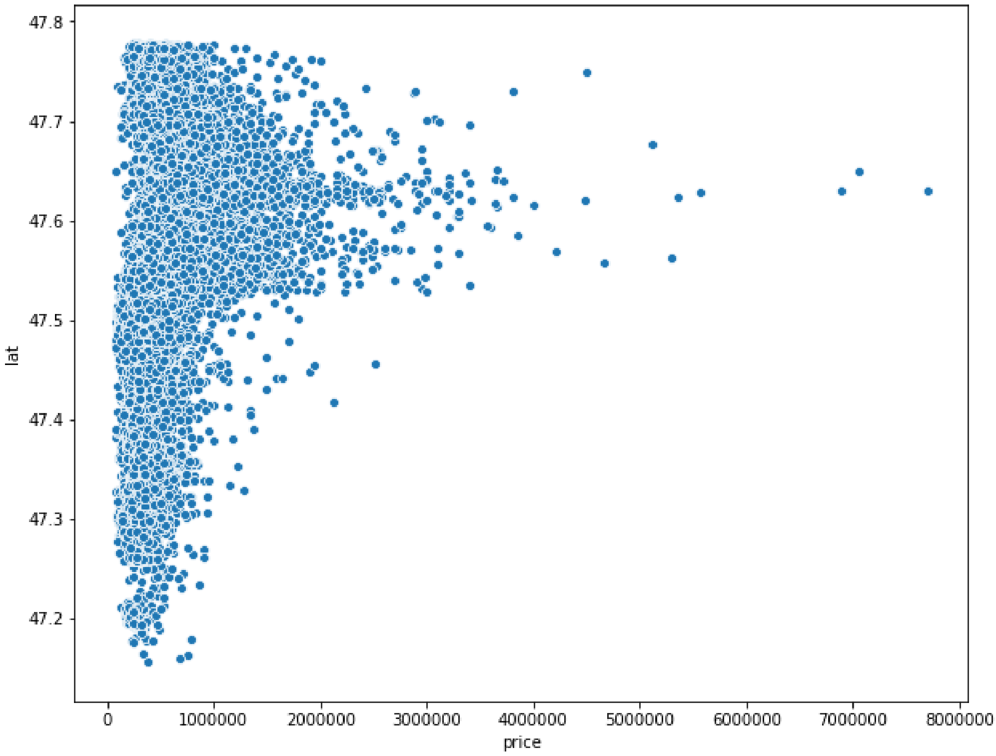
```
plt.figure(figsize=(10,8))
sns.scatterplot(x='price',y='long',data=df);
```





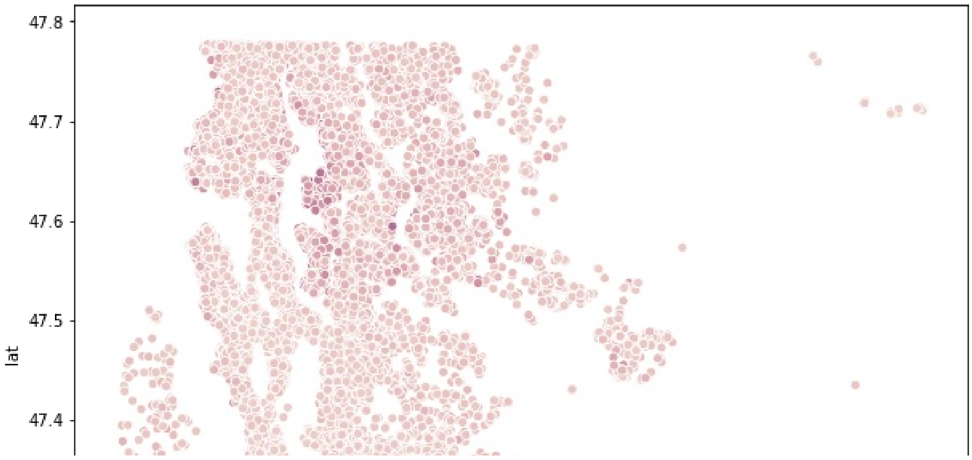
In [15]:

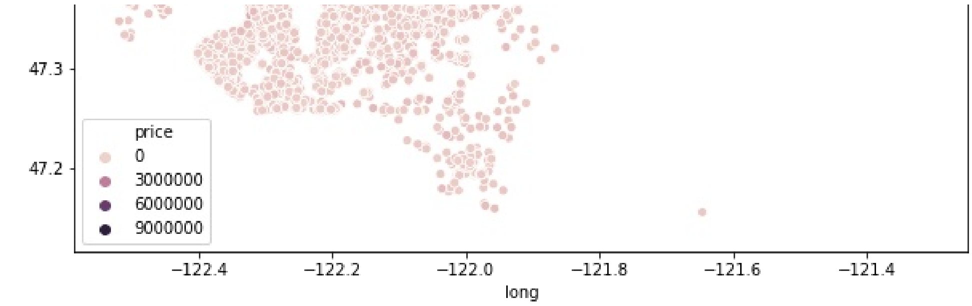
```
plt.figure(figsize=(10,8))
sns.scatterplot(x='price',y='lat',data=df);
```



In [16]:

```
plt.figure(figsize=(10,8))
sns.scatterplot(x='long',y='lat',data=df,hue='price');
```





In [17]:

```
len(df)*1/100
```

Out[17]:

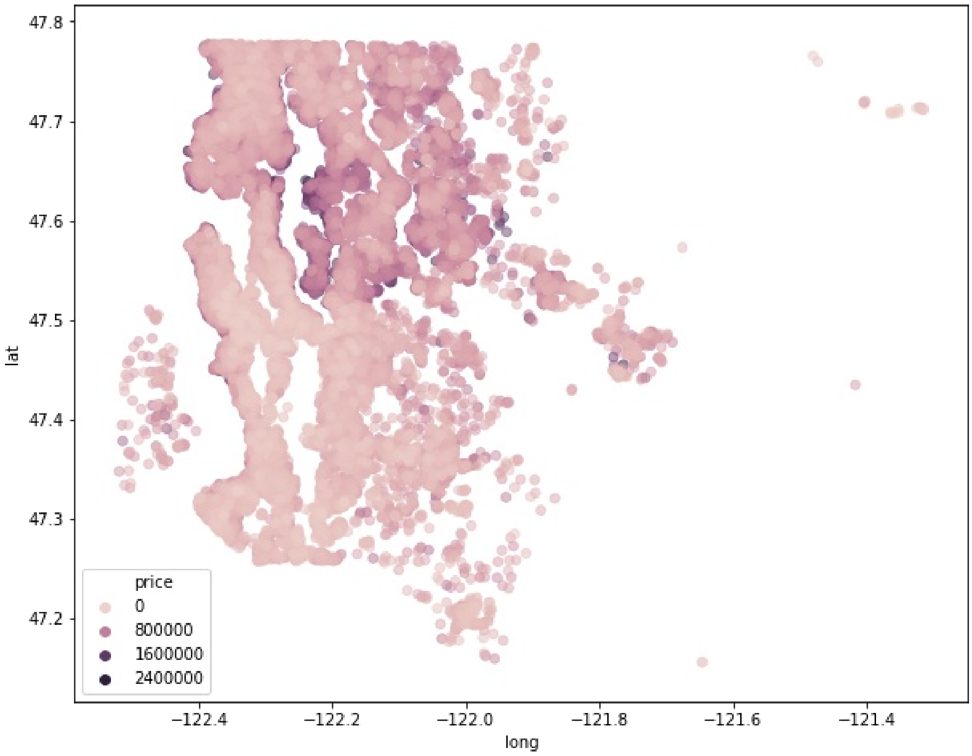
```
215.97
```

In [18]:

```
above=df.sort_values('price',ascending=False).iloc[216:]
```

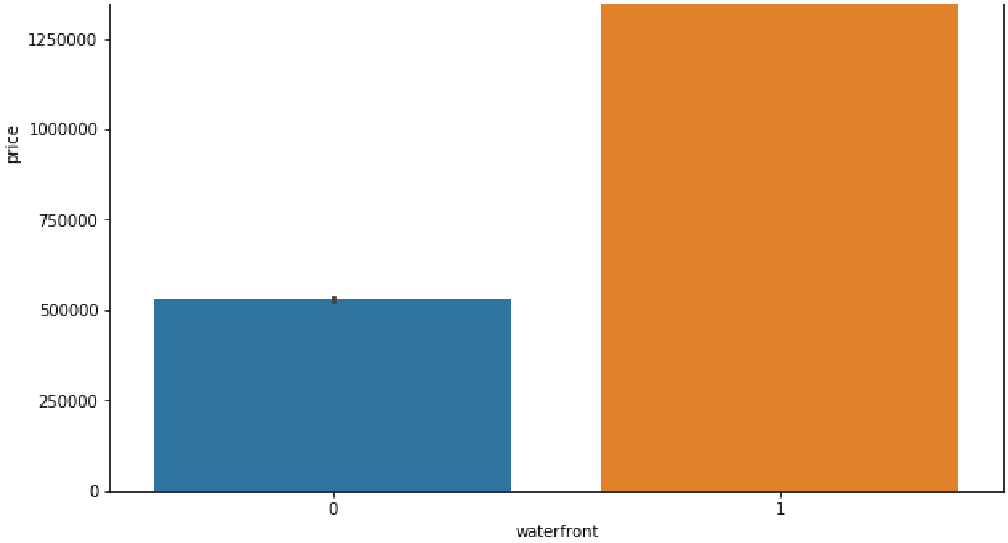
In [19]:

```
plt.figure(figsize=(10,8))
sns.scatterplot(x='long',y='lat',data=above,hue='price',alpha=0.5,edgecolor=None);
```



In [20]:

```
plt.figure(figsize=(10,8))
sns.barplot(x='waterfront',y='price',data=df);
```



In [21]:

```
df['waterfront'].value_counts()
```

Out[21]:

```
0    21434
1      163
Name: waterfront, dtype: int64
```

Analysing if Date play a role

In [22]:

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

In [23]:

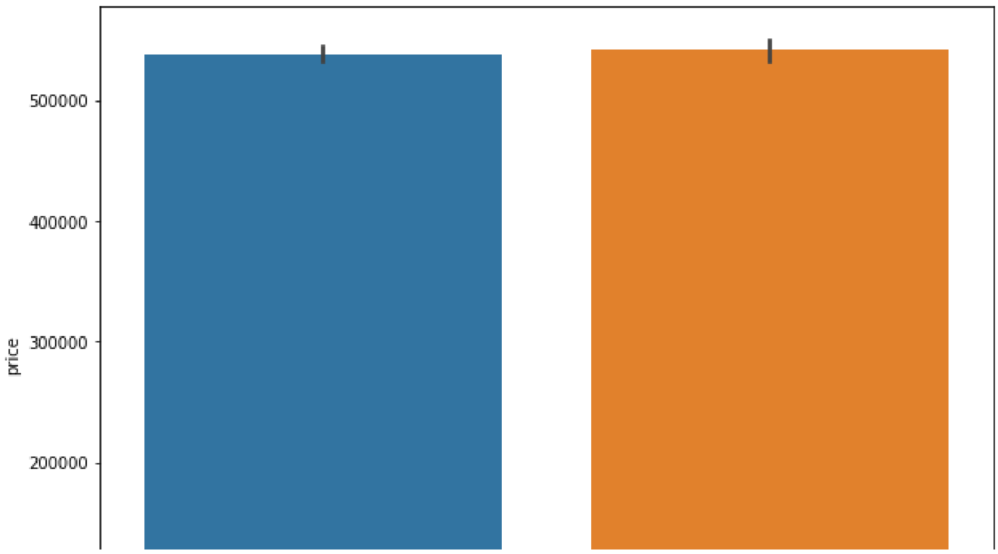
```
df['month']=df['date'].apply(lambda date:date.month)
```

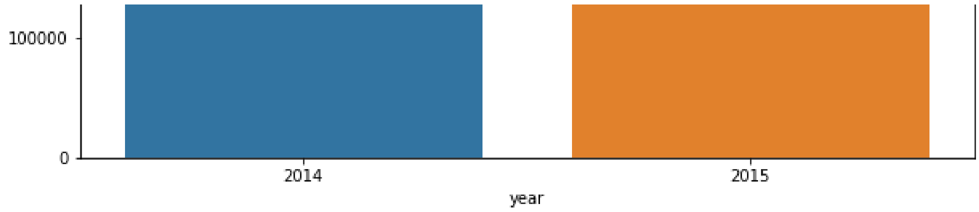
In [24]:

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

In [25]:

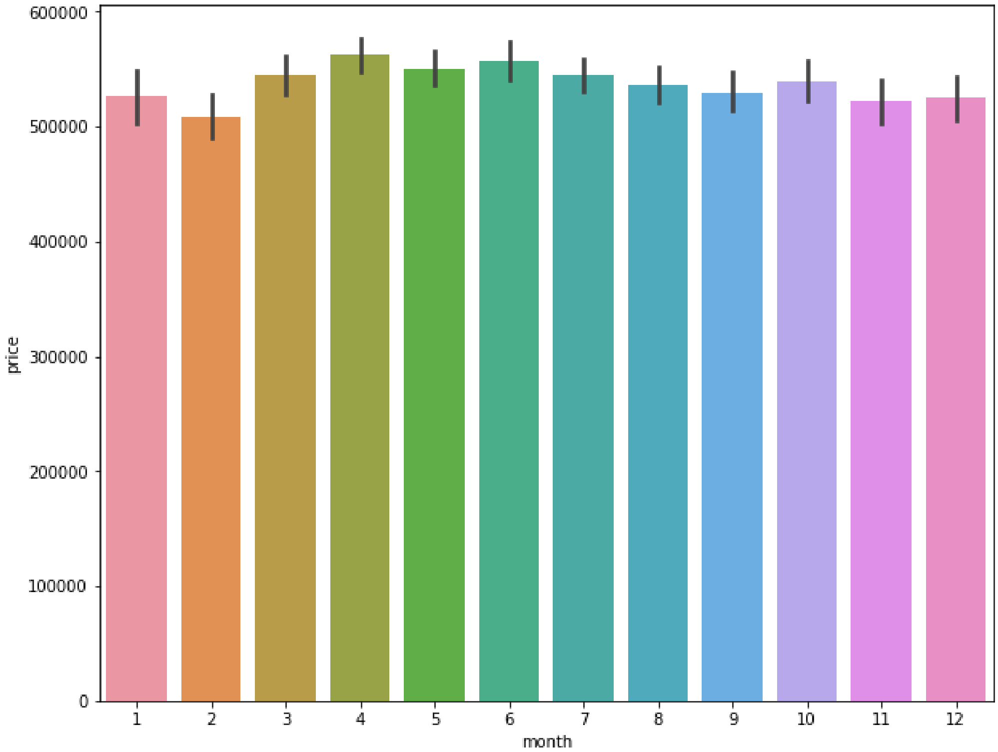
```
plt.figure(figsize=(10,8))
sns.barplot(x='year',y='price',data=df);
```





In [26]:

```
plt.figure(figsize=(10,8))
sns.barplot(x='month',y='price',data=df);
```

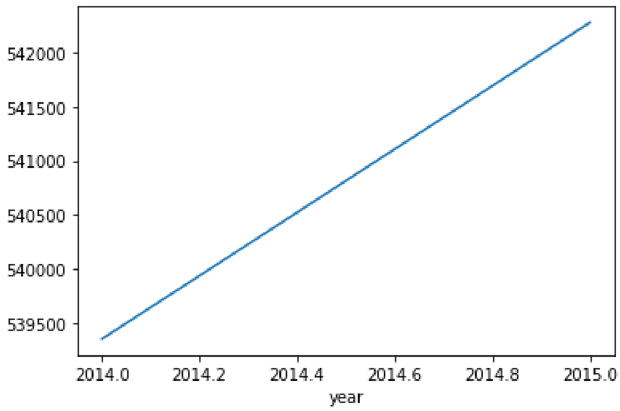


In [27]:

```
df.groupby('year').mean()['price'].plot()
```

Out[27]:

<matplotlib.axes._subplots.AxesSubplot at 0x1cdf2a7d588>

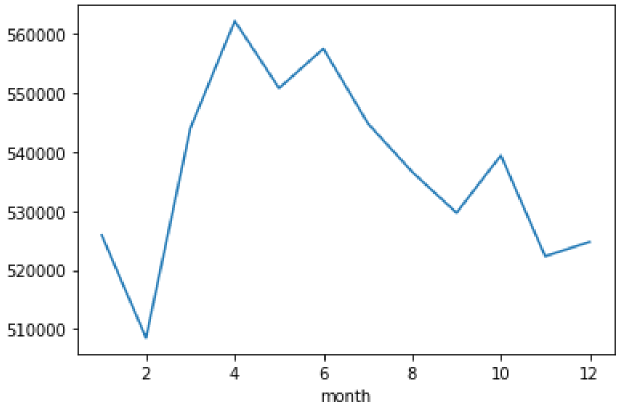


In [28]:

```
df.groupby('month').mean()['price'].plot()
```

Out[28]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1cdf2a34f08>
```



In [29]:

```
df.columns
```

Out[29]:

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

Data preprocessing and cleaning for our Machine learning and ANN Regression model to pridict price.Some of the features need to be clean in such a way that our algorithm can accept it and some will simply be droped,especially those with very little correlation with the price.

In [30]:

```
df=df.drop('id',axis=1)
df=df.drop('zipcode',axis=1)
df=df.drop('date',axis=1)
```

In [31]:

```
df.head(3)
```

Out[31]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	sqft_above	sqft_basement	yr_buil
0	221900.0	3	1.00	1180	5650	1.0	0	0	3	7	1180	0	195
1	538000.0	3	2.25	2570	7242	2.0	0	0	3	7	2170	400	195
2	180000.0	2	1.00	770	10000	1.0	0	0	3	6	770	0	193

Training a Linear Regression Model(sklearn model)

Here we have to split our data into Training and Test split

In [32]:

```
X=df.drop('price',axis=1)
y=df['price']
```

In [33]:

```python
from sklearn.model_selection import train_test_split
```

In [34]:

```python
X_train, X_test, y_train, y_test = train_test_split( X, y, test_size=0.30, random_state=101)
```

In [35]:

```python
from sklearn.linear_model import LinearRegression
```

In [36]:

```python
lr=LinearRegression()
```

In [37]:

```python
lr.fit(X_train,y_train)
```

Out[37]:

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

In [38]:

```python
# print intercept
print(lr.intercept_)
```

```
-116583510.48436856
```

In [39]:

```python
coeff=pd.DataFrame(lr.coef_,X.columns,columns=['cofficient'])
```

In [40]:

```python
coeff
```

Out[40]:

	cofficient
bedrooms	-35469.017138
bathrooms	42365.134436
sqft_living	106.699375
sqft_lot	0.176845
floors	2485.905619
waterfront	627723.871190
view	45669.377112
condition	30480.903119
grade	99672.034520
sqft_above	70.146415
sqft_basement	36.552960
yr_built	-2467.245878
yr_renovated	22.224492
lat	560933.319973
long	-142099.588905
sqft_living15	31.524857
sqft_lot15	-0.399282
month	1369.439270

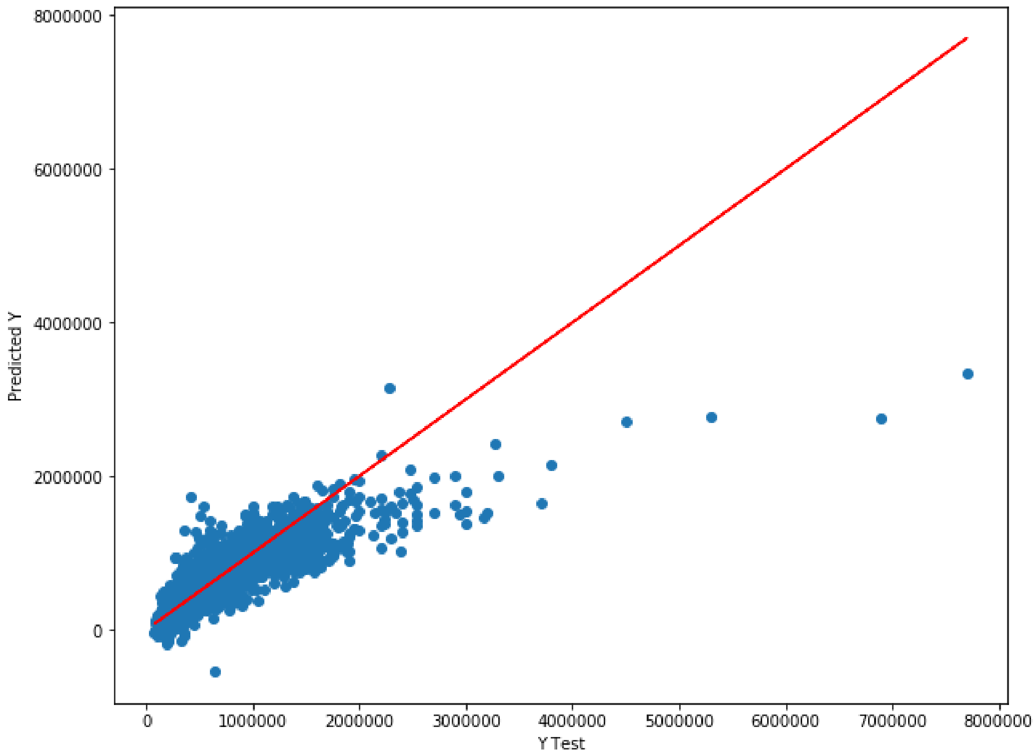
	cofficient
year	38055.891407

In [41]:

```
predictions=lr.predict(X_test)
```

In [56]:

```
plt.figure(figsize=(10,8))
plt.scatter(y_test,predictions)
plt.plot(y_test,y_test,'r')
plt.xlabel('Y Test')
plt.ylabel('Predicted Y');
```

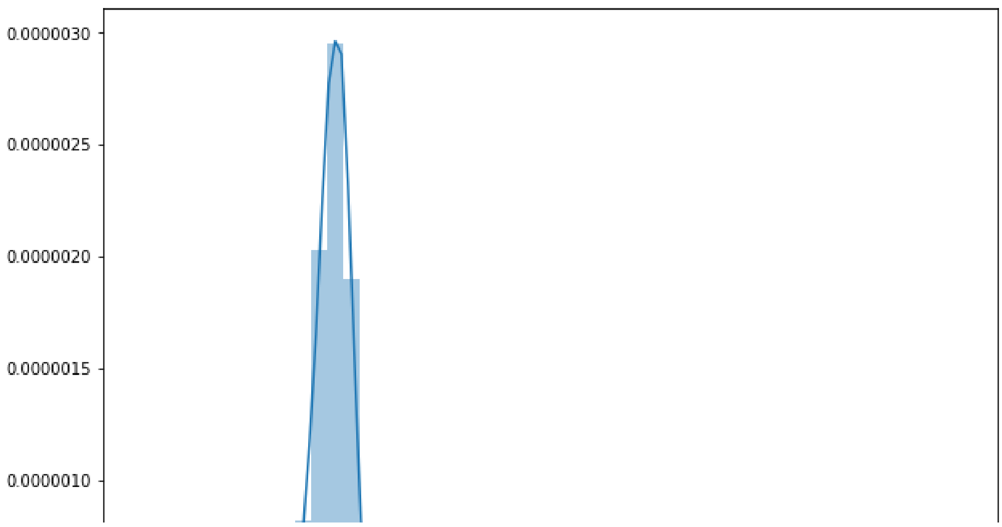


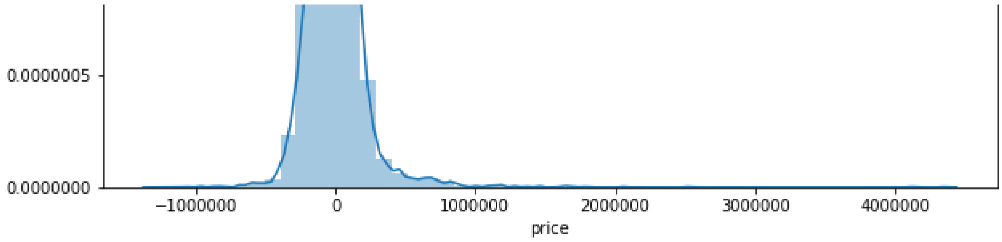
In [43]:

```
plt.figure(figsize=(10,8))
sns.distplot((y_test-predictions),bins=50)
```

Out[43]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1cdf309c1c8>
```





In [44]:

```
from sklearn import metrics
```

In [45]:

```
print('MAE:',metrics.mean_absolute_error(y_test,predictions))
print('MSE:',metrics.mean_squared_error(y_test,predictions))
print('RMSE:',np.sqrt(metrics.mean_squared_error(y_test,predictions)))
```

```
MAE: 123998.57212895666
MSE: 40433388708.44527
RMSE: 201080.55278530857
```

In [46]:

```
metrics.r2_score(y_test,predictions)
```

Out[46]:

```
0.6951102243222294
```

In [88]:

```
df.describe()['price']
```

Out[88]:

```
count    2.159700e+04
mean     5.402966e+05
std      3.673681e+05
min      7.800000e+04
25%      3.220000e+05
50%      4.500000e+05
75%      6.450000e+05
max      7.700000e+06
Name: price, dtype: float64
```

In [97]:

```
#predicting on a brand new house
New_house=df.drop('price',axis=1).iloc[0]
```

In [98]:

```
New_house=scaler.transform(New_house.values.reshape(-1,19))
```

In [92]:

```
New_house
```

Out[92]:

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

In [93]:

```
model.predict(New_house)
```

Out[93]:

```
array([[281312.56]], dtype=float32)
```

In [94]:

```
df.iloc[0]
```

Out[94]:

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

In [ ]:

```

```

Base on our prediction above,our model was able to predict well the house prices from 0.....1500000,above that the model was able to come out with a good prediction,thus that why our r2_score was able to explain just 69% of the variance

Using the ANN Approach

In [49]:

```
#Scaling
from sklearn.preprocessing import MinMaxScaler
```

In [50]:

```
scaler=MinMaxScaler()
```

In [51]:

```
X_train=scaler.fit_transform(X_train)
```

In [52]:

```
X_test=scaler.transform(X_test)
```

In [53]:

```
X_train.shape
```

Out[53]:

```
(15117, 19)
```

In [54]:

```
X_test.shape
```

Out[54]:

```
(6480, 19)
```

In [57]:

```
# creating model
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense,Activation
from tensorflow.keras.optimizers import Adam
```

In [58]:

```
model=Sequential()
```

In [59]:

```
model.add(Dense(19,activation='relu'))
model.add(Dense(19,activation='relu'))
model.add(Dense(9,activation='relu'))
model.add(Dense(1))
model.compile(optimizer='adam',loss='mse')
```

```
WARNING:tensorflow:From C:\Users\chumj\Anaconda3\Ben\lib\site-
packages\tensorflow\python\ops\init_ops.py:1251: calling VarianceScaling.__init__ (from
tensorflow.python.ops.init_ops) with dtype is deprecated and will be removed in a future version.
Instructions for updating:
Call initializer instance with the dtype argument instead of passing it to the constructor
```

In [60]:

```
#training model
model.fit(x=X_train,y=y_train.values,validation_data=(X_test,y_test.values),batch_size=100,epochs=3
00)
```

```
Train on 15117 samples, validate on 6480 samples
Epoch 1/300
15117/15117 [==============================] - 1s 64us/sample - loss: 430231519700.2072 -
val_loss: 418891592135.1111
Epoch 2/300
15117/15117 [==============================] - 0s 30us/sample - loss: 429580103309.6069 -
val_loss: 417182058116.7407
Epoch 3/300
15117/15117 [==============================] - 0s 28us/sample - loss: 425236880394.0930 -
val_loss: 409207712730.0741
Epoch 4/300
15117/15117 [==============================] - 0s 30us/sample - loss: 411206392565.7207 -
val_loss: 388165332385.1852
Epoch 5/300
15117/15117 [==============================] - 0s 28us/sample - loss: 380802693748.2050 -
val_loss: 348302157495.3087
Epoch 6/300
15117/15117 [==============================] - 0s 27us/sample - loss: 330377970061.7593 -
val_loss: 289254598377.8765
Epoch 7/300
15117/15117 [==============================] - 0s 29us/sample - loss: 263938714780.1368 -
val_loss: 219747064010.2716
Epoch 8/300
15117/15117 [==============================] - 0s 28us/sample - loss: 194991864049.8257 -
val_loss: 157151777905.7778
Epoch 9/300
15117/15117 [==============================] - 0s 30us/sample - loss: 141169925443.7214 -
val_loss: 117028887179.0617
```

```
Epoch 10/300
15117/15117 [==============================] - 0s 27us/sample - loss: 111946292784.6700 -
val_loss: 100313738865.7778
Epoch 11/300
15117/15117 [==============================] - 0s 29us/sample - loss: 101397364480.8975 -
val_loss: 95767917770.2716
Epoch 12/300
15117/15117 [==============================] - 1s 34us/sample - loss: 98478708704.7049 - val_loss:
94449023367.9012
Epoch 13/300
15117/15117 [==============================] - 0s 29us/sample - loss: 97232517953.3167 - val_loss:
93520386692.7407
Epoch 14/300
15117/15117 [==============================] - 0s 29us/sample - loss: 96183427261.3963 - val_loss:
92560502670.2222
Epoch 15/300
15117/15117 [==============================] - 0s 27us/sample - loss: 95136290205.4069 - val_loss:
91547494475.8519
Epoch 16/300
15117/15117 [==============================] - 0s 29us/sample - loss: 94046186414.6463 - val_loss:
90498554804.1481
Epoch 17/300
15117/15117 [==============================] - 0s 30us/sample - loss: 92929953524.5692 - val_loss:
89391993426.1728
Epoch 18/300
15117/15117 [==============================] - 0s 29us/sample - loss: 91785253917.3307 - val_loss:
88285573638.3210
Epoch 19/300
15117/15117 [==============================] - 0s 30us/sample - loss: 90585042653.6736 - val_loss:
87115786922.6667
Epoch 20/300
15117/15117 [==============================] - 1s 38us/sample - loss: 89363687079.2120 - val_loss:
85937746343.5062
Epoch 21/300
15117/15117 [==============================] - 0s 30us/sample - loss: 88086913137.8004 - val_loss:
84684562223.4074
Epoch 22/300
15117/15117 [==============================] - 0s 30us/sample - loss: 86775864767.4115 - val_loss:
83392530944.0000
Epoch 23/300
15117/15117 [==============================] - 0s 29us/sample - loss: 85436576801.2595 - val_loss:
82147696374.5185
Epoch 24/300
15117/15117 [==============================] - 0s 32us/sample - loss: 84076634728.4186 - val_loss:
80803735077.9259
Epoch 25/300
15117/15117 [==============================] - 0s 29us/sample - loss: 82675202342.3907 - val_loss:
79476714028.2469
Epoch 26/300
15117/15117 [==============================] - 0s 29us/sample - loss: 81234313807.7619 - val_loss:
78053861774.2222
Epoch 27/300
15117/15117 [==============================] - 0s 29us/sample - loss: 79754506122.6772 - val_loss:
76603606534.3210
Epoch 28/300
15117/15117 [==============================] - 0s 29us/sample - loss: 78246234381.1920 - val_loss:
75121302515.3580
Epoch 29/300
15117/15117 [==============================] - 0s 30us/sample - loss: 76724943108.2506 - val_loss:
73644955793.3827
Epoch 30/300
15117/15117 [==============================] - 0s 29us/sample - loss: 75132505900.9274 - val_loss:
72100071683.1605
Epoch 31/300
15117/15117 [==============================] - 0s 30us/sample - loss: 73564357127.1464 - val_loss:
70588930155.4568
Epoch 32/300
15117/15117 [==============================] - 0s 29us/sample - loss: 71991835029.4815 - val_loss:
69053899434.6667
Epoch 33/300
15117/15117 [==============================] - 0s 31us/sample - loss: 70406592365.5498 - val_loss:
67593757740.2469
Epoch 34/300
15117/15117 [==============================] - 0s 26us/sample - loss: 68835037531.9039 - val_loss:
66017270284.6420
Epoch 35/300
15117/15117 [==============================] - 0s 30us/sample - loss: 67268826013.3053 - val_loss:
```

```
15117/15117 [==============================] - 0s 30us/sample - loss: [illegible] - val_loss:
64525768204.6420
Epoch 36/300
15117/15117 [==============================] - 0s 31us/sample - loss: 65708616910.5341 - val_loss:
63027034921.0864
Epoch 37/300
15117/15117 [==============================] - 0s 31us/sample - loss: 64213752214.5653 - val_loss:
61584671377.3827
Epoch 38/300
15117/15117 [==============================] - 0s 28us/sample - loss: 62759419584.4107 - val_loss:
60282526189.0370
Epoch 39/300
15117/15117 [==============================] - 1s 42us/sample - loss: 61366316694.8193 - val_loss:
58957239220.1481
Epoch 40/300
15117/15117 [==============================] - 1s 43us/sample - loss: 60029391363.6240 - val_loss:
57681373304.0988
Epoch 41/300
15117/15117 [==============================] - 1s 44us/sample - loss: 58783377925.2497 - val_loss:
56532390425.2840
Epoch 42/300
15117/15117 [==============================] - 1s 44us/sample - loss: 57634602095.1586 - val_loss:
55451839386.8642
Epoch 43/300
15117/15117 [==============================] - 1s 51us/sample - loss: 56558761292.5951 - val_loss:
54490020826.0741
Epoch 44/300
15117/15117 [==============================] - 0s 27us/sample - loss: 55584592721.7093 - val_loss:
53570291231.6049
Epoch 45/300
15117/15117 [==============================] - 0s 26us/sample - loss: 54722195572.2389 - val_loss:
52809973867.4568
Epoch 46/300
15117/15117 [==============================] - 0s 28us/sample - loss: 53933704675.5838 - val_loss:
52076809566.8148
Epoch 47/300
15117/15117 [==============================] - 0s 26us/sample - loss: 53187255104.7748 - val_loss:
51410283463.1111
Epoch 48/300
15117/15117 [==============================] - 0s 26us/sample - loss: 52549855405.6810 - val_loss:
50840909255.1111
Epoch 49/300
15117/15117 [==============================] - 0s 28us/sample - loss: 51952240435.8367 - val_loss:
50306891380.9383
Epoch 50/300
15117/15117 [==============================] - 0s 26us/sample - loss: 51447934264.4768 - val_loss:
49813993206.5185
Epoch 51/300
15117/15117 [==============================] - 0s 27us/sample - loss: 50948950181.9589 - val_loss:
49384946014.8148
Epoch 52/300
15117/15117 [==============================] - 1s 41us/sample - loss: 50507440432.0095 - val_loss:
49003021321.4815
Epoch 53/300
15117/15117 [==============================] - 1s 45us/sample - loss: 50108691504.7038 - val_loss:
48619866105.6790
Epoch 54/300
15117/15117 [==============================] - 1s 39us/sample - loss: 49739821324.5147 - val_loss:
48287360790.1235
Epoch 55/300
15117/15117 [==============================] - 1s 44us/sample - loss: 49396609347.5182 - val_loss:
47990915621.9259
Epoch 56/300
15117/15117 [==============================] - 1s 46us/sample - loss: 49087099670.6415 - val_loss:
47685834202.0741
Epoch 57/300
15117/15117 [==============================] - 1s 35us/sample - loss: 48802307845.6392 - val_loss:
47443213963.0617
Epoch 58/300
15117/15117 [==============================] - 0s 26us/sample - loss: 48518953361.4172 - val_loss:
47173054786.3704
Epoch 59/300
15117/15117 [==============================] - 0s 27us/sample - loss: 48270417056.7430 - val_loss:
46955528286.8148
Epoch 60/300
15117/15117 [==============================] - 0s 31us/sample - loss: 48029043162.5746 - val_loss:
46718221005.4321
Epoch 61/300
```

```
Epoch 61/300
15117/15117 [==============================] - 1s 34us/sample - loss: 47790747452.3040 - val_loss: 46527536560.9877
Epoch 62/300
15117/15117 [==============================] - 1s 43us/sample - loss: 47570493334.5992 - val_loss: 46323840461.4321
Epoch 63/300
15117/15117 [==============================] - 1s 48us/sample - loss: 47375750964.3786 - val_loss: 46118656410.8642
Epoch 64/300
15117/15117 [==============================] - 0s 26us/sample - loss: 47184786431.9323 - val_loss: 45941589927.5062
Epoch 65/300
15117/15117 [==============================] - 0s 28us/sample - loss: 46983239586.9276 - val_loss: 45772906123.0617
Epoch 66/300
15117/15117 [==============================] - 0s 31us/sample - loss: 46817886361.3595 - val_loss: 45604916713.8765
Epoch 67/300
15117/15117 [==============================] - 1s 53us/sample - loss: 46658403389.4386 - val_loss: 45446707993.2840
Epoch 68/300
15117/15117 [==============================] - 1s 36us/sample - loss: 46482478089.9575 - val_loss: 45315923689.8765
Epoch 69/300
15117/15117 [==============================] - 1s 49us/sample - loss: 46331976510.8781 - val_loss: 45153931267.1605
Epoch 70/300
15117/15117 [==============================] - 0s 26us/sample - loss: 46185162350.5828 - val_loss: 45030558944.3951
Epoch 71/300
15117/15117 [==============================] - 0s 26us/sample - loss: 46044735165.1592 - val_loss: 44890757382.3210
Epoch 72/300
15117/15117 [==============================] - 0s 26us/sample - loss: 45912868067.5330 - val_loss: 44764164393.0864
Epoch 73/300
15117/15117 [==============================] - 0s 26us/sample - loss: 45779196959.9047 - val_loss: 44638274657.9753
Epoch 74/300
15117/15117 [==============================] - 0s 26us/sample - loss: 45640214410.1353 - val_loss: 44523984052.1481
Epoch 75/300
15117/15117 [==============================] - 0s 28us/sample - loss: 45522269101.2915 - val_loss: 44403915355.6543
Epoch 76/300
15117/15117 [==============================] - 0s 26us/sample - loss: 45417825363.7923 - val_loss: 44293238733.4321
Epoch 77/300
15117/15117 [==============================] - 0s 27us/sample - loss: 45299650463.4052 - val_loss: 44185232055.3086
Epoch 78/300
15117/15117 [==============================] - 0s 26us/sample - loss: 45168038001.9358 - val_loss: 44076169494.1235
Epoch 79/300
15117/15117 [==============================] - 0s 26us/sample - loss: 45061807022.3753 - val_loss: 43972886689.1852
Epoch 80/300
15117/15117 [==============================] - 0s 28us/sample - loss: 44956963827.8071 - val_loss: 43869458444.6420
Epoch 81/300
15117/15117 [==============================] - 0s 26us/sample - loss: 44841746152.1053 - val_loss: 43792754109.6296
Epoch 82/300
15117/15117 [==============================] - 0s 28us/sample - loss: 44738073146.8985 - val_loss: 43683812709.1358
Epoch 83/300
15117/15117 [==============================] - 0s 29us/sample - loss: 44636767108.7840 - val_loss: 43600585377.1852
Epoch 84/300
15117/15117 [==============================] - 0s 29us/sample - loss: 44535935876.1066 - val_loss: 43496961782.5185
Epoch 85/300
15117/15117 [==============================] - 0s 28us/sample - loss: 44457879733.4032 - val_loss: 43422441677.4321
Epoch 86/300
15117/15117 [==============================] - 1s 48us/sample - loss: 44349420099.0271 - val_loss: 43334585464.0988
```

```
43334385464.0988
Epoch 87/300
15117/15117 [==============================] - 0s 33us/sample - loss: 44255741779.2673 - val_loss: 
43245786974.8148
Epoch 88/300
15117/15117 [==============================] - 1s 45us/sample - loss: 44151940498.8397 - val_loss: 
43160219208.6914
Epoch 89/300
15117/15117 [==============================] - 1s 38us/sample - loss: 44085309862.8225 - val_loss: 
43088326150.3210
Epoch 90/300
15117/15117 [==============================] - 1s 38us/sample - loss: 43999374034.7677 - val_loss: 
43007956941.4321
Epoch 91/300
15117/15117 [==============================] - 1s 36us/sample - loss: 43898368753.5887 - val_loss: 
42924131448.0988
Epoch 92/300
15117/15117 [==============================] - 0s 29us/sample - loss: 43827636006.0859 - val_loss: 
42840933492.9383
Epoch 93/300
15117/15117 [==============================] - 0s 30us/sample - loss: 43729529949.4111 - val_loss: 
42766544004.7407
Epoch 94/300
15117/15117 [==============================] - 1s 42us/sample - loss: 43635290578.0396 - val_loss: 
42703047913.8765
Epoch 95/300
15117/15117 [==============================] - 1s 39us/sample - loss: 43560120859.2647 - val_loss: 
42620688523.0617
Epoch 96/300
15117/15117 [==============================] - 0s 30us/sample - loss: 43491227473.9125 - val_loss: 
42526895830.9136
Epoch 97/300
15117/15117 [==============================] - 1s 38us/sample - loss: 43407621202.1666 - val_loss: 
42457569488.5926
Epoch 98/300
15117/15117 [==============================] - 0s 31us/sample - loss: 43327676978.4989 - val_loss: 
42381365295.4074
Epoch 99/300
15117/15117 [==============================] - 0s 28us/sample - loss: 43243176188.4945 - val_loss: 
42299964766.8148
Epoch 100/300
15117/15117 [==============================] - 0s 31us/sample - loss: 43142746763.7780 - val_loss: 
42241754042.4691
Epoch 101/300
15117/15117 [==============================] - 1s 42us/sample - loss: 43098733191.7137 - val_loss: 
42157572361.4815
Epoch 102/300
15117/15117 [==============================] - 0s 33us/sample - loss: 43000214466.8323 - val_loss: 
42083408760.0988
Epoch 103/300
15117/15117 [==============================] - 0s 27us/sample - loss: 42926828714.2264 - val_loss: 
42009117297.7778
Epoch 104/300
15117/15117 [==============================] - 0s 29us/sample - loss: 42865478411.5324 - val_loss: 
41937405316.7407
Epoch 105/300
15117/15117 [==============================] - ETA: 0s - loss: 40811691620.848 - 0s 26us/sample - 
loss: 42752797873.0002 - val_loss: 41909863117.4321
Epoch 106/300
15117/15117 [==============================] - 0s 27us/sample - loss: 42696976602.6593 - val_loss: 
41794725044.1481
Epoch 107/300
15117/15117 [==============================] - 0s 28us/sample - loss: 42612091070.2092 - val_loss: 
41720766574.6173
Epoch 108/300
15117/15117 [==============================] - 0s 27us/sample - loss: 42536864719.7026 - val_loss: 
41654914345.0864
Epoch 109/300
15117/15117 [==============================] - 0s 27us/sample - loss: 42471485924.8708 - val_loss: 
41563829216.3951
Epoch 110/300
15117/15117 [==============================] - 1s 42us/sample - loss: 42387342730.7111 - val_loss: 
41541432231.5062
Epoch 111/300
15117/15117 [==============================] - 1s 45us/sample - loss: 42311703711.3882 - val_loss: 
41430478693.1358
Epoch 112/300
15117/15117 [==============================] - 0s 26us/sample - loss: 42251685098.7132 - val_loss: 
```

```
15117/15117 [==============================] - 0s 26us/sample - loss: 42251685098.7132 - val_loss:
41368194917.1358
Epoch 113/300
15117/15117 [==============================] - 0s 26us/sample - loss: 42159766202.9239 - val_loss:
41265590796.6420
Epoch 114/300
15117/15117 [==============================] - 1s 38us/sample - loss: 42069714462.6516 - val_loss:
41186218774.1235
Epoch 115/300
15117/15117 [==============================] - 1s 51us/sample - loss: 41984371563.5854 - val_loss:
41119713343.2099
Epoch 116/300
15117/15117 [==============================] - 0s 33us/sample - loss: 41901816960.7705 - val_loss:
41034322621.6296
Epoch 117/300
15117/15117 [==============================] - 1s 48us/sample - loss: 41818613636.3098 - val_loss:
40966782644.1481
Epoch 118/300
15117/15117 [==============================] - 0s 29us/sample - loss: 41748925938.3507 - val_loss:
40870931569.7778
Epoch 119/300
15117/15117 [==============================] - 0s 29us/sample - loss: 41681796715.0604 - val_loss:
40797690576.5926
Epoch 120/300
15117/15117 [==============================] - 0s 29us/sample - loss: 41576979496.9817 - val_loss:
40698323493.9259
Epoch 121/300
15117/15117 [==============================] - 0s 27us/sample - loss: 41494669263.6348 - val_loss:
40615791979.4568
Epoch 122/300
15117/15117 [==============================] - 0s 30us/sample - loss: 41428196528.2551 - val_loss:
40526521764.3457
Epoch 123/300
15117/15117 [==============================] - 1s 34us/sample - loss: 41328749528.5763 - val_loss:
40439712802.7654
Epoch 124/300
15117/15117 [==============================] - 1s 43us/sample - loss: 41243409155.2006 - val_loss:
40366907079.1111
Epoch 125/300
15117/15117 [==============================] - 1s 37us/sample - loss: 41167639361.9940 - val_loss:
40268700627.7531
Epoch 126/300
15117/15117 [==============================] - 1s 40us/sample - loss: 41073552461.2894 - val_loss:
40175090425.6790
Epoch 127/300
15117/15117 [==============================] - 0s 27us/sample - loss: 40991011597.9710 - val_loss:
40085877459.7531
Epoch 128/300
15117/15117 [==============================] - 0s 26us/sample - loss: 40919697056.0317 - val_loss:
40000525223.5062
Epoch 129/300
15117/15117 [==============================] - 0s 28us/sample - loss: 40800659862.0234 - val_loss:
39904691162.0741
Epoch 130/300
15117/15117 [==============================] - ETA: 0s - loss: 40498402133.333 - 0s 27us/sample -
loss: 40715170600.1857 - val_loss: 39848264539.6543
Epoch 131/300
15117/15117 [==============================] - 0s 30us/sample - loss: 40631324268.8893 - val_loss:
39711562581.3333
Epoch 132/300
15117/15117 [==============================] - 0s 30us/sample - loss: 40535971559.9698 - val_loss:
39615637513.4815
Epoch 133/300
15117/15117 [==============================] - 1s 42us/sample - loss: 40436164266.1925 - val_loss:
39516500922.4691
Epoch 134/300
15117/15117 [==============================] - 1s 54us/sample - loss: 40330232861.1952 - val_loss:
39454953389.8272
Epoch 135/300
15117/15117 [==============================] - 1s 43us/sample - loss: 40248832280.4366 - val_loss:
39330997197.4321
Epoch 136/300
15117/15117 [==============================] - 1s 55us/sample - loss: 40168735224.5149 - val_loss:
39214201353.4815
Epoch 137/300
15117/15117 [==============================] - 1s 53us/sample - loss: 40027516951.5729 - val_loss:
39106817349.5309
Epoch 138/300
```

```
Epoch 138/300
15117/15117 [==============================] - 1s 49us/sample - loss: 39921282143.6465 - val_loss: 
39021664126.4198
Epoch 139/300
15117/15117 [==============================] - 1s 55us/sample - loss: 39840071827.6695 - val_loss: 
38895871333.1358
Epoch 140/300
15117/15117 [==============================] - 1s 54us/sample - loss: 39741749825.4013 - val_loss: 
38791883222.9136
Epoch 141/300
15117/15117 [==============================] - 1s 46us/sample - loss: 39635126513.5548 - val_loss: 
38682428634.0741
Epoch 142/300
15117/15117 [==============================] - 1s 56us/sample - loss: 39516182180.5025 - val_loss: 
38554294461.6296
Epoch 143/300
15117/15117 [==============================] - 1s 53us/sample - loss: 39414182504.9605 - val_loss: 
38439957156.3457
Epoch 144/300
15117/15117 [==============================] - 1s 41us/sample - loss: 39301148157.0534 - val_loss: 
38327241481.4815
Epoch 145/300
15117/15117 [==============================] - 1s 56us/sample - loss: 39195678005.2254 - val_loss: 
38210468140.2469
Epoch 146/300
15117/15117 [==============================] - 1s 54us/sample - loss: 39094327054.9871 - val_loss: 
38103631890.9630
Epoch 147/300
15117/15117 [==============================] - 1s 43us/sample - loss: 38974494864.8245 - val_loss: 
37987583396.3457
Epoch 148/300
15117/15117 [==============================] - 1s 56us/sample - loss: 38843997288.2493 - val_loss: 
37869549896.6914
Epoch 149/300
15117/15117 [==============================] - 1s 54us/sample - loss: 38744461441.2447 - val_loss: 
37778474875.2593
Epoch 150/300
15117/15117 [==============================] - 1s 48us/sample - loss: 38622670334.5436 - val_loss: 
37621721394.5679
Epoch 151/300
15117/15117 [==============================] - 1s 57us/sample - loss: 38501464952.0153 - val_loss: 
37510313813.3333
Epoch 152/300
15117/15117 [==============================] - 1s 42us/sample - loss: 38407842361.3405 - val_loss: 
37380051354.8642
Epoch 153/300
15117/15117 [==============================] - 0s 29us/sample - loss: 38305638642.2322 - val_loss: 
37257171007.2099
Epoch 154/300
15117/15117 [==============================] - 0s 29us/sample - loss: 38207024017.9253 - val_loss: 
37149367751.1111
Epoch 155/300
15117/15117 [==============================] - 0s 28us/sample - loss: 38067421941.2465 - val_loss: 
37045009954.7654
Epoch 156/300
15117/15117 [==============================] - 0s 28us/sample - loss: 37979416396.4935 - val_loss: 
36917827309.0370
Epoch 157/300
15117/15117 [==============================] - 0s 25us/sample - loss: 37849061543.8555 - val_loss: 
36800716199.5062
Epoch 158/300
15117/15117 [==============================] - 0s 27us/sample - loss: 37780068463.9714 - val_loss: 
36686428542.4198
Epoch 159/300
15117/15117 [==============================] - 0s 27us/sample - loss: 37656981584.3376 - val_loss: 
36595907407.0123
Epoch 160/300
15117/15117 [==============================] - 0s 32us/sample - loss: 37565454645.8689 - val_loss: 
36479259606.9136
Epoch 161/300
15117/15117 [==============================] - 1s 40us/sample - loss: 37461686042.0962 - val_loss: 
36378519510.9136
Epoch 162/300
15117/15117 [==============================] - 1s 57us/sample - loss: 37359875768.8240 - val_loss: 
36299435915.0617
Epoch 163/300
15117/15117 [==============================] - 1s 53us/sample - loss: 37283517444.2675 - val_loss: 
```

```
36196504990.0247
Epoch 164/300
15117/15117 [==============================] - 1s 36us/sample - loss: 37186375672.8197 - val_loss:
36104895374.2222
Epoch 165/300
15117/15117 [==============================] - 0s 26us/sample - loss: 37134791276.7539 - val_loss:
36024906063.0123
Epoch 166/300
15117/15117 [==============================] - 0s 27us/sample - loss: 37045377919.0940 - val_loss:
35971806261.7284
Epoch 167/300
15117/15117 [==============================] - 0s 26us/sample - loss: 36986238833.0722 - val_loss:
35856583281.7778
Epoch 168/300
15117/15117 [==============================] - 0s 26us/sample - loss: 36897501176.8197 - val_loss:
35780485843.7531
Epoch 169/300
15117/15117 [==============================] - 0s 28us/sample - loss: 36833836797.4429 - val_loss:
35712100924.0494
Epoch 170/300
15117/15117 [==============================] - 0s 26us/sample - loss: 36766417383.7158 - val_loss:
35650183629.4321
Epoch 171/300
15117/15117 [==============================] - 0s 26us/sample - loss: 36714012980.6157 - val_loss:
35586535733.7284
Epoch 172/300
15117/15117 [==============================] - 0s 28us/sample - loss: 36645939243.3525 - val_loss:
35551344655.8025
Epoch 173/300
15117/15117 [==============================] - 0s 26us/sample - loss: 36595324042.1184 - val_loss:
35490637903.0123
Epoch 174/300
15117/15117 [==============================] - 0s 26us/sample - loss: 36554317233.7284 - val_loss:
35426091431.5062
Epoch 175/300
15117/15117 [==============================] - 0s 28us/sample - loss: 36485990836.6411 - val_loss:
35373848809.8765
Epoch 176/300
15117/15117 [==============================] - 0s 26us/sample - loss: 36446647411.6293 - val_loss:
35350674239.2099
Epoch 177/300
15117/15117 [==============================] - 0s 27us/sample - loss: 36374321303.0564 - val_loss:
35301835159.7037
Epoch 178/300
15117/15117 [==============================] - 0s 26us/sample - loss: 36367164614.6765 - val_loss:
35223297908.9383
Epoch 179/300
15117/15117 [==============================] - 0s 26us/sample - loss: 36316188040.6790 - val_loss:
35182559674.4691
Epoch 180/300
15117/15117 [==============================] - 0s 28us/sample - loss: 36275976965.3005 - val_loss:
35132624510.4198
Epoch 181/300
15117/15117 [==============================] - 0s 26us/sample - loss: 36235220315.1588 - val_loss:
35099964529.7778
Epoch 182/300
15117/15117 [==============================] - 0s 26us/sample - loss: 36195643125.1111 - val_loss:
35070518363.6543
Epoch 183/300
15117/15117 [==============================] - 1s 37us/sample - loss: 36147991562.0930 - val_loss:
35014691299.5556
Epoch 184/300
15117/15117 [==============================] - 1s 53us/sample - loss: 36127822339.6917 - val_loss:
34977627967.2099
Epoch 185/300
15117/15117 [==============================] - 1s 49us/sample - loss: 36091391662.7987 - val_loss:
34946140434.9630
Epoch 186/300
15117/15117 [==============================] - 0s 33us/sample - loss: 36043485994.9630 - val_loss:
34920142598.3210
Epoch 187/300
15117/15117 [==============================] - 0s 29us/sample - loss: 36015330309.0804 - val_loss:
34866072620.2469
Epoch 188/300
15117/15117 [==============================] - 1s 41us/sample - loss: 35969834859.2467 - val_loss:
34835953888.3951
Epoch 189/300
```

```
15117/15117 [==============================] - 0s 28us/sample - loss: 35944368925.5508 - val_loss:
34812835748.3457
Epoch 190/300
15117/15117 [==============================] - 0s 25us/sample - loss: 35902331900.3421 - val_loss:
34772606938.0741
Epoch 191/300
15117/15117 [==============================] - 0s 28us/sample - loss: 35863028224.2371 - val_loss:
34728817746.1728
Epoch 192/300
15117/15117 [==============================] - ETA: 0s - loss: 35815108562.149 - 0s 25us/sample -
loss: 35828551210.8445 - val_loss: 34707721136.9877
Epoch 193/300
15117/15117 [==============================] - 0s 27us/sample - loss: 35794970651.2308 - val_loss:
34708056727.7037
Epoch 194/300
15117/15117 [==============================] - 1s 44us/sample - loss: 35773132221.5149 - val_loss:
34628839240.6914
Epoch 195/300
15117/15117 [==============================] - 1s 48us/sample - loss: 35755443486.8040 - val_loss:
34615223665.7778
Epoch 196/300
15117/15117 [==============================] - 1s 33us/sample - loss: 35698261683.4049 - val_loss:
34584510106.8642
Epoch 197/300
15117/15117 [==============================] - 1s 35us/sample - loss: 35678850402.7455 - val_loss:
34530522661.9259
Epoch 198/300
15117/15117 [==============================] - 1s 36us/sample - loss: 35658492260.9809 - val_loss:
34517549852.4444
Epoch 199/300
15117/15117 [==============================] - 1s 37us/sample - loss: 35620335614.1033 - val_loss:
34498389595.6543
Epoch 200/300
15117/15117 [==============================] - 1s 41us/sample - loss: 35591036676.0135 - val_loss:
34437199081.8765
Epoch 201/300
15117/15117 [==============================] - 1s 44us/sample - loss: 35561408495.6073 - val_loss:
34405933334.1235
Epoch 202/300
15117/15117 [==============================] - 0s 27us/sample - loss: 35537998374.4415 - val_loss:
34379788885.3333
Epoch 203/300
15117/15117 [==============================] - 1s 34us/sample - loss: 35496963637.5471 - val_loss:
34352429861.9259
Epoch 204/300
15117/15117 [==============================] - 1s 50us/sample - loss: 35480327748.5850 - val_loss:
34389809572.3457
Epoch 205/300
15117/15117 [==============================] - ETA: 0s - loss: 35491623685.086 - 0s 30us/sample -
loss: 35466777895.4068 - val_loss: 34291404654.6173
Epoch 206/300
15117/15117 [==============================] - 0s 27us/sample - loss: 35422368174.0028 - val_loss:
34259027064.0988
Epoch 207/300
15117/15117 [==============================] - 0s 33us/sample - loss: 35405224928.0953 - val_loss:
34269151889.3827
Epoch 208/300
15117/15117 [==============================] - 0s 32us/sample - loss: 35378949209.4823 - val_loss:
34202287761.3827
Epoch 209/300
15117/15117 [==============================] - 0s 32us/sample - loss: 35353543482.9493 - val_loss:
34173599778.7654
Epoch 210/300
15117/15117 [==============================] - 0s 29us/sample - loss: 35338558581.5260 - val_loss:
34148956769.9753
Epoch 211/300
15117/15117 [==============================] - 0s 27us/sample - loss: 35286979149.5942 - val_loss:
34118387215.8025
Epoch 212/300
15117/15117 [==============================] - 0s 29us/sample - loss: 35262332359.1337 - val_loss:
34090356840.2963
Epoch 213/300
15117/15117 [==============================] - 0s 28us/sample - loss: 35225797020.5263 - val_loss:
34096685498.4691
Epoch 214/300
15117/15117 [==============================] - 0s 28us/sample - loss: 35217620588.2797 - val_loss:
34034582771.3580
```

```
Epoch 215/300
15117/15117 [==============================] - 0s 33us/sample - loss: 35188098472.8547 - val_loss:
34019898785.1852
Epoch 216/300
15117/15117 [==============================] - 1s 45us/sample - loss: 35145702910.2727 - val_loss:
34004666800.9877
Epoch 217/300
15117/15117 [==============================] - 0s 33us/sample - loss: 35137530931.2779 - val_loss:
33954605653.3333
Epoch 218/300
15117/15117 [==============================] - 1s 39us/sample - loss: 35101515246.6929 - val_loss:
33925707962.4691
Epoch 219/300
15117/15117 [==============================] - 0s 33us/sample - loss: 35080484330.6286 - val_loss:
33904270724.7407
Epoch 220/300
15117/15117 [==============================] - 0s 33us/sample - loss: 35052834184.6790 - val_loss:
33872535978.6667
Epoch 221/300
15117/15117 [==============================] - 1s 42us/sample - loss: 35020750613.8964 - val_loss:
33853898176.7901
Epoch 222/300
15117/15117 [==============================] - 1s 43us/sample - loss: 34995145272.3244 - val_loss:
33825929374.0247
Epoch 223/300
15117/15117 [==============================] - 1s 37us/sample - loss: 34963017752.9277 - val_loss:
33798204251.6543
Epoch 224/300
15117/15117 [==============================] - 1s 50us/sample - loss: 34937953039.8000 - val_loss:
33792623587.5556
Epoch 225/300
15117/15117 [==============================] - 1s 56us/sample - loss: 34920141980.6787 - val_loss:
33739450665.0864
Epoch 226/300
15117/15117 [==============================] - 1s 36us/sample - loss: 34892456335.7915 - val_loss:
33732678567.5062
Epoch 227/300
15117/15117 [==============================] - 0s 26us/sample - loss: 34859534311.0046 - val_loss:
33696002123.8518
Epoch 228/300
15117/15117 [==============================] - 0s 27us/sample - loss: 34857537332.1077 - val_loss:
33655653714.1728
Epoch 229/300
15117/15117 [==============================] - 0s 26us/sample - loss: 34809752174.7183 - val_loss:
33645829559.3086
Epoch 230/300
15117/15117 [==============================] - 0s 26us/sample - loss: 34798900120.8007 - val_loss:
33602714759.9012
Epoch 231/300
15117/15117 [==============================] - 0s 28us/sample - loss: 34761600549.0190 - val_loss:
33634832055.3086
Epoch 232/300
15117/15117 [==============================] - 0s 26us/sample - loss: 34754733342.0589 - val_loss:
33572905895.5062
Epoch 233/300
15117/15117 [==============================] - 0s 26us/sample - loss: 34714848769.2532 - val_loss:
33518616168.2963
Epoch 234/300
15117/15117 [==============================] - 0s 29us/sample - loss: 34682952706.7773 - val_loss:
33492720987.6543
Epoch 235/300
15117/15117 [==============================] - 1s 33us/sample - loss: 34669101319.5020 - val_loss:
33466988208.9877
Epoch 236/300
15117/15117 [==============================] - 1s 36us/sample - loss: 34657750854.6680 - val_loss:
33440243348.5432
Epoch 237/300
15117/15117 [==============================] - 1s 34us/sample - loss: 34635297941.4984 - val_loss:
33421665213.6296
Epoch 238/300
15117/15117 [==============================] - 1s 37us/sample - loss: 34614494396.3802 - val_loss:
33425980504.4938
Epoch 239/300
15117/15117 [==============================] - 1s 36us/sample - loss: 34550589979.3324 - val_loss:
33359630829.0370
Epoch 240/300
15117/15117 [==============================] - 1s 37us/sample - loss: 34540851400.7763 - val_loss:
```

```
33331953392.1975
Epoch 241/300
15117/15117 [==============================] - 0s 26us/sample - loss: 34545988559.4316 - val_loss: 33321171566.6173
Epoch 242/300
15117/15117 [==============================] - 0s 28us/sample - loss: 34513131513.5649 - val_loss: 33290671846.7160
Epoch 243/300
15117/15117 [==============================] - 1s 38us/sample - loss: 34476966412.7009 - val_loss: 33247659415.7037
Epoch 244/300
15117/15117 [==============================] - 1s 53us/sample - loss: 34450785111.4671 - val_loss: 33222823196.4444
Epoch 245/300
15117/15117 [==============================] - 1s 46us/sample - loss: 34421243894.7199 - val_loss: 33194982409.4815
Epoch 246/300
15117/15117 [==============================] - ETA: 0s - loss: 34003250874.542 - 1s 41us/sample - loss: 34413989213.7329 - val_loss: 33173009461.7284
Epoch 247/300
15117/15117 [==============================] - 0s 28us/sample - loss: 34377858100.0908 - val_loss: 33149073790.4198
Epoch 248/300
15117/15117 [==============================] - 0s 30us/sample - loss: 34359882042.8477 - val_loss: 33120634601.8765
Epoch 249/300
15117/15117 [==============================] - 0s 29us/sample - loss: 34335573911.5475 - val_loss: 33096211190.5185
Epoch 250/300
15117/15117 [==============================] - 0s 26us/sample - loss: 34311848596.8549 - val_loss: 33069839641.2840
Epoch 251/300
15117/15117 [==============================] - 0s 28us/sample - loss: 34298335844.7607 - val_loss: 33042481243.6543
Epoch 252/300
15117/15117 [==============================] - 0s 26us/sample - loss: 34276418743.3676 - val_loss: 33042531862.1235
Epoch 253/300
15117/15117 [==============================] - 0s 26us/sample - loss: 34247303047.4258 - val_loss: 33017545664.7901
Epoch 254/300
15117/15117 [==============================] - 0s 28us/sample - loss: 34227411720.4165 - val_loss: 32969401666.3704
Epoch 255/300
15117/15117 [==============================] - 0s 26us/sample - loss: 34214197579.1726 - val_loss: 32944271710.8148
Epoch 256/300
15117/15117 [==============================] - 0s 26us/sample - loss: 34170255953.9295 - val_loss: 32930951237.5309
Epoch 257/300
15117/15117 [==============================] - 0s 26us/sample - loss: 34159239961.6898 - val_loss: 32909324670.4198
Epoch 258/300
15117/15117 [==============================] - 0s 25us/sample - loss: 34135680604.9708 - val_loss: 32872769169.3827
Epoch 259/300
15117/15117 [==============================] - 0s 29us/sample - loss: 34111724200.7700 - val_loss: 32856405415.5062
Epoch 260/300
15117/15117 [==============================] - 0s 33us/sample - loss: 34087882858.2814 - val_loss: 32856168953.6790
Epoch 261/300
15117/15117 [==============================] - 1s 35us/sample - loss: 34074119183.3766 - val_loss: 32836069391.8025
Epoch 262/300
15117/15117 [==============================] - 0s 32us/sample - loss: 34055461474.5931 - val_loss: 32774781440.0000
Epoch 263/300
15117/15117 [==============================] - 1s 35us/sample - loss: 34022931917.2301 - val_loss: 32777917016.4938
Epoch 264/300
15117/15117 [==============================] - 1s 44us/sample - loss: 34006423657.2653 - val_loss: 32754212892.4444
Epoch 265/300
15117/15117 [==============================] - 1s 46us/sample - loss: 33973518013.2270 - val_loss: 32733260686.2222
Epoch 266/300
```

```
15117/15117 [==============================] - 1s 54us/sample - loss: 33973193431.7804 - val_loss: 32676748904.2963
Epoch 267/300
15117/15117 [==============================] - 1s 44us/sample - loss: 33940699523.9373 - val_loss: 32659493303.3086
Epoch 268/300
15117/15117 [==============================] - 1s 51us/sample - loss: 33911591132.9285 - val_loss: 32726748991.2099
Epoch 269/300
15117/15117 [==============================] - 0s 26us/sample - loss: 33900306483.4811 - val_loss: 32615402375.9012
Epoch 270/300
15117/15117 [==============================] - 0s 25us/sample - loss: 33878860137.5871 - val_loss: 32586628579.5556
Epoch 271/300
15117/15117 [==============================] - 0s 27us/sample - loss: 33865706471.0046 - val_loss: 32563314479.4074
Epoch 272/300
15117/15117 [==============================] - 0s 26us/sample - loss: 33854985870.8262 - val_loss: 32560929918.4198
Epoch 273/300
15117/15117 [==============================] - 0s 26us/sample - loss: 33813186417.2076 - val_loss: 32519902574.6173
Epoch 274/300
15117/15117 [==============================] - 0s 28us/sample - loss: 33796943777.4373 - val_loss: 32528424827.2593
Epoch 275/300
15117/15117 [==============================] - 0s 26us/sample - loss: 33781524361.3902 - val_loss: 32515596976.9877
Epoch 276/300
15117/15117 [==============================] - 0s 27us/sample - loss: 33768483435.2636 - val_loss: 32451439625.4815
Epoch 277/300
15117/15117 [==============================] - 0s 26us/sample - loss: 33739893387.2361 - val_loss: 32436150034.9630
Epoch 278/300
15117/15117 [==============================] - 0s 26us/sample - loss: 33719853893.2455 - val_loss: 32422675604.5432
Epoch 279/300
15117/15117 [==============================] - 0s 27us/sample - loss: 33716976252.3337 - val_loss: 32394395139.1605
Epoch 280/300
15117/15117 [==============================] - 0s 25us/sample - loss: 33678441257.2018 - val_loss: 32366962482.5679
Epoch 281/300
15117/15117 [==============================] - 0s 28us/sample - loss: 33662938013.1021 - val_loss: 32345767619.9506
Epoch 282/300
15117/15117 [==============================] - 0s 29us/sample - loss: 33634288681.3881 - val_loss: 32330125669.1358
Epoch 283/300
15117/15117 [==============================] - 0s 28us/sample - loss: 33626658573.2936 - val_loss: 32316313776.9877
Epoch 284/300
15117/15117 [==============================] - 0s 29us/sample - loss: 33606270260.4803 - val_loss: 32316545460.1481
Epoch 285/300
15117/15117 [==============================] - 0s 26us/sample - loss: 33595263302.2277 - val_loss: 32265308921.6790
Epoch 286/300
15117/15117 [==============================] - 0s 26us/sample - loss: 33568206810.8794 - val_loss: 32255782716.0494
Epoch 287/300
15117/15117 [==============================] - 0s 27us/sample - loss: 33533212101.5080 - val_loss: 32283378710.1235
Epoch 288/300
15117/15117 [==============================] - 0s 25us/sample - loss: 33507164575.7777 - val_loss: 32210717986.7654
Epoch 289/300
15117/15117 [==============================] - 0s 26us/sample - loss: 33518019936.9843 - val_loss: 32184571297.1852
Epoch 290/300
15117/15117 [==============================] - 1s 35us/sample - loss: 33490957495.2321 - val_loss: 32194438706.5679
Epoch 291/300
15117/15117 [==============================] - 1s 57us/sample - loss: 33484103433.2293 - val_loss: 32144282734.6173
```

```
Epoch 292/300
15117/15117 [==============================] - 1s 54us/sample - loss: 33473757975.0480 - val_loss: 32124350865.3827
Epoch 293/300
15117/15117 [==============================] - 1s 45us/sample - loss: 33449002785.8184 - val_loss: 32115240609.1852
Epoch 294/300
15117/15117 [==============================] - 1s 51us/sample - loss: 33436157319.7306 - val_loss: 32097239589.9259
Epoch 295/300
15117/15117 [==============================] - 1s 37us/sample - loss: 33404405230.1510 - val_loss: 32072230700.2469
Epoch 296/300
15117/15117 [==============================] - 1s 46us/sample - loss: 33384043612.5983 - val_loss: 32105864798.8148
Epoch 297/300
15117/15117 [==============================] - 0s 26us/sample - loss: 33397665502.6219 - val_loss: 32049007938.3704
Epoch 298/300
15117/15117 [==============================] - 0s 25us/sample - loss: 33359963547.6457 - val_loss: 32013674233.6790
Epoch 299/300
15117/15117 [==============================] - 1s 34us/sample - loss: 33345362975.2274 - val_loss: 31999053880.8889
Epoch 300/300
15117/15117 [==============================] - 1s 56us/sample - loss: 33370220876.0532 - val_loss: 31988941261.4321
```

Out[60]:

```
<tensorflow.python.keras.callbacks.History at 0x1cdfe88b708>
```

In [62]:

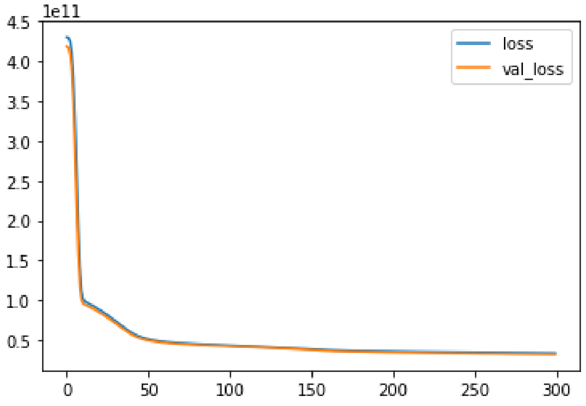
```
#model.history.history
```

In [63]:

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

In [65]:

```
losses.plot();
```



In [66]:

```
from tensorflow.keras.callbacks import EarlyStopping
```

In [70]:

```
#early_stop = EarlyStopping(monitor='val_loss', mode='min', verbose=1, patience=25)
```

In [71]:

```
#model.fit(x=X_train,y=y_train,epochs=600,validation_data=(X_test, y_test), verbose=1,callbacks=[e
arly_stop] )
```

In [73]:

```
#EVALUATING THE MODEL
from sklearn.metrics import mean_absolute_error,mean_squared_error,explained_variance_score
```

In [74]:

```
predictions1=model.predict(X_test)
```

In [75]:

```
mean_absolute_error(y_test,predictions1)
```

Out[75]:

99796.04556086034

In [76]:

```
mean_squared_error(y_test,predictions1)
```

Out[76]:

25483779352.2967

In [77]:

```
np.sqrt(mean_squared_error(y_test,predictions1))
```

Out[77]:

159636.39732935812

In [78]:

```
explained_variance_score(y_test,predictions1)
```

Out[78]:

0.8078840279886367

In [79]:

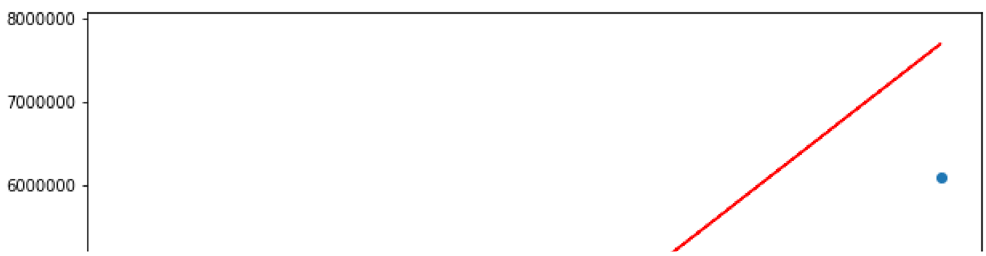
```
df['price'].mean()
```

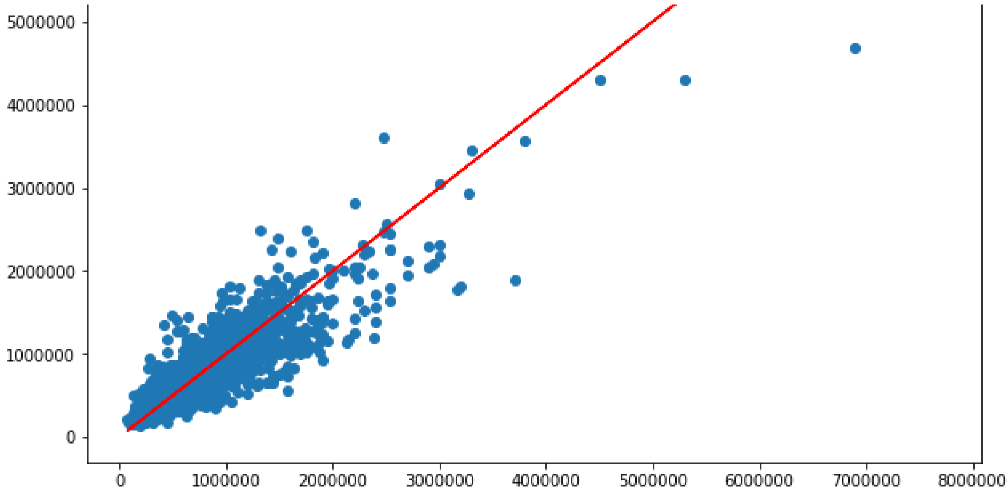
Out[79]:

540296.5735055795

In [81]:

```
plt.figure(figsize=(10,8))
plt.scatter(y_test,predictions1)
plt.plot(y_test,y_test,'r');
```



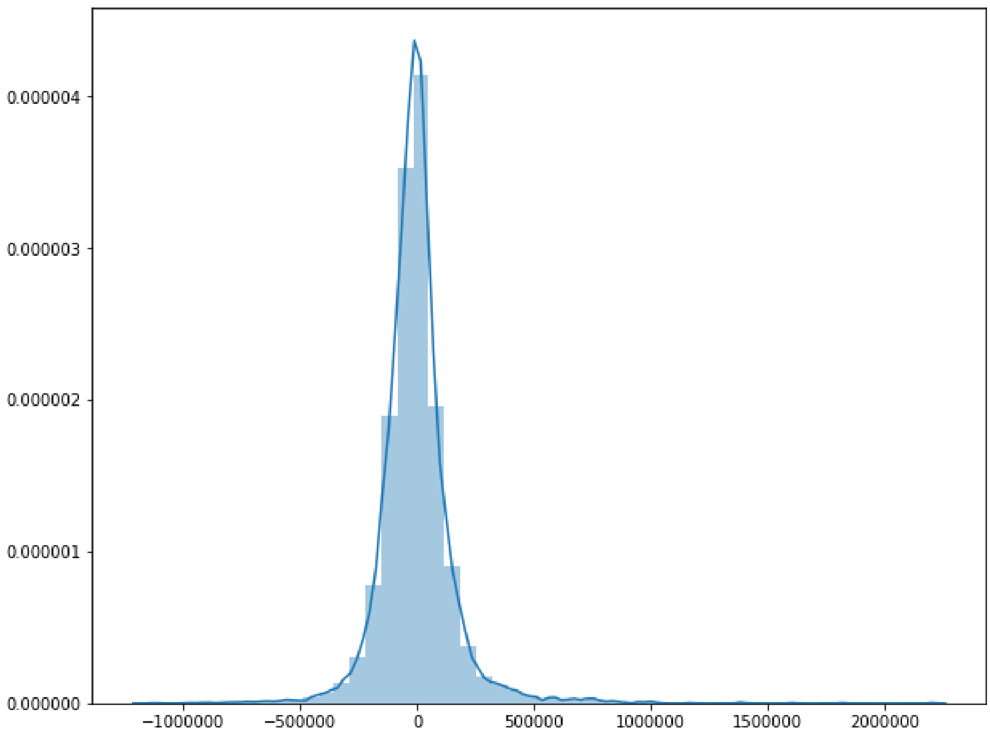


In [84]:

```
error=y_test.values.reshape(6480,1)-predictions1
```

In [87]:

```
plt.figure(figsize=(10,8))
sns.distplot(error);
```



In [99]:

```
New_brand2=df.drop('price',axis=1).iloc[1]
```

In [100]:

```
New_brand2=scaler.transform(New_brand2.values.reshape(-1,19))
```

In [101]:

```
New_brand2
```

Out[101]:

```
array([[0.2       , 0.28      , 0.22750776, 0.00407187, 0.4       ,
```

```
        0.        , 0.        , 0.5       , 0.4       , 0.23968043,
        0.08298755, 0.44347826, 0.98808933, 0.90895931, 0.16611296,
        0.22216486, 0.0081402 , 1.        , 0.        ]])
```

In [102]:

```
model.predict(New_brand2)
```

Out[102]:

```
array([[635116.75]], dtype=float32)
```

In [103]:

```
df.iloc[1]
```

Out[103]:

```
price            538000.000
bedrooms              3.000
bathrooms             2.250
sqft_living        2570.000
sqft_lot           7242.000
floors                2.000
waterfront            0.000
view                  0.000
condition             3.000
grade                 7.000
sqft_above         2170.000
sqft_basement       400.000
yr_built           1951.000
yr_renovated       1991.000
lat                  47.721
long               -122.319
sqft_living15      1690.000
sqft_lot15         7639.000
month                12.000
year               2014.000
Name: 1, dtype: float64
```

In [104]:

```
df['price']
```

Out[104]:

```
0        221900.0
1        538000.0
2        180000.0
3        604000.0
4        510000.0
           ...
21592    360000.0
21593    400000.0
21594    402101.0
21595    400000.0
21596    325000.0
Name: price, Length: 21597, dtype: float64
```

In [ ]:

```

```