

Regression to predict the price of house using Incremental Extreme Machine Learning

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import keras
import math
from keras.models import Sequential
from keras.datasets import mnist
from keras.layers import Dense
from keras.optimizers import Adam
import random
import keras
import keras.utils
from keras.utils.np_utils import to_categorical
from keras import utils as np_utils
from sklearn.preprocessing import OneHotEncoder
from sklearn.metrics import accuracy_score
import time
from sklearn.metrics import mean_squared_error

import statistics
```

Using TensorFlow backend.

In [2]:

```
df = pd.read_csv('kc_house_data.csv')
print (df)
```

| | price | bedrooms | bathrooms | sqft_living | sqft_lot | floors | \ |
|-------|----------|----------|-----------|-------------|----------|--------|---|
| 0 | 221900.0 | 3 | 1.00 | 1180 | 5650 | 1.0 | |
| 1 | 538000.0 | 3 | 2.25 | 2570 | 7242 | 2.0 | |
| 2 | 180000.0 | 2 | 1.00 | 770 | 10000 | 1.0 | |
| 3 | 604000.0 | 4 | 3.00 | 1960 | 5000 | 1.0 | |
| 4 | 510000.0 | 3 | 2.00 | 1680 | 8080 | 1.0 | |
| ... | ... | ... | ... | ... | ... | ... | |
| 21608 | 360000.0 | 3 | 2.50 | 1530 | 1131 | 3.0 | |
| 21609 | 400000.0 | 4 | 2.50 | 2310 | 5813 | 2.0 | |
| 21610 | 402101.0 | 2 | 0.75 | 1020 | 1350 | 2.0 | |
| 21611 | 400000.0 | 3 | 2.50 | 1600 | 2388 | 2.0 | |
| 21612 | 325000.0 | 2 | 0.75 | 1020 | 1076 | 2.0 | |

| | waterfront | view | condition | grade | sqft_above | sqft_basement | \ |
|---|------------|------|-----------|-------|------------|---------------|---|
| 0 | 0 | 0 | 3 | 7 | 1180 | 0 | |
| 1 | 0 | 0 | 3 | 7 | 2170 | 400 | |
| 2 | 0 | 0 | 3 | 6 | 770 | 0 | |
| 3 | 0 | 0 | 5 | 7 | 1050 | 910 | |
| 4 | 0 | 0 | 3 | 8 | 1680 | 0 | |

In [3]:

```
total_train = df.drop(columns="price")#-----to guess the condition of the
a = df.iloc[:, 0]
total_labels = pd.DataFrame(a)
print(type(total_train))
print(type(total_labels))
print(total_labels)

start = time.time()
```

```
<class 'pandas.core.frame.DataFrame'>
<class 'pandas.core.frame.DataFrame'>
   price
0    221900.0
1    538000.0
2    180000.0
3    604000.0
4    510000.0
...      ...
21608  360000.0
21609  400000.0
21610  402101.0
21611  400000.0
21612  325000.0
```

```
[21613 rows x 1 columns]
```

In [4]:

```
x_train = total_train.loc[0:10000, :]
y_labels = total_labels.loc[0:10000, :]

x_test = total_train.loc[10001:20000, :]
y_test_labels = total_labels.loc[10001:20000, :]
```

In [5]:

```
print(x_test)
```

| | bedrooms | bathrooms | sqft_living | sqft_lot | floors | waterfront | view |
|-------|----------|-----------|-------------|----------|--------|------------|------|
| \ | | | | | | | |
| 10001 | 5 | 3.25 | 3160 | 10587 | 1.0 | 0 | 0 |
| 10002 | 3 | 1.50 | 2020 | 11358 | 1.0 | 0 | 0 |
| 10003 | 4 | 3.75 | 3210 | 7054 | 2.0 | 0 | 0 |
| 10004 | 3 | 2.25 | 2350 | 51400 | 1.0 | 0 | 0 |
| 10005 | 4 | 2.50 | 1910 | 10221 | 2.0 | 0 | 0 |
| ... | ... | ... | ... | ... | ... | ... | ... |
| 19996 | 3 | 2.25 | 1530 | 1305 | 2.0 | 0 | 0 |
| 19997 | 3 | 2.50 | 1600 | 6315 | 2.0 | 0 | 0 |
| 19998 | 2 | 1.50 | 1000 | 1251 | 2.0 | 0 | 0 |
| 19999 | 4 | 3.50 | 2440 | 3012 | 3.0 | 0 | 1 |
| 20000 | 3 | 2.50 | 1260 | 1102 | 3.0 | 0 | 0 |

| | condition | grade | sqft_above | sqft_basement | yr_built | yr_renovated |
|-------|-----------|-------|------------|---------------|----------|--------------|
| \ | | | | | | |
| 10001 | 5 | 7 | 2190 | 970 | 1960 | 0 |
| 10002 | 4 | 6 | 1190 | 830 | 1956 | 0 |
| 10003 | 4 | 8 | 3210 | 0 | 1985 | 0 |
| 10004 | 3 | 7 | 1390 | 960 | 1977 | 0 |
| 10005 | 3 | 8 | 1910 | 0 | 1994 | 0 |
| ... | ... | ... | ... | ... | ... | ... |
| 19996 | 3 | 7 | 1116 | 414 | 2007 | 0 |
| 19997 | 3 | 8 | 1600 | 0 | 2013 | 0 |
| 19998 | 3 | 7 | 930 | 70 | 2006 | 0 |
| 19999 | 3 | 8 | 2440 | 0 | 2005 | 0 |
| 20000 | 3 | 8 | 1260 | 0 | 2007 | 0 |

| | zipcode | lat | long | sqft_living15 | sqft_lot15 |
|-------|---------|---------|----------|---------------|------------|
| 10001 | 98034 | 47.7238 | -122.165 | 2200 | 7761 |
| 10002 | 98033 | 47.6641 | -122.185 | 2370 | 9520 |
| 10003 | 98052 | 47.7268 | -122.103 | 2350 | 8020 |
| 10004 | 98077 | 47.7417 | -122.053 | 2350 | 51400 |
| 10005 | 98038 | 47.3810 | -122.035 | 2210 | 8705 |
| ... | ... | ... | ... | ... | ... |
| 19996 | 98177 | 47.7034 | -122.357 | 1320 | 1427 |
| 19997 | 98092 | 47.2611 | -122.198 | 1608 | 4300 |
| 19998 | 98199 | 47.6529 | -122.384 | 1420 | 1187 |
| 19999 | 98117 | 47.6923 | -122.392 | 1860 | 4650 |
| 20000 | 98107 | 47.6750 | -122.387 | 1320 | 2500 |

[10000 rows x 18 columns]

In [6]:

```
X = (x_train, y_labels)
Y = (x_test, y_test_labels)
```

In [7]:

```
print(x_train)
```

| | bedrooms | bathrooms | sqft_living | sqft_lot | floors | waterfront | view |
|-------|----------|-----------|-------------|----------|--------|------------|------|
| \ | | | | | | | |
| 0 | 3 | 1.00 | 1180 | 5650 | 1.0 | 0 | 0 |
| 1 | 3 | 2.25 | 2570 | 7242 | 2.0 | 0 | 0 |
| 2 | 2 | 1.00 | 770 | 10000 | 1.0 | 0 | 0 |
| 3 | 4 | 3.00 | 1960 | 5000 | 1.0 | 0 | 0 |
| 4 | 3 | 2.00 | 1680 | 8080 | 1.0 | 0 | 0 |
| ... | ... | ... | ... | ... | ... | ... | ... |
| 9996 | 3 | 1.50 | 1700 | 9579 | 1.0 | 0 | 0 |
| 9997 | 4 | 1.00 | 1550 | 4750 | 1.5 | 0 | 0 |
| 9998 | 3 | 1.75 | 1680 | 8100 | 1.0 | 0 | 2 |
| 9999 | 3 | 2.25 | 1680 | 35127 | 2.0 | 0 | 0 |
| 10000 | 4 | 2.50 | 1910 | 10300 | 1.0 | 0 | 0 |

| | condition | grade | sqft_above | sqft_basement | yr_built | yr_renovated |
|-------|-----------|-------|------------|---------------|----------|--------------|
| \ | | | | | | |
| 0 | 3 | 7 | 1180 | 0 | 1955 | 0 |
| 1 | 3 | 7 | 2170 | 400 | 1951 | 1991 |
| 2 | 3 | 6 | 770 | 0 | 1933 | 0 |
| 3 | 5 | 7 | 1050 | 910 | 1965 | 0 |
| 4 | 3 | 8 | 1680 | 0 | 1987 | 0 |
| ... | ... | ... | ... | ... | ... | ... |
| 9996 | 4 | 7 | 1100 | 600 | 1962 | 0 |
| 9997 | 3 | 7 | 1550 | 0 | 1919 | 0 |
| 9998 | 3 | 8 | 1680 | 0 | 1950 | 0 |
| 9999 | 3 | 7 | 1680 | 0 | 1987 | 0 |
| 10000 | 3 | 8 | 1910 | 0 | 1921 | 1968 |

| | zipcode | lat | long | sqft_living15 | sqft_lot15 |
|-------|---------|---------|----------|---------------|------------|
| 0 | 98178 | 47.5112 | -122.257 | 1340 | 5650 |
| 1 | 98125 | 47.7210 | -122.319 | 1690 | 7639 |
| 2 | 98028 | 47.7379 | -122.233 | 2720 | 8062 |
| 3 | 98136 | 47.5208 | -122.393 | 1360 | 5000 |
| 4 | 98074 | 47.6168 | -122.045 | 1800 | 7503 |
| ... | ... | ... | ... | ... | ... |
| 9996 | 98023 | 47.3209 | -122.338 | 1700 | 9628 |
| 9997 | 98117 | 47.6824 | -122.389 | 1320 | 4750 |
| 9998 | 98177 | 47.7212 | -122.364 | 1880 | 7750 |
| 9999 | 98092 | 47.3025 | -122.067 | 1820 | 35166 |
| 10000 | 98177 | 47.7581 | -122.359 | 1910 | 7750 |

[10001 rows x 18 columns]

In [8]:

```

x_train=pd.DataFrame(x_train).to_numpy()

#w = np.random.rand(18,1000)*100#-----creating random weight matrix
#weights = pd.DataFrame(w)

#weights =to_numpy.DataFrame(w)
#weights=pd.DataFrame(weights).to_numpy()

#weights_transpose = np.transpose(weights)
#print(weights.shape)
print(x_train.shape)
#print(type(weights))
#print(type(x_train))

y_labels=pd.DataFrame(y_labels).to_numpy()

```

(10001, 18)

In []:

In [9]:

```

print(x_train)

```

```

[[ 3.00000e+00  1.00000e+00  1.18000e+03 ... -1.22257e+02  1.34000e+03
   5.65000e+03]
 [ 3.00000e+00  2.25000e+00  2.57000e+03 ... -1.22319e+02  1.69000e+03
   7.63900e+03]
 [ 2.00000e+00  1.00000e+00  7.70000e+02 ... -1.22233e+02  2.72000e+03
   8.06200e+03]
 ...
 [ 3.00000e+00  1.75000e+00  1.68000e+03 ... -1.22364e+02  1.88000e+03
   7.75000e+03]
 [ 3.00000e+00  2.25000e+00  1.68000e+03 ... -1.22067e+02  1.82000e+03
   3.51660e+04]
 [ 4.00000e+00  2.50000e+00  1.91000e+03 ... -1.22359e+02  1.91000e+03
   7.75000e+03]]

```

In [21]:

```

start = time.time()
l=0
acc=0
l_max=50#-----setting up number neu
beta=0
error=0
rmse=0
final=0.1
d=0
p=0

for i in range(l_max):

    if(final>0.00005):
        w = np.random.rand(18,i)*100#-----creating random weight m
        weights = pd.DataFrame(w)

        #weights =to_numpy.DataFrame(w)
        weights=pd.DataFrame(weights).to_numpy()

        weights_transpose = np.transpose(weights)#-----transposing weight
        h_new = np.dot(x_train,weights)
        h_inv = np.linalg.pinv(h_new)

        beta = np.dot(h_inv, y_labels)
        #print(beta.shape)
        #print(h_new.shape)
        predicted_output = np.dot(h_new,beta)
        rounded_labels=np.round(predicted_output)
        rounded=pd.DataFrame(rounded_labels).to_numpy()
        #rmse = rmse + ((y_labels[i] - predicted_output[i])**2)
        #if(i==0):
            #i=i+1
        #rmse1=math.sqrt((1/i)*rmse)
        #print(rmse1)

        d = mean_squared_error(y_labels, rounded)
        rmse=1/10000*(math.sqrt(d))
        print("RMSE", + i, + rmse)

    #print(predicted_output.shape)

    # print(predicted_output[i][:])
    # print(predicted_output.shape)
    #print(y_train)

    # print("p",+ rounded)
    #print(type(predicted_output))

    #print("y",+rounded)

end = time.time()

```

```
print("Time elapsed",end - start)
    #print(h_inv.shape)
    #print(h_new.shape)
    #print(beta)
    #print(weights.shape)
#print(error[1][9])
```

```
RMSE 0 65.3187934906508
RMSE 1 58.59238919015065
RMSE 2 38.14558851827319
RMSE 3 37.68989053431443
RMSE 4 26.692054763073475
RMSE 5 26.616501627450887
RMSE 6 26.5393831050097
RMSE 7 25.954065728475634
RMSE 8 25.613605014950217
RMSE 9 24.65734693954081
RMSE 10 23.745741270183125
RMSE 11 23.041154691045442
RMSE 12 22.670759022773435
RMSE 13 22.677096144179103
RMSE 14 22.022490048761114
RMSE 15 21.975676470442103
RMSE 16 21.471165237021943
RMSE 17 20.80337475941956
RMSE 18 20.80337479162249
RMSE 19 20.80337478474516
RMSE 20 20.80337478474516
RMSE 21 20.80337478072643
RMSE 22 20.80337478474516
RMSE 23 20.803374781921402
RMSE 24 20.803374790262605
RMSE 25 20.803374790262605
RMSE 26 20.803374790262605
RMSE 27 20.80337478474516
RMSE 28 20.80337478474516
RMSE 29 20.80337478474516
RMSE 30 20.80337479308636
RMSE 31 20.803374790262605
RMSE 32 20.80337478474516
RMSE 33 20.80337479308636
RMSE 34 20.80337479308636
RMSE 35 20.80337478474516
RMSE 36 20.80337479308636
RMSE 37 20.80337478474516
RMSE 38 20.80337478474516
RMSE 39 20.803374790262605
RMSE 40 20.80337478474516
RMSE 41 20.80337478474516
RMSE 42 20.80337478474516
RMSE 43 20.80337478474516
RMSE 44 20.80337479308636
RMSE 45 20.80337478474516
RMSE 46 20.80337479308636
RMSE 47 20.80337478474516
RMSE 48 20.80337478474516
RMSE 49 20.80337479308636
Time elapsed 0.992955207824707
```


In []:

```
#h_inv = np.linalg.pinv(h_new)
#print(h_inv.shape)
```

In []:

```
#beta = np.dot(h_inv, y_labels)
```

In []:

```
#print(beta)
```

In []:

```
#predicted_output= np.dot(h_new, beta) #-----
#print(predicted_output.shape)
```

In []:

```
#print(np.round(predicted_output))
#rounded_labels=np.round(predicted_output)
#rounded=pd.DataFrame(rounded_labels).to_numpy()
#print(rounded_labels)
#print(type(y_labels))
#print(type(rounded_labels))
```

In []:

```
#acc = accuracy_score(rounded_labels,y_labels)#-----Finding accuracy
#print("Accuracy is", + acc*100, "%")
#end = time.time()
#print("Time elapsed",end - start)
```

In []:

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