

```
In [1]: # import the necessary packages
from keras.models import Sequential
from keras.layers import Dense, Dropout, Activation
from sklearn.preprocessing import LabelBinarizer
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
from keras.optimizers import Adam
import pandas as pd
import numpy as np
import glob
import cv2
import os
import locale
```

Introduction to the House Price Estimation Dataset This dataset was introduced and published in a 2016 paper titled '2016 House Price Estimation from Visual and Textual Features.

<https://github.com/emanhamed/Houses-dataset>

<https://arxiv.org/pdf/1609.08399.pdf>

```
In [2]: cols = ["bedrooms", "bathrooms", "area", "zipcode", "price"]
df = pd.read_csv("https://raw.githubusercontent.com/emanhamed/Houses-dataset/master/Houses%20Dataset/HousesInfo")
df.head()
```

```
Out[2]:
```

| | bedrooms | bathrooms | area | zipcode | price |
|---|----------|-----------|------|---------|--------|
| 0 | 4 | 4.0 | 4053 | 85255 | 869500 |
| 1 | 4 | 3.0 | 3343 | 36372 | 865200 |
| 2 | 3 | 4.0 | 3923 | 85266 | 889000 |
| 3 | 5 | 5.0 | 4022 | 85262 | 910000 |
| 4 | 3 | 4.0 | 4116 | 85266 | 971226 |

```
In [11]: zipcodes, counts = np.unique(df["zipcode"], return_counts=True)
```

```
In [12]: df["zipcode"].value_counts()
```

```
Out[12]:
```

| zipcode | count |
|---------|-------|
| 92276 | 100 |
| 93510 | 60 |
| 93446 | 54 |
| 92880 | 49 |
| 94501 | 41 |
| 91901 | 32 |
| 92677 | 26 |
| 94531 | 22 |
| 85255 | 12 |
| 96019 | 12 |
| 85266 | 11 |
| 81524 | 11 |
| 92021 | 11 |
| 93111 | 11 |
| 95220 | 10 |
| 92802 | 9 |
| 85262 | 9 |
| 62234 | 7 |
| 98021 | 4 |
| 62214 | 4 |
| 85377 | 3 |
| 60002 | 3 |

| | |
|-------|---|
| 91752 | 3 |
| 62025 | 2 |
| 81418 | 2 |
| 92692 | 2 |
| 60016 | 2 |
| 92253 | 2 |
| 62088 | 1 |
| 85331 | 1 |
| 36372 | 1 |
| 62034 | 1 |
| 81521 | 1 |
| 62249 | 1 |
| 92543 | 1 |
| 93105 | 1 |
| 60046 | 1 |
| 94568 | 1 |
| 90211 | 1 |
| 92040 | 1 |
| 93720 | 1 |
| 90038 | 1 |
| 93314 | 1 |
| 90265 | 1 |
| 93924 | 1 |
| 91915 | 1 |
| 94565 | 1 |
| 95008 | 1 |
| 90803 | 1 |

dtype: int64

```
In [13]: df.shape
```

```
Out[13]: (535, 5)
```

```
In [14]: # Get zipcodes with fewer than 25 occurrences
low_count_zips = df["zipcode"].value_counts()[df["zipcode"].value_counts() < 25].index

# Drop rows where the zipcode is in the low-count list
df.drop(df[df["zipcode"].isin(low_count_zips)].index, inplace=True)
```

```
In [15]: df.shape
```

```
Out[15]: (362, 5)
```

```
In [16]: # Split Dataset into Training and Testing Sets

(train, test) = train_test_split(df, test_size=0.25, random_state=42)
print(train.shape)
print(test.shape)
```

```
(271, 5)
```

```
(91, 5)
```

Preprocessing

```
In [17]: # find the largest house price in the training set and use it to
# scale our house prices to the range [0, 1] (this will lead to
# better training and convergence)
maxPrice = train["price"].max()
trainY = train["price"] / maxPrice
testY = test["price"] / maxPrice
```

```
In [18]: # initialize the column names of the continuous data
```

```
continuous = ["bedrooms", "bathrooms", "area"]

# perform min-max scaling each continuous feature column to
# the range [0, 1]
scaler = MinMaxScaler()
trainContinuous = scaler.fit_transform(train[continuous])
testContinuous = scaler.transform(test[continuous])
```

```
In [19]: # one-hot encode the zip code categorical data (by definition of
# one-hot encoding, all output features are now in the range [0, 1])
zipBinarizer = LabelBinarizer().fit(df["zipcode"])
trainCategorical = zipBinarizer.transform(train["zipcode"])
testCategorical = zipBinarizer.transform(test["zipcode"])
```

```
In [20]: zipBinarizer.classes_
```

```
Out[20]: array([91901, 92276, 92677, 92880, 93446, 93510, 94501])
```

```
In [21]: trainCategorical.shape
```

```
Out[21]: (271, 7)
```

```
In [22]: # construct our training and testing data points by concatenating
# the categorical features with the continuous features
trainX = np.hstack([trainCategorical, trainContinuous])
testX = np.hstack([testCategorical, testContinuous])

print(trainX.shape)
print(testX.shape)
```

```
(271, 10)
```

```
(91, 10)
```

Model Architecture

```
In [25]: dim = trainX.shape[1]

# define our MLP network
model = Sequential()
model.add(Dense(8, input_dim=dim, activation="relu"))
model.add(Dense(4, activation="relu"))
model.add(Dense(1, activation="linear"))
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/layers/core/dense.py:87: UserWarning: Do not pass an `input_shape` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

Compile Model

```
In [26]: from tensorflow.keras.optimizers import Adam











































opt = Adam(learning_rate=1e-3)
model.compile(loss="mean_absolute_percentage_error", optimizer=opt)
```









































Training Model

```
In [27]: model.fit(x=trainX, y=trainY, validation_data=(testX, testY), epochs=200, batch_size=8)
```

```
Epoch 1/200
34/34 ————— 3s 41ms/step - loss: 359.5607 - val_loss: 87.7315
Epoch 2/200
34/34 ————— 0s 6ms/step - loss: 78.5842 - val_loss: 59.4321
Epoch 3/200
34/34 ————— 0s 6ms/step - loss: 60.8043 - val_loss: 50.8352
Epoch 4/200
34/34 ————— 0s 6ms/step - loss: 53.0693 - val_loss: 49.9522
Epoch 5/200
34/34 ————— 0s 6ms/step - loss: 52.5476 - val_loss: 45.1922
Epoch 6/200
34/34 ————— 0s 4ms/step - loss: 44.8414 - val_loss: 42.1018
Epoch 7/200
34/34 ————— 0s 4ms/step - loss: 45.6417 - val_loss: 40.5503
Epoch 8/200
34/34 ————— 0s 4ms/step - loss: 34.8826 - val_loss: 39.6934
Epoch 9/200
34/34 ————— 0s 4ms/step - loss: 36.5405 - val_loss: 38.3746
Epoch 10/200
34/34 ————— 0s 4ms/step - loss: 40.7339 - val_loss: 42.2564
```

| | | | | | |
|--------------|-------------|----|----------|-----------------|---------------------|
| Epoch 11/200 | | | | | |
| 34/34 | <div></div> | 0s | 4ms/step | - loss: 38.0658 | - val_loss: 42.0305 |
| Epoch 12/200 | | | | | |
| 34/34 | <div></div> | 0s | 4ms/step | - loss: 46.6432 | - val_loss: 41.9934 |
| Epoch 13/200 | | | | | |
| 34/34 | <div></div> | 0s | 5ms/step | - loss: 38.6251 | - val_loss: 36.6947 |
| Epoch 14/200 | | | | | |
| 34/34 | <div></div> | 0s | 4ms/step | - loss: 32.1315 | - val_loss: 43.4227 |
| Epoch 15/200 | | | | | |
| 34/34 | <div></div> | 0s | 5ms/step | - loss: 37.8737 | - val_loss: 33.7932 |
| Epoch 16/200 | | | | | |
| 34/34 | <div></div> | 0s | 4ms/step | - loss: 33.5896 | - val_loss: 32.7498 |
| Epoch 17/200 | | | | | |
| 34/34 | <div></div> | 0s | 5ms/step | - loss: 35.7561 | - val_loss: 32.6412 |
| Epoch 18/200 | | | | | |
| 34/34 | <div></div> | 0s | 4ms/step | - loss: 33.5927 | - val_loss: 30.7087 |
| Epoch 19/200 | | | | | |
| 34/34 | <div></div> | 0s | 5ms/step | - loss: 37.5472 | - val_loss: 35.5517 |
| Epoch 20/200 | | | | | |
| 34/34 | <div></div> | 0s | 5ms/step | - loss: 35.0621 | - val_loss: 32.0010 |
| Epoch 21/200 | | | | | |
| 34/34 | <div></div> | 0s | 4ms/step | - loss: 36.0078 | - val_loss: 30.6190 |
| Epoch 22/200 | | | | | |
| 34/34 | <div></div> | 0s | 4ms/step | - loss: 28.7209 | - val_loss: 29.9543 |
| Epoch 23/200 | | | | | |
| 34/34 | <div></div> | 0s | 5ms/step | - loss: 32.2699 | - val_loss: 30.1895 |
| Epoch 24/200 | | | | | |
| 34/34 | <div></div> | 0s | 4ms/step | - loss: 28.7519 | - val_loss: 28.8938 |
| Epoch 25/200 | | | | | |
| 34/34 | <div></div> | 0s | 4ms/step | - loss: 28.1402 | - val_loss: 31.0161 |
| Epoch 26/200 | | | | | |
| 34/34 | <div></div> | 0s | 5ms/step | - loss: 29.4666 | - val_loss: 25.1727 |
| Epoch 27/200 | | | | | |
| 34/34 | <div></div> | 0s | 4ms/step | - loss: 29.6534 | - val_loss: 27.0787 |
| Epoch 28/200 | | | | | |
| 34/34 | <div></div> | 0s | 4ms/step | - loss: 28.4360 | - val_loss: 28.2032 |
| Epoch 29/200 | | | | | |
| 34/34 | <div></div> | 0s | 4ms/step | - loss: 26.6294 | - val_loss: 26.5421 |
| Epoch 30/200 | | | | | |
| 34/34 | <div></div> | 0s | 4ms/step | - loss: 29.6909 | - val_loss: 26.8652 |
| Epoch 31/200 | | | | | |
| 34/34 | <div></div> | 0s | 5ms/step | - loss: 27.0395 | - val_loss: 25.7563 |
| Epoch 32/200 | | | | | |
| 34/34 | <div></div> | 0s | 5ms/step | - loss: 24.3506 | - val_loss: 24.7811 |
| Epoch 33/200 | | | | | |
| 34/34 | <div></div> | 0s | 4ms/step | - loss: 26.3021 | - val_loss: 29.3698 |
| Epoch 34/200 | | | | | |
| 34/34 | <div></div> | 0s | 4ms/step | - loss: 34.9329 | - val_loss: 28.6809 |
| Epoch 35/200 | | | | | |
| 34/34 | <div></div> | 0s | 5ms/step | - loss: 32.1110 | - val_loss: 25.5586 |
| Epoch 36/200 | | | | | |
| 34/34 | <div></div> | 0s | 4ms/step | - loss: 24.1459 | - val_loss: 22.8389 |
| Epoch 37/200 | | | | | |
| 34/34 | <div></div> | 0s | 5ms/step | - loss: 27.5800 | - val_loss: 29.6645 |
| Epoch 38/200 | | | | | |
| 34/34 | <div></div> | 0s | 4ms/step | - loss: 26.0856 | - val_loss: 23.9648 |
| Epoch 39/200 | | | | | |
| 34/34 | <div></div> | 0s | 4ms/step | - loss: 25.1825 | - val_loss: 27.2061 |
| Epoch 40/200 | | | | | |
| 34/34 | <div></div> | 0s | 4ms/step | - loss: 28.7428 | - val_loss: 23.5188 |
| Epoch 41/200 | | | | | |
| 34/34 | <div></div> | 0s | 4ms/step | - loss: 26.2624 | - val_loss: 26.4126 |
| Epoch 42/200 | | | | | |
| 34/34 | <div></div> | 0s | 5ms/step | - loss: 26.1465 | - val_loss: 28.5407 |
| Epoch 43/200 | | | | | |
| 34/34 | <div></div> | 0s | 5ms/step | - loss: 24.3261 | - val_loss: 23.9442 |
| Epoch 44/200 | | | | | |
| 34/34 | <div></div> | 0s | 4ms/step | - loss: 28.3650 | - val_loss: 25.8906 |
| Epoch 45/200 | | | | | |
| 34/34 | <div></div> | 0s | 4ms/step | - loss: 24.9784 | - val_loss: 23.5004 |
| Epoch 46/200 | | | | | |
| 34/34 | <div></div> | 0s | 4ms/step | - loss: 26.4651 | - val_loss: 22.3469 |
| Epoch 47/200 | | | | | |
| 34/34 | <div></div> | 0s | 6ms/step | - loss: 24.4932 | - val_loss: 22.0481 |
| Epoch 48/200 | | | | | |
| 34/34 | <div></div> | 0s | 6ms/step | - loss: 24.3308 | - val_loss: 23.0816 |
| Epoch 49/200 | | | | | |
| 34/34 | <div></div> | 0s | 6ms/step | - loss: 24.8101 | - val_loss: 23.6150 |
| Epoch 50/200 | | | | | |
| 34/34 | <div></div> | 0s | 6ms/step | - loss: 24.7435 | - val_loss: 22.5557 |
| Epoch 51/200 | | | | | |
| 34/34 | <div></div> | 0s | 6ms/step | - loss: 26.5512 | - val_loss: 22.9687 |
| Epoch 52/200 | | | | | |

34/34  0s 6ms/step - loss: 24.0877 - val_loss: 23.2226
Epoch 53/200
34/34  0s 6ms/step - loss: 22.2317 - val_loss: 24.6844
Epoch 54/200
34/34  0s 4ms/step - loss: 26.5813 - val_loss: 23.8332
Epoch 55/200
34/34  0s 4ms/step - loss: 25.6845 - val_loss: 22.8730
Epoch 56/200
34/34  0s 5ms/step - loss: 25.8778 - val_loss: 26.9383
Epoch 57/200
34/34  0s 5ms/step - loss: 24.8951 - val_loss: 33.7059
Epoch 58/200
34/34  0s 5ms/step - loss: 26.0768 - val_loss: 27.0481
Epoch 59/200
34/34  0s 4ms/step - loss: 26.4867 - val_loss: 24.2107
Epoch 60/200
34/34  0s 5ms/step - loss: 23.5056 - val_loss: 31.6069
Epoch 61/200
34/34  0s 5ms/step - loss: 27.8041 - val_loss: 28.7031
Epoch 62/200
34/34  0s 5ms/step - loss: 26.3109 - val_loss: 28.4685
Epoch 63/200
34/34  0s 6ms/step - loss: 26.5222 - val_loss: 25.0000
Epoch 64/200
34/34  0s 4ms/step - loss: 24.3381 - val_loss: 21.5296
Epoch 65/200
34/34  0s 5ms/step - loss: 23.1700 - val_loss: 30.0455
Epoch 66/200
34/34  0s 4ms/step - loss: 22.5009 - val_loss: 22.2148
Epoch 67/200
34/34  0s 4ms/step - loss: 22.4289 - val_loss: 22.4954
Epoch 68/200
34/34  0s 4ms/step - loss: 23.3211 - val_loss: 23.2085
Epoch 69/200
34/34  0s 4ms/step - loss: 24.9167 - val_loss: 23.6924
Epoch 70/200
34/34  0s 4ms/step - loss: 22.8080 - val_loss: 24.1627
Epoch 71/200
34/34  0s 5ms/step - loss: 22.9999 - val_loss: 22.2948
Epoch 72/200
34/34  0s 4ms/step - loss: 23.7923 - val_loss: 22.1868
Epoch 73/200
34/34  0s 4ms/step - loss: 20.9798 - val_loss: 25.6939
Epoch 74/200
34/34  0s 4ms/step - loss: 23.6462 - val_loss: 23.4818
Epoch 75/200
34/34  0s 5ms/step - loss: 21.3040 - val_loss: 23.0798
Epoch 76/200
34/34  0s 4ms/step - loss: 24.3374 - val_loss: 24.8126
Epoch 77/200
34/34  0s 4ms/step - loss: 24.6415 - val_loss: 25.3480
Epoch 78/200
34/34  0s 4ms/step - loss: 20.4543 - val_loss: 21.3578
Epoch 79/200
34/34  0s 4ms/step - loss: 20.7021 - val_loss: 23.1566
Epoch 80/200
34/34  0s 4ms/step - loss: 22.0193 - val_loss: 20.3779
Epoch 81/200
34/34  0s 4ms/step - loss: 24.9985 - val_loss: 21.0474
Epoch 82/200
34/34  0s 4ms/step - loss: 23.6766 - val_loss: 28.8754
Epoch 83/200
34/34  0s 5ms/step - loss: 29.5400 - val_loss: 21.6691
Epoch 84/200
34/34  0s 4ms/step - loss: 20.7836 - val_loss: 24.6593
Epoch 85/200
34/34  0s 5ms/step - loss: 26.5100 - val_loss: 22.1215
Epoch 86/200
34/34  0s 4ms/step - loss: 24.7131 - val_loss: 22.0142
Epoch 87/200
34/34  0s 5ms/step - loss: 22.8340 - val_loss: 21.5252
Epoch 88/200
34/34  0s 4ms/step - loss: 19.2117 - val_loss: 20.1958
Epoch 89/200
34/34  0s 4ms/step - loss: 24.0715 - val_loss: 22.1395
Epoch 90/200
34/34  0s 4ms/step - loss: 21.4368 - val_loss: 21.8979
Epoch 91/200
34/34  0s 4ms/step - loss: 20.9031 - val_loss: 25.4160
Epoch 92/200
34/34  0s 4ms/step - loss: 22.5654 - val_loss: 21.7740
Epoch 93/200
34/34  0s 4ms/step - loss: 22.3762 - val_loss: 21.6578

Epoch 94/200
34/34  0s 4ms/step - loss: 19.2631 - val_loss: 21.5766
Epoch 95/200
34/34  0s 5ms/step - loss: 21.3431 - val_loss: 22.3872
Epoch 96/200
34/34  0s 4ms/step - loss: 24.5849 - val_loss: 23.1564
Epoch 97/200
34/34  0s 4ms/step - loss: 23.3232 - val_loss: 21.1023
Epoch 98/200
34/34  0s 4ms/step - loss: 22.3944 - val_loss: 20.0838
Epoch 99/200
34/34  0s 4ms/step - loss: 21.6315 - val_loss: 21.2997
Epoch 100/200
34/34  0s 4ms/step - loss: 23.8899 - val_loss: 23.0258
Epoch 101/200
34/34  0s 6ms/step - loss: 22.3193 - val_loss: 22.5128
Epoch 102/200
34/34  0s 6ms/step - loss: 19.7116 - val_loss: 21.0473
Epoch 103/200
34/34  0s 6ms/step - loss: 20.4691 - val_loss: 19.8493
Epoch 104/200
34/34  0s 5ms/step - loss: 23.2198 - val_loss: 20.8034
Epoch 105/200
34/34  0s 6ms/step - loss: 21.9026 - val_loss: 21.5575
Epoch 106/200
34/34  0s 6ms/step - loss: 20.7532 - val_loss: 26.7277
Epoch 107/200
34/34  0s 6ms/step - loss: 23.1217 - val_loss: 23.0243
Epoch 108/200
34/34  0s 5ms/step - loss: 21.2766 - val_loss: 21.1623
Epoch 109/200
34/34  0s 4ms/step - loss: 22.7730 - val_loss: 22.1956
Epoch 110/200
34/34  0s 4ms/step - loss: 29.6173 - val_loss: 22.7317
Epoch 111/200
34/34  0s 5ms/step - loss: 20.4445 - val_loss: 22.4498
Epoch 112/200
34/34  0s 5ms/step - loss: 20.3433 - val_loss: 22.3688
Epoch 113/200
34/34  0s 5ms/step - loss: 19.7608 - val_loss: 21.3308
Epoch 114/200
34/34  0s 4ms/step - loss: 22.5369 - val_loss: 21.4899
Epoch 115/200
34/34  0s 5ms/step - loss: 21.6808 - val_loss: 23.7512
Epoch 116/200
34/34  0s 4ms/step - loss: 20.7328 - val_loss: 21.6395
Epoch 117/200
34/34  0s 4ms/step - loss: 19.6031 - val_loss: 21.8037
Epoch 118/200
34/34  0s 5ms/step - loss: 22.6605 - val_loss: 21.7904
Epoch 119/200
34/34  0s 4ms/step - loss: 23.1402 - val_loss: 21.4837
Epoch 120/200
34/34  0s 4ms/step - loss: 22.0771 - val_loss: 21.4557
Epoch 121/200
34/34  0s 5ms/step - loss: 23.5371 - val_loss: 22.7775
Epoch 122/200
34/34  0s 4ms/step - loss: 20.6768 - val_loss: 23.2584
Epoch 123/200
34/34  0s 4ms/step - loss: 25.5297 - val_loss: 20.7067
Epoch 124/200
34/34  0s 4ms/step - loss: 19.4710 - val_loss: 20.3559
Epoch 125/200
34/34  0s 4ms/step - loss: 19.8663 - val_loss: 19.9299
Epoch 126/200
34/34  0s 5ms/step - loss: 20.7812 - val_loss: 21.8916
Epoch 127/200
34/34  0s 4ms/step - loss: 23.6632 - val_loss: 22.7265
Epoch 128/200
34/34  0s 4ms/step - loss: 22.4435 - val_loss: 23.0082
Epoch 129/200
34/34  0s 4ms/step - loss: 24.4367 - val_loss: 21.4001
Epoch 130/200
34/34  0s 4ms/step - loss: 21.2120 - val_loss: 20.8994
Epoch 131/200
34/34  0s 4ms/step - loss: 20.2671 - val_loss: 20.9803
Epoch 132/200
34/34  0s 4ms/step - loss: 22.4072 - val_loss: 20.0450
Epoch 133/200
34/34  0s 4ms/step - loss: 20.2578 - val_loss: 20.4564
Epoch 134/200
34/34 0s 4ms/step - loss: 22.6119 - val_loss: 21.0739
Epoch 135/200

34/34 — 0s 5ms/step - loss: 20.7687 - val_loss: 20.8468
Epoch 136/200
34/34 — 0s 4ms/step - loss: 21.1454 - val_loss: 24.3420
Epoch 137/200
34/34 — 0s 5ms/step - loss: 20.9576 - val_loss: 23.5121
Epoch 138/200
34/34 — 0s 4ms/step - loss: 19.7905 - val_loss: 23.0212
Epoch 139/200
34/34 — 0s 4ms/step - loss: 21.8259 - val_loss: 27.4385
Epoch 140/200
34/34 — 0s 5ms/step - loss: 27.7973 - val_loss: 22.7010
Epoch 141/200
34/34 — 0s 4ms/step - loss: 19.9341 - val_loss: 20.3348
Epoch 142/200
34/34 — 1s 13ms/step - loss: 22.0714 - val_loss: 20.5802
Epoch 143/200
34/34 — 0s 4ms/step - loss: 21.5928 - val_loss: 21.6372
Epoch 144/200
34/34 — 0s 9ms/step - loss: 19.2668 - val_loss: 22.4814
Epoch 145/200
34/34 — 0s 6ms/step - loss: 18.6560 - val_loss: 24.3076
Epoch 146/200
34/34 — 0s 5ms/step - loss: 21.8677 - val_loss: 23.3631
Epoch 147/200
34/34 — 0s 5ms/step - loss: 22.8311 - val_loss: 21.0723
Epoch 148/200
34/34 — 0s 9ms/step - loss: 20.9463 - val_loss: 21.6094
Epoch 149/200
34/34 — 0s 5ms/step - loss: 21.0882 - val_loss: 22.8630
Epoch 150/200
34/34 — 0s 6ms/step - loss: 21.1550 - val_loss: 20.8653
Epoch 151/200
34/34 — 0s 6ms/step - loss: 18.8452 - val_loss: 21.0553
Epoch 152/200
34/34 — 0s 6ms/step - loss: 21.2187 - val_loss: 21.0624
Epoch 153/200
34/34 — 0s 6ms/step - loss: 18.7667 - val_loss: 23.1227
Epoch 154/200
34/34 — 0s 6ms/step - loss: 20.3386 - val_loss: 20.7481
Epoch 155/200
34/34 — 0s 6ms/step - loss: 19.1562 - val_loss: 21.1813
Epoch 156/200
34/34 — 0s 6ms/step - loss: 20.5549 - val_loss: 21.6073
Epoch 157/200
34/34 — 0s 4ms/step - loss: 22.1148 - val_loss: 20.7381
Epoch 158/200
34/34 — 0s 5ms/step - loss: 21.1030 - val_loss: 21.5645
Epoch 159/200
34/34 — 0s 4ms/step - loss: 22.5731 - val_loss: 20.8638
Epoch 160/200
34/34 — 0s 5ms/step - loss: 20.0065 - val_loss: 21.6722
Epoch 161/200
34/34 — 0s 4ms/step - loss: 18.5337 - val_loss: 22.7306
Epoch 162/200
34/34 — 0s 4ms/step - loss: 20.6709 - val_loss: 23.9414
Epoch 163/200
34/34 — 0s 5ms/step - loss: 22.4941 - val_loss: 21.4207
Epoch 164/200
34/34 — 0s 5ms/step - loss: 20.2031 - val_loss: 22.7014
Epoch 165/200
34/34 — 0s 4ms/step - loss: 19.0177 - val_loss: 20.2194
Epoch 166/200
34/34 — 0s 4ms/step - loss: 20.8551 - val_loss: 22.2901
Epoch 167/200
34/34 — 0s 5ms/step - loss: 19.9144 - val_loss: 21.5469
Epoch 168/200
34/34 — 0s 4ms/step - loss: 19.2684 - val_loss: 21.6387
Epoch 169/200
34/34 — 0s 4ms/step - loss: 18.2818 - val_loss: 21.7216
Epoch 170/200
34/34 — 0s 5ms/step - loss: 20.3356 - val_loss: 21.1449
Epoch 171/200
34/34 — 0s 4ms/step - loss: 21.9780 - val_loss: 22.5393
Epoch 172/200
34/34 — 0s 4ms/step - loss: 23.3501 - val_loss: 20.0684
Epoch 173/200
34/34 — 0s 4ms/step - loss: 17.6064 - val_loss: 21.1621
Epoch 174/200
34/34 — 0s 4ms/step - loss: 19.6765 - val_loss: 23.3022
Epoch 175/200
34/34 — 0s 5ms/step - loss: 19.9272 - val_loss: 22.8083
Epoch 176/200
34/34 — 0s 5ms/step - loss: 19.7989 - val_loss: 22.9800

```

Epoch 177/200
34/34 ————— 0s 4ms/step - loss: 19.9853 - val_loss: 20.9606
Epoch 178/200
34/34 ————— 0s 4ms/step - loss: 18.2586 - val_loss: 24.4391
Epoch 179/200
34/34 ————— 0s 4ms/step - loss: 20.3191 - val_loss: 24.2425
Epoch 180/200
34/34 ————— 0s 5ms/step - loss: 19.6342 - val_loss: 22.0257
Epoch 181/200
34/34 ————— 0s 4ms/step - loss: 19.5726 - val_loss: 20.2465
Epoch 182/200
34/34 ————— 0s 4ms/step - loss: 18.6387 - val_loss: 22.6209
Epoch 183/200
34/34 ————— 0s 4ms/step - loss: 21.7868 - val_loss: 21.1666
Epoch 184/200
34/34 ————— 0s 4ms/step - loss: 21.1639 - val_loss: 24.2877
Epoch 185/200
34/34 ————— 0s 4ms/step - loss: 19.9585 - val_loss: 20.1272
Epoch 186/200
34/34 ————— 0s 5ms/step - loss: 20.5667 - val_loss: 20.0679
Epoch 187/200
34/34 ————— 0s 4ms/step - loss: 20.8001 - val_loss: 21.0872
Epoch 188/200
34/34 ————— 0s 9ms/step - loss: 19.5772 - val_loss: 23.3289
Epoch 189/200
34/34 ————— 0s 4ms/step - loss: 20.0305 - val_loss: 20.0644
Epoch 190/200
34/34 ————— 0s 4ms/step - loss: 20.4121 - val_loss: 21.6285
Epoch 191/200
34/34 ————— 1s 10ms/step - loss: 19.6436 - val_loss: 23.5675
Epoch 192/200
34/34 ————— 0s 4ms/step - loss: 20.8832 - val_loss: 21.4144
Epoch 193/200
34/34 ————— 0s 7ms/step - loss: 21.4291 - val_loss: 21.2854
Epoch 194/200
34/34 ————— 0s 4ms/step - loss: 18.3394 - val_loss: 21.3464
Epoch 195/200
34/34 ————— 0s 4ms/step - loss: 26.9490 - val_loss: 24.1224
Epoch 196/200
34/34 ————— 0s 6ms/step - loss: 20.5917 - val_loss: 22.4296
Epoch 197/200
34/34 ————— 0s 6ms/step - loss: 20.6004 - val_loss: 20.6738
Epoch 198/200
34/34 ————— 0s 5ms/step - loss: 18.8965 - val_loss: 20.7520
Epoch 199/200
34/34 ————— 0s 6ms/step - loss: 20.7672 - val_loss: 20.5307
Epoch 200/200
34/34 ————— 0s 5ms/step - loss: 21.7936 - val_loss: 22.9748

```

Out[27]: <keras.src.callbacks.history.History at 0x7de0760cfb10>

In [29]: preds = model.predict(testX)

```

3/3 ————— 0s 11ms/step

```

In [30]: *# make prediction on the testing data*

```

preds = model.predict(testX)

# compute the difference between the *predicted* house prices and the
# *actual* house prices, then compute the percentage difference and
# the absolute percentage difference
diff = preds.flatten() - testY
percentDiff = (diff / testY) * 100
absPercentDiff = np.abs(percentDiff)

# compute the mean and standard deviation of the absolute percentage
# difference
mean = np.mean(absPercentDiff)
std = np.std(absPercentDiff)

# finally, show some statistics on our model
locale.setlocale(locale.LC_ALL, "en_US.UTF-8")
print("avg. house price: {}, std house price: {}".format(
    locale.currency(df["price"].mean(), grouping=True),
    locale.currency(df["price"].std(), grouping=True)))
print("mean: {:.2f}%, std: {:.2f}%".format(mean, std))

```

```

3/3 ————— 0s 13ms/step
avg. house price: $533,388.27, std house price: $493,403.08
mean: 22.97%, std: 25.22%

```