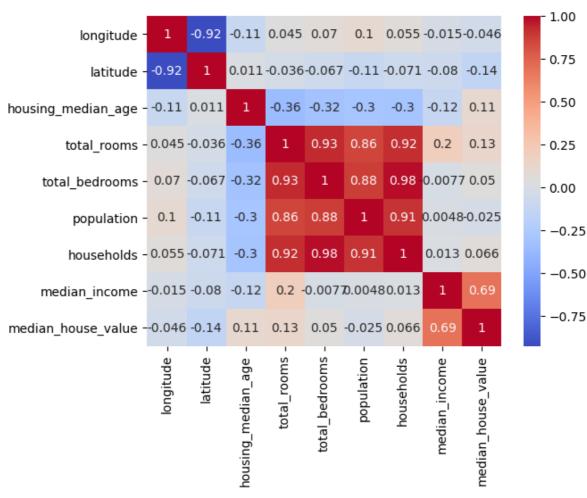
```
In [ ]: # General data analysis/plotting
        import pandas as pd
        import matplotlib.pyplot as plt
        import numpy as np
        # Data preprocessing
        from sklearn.preprocessing import StandardScaler
        from sklearn.model_selection import train_test_split
        # Neural Net modules
        import tensorflow as tf
        from tensorflow.keras.models import Sequential
        from tensorflow.keras.layers import Dense, Dropout
        from tensorflow.keras.callbacks import EarlyStopping
        # data visualization
        import seaborn as sns
        import matplotlib.pyplot as plt
In [ ]: df = pd.read_csv('boston.csv')
        df.info()
        <class 'pandas.core.frame.DataFrame'>
        RangeIndex: 20640 entries, 0 to 20639
        Data columns (total 10 columns):
         # Column
                                Non-Null Count Dtype
            -----
                                -----
         0
           longitude
                              20640 non-null float64
                                20640 non-null float64
            latitude
         1
            housing_median_age 20640 non-null float64
         2
           total_rooms
                           20640 non-null float64
         3
           total_bedrooms
                              20433 non-null float64
                               20640 non-null float64
         5
            population
                               20640 non-null float64
            households
            median income 20640 non-null float64
         7
            median_house_value 20640 non-null float64
                                20640 non-null object
            ocean_proximity
        dtypes: float64(9), object(1)
        memory usage: 1.6+ MB
In [ ]: sns.heatmap(df.corr(), annot=True, cmap='coolwarm')
Out[]: <AxesSubplot:>
```



```
In [ ]: df.dropna(axis=0, inplace=True)
        df = pd.get_dummies(df, columns=['ocean_proximity'])
In [ ]: y = df['median_house_value']
        X = df.drop(['median_house_value', 'households','total_bedrooms'], axis=1)
        print(X.shape, y.shape)
        # convert to numpy array
        X = np.array(X)
        y = np.array(y)
        # split into X_train and X_test
        # always split into X_train, X_test first THEN apply minmax scaler
        X_train, X_test, y_train, y_test = train_test_split(X, y,
                                                             test_size=0.25,
                                                             random state=43)
        # use minMax scaler
        s scaler = StandardScaler()
        X_train = s_scaler.fit_transform(X_train)
        X_test = s_scaler.transform(X_test)
        (20433, 10) (20433,)
In [ ]: model = Sequential()
        model.add(Dense(512, input_shape=(X_train.shape[1],),input_dim = 13 ,activation='re
        model.add(Dense(256, activation='relu'))
        model.add(Dense(128, activation='relu'))
        model.add(Dense(64, activation='relu'))
        model.add(Dense(32, activation='relu'))
        model.add(Dense(1, activation='linear')) # output node
```

Model: "sequential\_6"

Layer (type)	Output Shape	Param #
dense_36 (Dense)	(None, 512)	5632
dense_37 (Dense)	(None, 256)	131328
dense_38 (Dense)	(None, 128)	32896
dense_39 (Dense)	(None, 64)	8256
dense_40 (Dense)	(None, 32)	2080
dense_41 (Dense)	(None, 1)	33

Total params: 180,225 Trainable params: 180,225 Non-trainable params: 0

```
Epoch 1/100
mae: 73291.9531 - val_loss: 5420998144.0000 - val_mae: 51421.9609
Epoch 2/100
511/511 [============] - 3s 6ms/step - loss: 5185857536.0000 - m
ae: 51195.2812 - val loss: 5316182016.0000 - val mae: 50780.7461
Epoch 3/100
ae: 50728.6992 - val_loss: 5097619456.0000 - val_mae: 51521.8906
ae: 50200.0195 - val_loss: 4982257664.0000 - val_mae: 50927.1406
Epoch 5/100
ae: 49842.5820 - val_loss: 5025269760.0000 - val_mae: 50611.7227
Epoch 6/100
ae: 49638.3359 - val_loss: 4972419072.0000 - val_mae: 52027.3281
Epoch 7/100
ae: 49783.6523 - val_loss: 4993593856.0000 - val_mae: 49566.1914
Epoch 8/100
ae: 49422.3945 - val loss: 4978978816.0000 - val mae: 50714.8633
Epoch 9/100
ae: 49520.9297 - val_loss: 4883512832.0000 - val_mae: 50576.0000
Epoch 10/100
ae: 49337.8594 - val loss: 4989066752.0000 - val mae: 52870.0078
Epoch 11/100
ae: 49083.0898 - val_loss: 4864053248.0000 - val_mae: 49464.5508
Epoch 12/100
ae: 48818.9766 - val_loss: 4891373056.0000 - val_mae: 48472.4102
Epoch 13/100
ae: 48613.5898 - val loss: 4825642496.0000 - val mae: 48346.3477
Epoch 14/100
```

```
ae: 48345.5820 - val_loss: 4750699520.0000 - val_mae: 48226.9727
Epoch 15/100
ae: 48006.6523 - val_loss: 4710014464.0000 - val_mae: 50171.5625
Epoch 16/100
ae: 47422.9336 - val_loss: 4977218560.0000 - val_mae: 47455.8789
Epoch 17/100
ae: 47072.3906 - val_loss: 4588754432.0000 - val_mae: 46249.2031
ae: 46969.6758 - val_loss: 4547239424.0000 - val_mae: 48025.6914
Epoch 19/100
ae: 46493.2422 - val_loss: 4541491712.0000 - val_mae: 46313.8750
Epoch 20/100
ae: 46205.2070 - val_loss: 4530420736.0000 - val_mae: 47054.4219
Epoch 21/100
ae: 45801.9688 - val_loss: 4562729984.0000 - val_mae: 47065.4453
Epoch 22/100
ae: 45550.8203 - val_loss: 4499249152.0000 - val_mae: 47443.1719
Epoch 23/100
511/511 [============] - 3s 6ms/step - loss: 4229028864.0000 - m
ae: 45441.7656 - val_loss: 4525226496.0000 - val_mae: 48338.2539
Epoch 24/100
ae: 45227.0938 - val_loss: 4789961728.0000 - val_mae: 46385.0625
Epoch 25/100
ae: 45278.5625 - val_loss: 4306686464.0000 - val_mae: 46436.9766
Epoch 26/100
ae: 44911.1328 - val_loss: 4409722368.0000 - val_mae: 47949.9844
Epoch 27/100
511/511 [============] - 3s 6ms/step - loss: 4114443520.0000 - m
ae: 44735.5664 - val_loss: 4216388096.0000 - val_mae: 44228.5234
Epoch 28/100
ae: 44479.2070 - val_loss: 4363339776.0000 - val_mae: 46694.1211
ae: 44189.6367 - val_loss: 4202859264.0000 - val_mae: 44595.8594
Epoch 30/100
ae: 44209.7617 - val_loss: 4156551424.0000 - val_mae: 44343.3281
Epoch 31/100
ae: 43821.1172 - val loss: 4183682304.0000 - val mae: 45089.0508
Epoch 32/100
511/511 [=============] - 3s 6ms/step - loss: 3973111552.0000 - m
ae: 43848.7461 - val_loss: 4165714944.0000 - val_mae: 43837.4180
Epoch 33/100
ae: 43575.7461 - val loss: 4141255424.0000 - val mae: 44519.9062
Epoch 34/100
```

```
ae: 43458.9609 - val loss: 4079457792.0000 - val mae: 43027.4688
Epoch 35/100
ae: 43144.6680 - val loss: 4039629312.0000 - val mae: 43248.3828
ae: 43012.1367 - val_loss: 4205060608.0000 - val_mae: 43718.5664
Epoch 37/100
ae: 42926.8945 - val_loss: 4101959680.0000 - val_mae: 43598.7930
Epoch 38/100
ae: 42702.0977 - val_loss: 4037944576.0000 - val_mae: 43178.1719
Epoch 39/100
ae: 42548.2031 - val loss: 4113359104.0000 - val mae: 42875.7617
Epoch 40/100
ae: 42652.7500 - val_loss: 4013829632.0000 - val_mae: 44321.4883
Epoch 41/100
ae: 42500.6797 - val_loss: 3892360704.0000 - val_mae: 43342.0508
Epoch 42/100
ae: 42457.6406 - val_loss: 3849492736.0000 - val_mae: 42615.4297
Epoch 43/100
ae: 42132.7930 - val_loss: 3899945216.0000 - val_mae: 42056.6680
Epoch 44/100
ae: 42052.1016 - val_loss: 3940414464.0000 - val_mae: 44003.7578
Epoch 45/100
511/511 [============] - 3s 7ms/step - loss: 3663715840.0000 - m
ae: 41988.4375 - val_loss: 3956507648.0000 - val_mae: 41995.5078
Epoch 46/100
ae: 41759.9727 - val_loss: 3849888512.0000 - val_mae: 42606.6523
ae: 41945.3477 - val_loss: 4039291136.0000 - val_mae: 44923.1680
Epoch 48/100
ae: 41599.2734 - val_loss: 3775280128.0000 - val_mae: 42611.3867
Epoch 49/100
ae: 41675.8672 - val loss: 3939573504.0000 - val mae: 42518.7266
ae: 41677.1484 - val_loss: 3938314240.0000 - val_mae: 42117.1211
Epoch 51/100
ae: 41465.9141 - val loss: 3806544640.0000 - val mae: 41307.5938
Epoch 52/100
ae: 41235.1719 - val_loss: 3798776832.0000 - val_mae: 41941.0117
Epoch 53/100
ae: 41230.1094 - val loss: 3868542976.0000 - val mae: 41889.8828
Epoch 54/100
ae: 41558.3945 - val_loss: 3882894592.0000 - val_mae: 43735.3359
```

```
Epoch 55/100
ae: 41225.1914 - val loss: 4061195776.0000 - val mae: 45541.1328
Epoch 56/100
ae: 41067.1172 - val_loss: 3824217856.0000 - val_mae: 43826.7227
Epoch 57/100
ae: 40907.7773 - val loss: 4118211328.0000 - val mae: 46044.4336
Epoch 58/100
ae: 40828.5391 - val_loss: 3908294656.0000 - val_mae: 44974.0898
Epoch 59/100
ae: 40981.1484 - val_loss: 3688381696.0000 - val_mae: 41637.9375
Epoch 60/100
ae: 40939.0430 - val_loss: 3675129344.0000 - val_mae: 41649.6094
Epoch 61/100
ae: 40705.7461 - val_loss: 3712949760.0000 - val_mae: 42430.8477
Epoch 62/100
511/511 [============] - 3s 5ms/step - loss: 3458994944.0000 - m
ae: 40601.1484 - val_loss: 3741691648.0000 - val_mae: 41021.4727
Epoch 63/100
511/511 [============] - 3s 7ms/step - loss: 3418359296.0000 - m
ae: 40431.1328 - val loss: 3734126336.0000 - val mae: 40965.1562
Epoch 64/100
ae: 40334.9492 - val_loss: 3659560960.0000 - val_mae: 40682.8984
ae: 40576.1094 - val_loss: 3885162496.0000 - val_mae: 43255.5742
Epoch 66/100
ae: 40265.6602 - val_loss: 3731041536.0000 - val_mae: 40456.6562
Epoch 67/100
ae: 40171.5938 - val_loss: 3790061824.0000 - val_mae: 43463.7266
ae: 40183.0586 - val_loss: 3677695744.0000 - val_mae: 41758.4883
Epoch 69/100
ae: 40009.0469 - val loss: 3631145984.0000 - val mae: 41271.2930
Epoch 70/100
ae: 39998.0508 - val_loss: 4058229504.0000 - val_mae: 41996.5391
Epoch 71/100
ae: 39984.5820 - val loss: 3745303040.0000 - val mae: 41259.2578
Epoch 72/100
ae: 39543.5430 - val_loss: 3554318336.0000 - val_mae: 40330.1016
Epoch 73/100
511/511 [============] - 2s 4ms/step - loss: 3306288128.0000 - m
ae: 39671.5469 - val_loss: 3925644032.0000 - val_mae: 44143.8672
Epoch 74/100
ae: 39698.0078 - val loss: 3555836672.0000 - val mae: 41507.2344
Epoch 75/100
```

```
ae: 39769.6953 - val_loss: 3728927232.0000 - val_mae: 40604.2109
Epoch 76/100
ae: 39572.4414 - val_loss: 3558766336.0000 - val_mae: 40136.8281
Epoch 77/100
ae: 39573.6016 - val_loss: 3532697344.0000 - val_mae: 41205.7695
Epoch 78/100
ae: 39416.3203 - val_loss: 3623615744.0000 - val_mae: 42514.0938
ae: 39202.2852 - val_loss: 3544283136.0000 - val_mae: 40976.4062
Epoch 80/100
ae: 39258.2852 - val_loss: 3764462336.0000 - val_mae: 40718.5430
Epoch 81/100
ae: 39031.8789 - val_loss: 3524526336.0000 - val_mae: 40265.1172
Epoch 82/100
ae: 38995.3320 - val_loss: 3586610432.0000 - val_mae: 40498.1719
Epoch 83/100
ae: 38841.1016 - val_loss: 3474672384.0000 - val_mae: 40362.9258
Epoch 84/100
511/511 [============] - 2s 4ms/step - loss: 3192024064.0000 - m
ae: 38889.2812 - val_loss: 3477420288.0000 - val_mae: 39867.7578
Epoch 85/100
511/511 [============] - 2s 5ms/step - loss: 3156331264.0000 - m
ae: 38669.0234 - val_loss: 3584736256.0000 - val_mae: 41054.6836
Epoch 86/100
ae: 38613.8086 - val_loss: 3520935680.0000 - val_mae: 39648.2148
Epoch 87/100
ae: 38727.0273 - val_loss: 3858008576.0000 - val_mae: 44319.7266
Epoch 88/100
511/511 [============] - 3s 6ms/step - loss: 3147709184.0000 - m
ae: 38628.6094 - val_loss: 3536158976.0000 - val_mae: 39440.3008
Epoch 89/100
ae: 38339.0742 - val_loss: 3796092416.0000 - val_mae: 44517.2383
ae: 38527.7109 - val_loss: 3500600320.0000 - val_mae: 39898.3633
Epoch 91/100
ae: 38288.6289 - val_loss: 3564610304.0000 - val_mae: 40622.7812
Epoch 92/100
ae: 38137.7617 - val loss: 3532196096.0000 - val mae: 41157.0547
511/511 [============] - 3s 5ms/step - loss: 3063203840.0000 - m
ae: 38002.9453 - val_loss: 3378705664.0000 - val_mae: 39313.0312
Epoch 94/100
ae: 38033.8438 - val_loss: 3384985600.0000 - val_mae: 40099.3555
Epoch 95/100
```

```
ae: 37889.8398 - val_loss: 3356304128.0000 - val_mae: 38251.5352
      Epoch 96/100
      ae: 37857.7852 - val loss: 3312745984.0000 - val mae: 39033.9297
      ae: 37864.8828 - val_loss: 3345870592.0000 - val_mae: 38242.2148
      Epoch 98/100
      ae: 37603.5234 - val_loss: 3405945600.0000 - val_mae: 38791.7812
      Epoch 99/100
      ae: 37586.7500 - val_loss: 3597347584.0000 - val_mae: 39910.2617
      Epoch 100/100
      ae: 37525.2891 - val loss: 3355273728.0000 - val mae: 38712.0547
In [ ]: pred = model.predict(X_test)
     trainpreds = model.predict(X_train)
      from sklearn.metrics import mean_absolute_error
      print(mean_absolute_error(y_train, trainpreds)) # train
      print(mean_absolute_error(y_test, pred)) # test
      128/128 [========== ] - 1s 3ms/step
      511/511 [========== ] - 1s 3ms/step
      36437.57292757976
      38712.04663701217
In [ ]: # plotting validation and training error
      import matplotlib.pyplot as plt
      import seaborn as sns
      plt.plot(hist.history['loss'])
      plt.plot(hist.history['val_loss'])
      plt.title('model loss')
      plt.ylabel('loss')
      plt.xlabel('epoch')
      plt.legend(['train', 'test'], loc='upper left')
      plt.show()
```

