```
Learning Problem Description
         The goal of this project is to understand the relationship between housing features and housing prices in a California district through the training and novel
         application of a neural network.
         The function of the neural network involves taking data pertaining to the houses in a district (coordinates, population, income, etc), and using that data to
         predict the median house value of the area.
         The resulting model has possible applications in the real estate industry, being used to predict median house prices in an area.
In [ ]: import numpy as np
         import pandas as pd
         import torch
         from torch import (nn, optim)
         from torch.utils.data import (TensorDataset, DataLoader, random_split)
         import warnings
         warnings.filterwarnings('ignore')
In [ ]: | df = pd.read_csv('sample_data/california_housing_test.csv')
In [ ]: |len(df)
Out[]: 3000
In [ ]: df = pd.read_csv('sample_data/california_housing_train.csv')
         means, maxs, mins = dict(), dict(), dict()
         for col in df:
           vals = df[col].values #gets values for current column
           #saving for later reversal
           means[col] = vals.mean()
           maxs[col] = vals.max()
           mins[col] = vals.min()
           norms = (vals - vals.mean()) / (vals.max() - vals.min())
           df[col] = norms
         X = df.drop('median_house_value', axis=1).values
         y = df['median_house_value'].values
         X = torch.tensor(X, dtype=torch.float32)
         y = torch.tensor(y.reshape(-1, 1), dtype=torch.float32)
         dataset = TensorDataset(X, y)
In [ ]: df
Out[ ]:
                         latitude housing_median_age total_rooms total_bedrooms population households median_income median_house_value
               longitude
             0 0.523118 -0.152521
                                                   0.078248
                                                                                                 -0.164824
                                                                                                                  -0.289485
                                         -0.266458
                                                                 0.115392 -0.011620
                                                                                    -0.004805
             1 0.507182 -0.130205
                                         -0.188027
                                                   0.131971
                                                                0.211296 -0.008424
                                                                                    -0.006285
                                                                                                 -0.142314
                                                                                                                  -0.262269
             2 0.498218 -0.205656
                                         -0.227242
                                                   -0.050709
                                                                -0.056706
                                                                         -0.030734
                                                                                    -0.063184
                                                                                                 -0.153976
                                                                                                                  -0.250722
             3 0.497222 -0.210970
                                         -0.286066
                                                   -0.030122
                                                                -0.031411 -0.025633
                                                                                    -0.045259
                                                                                                 -0.047715
                                                                                                                  -0.276083
             4 0.497222 -0.218409
                                                                                                 -0.135072
                                         -0.168419
                                                   -0.031361
                                                                -0.033118 -0.022578
                                                                                    -0.039339
                                                                                                                  -0.292372
                                                                -0.022565 -0.014647
          16995 -0.467918 0.526544
                                         0.459032
                                                   -0.011247
                                                                                    -0.021743
                                                                                                 -0.105273
                                                                                                                  -0.197733
                                                                -0.001771 -0.006603
          16996 -0.468914 0.538233
                                         0.145307
                                                   -0.007768
                                                                                    -0.005957
                                                                                                 -0.094183
                                                                                                                  -0.264537
          16997 -0.471902 0.660444
                                         -0.227242
                                                    0.000879
                                                                 -0.001305
                                                                         -0.005201
                                                                                    -0.007437
                                                                                                 -0.058777
                                                                                                                  -0.213815
          16998 -0.471902 0.656193
                                         -0.188027
                                                    0.000747
                                                                 0.001954
                                                                         -0.003688
                                                                                    -0.003819
                                                                                                 -0.131300
                                                                                                                  -0.250516
          16999 -0.476882 0.522293
                                         0.459032
                                                   -0.021713
                                                                -0.037153 -0.017477
                                                                                    -0.038024
                                                                                                 -0.059922
                                                                                                                  -0.232372
         17000 rows × 9 columns
In [ ]: | df = pd.read_csv('sample_data/california_housing_train.csv')
Out[]:
               longitude latitude housing_median_age total_rooms total_bedrooms population households median_income median_house_value
             0 -114.31 34.19
                                                    5612.0
                                                                          1015.0
                                                                                     472.0
                                                                                                  1.4936
                                                                                                                  66900.0
                                           15.0
                                                                 1283.0
                                                                                                  1.8200
                                                                                                                  80100.0
                 -114.47 34.40
                                                    7650.0
                                                                 1901.0
                                                                          1129.0
                                                                                      463.0
                                           19.0
                 -114.56
                         33.69
                                           17.0
                                                     720.0
                                                                  174.0
                                                                           333.0
                                                                                     117.0
                                                                                                  1.6509
                                                                                                                  85700.0
                                                                                                  3.1917
                                                                                                                  73400.0
             3
                 -114.57
                         33.64
                                           14.0
                                                    1501.0
                                                                  337.0
                                                                           515.0
                                                                                     226.0
                 -114.57
                         33.57
                                           20.0
                                                    1454.0
                                                                  326.0
                                                                           624.0
                                                                                     262.0
                                                                                                  1.9250
                                                                                                                  65500.0
                 -124.26
                         40.58
                                            52.0
                                                    2217.0
                                                                  394.0
                                                                           907.0
                                                                                     369.0
                                                                                                  2.3571
                                                                                                                 111400.0
         16995
                 -124.27
                         40.69
                                           36.0
                                                    2349.0
                                                                  528.0
                                                                          1194.0
                                                                                      465.0
                                                                                                  2.5179
                                                                                                                  79000.0
          16996
                                           17.0
                                                    2677.0
                                                                  531.0
                                                                          1244.0
                                                                                      456.0
                                                                                                  3.0313
                                                                                                                 103600.0
         16997
                 -124.30
                         41.84
                                                                                     478.0
                                                                                                  1.9797
                                                                                                                  85800.0
                                                    2672.0
                                                                  552.0
                                                                          1298.0
          16998
                 -124.30
                         41.80
                                           19.0
                 -124.35
                                            52.0
                                                    1820.0
                                                                  300.0
                                                                           806.0
                                                                                     270.0
                                                                                                  3.0147
                                                                                                                  94600.0
         16999
         17000 rows × 9 columns
In [ ]: |#test the dataloader
         dataloader = DataLoader(dataset, batch_size=128, shuffle=True)
         xs, targets = next(iter(dataloader))
         print(xs.shape)
         print(targets.shape)
         torch.Size([128, 8])
         torch.Size([128, 1])
In [ ]: len(df.columns)
Out[ ]: 9
In [ ]: print(torch.cuda.is_available())
         # print(torch.cuda.get_device_name(0))
         device = torch.device("cuda") if torch.cuda.is_available() else torch.device("cpu")
         device
         True
Out[]: device(type='cuda')
         Creating the Linear regression model
In [ ]: class LinearRegression(nn.Module):
             def __init__(self, num_features):
                  super().__init__()
                  self.layer1 = torch.nn.Linear(num_features, 64).to(device)
                 self.layer2 = torch.nn.Linear(64,64).to(device)
                 self.layer3 = torch.nn.Linear(64,1).to(device)
                  self.relu = nn.ReLU().to(device)
                 self.sigmoid = nn.Sigmoid().to(device)
             def forward(self,x):
                 y_pred = self.layer1(x)
                 y_pred = self.relu(y_pred)
                 y_pred = self.layer2(y_pred)
                 y_pred = self.relu(y_pred)
                 y_pred = self.sigmoid(self.layer3(y_pred))
                 return y_pred
In [ ]: |!pip install torchmetrics
         Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
         Collecting torchmetrics
           Downloading torchmetrics-0.11.4-py3-none-any.whl (519 kB)
                                                                                 - 519.2/519.2 kB 28.2 MB/s eta 0:00:00
         Requirement already satisfied: numpy>=1.17.2 in /usr/local/lib/python3.9/dist-packages (from torchmetrics) (1.22.4)
         Requirement already satisfied: torch>=1.8.1 in /usr/local/lib/python3.9/dist-packages (from torchmetrics) (2.0.0+cu11
         8)
         Requirement already satisfied: packaging in /usr/local/lib/python3.9/dist-packages (from torchmetrics) (23.0)
         Requirement already satisfied: triton==2.0.0 in /usr/local/lib/python3.9/dist-packages (from torch>=1.8.1->torchmetri
         cs) (2.0.0)
         Requirement already satisfied: jinja2 in /usr/local/lib/python3.9/dist-packages (from torch>=1.8.1->torchmetrics) (3.
         Requirement already satisfied: typing-extensions in /usr/local/lib/python3.9/dist-packages (from torch>=1.8.1->torchm
         etrics) (4.5.0)
         Requirement already satisfied: filelock in /usr/local/lib/python3.9/dist-packages (from torch>=1.8.1->torchmetrics)
         Requirement already satisfied: networkx in /usr/local/lib/python3.9/dist-packages (from torch>=1.8.1->torchmetrics)
         (3.1)
         Requirement already satisfied: sympy in /usr/local/lib/python3.9/dist-packages (from torch>=1.8.1->torchmetrics) (1.1
         1.1)
         Requirement already satisfied: lit in /usr/local/lib/python3.9/dist-packages (from triton==2.0.0->torch>=1.8.1->torch
         metrics) (16.0.1)
         Requirement already satisfied: cmake in /usr/local/lib/python3.9/dist-packages (from triton==2.0.0->torch>=1.8.1->tor
         chmetrics) (3.25.2)
         Requirement already satisfied: MarkupSafe>=2.0 in /usr/local/lib/python3.9/dist-packages (from jinja2->torch>=1.8.1->
         torchmetrics) (2.1.2)
         Requirement already satisfied: mpmath>=0.19 in /usr/local/lib/python3.9/dist-packages (from sympy->torch>=1.8.1->torc
         hmetrics) (1.3.0)
         Installing collected packages: torchmetrics
         Successfully installed torchmetrics-0.11.4
In [ ]: from torchmetrics import Accuracy
         import itertools
         import time
In [ ]: | num_features = len(df.columns)-1
         Train the model
In [ ]: def train(model,
                   train_dataset: TensorDataset,
                   epochs: int,
                   max_batches=None):
             loss_fn = torch.nn.MSELoss(reduction = 'sum')
             optimizer = torch.optim.Adam(model.parameters())
             dataloader = DataLoader(train_dataset, batch_size=128, shuffle=True, pin_memory=True)
             start0 = time.time()
             start = time.time()
             for epoch in range(epochs):
                  #train logic
                 l_list = []
                 acc_list = []
                 count = 0
                 while (count < max_batches):</pre>
                      count += 1
                      x, target = next(iter(dataloader))
                      x, target = x.to(device), target.to(device)
                      y_{out} = model(x).to(device)
                      # print(y_out)
                      loss = loss_fn(y_out, target)
                      optimizer.zero_grad()
                      loss.backward()
                      optimizer.step()
                      with torch.no_grad():
                          l_list.append(loss.item())
                 train_loss = np.mean(l_list)
                 if epoch % 100 == 0:
                   duration = time.time() - start
                   start = time.time()
                   print("[%d (%.2fs)]: train_loss=%.2f" % (
                        epoch, duration, train_loss))
             duration0 = time.time() - start0
             print("== Total training time %.2f seconds ==" % duration0)
In [ ]: model = LinearRegression(8).to(device)
         train(model, dataset, epochs = 2500, max_batches = 500)
         [0 (3.06s)]: train_loss=7.24
         [100 (223.62s)]: train_loss=3.38
         [200 (224.66s)]: train_loss=3.36
         [300 (225.91s)]: train_loss=3.24
         [400 (224.52s)]: train_loss=3.21
         [500 (221.51s)]: train_loss=3.17
         [600 (216.88s)]: train_loss=3.16
         [700 (221.46s)]: train_loss=3.12
         [800 (221.90s)]: train_loss=3.09
         [900 (228.17s)]: train_loss=3.07
         [1000 (245.56s)]: train_loss=3.07
         [1100 (234.84s)]: train_loss=3.07
         [1200 (246.96s)]: train_loss=3.04
         [1300 (236.76s)]: train_loss=3.04
         [1400 (226.16s)]: train_loss=3.04
         [1500 (227.76s)]: train_loss=3.04
         [1600 (236.58s)]: train_loss=3.01
         [1700 (231.38s)]: train_loss=3.05
         [1800 (231.92s)]: train_loss=3.05
         [1900 (231.74s)]: train_loss=3.05
         [2000 (232.15s)]: train_loss=3.04
         [2100 (232.64s)]: train_loss=3.03
         [2200 (227.88s)]: train_loss=3.03
         [2300 (229.87s)]: train_loss=2.99
         [2400 (234.53s)]: train_loss=3.01
         == Total training time 5749.94 seconds ==
In [ ]: #save the model
         torch.save(model, '/content/mymodel.pt')
         Test the model
In [ ]: def test_saved_model(model = None):
             device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
             # test_dataset = torch.load('./sample_data/california_housing_test.csv')
             df = pd.read_csv('sample_data/california_housing_test.csv')
             std = np.std(df['median_house_value'])
             mean = np.mean(df['median_house_value'])
             means, maxs, mins = dict(), dict(), dict()
             for col in df:
                  vals = df[col].values #gets values for current column
                  #saving for later reversal
                  means[col] = vals.mean()
                  maxs[col] = vals.max()
                  mins[col] = vals.min()
                 norms = (vals - vals.mean()) / (vals.max() - vals.min())
                 df[col] = norms
             X = df.drop('median_house_value', axis=1).values
             y = df['median_house_value'].values
             X = torch.tensor(X, dtype=torch.float32)
             y = torch.tensor(y.reshape(-1, 1), dtype=torch.float32)
             test_dataset = TensorDataset(X, y)
             dataloader = DataLoader(test_dataset, batch_size=128, shuffle=True)
             prediction = pd.DataFrame(columns=['Actual Median House Price',
                                                   'Predicted Median House Price',
                                                   'Difference',
                                                   'Percentage Error'])
             i = 0
             with torch.no_grad():
                  for xs, targets in dataloader:
                      xs, targets = xs.to(device), targets.to(device)
                      ys = model(xs)
                      #Convert normalized values back to original
                      actual = round((targets[i].item()*std) + mean, 1)
                      predicted = round((ys[i].item()*std) + mean , 1)
                      prediction = prediction.append({'Actual Median House Price' : actual,
                                                        'Predicted Median House Price' : predicted,
                                                        'Difference' : actual - predicted,
                                                        'Percentage Error': np.abs((actual - predicted)/actual)},
                                                        ignore_index=True)
                      i += 1
                  print('mean error accuracy:',np.mean(prediction['Percentage Error']))
             return prediction
In [ ]: model = LinearRegression(8)
         model = torch.load('/content/mymodel.pt')
         # model.eval()
         test_saved_model(model.to(device))
         mean error accuracy: 0.20079277147555016
Out[]:
             Actual Median House Price Predicted Median House Price Difference Percentage Error
          0
                          184210.0
                                                  205846.3
                                                          -21636.3
                                                                        0.117455
                          180917.7
                                                  317644.6
                                                          -136726.9
                                                                         0.755741
          1
                          222226.0
                                                  229423.1
                                                            -7197.1
                                                                         0.032386
          3
                          198729.5
                                                  313148.2 -114418.7
                                                                        0.575751
                          178146.4
                                                  205846.3
                                                           -27699.9
                                                                         0.155490
                          185323.2
                                                  205846.3
                                                           -20523.1
                                                                        0.110742
                          207185.4
                                                  205846.8
                                                            1338.6
                                                                         0.006461
                          220970.7
                                                  318219.9
                                                           -97249.2
                                                                         0.440100
                          211354.1
                                                  205866.5
                                                            5487.6
                                                                         0.025964
                          210714.6
                                                  205846.3
                                                            4868.3
                                                                         0.023104
         11
                          211756.8
                                                  317003.9 -105247.1
                                                                         0.497019
         12
                          230350.3
                                                  223459.0
                                                            6891.3
                                                                         0.029917
                          189397.2
                                                  205846.3
                                                           -16449.1
                                                                         0.086850
         13
         14
                          236935.0
                                                  227945.0
                                                            8990.0
                                                                         0.037943
         15
                          212041.0
                                                  269430.9
                                                           -57389.9
                                                                        0.270655
         16
                          238143.0
                                                  251201.3
                                                           -13058.3
                                                                         0.054834
         17
                                                           -67431.0
                                                                         0.307299
                          219431.1
                                                  286862.1
         18
                          214670.2
                                                  318537.1 -103866.9
                                                                         0.483844
                          210264.6
                                                  205846.3
                                                                        0.021013
         19
                                                            4418.3
         20
                          228763.4
                                                  239233.6
                                                           -10470.2
                                                                         0.045769
         21
                          194537.1
                                                                         0.058134
                                                  205846.3
                                                           -11309.2
         22
                          180609.7
                                                           -25236.6
                                                                         0.139730
                                                  205846.3
                                                           20879.7
         23
                          226726.4
                                                  205846.7
                                                                        0.092092
         Demonstrate the model
In [ ]: def demonstrate_model(model, data):
           #For demonstration purposes, training data will be
           #used to preprocess new data
             #Preprocess
             df = pd.read_csv('sample_data/california_housing_train.csv')
             std = np.std(df['median_house_value'])
             mean = np.mean(df['median_house_value'])
             means, maxs, mins = dict(), dict(), dict()
             for col in df.drop('median_house_value', axis=1):
                 vals = df[col].values #gets values for current column
                  means[col] = vals.mean()
                  maxs[col] = vals.max()
                  mins[col] = vals.min()
                 norms = (data[col] - vals.mean()) / (vals.max() - vals.min())
                 data[col] = norms
             data = torch.tensor(data.values, dtype=torch.float32)
             output = 0.0
             with torch.no_grad():
               ys = model(data)
               output = round((ys.item()*std) + mean , 1)
             return output
         In a practical application, such as a real estate website, the pre-trained model could be loaded, and the user would enter data on the features of their district.
         The data would then be preprocessed, and given to the model, which would then output a prediction of the median house price of the area.
         For the purposes of this demonstration, data will be predefined in the cell below.
In [ ]: data = pd.DataFrame(
             {'longitude' : -120,
              'latitude' : 30,
              'housing_median_age' : 30.0,
             'total_rooms' : 2000.0,
             'total_bedrooms' : 400.0,
              'population' : 1000.0,
```

'households' : 400.0,

model = LinearRegression(8)

data = pd.DataFrame(

model = LinearRegression(8)

'median_income' : 2.0000}, index=[0])

print('Predicted median house price: ', output)

In []: | df = pd.read_csv('sample_data/california_housing_train.csv')

{'longitude' : np.random.uniform(df['longitude'].min(), df['longitude'].max()),
'latitude' : np.random.uniform(df['latitude'].min(), df['latitude'].max()),

'total_rooms' : np.random.uniform(df['total_rooms'].min(), df['total_rooms'].max()),

'population' : np.random.uniform(df['population'].min(), df['population'].max()), 'households' : np.random.uniform(df['households'].min(), df['households'].max()),

'total_bedrooms' : np.random.uniform(df['total_bedrooms'].min(), df['total_bedrooms'].max()),

'housing_median_age' : np.random.uniform(df['housing_median_age'].min(), df['housing_median_age'].max()),

'median_income' : np.random.uniform(df['median_income'].min(), df['median_income'].max())}, index=[0])

model = torch.load('/content/mymodel.pt')

output = demonstrate_model(model, data)

Predicted median house price: 236335.5

model = torch.load('/content/mymodel.pt')

print('Predicted median house price: ', output)

output = demonstrate_model(model, data)

Predicted median house price: 322062.9