Non-linear Regression Using 1DCNN.

Kushal Patel  
*dept. of Engineering*  
*Lakehead University*Thunder Bay, Canada  
kpatel57@lakeheadu.ca

*Abstract*—In this paper, idea is to construct one-dimension convolutional neural network for predicting median house value which directly takes values longitude, latitude, housing median age, total number of rooms, total number of bedrooms, population, number of households, and median income considering some parameters such as modular coding, over/under fitting issues, vanishing/exploding gradient issue.

Keywords—Nonlinear regression, 1D convolutional neural network, mean square error, r2 score, L1loss.

# Introduction

The name of the model is 1104361\\_con1d\\_reg and it is predicting the median house value from several data of the housing database using values of longitude, latitude, housing median age, total rooms, total bedrooms, population, households, median income and median house value. Basically, the idea is to implement (1DCNN) one dimensional convolution neural network to predict the value and the output must be non-linear regression. A 1D CNN is very effective when you expect to derive interesting features from shorter (fixed-length) segments of the overall data set and where the location of the feature within the segment is not of high relevance. In statistics, nonlinear regression is a form of regression analysis in which observational data are modeled by a function which is a nonlinear combination of the model parameters and depends on one or more independent variables.

# Modeling

Firstly, there are some libraries which needed to be instaled such as pandas library to read the dataset, sklearn library for preparing our dataset to train and test the model, numpy library to work with and manipulation of the data. To drop any incomplete enteries dropna() method is used so that it will not effect the prediction of value. To print the first 10 enteries of the dataset dataset.head(10) is used and output of it is shown in Fig 1.

![A screenshot of a cell phone

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1. First 10 records of the dataset.

Matplot library is used to plot each feature of the dataset on separate sub-plots which is shown in Fig 2 and each feature is shown clearly in the figure in a different colors. For each sub-plot is implemented using separate Y-axes and a shared X-axes.

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1. Visual plotting of each feature of the dataset on separate sub-plots.

## Splitting Dataset Into X and Y

For input and output of the model I am splitting the dataset as X an input and Y an input as shown in code snippet.

|  |
| --- |
| #output Y as prediction of median house value  Y = dataset['median\_house\_value']  #selecting rest of inputs as X  X =dataset.loc[:,'longitude':'median\_income'] |

## Split dataset into training and testing portions.

dataset is splitted 70\% for training and 30\% for testing which is shown in code snippet.

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| --- |
| x\_train, x\_test, y\_train, y\_test = train\_test\_split(X, Y, test\_size= **0.3**) |

## Converting Numpy Arrays To Work With Pytorch Model.

For the next step we are converting the datasets to numpy so that we can work with the pytorch model and it is shown in code snippet.

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| --- |
| x\_train\_np = x\_train.to\_numpy()  y\_train\_np = y\_train.to\_numpy()  x\_test\_np = x\_test.to\_numpy()  y\_test\_np = y\_test.to\_numpy() |

## Calculating mean square error

The mean squared error (MSE) or mean squared deviation (MSD) of an estimator (of a procedure for estimating an unobserved quantity) measures the average of the squares of the errors—that is, the average squared difference between the estimated values and the actual value. MSE is mentioned in code snippet.

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| --- |
| model = linear\_model.LinearRegression()  model.fit(x\_train, y\_train)  predictions = model.predict(x\_test)  mse = mean\_squared\_error(y\_test, predictions)  print("The model's mean squared error is: " + str(mse)) |

## Importing Important Libraries For Model.

Next step is to import important libraries for the model which are torch, dataloader, tensordataset and some of the layers such as 1 dimensional convolutional neural network, max pooling layer, flatten layer, linear layer, relu activation layer which are briefly shown in code snippet.

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| --- |
| **import** **torch**  **from** **torch.nn** **import** Conv1d  **from** **torch.nn** **import** MaxPool1d  **from** **torch.nn** **import** Flatten  **from** **torch.nn** **import** Linear  **from** **torch.nn.functional** **import** relu  **from** **torch.utils.data** **import** DataLoader, TensorDataset |

## Defining Model.

For defining the model class must be a subclass of torch.nn.Module and initialization method is been defined and batch size, inputs and outputs are given as an argument as Fig 8 presents.

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| --- |
| **class** **CnnRegressor**(torch.nn.Module):  **def** **\_\_init\_\_**(self, batch\_size, inputs, outputs):  super(CnnRegressor, self).\_\_init\_\_()  self.batch\_size = batch\_size  self.inputs = inputs  self.outputs = outputs |

Defining different layers as presented in code snippet as I have used different combination of layers to increase the accuracy.

|  |
| --- |
| self.input\_layer = Conv1d(inputs, batch\_size, **1**)  self.max\_pooling\_layer = MaxPool1d(**1**)  self.conv\_layer = Conv1d(batch\_size, **512**, **1**)  self.max\_pooling\_layer1 = MaxPool1d(**1**)  self.conv\_layer1 = Conv1d(**512**, **256**, **1**)  self.max\_pooling\_layer2 = MaxPool1d(**1**)  self.conv\_layer2 = Conv1d(**256**, **128**, **1**)  self.flatten\_layer = Flatten()  self.linear\_layer = Linear(**128**,**64**)  self.output\_layer = Linear(**64**, outputs) |

Then after I have defined a method called feed for input. Each layer is called in sequence and output of each layer is given as an input to the next layer which increases extra hidden layers to 8 instead of only one. Every convolution layer and input layer is passed through relu activation layer. And the final output of the last layer is returned through feed method.

# Training the model

kernel size used for the model is 1 and batch size of the model is 64 which trains the model after 64 entries. To train the model Adam optimizer is used. I have used different types of optimizers and collected data of each optimizers and the accuracy of the model for example, Stochastic gradient descent (SGD) gave me accuracy up to 40 percent and L1loss was also high around seventy thousand which is not good for a model. So I came up with the Adam optimizer from Gradient Descent, Mini Batch Gradient Descent, Momentum, Adagrad etc. To set the model to use GPU while runtime cuda() is used. For calculation purpose L1loss and R2Score packages are installed. After that to calculate L1loss and R2Score one method called model\_loss is defined and these scores are stored in a counter and it is been returned in last.

To get the better accuracy correct combination of epochs and batch size should be used. In my model epochs are set to 600 as considering overfitting and underfitting should not happen. Learning rate of the model is 1e-4 as considering epochs and batch size. For the training of the model every time code is been shuffled as you run the whole code so that we can not give the model same values every time while training the model. For every epoch L1loss and R2Score is been calculated and printed as shown in code snippet.

|  |
| --- |
| epochs = **600**  optimizer = Adamax(model.parameters(),  lr = **1**e-**4**)  inputs = torch.from\_numpy(x\_train\_np).cuda().float()  outputs = torch.from\_numpy(y\_train\_np.reshape(y\_train\_np.shape[**0**],**1**)).cuda().float()  tensor = TensorDataset(inputs, outputs)  loader = DataLoader(tensor,batch\_size, shuffle=**True**, drop\_last=**True**)  time1 = time.time()  **for** epoch **in** range(epochs):  avg\_loss, avg\_r2\_score = model\_loss(model, loader, train=**True**, optimizer=optimizer)  print("Epoch " + str(epoch + **1**) + ":**\n\t**Loss = " + str(avg\_loss) + "**\n\t**R^2 Score = " + str(avg\_r2\_score))  time2 = time.time()  print("Total time taken is "+str(time2 - time1) + " seconds " ) |

# dataset

The dataset used to train the model is the California housing data. Different attributes of Housing.CSV file is given as an input and the model is predicting the median house value. Dataset is shown in the Fig 3.

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1. *dataset*

# Testing the model

For testing of the model I am converting the testing set into torch variables. So average performance of the model is given by avg\_loss and avg\_r2\_score. In our case R2Score and L1loss is shown in code snippet.

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| --- |
| inputs = torch.from\_numpy(x\_test\_np).cuda().float()  outputs = torch.from\_numpy(y\_test\_np.reshape( y\_test\_np.shape[**0**],**1**)).cuda().float()  tensor = TensorDataset(inputs, outputs)  loader = DataLoader(tensor,batch\_size, shuffle=**True**, drop\_last=**True**)  avg\_loss, avg\_r2\_score = model\_loss(model, loader)  print("Loss = " + str(avg\_loss) + "**\n**R^2 Score = " + str(avg\_r2\_score)) |

# comparision of different models

For testing of the model I have tested different types of optimizers with the combination of different layers as already shown above and I have generated measuring parameters for 50 epochs which are shown in below Table one. By looking at the results R2Score of RMSprop is good but for the higher number of epochs as 600 Adam optimizer is giving best output measures like R2Score is equal to 0.6831815409053447 , loss is equal to 44847.28375822368, mean squared error is equal to 4778844240.921353 and the inference time is 564.6949813365936 seconds which is the best model accuracy I have achieved.

1. comparision of different models

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| --- | --- | --- | --- | --- |
| Model  Optimizer | Avg\_R2Score | Avg\_L1Loss | MSE | Inference Time |
| Adam | 0.3680549187 | 67315.652 | 0.4998e6 | 45.30 |
| RMSprop | 0.4175867325 | 68131.767 | 0.4909e6 | 42.53 |
| Adamax | 0.2685680069 | 75832.675 | 0.4853e6 | 53.85 |
| Adadelta | -0.915217697 | 114621.94 | 0.4875e6 | 48.25 |

1. *Different values of different model*

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