# Detecting the Equation of a Graph Using a Convolutional Neural Network

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CSE 5290 Artificial Intelligence

Oct 19, 2021 - Update

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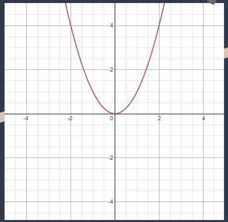
# Project Scope

$$f(x) = a_0x^0 + a_1x^1 + a_2x^2 + a_3x^3 + \ldots + a_nx^n$$

$$[a_1, a_2, a_3, a_4, a_5, a_6, a_7, a_8]$$

CNN Model



- CNN Multiple Regression Model to Detect Equation of Graph from Plot
- First with polynomials (n: integer ≥ 0)
- Starting with 8 coefficients corresponding to 8 degrees.
- Output is vector of coefficients (degree 0 represented by all coefficients = 0)
- Coefficients are integers in [-10, 10] inclusive

# Previously ...

Moving forward we are going to:

- Complete building the dataset
- Build an initial network model
- Build the training loop for the network
- Train the network

# ACHIEVED

# Data Source

```
#create plot
ax.plot(x, (coeff[8]*x**8)+(coeff[7]*x**7)+(coeff[6]*x**6)
        +(coeff[5]*x**5)+(coeff[4]*x**4)+(coeff[3]*x**3)
        +(coeff[2]*x**2)+(coeff[1]*x**1)+(coeff[0]),
        color='#000000')
```

| Filename | coeff1 | coeff2 | coeff3 | coeff4 | coeff5 | coeff6 | coeff7 | coeff8 |
|---|---|---|---|---|---|---|---|---|
| n5n10p3n | -5 | -8 | 5 | -3 | -3 | 3 | -10 | -5 |
| n7p5p4n4 | 9 | 7 | -6 | -1 | -4 | 4 | 5 | -7 |
| p9n3n9p3 | -10 | -3 | 9 | -1 | 3 | -9 | -3 | 9 |
| n7n9p4n6 | -9 | 7 | -5 | 2 | -6 | 4 | -9 | -7 |
| n6n2p3p1 | 9 | -9 | -4 | -3 | 10 | 3 | -2 | -6 |

Python’s Matplotlib library is used to automatically generate polynomial plots.

A script creates randomly generated plots and saves their corresponding filename and coefficients as a label in a csv file.

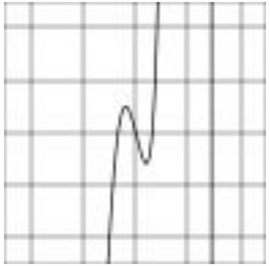
The current generated dataset is split as 85% to train the CNN and 15% for validation and testing.

Data loaders then feed the training set and test set to the CNN.

# Input Data

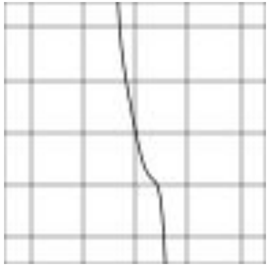
- 2D Single Channel Grayscale Images of polynomial graph plots
- 128×1×96×96 Images Tensor and 128×8 Labels Tensor
- Batchsize = 128
- Fixed standard resolution, dimensions, and centering
- 10 units width for both X-axis and Y-axis of the plot (numbers not displayed)

Current Training Plots:



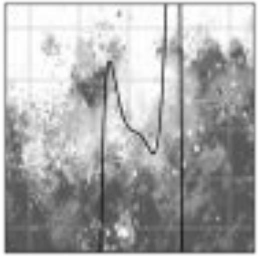
[-4, -1, 7, 1, 6, 6, 0, -1]

[-9, -1, 4, 6, -4, -9, 7, 10]

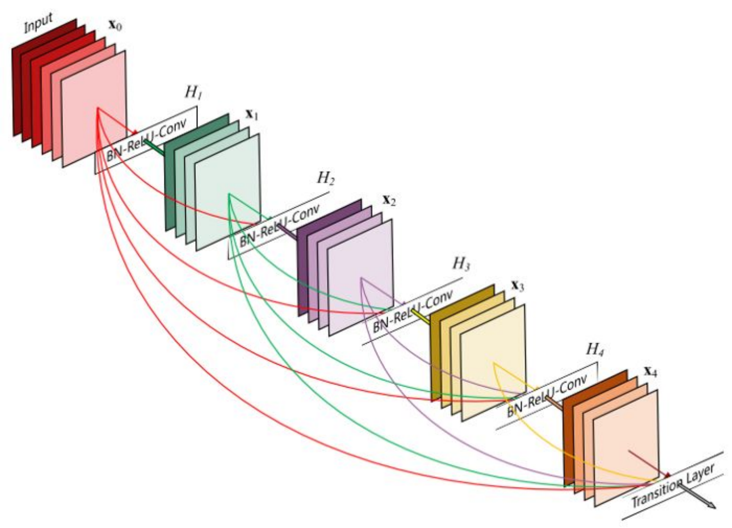


[-5, 2, 4, 0, -7, 7, 4, 0]

Planned Training Plots:



# Network Architecture




Following is our initial network design choices

- Architecture is split into
    - Convolutional Layer Blocks
    - Fully Connected Layer Blocks
- Activation: LeakyReLU (not bounded)
- Loss: Mean Square Error (MSE)

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$$

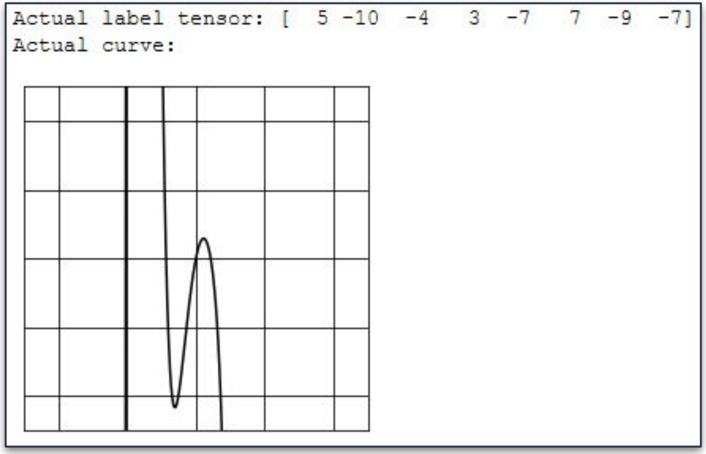
- Optimizer: Adam (.005 Learning Rate)
- Batchsize: 128
- Hyperparameters will be manipulated at training time (includes learning rate, number of epochs, dropout rate, etc)

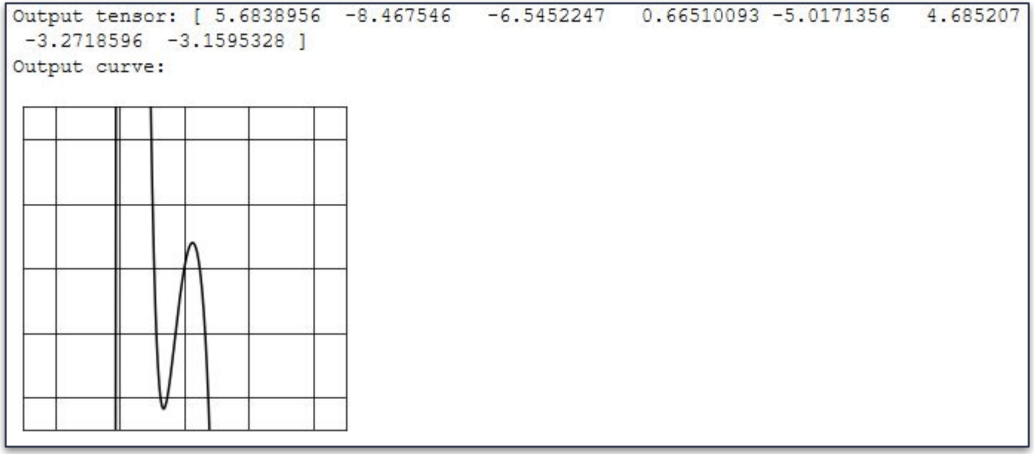
# Network Architecture

```
Network(
 (cnn_layers): Sequential(
  (0): Conv2d(1, 8, kernel_size=(3, 3), stride=(1, 1))
  (1): BatchNorm2d(8, eps=1e-05, momentum=0.1)
  (2): LeakyReLU(negative_slope=0.01)
  (3): MaxPool2d(kernel_size=2, stride=2,)
  (4): Conv2d(8, 16, kernel_size=(3, 3), stride=(1, 1))
  (5): BatchNorm2d(16, eps=1e-05, momentum=0.1,)
  (6): LeakyReLU(negative_slope=0.01)
  (7): MaxPool2d(kernel_size=2, stride=2,)
  (8): Conv2d(16, 32, kernel_size=(3, 3), stride=(1, 1))
  (9): BatchNorm2d(32, eps=1e-05, momentum=0.1,)
  (10): LeakyReLU(negative_slope=0.01)
  (11): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1))
  (12): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1))
  (13): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1))
  (14): BatchNorm2d(32, eps=1e-05, momentum=0.1,)
  (15): LeakyReLU(negative_slope=0.01)
  (16): MaxPool2d(kernel_size=2, stride=2, padding=0)
 )
 (fc_layers): Sequential(
  (0): Linear(in_features=1568, out_features=4096, bias=True)
  (1): LeakyReLU(negative_slope=0.01)
  (2): Linear(in_features=4096, out_features=4096, bias=True)
  (3): LeakyReLU(negative_slope=0.01)
  (4): Linear(in_features=4096, out_features=128, bias=True)
  (5): LeakyReLU(negative_slope=0.01)
  (6): Linear(in_features=128, out_features=64, bias=True)
  (7): LeakyReLU(negative_slope=0.01)
  (8): Linear(in_features=64, out_features=8, bias=True)
  (9): LeakyReLU(negative_slope=0.01)
 )
 (criterion): MSELoss()
 (dropout): Dropout(p=0.2, inplace=False)
)
```

# Current Results

- After 1500 epochs of training the CNN, the output is decently close to the actual coefficient values.
- Output curve is created based on the output labels tensor.

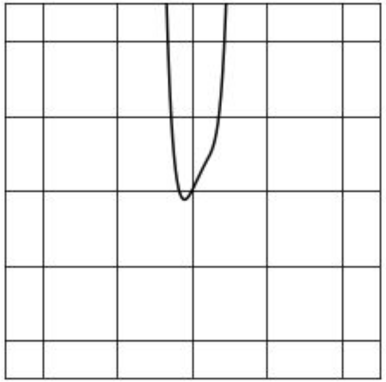


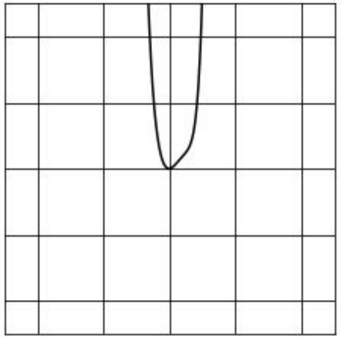
# Current Results

- Additional example at 1500 epochs.
- Output curve is created based on the output labels tensor.

```
Actual label tensor: [ 2  2 -8  7 -1  8 -5  3]
Actual curve:
```



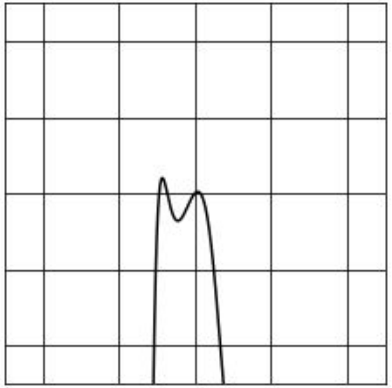
```
Output tensor: [ 0.1622504   4.2711864  -7.430684    3.355888   -0.03072323  5.581914
 -4.868897    4.496127  ]
Output curve:
```



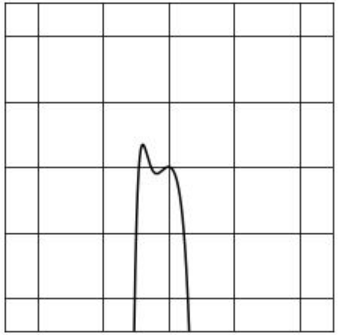
# Current Results

- Additional example at 1500 epochs.
- Output curve is created based on the output labels tensor.

```
Actual label tensor: [  1  -6 -10   0   1   9   5  -7]
Actual curve:
```

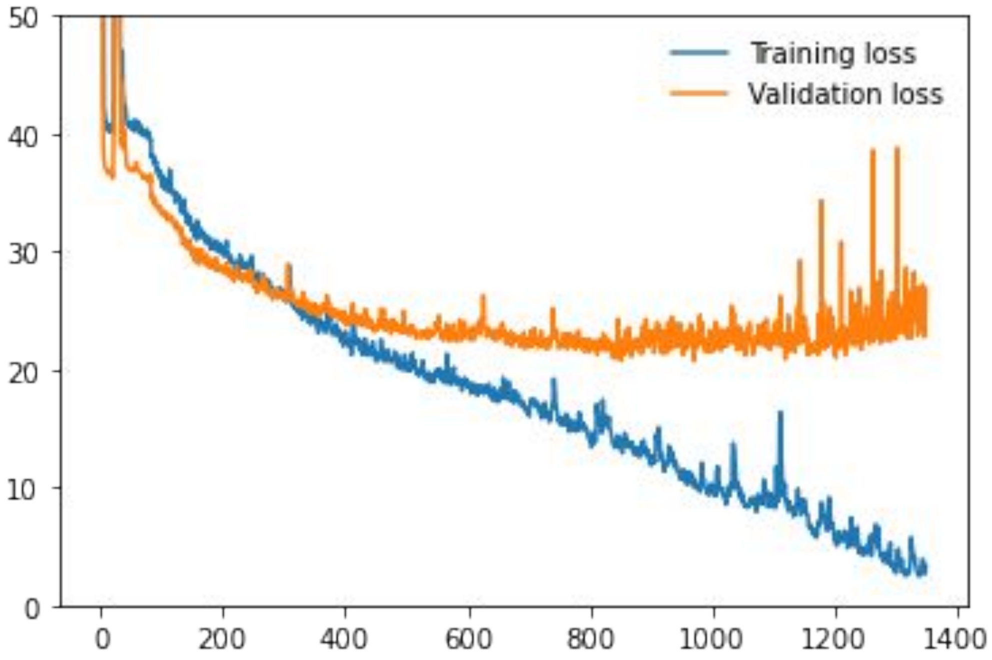


```
Output tensor: [-0.01907877 -4.4737     -6.916153   -0.02837024 -9.947171   -7.3853784
  1.9521291  -5.4963245 ]
Output curve:
```



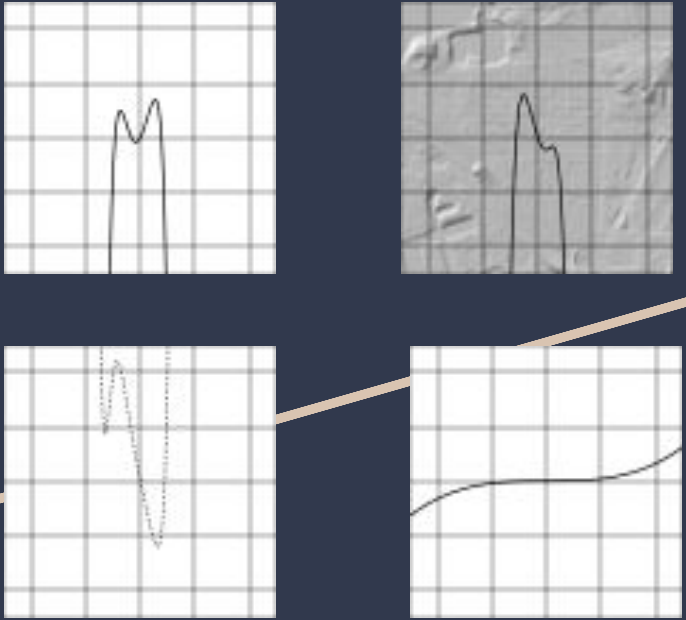
# Current Results

- Training loss and testing loss start very high.
- Training loss gradually approaches 0 as number of epochs increases.
- Testing loss levels at ~25 and even begins to increase towards the end.
- Test loss is too high, so we need to improve the performance of the network



# IN PROGRESS

# Data Augmentation And variability

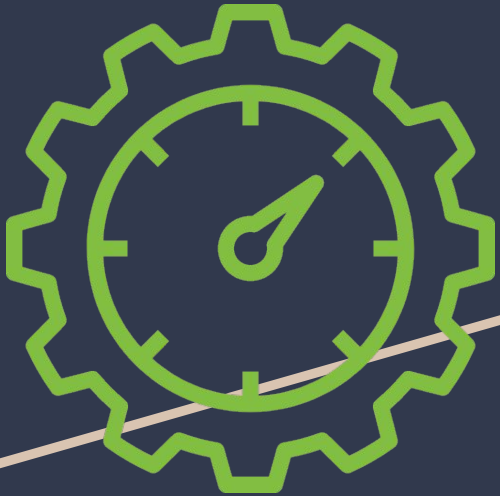


Making our dataset much richer with almost 1 million samples and statistically sound (with no severe bias)

As part of that process, we will:

- Randomize the background with added noise, blur, and occlusion
- Randomize the style, thickness, and hue of the curve
- Randomize the position of the curve on a the x-y plane (variable x and y coordinates)
- Expand to decimal value coefficients
- Possibly randomize the grid line visibility (grid lines might be leveraged by the model)

# Better performance metrics



Additional performance metrics to better understand and evaluate our model

- Find a way to measure accuracy of multiple regression network with some tolerance factor
- Explore statistical measure of error such as standard deviation, p-value, R-squared etc
- Display the layers output to explain what patterns are being picked up by the network.

# Next Design Steps

Moving forward we are going to:

- Incorporate a grid with finer blocks as part of the input pre-processing
- Revise the architecture (continuously)
- Add dropout to the learning process
- Apply cross validation to the training loop
- Building into our new training environment the following

Explore using hyperparameters tuning with Genetic Algorithms.

1. Encode all hyperparameters listed into a string representation "chromosome/gene"
2. Use the new measure of accuracy to gauge the "fitness" of the net
3. Design a function to allow for "crossover" between nets' genes
4. Design a "mutation" function that allows for variations in hyperparameters.

# Thank you!

Any questions?

# References


Matplotlib -https://matplotlib.org/

Train Convolutional Neural Network for Regression - https://www.mathworks.com/help/deeplearning/ug/train-a-convolutional-neural-network-for-regression.html

Neural Network visualization -https://github.com/HarisIqbal88/PlotNeuralNet