TC 5033

Deep Learning

Fully Connected Deep Neural Networks using PyTorch

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Team Members:

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Activity 2a: Implementing a FC for ASL Dataset using PyTorch

- Objective

  The primary aim of this activity is to transition from using Numpy for network implementation to utilizing PyTorch, a powerful deep learning framework. You will be replicating the work you did for the ASL dataset in Activity 1b, but this time, you'll implement a your multi layer FC model using PyTorch.

- Instructions

  Review Previous Work: Begin by reviewing your Numpy-based Fully Connected Network for the ASL dataset from Activity 1b. Note the architecture, hyperparameters, and performance metrics for comparison.

  Introduce PyTorch: If you're new to PyTorch, take some time to familiarize yourself with its basic operations and syntax. You can consult the official documentation or follow online tutorials.

Prepare the ASL Dataset: As before, download and preprocess the Kaggle ASL dataset.

Implement the Network: Design your network architecture tailored for the ASL dataset. Pay special attention to PyTorch modules like nn.Linear() and nn.ReLU().

Train the Model: Implement the training loop, making use of PyTorch's autograd to handle backpropagation. Monitor metrics like loss and accuracy as the model trains.

Analyze and Document: In Markdown cells, discuss the architecture choices, any differences in performance between the Numpy and PyTorch implementations, and insights gained from using a deep learning framework like PyTorch.

```
'2.1.0'
```

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True
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```
NVIDIA GeForce GTX 1650
(7, 5)
_CudaDeviceProperties(name='NVIDIA GeForce GTX 1650', major=7, minor=5, total_memory=4095MB,
multi_processor_count=14)
```

Always a good idea to explore the data

	label	pixel1	pixel2	pixel3	pixel4	pixel5	pixel6	pixel7	pixel8	pixel9	...	pixel775	pixel776
0	3	107	118	127	134	139	143	146	150	153	...	207	207
1	6	155	157	156	156	156	157	156	158	158	...	69	149
2	2	187	188	188	187	187	186	187	188	187	...	202	201
3	2	211	211	212	212	211	210	211	210	210	...	235	234
4	12	164	167	170	172	176	179	180	184	185	...	92	105

5 rows × 785 columns

Get training label data

```
(27455, 784)
(27455,)
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```
(7172, 784) (7172,)
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numpy.ndarray
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```
(3586, 784) (3586,)
(3586, 784) (3586,)
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24
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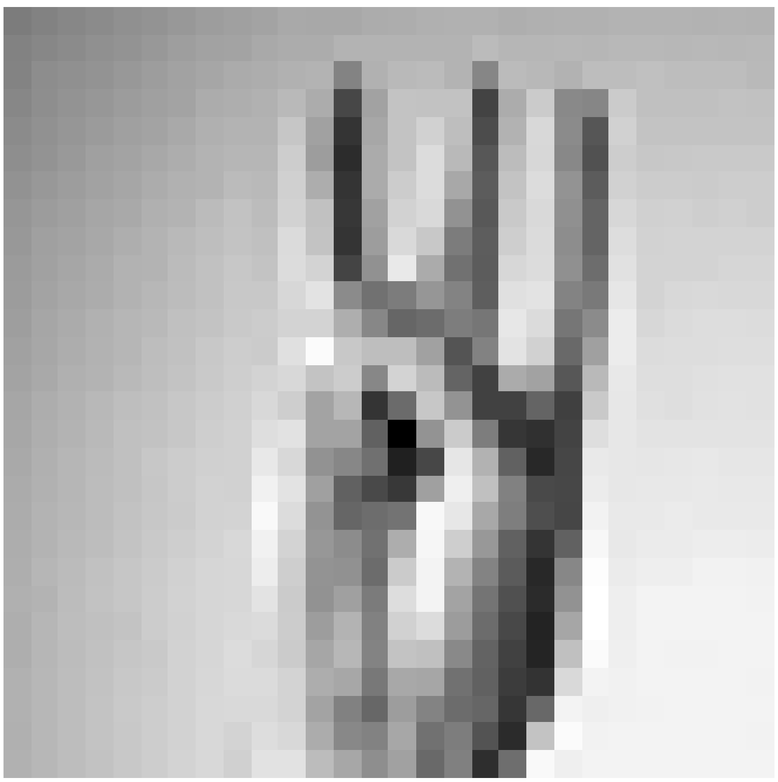
Normalise the data

```
(3.6268384e-06, 0.99999946)
```

```
numpy.ndarray
```

```
The sampled image represents a: w
```



The model

$$z^1 = W^1 X + b^1$$

$$a^1 = ReLU(z^1)$$

$$z^2 = W^2 a^1 + b^2$$

$$\hat{y} = \frac{e^{z^2{}_k}}{\sum_j e^{z_j}}$$

$$\mathcal{L}(\hat{y}^i, y^i) = -y^i \ln(\hat{y}^i) = -\ln(\hat{y}^i)$$

$$\mathcal{J}(w,b) = \frac{1}{num\_samples} \sum_{i=1}^{num\_samples} -\ln(\hat{y}^i)$$

Create minibatches

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Now the PyTorch part

```
cuda
```

Accuracy

Training Loop

Model using Sequential

Changing model hyperparameters to verify if accuracy can be improved

```
Epoch:0, train cost: 0.861163, val cost: 0.696276, train acc: 0.7290, val acc: 0.781372, lr: 0.004000
Epoch:20, train cost: 0.110764, val cost: 1.814120, train acc: 0.9760, val acc: 0.802844, lr: 0.004000
Epoch:40, train cost: 0.103240, val cost: 2.020840, train acc: 0.9790, val acc: 0.801729, lr: 0.004000
Epoch:60, train cost: 0.090984, val cost: 2.568904, train acc: 0.9816, val acc: 0.795594, lr: 0.004000
Epoch:80, train cost: 0.163161, val cost: 2.652196, train acc: 0.9732, val acc: 0.803681, lr: 0.004000
```

```
0.8218070273284998
```

```
The sampled image represents a: h
```

```
The predicted value is: h
```