Assignment 2

Parallel Deep Neural Networks and Data Augmentation

Due date: 25/12/2022 at 23:59

TA in charge of exercise: Orel Adivi

Reception hours for the exercise: Wednesday 16:30-17:30, at Taub 603 and Zoom
(please send an email in advance)

Questions:

- Questions about the exercise should be sent to Orel.
- Problems with connecting to servers should only be sent to Daniel.
- Postponements can only be authorized by the TA in charge Daniel.

Part 1

Brief Background

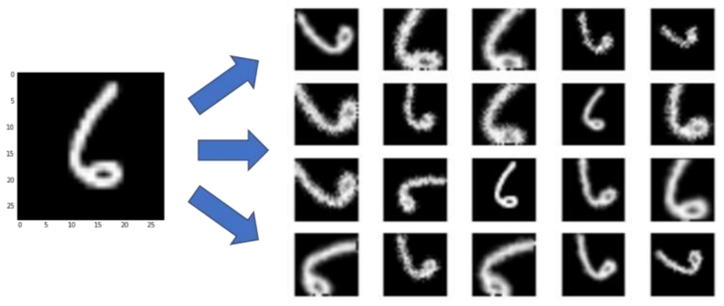
In class, we've seen that a DNN (Deep Neural Network) can be trained using a training dataset $\{(x, F(x))\}$ to approximate an unknown function F.

One of the biggest challenges with Deep Neural Networks is creating a training dataset large enough for the approximation to be accurate. Data collection comes with a cost – money, human effort, computational resources and, of course, time. This causes us to look for ways of expanding our dataset while minimizing data collection costs.

Data Augmentation

Data Augmentation is a technique that can be used to artificially expand our training dataset by modifying examples that are already in it.
The advantage of this technique is that without additional data collection costs we expand our dataset by better utilizing data we already have.

There are many ways to augment data. In images, you can rotate, zoom, crop, use filters and more. From one image you can generate many new images.



In the example above we show how using the Data Augmentation technique we can turn one image of the number 6 in handwriting to many more.

Our Goal

We will train a DNN with images generated by applying the Data Augmentation technique to the original MNIST dataset in order to reach higher accuracies.

https://en.wikipedia.org/wiki/MNIST_database

Implementation Overview

As a continuation of the last exercise (Ex 1 - part 1), you will implement two classes:

Worker **(under** ***preprocessor.py*****)**

This class inherits from “Process” (imported from the multiprocessing library in python) and contains multiple image augmentation operators (implemented as separate functions). The class must include the **job** queue member - containing the jobs needed to process, and a **result** queue member - containing the finished processed jobs. Additionally this class contains two functions:

1. ***process_image*** - applying all augmentation operations sequentially over an input image and returning the result.

2. ***run*** - process images from the jobs queue and adding their augmented variation to the result queue.

IPNeuralNetwork **(under** ***ip_network.py*****)**

This class Inherits from “NeuralNetwork” and overrides two methods:

1. **fit** - Originally this method encapsulates the training procedure of the DNN via Stochastic Gradient Descent. You are required to add the current logic, the creation and destruction of Preprocessor Workers responsible for producing augmented batches.

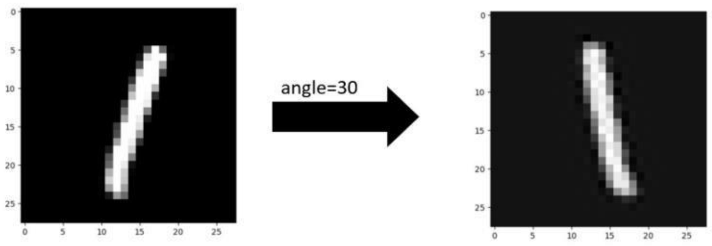
2. **create_batches** - This method receives an original dataset batch and returns an augmented variation of the batch, created by the Workers mentioned in the above method.

Implementation Internals

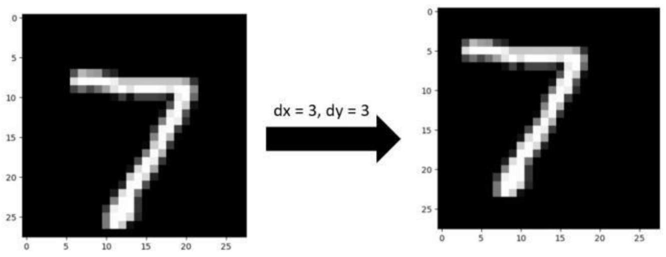
Worker methods under preprocess.py:

def __init__ (self, jobs, result):
Initializes the class and its members as you think will help you in this exercise.
Note you may add more arguments to the function.

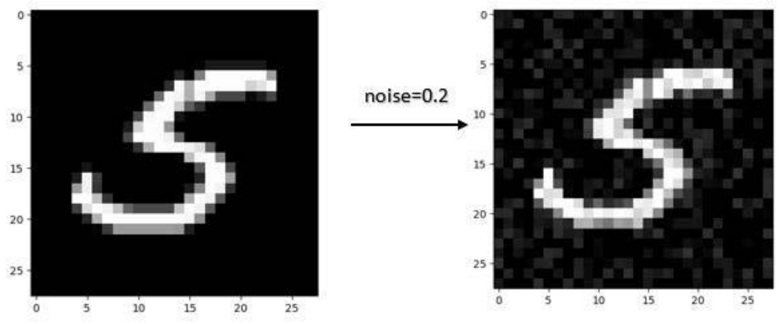
def rotate (image, angle): Rotate
the image by the given angle.
(Hint: You should look at SciPy library)
Example for using the rotate function



def shift (image, dx, dy):
Shift the given image by dx cells to the left and dy cells upwards.
If the coordinates are out of range replace it with black,
which is value 0 (Hint: You should look at NumPy library).
Example for using the shift function:



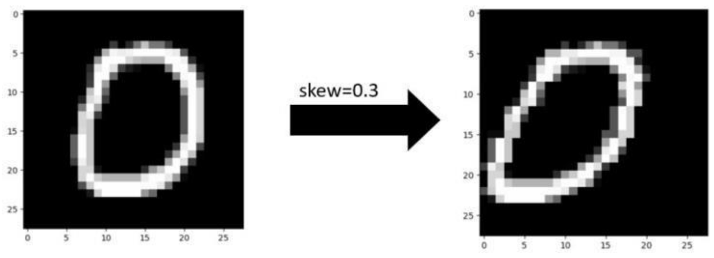
def add_noise (image, noise):
For each pixel in the image, uniformly select a value from [-max_noise, max_noise] and add it to the pixel's brightness value. Don't forget to make sure the pixel's brightness remains a legal value after the modification!



def skew (image, tilt):
Manipulate image by given tilt. For your convenience, we give you a skew formula to use:

$$SkewedImage[y][x] = Image[y][x + y * tilt]$$

If the coordinates are out of range replace it with black (0).
Use NumPy library in the function. Example:



def process_image (self, image):
Run the previous functions sequentially to manipulate the given image. You should use the functions you implemented above in any order you would like.
Use python's random to decide the arguments for the functions (experiment with the bounds to see which gives good results).
Try to get better accuracies when using the augmented data.

def run (self):
The function should produce augmented images as stated above.

IPNeuralNetwork Implementation ip_network.py:

def create_batches (self, data, labels, batch_size):
You should override this function, so it will create batches of augmented images from workers rather than using the original batches.

def fit (self, training_data, validation_data=None):
You should override this function, so it will create Preprocessor Workers depending on the number of CPUs used before running the super function and destroying them after. (use os.environ['SLURM_CPUS_PER_TASK']).

Trivial solution with only one Worker or a Worker for every single job will not get full points.

Part 1 Important Notices

1. You must add **utils.py** from the previous HW submission to your working directory in order to run NeuralNetwork, but do not submit it again!

2. You were provided an implementation of NeuralNetwork with some changes to the structure of the class. The changes are listed below:
    a. The class NeuralNetwork can now be supplied with number_of_batches.
    b. The function create_batches(...) is a class function (Instead of being in Utils.py)
    c. create_batches(...) implementation in NerualNetwork is returning random batches according to the number_of_batches.

3. Throughout the augmentation functions we advise using NumPy and SciPy library built-in functions rather than implementing them yourself.

Part 2

In this part, you will implement a simple queue and replace the result queue member in the IPNeuralNetwork class with this implementation (you don’t need to replace jobs queue!).

You will have to use **Pipe** and **Lock** which you have seen in class. The class needs to work on multiple writers and one reader (meaning – you can assume that in any given moment only one process may try to read from the Queue. However, any number of processes may try to write). Determine where we must synchronize and where synchronization is redundant.

In **my_queue.py** implement the following methods of the **MyQueue** class:

def __init__ (self):
Initialize the queue and it’s members.

def put (self, msg):
Send a message (object) through a pipe.

def get (self):
Read a message (object) from a pipe.

def length (self):
Get the number of elements that are currently in the queue.

Hint: this is a very easy and short part. Don’t write a complicated implementation (2-3 lines of code maximum for each function).

Part 3

Correlation

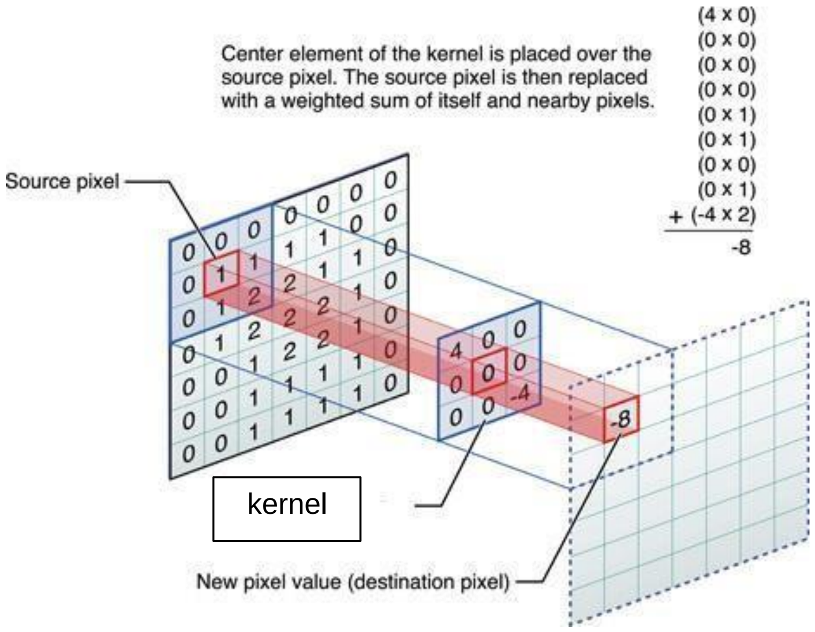
Correlation is a mathematical operation including a combination between two input signals to form a third signal. The correlation is commonly used in various fields and applications. In image processing it is used for blurring, sharpening, embossing, edge detection and much more.

Image Correlation

The correlation result between a given image and a kernel (In image processing, a kernel is a small matrix) could be thought of as replacing every pixel in the image with a weighted summation of its neighbors where the weights are configured by the kernel.

Example 1 - Let us examine the case of a 3 by 3 kernel of ones. In this case, the correlation result is exactly the summation of all joint neighbors.

Example 2 – as explained in the following image:


Center element of the kernel is placed over the source pixel. The source pixel is then replaced with a weighted sum of itself and nearby pixels.
(4 x 0)
(0 x 0)
(0 x 0)
(0 x 0)
(0 x 1)
(0 x 1)
(0 x 0)
(0 x 1)
+ (-4 x 2)
-8
Source pixel
kernel
New pixel value (destination pixel)

Note: some kernel elements can be out of bounds for near-edge pixels. In these cases, “pad” the image with zeros (meaning - all values outside the image are treated as zeros).

Implementations in filters.py:

In this part you will implement the correlation, once using **njit** to speedup calculations and another time using **GPU**.

1. def **correlation_numba (kernel, image):**
   Implement the function using njit to speed up the calculation

2. def **correlation_gpu (kernel, image):** Implement the function using cuda.jit

Make sure that the results of gpu and numba calculations with **kernel** and **image** are equal to scipy.signal convolve2d (**flipped_kernel**, **image**) where **flipped_kernel** is **kernel** after flipping the rows and columns in order (i.e essentially rotating the matrix by 180 degrees).

Part 4

Sobel Operator

In this part we will use the correlation function implemented in filters to see one of its applications. Under **sobel_operator(...)** (located in filters.py) load **“data/image.jpg”** and calculate the operations below. Use the numba correlation implementation from Part 3.

$$sobel\_filter_1 = \begin{pmatrix} +1 & 0 & -1 \\ +2 & 0 & -2 \\ +1 & 0 & -1 \end{pmatrix}, sobel\_filter_2 = \begin{pmatrix} +3 & 0 & -3 \\ +10 & 0 & -10 \\ +3 & 0 & -3 \end{pmatrix}$$

$$sobel\_filter_3 = \begin{pmatrix} +1 & 0 & -1 \\ +2 & 0 & -2 \\ +1 & 0 & -1 \\ +2 & 0 & -2 \\ +1 & 0 & -1 \end{pmatrix}, sobel\_filter_4 = \begin{pmatrix} +1 & 0 & 0 & 0 & -1 \\ +2 & 0 & 0 & 0 & -2 \\ +1 & 0 & 0 & 0 & -1 \\ +2 & 0 & 0 & 0 & -2 \\ +1 & 0 & 0 & 0 & -1 \end{pmatrix}$$

$$G_x = correlation(filter, Image)$$
$$G_y = correlation(filter^{Transpose}, Image)$$
$$Image - sobel_{i,j} = \sqrt{G_{X_{i,j}}^2 + G_{Y_{i,j}}^2}$$

Show the resulting image ($Image - sobel$) in the report for each of the 4 filters. Also show the result when using a 3×3 correlation matrix:

$$correlation = \begin{pmatrix} +1 & +1 & +1 \\ +1 & 0 & +1 \\ +1 & +1 & +1 \end{pmatrix}$$

Make sure that you get the same image when using the cpu correlation of sklearn (convolve2d with the flipped kernel as before). To view the image, run test_filters() on your local computer with the numba_correlation implementation.

For further reading on the sobel operator and it’s uses:
https://www.tutorialspoint.com/dip/sobel_operator.htm

Guidelines:

1. use **NumPy** for:
   a) transpose(...) - transposes matrix
   b) sqrt(...)
   c) pow(...)

2. use **imageio** for
   a) imread(...) - loads image 3. use **matplotlib.pyplot** for:
   b) a. imshow(image, cmap=’gray’) - displaying image

Report

Part 1

1. Run main.py with [8, 16, 32] cores (flag -c<core_number>)

2. Compare runtime of IPNerualNetwork between different core numbers. Include a screenshot and a short explanation about what number of cores gave the best performance and for what reason.

3. Run main.py again. Compare the accuracy percentage for different epochs between NeuralNetwork and IPNeuralNetwork. Include a comparison table and an explanation.

4. Answer: Why are we using processes and not threads?

5. Answer: Give two ideas how we could accelerate even more the training phase.

Part 2

6. Explain your implementation in part 2 and the reason you decided to implement it that way.

Part 3

7. Give a detailed explanation of your correlation_numba and correlation_gpu implementation.
8. Run filters_test.py on 1 core (flag -c1) to see time comparison.
9. Include screenshot and calculate the speedup between them and the SciPy's convolve2d.
10. Answer: what will happen if we use a larger kernel matrix?

Part 4

11. Show the result of the sobel operator (using the 7 filters) and the result of the correlation matrix, using matplotlib.pyplot for each filter with the numba_correlation implementation. To view the image, run test_filters() on your local computer.
12. Explain why the 4 images from the previous question are different (what the differences are and what the reasons for them are).

Notes and Tips

1. Notice that in part 1, the image is a NumPy array of size 784 while you should manipulate it as a matrix of size 28X28.
2. Notice that in part 1, rotate, shift, add_noise and skew are static functions.
3. In filters_test.py there is a function called show_image(image). It will help you understand what your filters are actually doing.
4. You can add variables and prints as you need, but your code must be clear and organized.
5. Don't remove prints or comments already in the code, adhere to instruction comments.
6. Document your code thoroughly.
7. It's recommended that you work with PyCharm, but performance should only be measured in the course server. You can simulate a gpu by setting the environment variable to 1, but take into NUMBA_ENABLE_CUDASIM consideration that it will be much slower.
8. Don't forget to install imageio on the server.

Server

all server instructions and installations are detailed here:
https://hpc.cswp.cs.technion.ac.il/2020/08/31/lambda-computational-cluster/

Submission

Submit a hw2.zip with the following files only:

1. preprocessor.py with your implementation.
2. ip_network.py with your implementation.
3. my_queue.py with your implementation.
4. filters.py with your implementations.
5. A hw2.pdf report of performance analysis of maximum 7 pages, make it concise.