**UIO**

**FYS-STK4155**

Project 3

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**ABSTRACT**

The growing processing power that has emerged withing the PC architecture (CPU & GPU), distributed sub-processing and on-demand cloud processing, opens up for more parallelism and distributed ML processing. The project will run instances of the same FFNN in parallel, based on the breast cancer dataset in Skilearn, but with distinct configurations on biases and weights. The parallel instances will synchronize and average out the cost, in timely intervals, for faster convergence.

**INTRODUCTION**

Parallel processing has been a growing architecture for many decades, not only on the chip side, with new inventions as multi-core concepts, to pure optimized graphical chips like the GPU. The latter are highly optimized chips to run thousands of graphical operations simultaneously. It has been seen that GPUs with highly optimized architecture for graphical manipulation, also are well suited for matrices manipulations, which is central for most of the ML algorithms.

In addition to the physical chip power, more software and protocols are emerging where processing power can be distributed in networks, for sub-tasks that need processing power, way beyond the capacity of a single machine.

As a first step this project will align FFNN in parallel instances (1..n) on one physical machine.

Enabling network parallelism, we will show that 2 or instances, with independent randomly initialized weights will converge faster, and add even better predictions.

All parallel instances will share the common input data Xi, but will have their unique set of Hyperparameters Hi, that will be adjusted and tuned independently.

The project will show that there is a clear correlation between the number of instances running in parallel and the time for the network to converge.

Three cases will be analyzed:

1. The instances will run isolated, with distinct hyperparameters (Hi) through all layers, expect for the output. The weights for all instances will be averaged-out for the last layer and used for backpropagation for all instances.
2. For this case, the weights are selected based of the min|y^ - y| difference between the predicted y-value and y.
3. We will now increase the award/penalty through the cross-entropy by adding a constant ∂ to the activation function.

* **Structure**

The analyses are done in a msCode environment and is using standard libraries as specified in the \*.py heading. All “imports” are based on standard libraries, commonly used for ML, and routines and code generated for this project, is located only in the python file.

We have used two datasets, one test-set, generated by extracting random numbers and a dataset from MNIST. Due to problems with tuning our first NN, we have loaded the breast cancer from sklearn.

The program is modularized, based on separate tasks, and we have modularized in such a way that the program itself, can run one, several or all modules, in one go for analyses. A separate test environment is, hence, not needed.

The reader can at any time reproduce any test-results or plots, by activating the selected part in the MainModule().

All plots are located in the ./Plots folder and they are named, based on function, parameters and methods. The naming convention is also indicating the size of the sample data, to ease the setup, and re-run the tests.

The MacBook Pro has 4 cores and the number of instances for the FFNN will be multiple of the number of cores.

**METHOD**

The “standard” FFNN algorithm will be expanded to incorporate the initiation of **i-instances** of the network, for **i** in **(2, 1\*C, 2\*C, 3\*C…**), where **C=4** (number of CPU cores)

The network will be expanded to include the module NetworkX. This will enable plotting snapshots of the weights **Wi**, of one or several of the parallel instances running, at selected epochs. This will be useful to better optimize the hyperparameters **Hi**, during the training part.

There will be added a plotting function that will compare the weights in a set of paired instances, like a “heat map” to see the difference in weight distribution, during conversion. This is only possible for networks that are configures with the exact same topology.

Bases on NN theory, the weights (memory) of the network will not converge to “one” specific weight “state”, even though the precision for the classification converge. We expect to show that

All instances of the network will share the common input data (observations) **X** with corresponding **Y** in global structures (read only). All other variables will be instance specific **Hi**, and some of the variables can be changed during run-time.

The project has invoked three different methods for instantiation of the FFNN Class.

1. Standard instantiation as implemented in std Python. A call with standard passing of hyperparameters and return of test-results.
2. For threading we have used the **treading** package which opens up for lighter sub-processing and enables all the threads to be ensembled in the threads.join() routine for synchronization of all threads to complete. The control is not passed back to “mother” process before all threads has completed. The Pipe function have been used to pass any return value back from the thread, for post processing (as for the plots) (ref. plot).
3. Multiprocessing is a sperate package **multiprocessing**, where process and freeze\_support is needed to parallelize. Also here, the Pipe function is used to hold any return value. Only after all sub-processes has finalized in process.join(), can return values

The network has added functionality to synchronize loss values between instances. The logic has been added to the self.fit() function in the class, to take action on this, at specific intervals of epochs.

**Overview of the logic:**

(This is a small state-machine implementation, using the Glogal Lock() functionality and will write and read the new calculated Global loss, en the proceed to next epoch.

-> Finalize calculation of Instance.loss()

-> while not read new Global.loss()

-> request to aquire Global.lock()

-> if aquired(), write Instance.loss() to global variable

-> GlobalLoack.wait() until all instances has written its instance loss to global variable

-> then calculate new global loss

-> request to aquire Global.lock()

-> read Global Loss and assign it to your instance loss variable,

->exit state machine

-> process next epoch.

Legg inn for cross-entropy of formel for cost function

RESULTS & DISCUSSIONS

The single instance of the FFNN implementation for breast cancer shows good performance and are suited to run on a laptop of any kind. For some cases the loss function gave **Inf** and **NaN** returns on the loss function and predictions could not be done. As far as I could see, this was only due to the randomized generation of weights and biases. Based on reference in [referanse til balancing], the balance in the data set is about 50/50 balanced between true **y’s** and hence, there should be no reason to balance the weights one way or the other. I took quite some time to distribute random weights between [-1,1] and also to conlude on recommendation in documentation of a multiplier of 1/SQR(instances). Reaching this conclusion, made conversion must faster an easier and all epoch produces and loss, that faster manage to converge.

Due to the Python´s GIL implementations, the findings for interchange of hyperparameters, like cost averaging within all instances of the network, are coynclusive. There were to many observations that, where aquire() lock got stuck and almost impossible to debug if this was due only to logic error in the small “state-machine” or if it was influenced by GIL’s context switching between the thread and processes.

We It is hard also to conclude that problems with GIL also cascaded further to It will also be open for discussion

Det routine SynchThreadLossFunction, will synchronize the loss values for all running instances. The firs thread entering the instance of the routine will fetch the GloblaLoack.aquire() and write its version of calculated loss to a global variable. All other instances will have to queue up until write is finalized and GlobalLock.notify\_all() broadcast

CONCLUSIONS & EXPECTATIONS

I was surprised to see that multi-threading managed to outperform multiprocessing. It’s clear that threading is a concept of sub-processing ”light”, with shared memory within its “mother” process, but should have faced limitations due to Pythons GIL implementation and limitations. I expect that this will be more of a problem as the architecture of the network grows deeper, and also for larger datasets, than what is presented for the breast cancer in Sklearn.

Synchronization of data within several threads might have an upper-hand, due to its shared process memory, and it’s expected that shared objects like structs and pipes, controlled by locks, can be more optimized within the same memory space. However, this has to be tested and confirmed in the future.

I experienced quite some “hangs” in the system, that I expect to be my mis-use of locks and that in particular aquire() (wait queue) and wait() functionality can get stuck and also time out, the might force the state machine out of synch.

The next two faces of the project will look into the optimization of the parallel processing even more and also utilize more underlying physical architecture of the platform you are running on.

It is clear that Python as an interpretive programming language, with its sequential limitations on the use of its interpreter, need to be considered for future implementations.

The second phase will be to integrate the parallel processes on common platforms like the Ray or Hadoop, which one that suits best for the specific task.

I see the possibility that parallel processing also can be an added factor for improvements in combination with SGD. Also, for small dataset, in combination with re-shuffle and resampling, parallel processing can be an added factor for improving the results.

Due to the limitations of the Pythons GIL implementation and problems with global locks, I have at this moment lack of evidence, to conclude, that averaging, optimizing, hyperparameters, during parallel processing will improve that over all performance. What seems to be quite clear is that classic implementations of networks today, solemnly basing the “compiler” and OS to utilize and optimize processing, is not optimal. We can see by the performance that single processing is limited by internal wait/io tasks.

I can also see this subject opening up for single source asynchronous input, or event driven input that continuously update your learning model – something down the line as face-recognition on your iPhone.

Lastly – instead of focusing purely on parallel processing interchanging hyperparameters, one can easily see the opportunity to link processing in a chain and pass experience to next process in line.

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