Project Proposal 15418

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1 TITLE

The title of this project is the following: "Parallelization of Inference on Recurrent Neural Networks". The team working on the project consists of Anupam Pokharel and Lisa Mishra.

2 WEBPAGE URL

`https://lmishr.github.io/15418_project.html`

3 SUMMARY

Our objective is to discover and exploit opportunities for parallelism in Recurrent Neural Networks' (RNNs') inference-time forward pass computations. We aim to effectively utilize synchronization and atomic operations to mitigate the purely-sequential nature to which the data dependencies within and across neural network layers lend themselves, so that we can use parallel computation APIs (e.g. `openmp`) and vectorized operations on GPUs for multiprocessor speedup.

4 BACKGROUND

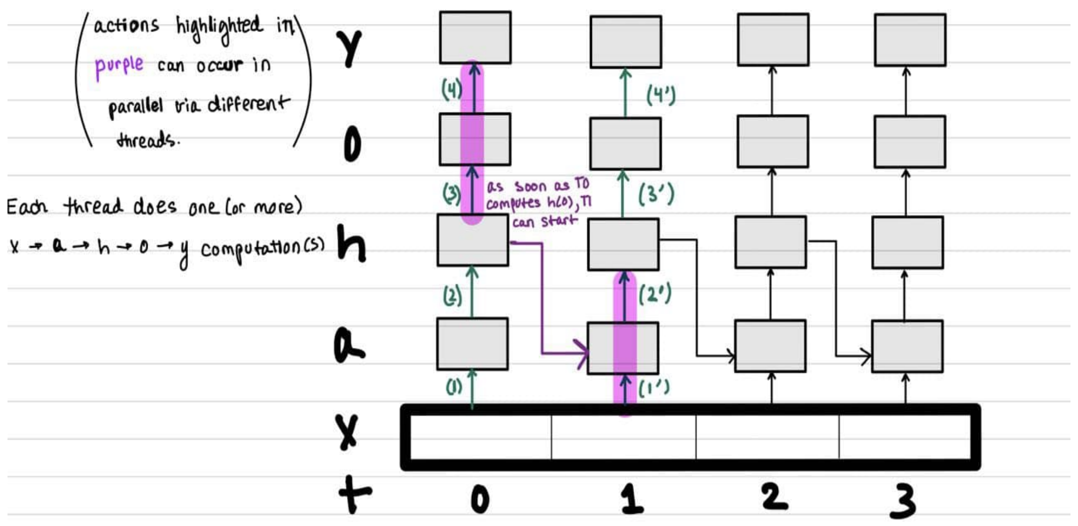
We are interested in finding effective ways to obtain speedup on the following basic algorithmic structure of a forward-pass computation in RNNs (source) :

```
// x is a vector of inputs
a[t] = b + W * h[t-1] + U * x[t]
h[t] = tanh(a[t])
o[t] = c + V * h[t]
y[t] = softmax(o[t])
```

where the following variables correspond to layers that are vectors of neurons, indexed by time and ordered by increasing proximity to the output layer, `y`: `a, h, o`.

We plan to find some ways to mitigate the constraints enforced by dependent data: for example, the constraint on `a[t]` is the completion of the computation for the hidden layer's (`h`'s) output at time `t-1`. If different threads were responsible for the forward-pass computations of adjacent time steps, there would need to communication of hidden-layer values that would inhibit speedup. We elaborate more on the complications that this plan generates in the "THE CHALLENGE" section.

The following figure demonstrates the dependencies that this psudocode's computation entails:


actions highlighted in purple can occur in parallel via different threads.
Each thread does one (or more) x → a → h → o → y computation(s)
y
o
h
a
x
t
0
1
2
3
(1)
(2)
(3)
(4)
(1')
(2')
(3')
(4')
as soon as T0 computes h(0), T1 can start

5 THE CHALLENGE

RNNs' layers are composed neurons that have dependencies both on the outputs from "below" layers and on outputs from previous time-steps, as illustrated in the BACKGROUND section. In the discussion from the previous section regarding forward passes for adjacent columns of neurons occurring on different processors, we alluded to the unavoidable necessity to communicate hidden-layer values. A salient topic to explore while implementing parallelization is whether this necessity is most efficiently met by using shared memory (which we will test using `OpenMP`), an orchestration of some form of point-to-point communication (we will test this as part of our additional goals, time permitting, with `OpenMPI`), and/or a tiering of caches that allows targeted memory-sharing among some processors.

6 RESOURCES

We will need access to a computer with a NVIDIA GPU, in order to implement GPU-based accelerations (more detail on this appears in the "PLATFORM CHOICE" section). Additionally, we will consult online resources that have psuedocode or python code for RNN inference computations (one such resource was already consulted in our discussion and is linked in-line). Additionally, we anticipate that we will consult online resources for CUDA programming, including formal developer guides published by NVIDIA.

7 GOALS AND DELIVERABLES

7.1 What we PLAN TO ACHIEVE

(a) Achieve speedup through a parallel implementation of RNN forward pass computations using OpenMP.

(b) Achieve speedup through a parallel implementation of RNN forward pass computations using CUDA.

(c) Compare and analyze speedups in both the OpenMP and CUDA implementations.

7.2 What we HOPE TO ACHIEVE

(a) Achieve speedup through a parallel implementation of RNN forward pass computations using MPI, and compare and analyze speedup to the CUDA and OpenMP implementations.

7.3 Our plans for the demo

We intend to have speedup graphs to compare the speedup between the CUDA and OpenMP (and potentially OpenMPI, if we have extra time to implement it) implementations.

8 PLATFORM CHOICE

Our intention is to implement our RNN inference computations in C++ with CUDA code for GPU-based acceleration. This is an especially apt choice for us for two reasons. The first is that one of the most popular Python Libraries for Machine learning and Deep Learning, PyTorch, has many back-end implementations in C++ (and even is complemented by an API to augment library code with customized C++ routines). Secondly, we already have experience from 15-418's Programming Assignment 2 in composing kernel code that executes operations on many threads at once, so this is a great entry-point for us to begin development on the project. We will run this code on any machine that has a NVIDIA GPU (or is connected to one).

9 SCHEDULE

WEEK OF	TO-DO ITEMS
10-31	- Write proposal report and populate website with proposal contents - Research C++ implementations of PyTorch library methods and how they are CUDA-accelerated
11-7	- Analyze dependencies, have an outline for implementation of RNN computations using CUDA acceleration
11-14	- Complete a basic implementation using the C++ implementations in PyTorch with CUDA Acceleration - Decide if project progress is sufficient to take on extension to compare additional implementation using OpenMPI
11-21	- Complete a basic implementation using OpenMP - Checkpoint meeting regarding milestone progress
11-28	- Obtain final results for both/all three implementations - Analyze data, compose graphs
12-5	- Polish results for demo