DEPARTMENT OF INFORMATICS

TECHNISCHE UNIVERSITÄT MÜNCHEN

Master's Thesis in Data Engineering and Analytics

Analyzing Bottlenecks in Hivemind

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Analysieren von Engpässen in Hivemind

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I confirm that this master's thesis in data engineering and analytics is my own work and I have documented all sources and material used.

München, September 26, 2022 Adrian David Castro Tenemaya

Acknowledgments

I was 4 years old and a half when I first arrived in Italy. Now, 20 years later (wow), I am completing my journey. Thanks to everyone who tagged along on my academic journey. Special thanks to my wonderful and supportive parents Laura and José; my "sore" Valeria, and my girlfriend Iris. Also, thanks to everyone who has believed in me and who didn't make me quit (you know who you are).

Abstract

The amount of computing resources required to train state-of-the-art deep neural networks is steadily growing. Most institutions cannot afford the latest technologies, which are sometimes needed to keep up with today's demanding deep neural network research. Access to powerful devices is therefore limited to few research institutions, slowing down research.

In [RG20a] they propose a novel concept for decentralizing deep neural network training using large amounts of consumer-grade hardware. The training algorithm described in the paper is called "Decentralized Mixture-of-Experts" (DMoE) and employs a combination of decentralized and Mixture-of-Experts [Sha+17] techniques. This allows thousands of computing devices to join forces and train a single neural network model together. DMoE achieves this by splitting the target neural network model into different parts called partitions, similarly to model parallelism. Each partition is then replicated across a subset of workers participating in the training. Next, a gating function is used to select which workers can perform the next operation on the given input. After the workers have been selected and located using a Distributed Hash Table (DHT), the input data is sent to the workers, and a forward pass is performed. A similar algorithm is applied during the backward pass. DMoE proved that scaling model training to thousands of heterogeneous compute nodes is possible, thus enabling large-scale community research projects.

Although DMoE is robust against training latency, it also requires large amounts of data to be exchanged between every participant worker. We may assume, however, that most participants in the network will not have datacenter-grade network connections and bandwidth. Therefore, the communications needed to perform training may saturate a worker's network. An approach suggested by [RG20a] to reduce the network load is to compress and convert tensors to a lower precision before transfer.

From the combination of features and findings of [RG20a; Rya+21], Hivemind was created. Hivemind [tea20] is an open-source framework that enables collaborative model training using a large number of heterogeneous devices from universities, companies, and volunteers. Every device participating in the computation may differ in its characteristics, featuring different architectures and network speeds.

In Hivemind interactive demonstration [tea20], 40 devices jointly trained a modified DALL-E [Ram+21] neural network model over 2.5 months. The reported results,

however, do not include the participant's device information and metrics. Without this type of information, it's not possible to perform an independent analysis of the effects of different configurations on training. In this paper, we intend to reproduce the results of [tea20] on our cluster using different device configurations to identify the impact of key system metrics on Hivemind.

Over the last years, research and software libraries like Hivemind have been focused on reducing and optimizing deep neural network model training times with techniques such as data and model parallelism. In [Xin+21] however, the authors show that as much as 45% of total training time may be spent on preprocessing tasks alone. Despite this, the impact of preprocessing pipelines is often ignored in current research. Therefore with this paper, we propose to explore the impact of preprocessing pipelines in [tea20].

As noted by [Ise+22], it is crucial to find and analyze bottlenecks during computation to maximize performance. In their work, they also detail several possible improvements that can be applied in preprocessing pipelines, increasing throughput under certain circumstances. Intuitively, given the high amount of communications and data loading that DMoE needs, the preprocessing pipeline may be subject to inefficiencies. Using the techniques and findings showcased in [Ise+22], this paper further aims to find bottlenecks in the Hivemind preprocessing pipeline.

In this paper, we will analyze the impact of Hivemind's different possible scenarios on preprocessing pipelines. As we test the software and its limitations, we might find possible areas of improvement in Hivemind. Whenever possible, we will further contribute using the knowledge gathered through our experiments by improving the Hivemind [tea20] source-code. Our contributions can be summarized as follows:

- We analyze the challenges of optimizing preprocessing pipelines in decentralized distributed training and provide insights on possible improvements
- We verify the effectiveness of Hivemind for different peer hardware configurations concerning preprocessing pipelines
- We use the gained knowledge and insights to contribute to the Hivemind open-source library.

Contents

1 Introduction

It is safe to say that the internet paved the way for many things for humanity. Media such as images, video and audio can be shared across websites and applications, knowledge can be stored in faraway servers and retrieved with ease in text format using mobile devices, and products and services can be bought with the click of a button or a tap on a screen. Interactions, media and information make up for massive amounts of data that flow through complex computer systems, which in turn generate even more data and information.

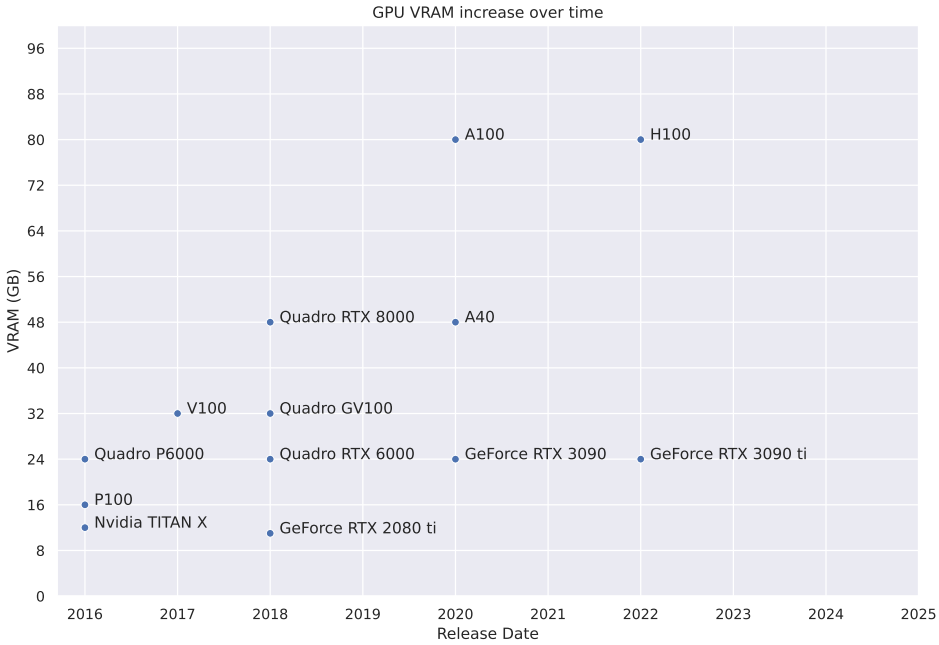
Researchers have found ways to leverage the magnitude of data that is being produced every second by countless systems all around the world. One of the most recent and most popular uses of this huge variety and quantity of data is machine learning (ML). Machine learning can be defined as a set of techniques that use data to improve performance in a set of tasks. Today, for example, we feed data to machine learning models to calculate what is the probability that a webpage visitor will buy certain products, or the chances that it is going to rain in a few days or to generate elaborate text and stunning, never-before-seen pictures.

Recently, models such as BERT [Dev+18], DALL-E [Ram+21], GPT-3 [Bro+20] and others have become incredibly popular thanks to their outstanding results and endless possibilities. DALL-E for example can generate high-quality realistic images and art starting from a text description written in natural language. These models however require massive amounts of data as well as very expensive computational resources, such as graphical processing units and tensor processing units (TPUs). In recent years, the size of neural network models has been steadily increasing exponentially, as shown by Figure 1.2. A simple calculation shows that the neural network model Megatron-Turing-NLG 530B [Smi+22] would take roughly $530 \times 4 = 2120\text{GB}$ of memory to simply hold its 530 billion weights.

Furthermore, training a neural network model requires even more memory. Intermediate computation outputs such as gradient and optimizer states sometimes require 2 or 3 times as much memory than just the model parameters, making GPU memory one of the main bottlenecks in training huge neural network models. While some of these issues can be tackled using clever techniques such as parameter quantization, pruning and compression, they must not be considered one-fits-all solutions. Some models are simply too big to be trained on a single device. This problem is exacerbated by factors

such as GPU prices and much slower growth of their memory size. Figure 1.1 shows how GPU memory has been increasing from 2016 to 2022.

Figure 1.1: GPU VRAM over the past 4 years. The growth is mostly linear, doubling



The characteristics of the latest GPU released by NVIDIA earlier in 2022, the H100 with 80GB of memory, an amount that hasn't changed since its direct predecessor A100.

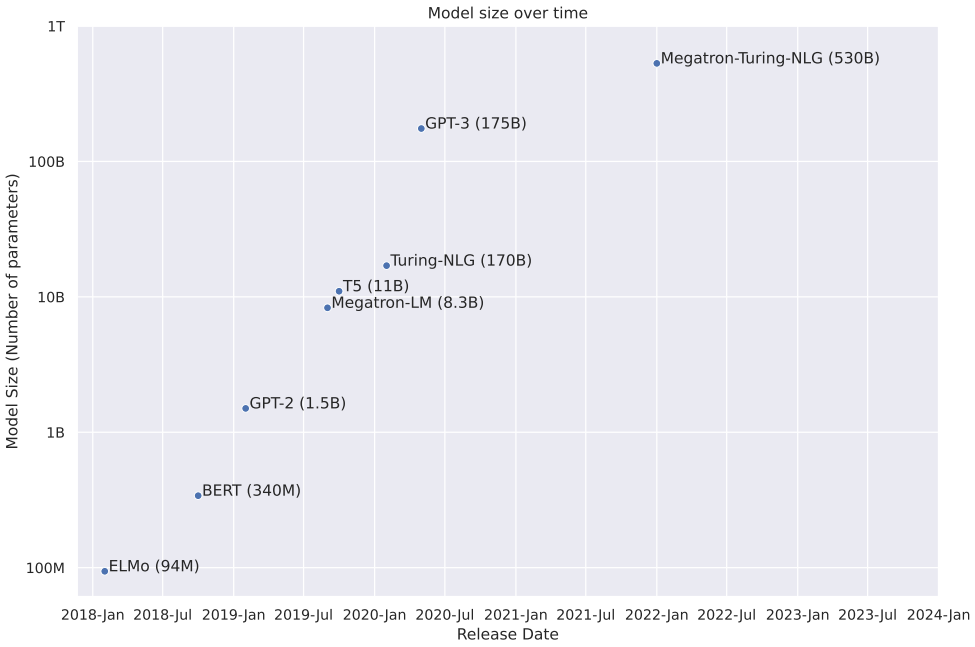
To tackle this problem, practitioners studied and developed distributed computing techniques to train models that do not fit entirely in a single GPU's memory, distributing the training load to potentially thousands of devices.

These techniques can be briefly categorized as follows:

- *Data parallelism*. Given a set of n devices, an instance of the model is trained on each one of the devices. Usually, gradients obtained during backpropagation are then aggregated across all the devices using techniques such as *AllReduce*. This technique however does not work very well with models that exceed a single device's available memory and is therefore used in applications with low-memory devices such as *Federated Learning* [Li+19].

- *Model parallelism*. A deep neural network is conceptually split into n partitions

Figure 1.2: Model size over the past 4 years: ELMo [Pet+18], BERT [Dev+18], GPT-2 [Rad+19], Megatron-LM [Sho+19], T-5 [Raf+19], Turing-NLG [Mic20], GPT-3 [Bro+20], Megatron-Turing-NLG [Smi+22]



across n devices, each hosting a different partition and set of weights. An early notable example of model parallelism is AlexNet [KSH12], where the authors decided to split the computation of some of the layers across two GPUs with 3GB of ram each, a concept illustrated in Figure 1.3. This technique relieves the burden of a single node to host all of the weights of a model but is also more sensitive to issues with communication across nodes.

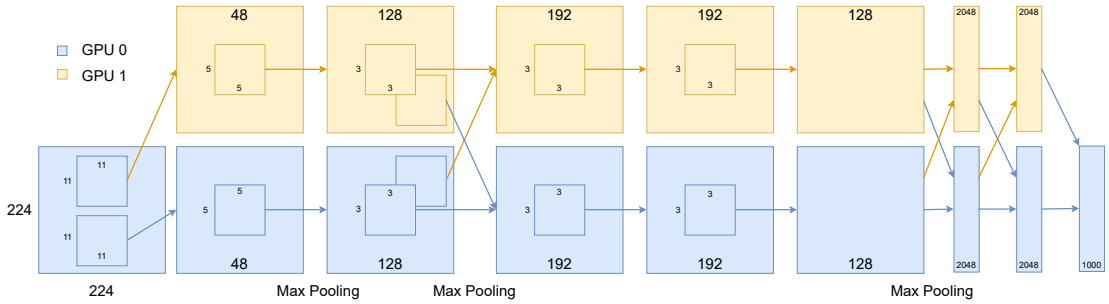
- *Pipeline parallelism*. A combination between model parallelism and data parallelism. Introduced by [Hua+18], pipeline parallelism consists in splitting a batch into micro-batches across the available computing devices, leading to fewer dead wait times.

- *Tensor parallelism*. Tensor operations for huge neural network models can become a bottleneck, as they can require more memory than the host's device can handle and can become slow in general. Tensor parallelism can alleviate a single node's

computational burden by splitting a tensor operation across many devices. This technique has been first introduced in neural network models in [Dea+12] with a framework called DistBelief.

- *Mixture-of-Experts*. Instead of conceptually splitting a model, we construct multiple, different models. Each of them specializes in a different subset of the complete set of training cases, helped by a gating function. This has been first introduced in 1991 by [Jac+91] but has recently gained traction due to its attractiveness in numerous tasks.

Figure 1.3: AlexNet [KSH12] architecture shows one of the first examples of model parallelism. The training of convolutional layers is split across two GPUs, as the size of the model during training exceeded the available memory of a single GPU.



Most of the frameworks and papers built on top of these techniques approach the issues that we have discussed before by employing tremendous amounts of expensive, top-of-the-art and heterogeneous technologies. However, universities, small companies and hobbyists that want to train the models described in these papers do not necessarily have access to a such vast amount of resources, limiting possibilities and research directions.

The framework Hivemind [RG20b] aims to help with these issues by allowing distributed neural network training across the internet using heterogeneous devices. The authors provide two types of training: *parameter averaging* and *mixture-of-experts*. In this paper, we will focus on analyzing bottlenecks of parameter averaging in a controlled environment.

Our contributions are as follows:

- We analyze the challenges of optimizing preprocessing pipelines in decentralized distributed training and provide insights on possible improvements

- We verify the effectiveness of Hivemind for different peer hardware configurations concerning preprocessing pipelines
- We use the gained knowledge and insights to contribute to the Hivemind open-source library.

2 Fundamentals

In this chapter, we are going to define the basic concepts needed to understand the contents of this paper. The mathematical details of algorithms or technical implementations of the presented technologies will not be described in depth, but rather briefly and concisely describe how they work.

@isenko: still working on this part!

We will formally define what are neural networks and how training works using a simple scenario. Following, we will introduce why and how distributed computing techniques are important in today's world, and how they can be used to facilitate neural network training. The topic of distributed neural network training is then presented. Finally, we describe Hivemind, how it works, why we chose this framework, which type of analysis we are going to conduct, and what kind of parameters are we focusing on in this paper.

2.1 Neural Networks

Neural networks (NNs) have been a major research area in the past decade. However, the basics of NNs as we know them today have been around for almost 70 years but did not gain much recognition until the 2010s. This is mostly because the success and viability of NNs are affected by two major factors, data availability and computational power, both of which were scarce or not advanced enough. As network-connected devices like smartphones and laptops started to become more widespread, the data that could be generated and gathered grew by several orders of magnitude. Today, NNs are used in many fields, from pharmaceutical to translation, from art generation to autonomous driving.

Let us introduce a simple example to support the following explanations. We might want to classify many images of cats and dogs using a NN so that its inputs are images of cats or dogs, and the output is a binary variable indicating 0 if the image is a cat and 1 if it is a dog.

To understand NNs, we have to look at their smallest components called *neurons*, which are functions that can be defined as follows:

$$y = g(X \cdot W + b) \tag{2.1}$$

where g is called the activation function, $X \in \mathbb{R}^n$ is the neuron's input, $y \in \mathbb{R}$ is the output, $W \in \mathbb{R}^n$ its weights or parameters, and $b \in \mathbb{R}$ its bias. Note that activation functions must be non-linear functions. We would like to use NNs to solve and predict non-linear problems such as our example, a task that can only be achieved by using non-linear functions. If we were to compose a neural network using only linear functions, the output would still be a linear function, regardless of a NN's complexity. Examples of non-linear functions commonly used inside NNs are the sigmoid and the rectified linear unit (ReLU). The weights W and the bias b define the result of the activation function g.

The first and most simple type of NN that was devised is called *feed-forward neural network* (FF) and is comprised of many neurons stacked together in *layers*. These layers f are then composed together to form a feed-forward NN:

$$Y = f_1 \circ f2 \circ \ldots \circ f_L \tag{2.2}$$

where L is called the *depth* of a FF neural network. The depth, as well as the types of layers and functions of a given neural network, define its *architecture*. A NN architecture can be changed to obtain different results in terms of effectiveness, speed or other criteria.

At this point, the model has fixed parameters W and b, so given the same input, the output will be the same. We would like to update the parameters in such a way that the output reflects some arbitrary characteristic of the input, a process called *training*.

2.1.1 Training

Using our example, the NN should learn over time and using many examples, which images represent a cat, and which ones represent a dog. We can provide information to the neural network about whether or not it is right or wrong, and update its parameters according to how much it is far from the truth.

Formally, the function determining how much a NN is wrong about a guess is called a *loss function*, which outputs a value called *loss*. For a binary value such as our example, we can use the *binary cross entropy* loss function. The lower this value is, the closest the NN is to the ground truth.

We can derive certain properties from this value, such as how much should we change the parameters of our NN model so that we get a lower value the next time we try. This approach can be formally described as an optimization problem, where the optimization function is defined as follows:

$$\arg\min_{W,b} \mathcal{L}(W, b) \tag{2.3}$$

This function is called optimization functions or *optimizers*, which define how the values of W and b should change to get a better loss, a process called *training*. Commonly used optimizers for NN training are *Stochastic Gradient Descent*, *Root Mean Square* (RMSProp), *Adam* and others.

The values obtained using these optimization functions are used to determine the best next local optima for the given parameters. This process can then be repeated multiple times until an arbitrary loss value is reached, and the training process is stopped. The final architecture of the neural network and the state of the weights and biases are then fixed, obtaining the final NN model.

At several stages during training, a neural network practitioner might want to validate the results obtained by using a set of data that is different from the one that has been used to train the NN. This is called the *validation step*, and it is performed without changing the network's parameters or architecture. Validation steps are crucial to understanding if the changes made to a model are biased towards a specific set of inputs, an effect denominated *underfitting*.

2.2 Distributed Computing and Storage for Neural Networks

2.3 Distributed Training

2.4 Hivemind

2.4.1 Bottleneck Analysis

2.4.2 Metrics

3 Related Work

4 Setup

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