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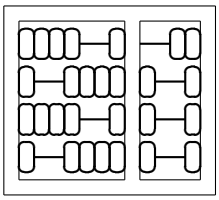

Efficient Memory Management in Data Parallel Computing: A Chunk Optimization Technique

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Abstract: Lorem ipsum dolor

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1 Introduction

Memory management is a crucial aspect of modern computer applications. Some problems, such as seismic processing, are particularly sensitive to the amount of available memory. Due to the large size of seismic data, even the most powerful supercomputers can not store the whole dataset on the memory while processing it, hence, this kind of data is usually partitioned and processed in chunks.

For some algorithms, choosing the right data partitioning strategy is quite straightforward, since some frameworks, like Dask [1], provides automatic chunking. On the other hand, the optimal strategy is not so obvious for others, usually because they require a large amount of work memory. For such algorithms, the amount of used memory is not limited by the size of the input data, since they may require additional memory to store intermediate results. The latter is true for some seismic processing algorithms, therefore the data partitioning strategy is usually defined after a series of trials and errors.

In this research proposal, I suggest the creation of an efficient data partitioning strategy for data parallelism. The proposed strategy is based on the memory footprint of the algorithm, which is the amount of memory required to execute it. This approach may be effective not only for seismic algorithms, but also for any other algorithm that has a predictable memory usage.

The proposal is based on discovering the relationship of the input data shape and the memory footprint of the algorithm. By discovering this relationship, we can define the optimal chunk size for the amount of available memory on the worker. This tool can be used by frameworks like Dask [1] to enhance their automatic chunking strategy, leading to a more efficient data partitioning.

During this research, I am planning to work with *DASF is an Accelerated and Scalable Framework* (DASF) [2] to implement the proposed strategy. DASF [2] is a library based on Dask [1] and created by the Discovery laboratory at *Universidade Estadual de Campinas* (UNICAMP) to simplify the development of seismic processing algorithms.

The following sections are organized as follows. I start by presenting the background on section 2, explaining relevant concepts for this research. Then, I present the related work on section 3, where I discuss the existing research on memory usage estimation. Finally, I present the research proposal on section 4, where I describe the research plan and the expected results.

2 Background

Sit lorem dolor

3 Related Work

(EB: Daniel, quando uma seção tem diversas subseções, sempre que possível, é bom colocar uma pequena introdução à seção. Talvez algo com: In this section we first discuss the existing research on resource-aware scheduling (Section 3.1), then we discuss ..., finally, we present a comparison table that summarizes our main findings.)

3.1 Resource-aware scheduling

Pupykina et al. [3] presets a nice(EB:por que ele é nice? :-)) overview of the memory management field until 2019. According to the authors, the main challenge on predicting memory usage is the lack of knowledge of the memory access patterns within an application. Most of current research focus on using machine learning techniques to bypass this problem. Although this approach has been successful, it is only capable of predicting the overall resource usage of a whole workload, and not the resource usage of a single task.

The observation made by Pupykina et al.(EB:*et al.* é uma expressão em Latin - como o texto está em inglês, esta é uma expressão em lingua extrangeira, portanto, deveria ser destacada. Eu costumo destacar palavras extrangeiras com a macro "emph") [3] is visible while evaluating recent work. Most of the research done so far focus only on the scheduler perspective, using memory usage history to predict the expected resource requirements of a given cluster.

E. R. Rodrigues et al. [4] presents a machine learning model that can easily be integrated into a scheduler to predict the resource requirements of a given task (EB: when executing on a cluster?). Their work is mainly focused on the scheduler perspective, since it uses past executions by the user to predict the resource requirements for future jobs. While submiting a new job to the cluster, the user must provide a manual estimate. This estimate is used by E. R. Rodrigues et al. [4] alongside with past executions to predict the actual resource requirements of the job. Although effective, this approach is vulnerable to spurious correlations, since past executions from other jobs by the same user can influence the prediction.

T. Mehmood et al. [5] presents an ensemble machine learning model that can predict the expected resource usage of a (EB: of a task? job? application? running on the cloud provider?) cloud

provider. Like E. R. Rodrigues et al. [4], T. Mehmood et al. [5] uses past executions to predict the resource requirements at a given time.

3.2 Resource-aware execution

(EB: Daniel, todos estes trabalhos preveem consumo de memória? Se for o caso, basta mencionar no texto, caso contrário, talvez seja bom adicionar uma coluna que indique o que está sendo predito)

Table 1: Related work comparison table

Work	**Used features**	**Prerequisites**	**Purpose**	**Perspective**
[4]	Memory usage history, user data, and job data	Past executions	Scheduler resource allocation	Scheduler
[5]	Memory usage history and job data	Past executions	Scheduler resource allocation	Scheduler
[6]	Memory usage history and input structure	Past executions	Scheduler resource allocation	Scheduler
[7]	Resources being used and user-provided information	Trial and error	Scheduler resource allocation	Scheduler
[8]	Resources being used and memory pressure	Resource competition	Scheduler resource allocation	Scheduler
[9]	Memory usage estimate	None	Resource-aware scheduling	Scheduler
[10]	Memory usage history, input structure, and run command flags	Past executions and code instrumentation	Recurrent task scheduling	Scheduler
[11]	Input data and hardware characteristics	None	Predict resource consumption	Algorithm
[12]	Memory usage history and executed query	Query logs	Query resource usage estimate	Algorithm
This work	Input data shape	None	Parallelism optimization	Algorithm

4 Research proposal

In this research proposal, I aim to explore how to predict the memory footprint of a single algorithm. As seen in section 3, while there have been numerous studies on historical analysis of memory usage to predict resource requirements, they are most from the scheduler perspective. There is a significant gap in research when it comes to predicting memory usage of a single algorithm, specially focusing on data parallelism optimization.

4.1 Problem statement

The Discovery [1] laboratory, located at UNICAMP [2], is working on a seismic analysis project with Petrobras [3]. This project aims at developing a framework called DASF [2], which facilitates the execution of machine learning algorithms and seismic attribute operators on computing clusters. However, the input of the graphs created for seismic analysis are massive datasets that can contain terabytes of data. Even supercomputers do not have enough memory to handle the computation on a single node. Therefore, usually the execution is distributed by using data parallelism.

To facilitate this process, DASF [2] has a parameter called "block size". With the value of that parameter, DASF [2] uses Dask's [1] automatic chunking feature to split the dataset into chunks. However, setting this parameter can be challenging because it required finding the optimal relationship between it and the network overhead caused by it.

To illustrate this challenge, I present image 1 which contains three computing graphs receiving input data from a seismic dataset. The first graph illustrates the situation in which the input data is processed as a whole, which requires a significant amount of memory to store the data during the execution. The second graph divides the data into thousands of small parts, reducing the memory requirements but adding network and scheduler overhead. The third graph divides the data into a smaller number of parts, minimizing both network and memory requirements.

While executing the graph, the developer must manually set the block size parameter. Setting a large number may lead to memory issues and cause significant delays due the trial-and-error nature of the execution flow. Since Petrobras uses supercomputers to execute those graphs, this delay is even larger considering the time it takes to submit a job due to the queue waiting time.

On the other hand, setting a small number may increase the execution time due to network and scheduler overhead. Since Petrobras have a large number of graphs to execute, and each graph usually takes a long time to execute, I need to find a way to optimize the block size parameter.

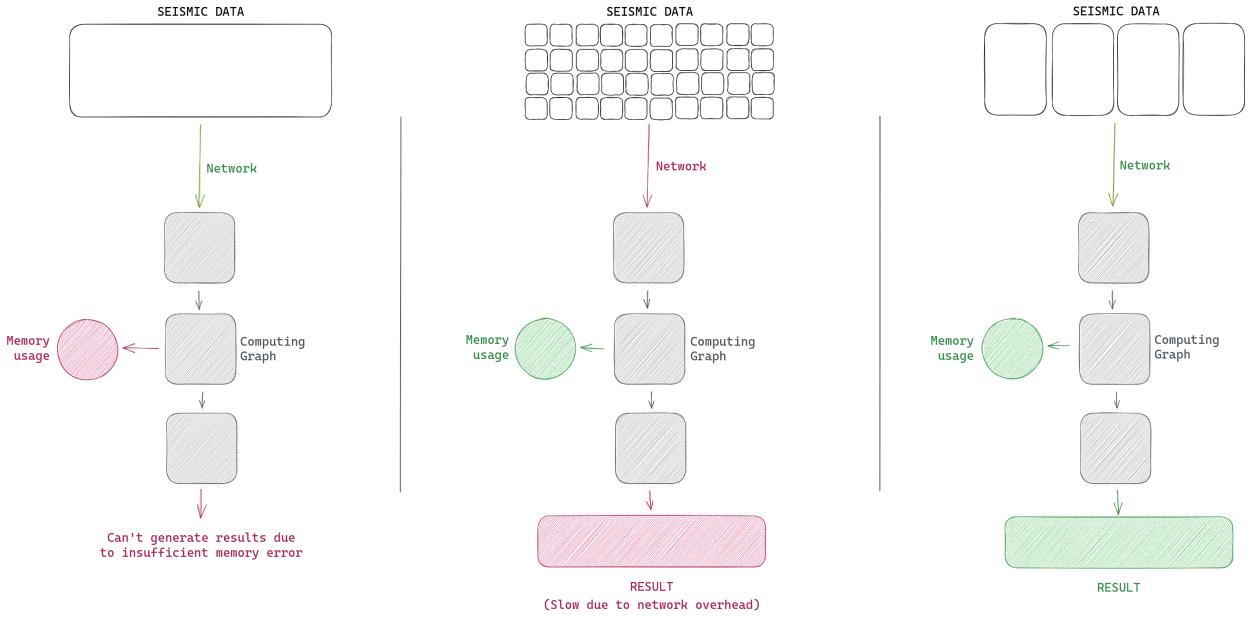
Dask [1] provides an automatic chunking feature, but it relies on the chunk size parameter, which is a static parameter defined prior to execution. Figuring out that parameter for algorithms that does not require a large working memory is easy, since the developer can set that to a percentage of the available memory. But, some of the seismic operators used by Petrobras generates a large working memory during the graph execution, which makes it difficult to determine the ideal chunk

[1] `https://discovery.ic.unicamp.br/`

[2] `https://ic.unicamp.br/`

[3] `https://petrobras.com.br/`

Figure 1: Block size impact on memory and network usage



size.

Based on this assumption, if someone predicts the memory usage of the graph that person can use Dask's [1] auto chunking feature to automatically split the data into the ideal number of chunks. Since DASF [2] uses Dask [1] under the hood, the block size parameter on DASF [2] is equivalent to the chunk size parameter on Dask [1]. Therefore, this research aims to develop a way to understand the memory-footprint of a graph to simplify the decision of the ideal chunk size.

As a practical usage, I aim to create a DASF [2] plugin that can automatically set the optimal block size parameter during execution based on a machine learning model that can predict the memory-footprint of the algorithm. This will help Petrobras to optimize resource utilization and minimize waiting and execution time. The model will provide a comprehensive understanding of memory usage patterns for different block sizes and contribute to the development of a more efficient data partitioning strategy to execute a graph in large-scale clusters.

4.2 Proposed solution

Most seismic operators are tensorial algorithms. Due to this fact, we can assume that the memory footprint of an algorithm is proportional to the shape of the input data. Based on this, to predict the memory-footprint of an algorithm I plan to create a machine learning model that would predict the memory usage of an algorithm based on the input data.

The proposed solution can be executed in two different ways:

1. **Algorithm-specific model:** train a model for each algorithm, considering its input parameters, shape, and size as the primary features for the prediction.
2. **Generic algorithm model:** train a model that is algorithm-agnostic, considering the source code as also a feature for the prediction.

Although creating a generic algorithm model is more flexible, I plan to start by coding an algorithm-specific model to understand the problem better. While coding the model, I expect to find input features that are relevant to he prediction. My initial hypothesis is that the input data's shape and size are the most relevant features, but I will experiment with other features to improve the prediction too.

Depending on the results of the initial experiments to create an algorithm-specific model, I may pursue the generic algorithm model. This secondary goal is to develop a model that is algorithm-agnostic. I understand that the source code of the algorithm contains relevant information, such as how the code author deals with memory management. However, I do not have a clear picture of the features that I could extract from the source code, but I believe that this is a possible experiment for this phase of the research.

4.2.1 Practical usage

To explore the practical usage of the proposed solution, I plan to automate the data partitioning process on DASF [2]. The goal is to create a plugin that can automatically set the optimal block size parameter during execution based on a machine learning model that can predict the memory-footprint of the algorithm. The plugin would be executed before the algorithm starts, and it would set the block size parameter based on the prediction of the model.

4.3 Potential risks and limitations

In this section, I will discuss the limitations of the proposed solution for both predicting memory consumption, as well as automatically partitioning the data.

4.3.1 Memory usage variance based on the input data

A possible limitation for this solution is that it may not work if the algorithm structure contains control statements that drastically change the memory usage of the algorithm. For example, if the

algorithm's memory usage varies depending on the data itself, then the proposed solution may not work.

It is important to mention that this limitation only happens if the control statement affects the memory allocation directly. Even if the algorithm has many control statements that change the execution flow drastically, this limitation can be ignored if the memory allocation of the algorithm happens before those.

Either way, all the seismic operators and machine learning models being used are tensorial algorithms, which means that their execution flow would not vary based on the input data. Therefore, I do not expect this possible limitation to be a problem during the research.

4.3.2 Unpredictable bottlenecks

There are two possible memory bottlenecks in the proposed solution: *Central Processing Unit* (CPU) and *Graphics Processing Unit* (GPU) memory consumption. Seismic operators are likely to be GPU-memory bounded, but I need to conduct experiments to verify this.

If the algorithms can be both GPU memory and CPU memory bounded, then the proposed solution must be able to handle both scenarios.

4.3.3 Language-agnosticity

The proposed solution is currently focused on using Python since it is the language used for the seismic operators and Dask [1] itself.

Although Python is a popular language in the scientific community, it may not be the language of choice for all researchers. This solution may not be language-agnostic at the moment. However, in the future, I can improve the solution to accept algorithms from any language.

In the case of the algorithm-specific model, I can improve the training structure to accept algorithms from any language. This can be done by allowing decoupling both the feature extraction, as well as the execution of the algorithm, from the training process.

In the case of the generic algorithm model, it is possible improve the feature-extraction part to allow more languages as well. Since the only difference between the two strategies is allowing to exract features from the source code, a specialized feature extractor per-language should be enough.

4.3.4 DASK's memory management

Since DASF [2] uses Dask [1] under the hood, I need to understand how Dask [1] manages memory. As far as my initial research went, Dask [1] has an automatic chunking feature that deals with executing the proper data partitioning as long as the developer can define the maximum chunk size in bytes.

This feature seems promising, and it may solve most of the challenges related to automatic data partitioning. But, I may need to conduct proper experiments to understand exactly how this feature works and what are its limitations. Depending on the results of such experiments, I may need to adapt the proposed solution to work with Dask's [1] memory management.

4.4 Problems to be addressed

In this section, I will outline the potential problems that I may encounter during our research and how I plan to address them. Each problem is going to be presented as a subsection, with a brief description of the problem and how I plan to address it.

4.4.1 How to measure memory usage

One of the primary challenges in our research is accurately measuring memory usage. This is particularly true for GPU memory, which may differ from CPU memory. I aim to explore different options to measure memory usage accurately.

I plan to start by investigating if there is an API to measure GPU memory consumption, and if not, I will explore common libraries that allow gathering memory consumption based on a specific process. I understand that the optimal approach would be to use a specific API for this, since this would allow more flexibility for our tool, but I will explore alternative options if necessary.

4.4.2 Historical data requirements

Many of the current approaches require a significant amount of historical data to train the models. This is not feasible for our research, as it would be time-consuming to generate such data for algorithm-specific models. I aim to overcome this limitation by creating a proper discovery approach by merging reinforcement learning with Bayesian analysis.

I plan to gather the minimal amount of data, even by executing the algorithm locally with a small amount of synthetic data, and then cover the exploration space for the input data for shapes

and data with features the model have never seen before. With this approach, I think the model will be able to learn while it is being used, and it will be able to generalize to new data.

4.4.3 Python's garbage collection

Python's garbage collector can pose a problem for us. Python uses reference-counting as its garbage collection strategy, and it is lazy, so it usually waits for the memory to be needed to collect the garbage and free memory space. If our operators are CPU memory bounded, I may need to figure out how to deal with Python's garbage collector to gather the real memory usage when collecting memory consumption information to train the ML models. However, I will only need to address this issue depending on the results of our experiments.

4.4.4 Graph execution

Another problem I may encounter is how to figure out the entire graph's memory requirements. While our proposed solution can help us find the amount of memory required for a specific algorithm, integrating multiple algorithms into a graph poses a challenge. I plan to address this issue by predicting not only the memory usage, but also the output shape of the algorithm and its features. By having prior knowledge of the algorithms in the graph, I can compose a graph with the models using the output of the first model as the input data of the second one.

4.5 Research questions and methodology

In this section, I present the research questions I aim to answer in this study and I will describe the methodology I will follow to answer those questions. Each research questions is going be answered by a set of experiments. To organize the execution of the experiments, I will divide the questions into different categories, including: (i) feasibility, (ii) accuracy, (iii) and applicability. Table 2 summarizes the research questions and their respective categories.

4.5.1 Feasibility

This experiment category aims to answer **RQ1**, **RQ2**, **RQ3**, and **RQ4**. The goal is to understand the feasibility of our seismic operators and their main characteristics. I plan to start with an experiment to explore how DASF [2] deals with automatic chunking (RQ1). Then, I will try to figure out the proper way to gather memory usage metrics from both the CPU and GPU (RQ2). After this, I aim to have an experiment that will explore if our seismic operators are GPU-memory

Table 2: Research questions

#	**Question**	**Category**
RQ1	How DASF [2] deals with automatic chunking?	Feasibility
RQ2	What is the optimal way of gathering memory-usage data?	Feasibility
RQ3	Are seismic tensorial algorithms memory bounded by the CPU or GPU?	Feasibility
RQ4	Which features do we need to extract from the input data?	Feasibility
RQ5	What is the memory-usage behavior of our algorithms?	Accuracy
RQ6	Under extreme circumstances, how is the memory usage of our algorithms?	Accuracy
RQ7	How to integrate a reinforcement learning model with Bayesian analysis?	Applicability

bounded or CPU memory bounded (RQ3). Lastly, I will explore multiple executions of our seismic operators, trying to understand possible features we can extract from the inputs, not only the shape, but also other possible features that we can extract from the data (RQ4).

4.5.2 Accuracy

This experiment cateogry aims to answer **RQ5** and **RQ6**. The goal is to understand how reliable the results can be. I will first explore the behavior of the seismic operators, exploring how they use memory in a set of different synthetic executions (RQ5). Finally, I will try pushing our algorithms to the limit to check if, under extreme circumstances (like uncommon inputs), the algorithm can break or display an unpredictable memory-usage pattern (RQ6).

4.5.3 Applicability

The third, and last, experiment category is applicability, which aims to answer RQ7. The goal is to act as a pre-prototype experiment. I aim to explore reinforcement learning models and Bayesian analysis to understand how I can apply the results from the previous experiments to predict memory usage.

4.5.4 Prototype development

After we execute all the experiments, I will implement a prototype. The idea for that prototype is to act as a plugin for DASF [2] and use it as a contribution to the active Petrobras seismic project in our laboratory. The plugin can act not only to tune the input block_size for every operator, but also as a decision heuristic for scheduling.

4.5.5 Research extension

Based on the results of all past experiments, I can focus on the second proposed solution. This part aims to explore the possibility of generalizing the developed machine learning model to be algorithm-agnostic. To implement this, I need to figure out how and which features to extract from the original source code. If this is possible, I can develop a generic model that can be used to predict memory usage for any seismic operator.

4.6 Work plan and schedule

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