A Report on the Feasibility of Using Elixir for Multiprocessing in the MMULT and TRAP Functions

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**Introduction**

For this report we will use Matrix Multiplication (MMULT) and the Trapezoidal Rule for Integration (TRAP) as benchmarks for evaluating the Elixir programming language’s multiprocessing ability. We will also be comparing the Elixir language to several C implementations of the functions, the C implementations using PThreads and OpenMP for parallelization. The goal of this report is to establish whether Elixir can be used as a suitable language for parallelization, and further establish areas where it excels over a C implementation of the same functions.

Elixir is a dynamic, functional programing language, that runs on a BEAM VM, and implements the Erlang programming language. As a functional programming language, its focus is on performing function operations in a lightweight manner. Elixir uses lightweight processes (an equivalent to threads in C) to perform various operations, allowing systems to run many processes at a single time. These processes are also fault-tolerant. For this reason, it is highly favored in web-development and used in embedded systems as well. Because of its predisposition towards multi-programming in its design, we expected Elixir to succeed very well with a parallelized Design.

**Syntax**

Elixir is a functional programming language, which means it was difficult for us to grasp at first, coming from an imperative programming background (mainly Java and C). Elixir does not use end of line statements such as semicolons, instead simply using the next line, or some pipeline operator to demonstrate that the data is meant to flow from one operation or another. Another aspect of Elixir that proved frustrating is that there are no loops, and recursion is required instead.

First let’s discuss typing and some basic Elixir types. There are the standard basic primitives: numbers, chars, Strings, and there are several other basic types: namely atoms and tuples. Atoms are pieces of data whose name is the same as its type. It is best to think of them much like a string, but more primitive. Atoms are declared with a semicolon before the variable. For example :Pittsburgh, is an atom representing Pittsburgh. Atoms are useful for control checks such as switches and if statements. Tuples are another basic Elixir type, that are made up of other sets of primitive data. Tuples form the basis for most data storage in Elixir, such as Maps and Arrays. They have a constant time lookup, but a linear modification time because saved data is inherently immutable by default in Elixir.

First, let’s look at a simple “Hello World” function:

IO.puts “Hello World”

This function will cause this statement to be written to the command line:

Hello World

:ok

This is a demonstration of Elixir’s use of tuples in returning function calls. IO.puts calls the “puts” function in the “IO” module. Most elixir functions implicitly return functions as a tuple with the expected output and a status update from the function. The :ok atom is there to show that the function was successfully completed and encountered no errors.

Other aspects of Elixir that were crucial to completing our project were Data Streams and Tasks. Streams are a way of abstracting a series of transformations on a single piece of data. An example from our code is:

hold = Stream.map([i\*1024+j], fn x -> (partial+Enum.at(inputArrayB, i\*size+j)) end)

The call to Stream.map() shows what the final product of the function is meant to be. The value [i\*1024+j] is how our code differentiated between locations in the matrix (Elixir has no nested array support, so we approximated to the best of our ability), and the other input “fn x -> (partial+Enum.at(inputArrayB, i\*size+j)) end” is the transformation to be done on the matrix. The values “fn x ->” is a means for a function to be defined in place in Elixir. Since functional programming treats functions as a basic unit, this is necessary to avoid clutter when using a file.

Elixir has a variety of tools for implementing multiprogramming. The simplest is the spawn(fn x) function, which spawns a new task that runs the given function. We chose to use a Task abstraction of the spawn function. The Task allows for creating multiple processes of program and makes inter-process communication easier for the calling process. Each Task stores the end value of the spawned process, to be called at a later time.

Task.async\_stream(1..numberProcesses, TrapIntegral, :trapezoidFun, [numberProcesses], timeout: 1000000) |> Enum.map(fn{:ok, result} -> result end) |> Enum.sum()

Here, the Task creates the number of processes that the user passes in and calls the function name “trapezoidFun” in the TrapIntegral module. It then stores the end value of the spawned process to be used afterward. The Enum.map() function enumerates the data of each process and then calls the function listed within it on each returned value. This separates the result from the atom and thus creates a single integer/float. Then all of the integer/floats are totaled from each process in the Enum.sum() function.

**Comparison**

**Elixir Data**

|  |  |
| --- | --- |
| **# of TRAP Processes** | **Time (microseconds)** |
| 1 | 2117000 |
| 5 | 1122000 |
| 10 | 978000 |
| 50 | 926000 |
| 100 | 885000 |
| 200 | 869000 |
| 500 | 907000 |
| 750 | 883000 |
| 1000 | 875000 |
| 1500 | 914000 |

|  |  |  |
| --- | --- | --- |
| **# MMULT Processes** | **Size** | **Time (seconds)** |
| 1 | 5 | 0.005 |
| 5 | 5 | 0.003 |
| 10 | 5 | 0.003 |
| 50 | 5 | 0.004 |
| 100 | 5 | 0.005 |
| 500 | 5 | 0.013 |

|  |  |  |
| --- | --- | --- |
| **# MMULT Processes** | **Size** | **Time (seconds)** |
| 1 | 50 | 155.066 |
| 5 | 50 | 69.01 |
| 10 | 50 | 60.932 |
| 50 | 50 | 50.349 |
| 100 | 50 | 131.399 |
| 500 | 50 | 166.094 |

|  |  |  |
| --- | --- | --- |
| **# MMULT Processes** | **Size** | **Time (seconds)** |
| 1 | 10 | 0.042 |
| 5 | 10 | 0.031 |
| 10 | 10 | 0.024 |
| 50 | 10 | 0.038 |
| 100 | 10 | 0.043 |
| 500 | 10 | 0.044 |

|  |  |
| --- | --- |
| Trapezoid Integral Approximation POSIX Threads | |
| **# Threads** | **Time (microseconds)** |
| 1 | 573536 |
| 5 | 151346 |
| 10 | 92293 |
| 50 | 43182 |
| 100 | 40171 |
| 200 | 39398 |
| 500 | 46039 |
| 750 | 49274 |
| 1000 | 54287 |
| 1500 | 71955 |
| Trapezoid Integral Approximation OpenMP | |
| **# Threads** | **Time (microseconds)** |
| 1 | 570197 |
| 5 | 154058 |
| 10 | 93036 |
| 50 | 51409 |
| 100 | 46209 |
| 200 | 51694 |
| 500 | 53857 |
| 750 | 60249 |
| 1000 | 69428 |
| 1500 | 87622 |

**Discussion**

As mentioned previously, one of the hurdles with Elixir was that collectively, we had little experience with functional programming, so it made implementing the solution more difficult. The other major hurdle we encountered was that Elixir has no native support for nested arrays to implement the Matrix’s data. We discussed a lot about the best way to implement the Matrix such that a) it would work with the best runtime, and b) that we could understand the implementation of it. Because of our lack of expertise with the language, that means that it could certainly be possible that our implementation is not the fastest. And as we can see from the data, speed certainly was a problem.

From the MMULT tests, we see that Elixir was extensively behind even the unparalleled C code, which we attribute to Elixir’s immutable stored data. The problem we get with Elixir is that by transforming the data, each operation becomes extremely costly as we try to write a new matrix. C allows for transformations within the array, as each modification only affect that location in the array. Elixir’s immutable data means that the entire object must be changed with each addition. This makes for extremely long runtimes with the stored data. We do see improvements from parallelization when comparing Elixir to itself, but the runtimes for the Elixir tests reach unsustainable levels at trivial problem sizes for C code.

Because we attribute the slowdown to Elixir’s data storage, that means that we haven’t truly evaluated Elixir’s parallelization. From research we know that Elixir is known for its super lightweight processes, and that it is ill-suited to handle the storage of data that undergoes frequent changes. Because of this we decided to test the TRAP Function to see if Elixir could do better than C’s PThreads or OpenMP library. Unfortunately, it did not, but it was able be competitive, staying roughly within the ballpark of the PThreads and OpenMP. This shows that Elixir can be used for successful parallelization but does not excel in this particular set of problems.

Despite the shortcomings that we have found with Elixir, it definitely has its place within the realm of parallel programming. Creating new processes is easy and communicating between processes is also simple. Elixir provides a number of tools in the base language to make concurrent programming simple and easy to understand to the implementor. It is less simple than OpenMP and does require the implementor to understand the basics of parallel programming, but that also means that you can do more with the processes that are spawned. With that in mind, we would not recommend Elixir to be taught for this class. While it definitely has its place within a technology stack, with the types of examples we are running for this class, Elixir falls woefully short.

**Conclusions**

Elixir’s major flaw as a language is its inability to be flexible with its weaknesses. Its strengths are its simplicity and lightweight processes, but its major weakness is in the immutability of its data. Some other functional languages, like Python, are able to offload extensive data operations into built in C code. While there are a number of Elixir libraries, we found to add this feature, we chose not to implement them since we felt it would defeat the purpose of the project. We don’t expect that Elixir will change to better support mutable data storage, but we personally found that to be our greatest disappointment with Elixir.