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| Diploma Thesis  **DYNAMIC PROGRAMMING:**  **AN EXPERIMENTAL ANALYSIS AND COMPARISON OF THE**  **TOP-DOWN AND BOTTOM-UP APPROACHES**  **Nicolas Zachariou**  **UNIVERSITY OF CYPRUS**    **DEPARTMENT OF COMPUTER SCIENCE**  **January 2021** |

**UNIVERSITY OF CYPRUS**

**DEPARTMENT OF COMPUTER SCIENCE**

**DYNAMIC PROGRAMMING:**

**AN EXPERIMENTAL ANALYSIS AND COMPARISON OF THE**

**TOP-DOWN AND BOTTOM-UP APPROACHES**

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**Summary**

Curiosity is key in evolution; may that be as a species or personal growth. But how good would curiosity be if one couldn’t answer any of his questions? Us, humans generally love knowing the answers to everything, and we continuously develop tools that help us answer our questions and finding the best solutions.

Dynamic Programming is an Algorithmic Approach that builds optimal solutions to problems by dynamically dividing a problem into smaller parts, and then combining these smaller so called “sub-problems” to find the optimal solution for bigger and bigger parts.

In this study, we investigate in depth the two basic implementation approaches of dynamic programming: bottom up and top down. The first is iterative and the second is recursive, which uses memoisation so that no subproblem is computed more than once. By implementing dynamic programming solutions of basic problems using both approaches, we aim in analysing their performance with respect to execution time, resource usage and ease of use (development time). The goal is to classify or rather, group dynamic programming solutions based on their performance and if possible, to find a trend or even discover a rule of thumb, that may be able to provide an insight, as to which implementation approach is more efficient for each problem.

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2. Introduction

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* 1. What is Dynamic Programming?

Dynamic Programming [1] is an algorithmic approach that helps solve problems with an optimal description quickly and efficiently. For an algorithm to be considered as a Dynamic Programming algorithm, it must fulfil two requirements. Firstly, it must have an explicit recursive description and / or it must be described by an optimal function. Additionally, it must store the value of each of its calculated sub-problems and use this information to solve others of its sub-problems.

A sub-problem is a problem described by the same function as the original problem that is (or may have) derived from the original problem. This is the essence of dynamic programming. When the problem is presented, smaller sub-problems can be derived from its optimal function, these sub-problems can also be divided in the same manner. By storing the values of each and every one of these sub-problems we can ensure that each sub-problem will be calculated once at most, preventing excess calculations.

This technique is very useful when dealing with recursive functions, however it can also be used to calculate optimal solutions quickly in an iterative manner. This is where the two implementations make their entrance.

* 1. Approaches to Dynamic Programming

The two implementation approaches of Dynamic Programming are the **Iterative** (also known as **Bottom-Up**) and the **Recursive** (also known as **Top-down**) approaches.

When dealing with recursive descriptions, we can use then to divide a problem into smaller sub-problems, with each sub-problem being an optimal solution to a part of the original problem. Using this knowledge, we can compute the value of each required sub-problem only once and find the solution to the original problem without unneeded computations. This approach is generally thought to have the worst performance of the two because of its recursive nature [4].

The other approach involves an iterative method. We start from smaller sub-problems that can easily be computed to find the optimal solution for bigger sub-problems. We continue this process for all possible sub-problems, and with every iteration we move into bigger and more complex sub-problems. This continues until all of the sub-problems have been calculated, and thus the final answer is found.

In both cases we use a table to store the states of any computed sub-problems and we use this table to retrieve any information that has already been calculated thus speeding up the process.

The iterative technique is also known as **tabulation**, as we ‘build’ or ‘fill’ an array / a table in a bottom – up manner. This is because we start from small, easy problems and we build into bigger ones. The Recursive technique is also known as **memoization** (or **memoisation**). This technique is what speeds up the recursion since it prevents the program from calculating a sub-problem more than once from different recursion branches (by storing already computed subproblems in a table).

Implementing a recursive problem is generally a fast process. On the other hand, the recursive approach is generally thought of as the slower one regarding execution times and memory usage, since its recursive nature slows it down and makes use of multiple stacks. *However, is this always the case?*

We failed to find in the literature any experimental study demonstrating that the iterative approach is more efficient in practice.

* 1. Objective of the study

The objective of this work is to study a variety of dynamic algorithms implemented with both approaches in order to find possible patterns, reach some conclusions and classify these algorithms in terms of their performance, both regarding execution time, memory usage and general efficiency. What affects an implementations performance is its input complexity, and the form of its input data. Another factor is the complexity of the solution. This study attempts to provide evidence that in practice, depending on the problem, the iterative approach is not always the best option.

* 1. Methodology

To make sure we had a better understanding of Dynamic Programming we made sure to study old courses to remind ourselves about the techniques used in Dynamic Programming [5]. We experimented with some problems to make sure we had a strong grip of the concept. Then we begun exploring new data structures, and ways that could increase the efficiency of either implementation. We later investigated different resource measuring tools to help us record the usage of resources like CPU utilization [9], memory usage [7] and execution time [10]. We began testing on data collection by developing scripts that would automate the process. After this we were ready to start implementing problems. We will view more details about the tools we use and the process behind the data collection in Chapter 2.

Then we will explore all problems individually. We will investigate problems concerning sequences, problems on tables, graphs and trees. We will view more information about each problem in their respective Chapter. Each chapter will include a description of the problem, its use and an explanation of the Dynamic Programming solution. We will define a set of variables which we will later be used to give a function description of the problem and all sub-problems. Later we will work on the two Dynamic Programming implementations (Bottom-Up and Top-Down) and we will discuss the results of each implementation in order to arrive to some conclusions.

We will finish by giving a conclusion to the whole paper with our final thoughts and general conclusions, expanding on the problems we faced while developing this project and possible future work.

* 1. Document Structure

In **Chapter 2** we will discuss the background research and the discoveries that lead us to record data usage as we do. We will also discuss about the tools we use, how we use them and what their use may imply regarding the data we collect.

In **Chapter 3** we explore the Most Common Sub-Sequence problem which concerns the longest common sequence contained in two other sequences. More detail will be given on the Chapter.

In **Chapter 4** we continue with another problem on sequences. That is the Longest Increasing Sub Sequence problem which we will solve in two ways. For the first solution we use a 1-Dimension array and a 2-Dimension array for the other solution.

In **Chapter 5** we implement the Chain Matrix Multiplication problem, which is the problem of finding the best order in which matrix multiplications should be done. Matrix multiplications have a cost. We aim to find the order in which the cost of multiplying a set of matrices is the smallest possible.

In **Chapter 6** we view the 0-1 Knapsack problem, which is a standard problem of Dynamic Programming. In a few words, it is the problem of finding the best combination of items to maximize the total value of a sack that can contain a certain weight.

In **Chapter 7** we explore the Dijkstra’s Shortest Path problem. It is a very useful problem on Graphs, which finds the shortest possible path between two given nodes.

In **Chapter 8** we move to problems on trees. The first problem we view is the Independent Sets problem which requires a set of nodes and returns its biggest independent set.

In **Chapter 9** we continue with problems on trees. The problem we discuss on this chapter is the problem of K-Trees, which is the problem of finding the amount of sub-tress in a given Tree of size K.

In **Chapter 10** we investigate the last problem which is the problem of the Tree Diameter. We find the diameter of the tree which is the maximum distance between any two nodes in a tree.

In **Chapter 11** we give our last thoughts and last conclusions after giving a small recap of all previous chapters. In this final chapter we also expand on the problems we faced during the development of this project and some possible future work based on our experience.

1. Background

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* 1. Preliminary Research

An introduction to Dynamic Programming can be had from the courses of University of Cyprus that study algorithms [5]. To understand the behaviour of each implementation we followed execution examples as well as pseudo code. We experimented with our own implementations and tried to follow through the implementations to better understand how each approach works.

* 1. Experimenting with other Data Structures

Before beginning with problem implementations and data collection we have experimented with different types of data structures. We questioned whether there was another data structure that allowed for better efficiency than the 2D array. We used lists, hash maps and even trees. But we realised that the selection complexity of the array was its biggest strength, something that could not be rivalled by any other structure. We also noticed that the pointer used to implement a linked list or any other structure that uses a “node” like a tree, made it very inefficient in storing data. To be more precise, lets calculate the required amount of memory in Bytes to store a single number (Integer). In a 64Bit computer, an integer most likely uses 4 Bytes to be stored. However, any pointer uses 8 (thus, 64Bits). Therefore, to store a single integer in a data structure with a “node” we would need 8+4 Bytes = 12 Bytes, which is 3 times more memory. Concluding to the following: For any “node” based data structure to be more efficient than an array, more than 1/3 of the array must be unused. Therefore, the number of unique branches a recursion must make should be less than 1/3 of N (if we assume than an iterative approach uses an NxN array).

* 1. Measuring Execution Time

After exploring other data structures and concluding to the table as the best option, I began researching ways to measure memory usage and execution time. I realised that some Dynamic Programming problems require some pre-processing, others require some data conversions. I concluded that I could not use any external process to capture the execution time because by doing that i would also measure the input generation or input reading as part of the execution. However, if any type of data conversion is required for either of the approaches to work, that would be measured since it is part of the calculation. The execution time between two identical runs may not be as consistent, to remove the effect of outliers in our data we will be taking the data of 12 runs for each execution. We will then remove the lowest and highest values before taking the average of the 10 remaining runs.

* 1. Memory Measurement

To measure the memory usage, we seeked the help of external tools. We used the **Valgrind** memory checking tool [7] available for Linux distributions. We realised that this tool allowed for a thorough inspection of all memory allocation calls by the system, giving a very precise answer as to how much **Heap** a program uses, as well as the **Extra Heap** allocated. This tool however does not measure the **Stack** usage of a program. To measure the Stack, we use a plugin of the Valgrind tool called **Massif** [8]. This tool however has a downfall which was not discovered at first. To closely inspect the stack usage of a program each allocation or call to the stack that occurs is measured, therefore each call requires even more memory, this means that recursive programs that usually require plenty of stack were not measured since the demand of the stack was bigger than the available system memory.

To get through this problem we began studying other memory measuring tools and methods. We realised that the system monitoring tool was our best bet. To capture the memory usage of a program, we start the program in a new process to capture its Process ID (PID). Then we inspect the memory usage of that process using the “**top**” tool [9] available for Linux. We capture the memory usage % in intervals of 0.1 seconds, and store it in a temporary file, later finding the maximum amount of memory usage from that file. If possible we use both the Valgrind and Top tools for the same problem comparing the results, and we found out that both techniques yielded very similar results. Because the memory measurements are very consistent and run very slowly we will be taking the average of 3 runs for every execution.

It should be noted that the Valgrind tool [7] retrieves the memory usage of a program in snapshots. Therefore, in rare cases the memory usage may seem inconsistent, this is why the memory usage was recorded as an average of 3 runs. On the contrary, the stack usage is inspected more carefully, this is also why it requires much more memory to be measured and is also much slower.

* 1. System Used

The System we will use to run the implementations and take our measurements has an AMD Ryzen 7 processor, namely the R7 4700U mobile APU. The total system memory is 16GB of ram.

The Operating System used during development was Ubuntu 20.04LTS. All programs were developed in C++ (C std 11) in visual studio code. We believe that C++ is the optimal language to allow for precise memory management and avoid unnecessary performance overheads, hence it allows for a more precise comparison between the two approaches, both regarding memory usage and execution time. To make sure we test our implementations to the limits allowed by our system we would choose the input sizes of our problems so that the biggest sizes would max out the memory usage where possible.

* 1. CPU Utilization Measurements

The CPU utilization was closely monitored via Ubuntu built in tools. The Ubuntu system monitor tool provided a general resource usage image while the “top” program and the resource monitoring tool was used to monitor CPU utilization specifically. We found that our implementations did not use any sort of multithreading optimizations and the CPU utilization ranged at the maximum of 12% (100% single core utilization, 12% of 8 cores). Therefore, no multithreading advantages were given to any of our implementations.

1. Most Common Sub Sequence

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* 1. Problem Description and Dynamic Programming Solution

The Most Common Sub-Sequence problem [1] regards two letter sequences *A* and *B* and seeks the biggest common sub-sequence of letters found in both *A* and *B* (not necessarily consecutive). A variation of this problem is used by biologists with strands of DNA to better understand it. All letters of the MCSS must be included in both Sequences.

For example, the MCSS of the sequence “**APPLES**” and “**PINEAPPLE**” has a length of 5. This example is shown in the following tables: Table 1 and Table 2.

****Definitions****

* Sequence *A*, *B*
* Alphabet size *S*
* *A(i)* is the *i-th* character of *A*
* *B(j)* is the *j-th* character of *B*
* *length(A) = N*, *length(B) = M*
* Array of *(N+1)x(M+1)*

****Sub-Problem****

is the most optimal solution for the first *i-th* letters of sequence *A* and *j-th* letters of sequence *B*. Since is the most optimal solution we can assume that:

* ***if******then***
* ***else***

Therefore. we derive the following recursive equation:

* *(end case)*

****Bottom-Up Approach (Iterative)****

We iterate through array elements 1-by-1 and calculate the value of the MCSS for every point of the sequences. An extra column and row are used to represent the end case. This approach calculates every possible combination of *i* and *j* (*N+1 x M+1* combinations).



****Example****

Following (**Table 1**) is the result of the iterative implementation for the given example.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Sequences |  | A | P | P | L | E | S |
|  | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| P | 0 | 0 | 1 | 1 | 1 | 1 | 1 |
| I | 0 | 0 | 1 | 1 | 1 | 1 | 1 |
| N | 0 | 0 | 1 | 1 | 1 | 1 | 1 |
| E | 0 | 0 | 1 | 1 | 1 | 2 | 2 |
| A | 0 | 1 | 1 | 1 | 1 | 2 | 2 |
| P | 0 | 1 | 2 | 2 | 2 | 2 | 2 |
| P | 0 | 1 | 2 | 3 | 3 | 3 | 3 |
| L | 0 | 1 | 2 | 3 | 4 | 4 | 4 |
| E | 0 | 1 | 2 | 3 | 4 | 5 | 5 |

Table

****Top-Down Approach (Recursive)****

Starting from the end of each sequence try to reverse engineer the MCSS by creating solution paths. Every time the corresponding letters of sequence *A* or *B* are matching, 1 possible solution path is created but when the letters differ 2 possible solution paths are created. There is an extra column and row to represent the end case. The array is initialized with -1 for the sake of **Memoization**. Recursion stops at the end cases, or when a value that is not ‘-1’ is reached. Which means the sub-problem has already been solved by another recursion instance.



****Example****

Following (**Table 2**) is the result of the recursive implementation for the given example

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Sequence |  | A | P | P | L | E | S |
|  | -1 | -1 | -1 | -1 | -1 | -1 | -1 |
| P | -1 | 0 | 1 | 1 | 1 | 1 | 1 |
| I | -1 | 0 | 1 | 1 | 1 | 1 | 1 |
| N | -1 | 0 | 1 | 1 | 1 | 1 | 1 |
| E | -1 | 0 | 1 | 1 | 1 | 2 | 2 |
| A | -1 | 1 | 1 | 1 | 1 | 2 | 2 |
| P | -1 | -1 | 2 | 2 | 2 | 2 | 2 |
| P | -1 | -1 | -1 | 3 | 3 | 3 | 3 |
| L | -1 | -1 | -1 | -1 | 4 | 4 | 4 |
| E | -1 | -1 | -1 | -1 | -1 | 5 | 5 |

Table

* 1. Experimental Comparison

Scenarios and Preparation

To evaluate the performance of the two implementations we will measure their execution time, and their memory usage with sequences of different lengths. The sequences will be randomly generated via a random sequence generator using the alphabet size variable *S.* A sequence can have up to *S* different characters.

We will take measurements of different sequence lengths *N* and *M*, as well as different alphabet sizes *S.*. All sequence lengths will be measured for the alphabet sizes of *1, 2, 6, 11, 16, 21, 26.* We want to observe whether the alphabet size has an impact on the performance of either implementation, and how each algorithm responds as the problem size (sequence length increases). This problem is a symmetrical problem. Therefore, by executing it with inputs *A* and *B* we can say we also executed inputs *B* and *A*. However we will be testing sequences of similar lengths (*N=M)*.

We realise that this problem has a rather slow execution, therefore to counter this we will be taking measurements of smaller problem sizes that do not push the system to its limits, since a single run of that calibre can take hours.

Results and Discussion

Figure 1 depicts the effect of the input size to the execution time of both implementations. In this example we tested with an alphabet size of 26 *(A-Z)*. Figure 2 presents the impact of the input size in total memory usage and % memory usage. These results were taken for the same alphabet size.

Figure 1

Figure 2

As one can easily observe, our results for the Most Common Sub Sequence Problem show that the execution time for the recursive approach yields much slower results while consuming more memory (Figure 1 and Figure 2). As we mentioned earlier, running the implementation for bigger problem sizes increased the execution time exponentially as our results show. Therefore, collecting data for bigger problems is not possible, however we observed that the memory usage for the recursive approach suffers in comparison to the iterative approach. On the contrary, this is not shown on our results, most likely because of the small input sizes for which we presented our data.

Even though our memory usage data shows that the two implementations have a similar performance in terms of memory consumption, the much faster execution times of the iterative approach make it the clear winner.

1. Longest Increasing Sub Sequence

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* 1. Problem Description and Dynamic Programming Solution

The problem of the Longest Increasing Sub-Sequence [1][2] is a problem that seeks the largest ascending (increasing) sub sequence from a given sequence of numbers. An increasing sub-sequence is a sequence where each of its values is followed by a greater value and is preceded by a smaller value. This problem is useful in the study of algorithms, mathematics and random matrix theory. This problem can be solved using a 2D array, however optimizations make it possible to solve it in a 1D array. We will examine both solutions.

Let’s view an example. Given the sequence *(3,10,2,1,20)* the longest increasing subsequence is *(3,10,20)* with a length of 3.

* 1. 2D Solution

****Definitions****

* Sequence *S* oflength *N*
* Cachearray *C* of size *N*
* Maximum Value *M*

****Sub-Problem****

is the most optimal solution for the *i-th* letter moving to the *j-th* letter, (letter *j* is the next number of the optimal sequence). If the value of *i* is bigger than the value of *j* then we can safely assume that *P(i,j)* is not part of the optimal subsequence, therefore we move to the next possibility *P(i,j+1).* Since *P(i,j)* is the most optimal solution we can assume that:

* ***if*** *S* ***then***
* ***otherwise***

****Bottom-Up Approach (Iterative)****



Top-Down Approach (Recursive)



* + 1. Experimental Comparison

Scenarios and Preparation

The problem requires a single number sequence. To test the performance of the approaches with different inputs we will first generate random number sequences. We use the *M* variable to determine the maximum value of the sequence, values start from 0 and the biggest possible number is equal to *M-1.*

Results and Discussion

**Figure 3** shows the impact of the input size of the problem in execution time (seconds). While **Figure 4** depicts the impact of the input size in memory usage (Gigabytes) and % total memory usage. To acquire these results, we used *M* of *1000*.

Figure

Figure

The extra consumption of the stack by the recursive implementation is minimal compared to the total heap consumption. The small discrepancies of the execution time of the two implementations is within error margin. Therefore, we can conclude that both approaches behave in a similar manner, both measurements (time and memory) seem to perform equally with either approach.

* 1. 1D Solution

This problem is a continuation of the LISS problem solved using a 2D array, however optimizations allow us to solve this problem using a 1D array as well. This means that the problem can be solved for much greater sizes while consuming much less memory. In more detail the memory usage is reduced by an exponential factor of 1 (reduction of dimensionality by 1).

Bottom-Up Approach (Iterative)



****Top-Down Approach (Recursive)****



* + 1. Experimental Comparison

Scenarios and Preparation

To compare the results we acquired by using the 2D solution with our new solution, we will use the same input parameters. These parameters are the *N* (sequence length) and *M* (amount of unique values) parameters. Similarly, to the 1D solution, our results show that the variable *M* does not affect performance.

Results and Discussion

**Figure 5** depicts the effect of the problem input size in execution time (seconds), and **Figure 6** depicts the effect it has on memory usage (Kilobytes) and % total memory usage. The variable *M* used was *1000*.

Figure

Figure

After viewing these results, we can see that this solution consumes very little memory, making it very efficient, with both approaches providing similar results. However, comparing the execution times of the two implementations we can also see that the iterative approach is pulls ahead with a slight lead.

* 1. Comparison between 1D and 2D solutions

The results of the two solutions show that the 1D solution is the clear winner in both aspects. It is very efficient when regarding the memory usage and it is even faster than the 2D solution. The iterative approach of the 1D solution provides the best results overall with a small lead in execution time over the recursive implementation.

1. Chain Matrix Multiplication

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* 1. Problem Description and Dynamic Programming Solution

Let two matrices *A* and *B* of size *NxI* and *JxM* respectively. The multiplication (dot-product) of these 2 matrices requires that *I* is equal to *J* and results in a new matrix of size NxM [1][2]. This process requires *NxIxM* operations, this is also set to be the cost of the multiplication. When multiple matrices have to be multiplied in a sequence, the order in which these matrices are multiplied has an effect in the resulting cost. The aim is to minimize this cost by choosing the optimal order in which these matrices should be multiplied.

We use a ‘step’ variable, let ‘step’ be s. We start solving *P(i, i+s)* for every *i,* increasing *s* by 1 after each iteration until the problem is solved. The idea is that since *P(i,i+s)* is known, *P(i,i+s+1)* can be calculated in *O(1*).

****Definitions****

* Set *S* of *N* Matrices *(WixHi)*
* *( S(i).w, S(i).h )* are the dimensions of the *i-th* matrix in the list, where ‘*w’* is its width and ‘*h’* is its height.
* *S* contains the matrices in order; therefore we can assume, *S(i).w = S(i+1).h* since the matrix multiplication operation requires that the width of the preceding array is equal to the height of the following array. Now assume list *L*. We can assume *L* is a list of *N+1* values, and *N(i)* is equal to *S(i).*w and *N(i)* is also equal to *S(i+1).h*.
* Maximum value of matrix width and height *M*

****Example****

Table 3 contains the result of both implementations with the given matrices and generated list L.

Matrices*: [5x10], [10x12], [12x8], [8x7], [7x11]* (5) 🡺 L: *[5,10,12,8,7,11]* (6)

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Matrix | 0 | 1 | 2 | 3 | 4 |
| 0 | 0 | 600 | 1080 | 1360 | 1745 |
| 1 | 0 | 0 | 960 | 1512 | 2282 |
| 2 | 0 | 0 | 0 | 672 | 1596 |
| 3 | 0 | 0 | 0 | 0 | 616 |

Table

****Sub-Problem****

* *P(i,j)* is the most optimal solution for matrices *i* up to *j*
* *P(i,i) = 0* is the end case.
* The actual problem is solved when *P(0,N)* is solved.

We use the step variable to calculate using a pivot, therefore:

****Bottom-Up Approach (Iterative)****



****Top-Down Approach (Recursive)****



* 1. Experimental Comparison

Scenarios and Preparation

To test the efficiency and performance of each approach we will generate a random list ‘*L’* of size *N+1* values and the specified maximum value of *M.* There can be *M* unique values within the list *L* (from *0 to M-1*). The Chain Matrix Multiplication is the problem tested with the most required computation needed since it has a complexity *of* , therefore we will take measurements of smaller problem sizes *N*. The variable *M* does not affect the performance of either implementation.

Results and Discussion

**Figure 7** depicts the impact of the problem input size in execution time (seconds) while **Figure 8** shows the memory usage in Megabytes and % total memory usage in regards to the input size. The variable *M* was set to *20*.

Figure

Figure

From these results we can view that while the memory usage is similar for both implementations, the recursive approach falls behind when it comes to execution time. The iterative approach is the much better choice. This results mimic the results we saw from the MCSS (Chapter 3) with an alphabet of size 26.

1. 0-1 Knapsack

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* 1. Problem Description and Dynamic Programming Solution

The Knapsack problem [3] is to find the selection of items within a certain weight limit *C*, with the most value. Each item has its own cost (weight) and value. This problem is very useful, it is used to capture the customer values and the discrete characteristics of loads. The objective of the model is to maximize customer values within given supply.

For the ‘0-1’ version of the problem we assume an item can either be completely inside the sack or completely out. We also assume that weights are natural numbers. The idea is that we create *C* sacks, and then we choose an item arbitrarily and attempt to place the item in these sacks to maximize the sacks value. The choice is to either place the item in the sack or not. When all items have been processed for all *C* sacks the solution will be found.

****Definitions****

* Weight limit *C* (capacity of the knapsack)
* List of items *N*, each item has its own weight *Wi* and value *Vi*
* *C* sacks with capacity *Ci*, sacks begin with capacity *0* up to *C*.
* Maximum weight *Wmax* and value *Vmax*

****Sub-Problem****

* *P(i,j)* is the most optimal value for all items up to the *i-th* item in the *j-th* sack (sack with capacity *j*).
* An item can either be placed in the *j-th* sack or not, it can only be placed if it can fit inside the sack.

Therefore, we derive the following equation:

**if** **or**  j **(end cases)**

**if**  **(item can fit in sack)**

**otherwise**

****Example****

The following table (**Table 4**) shows a randomly generated list of items that were generated with the following parameters:

*Sack capacity C: 5 Items: 8 (weight: 1-3, value: 1-30)*

|  |  |  |
| --- | --- | --- |
| Item | Weight | Value |
| 1 | 3 | 4 |
| 2 | 3 | 13 |
| 3 | 2 | 15 |
| 4 | 1 | 26 |
| 5 | 3 | 2 |
| 6 | 2 | 5 |
| 7 | 3 | 12 |
| 8 | 1 | 12 |

Table

We will view the results of both implementations later.

****Bottom-Up Approach (Iterative)****



We begin from item with index 1 and attempt to place the item in the sacks. Sack values are initialized to 0, and we strive to find the combination of items for each sack that maximizes its value.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Item \ Sack |  | 1 | 2 | 3 | 4 | 5 |
|  | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 0 | 0 | 0 | 4 | 4 | 4 |
| 2 | 0 | 0 | 0 | 13 | 13 | 13 |
| 3 | 0 | 0 | 15 | 15 | 15 | 28 |
| 4 | 0 | 26 | 26 | 41 | 41 | 41 |
| 5 | 0 | 26 | 26 | 41 | 41 | 41 |
| 6 | 0 | 26 | 26 | 41 | 41 | 46 |
| 7 | 0 | 26 | 26 | 41 | 41 | 46 |
| 8 | 0 | 26 | 26 | 41 | 53 | 53 |

Table

****Top-Down Approach (Recursive)****



|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Item \ Sack |  | 1 | 2 | 3 | 4 | 5 |
|  | -1 | -1 | -1 | -1 | -1 | -1 |
| 1 | 0 | 0 | 0 | 4 | 4 | 4 |
| 2 | 0 | 0 | 0 | 13 | 13 | 13 |
| 3 | 0 | 0 | 15 | 15 | 15 | 28 |
| 4 | 0 | 26 | 26 | 41 | 41 | 41 |
| 5 | 0 | 26 | 26 | 41 | 41 | 41 |
| 6 | -1 | 26 | 26 | -1 | 41 | 46 |
| 7 | -1 | -1 | -1 | -1 | 41 | 46 |
| 8 | -1 | -1 | -1 | -1 | -1 | 53 |

Table

* 1. Experimental Comparison

Scenarios and Preparation

To test the efficiency of each approach we will generate a random list of N items, each with weight in the range of [*1,wMax*] and value within the range of [*1,vMax*]. We want to investigate if these parameters affect the performance of either approach. We realised that the *vMax* and *wMax* variables do not affect performance. However, the Sack size *C* does.

Results and Discussion

**Figure 9** shows the effect of the problem input size in execution time (seconds) and **Figure 10** shows the memory consumption in Gigabytes and % total memory for the same input sizes. For all measurements *C* was set to be equal to of *N*.

Figure

Figure

Our results follow a similar trend to previous problems using a 2D array solution. In more detail, the memory usage seems to be very similar in both approaches while the execution is much slower in the recursive approach yielding bigger execution times. We can see that the memory usage follows an exponential growth in regards to the problem size. This growth is also present in the execution time of the recursive approach. While the growth of the iterative approach is so small in comparison that it looks to be linear (even though it is still exponential, but with a much smaller growth). This results in much faster executions as the problem size increases making it even more efficient the bigger the input size is.

1. Dijkstra’s Shortest Path

|  |  |
| --- | --- |
| * 1. Problem Description and Dynamic Programming Solution | 39 |
| * 1. Experimental Comparison | 41 |

* 1. Problem Description and Dynamic Programming Solution

Finding the shortest path (and therefore the smallest distance) between two nodes in a graph is equally useful and important. It is useful in multiple fields, from general research to AI in game development. Dijkstra’s algorithm does exactly that, given a Graph *G*, a pair of nodes, namely the starting point and the end point, it finds the shortest path between the two (2) nodes from inside the given graph. There’s a debate as to where this algorithm should be considered a Dynamic Programming algorithm or a Greedy algorithm, but for the sake of this study we will consider it a DP algorithm. Variations of this algorithm exist that may yield better results, one of these variations is the A\* (A-star) algorithm that introduces a cost variable and a heuristic variable. These variables are used to make more informed choices contrary to Dijkstra’s approach, this is why A\* is considered a greedier algorithm.

As aforementioned, Dijkstra’s algorithm finds the closest path between two nodes inside a graph, to do this it starts from the given start node and it iteratively explores all its adjacent nodes until the end node is reached. To ensure that the optimal answer (or in other words, the shortest path between the two nodes) is found, the node explored in every iteration has to be the closest node to the starting node. The algorithm can end before looping through all the nodes if the end point has been visited once because of this detail, as this detail provides the optimal answer of each state / sub-problem.

****Definitions****

* Graph *G* of *N* nodes, with density *D* and *wMax*
* Nodes *S* (‘Start node’) and node *T* (‘Finish’ / ‘End node’)
* ‘Visited’ array *V* of size *N*
* ‘Cache’ array *C* of size *N*

****Sub-Problem****

* is the shortest distance between start node S and node j.
* Recursive function for intermediate node i:
* Solution at:

Therefore:

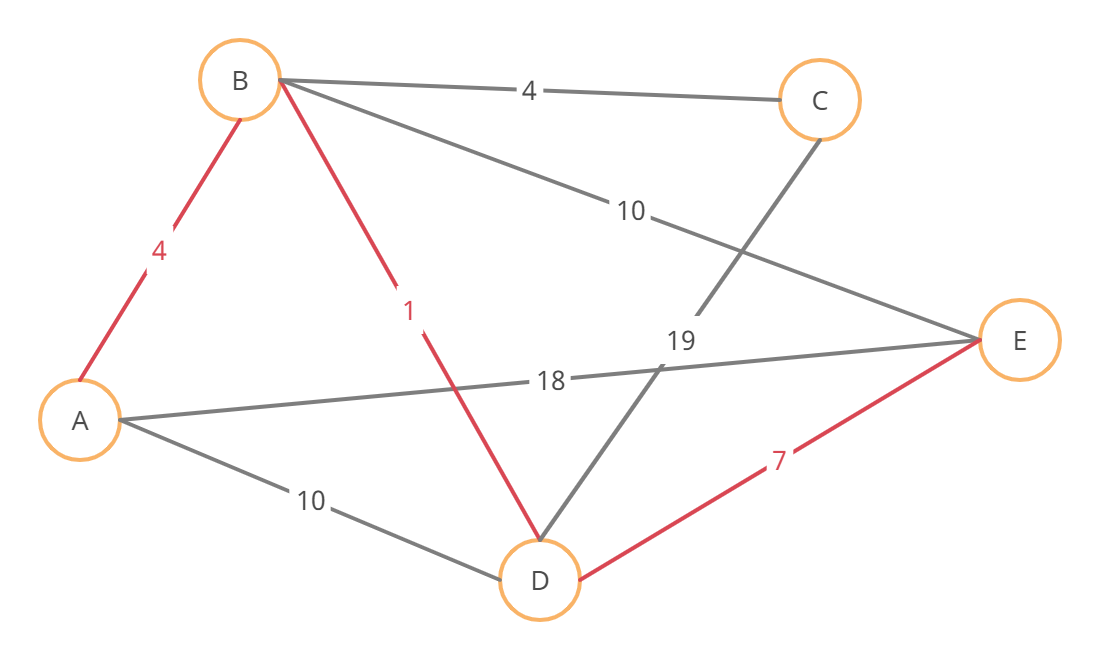


****Algorithm****



****Examples****

In the following example we present a randomly generated graph *G* (**Figure 11** & **Table 7**) of 5, and the state array (**Table 8**) that occurs from our implementation.



Figure

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Node | A | B | C | D | E |
| A | -1 | 4 | -1 | 10 | 18 |
| B | 4 | -1 | 4 | 1 | 8 |
| C | -1 | 4 | -1 | 19 | 1 |
| D | 10 | 1 | 19 | -1 | 7 |
| E | 18 | 8 | 1 | 7 | -1 |

Table

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Iteration \ Node | A | B | C | D | E |
| 0 – A | **- \ -** | **4 \ A** | **- \ -** | **10 \ A** | **18 \ A** |
| 1 – B | **- \ -** | 4 \ A | **8 \ B** | **5 \ B** | **14 \ B** |
| 2 – D | **- \ -** | 4 \ A | 8 \ B | **5 \ B** | **12 \ D** |
| 3 – C | **- \ -** | 4 \ A | 8 \ B | 5 \ B | 12 \ D |
| 4 – E | **- \ -** | 4 \ A | 8 \ B | 5 \ B | 12 \ D |

Table

* 1. Experimental Comparison

Scenarios and Preparations

Since the input of the problem is a graph, we can compare the performance of the 2 approaches with different graphs. Firstly, we create *N* nodes, then we iterate through all the nodes to connect them to each other. We use the density variable *D* to determine the maximum number of neighbours (adjacent nodes) a node can have. For each node we choose a random amount of connected nodes such *Hi,* such that , Then we connect every node to *Hi* other nodes. This way we ensure the graph is connected, and that the bigger the density, the more the average connections of the nodes. Every time we connect two nodes we generate a random weight value for their connection. During our experimentation with this problem we realised that the weight of the connections of the graph does not affect the performance of any of the approaches.

Results and Discussion

**Figure 12** and **Figure 13** show the effect of the problem input size in execution time (seconds) and memory usage in Gigabytes and % total memory, respectively. The graphs generated for this data had a density of 20 and a maximum weight size of 20 as well.

Figure

Figure

Our results show a different story to all previous problems. While the memory usage is similar in both implementations the execution time is also similar. While this may seem unreasonable at first after a deeper look in our implementation we can see why this is. Dijkstra’s optimal description requires that for every iteration the node we explore must be the one closest to the starting node. This means that for both implementations the same work is done, however we can see the iterative approach has a slight overhead, which is perhaps introduced because of the extra data structures required (pre-processing) to run a problem on graphs iteratively.

1. Independent Sets

|  |  |
| --- | --- |
| * 1. Problem Description and Dynamic Programming Solution | 44 |
| * 1. Experimental Comparison | 47 |

* 1. Problem Description and Dynamic Programming Solution

The Independent Sets problem concerns a set of nodes *S* and the creation of a new set *S’* where for every node in *S’* one rule applies: no adjacent nodes are included in the set. In more detail, when a node is included in *S’*, all of its adjacent nodes are excluded. However, the adjacent nodes of all these excluded nodes can now be included in the new set (*S’*). The goal is to create the largest independent set *S’* possible. To do this we must include as many nodes as possible, however due to the aforementioned rule we must also exclude the least nodes possible. The exclusion of some nodes may have an overall positive effect, while the opposite is also possible.

To solve this problem, we assume a graph of nodes *G* as the set of nodes *S*. We proceed into rooting the graph *G* into a tree *T* at a random node *R* (root). To solve this problem, we assume that no cycles exist in the transformed tree.

**Figure 14** and **Figure 15** show examples of the biggest independent sets in two different graphs. Nodes inside the solution are marked red. **Figure 15** can also be considered as a tree rooted at node 1. We can see that certain nodes can have a bigger negative impact than other when included in the solution. For example node 4 of **Figure 15** has 3 children leaves, which means by including it in the solution we would automatically lose 3 nodes. From this, it is now clear that the nodes must be computed in DFS order.

|  |  |
| --- | --- |
| Figure | Figure |

****Definitions****

* Graph of *N* nodes and density *D*
* Rooted graph (tree) *T*
* A root node *R*

****Sub-Problem****

**P(i) contains the optimal solution for node i.**

****Bottom-Up Approach (Iterative)****



****Top-Down Approach (Recursive)****



* 1. Experimental Comparison

Scenarios and Preparations

Our solution does not work on graphs containing cycles. Therefore, instead of generating a graph *G* which will later be rooted. We generate a tree to represent *S*.

This tree will be generated with a specific density *D* which represents the degree of the tree. Each node can have up to *D* children nodes, and every node is connected to at least 1 node, since every node is connected to their parent, the tree is connected. The root is exempt from this rule because it has no parent node.

Results and Discussion

**Figure 16** and **Figure 17** show the effect of input problem size in execution time (seconds) and total memory usage in Gigabytes and % memory usage respectively. To take these measurements we used connected graphs with a degree of 2.

Figure

Figure

This is where things get interesting. This problem is a problem solved on Trees. It may be presented as a Graph (or a Set), but to solve it we have to root this graph to traverse it, and this is why cycles should not be included in the generated Tree.

The results show that contrary to all previous results, the execution of the recursive approach seems to be much faster while consuming the same amounts of memory as the iterative approach. The results at first seem unreasonable, however after some thorough investigation on the implementations things start to make sense.

The flaw of the iterative approach for this problem quickly became apparent. This problem requires the traversal of the tree in a Depth First manner (DPS). The leaves of the tree have to be computed, following them are their parent nodes, and this continuous up to the root. In other words, before computing a node we have to compute its children (if they exist).

Using recursion this can easily be done, however this is much harder and computationally intensive otherwise. This can easily be seen by comparing the two implementations. To come around this issue, we have to use new data structures, and creating these data structures is what results in the overhead of the iterative approach. Mainly, we have to put all the nodes of the tree in a list to be able to traverse them, on top of that, at every iteration we have to check which nodes can be computed. A node can be computed only if it has no children nodes or all of its children nodes have been already computed.

This results in what we see in the graphs, memory usage is similar in both approaches, since the recursive approach uses a tree to store its nodes and a 2D array to store the sub-problem data. The iterative approach however uses a queue to store the tree and the same 2D array for the problem data.

On the other hand, as previously mentioned, even if both approaches follow an exponential growth, the execution time of the iterative approach has a steeper growth, making the recursive approach much more efficient. The Top-Down approach is much faster in both execution and development / implementation time while being much easier to understand.

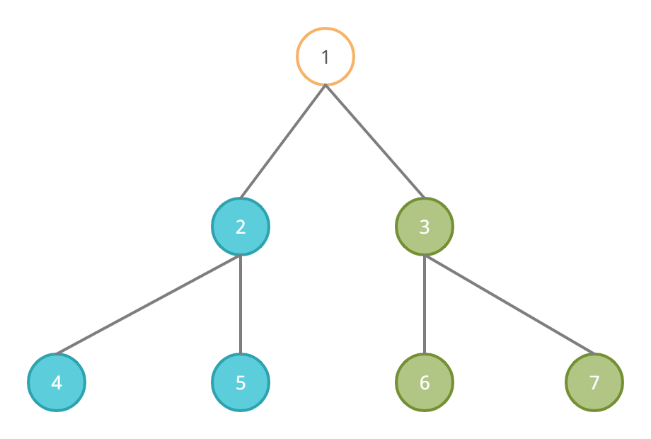
1. K-Trees

|  |  |
| --- | --- |
| * 1. Problem Description and Dynamic Programming Solution | 50 |
| * 1. Experimental Comparison | 52 |

* 1. Problem Description and Dynamic Programming Solution

This problem involves finding the number of subtrees of size *K*, from a tree rooted at *R*. The size of the tree is determined by the number of all its nodes including its root. Therefore, a sub-tree of size *K* is a tree with exactly *K* nodes. This problem is a very useful problem used in even distributions on trees.

**Figure 18** shows an example tree of 7 nodes (numbered from 1 to 7) rooted at node 1. Coloured are its 2 k-trees of size 3 (green and blue).



Figure

****Definitions****

* Tree of *N* nodes of degree *D*
* A root node *R*
* Cache array *C* of size *N*

****Sub-Problem****

**P(i) contains the optimal solution for node i.**

**C[i] contains the size of the sub-tree rooted at i.**

****Bottom-Up Approach (Iterative)****



****Top-Down Approach (Recursive)****



* 1. Experimental Comparison

Scenarios and Preparation

To change the structure of the tree we introduce the degree variable *D*. This variable determines the maximum number of children any node can have (Degree). Firstly, we create *N* nodes and we iterate through all of them, assigning up to *D* childrenuntil all nodes receive a parent node. Each node can have 0 to *D* children except the root which must have at least 1 (the root has no parent). We want to investigate whether the degree of the tree affects the performance of any of the implementations.

Results and Discussion

Figure 19 and Figure 20 depict the effect of input problem size in execution time (seconds) and % total memory usage respectively. The connected tree generated for these measurements had a degree of 2.

Figure

Figure

What we observe is that the memory usage growth is linear to the problem size. Likewise, the execution time is linear to the problem size. However, what we see is that the iterative approach consumes just a little more memory. What we also see is that even though both approaches run in linear time, the iterative approach is also slower.

The last data point of the graph shows an immediate increase in the execution time, while the memory usage seems to drop a bit in comparison to the general trend of the iterative approach. Our explanation is that this instance of the problem pushed the system to its outmost limits. The RAM of the computer was full, and the swap memory was used. The swap memory is far slower than the system memory, this explains the drop on the memory usage, since the program didn’t measure the swap memory used, this also explains the slower execution.

The recursive approach is a clear winner in both aspects for this problem.

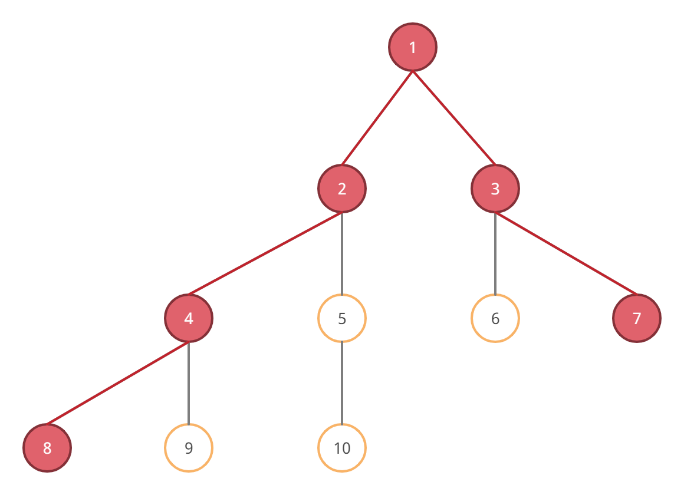
1. Tree Diameter

|  |  |
| --- | --- |
| * 1. Problem Description and Dynamic Programming Solution | 55 |
| * 1. Experimental Comparison | 58 |

* 1. Problem Description and Dynamic Programming Solution

This problem involves finding the diameter of a tree rooted at R. The diameter is the maximum distance between any two nodes inside the tree.

Following (**Figure 21**) is an example of this problem on a tree of 10 nodes. The red nodes are part of the diameter of the tree. The diameter shown is just one of the possible solutions. Another possible solution would occur if we excluded node 8 and included node 9.



Figure

* + 1. ****Definitions****
* Tree of N nodes of Degree *D*
* A root node R
* Caching arrays *max1\_array* and *max2\_array* of size N
  + 1. ****Sub-Problem****

**From the example on** Figure 21 **we make two observations. A node can either not be included in the solution or be included with at most 2 of its children. Only 1 node of the solution can have 2 of its children be included in the solution path. The rest of the nodes can either have 1 or none (leaves only). Therefore, we will keep track of the two longest paths that occur at every node. Then the parent of each node will compare these paths to find the global maximum.**

* ***max1\_array[i]* contains the longest path of node *i* including itself with 1 of its children.**
* ***max2\_array[i]* contains the longest path of node *i* including itself with 2 of its children.**
* ***P(i)* contains the optimal solution for node i (max of *max1\_array[i]* and *max2\_array[i])*.**
* **We use DFS (Depth First Search) to traverse the tree from its leaves first**

**From this we derive the following:**



Note: The root might not be included in the solution, so we have to keep track of the diameter of the tree at a global scope. Another solution would be to keep track of the node with the biggest *max2\_array* value since it will contain the value of the diameter (only 1 node contains two paths).

* + 1. ****Bottom-Up Approach (Iterative)****



* + 1. ****Top-Down Approach (Recursive)****



* 1. Experimental Comparison

Scenarios and Preparation

Similarly, to previous tree problems, we use the degree variable *D* to change the structure of the tree. The tree is fully connected. Each node has a single parent (except the root) and all nodes have up to *D* children (the root has at least 1). We change the degree of the tree to investigate whether the structure of the tree affects the performance of any of the two implementations.

Results and Discussion

Figure 22 and Figure 23 depict the effect of input problem size in execution time (seconds) and % total memory usage respectively. The connected tree generated for these measurements had a degree of 2.

Figure

Figure

The first observation is that the efficiency of the recursive approach is greater in both aspects. We see a linear increase in both the memory usage and the execution time for both approaches. However, the rate of increase of the iterative approach is greater. In more detail, the execution time is much greater but the memory usage not so much, however it was enough to make this approach unable to run the problem for the last input size. The recursive approach is a clear winner in both aspects, especially in execution time.

1. Conclusion

|  |  |
| --- | --- |
| * 1. Summary | 60 |
| * 1. Problems Faced | 62 |
| * 1. Future Work | 62 |

* 1. Summary

After close inspection of the obtained results we came to some surprising conclusions. The type of the input of the problem plays a huge role in its performance. We will categorize the problems into the following categories: Input Complexity.

Problem Categorization

|  |  |
| --- | --- |
| **Input** | |
| Array (1D or 2D) | MCSS, LISS 1D, LISS 2D, Chain Matrix Multiplication, Knapsack |
| Graph | Dijkstra |
| Tree | Independent Sets, K-Trees, Tree Diameter |

Through all the experiments we conclude the following:

|  |  |  |
| --- | --- | --- |
| **Input** | **Problems** | **Conclussion** |
| 2D Array | * MCSS * LISS 1D * LISS 2D * Chain Matrix Multiplication * Knapsack | These problems are heavily favoured by the iterative approach in regards to the Execution time. The memory usage is very similar for either approach, however we have reason to believe that some problems may even favour the iterative approach in memory usage as well. |
| Graphs | * Dijkstra’s Shortest Path | This problem is a problem presented on a Graph. The limitation of the iterative approach becomes clear here. A problem that is declared in a “pointer style” data structure is hard to traverse in an iterative manner. Even when we use an array to represent the graph it is even harder to traverse the graph in DFS order. Dijkstra’s algorithm however requires the traversal of the graph in a specific manner, therefore the results of the two implementations are very similar. The iterative approach had a slight overhead in execution time caused by the pre-processing of the data. |
| Trees | * Independent Sets * K-Trees * Tree Diameter | Here is where things got interesting. When solving problems on graphs the weakness of the iterative approach showed itself. However, problems on trees showed something more, a strength of the recursive approach. Traversing trees is very easy in a recursive manner, making it both faster in development (implementation) and in execution. Yielding better results both in memory usage and execution time. The difference was not as much in the memory used, however the execution was a lot faster, making the recursive approach the clear winner for problems on trees. |

Tree and Graph traversal is both more intuitive, faster and more memory efficient in a recursive manner instead of an iterative manner.

* 1. Problems Faced

There were several problems encountered during this study. Most of the problems had to do with data collection. As mentioned at the beginning measuring the memory usage of a program can be tedious, especially when dealing with problems that consume a lot of memory which was the case for the project. The tools we used were unable to function because of the high memory demands, so we had to resort in different methods.

The biggest problem faced however was the time it took to collect the data. This was the case with problems like the MCSS and the Chain Matrix Multiplication. For big problem sizes, that would use up most of the memory, the execution of the program would take hours. In the case of the Chain Matrix Multiplication program the execution would take weeks and even months. Therefore, we had to change our input sizes.

* 1. Future Work

Finding out about the behaviour of the recursive approach on different data structures was not something we suspected at first. However just when we began developing the programs we realised how useful recursion is on some data structures like trees. Discovering more of these behaviours would be interesting.

An interesting extension of this work would also be to further investigate how other parameters would affect the performance of each implementation. A comparison between the same implementation in two different programming languages would be interesting. The effect of the Operating System may also be important, both in resource usage and execution time.

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