

STA2005S - Experimental Design Assignment

Jing Yeh

yhxjin001@myuct.ac.za

Saurav Sathnarayan

sthsau01001@myuct.ac.za

2024-09-15

Abstract

In this report, we explored the efficiency of 6 programming languages through the approximation of π . We found that efficiency of various programming languages can vary widely, with C and C++ being the most efficient programming languages. We also demonstrated evidence for compiled languages having better performance than interpreted languages. Our results suggest that programmers can benefit from taking the efficiency of various programming languages into account, rather than simply opting for simplicity in the syntax of these languages .

Keywords: Programming Languages, Efficiency, Large-Scaled Iterative Computations

Contents

1	Introduction	3
1.1	Compiled vs Interpreted Languages	3
1.2	Distribution of Execution Times (Pilot Experiment Part 1):	4
2	Methods	5
2.1	Setting	5
2.2	Approximation of π	5
2.3	Sampling Procedure	5
2.4	Sources of Variation	6
2.5	Experimental Units:	6
2.6	Randomisation Procedure	6
2.7	Planned Comparisons	6
2.8	Pilot Experiment Part II	7
2.9	Design	7
3	Results	9
3.1	Verifying Model	9
3.2	Pairwise Comparisons	10
3.3	Compiled vs Interpreted	10
4	Discussion	12
5	Conclusion:	12
6	Appendix	14
7	Reference	15

1 Introduction

Computation has played a major role in human history ever since people began living in cities. The need to calculate taxes motivated the invention of various computing devices that aided such computations, such as the Sumerian abacus, invented in Babylon at around 2500BC [7]. In the 21st century, the capability of our digital computing devices have vastly surpassed the capacity of those proto-computers, but so has our need for computational power. Everything in our daily life requires some form of computers: from our phones, cars, to even our refrigerators (side note: initially, Java was invented for refrigerators).

However, with large computation capability comes complexity in the design of these devices: to speak plainly, they are damn difficult to use. Computer scientists have therefore invented numerous *programming languages* that allow us to harness the power of these devices more easily.

Nowadays, programming languages have become the primary medium for instructing computers to perform our increasingly complex tasks. Understanding which programming languages offer superior execution speed is therefore crucial for developers, especially in domains requiring real-time processing, large-scale data analysis, and other resource-intensive computations. The goal of this experiment is to identify such languages that deliver the fastest execution time.

1.1 Compiled vs Interpreted Languages

In a compiled language, the source code is translated into machine code by a compiler before execution, which produces an executable that can be run directly by the machine. In an interpreted language, however, the source code is executed line-by-line by its interpreter at runtime. The interpreter reads the code, translates it into machine code, and executes it all at once. This machine code, often called an executable, can be run directly by the computer's hardware. Compiled languages tend to have better performance due to the pre-compiled nature of the code, whereas interpreted languages are more flexible but slower due to the runtime translation.

Examples: C, C++, Rust, and Java are examples of compiled languages. Python, JavaScript, Ruby, and R are examples of interpreted languages.

1.2 Distribution of Execution Times (Pilot Experiment Part 1):

Since existing literature on the execution times of programming languages when applying Leibniz's formula is limited, we conducted a mini pilot experiment on a single machine to gauge the execution times for the programming languages we planned on experimenting with. We performed 500 approximations using the algorithm for each programming language and obtained the following jittered graph.

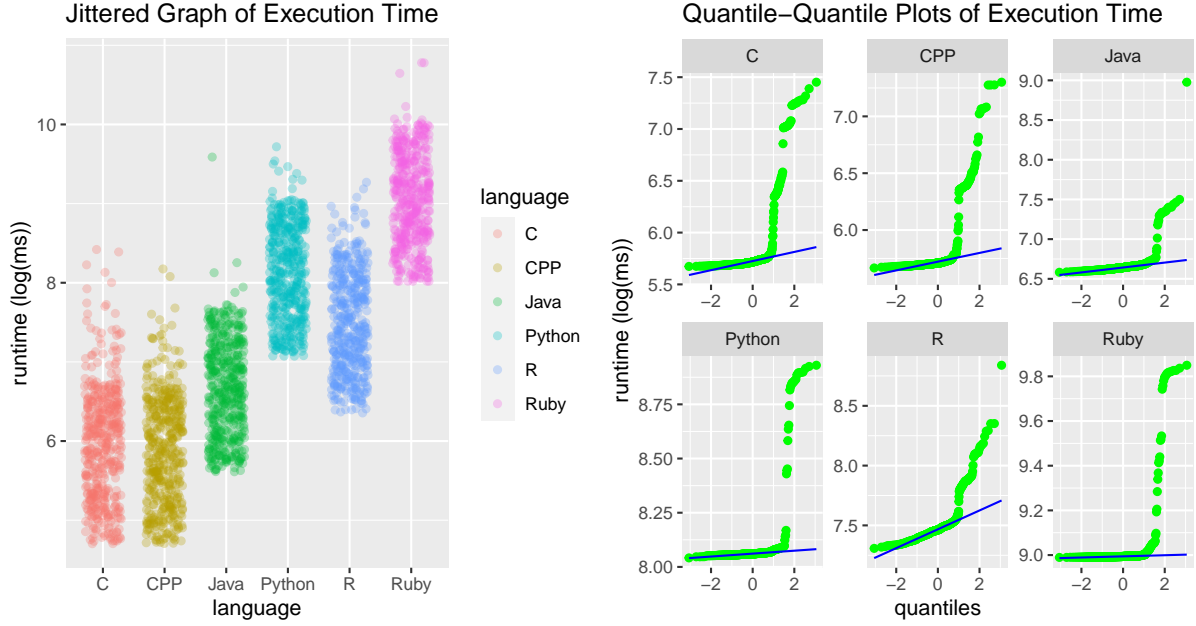


Figure 1: Runtimes of Programming Languages of Interest When Applying Leibniz's Formula up to 100 million terms

We can observe that C and C++ seem to be the fastest languages on this particular machine, though further analyses are needed. We can also see from the Quantile-Quantile(Q-Q) plots that the execution times are clearly not normally distributed.

2 Methods

2.1 Setting

This study was mostly conducted at the University of Cape Town, utilising the computers available on campus. We found that there are only 5 different hardware setups available. Thus, to supplement the range of our hardware setups, we also borrowed machines of 2 more hardware setups from our friends.

2.2 Approximation of π

The number π , the ubiquitous and equally mysterious irrational number, has been fascinating the humankind since time immemorial. Mathematicians from 4000 years ago to the present day have devised various methods to get closer to the true value of π . One such method is using Leibniz's formula:

$$4 \left(1 - \frac{1}{3} + \frac{1}{5} - \frac{1}{7} + \frac{1}{9} \dots \right) = \sum_{k=0}^{\infty} \frac{(-1)^k}{2k+1}$$

Leibniz, whom the formula is named after, proved that the series above eventually converges to π . That is:

$$\pi = 4 \left(1 - \frac{1}{3} + \frac{1}{5} - \frac{1}{7} + \frac{1}{9} \dots \right) = \sum_{k=0}^{\infty} \frac{(-1)^k}{2k+1}.$$

We applied this algorithm in 6 programming languages, including 3 compiled languages: C, C++, Java, and 3 interpreted languages: Python, R, Ruby, up to a 100×10^6 terms.

2.3 Sampling Procedure

Existing literature suggests that execution times of programming languages are typically not normally distributed [10]. We confirmed this in part I of our pilot experiment that none of our languages has normally distributed runtime when performing the algorithm. This is an issue as it prevented us to apply anova models. To address this, we applied the Central Limit Theorem (CLT) to obtain a normal distribution for the average execution times. We ran the program 15 times per sample for each programming language, and repeated the process 30 times. Applying CLT, it is relatively safe to assume the distribution of sample means is approximately normal [2]. If we assume sample means to be normally distributed, the mean of the distribution of sample means is then an unbiased estimator for the true run time of each programming language [2], which we will take as a single observation. (Note: We arrived at the number 15 through trial and error, and 30 from [8])

2.4 Sources of Variation

Treatments: We have 6 treatment factors, which are the programming languages we applied the algorithm to. Each treatment has one level (applying the formula up to 100×10^6 terms). We selected this particular level because it is the largest, practical number of terms we could apply with our hardware setups (For some setups, it may take up to 4 hours to arrive at a single observation), and fewer terms imply larger relative measurement error [7]. We cannot include more levels because in the existing literature, most studies of such kind choose to run all languages on the same machine. However, since we would like to avoid pseudo replication as much as possible we used one machine per observation. The downside of this approach is that we do not have sufficient machines to perform more than one levels.

Blocks: We know that the hardware setup of a computer can significantly affect its speed, and therefore the execution time of our algorithm. We also know that, two computers with the same hardware setup should have relatively the speed, provided that they run on the same operating system, and no major damage has been done to either of them. This motivated us to block for the hardware setup of computers, our experimental units.

2.5 Experimental Units:

As mentioned earlier, we would like to avoid pseudo replication as much as possible. Therefore, we deviated from the tradition of running all programming languages on the same machine, and test only one language per machine. Our experimental units are therefore the individual machines we ran each test on.

2.6 Randomisation Procedure

We first ordered the computers belonging to each block from 1 to 6. We then used the random number generator from Python's *random* module to randomly shuffle, and thus producing a permutation of the list, [C, C++, Java, Python, Ruby, R]. The index of each programming language in the permutation would then be paired to the computer with the same assigned number.

2.7 Planned Comparisons

We planned to conduct pairwise comparisons on all treatments. That is, a total of $\binom{6}{2=15}$ comparisons. We assume this would help us find the most efficient language(s). It would also serve our interest by comparing the efficiency of compiled languages (C, C++, Java) and interpreted languages (Python, Ruby, R), as the latter are oftentimes

easier to program with. This allows us to better asses the time-cost trade off of these programming languages.

2.8 Pilot Experiment Part II

We followed this direction and performed part II of our pilot study to obtain the following execution times of programming languages on 4 hardware setups

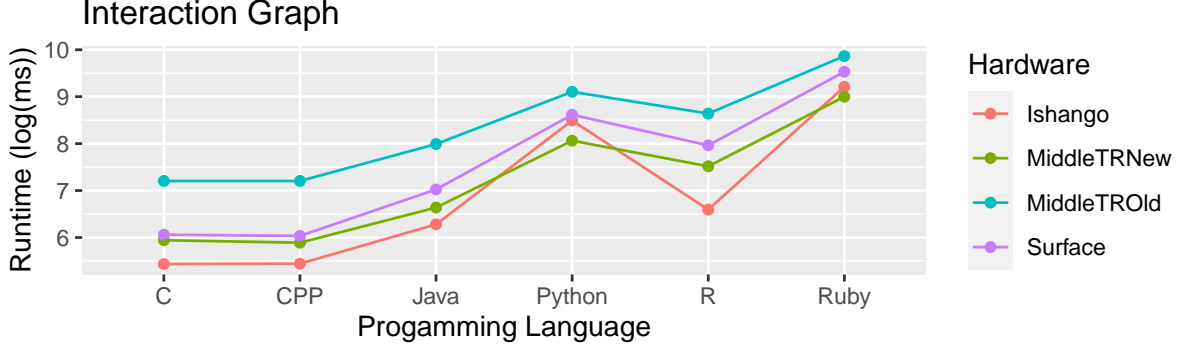


Figure 2: Interaction Graph of Programming Languages and Blocks

From the data collected, we observed that the results collected from Ishango do not follow the general trends established by the other three setups. Firstly, the hardware setup in Ishango lab is significantly less advance than MiddleTRNew. Yet, most programming languages tend to perform better on the Ishango machine. Secondly, to add to the first observation, not all programming languages perform better on the Ishango machine.

After further investigation, we learned that programming languages perform differently on various operating systems [4]. We hypothesised that this is the main reason for the deviation, though further studies are needed to confirm this (we lack access to machines with the same hardware setup but run on different operating system).

Therefore, we added another constraint for selecting suitable machines: the machines must all run on Windows 10, as these machines are the most widely available. Other than than that, the results verified our motivation for blocking various hardware setups.

2.9 Design

We assume that:

$$e_{ij} \sim \mathcal{N}(0, \sigma^2)$$

We use the following anova model for our response variables:

$$Y_{ij} = \mu + \alpha_i + \beta_j + e_{ij}$$

$$i = 1 \dots a$$

$$j = 1 \dots b$$

With the following constraints:

$$\sum_{i=1}^a \alpha_i = \sum_{j=1}^b \beta_j = 0$$

Where:

μ	overall mean
α_i	effect of i^{th} treatment
β_j	effect of j^{th} block
e_{ij}	random error of the observation

We also assume that each e_{ij} is independent to each other, which allows us to assume that each Y_{ij} is also independent to each other, and are normally distributed. If there are no blocking and treatment effects, then:

$$Y_{ij} \sim \mathcal{N}(\mu, \sigma^2)$$

Otherwise, if there are blocking and treatment effects, then:

$$Y_{ij} \sim \mathcal{N}(\mu + \alpha_i + \beta_j, \sigma^2)$$

Below is the layout of the design

PC Spec	Treatment					
Ishango	Java	C	Python	Ruby	C++	R
MiddleTROld	R	C++	Python	C	Ruby	Java
MiddleTRNew	Python	R	Java	C	C++	Ruby
ScilabB	Python	Java	Ruby	R	C	C++
ASUS (i7-5500u)	C	C++	R	Ruby	Python	Java
ScilabD	C	Python	Java	R	Ruby	C++
LT	C	Java	R	C++	Ruby	Python
HP (i5-7200)	R	Python	Ruby	C++	Java	C

Figure 3: Diagram of the Design

3 Results

We performed the experiment described above on 7 different hardware setups and applied all 6 treatments. Detailed tables for data and for hardware setups can be found in the appendix. The Analysis of Variance (ANOVA) table is shown below:

Table 1: Analysis of Variance Table

	Df	Sum sq	Mean sq	F value	Pr(>F)
Language	5	65.2112	13.0422	285.9459	< 0.0001
Hardware	6	6.5717	1.0953	24.0136	< 0.0001
Residuals	30	1.3683	0.0456		

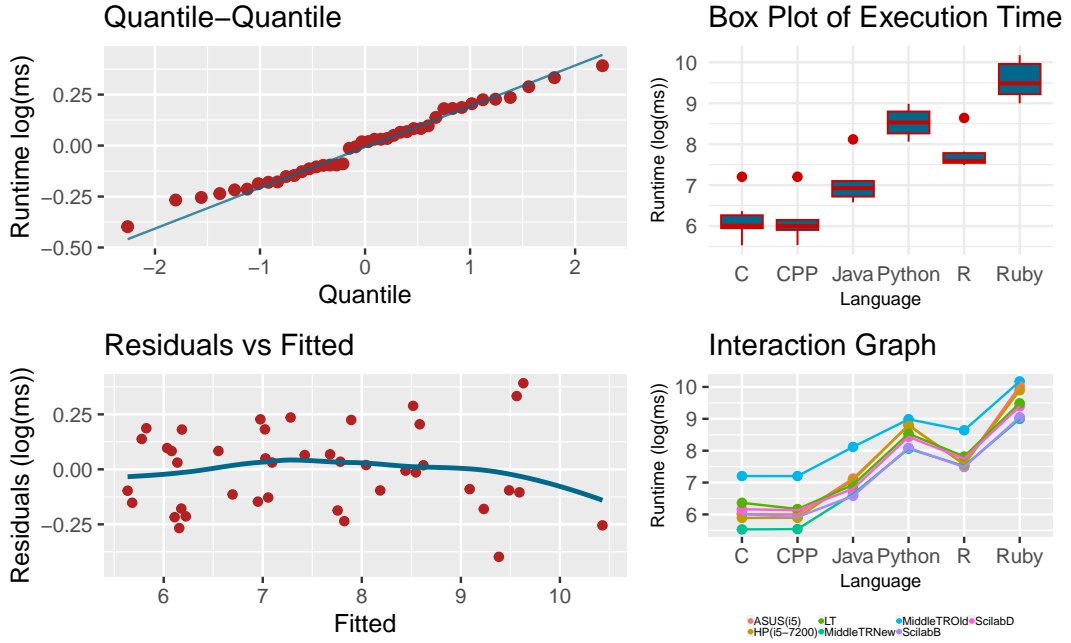


Figure 4: Diagnostic Plots

3.1 Verifying Model

We verified our model by observing the Fitted vs Residuals graph: the residuals seem to be randomly spread, with no obvious patterns to be discerned. This shows that assuming homoscedasticity (equal variance) is not non-sensical [7]. Also, the Quantile-Quantile graph offers a fairly good fit, providing evidence for residuals being normally distributed.

We further verified our assumptions by performing Shapiro Wilk test to test against the normality assumption of residuals. We obtained a fairly large p-value of 0.7521, indicating that we have little evidence to suggest otherwise. Further, we also got that the mean of the residuals is extremely closed to zero ($< 10^{-15}$), indicating that it is sensible to assume $e_{ij} \sim \mathcal{N}(0, \sigma^2)$

3.2 Pairwise Comparisons

Table 2: Table of Logarithmic Mean Execution Time

C	CPP	Java	Python	Ruby	R
2.6786	2.6586	3.0568	3.7041	4.1582	3.3732

Given that we knew our response variables are normally distributed, we opted for the more powerful Tukey’s Method, rather than Scheffe’s, to construct 95% confidence intervals that compare the execution time of every possible pair of our 6 programming languages. We use the following R function to achieve this. (The full table of the output can be found in the appendix.)

We can observe that we have strong evidence to suggest that the efficiency of various programming languages when approximating π is ranked as followed.

$$t(C) \approx t(C++) < t(Java) < t(R) < t(Python) < t(Ruby)$$

We can also see that the efficiency of programming languages can vary significantly, with the 95% confidence interval of the estimated difference in execution time between C++ and Ruby being: $(e^{3.1058}, e^{3.4530}) = (22.32, 31.60)$. That is, C++ is between 22.32 to 31.60 times faster than Ruby at 95% Confidence!

It would also be interesting to see, from a statistician’s point of view, which of the two most widely used languages in data analysis is more efficient. That is, an answer to the age old question: “Python or R?”. We will attempt to present an answer here from the perspective of efficiency: R is estimated to be between 2.01 to 4.03 times faster than Python when performing our algorithm.

3.3 Compiled vs Interpreted

We were also interested in comparing the execution times of compiled languages and interpreted languages. The contrast, L , can be stated as follows:

$$L = \frac{1}{3}(\mu_C + \mu_{C++} + \mu_{Java}) - \frac{1}{3}(\mu_{Python} + \mu_{Ruby} + \mu_R)$$

We can estimate the values relevant to the contrast as follows:

$$\begin{aligned}
\hat{L} &= \frac{1}{3}(\bar{y}_C + \bar{y}_{C++} + \bar{y}_{Java}) - \frac{1}{3}(\bar{y}_{Python} + \bar{y}_{Ruby} + \bar{y}_R) \\
&= -0.9198 \\
\widehat{Var}(\hat{L}) &= s^2 \sum_{i=1}^6 \frac{h_i^2}{n} \\
&= 0.0456 \sum_{i=1}^6 \frac{1}{7} \\
&= 0.004343 \\
SE(\hat{L}) &= \sqrt{\widehat{Var}(\hat{L})} \\
&= \sqrt{0.004343} \\
&= 0.0659
\end{aligned}$$

We first note that $t_{0.025}^{30} = 2.0422$. We will then construct a 95% confidence interval as follows:

$$\begin{aligned}
&\hat{L} \pm SE(\hat{L}) \times t_{0.025}^{30} \\
&-0.9198 \pm 0.0659 \times 2.0422
\end{aligned}$$

Thus, the 95% Confidence interval is as follows:

$$95\%C.I. = (-1.0544, -0.7852)$$

The means that, at 95% confidence level, the average execution times of compiled languages is estimated to be between 2.19 to 2.87 times shorter than that of the interpreted languages . We therefore have strong evidence to suggest that compiled languages have shorter execution times when applying Leibniz's formula up to a very large term.

4 Discussion

The experiment aimed to analyze the execution time of different programming languages when applying Leibniz’s formula across 7 hardware setups and 6 treatments. The ANOVA diagnostic plots (quantile-quantile and residuals vs. fitted) indicate a well-fitted model, with residuals demonstrating no major deviations from normality and homoscedasticity, supporting the robustness of the analysis. The ANOVA results indicate significant differences amongst the execution times of various languages. The p value for hardware is also very low (< 0.0001) which indicates that hardware setup does have an effect on the execution time of different programming languages.

From the Tukey’s HSD post-hoc tests, it is clear that C and C++ have the fastest execution times, as reflected by their significantly lower mean execution times compared to other languages. Java, a semi-compiled language, performed moderately well, trailing behind C and C++ but significantly ahead of interpreted languages like Python and Ruby. We compared languages that serve similar purpose, such as R and Python in data analysis, and we found, at 95% confidence level, that R is around 2 to 4 times faster than Python when performing large amount of simple mathematical multiplication and addition.

We also collected strong evidence to suggest differences in the performance of compiled and interpreted languages. The compiled languages (C, C++, Java) outperformed interpreted languages (R, Python, and Ruby) by 200% to 300% in our results. Interpreted languages are typically easier to program in than compiled languages and are thus favoured by some programmers. However, our results suggest that less difficulty in the coding stage often implies less efficiency in the final programs produced. We thus strongly recommend programmers to take the efficiency of various programming languages into account when selecting one for their project.

5 Conclusion:

The results of this experiment confirmed that compiled languages (C and C++) exhibit significantly faster execution times compared to both semi-compiled (Java) and interpreted languages (R, Python, Ruby). The performance gap between compiled and interpreted languages becomes particularly evident with large-scale computations, such as, in our case, applying Leibniz’s formula up to 100 million terms. Based on the ANOVA and post-hoc analysis, we found , for large-scale simple mathematical operations, that: 1.C and C++ are the most efficient languages, followed by Java, R, Python, and then Ruby, in order. 2.Compiled languages provide a substantial performance advantage over interpreted languages. These findings can be useful for developers when selecting a programming language for performance-critical applications, and large-scale iterative com-

putations.

6 Appendix

	PC	CPU	RAM	OS
1	Ishango PC	9th Gen Intel® Core™ i3-9100	8.0 GB	Ubuntu 22.04
2	MiddleTROld	9th Gen Intel(R) Core(TM) i5-9500 CPU	8.0 GB	Windows 10
3	MiddleTRNew	12th Gen Intel(R) Core(TM) i5-13400	16.0 GB	Windows 10
4	ScilabB	12th Gen Intel(R) Core(TM) i5-12400	16.0 GB	Windows 10
5	Surface	9th Gen Intel(R) Core(TM) i5-8250 CPU	16.0 GB	Windows 10
6	ASUS (i7-5500u)	5th Gen Intel(R) Core(TM) i7-5500U CPU	6.0 GB	Windows 10
7	ScilabD	10th Gen Intel(R) Core(TM) i5-10500	16.0 GB	Windows 10
8	LT	9th Gen Intel(R) Core(TM) i5-9400f	8.0 GB	Windows 10
9	HP (i5-7200)	7th Gen Intel(R) Core(TM) i5-7200	8.0 GB	Windows 10

Table 3: Table of Pcs used and their respective specifications

	Hardware	C	CPP	Java	Python	Ruby	R
1	MiddleTROld	3.13	3.13	3.53	3.90	4.42	3.75
2	MiddleTRNew	2.40	2.41	2.88	3.50	3.91	3.26
3	ScilabB	2.61	2.57	2.86	3.51	3.93	3.25
4	ASUS(i5)	2.61	2.61	3.09	3.82	4.35	3.30
5	HP(i5-7200)	2.56	2.56	3.07	3.82	4.30	3.29
6	ScilabD	2.68	2.66	2.96	3.66	4.08	3.37
7	LT	2.76	2.68	3.01	3.71	4.12	3.40

Table 4: Table of data used for analysis

	diff	lwr	upr	p adj
CPP-C	-0.046023	-0.393240	0.301194	0.998485
Java-C	0.870722	0.523505	1.217939	0.000000
Python-C	2.361294	2.014077	2.708512	0.000000
R-C	1.599346	1.252129	1.946563	0.000000
Ruby-C	3.407019	3.059802	3.754236	0.000000
Java-CPP	0.916745	0.569528	1.263962	0.000000
Python-CPP	2.407317	2.060100	2.754534	0.000000
R-CPP	1.645369	1.298152	1.992586	0.000000
Ruby-CPP	3.453042	3.105824	3.800259	0.000000
Python-Java	1.490572	1.143355	1.837789	0.000000
R-Java	0.728624	0.381407	1.075841	0.000007
Ruby-Java	2.536297	2.189079	2.883514	0.000000
R-Python	-0.761948	-1.109166	-0.414731	0.000003
Ruby-Python	1.045724	0.698507	1.392942	0.000000
Ruby-R	1.807673	1.460456	2.154890	0.000000

Table 5: Table of Differences in Log Execution Time with Tukey’s Method

7 Reference

- [1] Juritz J, Little F, Erni B. Design of Experiment: Course Notes for STA2005S. University of Cape Town; 2023.
- [2] Mavuso M, Robbertze Y. Order Out of Chaos I and II: STA2004F Notes. University of Cape Town; 2019.
- [3] Dean AM, Voss D. Design and Analysis of Experiments. Springer Science & Business Media; 2006.
- [4] Braun J. Is Linux Faster Than Windows? Speed Comparison & Analysis [Internet]. Linux JournalDigital. 2022. Available from: <https://www.linuxjournaldigital.com/is-linux-faster-than-windows/>.
- [5] Greenwood MC. Intermediate Statistics with R. 2021.
- [6] Fourment M, Gillings MR. A comparison of common programming languages used in bioinformatics. BMC Bioinformatics. 2008;9.
- [7] Rhodes B. Computing is Born: The Sumerian Abacus [Internet]. #TechIsATool. 2020. Available from: <https://medium.com/tech-is-a-tool/the-dawn-of-computing-sumerian-abacus-83bdefb697ba>.
- [8] Underhill LG, Bradfield D. Introstat. University of Cape Town; 2007.
- [9] Residuals vs. Fits Plot | STAT 501 [Internet]. PennState: Statistics Online Courses. University of Pennsylvania; Available from: <https://online.stat.psu.edu/stat501/lesson/4/4.2>.
- [10] Chapter 16 - Anova [Internet]. University of South Carolina; 2018 [cited 2024 Sep 14]. Available from: <https://www.biostat.jhsph.edu/~iruczins/teaching/jf/ch16.pdf>.
- [11] Matheus, Adriano Kamimura Suzuki. Determining the Probability Distribution of Execution Times. 2021 IEEE Symposium on Computers and Communications (ISCC). 2021;