<RL4Water: Climate-Resilient Water Management via Reinforcement Learning>

<Investigation of Different Visualization Techniques for the Multi-Objective Reinforcement Learning Results>

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Abstract

This paper studies the simulation of the Nile River as a multi-objective reinforcement learning problem. The main goal of this essay is to develop and evaluate the visualization techniques to effectively present the results of reinforcement learning models. Using a multi-objective approach, visualizations are very important for understanding the trade-offs and complexities in managing the Nile River problem.

This study includes a user evaluation to compare different visualizations, analyzing their effectiveness in terms of their clarity and usefulness using ANOVA test. Additionally, the effectiveness of clustering and full data points will be analyzed using a chi-square test to choose which visualisation technique works the best.

According to the results, stacked bar chart and parallel coordinates plot performed the best, while the spider plot performed the worst. Additionally, there is no preference between clustered and full data points visualizations based on the user evaluation.

1 Introduction

Machine learning (ML) is a term that is becoming more popular every day by the latest developments in technology. These developments influence how scientists can solve complex real-life problems, which usually have multiple contradictory objectives (Jordan & Mitchell, 2015). Specifically, multi-objective reinforcement learning (MORL), which extends the single reward sognal in reinforcement learning to multiple reward signals—one per objective—is a popular tool that can be used for multi-objective problems (Van Moffaert & Nowé, 2014). The algorithm takes an action based on the observation space, and then either positive or negative rewards can be received dependent on the outcomes of the actions. (Brink et al., 2016; Cosgrove & Loucks, 2015).

As an example of a complex real-life problem, the water management of the Nile River is one of the complex problems where we need the help of computers to solve. In this complex problem, there are three countries: Egypt, Sudan, and Ethiopia. Sudan wants to minimize their water deficits, Ethiopia wants to maximize their energy production by their hydroelectric power plant, and Egypt wants to minimize their water deficits and the frequency of months below the minimum power generation level of the High Aswan Dam (HAD) (Sari, 2022). There are four objectives for three countries, and the task is to provide a water management system that can be beneficial for all the countries. We believe that MORL algorithms can provide better water policies compared to the current ones. Additionally, even though the MORL algorithms can provide solutions, the correct visualization techniques need to be implemented to see the results more effectively since the vector of results can look complicated without any visuals. In this research, different visualization approaches for the water management policies of the Nile River will be investigated.

The question that will be answered in this essay is: How can you present the outputs of the multi-objective reinforcement learning algorithm to the decision makers? To answer this question, several visualization techniques will be implemented, and data about the visuals' effectiveness will be collected through user evaluations and analyzed using several analytical techniques.

In this research, our main goal is to investigate possible visualisations techniques for showing the results of MORL. To achieve this, several visualisation techniques, such as stacked bar charts and heat maps, were implemented, and users were asked to test the visuals' effectiveness in the MORL. Users filled out a user evaluation form to share their opinions about the visuals. These results were later analyzed using chi-square tests, to test whether clustered or full data points are preferred for visualization, and ANOVA, to test the effectiveness of visuals in terms of clarity and usefulness. According to this experiment, people mostly preferred the parallel coordinates plot and stacked bar chart, while the least popular visual was the radar plot.

In this research paper, the sections are organized as follows: Related Work, Methodology, Results, Responsible Research, Discussions, and finally Conclusions and Future Work.

2 Related Work

In this section, the related work about this paper will be discussed. Firstly, there will be explanation about Multi-Objective Reinforcement Learning (MORL). In the following sub-section, the EMODPS algorithm and the Nile Simulation will be described. More details on the simulation and EMODPS algorithm can be found in this part. In the last sub-section, detailed information about different visualization techniques and clustering methods will be given.

2.1 MORL

On one hand, in single-objective reinforcement problems, there is only one unique optimal value V*, and multiple optimal policies π* may have this value. The main aim of the single-objective reinforcement learning is to learn an optimal policy.

On the other hand, in Multi-Objective Reinforcement Learning (MORL), multiple optimal value vectors V* can exist without any additional information about the user's utility (Hayes et al., 2022). Since the reward vector includes multiple components representing different objectives, conflicts often arise during objective optimization. In these cases, objective trade-offs have to be applied, which creates the policies. The optimal policies for each objective or set of objectives are known as the Pareto optimal set (Van Moffaert et al., 2013).

2.2 EMODPS and Nile Simulation

This study will be using Nile case study, which is a simulation of a Nile river (Sari, 2022). The Evolutionary Multi-Objective Direct Policy Search (EMODPS) method was used as the algorithm for water management in the Nile simulation.

In EMODPS, the Artificial Neural Network (ANN) output is the water release, which is calculated based on the time of the year, initial water storage, and water inflow. Later, the water release is integrated into the water reservoir model for updating the reservoir state and predicting optimization objectives and constraints. Policy optimization and reservoir simulation can be done since the decision variables are ANN parameters. NSGA-II genetic algorithm from pymoo, which is a Python library, and three-layer network can be used to optimize the policy (Wu et al., 2022).

In order to visualize the results, several different visualization approaches were used, such as pair plot and parallel coordinate plot, and dimensional stacking (Sari,2022). However, these visuals provides dual comparisons without considering deeply comprehensive, simultaneous comparisons of all elements in one visual.

2.3 Visualisation techniques for Multi-objective decision making

As the number of objectives increase, the alternative solutions for MORL increase (Osika et al, 2023). Thus, it becomes more complex to visualize the results. However, there are still some visualization techniques that can be used to display the MORL results.

The common visualization techniques for MORL are parallel coordinates plots (PCPs), heat maps, pair-wise scatterplot, radar charts. Besides these, stacked bar chart and bubble chart are popular visualization techniques (Bandaru et al.,2017;Muzammil & Sarwar, 2011). If the data set is very large, a clustering method for the data can be used to improve the clarity.

In K-means clustering, k value is chosen first, which is equal to the number of clusters. After that, k amount of data is selected randomly from the dataset, which will represent the cluster centers. Finally, each remaining data is added to the nearest cluster based on the distance and cluster means are updated each iteration until all the cluster means stay the same or the criterion function converges (Yadav & Sharma, 2013).

For bubble chart, it is possible to show 4 variables in the bubble chart. X-axis, y-axis, bubble size and colors can be used to symbolize different variables (Muzammil & Sarwar, 2011).

Heat map can display the data with colors representing the values of the objectives for each approach (Bandaru et al., 2017). Clustering methods, such as k-means, can be used to provide clear visualizations if there are many solutions. The objectives can be normalized if the max values are more than 1 or min values are less than 0.

Spider plots can be used to plot each solution on a separate axis representing each objective. Each variable is normalized first and the polygons can be drawn by the variable values in each solution. The number of variables should be equal to number of vertices. Each polygon symbolize one solution (Bandaru et al., 2017).

Stacked bar chart can be used to show how the variables performed per solution. All the variables are normalized first to compare clearly. Each bar represents a different solution and consists of the value of each variable (Bandaru et al., 2017). Clustering methods, such as k-means, can be used to provide clear visualizations if there are many solutions. If one variable is high in one solution, then the area of that variable should be big as well. In this visualization, the variable values are stacked for each solution.

For parallel coordinates plot, the range of each variable is normalized and represented by a vertical line. All vertical lines are equally distant between each other. Each horizontal line represents one solution, which is dependent of the value in each variable (Bandaru et al., 2017).

Pair-wise scatter plot can be done in 2D or 3D depending on how many variables we want to compare at the same time - 2D for 2 variables and 3D for 3 variables. It is used to show different variable combinations by matrix of plots (Bandaru et al., 2017).

3 Methodology

This chapter explains the methodology that can be used to answer the research question. Firstly, the simulation will be mentioned. In this sub-section, the information will be provided about the Nile simulation. It will be followed by the visualization, where the chosen visualizations and its reasons will be stated. Next, data collection will be pointed out. In this part, the information can be found about how the data will be collected. Finally, data analysis will be given. Different analytic options will be mentioned in this part.

3.1 Simulation

The Nile simulation works with the Nile data of the past 20 years,which contains irrigation districts, water catchments, dams. Reinforcement learning is used to first learn the environment of the Nile simulation and then generate a policy, which can be useful for Egypt, Sudan and Ethiopia objectives. Multi-Objective Natural Evolution Strategies (MONES) algorithm is used for the learning of the simulation by the help of gymnasium library, which is a reinforcement learning library where you can get reward based on your actions. For the irrigation systems, if the water demand is lower than the water in the reservoir, then the algorithm gives the negative reward. For the dams, the algorithm gives positive reward based on how much energy the dam produced. For the water level objectives, if the water level is higher than the specifc level, then the algorithm gives 1 for that objective otherwise 0.

3.2 Visualization

The implemented visualization techniques are bubble chart, heat map, stacked bar chart and spider plot. Bubble chart was chosen because of its ability to provide 4 variables in a 2D image, and full data visualization option. Stacked bar chart can provide a clear and clustered data visualization option. Spider plot was offered for showing the best and worst objective values interactively, and full data visualization option. Finally, heat map was offered for showing the trade-offs more clear, and clustered data visualization option. In addition, pair-wise scatter plot and PCP were taken from the Yasin Sari's Exploring Trade-offs in Reservoir Operations through Many Objective Optimisation: Case of Nile River Basin thesis for the comparison of the current visualization options with the new visuals (Sari, 2022).

3.3 Data Collection

After getting the visuals from the simulation, feedbacks for the visuals can be collected by the user evaluation. The survey for user evaluation can be done on Google Forms since it provides different question types, such as open-ended and multiple choice, and comparison questions. In open-ended questions, users can provide comprehensive answers. In multiple-choice questions, the users can give a rate their opinions on a scale from 1 to 5. Finally, in the comparison questions, the users can compare several options and choose the one that they believe is most accurate (Appendix A).

3.4 Data Analysis

For the analysis, qualitative analysis and quantitative analysis can be used. In this subsection, the detailed information about the quantitative analysis options, such as One-Way ANOVA, chi-square value will be given. The formulas of these statistical data can be found in Appendix B and Appendix C. Later, in the qualitative analysis, information will be given about the thematic analysis.

3.4.1 Quantitative Analysis

This analysis can be done by numerical data collected during the evaluation. These numerical data include statistical data, such as standard deviation, median, mean (Sandelowski, 2000). In addition to these fundamental statistical data, One-Way ANOVA, chi-squared test can be used too. Specifically:

- **One-Way ANOVA** (Analysis of Variance) is a statistical method for testing the hypothesis. It calculates the ratio of the variance between groups and the variance within groups. If F value is higher than 1, then there are significant differences between means of the variables ((Ståhle & Wold, 1989). (The formula can be found in the Appendix B)
- **Chi-squared test** is a significance statistic, which can be used to test whether one categorical value is preferred more than another one. If the chi-squared value is higher than the critical value, then one categorical variable is preferred compared to other categorical value, otherwise there is no preference between these 2 categorical variables (McHugh, 2013). (The formula can be found in the Appendix C)

3.4.2 Qualitative Analysis

This analysis is focused on understanding and explaining the data without statistical numbers. This analysis is a non-statistical (Sandelowski, 2000). One of qualitative analysis technique can be:

- Thematic analysis is a method for analyzing a qualitative data by looking for recurrent ideas within a collection of data (Riger & Sigurvinsdottir,2016). In this analysis, a table needs to be created with 2 columns: 'Theme' and 'Frequency'. The 'Theme' column lists the names of each distinct theme, while the 'Frequency' represents the number of times each theme is repeated.

4 Results

In this experiment, 6 visuals were shown to the users, which are bubble chart, pair-wise plot, heat map, PCP, stacked bar chart and spider plot. The main focus of the experiment was to collect data about the visuals from 16 computer science students.

4.1 Experimental Setup

The data was collected by the user evaluation, where the users answered several questions on the survey. In the beginning of the user evaluation form, the situation was described to users to inform them what they will do in this evaluation. The survey includes three parts:

- Multiple Choice Questions: The users will rate the visuals in scale of 1 to 5 for different aspects, such as clarity, usefulness.
- Open-Ended Questions: In this part, the users will make suggestions about how to improve the visuals.
- Comparison Questions: In this part, the users compare the options and choose which one they find the most and worst useful compared to other visuals or whether they prefer cluster or full data visuals.

After sending the survey to users, the implemented Python file was sent to all the participants since spider chart is interactive. Thus, each user had to run the code from their local computers. After seeing the visuals, the users answered the questions on Google Form survey.

Later, the ANOVA and chi-squared test analysis were made by the scipy Python library in order to prevent the human error while doing the calculations (Rajagopalan, 2021).

4.2 Visualizations

In this subsection, 6 visuals will be presented.

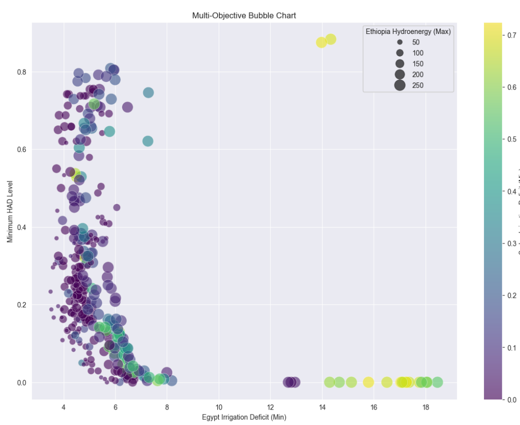

Figure 1: Bubble Chart

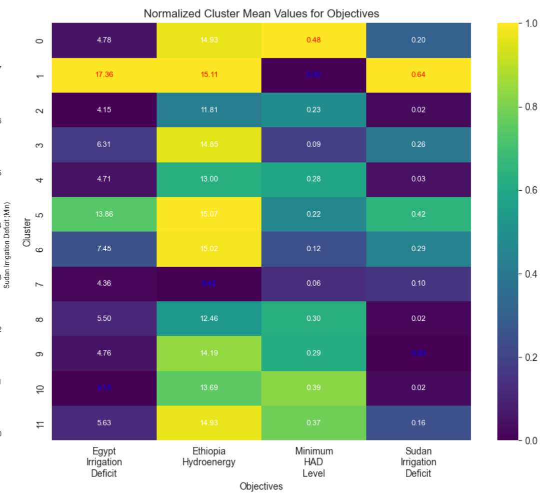

Figure 2: Heat Map

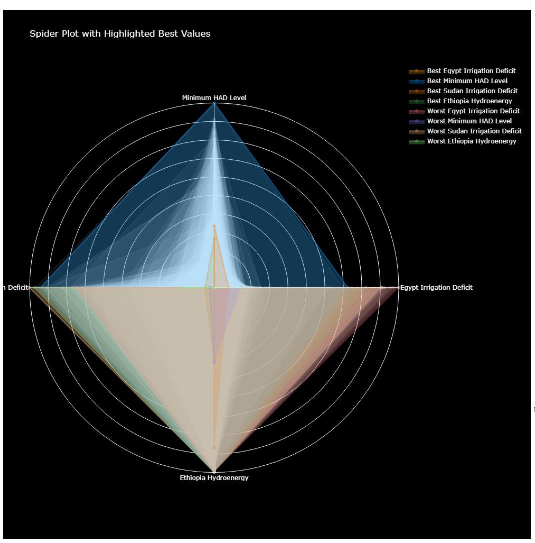

Figure 3: Spider Plot

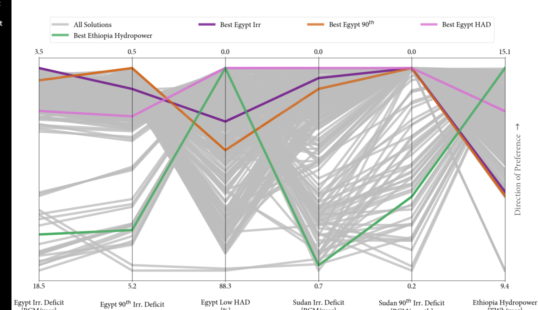

Figure 4: Parallel Coordinates Plot

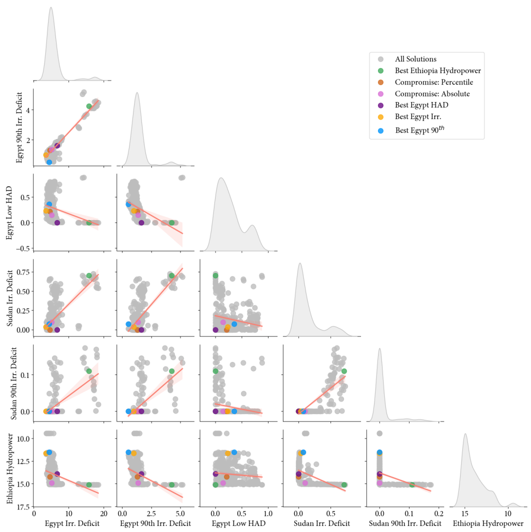

Figure 5: Pair-wise Scatter Plot

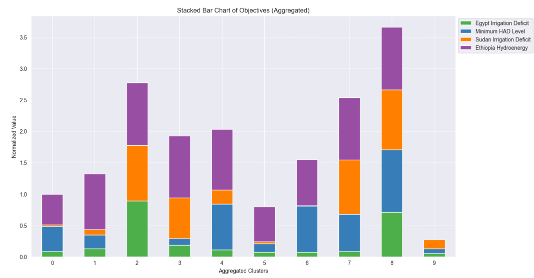

Figure 6: Stacked Bar Chart

For the bubble chart, bubble size represents the amount of energy produced in Ethiopia. Bubble color represent the water deficit in Sudan. The color is changing from min to max by the change from purple to yellow. X axis of the graph represents the water deficit in Egypt. Y axis of the graph represents the water level in the HAD dam.

For the heat map, X axis represents the objectives and Y axis represents the clusters. The data was clustered by k-means to make it more visible. Each data represent the objective mean of the elements in that cluster. The value is getting closer from min to max by the change from purple to yellow. The red texts represent the maximum values and blue texts show the minimum values for each objective.

For the stacked bar chart, X axis represents the clusters and Y axis represents the sum of objectives normalized value. K-means clustering method is used to visualize the results clearly.

For spider plot, Each axis represents different objective. To provide more information, the best and the worst values of each objective were added to the visual. Plotly library was used to make this visual interactive (Stančin & Jović, 2019). Hence, the bests and the worsts can be hidden to see the visual more clearly. Besides that, some people had some problems about running the Python file. That's why, it might affect some users' results.

For the parallel coordinates plot, the values at the top show the best for the objectives, and bottom show the worst for the objectives. The solutions with a best objective value were colored differently.

For the pair-wise scatter plot, there are 6 objectives. The pairwise comparison can be shown in a matrix form like this visual.

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4.3 User Evaluation

This subsection gives information about the quantitaive and qualitative results. For the quantitative analysis, the general result table,chi-square value, Anova values can be found in this section. The specific results can be found in Appendix D and Appendix E.

For the qualitative analysis, the general result table, and specific results can be found in this section.

4.3.1 Quantitative Results

One graph was made for each visual to show the rating in 2 different aspects - clarity, usefulness. X axis represents the criteria and y axis represents the rating. These ratings were calculated by taking the average ratings of all the answers. Microsoft Excel was used to calculate the standard deviation, median, mean (Appendix D).

For the comparison results, 3 visuals were made, which are the preference between full data points and cluster points, the most preferred visual, and the least preferred visual. The first visual shows a pie chart for showing the ratio of preferred option between clustered and full data points. For the last 2 visuals, x axis represents the name of the visuals and y axis represents the amount of people who choose that visual for either the best or worst (Appendix E).

The last 2 visuals show more detailed results. The table shows the mean,median and standard deviation of both clarity and usefulness, and the mean of these 2 sub-ratings. The graph shows the average rating of each visuals after taking the average of the sub-criteria.

Visualization Type	Clarity Mean	Clarity Median	Clarity StDev	Usefulness Mean	Usefulness Median	Usefulness StDev	Most Useful	Worst Useful	Overall Mean
Bubble Chart	3.1875	3	1.0468	3.375	3.5	1.0247	0	3	3.2813
Stacked Bar Chart	4.25	4.5	0.9309	3.875	4	1.2042	5	1	4.0625
Heat Map	4	4	1.0954	3.875	4	1.0247	2	1	3.9375
Spider Plot	2.625	2	1.2583	2.6875	3	1.0145	0	11	2.6563
Pairwise Plot	3.5	4	1.1547	3.9375	4	1.1815	4	0	3.75
Parallel Coordinates Plot	4	4	0.6325	4	4	0.8944	5	0	4.75

Table 1: Final Results

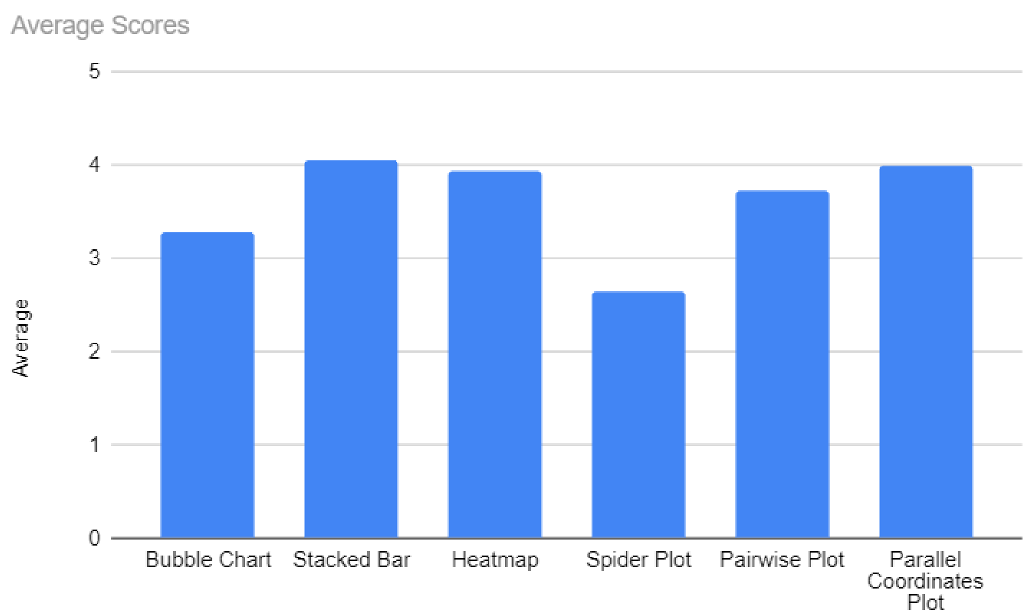

Figure 7: Result

After calculating all these results, F-statistics were used for clarity and usefulness separately to see whether there is a preferred option or not among all the visuals. Next, chi-squared test was implemented to see whether there is a preferred option between full points and cluster points.

- F - statistics for clarity: 4.669985775248935
- F - statistics for usefulness: 3.4190860215053753
- Chi-squared value:0.0

4.3.2 Qualitative Results

Thematic analysis was used for analyzing qualitative results. For the next 6 tables, the first column represents the name of the suggestion and the second column represents the frequency of the suggestion.

Bubble Chart

Theme	Frequency
Add a label	2
Clusterize data	1
Incompatibility between bubble color and size	2
Complex data representation	4
Color distinction	1
Unnecessary amount of data	1
Unclear naming	1
Wrong X-Y axis selection	1
Log scale on X axis	1

Table 2: Bubble Chart

Heat Map

Theme	Frequency
Mismatch between text color and box color	4
Suitability for color blind people	2
Confusion due to mix objectives (Max,Min)	2
Highlight the best solution	1
Unnecessary amount of data	1
Confusion due to clustering	1

Table 3: Heat Map

Stacked Bar Chart

Theme	Frequency
Not clear trade-offs	3
Descriptive caption	1
Confusion due to mix objectives (Max,Min)	4
Suitability for color blind people	1
Confusion due to clustering	2

Table 4: Stacked Bar Chart

Pairwise Plot

Theme	Frequency
Initial understanding	2
Complex data representation	2
Not clear trade-offs	1
Unnecessary amount of data	1
Color distinction between line color and data points	1
Not show correlation if it is not meaningful	1

Table 5: Pairwise Plot

Spider Plot

Theme	Frequency
Complex data representation	5
Not clear trade-offs	3
Color distinction	4
Too many highlighted scenario	1
Add the objective values	1

Table 6: Spider Plot

Parallel Coordinates Plot

Theme	Frequency
Highlight the worst	2
Suitability for color blind people	1
Observing multiple paths	1
Bigger texts	1
Not clear gray parts	2
Add the objective values	1
Highlight the best solution	1
Unnecessary amount of data	1

Table 7: PCP

The suggestions can be combined in 4 main suggestions, which are visual accessibility, complex data representation, data representation, and additional insights. In this general table, the general theme represents the main suggestions, second table represents the names of the suggestions which are elements of the main suggestion, and finally the last column represents the frequency of the main suggestion.

General

General Theme	Themes	Frequency
Visual Accessibility	Suitability for color blind people, Mismatch between text color and box color, Color distinction, Incompatibility between bubble color and size, Color distinction between line color and data points, Not clear gray parts,	18
Complex Data Representation	Complex data representation, Confusion due to clustering Not clear trade-offs, Confusion due to mix objectives (Max, Min), Initial understanding problem, Unnecessary amount of data, Wrong X-Y axis selection, Log scale on X axis, Too many highlighted scenario, Not show correlation if it is not meaningful	37
Data Presentation	Add a label, Descriptive caption, Clusterize data, Unclear naming, Add the objective values, Bigger texts	8
Additional Insights	Observing multiple paths, Highlight the worst, Highlight the best solution	8

Table 8: General Results

5 Discussion

This chapter will discuss the obtained results from the visuals and the user evaluation. In the first sub-section visuals will be mentioned. In this part, detailed analysis about each visual will be given. In the sub-section, detailed discussion about both quantitative and qualitative analysis will be noted.

5.1 Visuals

According to the bubble chart, even though the HAD level and Egypt deficit are not correlated, bubbles are small when water deficit in Egypt is small. In addition to that, bubble chart shows that water deficit in Sudan is usually zero. That is why, it is mostly purple. However, it is changing when the bubbles are getting bigger and Egypt water deficit is increasing at the same time.

According to the heat map, it can be concluded that the second cluster has the max value in Egypt deficit, Sudan deficit, and Ethiopia energy, also the min value in the minimum HAD level. This shows that second cluster is only effective for Ethiopia and not effective for the other 2 countries.

It can be concluded from the spider plot that the max value for Ethiopia energy is also increasing the water deficit of Sudan and Egypt and decreasing the minimum water level in HAD. Thus, it can be seen it is only beneficial for Ethiopia. Besides that, in general, although Egypt water deficit is high when Ethiopia power generation is high, Sudan water deficit usually stayed the same even Ethiopia produced high energy. Furthermore, when the minimum water level in HAD is high, the water deficit in Sudan and Egypt are usually low.

According to the stacked bar chart, there can be seen that ninth cluster has a high value for all the objectives, which is good for HAD level and Ethiopia energy generation, but bad for water deficit in Sudan and Egypt.

In the pairwise scatter plot, it can be concluded that there is a negative correlation between the Ethiopia energy and the other objectives. Furthermore, there is a positive correlation between water deficit in Sudan and Egypt. Lastly, this visual shows that there is a negative correlation between Egypt Low HAD and all the other objectives.

Finally, the PCP shows that water deficit in Sudan and Egypt have a positive correlation while they have negative correlations with Ethiopia energy generation. Water level in HAD and Ethiopia energy generation do not have a correlation at all.

5.2 User Evaluation

This sub-section includes two parts: Qualitative and quantiative analysis. For the quantitative analysis, mean, standard deviation of the results will be analyzed first. Later, Anova and chi-square tests will be analyzed.

For the qualitative analysis, thematic analysis for each objective will be given.

5.2.1 Quantitative Analysis

Chi-squared test was used to determine whether users preferred between full data points or cluster data points. According to the results, 8 people preferred full data points and 8 people preferred cluster data points, and thus, the chi-square value is 0 between them. This shows that there is no preferred option among cluster data points and full data points. However, the sample size was slightly less than the sufficient amount for chi-squared testing.

According to the user evaluation, the most preferable to the least preferable order is Stacked Bar, PCP, Heat Map,Pair-wise, Bubble Chart,and Spider Plot.

In terms of clarity scoring, Stacked Bar had the highest score (4.25) while Spider Plot had the lowest (2.625). In addition to that, PCP had the lowest standard deviation (0.6325), and Spider Plot had the highest standard deviation (1.2583). This shows that even though stacked plot had the highest clarity score, people gave more similar ratings for PCP. Furthermore, spider plot had the lowest ratings and also least stable visual compared to others.

In terms of Usefulness, PCP had the highest score (4) while spider plot had the lowest (2.6875). In addition to that, PCP had the lowest standard deviation (0.8944), and Stacked Bar Chart had the highest standard deviation (1.2042). This shows that for PCP was the favourite option for usefulness because of the highest usefulness score and lowest standard deviation while spider plot had the lowest usefulness rating, and stacked bar chart had the highest standard deviation value.

Although, stacked bar chart's average rating is slightly higher than that for PCP, both visuals are equally preferred, with each receiving 5 preferences.

ANOVA analysis is made for both sub-ratings. For the clarity , F-value is 4.669985775248935. Furthermore, F-value is 3.4190860215053753 for the usefulness. It can be concluded that, there are significant differences between the visuals for both clarity and usefulness, since F-values are higher than 1. Thus, all the visuals are not equally effective in terms of clarity and usefulness.

5.2.2 Qualitative Analysis

From the thematic analysis, it can be concluded that the majority of the improvement suggestions for 6 visuals were came from the complex data representation with 37 suggestions, while 18 suggestions were received from the visual accessibility and both data presentation and additional insights had 8 suggestions.

For the bubble chart, 4 suggestions were about the complex data representation. It is because 4 variables were tried to fit in 2D visual, which is usually used for 2 variable comparison. Thus, it made the visual complex and made it hard to observe the trade-offs.

For the heat map, 4 suggestions were about the mismatch between text color and box color. It is because the standard text color was white, while blue text was used to highlight the minimum objective values, and red text highlighted the maximum objective values. Additionally, the objective value transition from minimum to maximum objective values was represented by colors changing from purple to yellow. This often resulted in problematic color combinations, such as purple box color and blue text color. For this reason, more compatible color combinations need to be used.

For the stacked bar chart, 4 suggestions were about the confusion due to mix objectives (Min,Max). It is because even though, the objective values were normalized to make the visual clearly, all the objectives do not have the same purpose. Some objective goals are maximisation, while some objective goals are minimisation. Thus, the objective's bar value had to be related to the objective's goal, not only related to the number itself.

For the spider plot, 5 suggestions were about the complex data representation and 4 suggestions were made for the color distinction. Since there are many best values and worst values for this visual, the color choice is very important to make the visual clear. For this case, it was not liked by the users. Thus, more distinct colors need to be chosen. In addition, to make the data representation less complex, some of the highlighted alternatives can be removed.

For the parallel coordinates plot, 2 suggestions were about the highlighting the worst objectives as well. This could be added to the visual to provide more information about the trade-offs.

For the pair-wise scatter plot, 2 suggestions were about the initial understanding of the linear trend lines. It can be either removed from the visuals or can be added to visuals which have a meaningful correlation between the objectives.

6 Responsible Research

In order to make this research responsible, we obtained a permission from Yasin Sari to use Pair-wise Scatter Plot and Parallel Coordinates Plot visuals, as well as his data from the Exploring Trade-offs in Reservoir Operations through Many Objective Optimisation: Case of Nile River Basin thesis for the comparison of visuals. The team worked transparent and collaboratively with the supervisor and professor. All the information found from internet were cited correctly.

In order to improve the visualisation approaches, ChatGPT was used when the useful information could not be found on the internet. All the data which were used can be found online, that's why, none of the sensitive information was shared with ChatGPT.

7 Conclusions and Future Work

To conclude, this paper focused on the different visualization techniques to show the multi-objective reinforcement learning results, which were gathered from the Nile River simulation. Related works were first discussed, then methodology, later results, and finally discussions and responsible research were mentioned in this paper. The visualization techniques, bubble chart, stacked bar chart, heat map, and spider plot were implemented and in addition to those parallel coordinates plot and pair-wise scatter plot were taken from Yasin's thesis for the comparison for the user evaluation. As a result, parallel coordinates plot and stacked bar chart performed the best according to the user evaluation. In addition, pairwise plot and heat map still performed effective in general. However, the spider plot and bubble chart performed lower compared to the other options. ANOVA test showed that there is a significant preferred option among the 6 visuals. Chi-square test showed that there is not a preferred option between clustered and full data points. In short, the multi-objective reinforcement learning results are complex to show because of its vector results instead of a single result, but the visuals, such as parallel coordinates plot, stacked bar chart or heat map, either with cluster or showing all the data points, can be used to visualize the trade-offs more effectively.

For the limitations, one of the example can be given about chi-squared test. The sample size needs to be at least 5 times more than the number of cells in the experiment (McHugh, 2013). In this experiment, 16 people participated and there are only 4 cells, which are prefer cluster, prefer full data, do not prefer cluster, and do no prefer full data. Hence, the sample size needs to be increased for the further research. Besides that, some users had several problems about running the Python file for spider plot. In the further researches, instead of providing the programming file, the video of the interactive visuals can be provided to make the user evaluation less risky.

8 References

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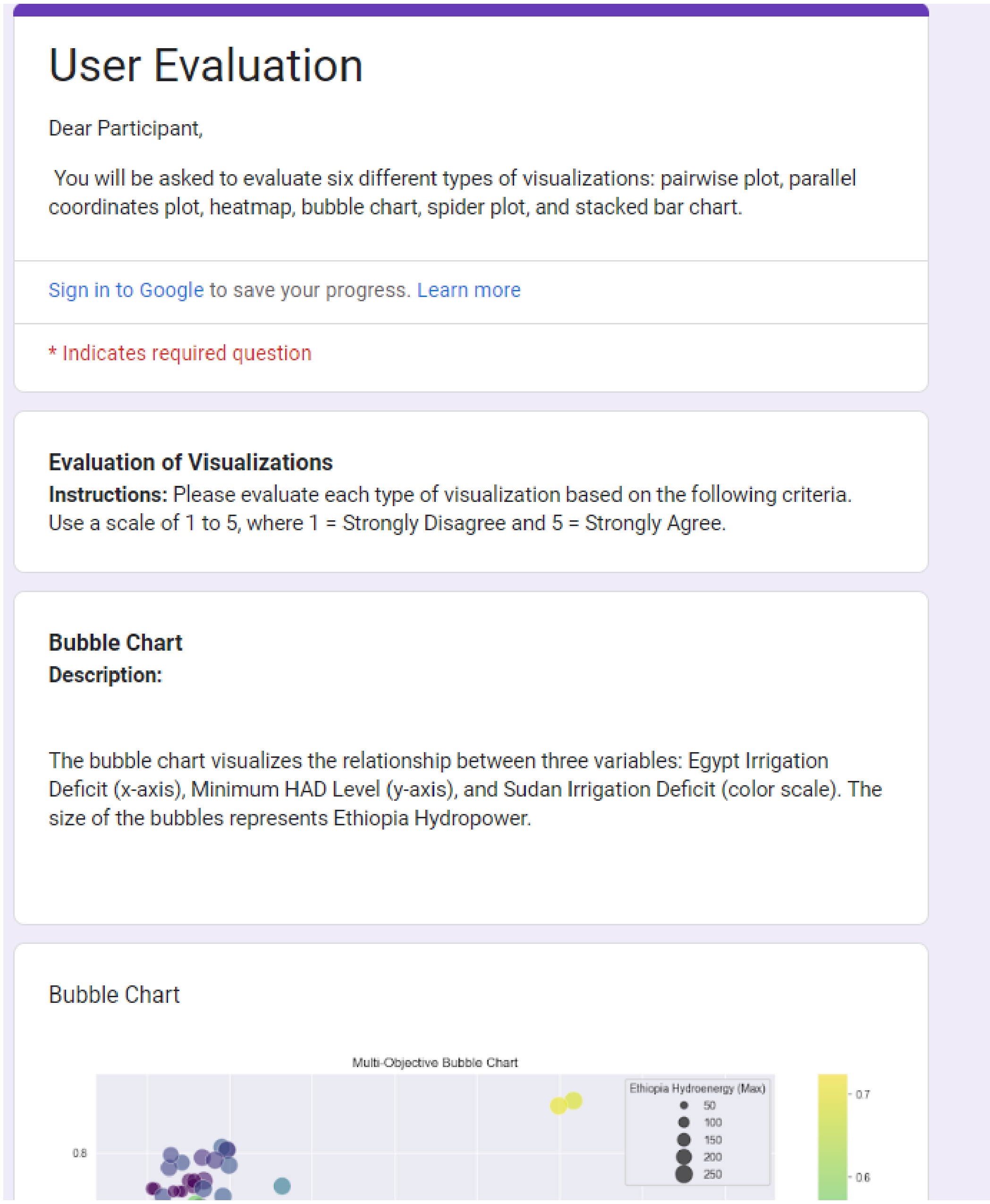
9 Appendices

9.1 Appendix A


User Evaluation

Dear Participant,

You will be asked to evaluate six different types of visualizations: pairwise plot, parallel coordinates plot, heatmap, bubble chart, spider plot, and stacked bar chart.

Sign in to Google to save your progress. Learn more

* Indicates required question

Evaluation of Visualizations

Instructions: Please evaluate each type of visualization based on the following criteria. Use a scale of 1 to 5, where 1 = Strongly Disagree and 5 = Strongly Agree.

Bubble Chart

Description:

The bubble chart visualizes the relationship between three variables: Egypt Irrigation Deficit (x-axis), Minimum HAD Level (y-axis), and Sudan Irrigation Deficit (color scale). The size of the bubbles represents Ethiopia Hydropower.

Bubble Chart

Figure 8: Introduction

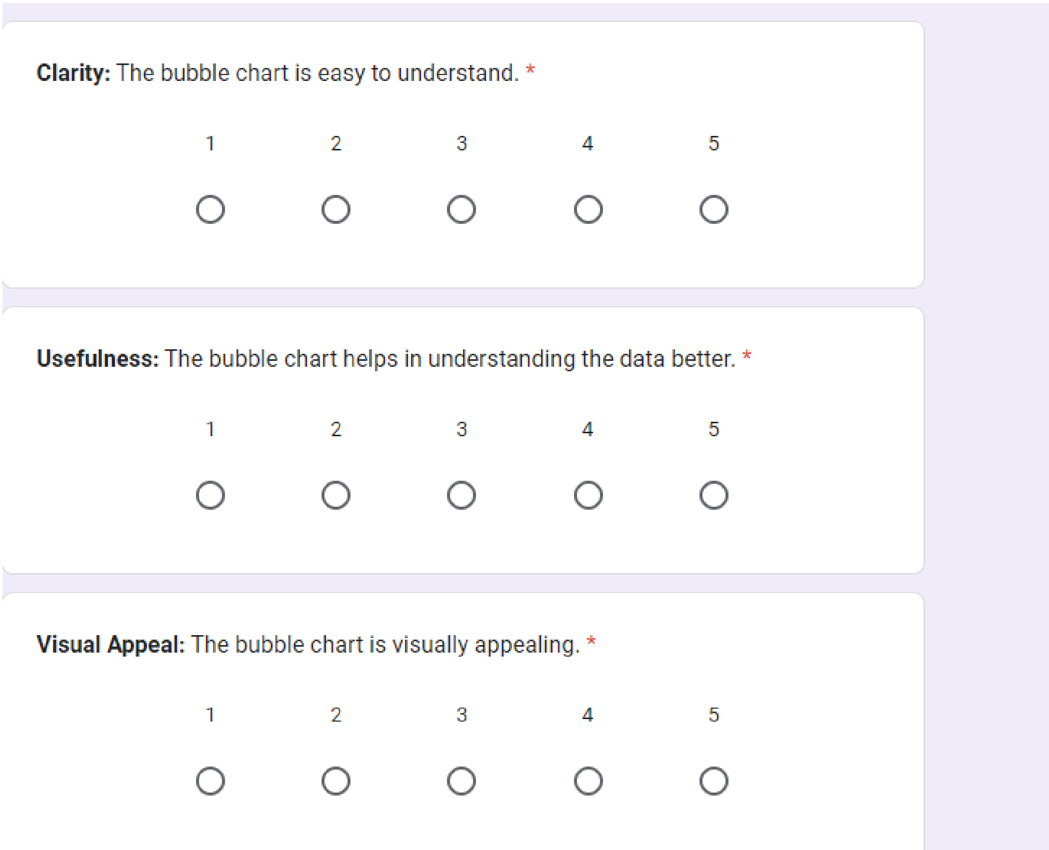
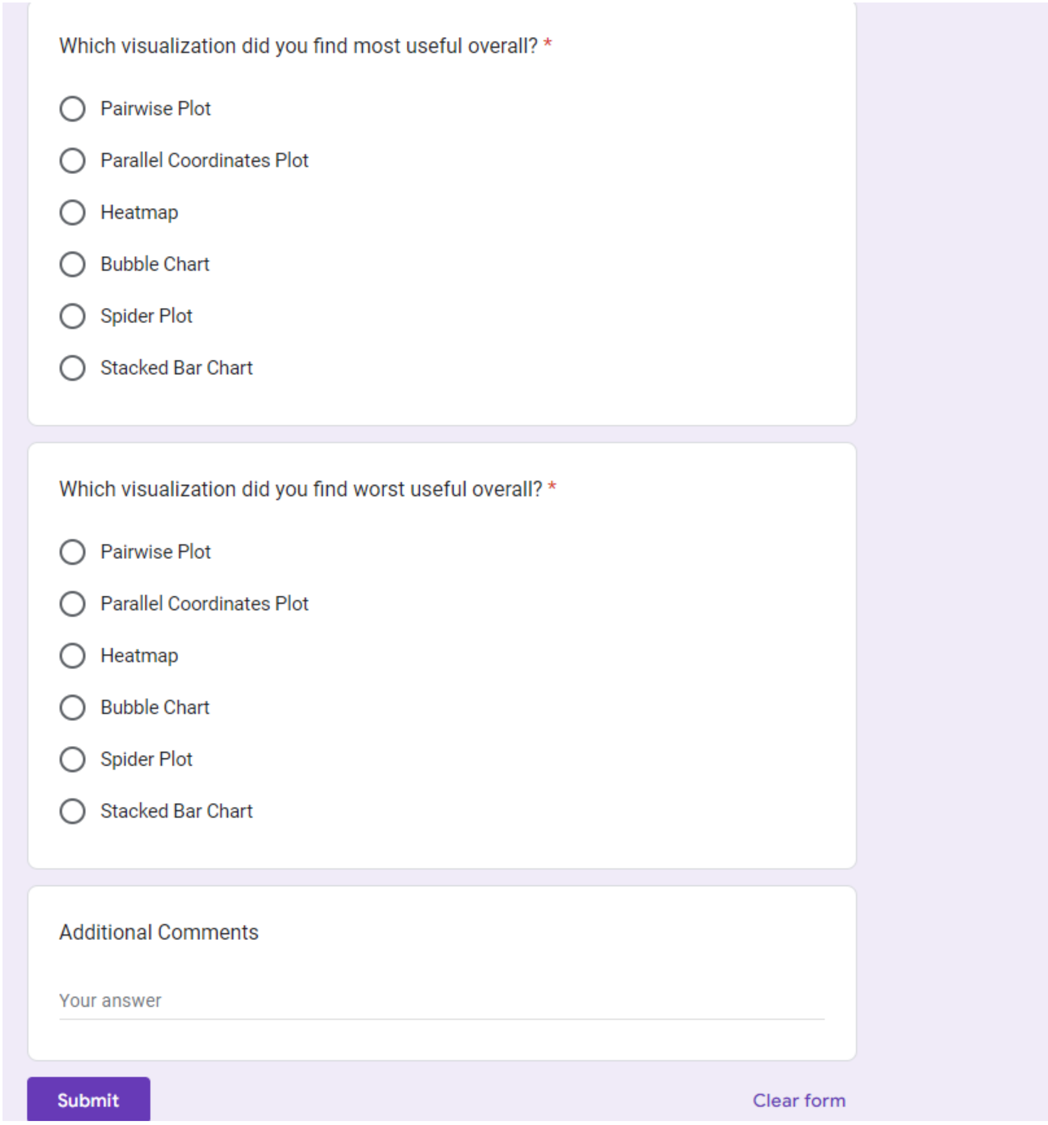


Figure 9: Question Types



Which visualization did you find most useful overall? *

- ◯ Pairwise Plot
- ◯ Parallel Coordinates Plot
- ◯ Heatmap
- ◯ Bubble Chart
- ◯ Spider Plot
- ◯ Stacked Bar Chart

Which visualization did you find worst useful overall? *

- ◯ Pairwise Plot
- ◯ Parallel Coordinates Plot
- ◯ Heatmap
- ◯ Bubble Chart
- ◯ Spider Plot
- ◯ Stacked Bar Chart

Additional Comments

Your answer

Submit

Clear form

Figure 10: Ending

9.2 Appendix B

$$SSW = \sum_{i=1}^{k}\sum_{j=1}^{n_i}(Y_{ij} - \bar{Y}_i)^2 \quad SSB = \sum_{i=1}^{k} n_i(\bar{Y}_i - \bar{Y})^2 \quad dfB = k - 1 \quad dfW = n - k \tag{1}$$

$$MSB = \frac{SSB}{dfB} \quad MSW = \frac{SSW}{dfW} \quad F = \frac{MSB}{MSW} \tag{2}$$

where:

$$\begin{aligned}
n &= \text{Total sample size} \\
SSW &= \text{Sum of squares within groups} \\
SSB &= \text{Sum of squares between groups} \\
dfB &= \text{Degrees of freedom between groups} \\
dfW &= \text{Degrees of freedom within groups} \\
MSB &= \text{Mean square between groups} \\
MSW &= \text{Mean square within groups} \\
F &= \text{F-statistic} \\
k &= \text{Number of groups} \\
n_i &= \text{Sample size of group } i \\
Y_{ij} &= \text{Value of the } j\text{th observation in the } i\text{th group} \\
\bar{Y}_i &= \text{Mean of the } i\text{th group} \\
\bar{Y} &= \text{Overall mean of all groups}
\end{aligned}$$

9.3 Appendix C

$$E_{ij} = \frac{M_R \times M_C}{n} \quad \chi^2 = \sum \frac{(O_{ij} - E_{ij})^2}{E_{ij}} \quad df = (r-1) \times (c-1) \tag{3}$$

where:

$$\begin{aligned}
n &= \text{Total sample size} \\
E_{ij} &= \text{Cell expected value in row } i \text{ and column } j \\
MR &= \text{Sum of that cell's row} \\
MC &= \text{Sum of that cell's column} \\
df &= \text{Degrees of freedom} \\
r &= \text{Row count} \\
c &= \text{Column count} \\
O_{ij} &= \text{Actual count for cell in row } i \text{ and column } j \\
\chi^2 &= \text{Total Chi-squared value}
\end{aligned}$$

9.4 Appendix D

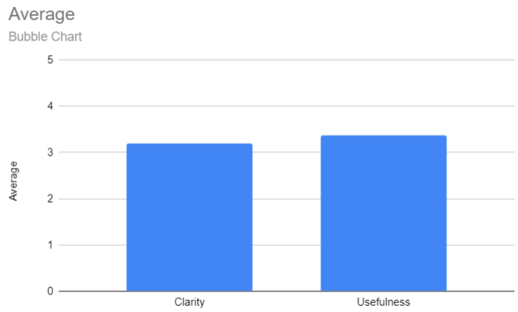


Figure 11: Bubble Chart

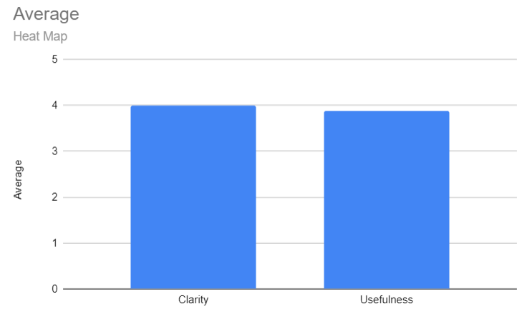


Figure 12: Heat Map

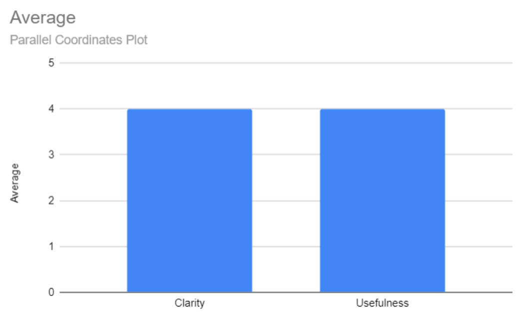


Figure 13: PCP

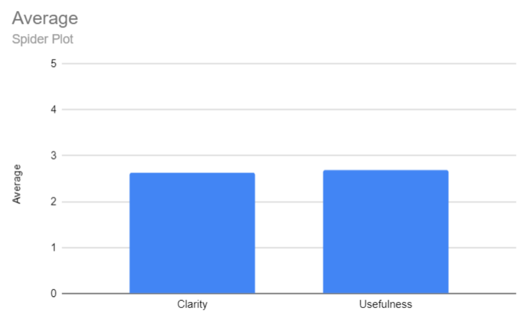


Figure 14: Spider Plot

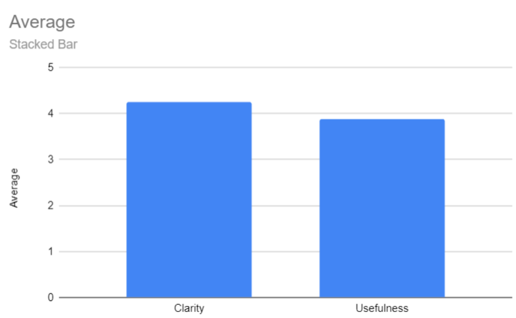


Figure 15: Stacked Bar

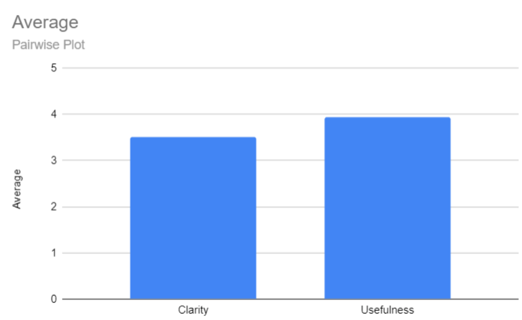


Figure 16: Pairwise Plot

9.5 Appendix E

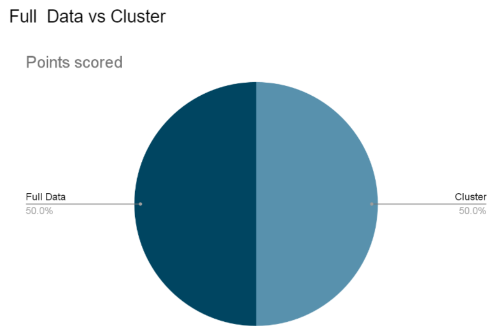


Figure 17: Full Data vs Cluster

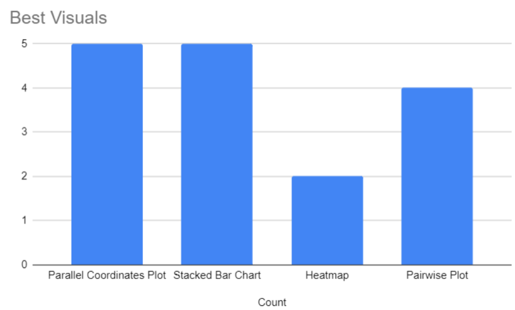


Figure 18: Best Visual

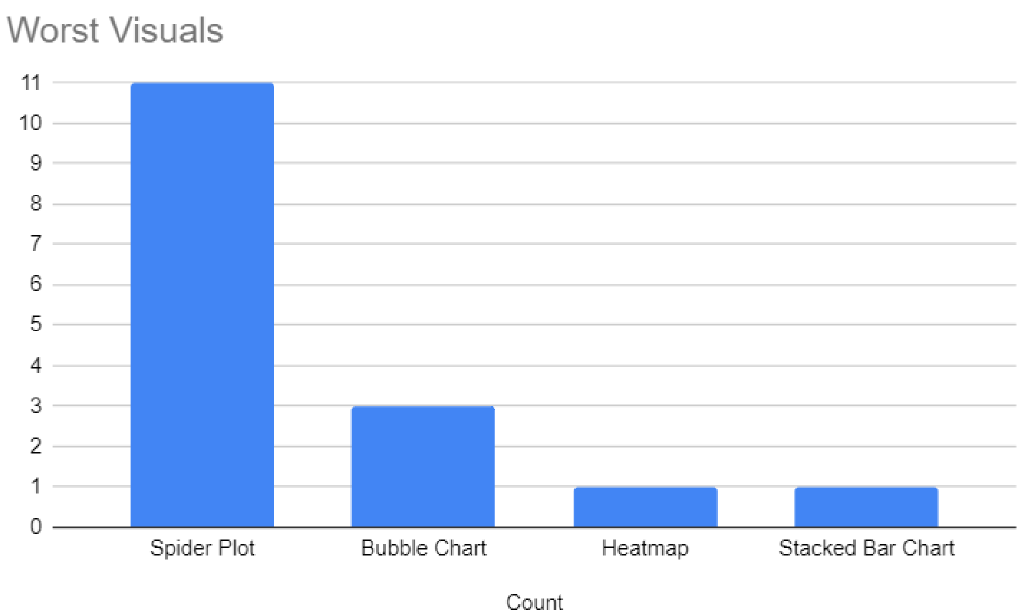


Figure 19: Worst Visual