Interactive Narrative Visualization for Learning Markov Decision Process

B. Mbuu Mutua
Computer Laboratory
University of Cambridge
bmm51@cam.ac.uk

Alan F. Blackwell
Computer Laboratory
University of Cambridge
Alan.Blackwell@cl.cam.ac.uk

Abstract

This paper asks how we can use visualization tools to help learners develop intuition on probabilistic programming and how Markov Decision Processes (MDP) algorithm models problems in probabilistic planning. The project seeks to address this question by presenting a novel pedagogical technique that brings together visualization, use of interactive interfaces and a practical application of the semantic wave theory in a learning environment. We also present an evaluation study with university students in Kenya, focusing on use of narrative for teaching in that context.

1. Introduction

This paper adds to the existing literature on probabilistic planning and modeling using Markov Decision Process (Alagoz, Hsu, Schaefer, & Roberts, 2010), but on the perspective of computing and programming education. To fashion our motivation as a research question; how can we use visualization tools to help learners develop intuition for how Markov decision processes works and its use in probabilistic planning? This project seeks to address this question, by presenting a novel pedagogical technique that brings together visualization, use of interactive interfaces in computing and programming education and a practical application of the semantic wave theory (Maton, 2013) in a learning environment.

1.1. Research Objectives

The objectives of this paper can be stated in three points as follows:

1. To advance the acquisition of probabilistic reasoning and planning skills among undergraduate computer science students through an introduction of a novel technique of learning Markov Decision Process (MDP) as an important concept in Artificial Intelligence.

2. To further the work done by other researchers in the field on Computing and Programming Education especially on integration of digital aids/tools with learning;

3. To lay a foundation for the long term learning of probabilistic programming which underlies the idea of probabilistic planning and modeling. Numerous problems in AI and in real life necessitate that the agent operates with incomplete or uncertain information.

1.2. A brief review of Markov Decision Process (MDP)

For probabilistic planning, MDP uses a parametric probability distribution (Mausam & Kolobov, 2012) to model the various states that the agent or decision maker goes through while it transitions from the initial state to the final state of the planning environment. Through this distribution, we get a clearly defined mechanism of how an action taken at one state leads to another state; whereas a reward function determines the cumulative reward values the decision maker receives from the actions they have taken and the states they have transitioned through to get to the current state.

Since the determination of what action is to be taken is done at the current state, the whole MDP planning process is guided by the Markov Property, that is; For a stochastic process, the probability distribution of future states depends only on the present state (there are no dependencies on previous states or actions) (Khoshnevisan & Schilling, 2016).

In the interactive visual interface we have developed as an implementation of the ideas presented in this paper, we achieve that by presenting an interactive state chart to the learners as the first point of contact with the tool.

The state chart (which can be recreated to model different scenarios) introduces the learners to Markov Decision Process planning using well labeled states, actions, transitions and rewards, but more importantly, the concept of Markov Property where decisions are made at each state independent of prior actions or states.

1.3. Semantic Wave Theory

Semantic Wave Theory (Maton, 2013), a framework invented by Karl Malton as part of the Legitimation Code Theory project, describes a process where concepts are presented to learners with language that changes from technical to simple meanings and back (Curzon, 2019). Semantic wave theory has been used to structure learning across numerous disciplines since its invention, and it has been applied in computing and programming education with tremendous success.

A semantic wave illustrates the learning transition between the abstract and highly condensed technical explanation of a concept to the concrete, contextualised and simple language used to unpack the abstract concept and help learners understand it (Waite, Maton, Curzon, & Tuttiett, 2019).

Computing education, especially programming, is a subject that has benefited hugely from this theory since it has more than its fair share of technical terms (Curzon, Waite, Maton, & Donohue, 2020). These jargons form the basis of abstract concepts in Semantic Wave Theory. Learners are tasked with understanding these terms well while still applying them in programming exercises.

To illustrate the application of the Semantic Wave Theory in a pedagogical setting, when an educator walks into a class and introduces the concept of probabilistic planning using Markov Decision process (MDP), the learners are at the top of the semantic wave as the educator defines the technical terms such as uncertainty, probability distribution, transition function, state space, reward function and so on.

To help learners descend the semantic wave, the educator might give a day to day example of a student who wishes to plan their day that is full of demanding activities with the goal of saving as much time as possible to attend a movie show in the evening. Such student needs to come up with an optimal plan of how she will attend to both indoor and outdoor activities, factoring uncertainties such as the possibilities of rain falling any time of the day or the movie theatre management cancelling the show or a lecture taking longer than planned.

The educator must then go further to help the learners link this practical contextual scenario back to the abstract concept of probabilistic planning using Markov Decision Process (MDP); otherwise the wave will be incomplete. This will take the learners from the bottom of the wave where the language is contextual, back to the top of the wave where the educator can introduce more technical terms.

1.4. Computer Science Education in non-western settings

Use of visualization tools developed on digital interfaces is a practice that is gaining traction in education in general, but more so in computing education (Rosminah, 2013; Blackwell et al., 2019; Maloney et al., 2004). Computer science and programming education in Kenya, like in many other non-western settings, is done mainly using the traditional techniques of lectures and occasional lab sessions.

Research on the pedagogical approaches and resources invested towards this goal is still very limited; just like in many other sub Saharan African countries (Engineer Bainomugisha & Irungu, 2023), perhaps due to the sub-population disparities as outlined in the Capacity for, Access to, Participation in, and Experience of computer science education (CAPE) Framework (Fletcher & Warner, 2021).

In a pilot study carried out to understand computing education in four sub-Saharan African countries (Botswana, Kenya, Nigeria and Uganda) (Tshukudu et al., 2023), the authors collected data from teachers in these countries to investigate the resources available to them and the curriculum for computing, vis-a-vis teachers from developed countries.

The results showed that access to resources by teachers in these countries was alarmingly low as compared to teachers from other regions. Further, the authors argue that because of such reasons, there were very little efforts put by the teachers to teach algorithms and programming as compared to education settings in high-income countries (Tshukudu et al., 2023).

With the increasing penetration of digital devices among the student population in these countries, there is a very good cause for shifting the pedagogical approach towards use of digital interfaces, visualization and smart learning interactive screens (Morgado & Kahn, 2008). This approach has so far met tremendous success in the western setting where we find most high income countries, and in this project work we work towards the goal of creating one such learning tool tailored for a non-western education setting.

Our interactive tool for learning Probabilistic Planning using Markov Decision Process (MDP) received positive rating from the learners, and as we show in study results section of this paper, learners who used our interface to learn Probabilistic Planning and MDPs scored significantly higher points in a standardized test than those who depended on books and lectures.

2. Related work

2.1. Use of Visualization and Interactive Interfaces in Computing and Programming Education

In his work on the importance of Visualization in Education, Veřmiřovský (Veřmiřovský, 2013) argues that visual representation of concepts achieves very high level of clarity regardless of other factors such as the language used, difficult level and understanding ability of the learner. This has informed it's widespread use in all scientific fields including technology, construction, engineering, and architecture, just to mention a few (Veřmiřovský, 2013).

In relation to this work, one closely related project that we have drawn great inspiration from is by Erwig and Walkingshaw 2013 ("erwig2013Vis", n.d.). The authors of this work borrow the concept of explainable AI to present an explanation based and domain specific platform for visualizing probabilistic reasoning. On this platform, well understandable metaphors in form of stories that take the users of the tool through the steps involved in solving a probabilistic reasoning problem are presented. For interactivity, the in-coded programs in the platform can be edited to generate different versions of the same explanation.

In a different but closely related work on the use of digital interfaces in computing education, Blackwell et al (Blackwell et al., 2019), describe an approach to learning conditional probability in the context of Bayesian framework. This visual teaching tool (the spinner app) that is developed to be interactive, seeks to engage the the Ju|'hoan people who live in the Namibian region of the Kalahari, in probabilistic reasoning. The spinner app shows a number of spinners representing a binary choice with two sectors of different likelihood. The spinners flick on tapping the screen, and the app visually records the results of each 'tap' on a row of tally marks which accumulate over time, and a pie chart that shows the corresponding proportion of each outcome.

In (Zainab Attahiru, 2022), the authors build on the above work by Blackwell et. al. 2019 (Blackwell et al., 2019) to propose an interface for visualizing Bayesian probability in a school in Nigeria where the dynamics of learning and the pedagogical approaches differ from those found in a typical western education setting. The authors develop and present a web application that introduces users to the concept of Bayesian reasoning with the main goal being to nudge the users into the realization of importance of evidence in their beliefs.

2.2. Application of Semantic Wave Theory in Computing and Programming Education

Semantic wave Theory (Maton, 2013) has been successfully applied in education particularly in teaching computing and programming and has had revolutionary impact (Waite et al., 2019; Curzon et al., 2020). In a study published by the National centre for Computing Education on "Improving explanations and learning activities in computing using semantic waves" (Curzon, 2019), the authors argue that Semantic Wave Theory has had a far reaching impact in teaching programming through the use of unpacking / repacking techniques to decrease the complexity and precision of terminologies that have for long acted as hindrance to understanding of different programming paradigms by learners.

In “Teaching London Computing: Application of Semantic Waves” project, Curzon P, 2019 (Curzon, 2019) argues that programming, being a very technical subject with a lot of precise technical vocabulary to learn, requires a multifaceted approach in teaching, and making explanations and learning activities follow the semantic wave structure is a successful way of making the learning experience unforgettable.

Further, the author of this article cautions against flatlining when using semantic wave theory. Flatlining is a term given to a scenario where the teacher moves along same level of abstraction in the whole lesson. In a semantic profile, this can manifest as either high flatlining (Waite et al., 2019) – where explanations are done using completely technical language, as found in conversations involving experts, or low flatlining (Curzon et al., 2020) – where the educator makes everything overly simple using contextual language.

2.3. Use of narrative as a Tool in Learning

Narrative (also known as storytelling), is an implicit cultural practice in Africa and has been a medium of passing information from one generation to another for centuries (Osei-Tutu, 2022; Huber & Jonaitytė, 2020). Numerous studies conducted in the western culture also attest to the use of narrative as a tool of knowledge sharing not only in past centuries but also in modern era (Dimaculangan, Hadji Abas, & Quinto, 2022; Guillemin & Heggen, 2011; Hoggan & Strong, 1994; Ironside, 2006) So much is this practice prevalent that Butcher, S. 2006 in her work on “Narrative as a Teaching Strategy (Butcher, 2006)” explores narrative as a medium of teaching in modern educational setting, its effectiveness, and the role it plays in teacher and student connection, validation of student experience, and student perspective. The conclusion of this study is that narrative/storytelling is a practice so intertwined in education that it occupies two thirds of teacher student interactions in the form of examples, metaphors and explanations.

Similar observations have been made in several other studies (Forrest, Keener, & Harkins, 2010; Rogers, Marshall, & Tyson, 2006; Zander, 2007). The authors in (Dreon, Kerper, & Landis, 2011) also support Butcher’s conclusion on the influence narrative has in education, and goes ahead to argue that the shift from traditional storytelling to digital storytelling through YouTube as witnessed in recent times should offer teachers a platform to reach their students by creating educational content videos. A similar call is made by the authors of (Chung, 2007) and (Hung, Hwang, & Huang, 2012).

Scott Christian University Computer Science undergraduate students, who are the target users of our learning tool and where the evaluation study was done, come from different economic backgrounds ranging from agricultural practices, pastoralists communities, small business traders, transport sector and fishing. We targeted these backgrounds because a story related to any of them will work well in unpacking and explaining a technical concept.

For instance, the first scenario narrative that introduces the concepts of state space, action space and reward function in Markov Decision Process (MDP) tells a story of a cattle farmer who visits a business store to purchase milking jelly for his cows. The farmer has to satisfy constraints of time, sequentially chose an action at each step (in the face of multiple options) that take him to different states, while still maximizing his reward points for shopping in that particular store.

Whereas this story might look simplistic and slightly out of scope in a class that teaches probabilistic planning using Markov decision process, it is more relevant to a student who has grown up in agricultural practice environment than a story talking about robots and agents that might be of help to another student in a western education setting.

3. Implementation

3.1. Policy Graphs generation

The end product of a probabilistic planning process is a policy graph that outlines the sequential order of states and actions a decision maker need to take from the initial state to the goal state. With probabilistic

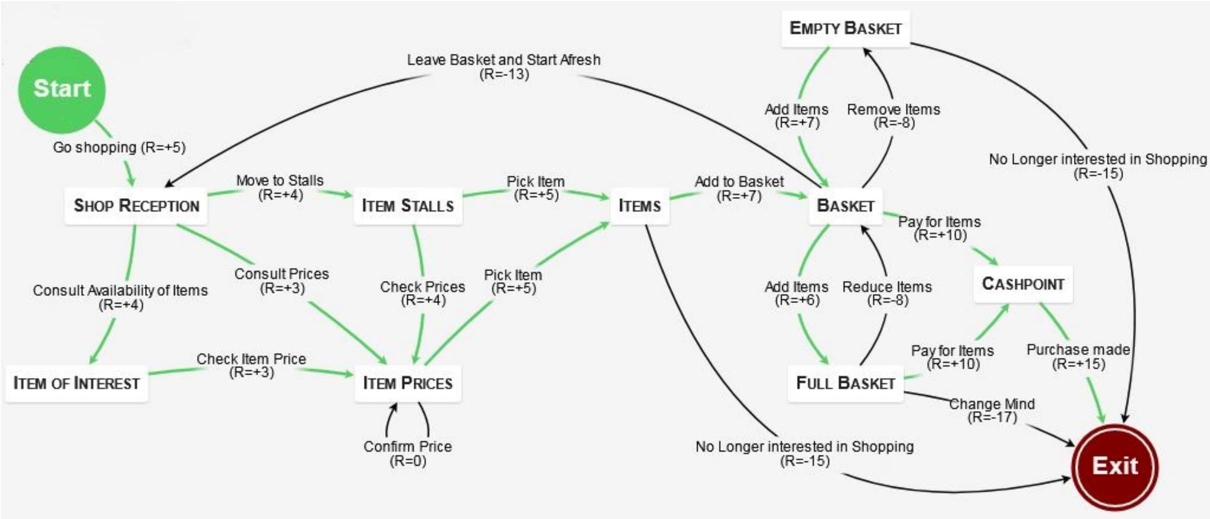

Figure 1 – Snippet of the MDP state Chart on our interface

planning using Markov Decision process, this policy graph presents the optimal set of states with their associated actions, all determined from the probability distribution that maps state space to action space, and the associated accumulative reward calculated using the reward function. Our interface is integrated with a policy graph generator algorithm that is developed using the RStan Probabilistic Programming Language (Guo, Gabry, Goodrich, & Weber, 2020).

3.2. Narrative

As explained in the background section of this report, semantic wave theory is based on two key components: abstract concept and concrete context. The section went further to justify our choices of Probabilistic Planning using Markov Decision Process as abstract concept and narrative as our concrete context presentation. Narrative is one of the core features implemented on our interactive interface to augment the learning experience of our educational tool. It also distinguishes our learning tool from hundreds of other tools used in computing and programming education.

3.3. User Interface Development

The user interface of our tool has mainly three sections: a Markov Decision Process state chart with well labeled actions, states and rewards, a JavaScript Object Notation script linked to the dimensional specifications of the state chart, and a narrative section that breaks down the abstract concepts of the MDP and which is connected to a probabilistic programming language policy graph generator algorithm.

The MDP state chart story-boards a typical shopping experience in a Kenyan Supermarket. The green transitions are for progress and they have positive reward values, while black transitions are for regress and they have zero or negative reward values. This chart introduces the learner to the concepts of state space, action space and reward function, where the learner can visually see the goal of probabilistic planning which is optimization of rewards or minimization of penalties/costs associated with each action. The business environment that the above chart is based on was chosen to align with the target user's daily encounters. Business education is a common subject taught to students in all programs in Scott Christian University in Kenya, and therefore it was prudent for the learning of probabilistic planning using MDPs to be based on a typical trip to a shopping mall by the students. That way the concepts would be easily relatable to the learners.

This state chart is developed to be interactive such that users can use drag and drop method to reorder the states and transition links and recreate a whole new scenario. This is handled by the controller program.

3.4. Optimal Policy Graphs Generation Algorithm

The outcome of a probabilistic planning process is an optimal policy. Optimal policies can be shown using an equation, a matrix or graph. For the sake of visualization, we chose to illustrate the optimal policies in our interface using state graphs. That justifies our integration of the optimal policy graph generator with the narrative section of our interface. Users can view a scenario and by a click of a button display the optimal policy graph generated from that particular scenario.

For this project, we sought a probabilistic programming environment where we could encode our state space, action space, probability distribution and reward function. We found RStan's Partially Observable Markov Decision Process (POMDP) library a perfect fit for our project. RStan is a combination of R and Stan, or simply put, the R interface to Stan (Guo et al., 2020). Stan is a probabilistic programming language extended from BUGs, while R is a free software environment for statistical computing and design.

4. Experimental Study Design

4.1. Target Users of our interface

Our interface was developed with the following target group in mind: Undergraduate Computer Science students in an institution based in a non-western learning environment; in particular, a university based in Kenya, where the cultural practices of the people are significantly different from those found in western countries.

We chose Kenya because there is no recorded use of interactive interfaces in computing and programming education, and therefore evaluation of our interface in the country's learning institutions is likely to give us an unbiased feedback on the efficacy of our tool in facilitating understanding of concepts.

4.2. The host institution

To achieve the goals of this project, Scott Christian University in Kenya was chosen as the study venue. The reason behind this choice is that the first author of this paper was a lecturer of computer science at the institution between 2019 and 2022 (just before joining the University of Cambridge), and therefore understands the teaching practices at the institution, and in Kenyan universities in general. This host institution was also settled at in order to reduce the bureaucracy common in Kenyan institutions of higher learning when requesting for approval to conduct these kinds of studies. This study was carried out on 12th April 2023 inside the Scott Christian University Computer Lab 1, between 10 AM and 1 PM.

4.3. Participants Recruitment

Probabilistic planning and Markov Decision Process being sub topics in Artificial Intelligence, we saw it prudent to recruit undergraduate computer science students taking Artificial Intelligence subject in the January to April 2023 semester at Scott Christian University. AI in the university's computer science department is taught when the students are in their third year of study (computer science program takes 4 academic years at the institution).

It is worth noting that apart from the undergraduate computer science program, the CS department also offers another related undergraduate program namely Bachelor of Business Information Technology (BBIT). These two programs have several common subjects, one of them being Artificial Intelligence, taught to students in both groups in their third year. For this study, I recruited both groups as participants because they were all taking Artificial Intelligence in the January to April 2023 semester. The Bachelor of Science in Computer Science group has 30 students, while the BBIT group has 17 students. All students in these two groups were present for the study, making the total number of participants in the study 47.

4.4. Set up of the study

For easy access the interface was hosted on the internet and the link and login details given to the participants. The venue where this study was conducted (Scott Christian University Computer Lab 1) has 53 desktop computers all connected with internet, and this made access to our interface challenge-free. However, some students requested to be allowed to access the interface using their tablets, for comfort.

Since the purpose of this study was to understand the impact of a digital interactive interface in facilitating understanding of computing concepts vis-a-vis the conventional method of teaching, the two groups of participants in this study were taught probabilistic planning and Markov Decision Process using the two different techniques. This was done on the material day of study (12th April 2023) between 10 AM and 11 AM. I used our interface to take the first group of participants through the concepts. This group comprised of students taking BSc Computer Science (30 students). The second group made of students taking BBIT (17 students) were taken through the topic by the means of a lecture by Dr. Ratemo, a senior lecturer in the computer science department of Scott Christian University. Both groups were then combined to tackle tasks testing their understanding of the concepts.

4.5. The Study Tasks

There were two set of tasks tackled by the participants. The first set consisted of the tasks on the interface, and required participants to perform the following:

1. Interact and recreate (model) a planning situation on the interface
2. Describe and illustrate the probabilistic planning process given a scenario in a narrative on the interface
3. Trace the optimal set of states and actions that take the decision maker from the initial / start state to the final state earning maximum rewards
4. Given a scenario in form of a narrative, identify the action space, state space, probability distribution of actions over the states, and the reward function
5. Analyse given scenarios and plot optimal policy graphs clearly showing the states, actions, related rewards and probability distributions

Participants who completed the tasks within the set time were allocated points according to the level of accuracy attained. For the tasks that required the participants to describe / illustrate a probabilistic planning process by plotting an optimal MDP policy graph, sheets of paper were distributed to the participants for writing the responses and collected at the end of the study for marking.

For the second set of tasks in the study, the participants who used our interface to learn (those in group one) were issued with evaluation survey forms with items that they were required to rate between 1 (Strongly Agree) to 5 (Strongly Disagree). These evaluation items were set to cover major usability areas of the interface:

1. Its success in facilitating the understanding of probabilistic planning and MDP concepts (without the learner needing to have studied the concepts elsewhere)
2. The ease of using the interface, for instance, was it easy to navigate across the sections of the interface?, likability (color, interface design etc), and user comfort while using it
3. Relevance of the text presented on the narratives, for instance, were the scenarios relatable?, was there excess/unnecessary text on the interface?
4. Accessibility, for instance, did the interface load on each device used?, were there any significant delays in loading (apart from those caused by a device's processing capacity)?
5. Lastly, the open comment section. This asked the participants for their opinions on the interface. For instance, there were questions such as: What did you like most about the interface? Which part interested you the least? Please suggest ways we can improve this tool

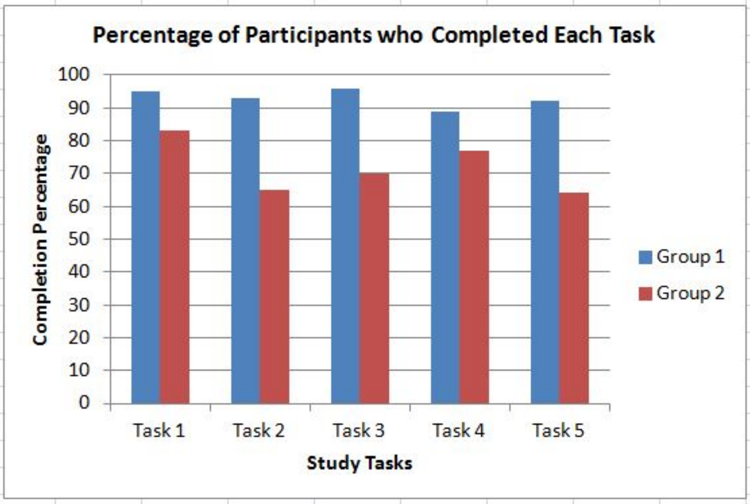

Figure 2 – A Bar Chart showing the percentage of participants who completed each task, from both groups

5. Study Results

The two groups of participants were taken through the concepts using two different techniques (one group learnt using our interface while the other learnt through the conventional method of a class lecture). Therefore, administering a standardized test to both groups was a sure way of finding out which group understood the concepts better and what the impact of our tool in learning is.

The results of the first section of the study that engaged participants in solving probabilistic planning tasks using Markov Decision Process concepts were analyzed based on a number of parameters. Such parameters included the number of students who were able to complete the tasks on time in each of the two groups, the response accuracy achieved by participants in each of the groups, and the average scores attained by participants in the two groups. Since both moderators of this study (Dr. Ratemo and I) have been examiners in the department for years, setting time for each task was not a challenge, and was done in a way that does not limit the participants' ability to tackle the study tasks, but at the same time encourages competence and quick thinking.

The bar chart in Figure 2 plots the percentages of participants from each group who completed the specific tasks within the set time. The results have been presented using percentage in order to avoid bias that might arise due to the difference between the numbers of participants in the two groups.

Still on the completion rates, we also sought to compare the two groups on the total tasks completion rate. That is, of all the participants who completed the five tasks within the set time, how many were part of group one and how many were part of group two. In total, 29 participants completed all the tasks in the study within the set time. 20 were from group one, whereas 9 were from group two. Since the higher number of total participants in group one influenced this composition, our interpretation of these results will be based on the ratio of total participants in group one to the total participants in group two. That way the bias attributed to the different numbers of participants will be eliminated. These completion rates translates to 62 percent and 38 percent for groups 1 and 2 respectively.

Lastly and equally important are the scores of the participants on each of the tasks in the first part of the study. Again to avoid bias, the results have been converted into average scores of the participants from each group and in each of the five tasks. The total scores of all the group members on a certain task are put together and then divided by the number of members; 30 for group one and 17 for group two. These scores are presented in the plot in Figure 4.

To ascertain that the differences between the task completion rates of group one and group two resulted from the effectiveness of our learning interface and not from a random variation, we conducted a chi

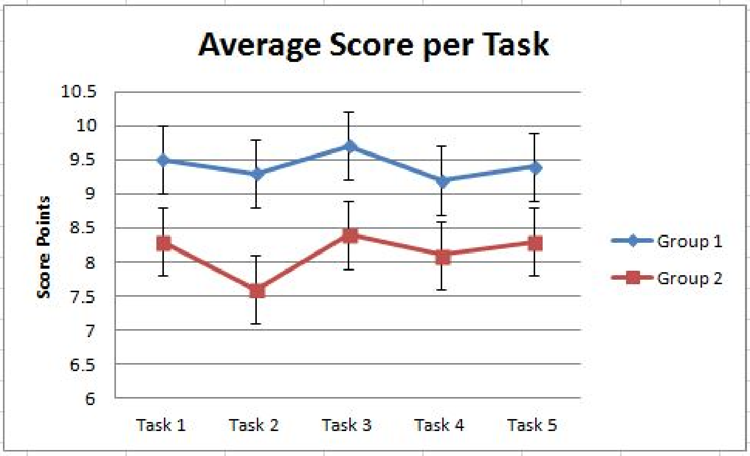

Figure 3 – A Plot of the average scores attained by participants of both groups in each task, with Error Bars of 1 Standard Deviation

square test of independence and a T-Test on the percentages of completion attained by both groups for each task. We conducted the test with 0.05 as the set level of significance (alpha value) and 4 Degrees of Freedom. The chi-square test gave us a P - value of 0.020728, while from the t-test we obtained a p-value of 0.023, both of which are below our set significance value of 0.05.

For the interface usability evaluation which was the second part of the study, 29.3 participants (on average) out of 30 strongly agreed that our interface facilitated their understanding of the presented concepts better than their current way of learning. On the ease of using the interface, 28.7 participants on average strongly agreed that the tool is easy to use, and transitioning from the basic concepts to the intermediary understanding to the more complex details was seamless.

The relevance of the material on the interface including the narratives scored equally high among the participants, with averagely 29.5 participants agreeing that the materials are highly relevant. All participants in this second part of the study were able to access the learning tool from their devices; therefore our interface recorded an accessibility score of 30 (out of 30). Lastly, the most common comments on the open comments section of the survey form were: "create an interface for other difficult concepts", and "digital learning interfaces are more effective than books".

We conclude:

- That our learning interface is more effective in facilitating understanding of probabilistic Planning and Markov Decision Process concepts as compared to the teaching method of lectures and textbooks.
- That the majority of participants (who are current undergraduate students) are more inclined towards learning using interactive interfaces as compared to the traditional and conventional method of books and lectures.

6. Conclusion and Future Work

6.1. Conclusion

This project work has built a case for the use of Markov Decision process (MDP) to model probabilistic planning problems. The project has gone ahead to fill the gap created by the absence of any existing work that creates a visualization of this concept (Probabilistic Planning using Markov decision Process). An interactive learning interface developed as an implementation of ideas in this report has also been presented.

This interface, as it has been proven in the paper, is an effective tool for teaching the concepts in an Artificial Intelligence class. This has been shown through results of an evaluation study conducted with participants recruited from an undergraduate computer science program in Scott Christian University in Kenya. The results show that participants who used the interface to learn the concepts scored three times higher in a standardized test than those who learnt the concepts through lectures and books. This attests to its efficacy.

6.2. Future Work

Subsequent work on the use of visualization, interactive interfaces and narratives in computing education will need to address the pertinent issue of scope. Whereas a text book takes learners from basic understanding to the complex concepts linking the ideas in between with everything else that the learner needs to understand, most interfaces used in education are too focused on the concept they seek to teach. Although this focus is their beauty, most often they leave the learners with knowledge gaps that have to be filled for the tool to be useful.

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