How to Teach Machine Learning in an Engaging Way

An Analysis of Machine Learning Teaching Methods Aimed at Student Engagement

Mihnea Liute[1]

Supervisor: Gosia Migut

[1]**EEMCS, Delft University of Technology, The Netherlands**

A Thesis Submitted to EEMCS Faculty Delft University of Technology,
In Partial Fulfilment of the Requirements
For the Bachelor of Computer Science and Engineering
June 21, 2024

Name of the student: Mihnea Liute
Final project course: CSE3000 Research Project
Thesis committee: Gosia Migut, Mark Neerincx

Abstract

Machine learning education often involves complex topics that can be challenging to teach engagingly, leading to difficulties in maintaining student focus and achieving optimal learning outcomes. This study aims to bridge the gap between machine learning-specific teaching techniques and those centred on student engagement by conducting a comprehensive analysis of related works and an empirical experiment. The related works section reveals differences between traditional and engagement-focused teaching methods. To address the knowledge gap regarding the impact of engagement-focused methods on learning outcomes, a controlled experiment was conducted, comparing a conventional 16-minute video lecture followed by practice questions against the same content divided into four shorter video segments, each followed by a subset of the practice questions. The results demonstrate that the experimental group achieved significantly higher average quiz scores and reported consistently higher satisfaction ratings, suggesting that even a simple engagement-boosting technique can substantially improve learning outcomes and student satisfaction in machine learning education. This study highlights the importance of prioritising student engagement as the field of machine learning continues to evolve.

1 Introduction

The subject of Machine Learning presents a number of complex topics, which can prove problematic to teach in a way that helps students maintain their focus and achieve good learning outcomes. Indeed, there are a number of academic papers calling for further research into teaching methods for this subject [1] [2] [3] [4].

In this context, the necessity of teaching methods focused on increasing student engagement seems like a foregone conclusion. However, there has been little research to test this safe-seeming yet important assumption [1]. Traditionally, teaching techniques for Machine Learning education and teaching techniques centred on student engagement have been studied separately.

The current body of research on machine learning education brings together many different approaches and perspectives. The AI-Atlas of Stadelmann et. al [5] emphasises foundational understanding, practical skills, active learning and real-world relevance as key to effectively teaching machine learning to an interdisciplinary audience with diverse backgrounds and career goals. Meanwhile, Sanusi et. al [6] find that learner-centered pedagogies focused on active participation, collaboration, real-world projects, and accessible tools are most effective at introducing machine learning concepts to K-12 students, with the report advising the use of a mix of instructional lectures and hands-on, interactive methods. In terms of teaching methods focused on student engagement, there are studies that suggest that the introduction of interactivity increases viewing time and completion of video lectures [7]. At the same time, gamification is put forward as an effective way of increasing student engagement [8].

Understanding the current teaching methods and practices for machine learning is crucial for educators and researchers seeking to improve the accessibility, effectiveness, and relevance of machine learning education. By examining the similarities and differences between traditional and engagement-focused teaching techniques, the strengths and limitations of each approach can be identified. This knowledge allows for the development and refinement of instructional strategies that cater to the diverse needs and backgrounds of students. Furthermore, by investigating the impact of different teaching methods on learning outcomes and student satisfaction, evidence-based decisions can be made to optimise machine learning curricula and create more engaging, inclusive, and impactful learning experiences.

The purpose of this research is to to bridge the gap between the teaching methods specific to machine learning and those focused on student engagement. It aims to do so by analysing current scientific literature on the two suites of teaching methods, then conducting an experiment to gauge the impact of an engagement-oriented approach. Finally, conclusions will be drawn on the extent to which engagement-focused teaching methods can improve learning outcomes within Machine Learning education.

Research Question

In attempting to bridge this knowledge gap, the research question of this paper is "To what extent do Machine Learning teaching methods focused on student engagement improve learning outcomes as measured by test performance and student satisfaction?"
From this research question, three sub-questions arise:

1. What are the teaching techniques and best practices currently used in Machine Learning education? What is their approach to student engagement?
2. Which teaching methods are effective at fostering student engagement? How they compare to the established machine learning teaching methods?
3. How do the two suites of teaching methods compare in terms of resulting test results and student satisfaction?

Once the initial two sub-questions have been answered through analysis of related works, the third will be answered by means of an experiment.

2 Related Works

A deeper understanding of current teaching practices lays the foundation for shaping the future of machine learning education and preparing students to become competent and creative practitioners in this rapidly evolving field.

2.1 The Current Paradigm for Teaching Machine Learning

Traditional teaching methods for machine learning have primarily been geared towards students in computer science or related technical fields. These methods often involve abstract mathematical concepts, algorithms, and software-based demonstrations [9] [10]. Lectures, textbooks, and screen demos are common tools used in this approach, which may be less accessible or engaging for students without a strong affinity for technology or mathematics [9] [10].

The focus of traditional methods tends to be on theoretical understanding and software implementations, with less emphasis on hands-on, practical applications [10]. This approach may not always adequately address the needs of students from non-technical backgrounds, such as design students, further emphasising the need for more engaging teaching techniques to become commonplace in machine learning education [10].

2.2 Teaching Methods for Machine Learning Geared Towards Fostering Student Engagement

In recent years, there has been a growing interest in developing teaching methods that foster student engagement and make machine learning more accessible to a broader range of learners. These engagement-focused approaches often incorporate hands-on, interactive learning experiences using tangible tools, such as robotics kits, and emphasise project-based learning [11]. One notable example is the embodied intelligence method, which allows students to interact with and understand learning systems through tangible experiences, making abstract concepts more concrete and accessible [10]. By leveraging familiar tools and positive associations, engagement-focused methods can lower barriers and increase motivation for students who may not have a strong technical background [10].

Stadelmann et al, in The AI-Atlas [5], present a coherent set of best practices for teaching AI and machine learning. It emphasises the importance of engaging students through a combination of objectivist and constructivist pedagogies. This approach involves starting with objectivist-style lectures to build a solid technical foundation and then transitioning to more constructivist, project-based learning [5]. Other engagement-focused methods include the use of visual tools for teaching machine learning. By integrating machine learning capabilities into popular block-based programming environments, these visual tools provide a low threshold for entry, allowing students to quickly create meaningful projects that leverage machine learning models, while also offering opportunities for more advanced exploration [12].

In a particularly striking instance, a Kaggle competition was successfully used to teach machine learning to master's students [4]. By creating a fun social learning environment, a great increase in student engagement was achieved, leading to better levels of motivation, satisfaction and ultimately to improved learning outcomes in the form of deeper understanding of the subject matter by students. While this particular study's findings are based on the experiences of teaching staff, the overwhelmingly positive results led the author to call for further research using more rigorous methods.

2.3 Comparative Analysis

This analysis of relevant scientific works reveals significant differences between the approaches and emphases of traditional and engagement-focused teaching methods for machine learning. Traditional methods, geared primarily towards computer science students, emphasise theoretical understanding, abstract mathematical concepts, and software implementations [9] [10]. Lectures, textbooks, and screen demos are common tools, which may be less accessible or engaging for students without strong technical backgrounds [9] [10].

In contrast, engagement-focused methods prioritise hands-on learning, accessibility, creativity, and practical problem-solving [10] [11] [5] [12]. These approaches aim to make machine learning more engaging and relevant for a diverse range of students, including those from non-technical fields [10] [5] [12]. The AI-Atlas highlights the importance of combining objectivist lectures to build a solid technical foundation with constructivist, project-based learning [5]. Visual tools and block-based programming environments have emerged as powerful means to engage students, offering low barriers to entry and opportunities for creative exploration [12].

While traditional methods focus on theoretical understanding and software implementations, engagement-focused methods emphasise hands-on, interactive learning experiences using tangible tools and project-based learning [10] [11]. Engagement-focused approaches also prioritise accessibility and relevance for students from diverse backgrounds, whereas traditional methods tend to cater to those with strong technical or mathematical skills [9] [10].

Despite these differences, both approaches recognise the importance of addressing programming concepts and providing a solid technical foundation [5] [9]. However, engagement-focused methods go further in fostering creativity, practical problem-solving, and making machine learning more accessible and relevant to a broader range of students [10] [5] [12].

To better understand the effectiveness of engagement-focused methods in improving learning outcomes compared to traditional approaches, further research and experimental studies are needed [9]. By examining the impact of different teaching methods on student learning and satisfaction, educators can make evidence-based decisions to optimise machine learning curricula and create more engaging, inclusive, and impactful learning experiences [9] [5] [12].

3 Methodology

Building upon the similarities and differences between traditional and engagement-focused teaching techniques for machine learning, it is essential to investigate whether engagement-focused methods lead to improved learning outcomes compared to the traditional teaching paradigm. To address this question, an experimental study was designed to directly compare the two instructional approaches.

Participants will be divided into two groups, each exposed to either traditional or engagement-focused teaching methods. To ensure a fair comparison, both groups will be assessed using the same quiz, evaluating their understanding and application of machine learning concepts. Additionally, participants will be asked to provide feedback on their satisfaction with the learning experience, offering insights into the perceived effectiveness of and satisfaction with each teaching approach.

This combination of quantitative and qualitative metrics allows for a rigorous evaluation of the benefits of engagement-focused teaching methods in machine learning education, as called for in papers based on the experiences of teaching staff [4].

3.1 Experiment Design

An experiment involving two groups will be carried out, comparing two instructional approaches. The first group (control group) will be exposed to a conventional 16 minute video lecture covering the basics of the concept of artificial neural networks, followed by 14 practice questions, a satisfaction survey and a quiz. In contrast, the second group (experimental group) will engage with the same video lecture and practice questions, but broken down into four parts, each consisting of a roughly four minute video followed by three or four practice questions. Finally, the experimental group will complete the same satisfaction survey and quiz as the control group (See Figure 1). Notably, both groups were presented with the answers to the set of 14 practice questions after they had filled in the satisfaction survey, but before being asked to complete the quiz.

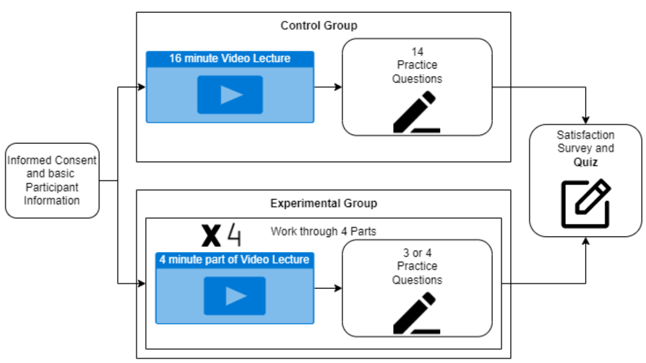


Figure 1: Diagram depicting the Experiment Design. The control group watches a 16 minute video, followed by 14 practice questions, while the experimental group engages with the same materials, but broken down into four parts, each consisting of a four minute video followed by three or four practice questions. Finally, the same satisfaction survey and quiz are administered to both groups.

By subjecting participants to distinct teaching methods and gathering both quantitative performance metrics and qualitative feedback, the practical ramifications and effectiveness of the pedagogical strategies will be evaluated and contrasted.

In attempting to study the impact of different teaching methods on learning outcomes, using the same teaching materials and teaching the same topic to both the control and experimental groups is imperative in order to achieve a controlled experiment. Since the same materials have to be used to teach the same subject, a between-subjects design is the only option for this experiment.

To motivate the choice of an introduction to artificial neural networks as the topic to be taught in this experiment, multiple factors come together. Firstly and most importantly, this is one of the topics within machine learning with relatively broader appeal, presumably making it more feasible to attract participants with a genuine interest in learning. Secondly, according to Sulmont el. al, it is not algorithms, but higher-level design decisions that are difficult to teach to students without a background in machine learning [13]. For this reason, the choice was made to use Grant Sanderson's introduction to neural networks [14], which, while it touches upon a few technical aspects, has its main focus trained on imparting an understanding of the principles and design decisions that underpin a multi-layer Perceptron.

The video lecture covers several key aspects of artificial neural networks, including:

1. The fundamental concept of artificial neurons.
2. The structure of neural networks as layers of these artificial neurons.
3. How pixel values can serve as an input layer for image processing tasks.
4. The role of weights and biases in shaping the network's behavior and outputs.
5. The application of linear algebra as a mathematical framework for representing and manipulating neural networks.

The quiz questions, identical for both groups, are based on the contents of the video lecture, and are presented to participants in increasing order of complexity. Following Bloom's taxonomy, the first two questions ask the participant to remember some basic aspects about artificial neural networks, while the third requires some understanding of the topic. Building upon that, the last three questions ask the participant to apply their knowledge by engaging in problem solving, with the level of difficulty increasing from accessible to moderate and finally to challenging.

3.2 Participant Inclusion Criteria

The experiment will enrol university students from various non-computer science disciplines to ensure a diverse and representative sample. Informed consent will be obtained from all participants, ensuring they understand the study's purpose, procedures, risks, and benefits. Participation will be strictly voluntary, with no coercion or undue influence from teachers or researchers. Inclusion of participants from different backgrounds will be emphasised in order to promote diversity, reduce bias, and foster inclusivity.

3.3 Participant Exclusion Criteria

Participants who declared prior knowledge of machine learning and neural networks will be excluded to ensure a uniform baseline understanding across the sample. Only individuals above 18 years of age will be enrolled to ensure legal capacity to provide informed consent. A requirement will be imposed for participants to have a self-reported English language proficiency better than 5 out of 10 to ensure they can comprehend the teaching materials adequately.

To safeguard participants' well-being and privacy, several exclusion criteria will be applied. Those unable to provide informed consent or follow study procedures due to cognitive impairments will not be enrolled. Participants whose data, if kept and shared, could lead to their personal identification, will be excluded. Finally, the experiment will be conducted anonymously, with no personal information other than gender, age group and educational level being collected.

Technical Setup

The experiment will be carried out using Microsoft Forms to host the learning material and quiz. First, informed consent will be asked, then some relevant background information about the participant, followed by presenting the instructional content and practice questions. Finally, the participants will be asked to rate their satisfaction with various aspects of the teaching method, and then they will be presented with the quiz. The results will be stored in Microsoft Onedrive, processed using Microsoft Excel and Python and presented in this report by means of charts made in Microsoft Excel and Python.

4 Responsible Research

4.1 Ethical Aspects

This study has been designed and conducted with a strong emphasis on research integrity and ethical principles, in alignment with the TU Delft Vision on Integrity 2018-2024 and the Netherlands Code of Conduct for Research Integrity 2018. Approval of this study from the TU Delft Human Research Ethics Committee has been applied for and is pending as of the time of writing. Informed consent was obtained from all participants, ensuring their understanding of the study's purpose, procedures, risks, and benefits. The voluntary nature of participation was emphasised, and no coercion or undue influence was exerted by teachers or researchers.

To promote inclusivity and avoid bias, participants from diverse backgrounds were included, ensuring a representative sample. Participants' privacy was protected by keeping the experiment entirely anonymous and excluding individuals whose data could potentially lead to their identification. The well-being of participants was prioritised by making it clear that every part of the experiment is entirely optional and carries no consequence to participants, thus minimising the risk of psychological distress.

4.2 Reproducibility of Methods

Transparency and reproducibility were key considerations throughout the research process. The study's design, methods, and data analysis have been clearly described in Section 3 of this report, facilitating replication and verification by other researchers. Proper data management practices were followed, ensuring secure storage and accessibility of data for future use. Results have been reported accurately, completely, and objectively, including any limitations (covered in Section 7), thus providing a comprehensive and unbiased account of the findings.

Throughout the study, the principles of honesty, transparency, independence, and responsibility have been upheld, adhering to the highest standards of research integrity. By addressing these aspects throughout the study a commitment to conducting ethical and reproducible research in alignment with the TU Delft Vision on Integrity and the Netherlands Code of Conduct for Research Integrity has been clearly demonstrated.

5 Experiment Results

With a total of 51 participants divided between the control group's 27 and the experimental group's 24, striking results were obtained. A number of participants had to be excluded, because they met the exclusion criteria (see Section 3.1 Experiment Design), leaving this study to draw upon the data from 23 control group participants and 18 experimental group participants. Given the voluntary nature of each question, some participants chose not to answer all items. Despite almost identical group compositions in terms of gender, age group and educational level, significant and consistent trends are quickly evident.

Quiz Scores

The experimental group performed significantly better in the quiz, with an average score of 3.83 out of 6. This, in contrast to the control group's average quiz score of 1.56 out of 6, makes for a staggering improvement, suggesting that the engagement-focused approach is overwhelmingly more effective in this regard (See Figure 2).

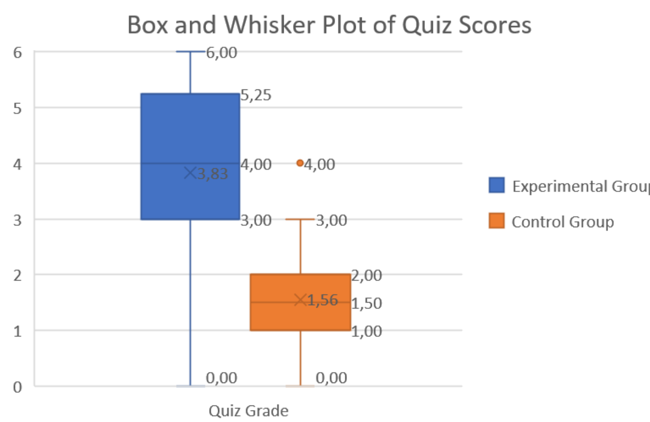


Figure 2: Box and Whisker plot comparing the quiz scores (out of a maximum of 6 points) obtained by the control and experimental group, respectively. The ends of each box represent the lower and upper quartiles, while the median (second quartile) is marked by a line inside the box. The whiskers extend from the ends of the box to the minimum and maximum value for the corresponding group, excluding outliers, which are plotted individually. Numeric values are overlayed on the plot for each of the aforementioned points, as well as for the mean quiz grade.

Participant Satisfaction Ratings

In terms of the satisfaction ratings reported by participants (Figure 3), the experimental group is in the lead in all categories, although by a narrower margin than in terms of quiz scores.

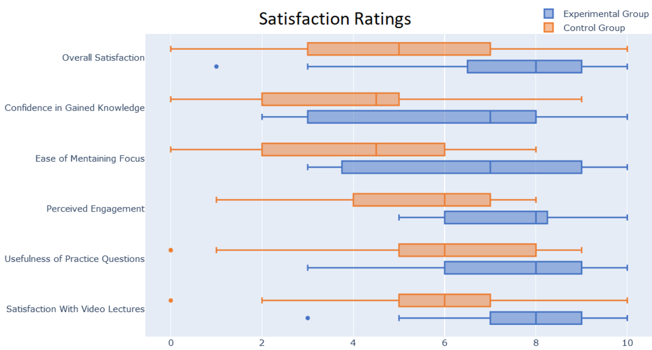


Figure 3: Box and Whisker plot comparing various satisfaction ratings (out of a maximum of 10 points) reported by the control and experimental groups, respectively. The ends of each box represent the lower and upper quartiles, while the median (second quartile) is marked by a line inside the box. The whiskers extend from the ends of the box to the minimum and maximum value for the corresponding variable, excluding outliers, which are plotted individually.

Participant Video Lecture Viewing Behaviour

Regarding the participants' video lecture viewing behaviour (Figure 4) a clear difference is obvious. Of the control group's 23 participants, only 13 said they watched the whole 16 minute video lecture, whereas eight reported watching part of it and two participants said they skipped the video lecture entirely.

Meanwhile, of the experimental group's 18 participants, a plurality of 15 reported watching every four minute video lecture in its entirety, while the numbers of participants who reported having watched the videos partially was relatively low, with a maximum of three. Most remarkably, there were no participants who reported having skipped any of the four minute video lectures.

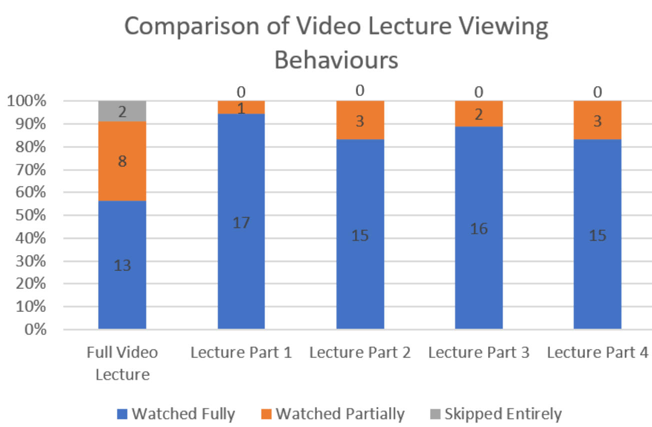


Figure 4: Stacked bar chart showcasing the self-reported video lecture viewing behaviour of the control group (N=23) with regards to the single video lecture of roughly 16 minutes compared to that of the experimental group (N=18) across the four video lecture parts of roughly four minutes each. It can be seen that the rate of complete watching is much higher in the experimental group, while that of partial watching is significantly lower and skipping is entirely absent.

Statistical Significance

In order to ascertain the statistical significance of the results, a T-test for independent samples was performed for each relevant category, the results of which can be seen in Table 1. In interpreting its results, this study uses the standard significance level of 0.05.

The T-test is a parametric test used to determine if there is a significant difference between the means of two groups. It assumes that the data is normally distributed and the variances of the two groups are equal. In this study, a T-test could be used to compare the mean quiz scores and satisfaction ratings between the control and experimental groups.

The Mann-Whitney U test, on the other hand, is a non-parametric test that does not make assumptions about the distribution of the data. It is used to compare differences between two independent groups when the dependent variable is either ordinal or continuous, but not normally distributed. This test is particularly useful if the sample size is small or if the data does not meet the assumptions required for a T-test, which is the case for certain variables in this dataset.

Between Group Differences T-Test

Variable	Group	Size	Parametric test Independent samples t test			
			Mean	SD	t	p (2-tailed)
Quiz Score	Experimental	18	3,83	1,886	4,966	0,000
	Control	23	1,57	0,992		
Self Assessment	Experimental	16	7,06	2,265	3,803	0,001
	Control	23	4,13	2,510		
Confidence (pre-quiz)	Experimental	18	6,06	2,754	1,591	0,121
	Control	22	4,77	2,245		
Overall Satisfaction	Experimental	18	7,56	1,947	2,639	0,012
	Control	22	5,73	2,434		
Focus	Experimental	18	6,56	2,479	2,953	0,006
	Control	22	4,27	2,374		
Engagement	Experimental	18	7,22	1,865	2,975	0,005
	Control	22	5,36	2,083		
Satisfaction_video	Experimental	18	7,78	1,768	2,765	0,009
	Control	22	6,09	2,091		
Satisfaction_questions	Experimental	18	7,44	1,917	1,875	0,069
	Control	22	6,18	2,343		
Math Skills	Experimental	18	6,39	1,614	1,958	0,057
	Control	23	5,09	2,429		
Coding Skills	Experimental	18	3,44	1,886	-1,481	0,147
	Control	23	4,52	2,761		
ML Knowledge	Experimental	18	1,94	1,392	-1,914	0,063
	Control	23	3,04	2,099		

Table 1: Table analysing the statistical significance of the results obtained by the control and experimental groups across all (potentially) relevant categories. The table shows the mean value and standard deviation for either group, followed by the T-test value and resulting p-value, per variable.

Given the relatively small sample size in this study (23 participants in the control group and 18 in the experimental group), a Mann-Whitney U-test might be more appropriate than a T-test, as it does not rely on the assumptions of normality or equal standard deviations. Hence, a Mann-Whitney U test was also performed (see Table 2) in order to cross-validate the statistical significance of the results.

The T-test and Mann-Whitney U-test results are highly consistent, leading to the same conclusions for all variables. Both tests show statistically significant differences between the experimental and control groups for quiz scores, self-assessment (post-quiz), overall satisfaction, self-reported focus and engagement, and satisfaction with the video lectures.

Between Group Differences Mann-Whitney U-Test						
			Non-parametric test Mann-Whitney U test			
Variable	Group	Size	Mean Rank	Sum of Ranks	Mann-Whitney U	p (2-tailed)
Quiz Score	Experimental	18	29,08	523,50	61,500	0,000
	Control	23	14,67	337,50		
Self Assessment	Experimental	16	27,13	434,00	70,000	0,001
	Control	23	15,04	346,00		
Confidence (pre-quiz)	Experimental	18	23,83	429,00	138,000	0,100
	Control	22	17,77	391,00		
Overall Satisfaction	Experimental	18	25,67	462,00	105,000	0,011
	Control	22	16,27	358,00		
Focus	Experimental	18	26,00	468,00	99,000	0,007
	Control	22	16,00	352,00		
Engagement	Experimental	18	26,03	468,50	98,500	0,006
	Control	22	15,98	351,50		
Satisfaction_video	Experimental	18	26,00	468,00	99,000	0,006
	Control	22	16,00	352,00		
Satisfaction_questions	Experimental	18	24,31	437,50	129,500	0,058
	Control	22	17,39	382,50		
Math Skills	Experimental	18	24,83	447,00	138,000	0,066
	Control	23	18,00	414,00		
Coding Skills	Experimental	18	17,83	321,00	150,000	0,131
	Control	23	23,48	540,00		
ML Knowledge	Experimental	18	17,58	316,50	145,500	0,101
	Control	23	23,67	544,50		

Table 2: Table analysing the statistical significance of the results obtained by the control and experimental groups across all (potentially) relevant categories. The table shows the mean rank and sum of ranks across either group, followed by the Mann-Whitney U-test value and resulting p-value, per variable.

Moreover, both tests indicate no statistically significant differences for pre-quiz confidence, satisfaction with the practice questions, and prior knowledge of mathematics, coding or machine learning.

6 Discussion

While the analysis of related works does indicate the effectiveness of engagement-focused teaching methods for machine learning, it fails to convey the scale of their impact. Furthermore, the techniques and methods presented in literature vary widely and a great proportion of them are complex. All this amounts to a vague academic consensus about teaching techniques geared towards student engagement being beneficial in machine learning education, but without a clear guide to what those techniques might be and what kind of impact they actually make on learning outcomes.

To address the research question adequately in this study of very limited means, a simple experiment was devised to assess the impact on quiz scores and student satisfaction of a most rudimentary form of engagement-boosting technique, in the form of breaking up a 16 minute video lecture followed by 14 practice questions into four mini-lecture videos of roughly four minutes, each followed by three or four practice questions. Both the video material and the practice questions were identical for all participants, with the aim being to determine the effects of breaking the learning process down into bite-sized parts.

The results, presented in the previous section, constitute clear evidence of the effectiveness of this simple method. With no other difference between groups, it alone appears to have accounted for the more than doubling of the average quiz score obtained by the experimental group, as opposed to that of the control group. In addition to the remarkably large increase in test performance, satisfaction with the learning materials and experience was also improved consistently across all metrics, similarly to participants' confidence in the knowledge they had gained, as reported both before and after the quiz.

The improvement in learning outcomes between the control and experimental groups is far more pronounced and consistent across metrics than expected. The stark contrast can be attributed to the overwhelming increase in engagement with the teaching materials, as evidenced by the participants' viewing behaviour. While coincidence may have played a role given the small scale of the study, self-reported focus and engagement ratings were also found to have (statistically) significantly higher mean values for the experimental group, suggesting that student engagement was indeed the root cause of the improved learning outcomes.

The cross-analysis of the statistical significance of the results using a T-test and a Mann-Whitney U-test strengthens the findings that the engagement-focused teaching method positively impacted learning outcomes and student satisfaction compared to the traditional method. The consistency between the parametric (T-test) and non-parametric (Mann-Whitney U-test) results increases confidence in the study's conclusions, as the findings are robust to different statistical assumptions.

Overall, the results of this study provide significant evidence that machine learning teaching methods focused on student engagement can considerably improve learning outcomes, as measured by test performance and student satisfaction. The findings highlight the importance of designing instructional strategies that cater to the diverse needs and backgrounds of students, and the potential for engagement-focused approaches to make machine learning education more accessible, effective, and impactful. As the field of machine learning continues to evolve in both its scope and prevalence, it is crucial for educators to prioritise student engagement in order to prepare learners to become competent and creative practitioners.

7 Conclusions and Future Work

This study set out to answer the research question: "To what extent do Machine Learning teaching methods focused on student engagement improve learning outcomes as measured by test performance and student satisfaction?" Through comprehensive analysis of related scientific works and a controlled experiment, it has been demonstrated that engagement-focused teaching methods can significantly enhance both quiz scores and student satisfaction in the context of an introductory machine learning lesson on artificial neural networks.

The related works section revealed that while traditional machine learning teaching methods emphasise theoretical understanding and software implementations, engagement-focused approaches prioritise hands-on learning, accessibility, and practical problem-solving. However, the impact of these engagement-focused methods on learning outcomes remained vaguely defined.

To address this knowledge gap, an experiment was conducted in which participants were divided into a control group exposed to a conventional 16-minute video lecture followed by practice questions, and an experimental group that engaged with the same content broken down into four shorter video segments, each followed by a subset of the practice questions. Both groups completed the same satisfaction survey and quiz.

The results were striking, with the experimental group achieving an average quiz score of 3.83 out of 6, compared to the control group's average of 1.56. Furthermore, satisfaction ratings were consistently higher for the experimental group across all metrics. These findings suggest that even a simple engagement-boosting technique, such as breaking down a lesson into smaller, more manageable parts, can have a profound impact on learning outcomes and student satisfaction in machine learning education.

Limitations

While the results of this study are significant, there are a number of factors limiting the scope and reach of the findings. Firstly, the number of experiment participants whose data could be used was small, coming in at only 41. As a result of the small sample size, certain irregularities might not be accounted for. For example, with only a few dozen participants it is entirely possible for one group to have coincidentally had a significantly higher level of innate motivation than the other, potentially influencing results. To generalise, a small sample such as this carries a significant risk of individual circumstances influencing results, for which no amount of statistical validation can compensate.

Secondly, this being a study organised by a bachelor's student, the duration of the experiment, at 30 minutes long, was already problematic in terms of the participants' willingness to fully engage with the materials. At the same time, the 30 minute duration imposed severe limitations on what material could be taught and tested within the allotted time, constraining the experiment to a basic introduction to neural networks. Exploring a broader range of topics would have made the results more meaningful and more representative of the impact of the teaching methods evolved on machine learning education in general, and not just a particular small topic within the subject. Furthermore, because of the time constraints, the experiment focused on only one specific engagement-boosting technique, whereas more could be explored comparatively in an ampler study.

Finally, the nature of the experiment presents a unique type of limitation in terms of the willingness of participants to put significant mental effort into learning a new concept and then completing a quiz composed of questions of increasingly more challenging questions. With nothing at stake, which is one of the ethics requirements for the present research, it would stand to reason that the participants' motivation to make an effort is significantly lower than in a traditional educational setting.

Future Work

To overcome the limitations following from the small sample size of this study, it would be relevant to conduct another experiment in a similar fashion, but involving hundreds of participants. This would reduce the granularity of the data, improve diversity and further increase the statistical significance of the findings.

Meanwhile, in tackling the limitations imposed by the 30 minute duration of the experiment, one could expand upon this study with a comparison of the outcomes of engaging versus traditional teaching methods over a longer term. It would also be worthwhile to compare multiple different engagement-focused techniques and analyse their impact when applied both separately and jointly.

In both the above-mentioned cases, as well as in that of attempting to improve participant motivation and willingness to make an effort, the most prominent solution that springs to mind for overcoming the limitations of this study is to run a similar experiment in a formal educational setting. This would amount to comparing the effects of engaging versus traditional teaching methods on different cohorts of students participating in a machine learning course. This solution, however, presents significant ethical dilemmas, such as educators prioritising the use of their students as research test subjects over the quality and integrity of their education.

Appendices: Experimental Material and Results

The online forms used to run the experiment, as well as the results, can be found in this paper, after the references. Note that "v39" refers to the control group, while "v42" refers to the experimental group.

References

[1] P. Steinbach, H. Seibold, and O. Guhr, "Teaching machine learning in 2020," in *Proceedings of the First Teaching Machine Learning and Artificial Intelligence Workshop* (B. Bischl, O. Guhr, H. Seibold, and P. Steinbach, eds.), vol. 141 of *Proceedings of Machine Learning Research*, pp. 1–6, PMLR, 14 Sep 2021.

[2] N. Sinha, R. F. Evans, and M. Carbo, "Hands-on active learning approach to teach artificial intelligence/machine learning to elementary and middle school students," in *2023 32nd Wireless and Optical Communications Conference (WOCC)*, pp. 1–6, 2023.

[3] S. ki Kim, T. Kim, and K. Kim, "Analysis of teaching and learning environment for data science and ai education (focused on 2022 revised curriculum)," in *2023 International Conference on Artificial Intelligence in Information and Communication (ICAIIC)*, pp. 788–790, 2023.

[4] W. Chow, "A pedagogy that uses a kaggle competition for teaching machine learning: an experience sharing," in *2019 IEEE International Conference on Engineering, Technology and Education (TALE)*, pp. 1–5, 2019.

[5] T. Stadelmann, J. Keuzenkamp, H. Grabner, and C. Würsch, "The ai-atlas: Didactics for teaching ai and machine learning on-site, online, and hybrid," *Education Sciences*, vol. 11, no. 7, 2021.

[6] I. T. Sanusi, S. S. Oyelere, H. Vartiainen, J. Suhonen, and M. Tukiainen, “A systematic review of teaching and learning machine learning in k-12 education,” *Education and Information Technologies*, vol. 28, p. 5967–5997, Nov. 2022.

[7] N. Geri, A. Winer, and B. Zaks, “Challenging the six-minute myth of online video lectures: Can interactivity expand the attention span of learners?,” *Online Journal of Applied Knowledge Management ISSN 2325-4688*, vol. 5, pp. 101–111, 05 2017.

[8] I. Osipov, E. Nikulchev, and A. Prasikova, “Study of gamification effectiveness in online e-learning systems,” *International Journal of Advanced Computer Science and Applications*, vol. 6, pp. 71–77, 02 2015.

[9] E. Sulmont, E. Patitsas, and J. R. Cooperstock, “Can you teach me to machine learn?,” in *Proceedings of the 50th ACM Technical Symposium on Computer Science Education*, SIGCSE ’19, (New York, NY, USA), p. 948–954, Association for Computing Machinery, 2019.

[10] B. Vlist, R. Westelaken, C. Bartneck, J. Hu, R. Ahn, E. Barakova, F. Delbressine, and L. Feijs, “Teaching machine learning to design students,” pp. 206–217, 06 2008.

[11] G. Karalekas, S. Vologiannidis, and J. Kalomiros, “Teaching machine learning in k–12 using robotics,” *Education Sciences*, vol. 13, no. 1, 2023.

[12] C. Gresse von Wangenheim, J. Hauck, F. Santana Pacheco, and M. Bueno, “Visual tools for teaching machine learning in k-12: A ten-year systematic mapping,” *Education and Information Technologies*, vol. 26, pp. 1–46, 09 2021.

[13] E. Sulmont, E. Patitsas, and J. R. Cooperstock, “What is hard about teaching machine learning to non-majors? insights from classifying instructors’ learning goals,” *ACM Trans. Comput. Educ.*, vol. 19, jul 2019.

[14] G. Sanderson, “But what is a neural network? — chapter 1, deep learning.” https://youtu.be/aircAruvnKk, Oct 2017. [Online; accessed 20 May 2024].

Intro to Artificial Neural Networks v39

11 June 2024

Total: 6 Points

* Required

Informed Consent

You are being invited to participate in a research study titled "How to Teach Machine learning in an Engaging Way". This study is being done by Mihnea Liute, an undergraduate student from the TU Delft.

The purpose of this research study is to assess the impact of engagement-focused techniques for Machie Learning education on learning outcomes, and will take you approximately 30 minutes to complete. The data will be used for furthering scientific knowledge about teaching methods for Machine Learning, as well as potential publication and teaching. We will be asking you to learn about a Machine Learning topic using materials provided to you and then complete a quiz about what you learned and rate your learning experience.

As with any online activity the risk of a breach is always possible. To the best of our ability your answers in this study will remain confidential. We will minimise any risks by keeping the quiz entirely anonymous and collecting no personal or potentially identifiable data from participants, except for their age group and gender.

Your participation in this study is entirely voluntary and you can withdraw at any time. You are free to omit any questions.

You can contact the responsible researcher at m.liute@student.tudelft.nl

By filling in and submitting this survey, you are agreeing to these conditions.

1

I have read and understood the above information about this study, or it has been read to me. I have been able to ask questions about the study and my questions have been answered to my satisfaction. I agree to these terms. *

- ○ I agree
- ○ I disagree

Participant Information

2

To which of the following age groups do you belong?

- under 18
- 18 to 24
- 25 to 29
- 30 to 34
- 35 to 49
- 50 to 64
- 65 and over

3

What is your gender?

- Female
- Male
- Non-binary
- Other
- Prefer not to say

4

What is the highest-level diploma that you currently hold?

- Doctoral Diploma
- Master's Diploma
- Bachelor's Diploma
- High School Diploma
- Primary School Diploma

5

Have you studied Machine Learning or Neural Networks as part of you education?

- Yes
- No

6

In what region of the world do you currently reside?

- Africa
- Asia
- Central or South America
- Europe (EU)
- Europe (non-EU)
- North America
- Oceania

7

How would you rate your English language proficiency in terms of you ability to understand a video teaching material in English?

0	1	2	3	4	5	6	7	8	9	10

Non-existent — Perfect

8

How would you rate your current level of technical profficiency in regards to coding and computer science more broadly?

0	1	2	3	4	5	6	7	8	9	10

No profficiency — Full profficiency

9

How would you rate your current level of profficiency in regards to linear algebra, calculus and mathematics more broadly?

0	1	2	3	4	5	6	7	8	9	10

No profficiency — Full profficiency

10

How would you rate your knowledge of Machine Learning and Neural Networks at this time?

0	1	2	3	4	5	6	7	8	9	10

No knowledge

Advanced knowledge

Content and Practice Questions

You will now watch a video lecture which covers the topic of Artificial Neural Networks, followed by some practice questions pertaining to its content.
Please note that the practice questions carry no points or consequence and are not mandatory. They are, however, important and meant to improve your learning and prepare you for the quiz.

11

Neural Networks Video Lecture *

Original Video: https://youtu.be/aircAruvnKk Full credits for creating this video go to the creator of the original video, Grant Sanderson a.k.a. 3Blue1Brown: https://www.youtube.com/@3blue1brown This is a segment of the original video, uploaded to YouTube as an unlisted video, to be used as an instructional material as part of scientific research. The creator of the original video will be credited in the instructional materials as well as in the papers that may result from the research.

- ◯ I have fully watched this video
- ◯ I stopped watching before the end of the video
- ◯ I skipped this video entirely

12

Can Neural Networks take an image (grid of pixels) as an input and, based on those pixel brightness values representing the content of the image, roughly categorise the image based on its content?

- ◯ Yes
- ◯ No

13

What is a simple, "vanilla" artificial neural network called?

- Long short-term Memory Network
- Convolutional Neural Network
- Multilayer Perceptron

14

What does an artificial neuron hold? (What is an artificial neuron's activation?)

- A value between -∞ and +∞
- A value between -1 and + ∞
- A value between 0 and 1
- A value between 0 and ∞
- Thoughts and (controversial) opinions

15

Which layers of an artificial neural network made for image recognition are formed of artificial neurons measuring pixel brightness values?

- Just the first
- All the layers
- The first two
- The middle layer

16

What does the final layer of artificial neurons in an artificial neural network represent?

- Outputs, such as rough probabilities that the input belongs to one of a number of types of inputs
- Mysteries
- An intermediate step in calculating the final output
- Neurons

17

How many layers should an artificial neural network ideally contain for a hand-written digit classification task?

- ◯ 2
- ◯ 16
- ◯ irrelevant
- ◯ it depends

18

Does each intermediate layer in an artificial neural network represent a "step" towards the solution the network is trying to reach?

- ◯ No. Never.
- ◯ Yes. Always.
- ◯ Yes, but only for image recognition.
- ◯ Roughly, sometimes. It varies and depends.

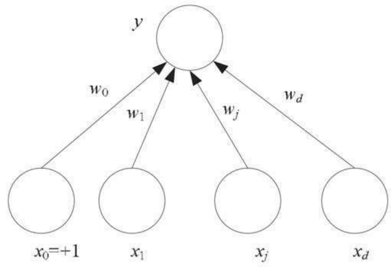
19

What are the parameters of an artificial neural network and what are they used for?

- ◯ Weights, biases and activation functions are used to tweak the artificial neural network in order to make it perform the desired function.
- ◯ Inputs are taken in and outputs come out, producing the desired result. Black Magic!

20

Here you see a graphical depiction of a perceptron.
What do the x, w, and y denote?



- x = input value; w = activation/output value; y = weight
- x = weight of the input nodes; w = activation score; y = output value
- x = input value; w = weight; y = activation/output value
- x = weight of the input nodes; w = weight; y = activation/output value

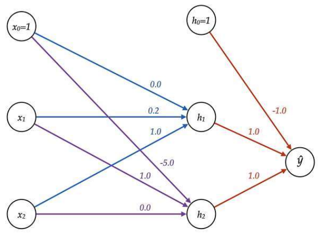
21

What does the Sigmoid (a.k.a Logistic) function do?

- It maps or "squishes" values in the interval [-∞, +∞] to values in the interval [0, 1], making it ideal for transforming any real value into a value between 0 and 1, which could represent a neuron's activation level
- It... functions?

22

Consider the multi-layer perceptron depicted in the figure, where the numbers next to the edges denote the weight of each connection. Suppose we use a Sigmoid activation function for all nodes (neurons). If the input to this model is x1 = 5, x2 = -2, what will the value for y be?



- y = 0.0
- 0.0 < y < 0.5
- y = 0.5
- y=1.0

23

What is a compact way of representing and an efficient way of calculating the output of an artificial neuron given its activation function, bias and the weights of the edges leading to it, as well as as the inputs coming in through those edges?

- Hyeroglyphs
- Organic chemistry
- Matrix multiplication, which can be executed VERY efficiently in parallel on graphics cards
- Black Magic

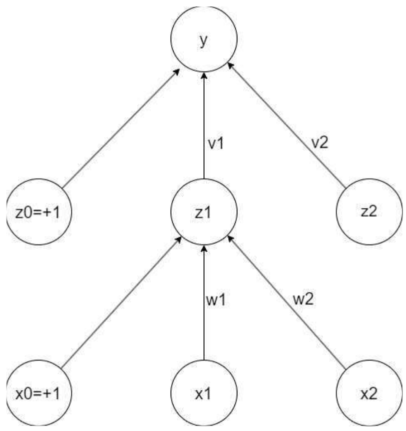
24

What are, in essence, both an artificial neural network and every artificial neuron in it, individually?

- Functions!
- Alive??!!

25

Here you see a graphical depiction of a multi-layer perceptron. How is the value of z1 calculated?



- An activation function is applied to the sum of the multiplications of the input x1 and the weight w1, and that of the input x2 and the weight w2 plus the bias x0. Mathematically: activationFunc(x1 * w1 + x2 * w2 + x0)
- By the sum of multiplications of the inputs x1 and x2 and the weights w1 and w2, plus bias x0. Mathematically, x1 * w1 + x2 * w2 + x0
- By the sum of multiplications of the inputs x1 and x2 and the weights w1 and w2 plus bias z0. Mathematically, x1 * w1 + x2 * w2 + z0
- An activation function is applied to the sum of multiplications of the inputs x1 and x2 and the weights w1 and w2, plus the bias z0. Mathematically: activationFunc(x1 * w1 + x2 * w2 + z0)

Learning Experience

This section asks you to rate you learning experience. Please feel free to be honest in regards to all aspects, positinge and negative alike.

26

How would you rate your satisfaction with the video lecture as a means of presenting the material, on a scale of 0 to 10?

Feel free to be honest

0	1	2	3	4	5	6	7	8	9	10

Terrible beyond Description — Literal Perfection

27

How would you rate the usefulness of the practice questions as a means of rehearsing the material, on a scale of 0 to 10?

Feel free to be honest

0	1	2	3	4	5	6	7	8	9	10

Terrible beyond Description — Literal Perfection

28

How would you rate your level of engagement with the learning material provided (video lecture and practice questions), on a scale of 0 to 10?

How engaging did you find this presentation format?

0	1	2	3	4	5	6	7	8	9	10

I felt no engagement at all — I felt fully immersed

29

How easy was it to stay focused on the material in the video lecture and practice questions, on a scale of 0 to 10 (higher is better)?

Feel free to be honest

0	1	2	3	4	5	6	7	8	9	10

Impossible — Effortless

30

How would you rate your level of confidence in your knowledge of the content on Artificial Neural Networks covered by the learning materials, on a scale of 0 to 10?

0	1	2	3	4	5	6	7	8	9	10

Not confident at all — Very confident

31

How would you rate your overall satisfaction with the learning experience, on a scale of 0 to 10?

Feel free to be honest

0	1	2	3	4	5	6	7	8	9	10

Terrible beyond Description

Literal Perfection

Answers to Practice Questions

This section provides the answers to the Practice Questions from the previous section. Feel free to go back and take another look at any question that you may have found difficult.

32

Below are the Answers to the Practice Questions from the previous section. Feel free to go back and take another look at any question that you may have found difficult.
Part 1, Intro
Question 12: Yes
Question 13: Multilayer Perceptron
Question 14: A value between 0 and 1
Part 2, Layers
Question 15: Just the first
Question 16: Outputs, such as rough probabilities thath the inpout belongs to a number of types of inputs
Question 17: It depends.
Question 18: Roughly, sometimes. It varies and depends.
Part 3, Weights, Biases and Activation Functions
Question 19: Weights, biases and activation functions are used to tweak the artificial neural network in order to make it perform the desired function.
Question 20: x = input value; w = weight; y = activation/output value
Question 21: It maps or "squishes" values in the interval $[-\infty, +\infty]$ to values in the interval $[0, 1]$, making it ideal for transforming any real value into a value between 0 and 1, which could represent a neuron's activation level
Question 22: $0.0 < x < 0.5$
Part 4, Math and Conclusions
Question 23: Matrix multiplication, which can be executed VERY efficiently in parallel on graphics cards
Question 24: Functions!
Question 25: An activation function is applied to the sum of the multiplications of the input x1 and the weight w1, and that of the input x2 and the weight w2 plus the bias x0. Mathematically:
activationFunc(x1 * w1 + x2 * w2 + x0)

Quiz

The 6 questions in this quiz are the only ones with points attached to them. However, feel free not to answer some or any of the questions if they make you uncomfortable.
Note that there is only one correct answer per question.

33

What is TRUE about artificial neural networks? (1 Point)

- An artificial neuron holds an activation value between 0 and 1.
- A simple, "vanilla" artificial neural network is called a multi-layer Perceptron.
- A neural network can take an image (grid of pixels) as an input and, based on those pixel brightness values representing the content of the image, roughly categorise the image based on its content?
- All of the above.

34

What is FALSE about layers in an artificial neural network? (1 Point)

- The first and last layer of an artificial neural network are called the input and output layers, respectively.
- The optimal number of layers in an artificial neural network varies and depends on multiple factors.
- Each intermediate layer in an artificial neural network ALWAYS represents a "step" towards the solution the network is trying to reach.
- All of the above.

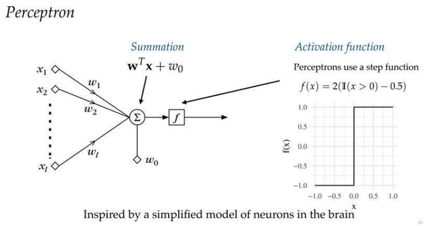
35

What is TRUE about artificial neural networks (aNNs)? (1 Point)

- Atrificial neural networks "chain" interconnected layers of polynomial functions in the form of neurons. Using the neurons' activation biases and the weights of the connections between them, aNNs tweak their behaviour to achieve the desired functionality, which amounts to a single highly complex function.
- The activation of an artificial neuron is determined by the sum of products of corresponding inputs and weights from its incoming edges, plus a bias value, all passed through an activation function, such as a Sigmoid, that squishes all real values to the interval [0, 1].
- Using matrix multiplication to represent complex calculation that determines the activation of a neuron enables artificial neural networks to be somewhat computationally efficient relative to the complexity of their tasks.
- All of the above.

36

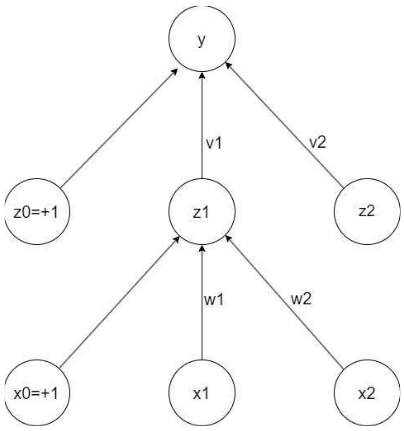
Here is a (single layer) Perceptron that uses a step activation function (which outputs 1 if its input is bigger than 0, and outputs 0 otherwise) instead of a sigmoid function.
What would this perceptron's output be equal to if it was given inputs x1 = 1, x2 = -0.5, x3 =-0, x4 = 2 and weights w1 = -1, w2 = 2, w3 = 4, w4 = 1 (1 Point)



- 6
- 1
- 0
- -2

37

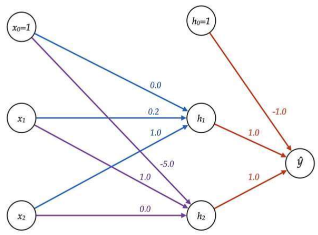
Here you see a graphical depiction of a multi-layer perceptron. How is the value of y calculated? (1 Point)



- An activation function is applied to the sum of the multiplications of z1 with v1 and z2 with v2, plus the bias z0. Mathematically, activationFunc(z1*v1 + z2*v2 + z0)
- By the sum of the multiplications of z1 with v1 and z2 with v2, plus the bias v0. Mathematically, z1*v1 + z2*v2 + v0
- An activation function is applied to the sum of the multiplications of z1 with v1 and z2 with v2, plus the bias x0. Mathematically, activationFunc(z1*v1 + z2*v2 + x0)
- By the sum of the multiplications of z1 with v1 and z2 with v2, plus the bias x0. Mathematically, z1*v1 + z2*v2 + x0

38

Consider the multi-layer perceptron depicted in the figure, where the numbers next to the edges denote the weight of each connection. Suppose we use a step activation function (which outputs 1 if its input is bigger than 0, and outputs 0 otherwise) for both all nodes.
If the inputs to this model are x1 = 10 and x2 = −1, what will the values for h1, h2 and y be?
Remember to put the sum of the incoming values through the activation function in order to obtain the value in a node! (1 Point)



- ◯ h1 = 1; h2 = 0; y = 0.5
- ◯ h1 = 1; h2 = 0.5; y = 0
- ◯ h1 = 1; h2 = 1; y = 1
- ◯ h1 = 1; h2 = 0; y = 0

39

How well do you think you have done on this quiz?

0	1	2	3	4	5	6	7	8	9	10

I probably got everyt
hing wrong

I think I got everythin
g right

Intro to Artificial Neural Networks v42

11 June 2024

Total: 6 Points

* Required

Informed Consent

You are being invited to participate in a research study titled "How to Teach Machine learning in an Engaging Way". This study is being done by Mihnea Liute, an undergraduate student from the TU Delft.

The purpose of this research study is to assess the impact of engagement-focused techniques for Machie Learning education on learning outcomes, and will take you approximately 30 minutes to complete. The data will be used for furthering scientific knowledge about teaching methods for Machine Learning, as well as potential publication and teaching. We will be asking you to learn about a Machine Learning topic using materials provided to you and then complete a quiz about what you learned and rate your learning experience.

As with any online activity the risk of a breach is always possible. To the best of our ability your answers in this study will remain confidential. We will minimise any risks by keeping the quiz entirely anonymous and collecting no personal or potentially identifiable data from participants, except for their age group and gender.

Your participation in this study is entirely voluntary and you can withdraw at any time. You are free to omit any questions.

You can contact the responsible researcher at m.liute@student.tudelft.nl

By filling in and submitting this survey, you are agreeing to these conditions.

1

I have read and understood the above information about this study, or it has been read to me. I have been able to ask questions about the study and my questions have been answered to my satisfaction. I agree to these terms. *

- ◯ I agree
- ◯ I disagree

Participant Information

2

To which of the following age groups do you belong?

- ◯ 18 to 24
- ◯ 25 to 29
- ◯ 30 to 34
- ◯ 35 to 49
- ◯ 50 to 64
- ◯ 65 and over

3

What is your gender?

- ◯ Female
- ◯ Male
- ◯ Non-binary
- ◯ Other
- ◯ Prefer not to say

4

What is the highest-level diploma that you currently hold?

- ◯ Doctoral Diploma
- ◯ Master's Diploma
- ◯ Bachelor's Diploma
- ◯ High School Diploma
- ◯ Primary School Diploma

5

Have you studied Machine Learning or Neural Networks as part of you education?

- Yes
- No

6

In what region of the world do you currently reside?

- Africa
- Asia
- Central or South America
- Europe (EU)
- Europe (non-EU)
- North America
- Oceania

7

How would you rate your English language profficiency in terms of you ability to understand a video teaching material in English?

0	1	2	3	4	5	6	7	8	9	10

Non-existent — Perfect

8

How would you rate your current level of technical profficiency in regards to coding and computer science more broadly?

0	1	2	3	4	5	6	7	8	9	10

No profficiency — Full profficiency

9

How would you rate your current level of profficiency in regards to linear algebra, calculus and mathematics more broadly?

0	1	2	3	4	5	6	7	8	9	10

No profficiency — Full profficiency

10

How would you rate your knowledge of Machine Learning and Neural Networks at this time?

0	1	2	3	4	5	6	7	8	9	10

No knowledge Advanced knowledge

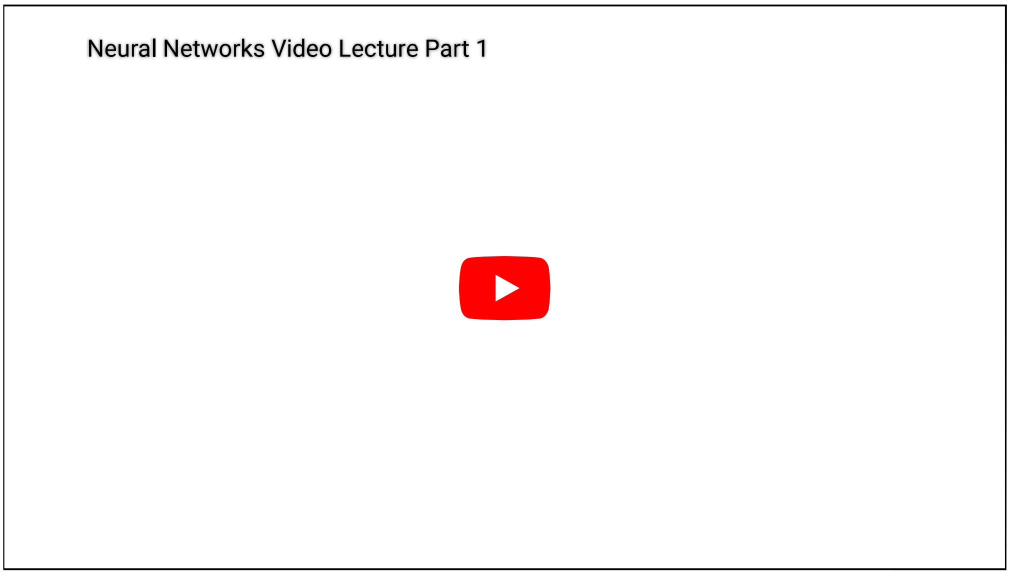
Content and Practice Questions

You will now watch four short videos which toghether cover the topic of Artificial Neural Networks, each one followed by a few practice questions pertaining to its content.
Please note that the practice questions carry no points or consequence and are not mandatory. They are, however, important and meant to improve your learning and prepare you for the quiz.

11

Introduction to Neural Networks (Mulilayer Perceptron) *

Original Video: https://youtu.be/aircAruvnKk Full credits for creating this video go to the creator of the original video, Grant Sanderson a.k.a. 3Blue1Brown: https://www.youtube.com/@3blue1brown This is a segment of the original video, uploaded to YouTube as an unlisted video, to be used as an instructional material as part of scientific research. The creator of the original video will be credited in the instructional materials as well as in the papers that may result from the research.



- ◯ I have fully watched this video
- ◯ I stopped watching before the end of the video
- ◯ I skipped this video entirely

12

Can Neural Networks take an image (grid of pixels) as an input and, based on those pixel brightness values representing the content of the image, roughly categorise the image based on its content?

- ◯ Yes
- ◯ No

13

What is a simple, "vanilla" artificial neural network called?

- Long short-term Memory Network
- Convolutional Neural Network
- Multilayer Perceptron

14

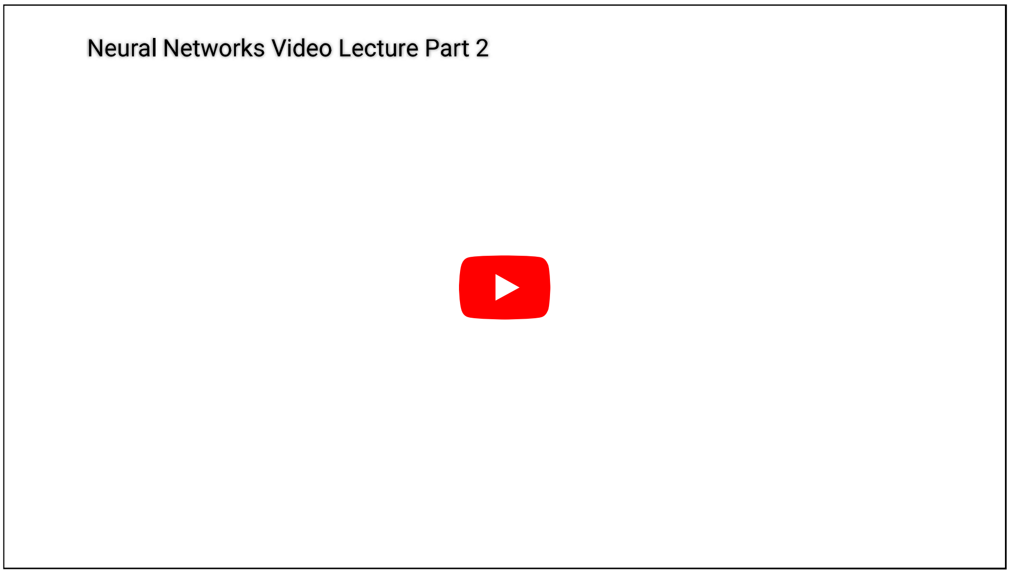
What does an artificial neuron hold? (What is an artificial neuron's activation?)

- A value between $-\infty$ and $+\infty$
- A value between -1 and $+\infty$
- A value between 0 and 1
- A value between 0 and ∞
- Thoughts and (controversial) opinions

15

Part 2: Layers *

Original Video: https://youtu.be/aircAruvnKk Full credits for creating this video go to the creator of the original video, Grant Sanderson a.k.a. 3Blue1Brown: https://www.youtube.com/@3blue1brown This is a segment of the original video, uploaded to YouTube as an unlisted video, to be used as an instructional material as part of scientific research. The creator of the original video will be credited in the instructional materials as well as in the papers that may result from the research.



- I have fully watched this video
- I stopped watching before the end of the video
- I skipped this video entirely

16

Which layers of an artificial neural network made for image recognition are formed of artificial neurons measuring pixel brightness values?

- Just the first
- All the layers
- The first two
- The middle layer

17

What does the final layer of artificial neurons in an artificial neural network represent?

- Outputs, such as rough probabilities that the input belongs to one of a number of types of inputs
- Mysteries
- An intermediate step in calculating the final output
- Neurons

18

How many layers should an artificial neural network ideally contain for a hand-written digit classification task?

- 2
- 16
- irrelevant
- it depends

19

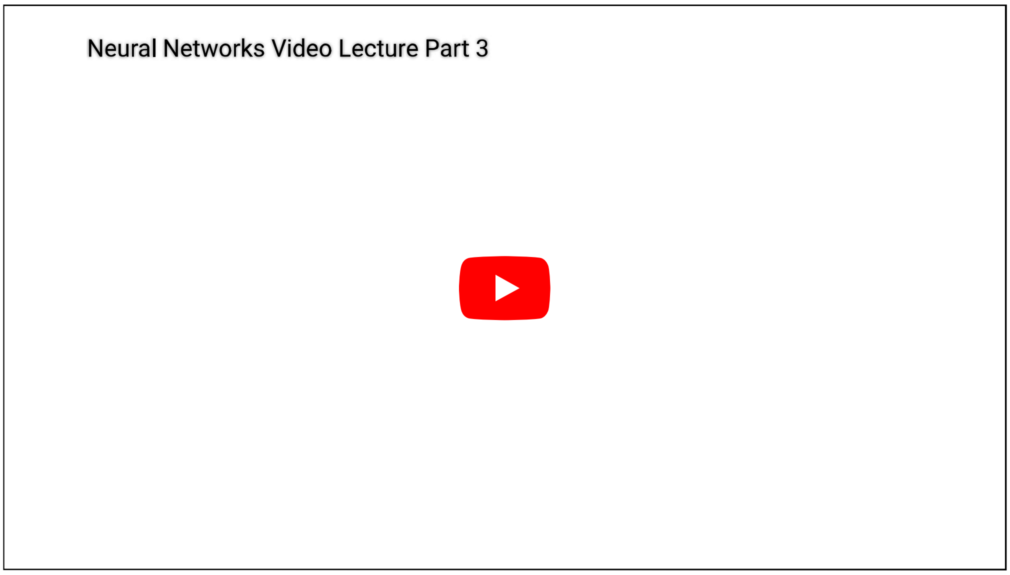
Does each intermediate layer in an artificial neural network represent a "step" towards the solution the network is trying to reach?

- No. Never.
- Yes. Always.
- Yes, but only for image recognition.
- Roughly, sometimes. It varies and depends.

20

Part 3: Weights and Biases, Sigmoid Activation Function *

Original Video: https://youtu.be/aircAruvnKk Full credits for creating this video go to the creator of the original video, Grant Sanderson a.k.a. 3Blue1Brown: https://www.youtube.com/@3blue1brown This is a segment of the original video, uploaded to YouTube as an unlisted video, to be used as an instructional material as part of scientific research. The creator of the original video will be credited in the instructional materials as well as in the papers that may result from the research.



- ○ I have fully watched this video
- ○ I stopped watching before the end of the video
- ○ I skipped this video entirely

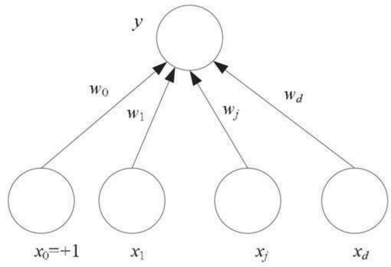
21

What are the parameters of an artificial neural network and what are they used for?

- ○ Weights, biases and activation functions are used to tweak the artificial neural network in order to make it perform the desired function.
- ○ Inputs are taken in and outputs come out, producing the desired result. Black Magic!

22

Here you see a graphical depiction of a perceptron.
What do the x, w, and y denote?



- x = input value; w = activation/output value; y = weight
- x = weight of the input nodes; w = activation score; y = output value
- x = input value; w = weight; y = activation/output value
- x = weight of the input nodes; w = weight; y = activation/output value

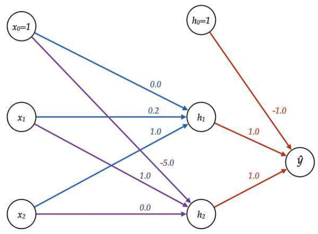
23

What does the Sigmoid (a.k.a Logistic) function do?

- It maps or "squishes" values in the interval [-∞, +∞] to values in the interval [0, 1], making it ideal for transforming any real value into a value between 0 and 1, which could represent a neuron's activation level
- It... functions?

24

Consider the multi-layer perceptron depicted in the figure, where the numbers next to the edges denote the weight of each connection. Suppose we use a Sigmoid activation function for all nodes (neurons). If the input to this model is x1 = 5, x2 = -2, what will the value for y be?



- y = 0.0
- 0.0 < y < 0.5
- y = 0.5
- y=1.0

25

Part 4: Math and Conclusions *

Neural Networks Video Lecture Part 4

- I have fully watched this video
- I stopped watching before the end of the video
- I skipped this video entirely

26

What is a compact way of representing and an efficient way of calculating the output of an artificial neuron given its activation function, bias and the weights of the edges leading to it, as well as as the inputs coming in through those edges?

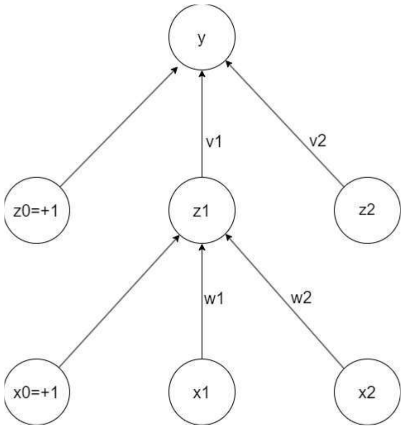
- Hyeroglyphs
- Organic chemistry
- Matrix multiplication, which can be executed VERY efficiently in parallel on graphics cards
- Black Magic

27

What are, in essence, both an artificial neural network and every artificial neuron in it, individually?

- Functions!
- Alive??!!

Here you see a graphical depiction of a multi-layer perceptron. How is the value of z1 calculated?



- [ ] An activation function is applied to the sum of the multiplications of the input x1 and the weight w1, and that of the input x2 and the weight w2 plus the bias x0. Mathematically: activationFunc(x1 * w1 + x2 * w2 + x0)
- [ ] By the sum of multiplications of the inputs x1 and x2 and the weights w1 and w2, plus bias x0. Mathematically, x1 * w1 + x2 * w2 + x0
- [ ] By the sum of multiplications of the inputs x1 and x2 and the weights w1 and w2 plus bias z0. Mathematically, x1 * w1 + x2 * w2 + z0
- [ ] An activation function is applied to the sum of multiplications of the inputs x1 and x2 and the weights w1 and w2, plus the bias z0. Mathematically: activationFunc(x1 * w1 + x2 * w2 + z0)

Learning Experience

This section asks you to rate you learning experience. Please feel free to be honest in regards to all aspects, positinge and negative alike.

29

How would you rate your satisfaction with the videos as a means of presenting the material, on a scale of 0 to 10?

Feel free to be honest

0	1	2	3	4	5	6	7	8	9	10

Terrible beyond Description

Literal Perfection

30

How would you rate the usefulness of the practice questions as a means of rehearsing the material, on a scale of 0 to 10?

Feel free to be honest

0	1	2	3	4	5	6	7	8	9	10

Terrible beyond Description

Literal Perfection

31

How would you rate your level of engagement with the learning material provided (videos and practice questions), on a scale of 0 to 10?

How engaging did you find this presentation format?

0	1	2	3	4	5	6	7	8	9	10

I felt no engagement at all

I felt fully immersed

32

How easy was it to stay focused on the material in the videos and practice questions, on a scale of 0 to 10 (higher is better)?

Feel free to be honest

0	1	2	3	4	5	6	7	8	9	10

Impossible

Effortless

33

How would you rate your level of confidence in your knowledge of the content on Artificial Neural Networks covered by the learning materials, on a scale of 0 to 10?

0	1	2	3	4	5	6	7	8	9	10

Not confident at all

Very confident

34

How would you rate your overall satisfaction with the learning experience, on a scale of 0 to 10?

Feel free to be honest

0	1	2	3	4	5	6	7	8	9	10

Terrible beyond Description

Literal Perfection

Answers to Practice Questions

This section provides the answers to the Practice Questions from the previous section. Feel free to go back and take another look at any question that you may have found difficult.

35

Below are the Answers to the Practice Questions from the previous section. Feel free to go back and take another look at any question that you may have found difficult.
Part 1, Intro
Question 12: Yes
Question 13: Multilayer Perceptron
Question 14: A value between 0 and 1
Part 2, Layers
Question 16: Just the first
Question 17: Outputs, such as rough probabilities thath the inpout belongs to a number of types of inputs
Question 18: It depends.
Question 19: Roughly, sometimes. It varies and depends.
Part 3, Weights, Biases and Activation Functions
Question 21: Weights, biases and activation functions are used to tweak the artificial neural network in order to make it perform the desired function.
Question 22: x = input value; w = weight; y = activation/output value
Question 23: It maps or "squishes" values in the interval [-∞, +∞] to values in the interval [0, 1], making it ideal for transforming any real value into a value between 0 and 1, which could represent a neuron's activation level
Question 24: 0.0 < x < 0.5
Part 4, Math and Conclusions
Question 26: Matrix multiplication, which can be executed VERY efficiently in parallel on graphics cards
Question 27: Functions!
Question 28: An activation function is applied to the sum of the multiplications of the input x1 and the weight w1, and that of the input x2 and the weight w2 plus the bias x0. Mathematically: activationFunc(x1 * w1 + x2 * w2 + x0)

Quiz

The 6 questions in this quiz are the only ones with points attached to them. However, feel free not to answer some or any of the questions if they make you uncomfortable.
Note that there is only one correct answer per question.

36

What is TRUE about artificial neural networks? (1 Point)

- An artificial neuron holds an activation value between 0 and 1.
- A simple, "vanilla" artificial neural network is called a multi-layer Perceptron.
- A neural network can take an image (grid of pixels) as an input and, based on those pixel brightness values representing the content of the image, roughly categorise the image based on its content?
- All of the above.

37

What is FALSE about layers in an artificial neural network? (1 Point)

- The first and last layer of an artificial neural network are called the input and output layers, respectively.
- The optimal number of layers in an artificial neural network varies and depends on multiple factors.
- Each intermediate layer in an artificial neural network ALWAYS represents a "step" towards the solution the network is trying to reach.
- All of the above.

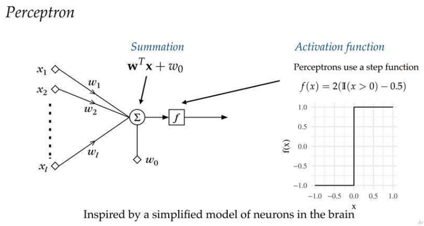
38

What is TRUE about artificial neural networks (aNNs)? (1 Point)

- Atrificial neural networks "chain" interconnected layers of polynomial functions in the form of neurons. Using the neurons' activation biases and the weights of the connections between them, aNNs tweak their behaviour to achieve the desired functionality, which amounts to a single highly complex function.
- The activation of an artificial neuron is determined by the sum of products of corresponding inputs and weights from its incoming edges, plus a bias value, all passed through an activation function, such as a Sigmoid, that squishes all real values to the interval [0, 1].
- Using matrix multiplication to represent complex calculation that determines the activation of a neuron enables artificial neural networks to be somewhat computationally efficient relative to the complexity of their tasks.
- All of the above.

39

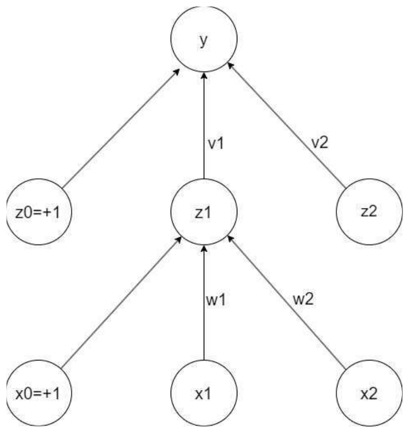
Here is a (single layer) Perceptron that uses a step activation function (which outputs 1 if its input is bigger than 0, and outputs 0 otherwise) instead of a sigmoid function.
What would this perceptron's output be equal to if it was given inputs x1 = 1, x2 = -0.5, x3 =-0, x4 = 2 and weights w1 = -1, w2 = 2, w3 = 4, w4 = 1 (1 Point)



- 6
- 1
- 0
- -2

40

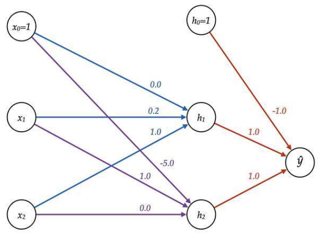
Here you see a graphical depiction of a multi-layer perceptron. How is the value of y calculated? (1 Point)



- An activation function is applied to the sum of the multiplications of z1 with v1 and z2 with v2, plus the bias z0. Mathematically, activationFunc(z1*v1 + z2*v2 + z0)
- By the sum of the multiplications of z1 with v1 and z2 with v2, plus the bias v0. Mathematically, z1*v1 + z2*v2 + v0
- An activation function is applied to the sum of the multiplications of z1 with v1 and z2 with v2, plus the bias x0. Mathematically, activationFunc(z1*v1 + z2*v2 + x0)
- By the sum of the multiplications of z1 with v1 and z2 with v2, plus the bias x0. Mathematically, z1*v1 + z2*v2 + x0

41

Consider the multi-layer perceptron depicted in the figure, where the numbers next to the edges denote the weight of each connection. Suppose we use a step activation function (which outputs 1 if its input is bigger than 0, and outputs 0 otherwise) for both all nodes.
If the inputs to this model are x1 = 10 and x2 = −1, what will the values for h1, h2 and y be?
Remember to put the sum of the incoming values through the activation function in order to obtain the value in a node! (1 Point)



- ◯ h1 = 1; h2 = 0; y = 0.5
- ◯ h1 = 1; h2 = 0.5; y = 0
- ◯ h1 = 1; h2 = 1; y = 1
- ◯ h1 = 1; h2 = 0; y = 0

42

How well do you think you have done on this quiz?

0	1	2	3	4	5	6	7	8	9	10

I probably got everyt hing wrong

I think I got everythin g right

Control Group (v39) Results

Id	Total point	I have read	To which o	What is yo	What is the	Have you s	In what reg	How would	How would	How would	How would	Neural Net	Can Neural	What is a si	What does	Which laye	What does	How many	Does each	What are tl	Here you s	What does
4	1	I agree	25 to 29	Male	Bachelor's	No	Europe (EU	8	3	3	2	I skipped th	Yes	Multilayer F	A value bet	The first tw	Outputs, su	it depends	Yes. Alway	Weights, bi	x = weight c	It maps or "
5	2	I agree	18 to 24	Male	Bachelor's	No	Europe (EU	10	3	4	0	I stopped w	Yes	Long short-	A value bet	The middle	Outputs, su	irrelevant	Yes. Alway	Inputs are t	x = input va	It maps or "
6	2	I agree	18 to 24	Female	Master's Di	No	Europe (EU	6	5	8	5	I stopped w	Yes	Long short-	A value bet	The middle	Outputs, su	it depends	Yes, but on	Weights, bi	x = input va	It maps or "
7	2	I agree	18 to 24	Female	Bachelor's	No	Europe (EU	6	7	3	5	I have fully	Yes	Convolutio	A value bet	All the layer	An interme	it depends	Yes, but on	Weights, bi	x = input va	It maps or "
9	1	I agree	25 to 29	Female	Master's Di	No	Europe (EU	9	0	2	2	I skipped th	Yes	Multilayer F	A value bet	Just the firs	Mysteries	16	Yes. Alway	Weights, bi	x = weight c	It... functio
11	0	I agree	18 to 24	Male	Bachelor's	No	Europe (EU	10	4	6	2	I stopped w	Yes	Multilayer F	A value bet	All the layer	Outputs, su	16	Roughly, sometimes.		It varies and c	It... functio
12	0	I agree	25 to 29	Male	Master's Di	No	Europe (EU	10	2	5	1	I stopped w	Yes	Multilayer F	A value bet	Just the firs	Outputs, su	irrelevant	Yes. Alway	Inputs are taken in and		It maps or "
13	0	I agree	25 to 29	Female	Master's Di	No	Europe (EU	10	1	7	1	I stopped w	Yes	Long short-	A value bet	Just the firs	Neurons	16	Yes, but on	Weights, bi	x = input va	It maps or "
15	3	I agree	18 to 24	Female	High Schoo	No	Europe (EU	10	0	4	0	I have fully	Yes	Multilayer F	A value bet	All the layer	Outputs, su	it depends	Roughly, sc	Weights, bi	x = input va	It maps or "
16	1	I agree	18 to 24	Female	Bachelor's	No	Europe (EU	7	6	8	1	I have fully	Yes	Convolutio	A value bet	Just the firs	Outputs, su	16	Roughly, sc	Weights, bi	x = input va	It maps or "
17	4	I agree	18 to 24	Female	Bachelor's	No	Europe (EU	10	3	8	0	I have fully	Yes	Multilayer F	A value bet	Just the firs	Outputs, su	it depends	Yes, but on	Weights, bi	x = weight c	It maps or "
18	1	I agree	18 to 24	Female	Bachelor's	No	Europe (EU	7	0	5	2	I stopped w	Yes	Multilayer F	A value bet	Just the firs	Outputs, su	16	Roughly, sc	Weights, bi	x = input va	It maps or "
19	2	I agree	18 to 24	Female	Bachelor's	No	Europe (EU	6	6	3	2	I have fully	Yes	Multilayer F	A value bet	Just the firs	Outputs, su	2	Yes. Alway	Weights, bi	x = input va	It maps or "
20	1	I agree	18 to 24	Female	Bachelor's	No	Europe (EU	9	6	8	6	I have fully	Yes	Multilayer F	A value bet	All the layer	Outputs, su	2	Roughly, sc	Weights, bi	x = input va	It maps or "
21	2	I agree	18 to 24	Female	Bachelor's	No	Europe (EU	5	5	3	3	I have fully	Yes	Convolutio	A value bet	Just the firs	Mysteries	16	Yes. Alway	Weights, bi	x = input va	It maps or "
22	1	I agree	18 to 24	Male	Bachelor's	No	Europe (EU	4	6	3	4	I stopped w	Yes	Convolutio	A value bet	The first tw	Outputs, su	16	Yes, but on	Weights, bi	x = input va	It maps or "
23	3	I agree	18 to 24	Male	Bachelor's	No	Europe (EU	4	6	5	3	I stopped w	Yes	Long short-	A value bet	All the layer	Outputs, su	2	Yes, but on	Weights, bi	x = input va	It... functio
24	2	I agree	18 to 24	Female	Bachelor's	No	Europe (EU	4	5	2	7	I have fully	Yes	Convolutio	A value bet	The first tw	Outputs, su	16	Yes. Always.		x = weight c	It maps or "
25	1	I agree	18 to 24	Female	Bachelor's	No	Europe (EU	5	8	9	6	I have fully	Yes	Multilayer F	A value bet	The first tw	An interme	it depends	Yes, but on	Inputs are t	x = input va	It maps or "
26	2	I agree	18 to 24	Male	Bachelor's	No	Europe (EU	8	10	7	5	I have fully	Yes	Convolutio	A value bet	All the layer	Outputs, su	it depends	Yes. Alway	Weights, bi	x = input va	It maps or "
27	2	I agree	18 to 24	Female	Bachelor's	No	Europe (EU	7	4	2	4	I have fully	Yes	Convolutio	A value bet	Just the firs	An interme	it depends	Yes, but on	Weights, bi	x = input va	It maps or "
28	1	I agree	18 to 24	Female	Bachelor's	No	Europe (EU	6	9	9	5	I have fully	Yes	Convolutio	A value bet	The middle	An interme	it depends	Yes, but on	Weights, bi	x = input va	It maps or "
30	2	I agree	18 to 24	Female	Bachelor's	No	Europe (EU	7	5	3	4	I have fully	Yes	Convolutio	A value bet	All the layer	Outputs, su	it depends	Yes. Alway	Inputs are t	x = weight c	It maps or "
	1,565217							7,304348	4,521739	5,086957	3,043478											

Consider tl	What is a c	What are, I	Here you s	How would	How would	How would	How easy v	How would you r	Ho	What is TRI	Points - Wh	What is FAI	Points - Wh	What is TRI	Points - Wh	Here is a (s	Points - He	Here you s	Points - He	Consider tl	Points - Co	How well d	Individual
0.0 < y < 0.!	Organic ch	Functions!	By the sum	3	1	1	2	2	2	An artificial	0	The optimal	0	Atrificial ne	0	0	1	By the sum	0	h1 = 1; h2 =	0	2	1
0.0 < y < 0.!	Matrix mult	Functions!	An activatic	3	8	3	2	3	3	All of the at	1	The optima	0	The activati	0	0	1	An activatic	0	h1 = 1; h2 =	0	2	2
0.0 < y < 0.!	Matrix mult	Functions!	An activatic	10	9	8	6	9	10	A neural ne	0	Each interm	1	The activati	0	1	0	An activatic	1	h1 = 1; h2 =	0	6	2
0.0 < y < 0.!	Matrix mult	Functions!	By the sum	7	8	8	8	8	8	A neural ne	0	Each interm	1	The activati	0	6	0	An activatic	0	h1 = 1; h2 =	1	9	2
y = 0.0	Organic ch	Functions!	By the sum	5	5	5	5	5	5	A simple, "\	0	The optima	0	Atrificial ne	0	0	1	By the sum	0	h1 = 1; h2 =	0	5	1
ns?		Functions!		5	5	5	1	1	5		0		0		0		0		0		0	0	0
squishes" values in the interval [-∞,			By the sum	6	6	4	3	5	6	An artificial	0	The first an	0		0		0		0		0	1	0
squishes" values in the i		Functions!	By the sum	7	5	5	5	5	5	An artificial	0	The first an	0	Atrificial ne	0	1	0	By the sum	0	h1 = 1; h2 =	0	5	0
y = 0.5	Matrix mult	Functions!	An activatic	8	8	4	2	3	5	All of the at	1	Each interm	1	The activati	0	0	1	An activatic	0	h1 = 1; h2 =	0	2	3
0.0 < y < 0.!	Matrix mult	Functions!	An activatic	5	7	6	6	7	7	A neural ne	0	The optima	0	Atrificial ne	0	1	0	An activatic	1	h1 = 1; h2 =	0	7	1
y = 0.5	Matrix mult	Functions!	An activatic	10	9	5	5	5	10	An artificial	0	Each interm	1	All of the at	1	0	1	An activatic	1	h1 = 1; h2 =	0	3	4
0.0 < y < 0.!	Matrix mult	Functions!	By the sum	7	6	6	4	2	6	All of the at	1	The optima	0	The activati	0	1	0	An activatic	0	h1 = 1; h2 =	0	3	1
0.0 < y < 0.!	Matrix mult	Functions!	An activatic	8	6	7	2	3	6	A neural ne	0	All of the at	0	The activati	0	0	1	An activatic	1	h1 = 1; h2 =	0	2	2
y = 0.0	Matrix mult	Functions!	An activatic	7	9	8	7	7	8	A neural ne	0	The first an	0	The activati	0	0	1	By the sum	0	h1 = 1; h2 =	0	5	1
0.0 < y < 0.!	Hyeroglyph	Functions!	An activatic	7	5	6	6	5	5	An artificial	0	The first an	0	Atrificial ne	0	0	1	By the sum	0	h1 = 1; h2 =	1	7	2
y = 0.0	Matrix mult	Functions!	An activatic	2	0	2	0	2	0	A neural ne	0	The optima	0	The activati	0	1	0	An activatic	1	h1 = 1; h2 =	0	1	1
0.0 < y < 0.!	Matrix mult	Functions!	An activatic	5	5	3	3	4	3	A neural ne	0	The first an	0	The activati	0	0	1	An activatic	1	h1 = 1; h2 =	1	4	3
0.0 < y < 0.!	Matrix mult	Functions!	An activatic	6	5	7	8	6	6	A neural ne	0	Each interm	1	The activati	0	6	0	An activatic	1	h1 = 1; h2 =	0	6	2
0.0 < y < 0.!	Matrix mult	Functions!	An activatic	8	8	8	8	8	8	A simple, "\	0	Each interm	1	Atrificial ne	0	6	0	An activatic	0	h1 = 1; h2 =	0	8	1
y = 0.5	Matrix mult	Functions!	An activatic	6	7	7	5	5	7	All of the at	1	The optima	0	Atrificial ne	0	1	0	An activatic	0	h1 = 1; h2 =	1	6	2
0.0 < y < 0.!	Matrix mult	Functions!	By the sum of multiplications of the inputs x1 and x2 and the weights w1 and w2,							All of the at	1	Each interm	1	The activati	0	1	0	By the sum	0	h1 = 1; h2 =	0	4	2
y = 0.5	Organic ch	Functions!	By the sum	5	6	7	4	7	7	A simple, "\	0	The optima	0	The activati	0	1	0	An activatic	0	h1 = 1; h2 =	1	6	1
y = 0.5	Matrix mult	Functions!	An activatic	4	8	3	2	3	4	All of the at	1	All of the at	0	Atrificial ne	0	0	1	By the sum	0	h1 = 1; h2 =	0	1	2
				4,5	7	5	3	5	6													4,130435	1,565217

Experimental Group (v42) Results

Id	Total point	I have read	To which o	What is yo	What is the	Have you studied Machine	In what re	How would	How would	How would	How would you	Introductio	Part 2: Law	Part 3: Wei	Part 4: Mat	How would	How would	How would
6	3	I agree	18 to 24	Female	Bachelo's	No	Europe (EU	6	4	6	6	I have fully	I have fully	I stopped w	I stopped w	3	6	6
7	0	I agree	18 to 24	Female	Bachelo's	No	Europe (EU	10	4	4	3	I stopped w	I stoppedv	I stopped w	I stopped w	5	5	5
8	6	I agree	18 to 24	Male	Bachelo's	No	Europe (EU	9	2	5	2	I have fully	I have fully	I have fully	I have fully	9	9	9
10	6	I agree	18 to 24	Female	Bachelo's	No	Europe (EU	10	5	7	1	I have fully	I have fully	I have fully	I have fully	10	10	10
11	3	I agree	25 to 29	Female	Master'sDi	No	Europe (EU	8	4	5	0	I have fully	I have fully	I have fully	I have fully	9	9	8
12	3	I agree	18 to 24	Female	Bachelo's	No	Europe (EU	8	0	8	3	I have fully	I have fully	I have fully	I have fully	7	8	6
14	0	I agree	18 to 24	Male	Bachelo's	No	Europe (EU	9	5	5	3	I have fully	I have fully	I have fully	I have fully	7	0	6
15	2	I agree	18 to 24	Male	Bachelo's	No	Europe (EU	8	2	8	2	I have fully	I have fully	I have fully	I have fully	8	7	8
16	3	I agree	18 to 24	Male	Bachelo's	No	Europe (EU	8	8	4	3	I have fully	I have fully	I have fully	I stopped w	6	3	5
18	3	I agree	18 to 24	Male	Bachelo's	No	Europe (EU	9	2	5	0	I have fully	I have fully	I have fully	I have fully	9	6	9
19	5	I agree	18 to 24	Male	Bachelo's	No	Europe (EU	9	4	8	4	I have fully	I have fully	I have fully	I have fully	9	8	7
20	6	I agree	25 to 29	Female	Bachelo's	No	Europe (EU	10	1	5	1	I have fully	I have fully	I have fully	I have fully	8	9	8
23	4	I agree	18 to 24	Male	High Schoc	No	Europe (EU	10	4	7	2	I have fully	I stoppedv	I have fully	I have fully	7	7	7
24	5	I agree	18 to 24	Female	Bachelo's Diplema			10	3	8	2	I have fully	I have fully	I have fully	I have fully	9	9	8
25	6	I agree	18 to 24	Female	Bachelo's	No	Europe (EU	10	1	7	1	I have fully	I have fully	I have fully	I have fully	8	9	8
26	5	I agree	18 to 24	Female	High Schoc	No	Europe (EU	10	4	9	2	I have fully	I have fully	I have fully	I have fully	10	9	9
27	5	I agree	18 to 24	Female	High Schoc	No	Europe (EU	0	1	7	0	I have fully	I have fully	I have fully	I have fully	8	6	3
28	4	I agree	18 to 24	Female	High Schoc	No	Europe (EU	10	2	8	1	I have fully	I stoppedv	I have fully	I have fully	8	9	9
	3,833333							9,055556	3,444444	6,388889	1,944444444					7,777778	7,444444	7,222222

How easy v	How would you rate your level of confidence i	How would	What is TRI	Points - Wh	What is FAI	Points - Wh	What is TRI	Points - What is TRUE	Here is a (single la	Points - He	Here you s	Points - He	Consider tl	Points - Co	How well d	Individual
3	3	4	A neural ne	0	Each interm	1	Atrificial ne	0	0	1	An activatic	1	h1 = 1; h2 =	0	3	3
5	5	5		0		0		0		0		0		0		0
9	9	9	All of the at	1	Each interm	1	All of the at	1	0	1	An activatic	1	h1 = 1; h2 =	1	9	6
10	10	10	All of the at	1	Each interm	1	All of the at	1	0	1	An activatic	1	h1 = 1; h2 =	1	10	6
8	7	8	All of the at	1	The first an	0	The activati	0	0	1	An activatic	1	h1 = 1; h2 =	0	7	3
3	2	10	All of the at	1	Each interm	1	Atrificial ne	0	1	0	An activatic	1	h1 = 1; h2 =	0	4	3
4	2	7		0		0		0		0		0		0		0
6	6	8	All of the at	1	All of the at	0	The activati	0	1	0	An activatic	0	h1 = 1; h2 =	1	9	2
3	3	3	All of the at	1	Each interm	1	Using matri	0	-2	0	By the sum	0	h1 = 1; h2 =	1	5	3
10	6	9	All of the at	1	The optima	0	All of the at	1	1	0	An activatic	1	h1 = 1; h2 =	0	6	3
7	8	9	All of the at	1	The first an	0	All of the at	1	0	1	An activatic	1	h1 = 1; h2 =	1	7	5
8	8	8	All of the at	1	Each interm	1	All of the at	1	0	1	An activatic	1	h1 = 1; h2 =	1	8	6
7	7	7	All of the at	1	The optima	0	All of the at	1	0	1	By the sum	0	h1 = 1; h2 =	1	8	4
8	8	8	All of the at	1	The optima	0	All of the at	1	0	1	An activatic	1	h1 = 1; h2 =	1	7	5
7	7	8	All of the at	1	Each interm	1	All of the at	1	0	1	An activatic	1	h1 = 1; h2 =	1	9	6
9	9	9	All of the at	1		0	All of the at	1	0	1	An activatic	1	h1 = 1; h2 =	1	9	5
3	1	6	All of the at	1	Each interm	1	All of the at	1	1	0	An activatic	1	h1 = 1; h2 =	1	3	5
8	8	8	An artificial	0	Each interm	1	All of the at	1		0	An activatic	1	h1 = 1; h2 =	1	9	4
6,555556	6,055555556	7,555556													7,0625	3,833333