A Moderate Experiential Learning Approach Applied on Data Science

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Abstract. A moderate experiential learning is proposed as a framework to provide learners with significant experiences in data science. In this approach, the student learns through reflection on doing, abstract conceptualization, gamification and learning transferring; instead of being a recipient of already made content. Data science pedagogy has repeated a number of patterns that can be detrimental to the student. The proposed moderate experiential learning has been adopted together with other two learning approaches in a data science master subject for comparative purposes: a traditional learning approach, and a strict experiential learning adoption. Two evaluation studies have been conducted to compare these three different learning approaches. The results indicate that students do not actively support the strict experiential learning, but the moderate approach, where some guidelines are provided to face the realistic experience.

Keywords: active learning, experiential education, project-based learning, game-based learning, data science, graduate students

1 Introduction

Experiential learning (EL) is more than just getting learners to do something: *unless experiences outside the classroom are brought into the classroom and integrated with the goals and objectives of the discipline theory, students will continue to have amazing outside experiences but will not readily connect them to their in-class learning* [6]. Even when the term experiential learning is sometimes used to define any training that is interactive, with minimal lecture and slides [10], the students reflecting on their product is a fundamental part of EL. Without a careful curriculum involving structured, reflective skill building, students may never learn what we hope outside the four walls of the classroom [6]. As the Association for Experiential Education [1] claims, to ensure that EL is effective, the learner has to be actively engaged in posing questions, investigating, experimenting, being curious, solving problems, assuming responsibility, being creative, and constructing meaning. The educator and learner may experience success, failure, adventure, risk-taking and uncertainty because the outcomes of experience cannot totally be predicted. Therefore, EL is an approach that encourages collective and critical reflection, as well as individual learning [7].

Data science (DS) is an interdisciplinary field devoted to extracting knowledge from complex big data [5]. The great diversity of applications and the growing demand of experts in the DS field has made courses, books and manuals in DS proliferate. The standard pedagogical method in DS that can be appreciated basically consists of four steps: the explanation of different DS techniques; the detail on some specific approaches or paradigms; the illustration of these paradigms using toy, and well known, datasets [11]; and the assignments with a straightforward application of the ideas previously exposed using some DS framework [4]. We also adopted this traditional learning approach over the last few years in a data science related course as part of a University master degree program. This experience revealed some limitations of this method. Firstly, students showed difficulties in selecting relevant information about how different machine learning approaches work and what kind of problems they are suitable for. As a result, the student usually obviated the details and data of a concrete problem. As Witten et al. declare in [11], nothing replaces a good understanding of the data. Finally, the creativity in solving problems is considerably restricted because DS is perceived as the application of well-known solutions to well-known problems.

EL would naturally mitigate these tendencies when learning DS because it focuses on problems to be solved instead of on specific methods. In addition, starting with realistic experiences gives students more experience in real-world problems. More importantly, creativity and divergent thinking are encouraged when searching for solutions to a concrete experience. The existence of different dataset repositories on which to build knowledge offers a privileged breeding ground for designing a DS course as a series of experiences in real-world problems [2, 9].

This paper presents a moderate experiential learning approach, supported by open and free software framework [8]. This approach has been deployed in a deep learning course, which is part of the official Master's Programme in ICT Innovation: Data Science (EIT Digital Master School). Deep learning is nowadays a very demanding working and studying area due to its dramatically improved results in many domains such as classification, computer vision and sequential data problems. These are, precisely, the three units in which the course is divided. For comparison purposes, the traditional learning approach is involved in the first unit: deep artificial neural networks for classification problems. The proposed approach in the second unit: computer vision; and a strict experiential learning adoption is deployed in the third unit for natural language processing, i.e. a sequential data problem. The experience gathered over the 2016-17 academic year is also presented in terms of the level of students' satisfaction for each of the three deep learning course units / learning approaches.

2 The Moderate Experiential Learning Approach

EL theory is typically represented by a four-stage learning cycle [3]: effective learning involves progressing through this cycle: first, having a concrete experience or situation; then, the observation of and reflection on that experience; later, the formation of abstract concepts (analysis) and generalizations (conclusions); and finally, testing them by active experimentation, resulting in new experiences (iterations in the cycle). In the scope of our moderate EL approach, this learning cycle is reviewed and instantiated for the computer vision unit, within the deep learning course.

Deep learning is a second year 3-ECTS (European credit transfer and accumulation system) master course, with a duration of one semester (15 weeks) and 81 hours of student workload distributed as follows: 30 hours to fifteen 2-hours face-to-face classroom sessions, one per week, and the remaining 51 hours to workgroup and individual activities. The course kicks off with a one-day face-to-face session where the learners have the chance to meet the instructor or facilitator. Since this is a second-year course, learners already meet each other, what would be another objective of this session in case of a first-year course. The instructor introduces the course topics, presents the learning objectives, and discusses the most significant knowledge to acquire. Then, the instructor explains the three different learning methods that will be adopted for each of the three units: traditional learning for deep artificial neural networks for classification problems, the proposed moderate EL for computer vision and EL for natural language processing. The instructor also encourages the students to form workgroups of three or four members during the rest of this course week.

Every week, there is a two-hour face-to-face session where some experiential learning activities take place depending on the learning approach for the unit. Additionally, the instructor presents the most important contents to learn over the following week. Students have also the opportunity to put in common questions to be discussed. Learners can meet the instructor, individually or in group, six hours a week to clarify contents and receive support on how to solve problems or experimental activities. Students regularly meet at their discretion in workgroups to discuss the experiences presented in class or possible solutions, to accomplish the active experimentation or to solve the assessment activities. An assessment activity is set immediately after each unit has finished, related to a real-world problem that involves a dataset extracted from a public web repository. Learner evaluation also considers the scores achieved in the solutions given to the assessment activities, which are the same for all the members of a workgroup.

2.1 The Three Learning Approaches

The first unit, deep artificial neural networks for classification problems, takes five weeks. It follows the classical flow in a DS course. Firstly, artificial neural networks theory is explained. Secondly, practical advice in solving problems are described along with deep learning frameworks. Finally, an assessment activity to solve in workgroup a classification problem using a public dataset is set to apply the explained ideas.

The second unit, computer vision, takes the following five weeks. It adopts a moderate EL approach. After introducing the topic, a contest is proposed for the workgroups to use the methods learned in the previous unit to a computer vision problem using a specific dataset. The experience allows a reflective observation of the low accuracy achieved, and an abstract conceptualization of some of the challenges of computer vision. Then, convolutional neural networks are explained. This allows students to retake the contest and observe the improvement achieved by the new ideas introduced in the course. Finally, the same approach is followed for a transfer learning problem, proposing a new experience for images object classification as an assessment activity. The key in this moderate experiential approach adopted in this unit is that students get their prior knowledge challenged by new problems. Learners have time to try known methods to new situations and to reflect on the results. Moreover, the contests act as a game-based approach for the EL [9]. Students are not required to research new methods for the new experiences proposed as planned in a stricter EL approach.

The third unit, natural language processing, adopts a strict experiential learning approach to learn the educational contents for four weeks. The learners, also in workgroups, face a realistic experience: they are asked to design a solution to predict the relevance of an article headline regarding its body from a dataset. First, workgroups carry out an investigation into the problem and present a manuscript with the solution design. Bibliographic references discussing natural language processing methods are provided afterwards to reflect on possible changes in the solution. Then, the workgroups have the opportunity to present their solutions to be discussed with the other groups in a face-to-face session moderated by the facilitator. Finally, a brief lecture on natural language processing concepts and how to apply them to the case study is offered. The assessment activity consists of delivering a report with the final solution design. A key differentiator of this strict EL adoption is that it makes the learners feel free in the investigation and proposal of solutions to a problem, instead of following instructor instructions.

3 Results

Two evaluation studies have been conducted to analyze the level of learners' satisfaction using three different learning approaches for the deep learning course. The first study evaluates each learning approach with the same set of questions. In the second study, each learning approach is voted against the other two based on some affirmations. This course has been taught over the 2016-17 academic year to computer science graduates as part of a Data Science Master Degree Program. A total of 25 students attended the course, from which 24 participated in the study. They come from European countries and are of very similar ages, ranging from 22 to 24 years old. The course was taught by the same teachers using the three learning approaches. Additionally, each learner is exposed to the three learning methodologies, avoiding this way the residual variation due to differences between subjects.

Data were obtained from a questionnaire administered to students at the end of the course. The questionnaire is divided into two sections: one for each

Table 1. Descriptive statistics for learners' satisfaction, evaluated by the three questions Q1, Q2, and Q3 for each of the three learning methodologies adopted

Q:U	N	Mean	Std. Dev.	Std. Error	Min.	Max.	95% CIM	
							Lower B.	Upper B.
Q1:U1	24	3.38	1.06	0.2164	1	5	2.95	3.80
Q1:U2	24	4.50	0.59	0.1204	3	5	4.26	4.74
Q1:U3	24	4.13	0.68	0.1387	3	5	3.85	4.40
Q2:U1	24	3.58	0.78	0.1592	2	5	3.27	3.89
Q2:U2	24	4.46	0.51	0.1041	4	5	4.25	4.66
Q2:U3	24	4.08	0.97	0.198	2	5	3.69	4.47
Q3:U1	24	3.08	0.97	0.198	1	5	2.69	3.47
Q3:U2	24	4.00	0.88	0.1806	2	5	3.65	4.35
Q3:U3	24	4.21	0.93	0.191	2	5	3.84	4.58

of the two evaluation studies. The first section comprises the same three questions for each learning methodology. The second section comprises four affirmations in which the learner has to decide (or vote), for each of them, the course unit/learning methodology that best fits it.

3.1 Learning Approaches Evaluation

The first section of the questionnaire administered to the students to evaluate each of the three learning approaches comprises the following three questions: Q1: *the unit content meets my training needs*, Q2: *what I learned will be applicable in my job"*, and Q3: *the applied methodology, technical resources and teaching materials were appropriate*. Participants responded to these questions based on a five-point Likert scale, ranging from strongly disagree (scored as 1) to strongly agree (scored as 5). The learning methodology served as the independent variable, with three levels: traditional learning for unit 1 (U1), moderate EL for unit 2 (U2) and strict EL for unit 3 (U3). The dependent variable for this study is the level of learners' satisfaction, represented by the learners' responses to Q1, Q2, and Q3. Table 1 shows descriptive statistics for the responses to each question related to each unit. From left to right: number of responses gathered, standard deviation, standard error, minimum and maximum values, and 95% confidence interval with lower and upper bounds.

Since the same students faced the three learning methodologies and, therefore, the same subjects responded to the questionnaire, a one-way repeated-measures analysis of variance (rANOVA) was conducted to gather empirical evidence of whether the differences between the means are statistically significant. Therefore, the learning methodology (the independent variable) is the within-subjects factor. The Shapiro-Wilk and Levene tests confirm that the rANOVA assumptions (normality and homoscedasticity, respectively) are met. Since there are three groups with 24 observations each, the degree of freedom, df, between groups is 2, and within groups is 69. The results of the three rANOVA tests show

Table 2. Tukey HSD test for Q1. $p < 0.05$

Learning condition a	Learning condition b	Mean difference	Sig.
Q1:U1	Q1:U2	-1.125*	.000*
Q1:U1	Q1:U3	-0.75*	.005*
Q1:U2	Q1:U3	0.375	.055

that the null hypothesis (responses to questions Q1, Q2, and Q3 are the same for each of the three learning conditions) are rejected since $F(df = 2/69) = 12.28$, $p < 0.01$; $F(df = 2/69) = 7.67$, $p < 0.01$, and $F(df = 2/69) = 9.92$, $p < 0.01$, respectively. Thus, the learners' satisfaction depends on the learning approach.

As there are sizeable differences between the three groups of each question Q1, Q2, and Q3 concerning the learning approach, the Tukey HSD (honestly-significant-difference) test was used to make post hoc comparisons to demonstrate where are the statistically significant differences. Table 2 shows the results of these multiple comparisons for Q1, which are similar to Q2, and Q3, considering that the significance level for the mean difference is $p < 0.05$, marked by an asterisk. The conclusions that arise from Table 2 are the same for Q2 and Q3: there are significant differences between the classical learning approach (U1) and the moderate EL (U2), and between the classical approach and the strict EL (U3). However, there are no differences between the two EL approaches (U2 and U3). From these results, the homogeneous subsets for $\alpha = 0.05$ have been also statistically calculated, as a function of the mean, to group the three learning conditions applied. The result was the same: a subset formed exclusively by the classical learning approach and another subset containing the proposed moderate EL, plus strict EL. The values obtained from Q1, Q2, and Q3 for either moderate or strict EL are, statistically, greater than for learners responding to the questionnaire in relation to the classical learning approach. It is also noteworthy that, although the means for Q1, Q2, and Q3 using the proposed moderate EL approach appears to be higher (4.50, 4.46, and 4.00, respectively. See Table 1) than using the strict EL approach (4.13, 4.08, and 4.21, respectively), there are no significant differences in terms of the learners' satisfaction.

3.2 Confronting The Three Learning Approaches

The second section of the questionnaire administered to students at the end of the course is involved in this second evaluation study. Four affirmations are presented: A1: *my favourite methodology is the one used in...*, A2: *the methodology that allows me to learn the most is...* , A3: *the methodology that (I believe) allows the longest lasting learning is...*, and A4: *the methodology that is closest to a data scientist's daily tasks is...*. The learner is asked to vote the learning condition that best fits each of these affirmations. The aim of this second evaluation study is to deepen the comparison of the three learning approaches, especially in the cases of moderate and strict EL, since both were grouped in the same homogeneous mean subset in the previous evaluation study. Figure 1 shows a histogram

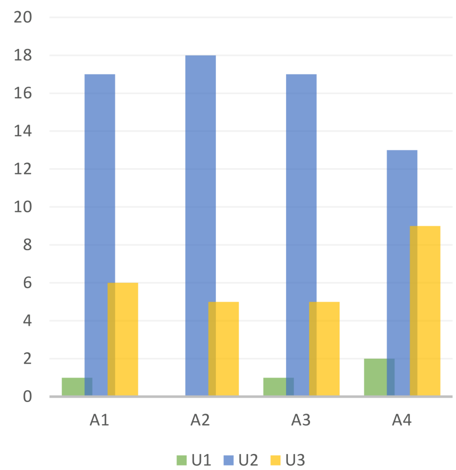

Fig. 1. Votes for each learning condition

of the votes cast for each learning condition. The affirmations are represented in the abscissa axis and the votes cast for each learning condition in the ordinate axis. It is clear that the preferred learning condition is the moderate EL approach (represented by blue bars), except for the affirmation marked as A4. In this case, moderate and strict EL approaches are closed to each other, with 13 and 9 votes, respectively. Therefore, it can be concluded that although these two EL approaches seem to be equivalent from the first evaluation study, students prefer the proposed moderate approach when they have to decide between the moderate against the strict approach.

4 Conclusions

This article presents what is classed as a moderate experiential learning approach, since students get their prior knowledge challenged by new problems, instead of freely researching new methods for the new experiences proposed. It is a general-purpose learning approach, supported by an open and free software framework, that can be applied when realistic experiences are available. This is the case of data science, where the proposed moderate EL approach is now being successfully applied to computer science graduates. We have also presented the results in terms of learners' satisfaction from experience gathered over the 2016-17 academic year, comparing three different learning approaches for a deep learning course: the classical flow followed in data science courses, the proposed moderate EL, and a strict EL adoption. Two evaluation studies have been conducted, using data obtained from a questionnaire administered to students at the end of the course.

The first study involved one-way repeated-measures analysis of variance. The results provide empirical evidence that the level of learners' satisfaction is higher in the case of the moderate and strict EL than for the classical approach. However, there are not statistically significant differences between moderate and strict EL methods, even though the learners' responses to the questions evaluated in this study favor, on average, the moderate EL prescriptions. The second study consisted of voting for each of the three learning approaches under study to resolve the statistical tie between the moderate and strict EL approaches. This way the student had to decide the most satisfying learning condition against the other two. The results achieved show a superiority of the proposed moderate EL approach, with more than 70% of the votes cast in three out of four affirmations evaluated, and also winning the vote in the last case, although with a closer result.

Future research work focuses on to strengthen the findings and conclusions arisen from this study by increasing the sample sizes and a more in-depth analysis of where the differences are between the moderate and strict EL.

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References

1. Association for Experiential Education: The principles of experiential education in practice (2018), http://www.aee.org/index.php?option=com_content&view=article&id=110:what-is-ee&catid=20:other&Itemid=260
2. Bennett, J., Lanning, S.: The netflix prize. In: KDD Cup and Workshop in conjunction with KDD. ACM, San Jose, CA (2007)
3. Kolb, D.A.: Experiential learning: experience as the source of learning and development. Pearson Education, Upper Saddle River, NJ, second edn. (2015)
4. Kuhn, M.: Caret: classification and regression training (2018), https://CRAN.R-project.org/package=caret
5. Mayer-Schonberger, V., Cukier, K.: Big Data: A Revolution That Will Transform How We Live, Work, and Think. Houghton Mifflin Harcourt, Boston, MA (2013)
6. Qualters, D.M.: Making the most of learning outside the classroom. New Directions for Teaching and Learning 124, 95–99 (2010)
7. Reynolds, M., Vince, R.: Handbook of Experiential Learning and Management Education. Oxford University Press, Oxford, UK (2008)
8. Serrrano, E., Manrique, D., Amador, E.: JupyterDS: a software tool for experiential learning in data science. Registration in the intellectual property registry of Madrid No. M-004029/2018 (2018)
9. Shiralkar, S.: IT through experiential learning: learn, deploy and adopt IT through gamification. Apress, New York (2016)
10. Silverman, M.L.: The Handbook of Experiential Learning. Pfeiffer, San Francisco, CA (2007)
11. Witten, I.H., Frank, E., Hall, M.A.: Data mining: practical machine learning tools and techniques. Morgan Kaufmann, Burlington, MA (2011)