TEACHING MACHINE LEARNING TO PROGRAMMING NOVICES – AN ACTION-ORIENTED DIDACTIC CONCEPT

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DOI: 10.35011/IDIMT-2024-123

Keywords

Machine learning, education, didactic concept, interdisciplinarity

Abstract

Machine Learning (ML) techniques are encountered nowadays across disciplines, from social sciences, through natural sciences to engineering. However, teaching ML is a daunting task. Aside from the methodological complexity of ML algorithms, both with respect to theory and *implementation, the interdisciplinary and empirical nature of the field need to be taken into consideration. This paper introduces the MachineLearnAthon format, an innovative didactic concept designed to be inclusive for students of different disciplines with heterogeneous levels of mathematics, programming, and domain expertise. The format is grounded in a systematic literature review and the didactic principles action orientation, constructivism, and problem orientation. At the heart of the concept lie ML challenges, which make use of industrial data sets to solve real-world problems. Micro-lectures enable students to learn about ML concepts and algorithms, and associated risks. They cover the entire ML pipeline, promoting data literacy and practical skills, from data preparation, through deployment, to evaluation.*

1. Introduction

In an era marked by rapid digitalization, developing data literacy and Machine Learning (ML) skills became crucial (Abedjan, 2022). In recent years, ML has led to many technological advancements, e.g. in the context of Industry 4.0 (Lee & Lim, 2021) or large language models (Vaswani et al., 2017), such as chat GPT. ML competencies, particularly with respect to algorithm contextualization and evaluation, are vital for creating not only efficient and practical but also safe and fair ML solutions. To address these challenges, ML teams should be comprised not only of ML but also of application domain experts. Educating domain experts in ML can be a demanding task. ML spans several paradigms with each category containing a plethora of algorithms of considerable complexity. To make matters worse, owing to the data-driven nature of the field, considerable skills are required to acquire and manipulate the algorithm inputs, and evaluate the achieved results (Domingos, 2012). As such, ML primarily involves applied learning, often intertwined with intricate mathematical theory.

Subsequently, the research question is: How should a didactical concept tailored for teaching ML to domain-novices at universities look like? To answer this question, the paper is structured as follows: Section 2 presents a systematic literature review on existing teaching formats of ML, including a detailed description of the methodology and the results. In Section 3, the didactic concept, the MachineLearnAthon format, is derived based on the findings from the literature review and the didactic principles action orientation, constructivism and problem orientation. The course structure and an exemplary course timeline are introduced. In the conclusion, the main findings are summarized. This paper is part of the Erasmus+ project MachineLearnAthon (funding code 2022-1-DE01-KA220_HED-000086932). Further information can be found on the website https://dss.lfo.tu-dortmund.de.

2. Systematic Review of Machine Learning Teaching Formats

To systematically search papers on ML education, we filter articles indexed by Scopus. This academic database was selected because of its comprehensive indexing of publication venues and its reproducible queries (Mongeon & Paul-Hus, 2016). By setting inclusion criteria and employing a search syntax, we narrowed down over a thousand articles to only 12. This chapter discusses the steps taken to arrive at these findings and what they suggest about the current state of ML education.

2.1 Review Methodology

We started by creating a search string syntax. The string is intentionally designed to be broad such that the risk of missing pertinent articles is minimized. To identify and examine publications on teaching ML methods, we divide the search string into two segments:

- ML segment represented by words: “machine learning”, “deep learning”, “analytics”
- Educational segment includes words: “education”, “lesson”, “didactic”, “pedagogic”, “university”, “exercise”

We utilized the logical conjunction “AND” to bridge these two segments, while “OR” was employed to link the keywords within each segment. We established stringent inclusion and exclusion parameters. The selection was limited to scholarly, peer-reviewed articles penned in English, with an explicit mention of concrete ML techniques. The scope of our research is demarcated to encompass disciplines such as “Computer Sciences”, “Business”, “Multidisciplinary”, and “Economics”, while omitting any literature accentuating health and medicine-oriented keywords like “disease”, “psychology”, “health”, “medicine”, “tumor”, “enzymes”, “diagnosis”. The temporal boundary for the review was set from the year 2006 onward, marking the dawn of deep learning’s emergence.

The application of our search syntax to the academic databases yields a total of 1,377 articles. These articles underwent a preliminary review, whereby the abstracts were scrutinized for relevance. This evaluation decreased the number down to 104 articles, which were then subjected to a full-text review. This further distilled the selection to a mere 12 scholarly articles. The 12 final articles specifically focus on pedagogical strategies pertinent to the instruction of ML. This striking constriction in number from the initial pool highlights a significant gap within the existing literature, signalling an imperative need for an enhanced scholarly focus.

2.2 Results

The review encompasses 12 articles (see Table 1) published between 2018 and 2022. From the development of AI education models for non-computer majors to the integration of ML in business analytics and audit curricula, the articles collectively highlight the multifaceted nature of ML teaching. They address various learning environments and examine the effectiveness of different teaching methods. This review not only reflects the current trends in ML education but also sheds some light on practical ML applications, evaluation methods, and impact on students in various academic stages. As such, the present elaboration can serve as a seed for future investigations of educational practices.

By analyzing the 12 articles featured in our literature review, several noteworthy trends and gaps in the field of ML education become apparent. Firstly, a predominant number discusses the use of online, ML-based environments for the assessment and evaluation of students. This trend highlights the growing reliance on digital platforms to facilitate learning and underscores the need for robust and interactive online educational tools. Secondly, several articles emphasize the integration of ML in business analytics education, where students are encouraged to apply ML techniques to solve specific business problems. This direct application of ML in a business context mirrors the challenges business students will face in their careers and provides a strong foundation for understanding the potential of ML to transform industries. Furthermore, it is notable that only one paper discusses the use of competition or skill comparison as a pedagogical tool. This singular mention of competitive learning indicates that this approach is not widely adopted in ML education, despite its potential to enhance student engagement and learning outcomes. Moreover, the articles describe various learning environments from traditional classroom settings to online platforms, suggesting a flexible approach to ML education that can cater to a diverse range of learning preferences. Five articles mention the application of hands-on projects and collaborative learning.

Table 1. Identified papers in the systematic literature review

Year	Authors	Use Case	Learning Environment	Teaching Evaluation	Programming Language	Platforms Used	Teaching Process Description
2018	(Kopcso & Pachamanova, 2017)	No	Undergraduate students, MBA students, and exec- Utives	Survey among students	R	Not mentioned	Suggests ways to frame classroom discussion around the business value of models in data science, predictive analytics, and management science classes
2020	(Marques, Gresse von Wangenheim, & Hauck, 2020)	No	K12 students from pri- mary to high school	Generally through questionnaires, mostly not systematically evaluated	Python	Focus on instructional methods rather than platforms	Systematic review of ML teaching in schools, analyzing "Instructional Units" from literature in terms of ML content, teaching methods, and evaluation
2021	(Alexandre et al., 2021)	Yes	Citizens 15 years and older, including schools and the public	Learning analytics, quan- titative and qualitative evaluations	Not mentioned	MOOC platform	Discusses an open educational approach to AI using a hybrid MOOC. It focuses on engaging citizens and investigates pedagogical methods and citizen education in AI
2021	(Blix, Edmonds, & Sorensen, 2021)	No	Accounting graduates and educators	Examination of text- books and online resources	Not mentioned	Textbooks and online resources	Evaluates the integration of data analytics content in prominent auditing textbooks, focusing on technologies, software-based exercises, and alignment with professional standards
2021	(Brown-Devlin, 2021)	Yes	Analytics-focused course for advertising students	Through course modules and various assignments	Not mentioned	Resources, datasets, software	Provides an overview of teaching an analytics-centered course in a leading advertising program, including descriptions of course modules, assignments, and references to teaching resources and software
2021	(Lee & Cho, 2021)	Yes	Non-computer majors for general AI education	Experimenting with AI tools	Python	AI education tools, teachable machines	Discusses classifying ML models and introducing an AI education model using teachable machines for individuals without deep math or computing knowledge
2021	(Lim & Heinrichs, 2021)	Yes	Senior-level business students	Through a marketing an- alytics project develop- ment model and course evaluations	Not mentioned	HubSpot's CRM soft- ware tools and a learning management system	Introduces a marketing analytics project development model in a senior-level course. Uses CRM software tools to expose students to data visualizations and analytics
2021	(Luo, 2021)	No	Auditing educators	Integration of analytics mindset into the curricu- lum	Not mentioned	Not specified	Emphasizes the importance of audit data analytics in the audit profession and advocates for auditing educators to integrate an analytics mindset into their curriculum
2021	(Pudil, Somol, Mikova, Pribyl, & Komarkova, 2021)	Yes	Further education and training of employees	Analyzing the associa- tion between specific ed- ucational methods and profitability indicators	Not mentioned	Not mentioned	Focuses on the relationship between specific methods of employee education and financial performance of organizations in the Czech Republic, highlighting the importance of instructing, coaching, mentoring, and talent management
2022	(Anand & Mitchell, 2022)	No	University students in the business school at the University of Texas, Austin, aged 17-40	Teaching evaluation, open-ended survey questions, employment outcomes	Python	Not mentioned	Creation of teams, interaction with sponsors, tailoring of in-class learning, execution of business analytics projects, bi-weekly mentoring meetings, project assessments
2022	(Irgens, Vega, Adisa, & Bailey, 2022)	No	Children aged 9-13 at an after-school center	Pre- and post-drawings	Scratch, Google Quick Draw	MIT's How to Train Your Robot, AI+Ethics for Middle School Curriculum	Activities included sketching tasks, group algorithm writing, discussions about ML in daily life
2022	(Kaspersen et al., 2022)	No	High aged Students school 17-20	Not clearly specified	No specific language; tool with GUI	VotestratesML, an ethics-first learning tool	Introduction to tools, group work on model creation, discussions on feature selection and algorithm parameters

3. Didactic Design

Based on the results of our literature review, we developed a didactic concept for ML, which we present in the following. We start by specifying the learning goals. Then, we provide some additional theoretical background on didactic principles. Incorporating these principles into the results from our literature review, we present the content and organizational structure of the MachineLearnAthon. Finally, we outline how the course can be integrated into university curricula. The main goal is to teach ML to students with little or no prior programming knowledge. This entails the following sub-goals: 1. Data literacy improvement 2. Conveying a basic understanding of ML paradigms and widespread models 3. Developing the skill to employ ML models using Python 4. Increasing the awareness of risks and limitations associated with ML 5. Fostering cooperation in working groups (interdisciplinary and international) 6. Encouraging application-oriented thinking.

3.1 Foundational Didactic Principles

As our literature review showed, there has been only little research on how to teach ML competencies to students. Due to this research gap, we build on the few findings from the review and on general didactic principles to derive the MachineLearnAthon concept. In the following, we elaborate on the pedagogical concepts of action orientation, constructivism, and problem orientation.

Action Orientation: In a didactic context, a basic distinction can be made between subject-systematic and action-systematic orientation. The subject-systematic approach distributes learning objectives and learning content to individual subjects. In this way, the learning objects are considered in isolation and treated separately from each other. With an action-systematic orientation, learning content can be re-organized on an interdisciplinary basis according to professional action structures and traditional subjects can be dissolved. The aim is to prepare learners well for professional practice through work-related learning situations. If this is implemented consistently, it leads to project-like learning in action situations (Riedl & Schelten, 2000). It is important that the learning process corresponds to a complete action process. Action-based learning is made up of an interplay of different sub-processes. The task-related level consists of the following steps: Clarifying the task or defining the goal, planning, realizing, presenting and evaluating. This level requires support from the individual's motivation, organization and intuition. In this way, the ability to act in similar situations is built up by meta-cognitive processes transforming concrete experiences into insights (Pfäffli, 2015).

Constructivism From a learning theory perspective, knowledge cannot be stored and retrieved (cognitivism) or acquired through the reinforcement or attenuation of behaviour (behaviourism). Constructivists believe that knowledge is constructed by the individual (Kerres, 2018). Prior knowledge plays an important role here, as new information is linked to experiences and knowledge that have already been incorporated (Looi & Seya, 2014). It follows that the student must become active in order to acquire knowledge. The learning environment aims to support students by allowing them to make decisions regarding learning content, styles and strategies. The teacher primarily provides the "tools" for acquiring knowledge (Reinmann & Mandl, 2006). Ideally, the individual construction process should not be disturbed (Looi & Seya, 2014). Students should work with authentic problems. Thus, knowledge is acquired directly with application aspects (Reinmann & Mandl, 2006).

Problem Orientation Problem-orientated learning approaches are used in the design of the activity-based format. The focus is on dealing with authentic problems. This corresponds to the findings of constructivism (Weber, 2004) and action-orientation. First, students are given a task, e.g. as a problem to be solved. Then, a solution is developed by analyzing and researching the task. The result is presented and the entire process reflected. Problem-based learning approaches are therefore particularly suitable for developing students' skills in dealing with complex problems (Kerres, 2018).

3.2 Course Structure

A prominent method emerging within the ML sphere for educational purposes is the incorporation of action-oriented modules, such as open challenges (Chow, 2019). A well-known example of such a concept is the widespread use of Kaggle ("Kaggle: Your Machine Learning and Data Science Community"), a platform where researchers, educators, and companies publish various ML challenges. Interactive ML education elements are often inaccessible to novices in ML and programming owing to the large spectrum of choice, and problem and solution complexity.

Setting up real-world challenges is an intensive task, involving collaboration with companies for data and use case provision, data anonymization and preparation, and detailed use case description. To enable the re-use of material while accounting for the significant variance of ML challenges, a micro-lecture format is appropriate. This allows the introduction of new, challenge-specific content, since more the general methodological concept does not need to be re-designed. Additionally, the micro-lecture format combined with challenges allows educators to adapt to the audience's skill level by varying task difficulty and employing tool introduction units.

Thus, we build our didactic concept on the following assumptions about teaching ML:

- ML is best taught "hands on" using challenges based on real-world problems and data
- ML can be operationalized by students of low to intermediate levels of methodological expertise, given a tailored content selection
- Content tailoring (both theoretical methods, and practical tools) can be best achieved using a micro-lectures format
- Interdisciplinary collaboration should be encouraged so as to bring methodological and domain expertise together

In terms of content, the MachineLearnAthon should encompass the most widespread ML categories along with exemplary models. As such, in terms of supervised learning, the MachineLearnAthon must include Classification and Regression and for the category of unsupervised learning Association Rule Mining and Clustering. These problems along with selected solution algorithms and basic knowledge of ML tools (e.g. Python libraries scikit-lean, and keras) will empower students to frame and solve many real-world problems. Additionally, the listed content sets the stage for more advanced techniques from the field of semi-supervised learning, reinforcement learning, or AutoML.

3.3 Exemplary Course Timeline

We developed the MachineLearnAthon concept based on the didactic concepts of action- and problem-orientation, and constructivism. The course timeline and organization are displayed in Figure 1. The course consists of two parts, the first is about learning the basics of ML and Python and the second about hands-on application. Following the action orientation approach, the students will be able to undergo the process of goal clarification, planning, realizing, presenting, and evaluating. During the kick-off, the outline and goal of the course will be presented to the students. The goal is to empower the students to solve a real-world use case with ML techniques. The groups will consist of three to five participants. This is the recommended group size for action-based learning projects (Helle, Tynjälä, & Olkinuora, 2006).

In the realization phase of the first part of the course, students are be provided with micro-lectures on relevant topics and tutorials for the practical implementation. Thus, they are able to learn the required methods through tools, as constructivism suggests. The tutorials contain well-documented exemplary code and tasks about code modification. The combination of micro-lectures and tutorials ensures that the students both understand how the ML algorithms work and are able to implement them. The material will be provided online. As the literature review showed, online learning proved to be effective and suited for teaching ML. Every student needs to watch all micro lectures and tutorials but each group will focus on one specific topic, which they will present in class. The first part of the course will end with a presenting and evaluating phase, in which the students will receive feedback.

The second part of the course will focus on the implementation of ML. The students will work on real-world problems and finally present their results and obtain feedback. In contrast to classical classroom teaching, they have to actively deal with the learning material, which helps them to activate their knowledge later when applying it (Pfäffli, 2015). The course can be offered at universities as a lecture or laboratory.

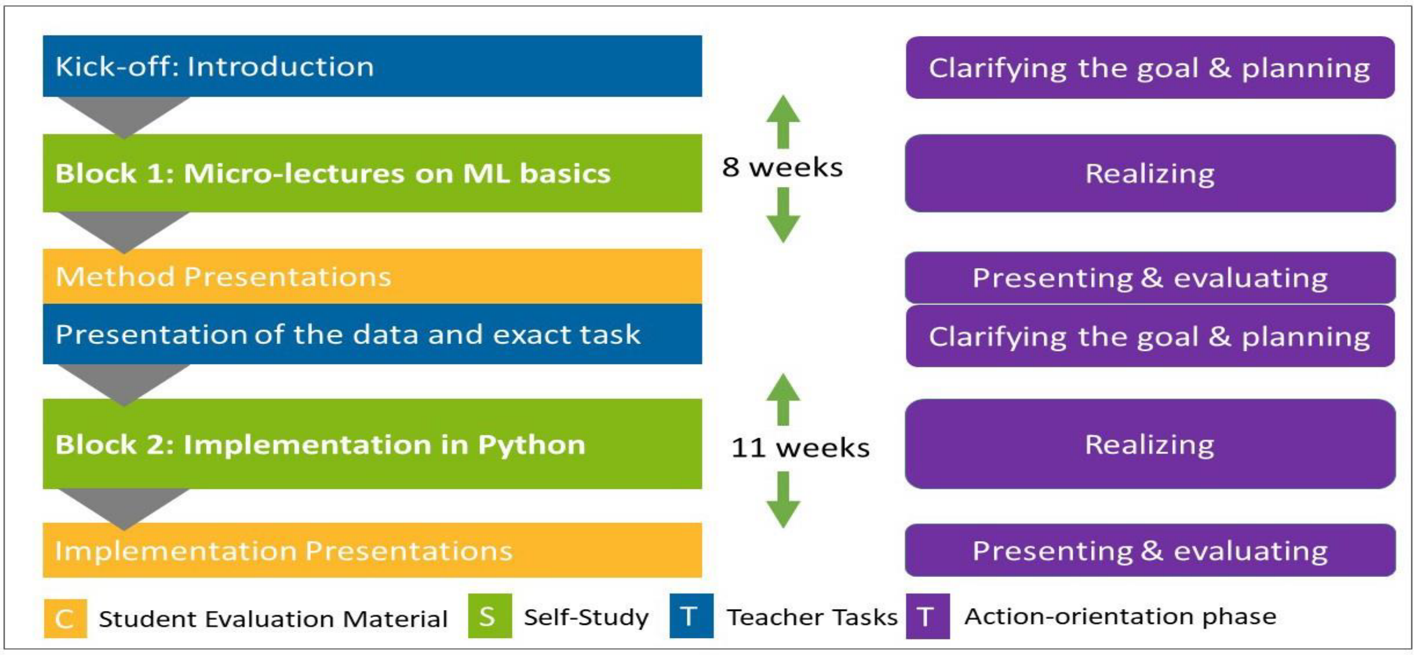

Figure 1. Timeline of the ML course

4. Conclusion

This paper presents the innovative didactic MachineLearnAthon concept. It addresses the challenges of teaching ML to students with diverse levels of expertise in programming, statistics, and ML. Grounded in a systematic literature review and the robust didactic principles of action orientation, problem orientation and constructivism, the model emphasizes hands-on learning, interdisciplinary collaboration, and problem-solving skills. The inclusivity combined with modern teaching principles and a strong emphasis on active learning makes the MachineLearnAthon concept highly engaging. Real-world industrial problems serve to enhance student motivation. Micro-lectures on ML basics and essential ML tools teach data literacy and practical project skills, from data preparation over deployment to evaluation, while also raising awareness about the potential risks associated with ML. The work at hand should be regarded as the beginning of a long road towards ML teaching standardization.

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