# Learning Machine Learning: A Case Study

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*Abstract* - This paper investigates issues related to the teaching and learning of Machine Learning. In recent years, the number of applications to Computer Science programs has dropped dramatically. In addition, the mathematical skills of undergraduates have been reported as low across Europe and in the United States. These factors make it difficult to teach advanced Computer Science courses, since the students in general might not have the prerequisites needed in order to understand the content. Machine Learning, often regarded as a branch of Artificial Intelligence, is the study of software programs that improve their ability to solve tasks through experience. A common misconception of the students is that the computers do all the learning. However, as the field has matured over the last decade, it has become increasingly mathematically sophisticated. We report on a case study conducted in the Master level Machine Learning course at Blekinge Institute of Technology in Sweden. The students participated in a self assessment test and a diagnostic test of prerequisite subjects and we correlate their results on these tests with the fulfillment of learning objectives, which are measured objectively by using the assignment and written examination scores and subjectively by the standardized course evaluation questionnaire and complementary interviews.

*Keywords*: Artificial intelligence, Education, Learning systems, Prior Knowledge, Study Result

**1. Introduction**

Students are attracted to courses in Machine Learning (ML) via their enthusiasm for Artificial Intelligence (AI), although the reality is that Machine Learning has become aligned with increasingly sophisticated mathematical and statistical techniques in recent years. At the same time, the analytical and mathematical skills of today’s undergraduates are generally perceived as low (Barber, 2008). Several works in Higher Education research report on the low student pass rate in Mathematics. As a consequence, research into Mathematics education at the undergraduate level has received great impetus in the last decade (Divjak & Erjavec, 2007), e.g., by projects under the influence of the Bologna process in Europe and similar projects in the Unites States. Moreover, recent years have shown an alarming drop in Computer Science applications across Europe (Gavaldà, 2008) and the students that apply do not seem to have as strong Programming skills as earlier students. Consequently, many universities seem to be lowering their bars in order to get a sufficient student quota. For example, some Swedish Universities have decreased the level of mathematical experience needed for getting admitted to their Engineering programs.

To conclude, machine Learning is generally categorized as a Computer Science subject and, as already stated, it has become increasingly aligned with theory and techniques from mathematics and statistics. At the same time, the recruited students seem to have a decreasing prior knowledge of computer science, mathematics, and statistics in general as well as programming in particular. A question can be raised as to whether this changed situation in terms of prior knowledge and subject complexity is going to affect the type and amount of knowledge that can actually be gathered by current and future students.

In this paper, we address the above stated question by investigating the relationship between prior knowledge and study results in the context of the Machine Learning subject. The investigation has been conducted by performing a case study of a group of students enrolled to an advanced level Machine Learning course at Blekinge Institute of Technology in Sweden.

*1.1 Outline*

The remainder of this paper is organized as follows: firstly, we discuss the role of prior knowledge and its influence on the type and amount of knowledge that is acquired as well as the examination results. Secondly, we review related work. We then continue by presenting some background to the Machine Learning area of research and the Machine Learning education subject. Next, our case study is introduced in Section 3, followed by a review of the results in Section 4. We discuss the results and give some examples of how to improve the learning and teaching of Machine Learning in Section 5. Finally, conclusions and pointers to future work are presented in Section 6.

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**2. Background**

Machine learning is the study of computer programs that improve automatically through experience (Mitchell, 1997). It is generally regarded as a branch of Computer Science and more specifically as a subfield of Artificial Intelligence. Much like Artificial Intelligence, Machine Learning is a multidisciplinary research field, drawing from work conducted in, e.g.: statistics, mathematics, biology, control theory, philosophy, information theory, and psychology.

Successful applications of Machine Learning range from, e.g.: filtering junk E-mails (Sahami et al., 2001), detecting fraudulent behavior (Hilas & Mastorocostas, 2008), diagnosis of patients (Huang et al., 2007), to onboard experimental analysis and opportunistic science features in the NASA Mars rovers (Castano et al., 2003). As information technology continues to spread globally, the number of applications powered by Artificial Intelligence and Machine Learning techniques grows each day. Correspondingly to computer programs in general, we constantly demand more from these applications in terms of computational power, ease of use, and intelligent behavior.

Unfortunately, the public fascination for Artificial Intelligence and Machine Learning seems to stem from written fiction and movies and is mostly focused on what these subjects can do, i.e., their applications, and not how it is done. The reality of the technical requirements of Machine Learning often leaves students initially rather surprised and disappointed (Barber, 2008). Contrary to initial beliefs, there is no “magic” involved and very little of the seemingly intelligent behavior found in existing software can be said to have evolved without being carefully designed to do so by humans. In fact, serious engineering skills and a sound knowledge of programming, statistics, and mathematics are usually the real factors behind the intelligent behavior and learning capabilities of such software systems.

*2.1 Machine Learning Research*

The Machine Learning research field is closely related to pattern recognition and statistical inference (Mjolsness & DeCoste, 2008). It emerged in the late seventies and in 1980 the first Machine Learning workshop was held in Pittsburgh, Pennsylvania. The first edition of the Journal of Machine Learning was published in 1986. From 1988 and onwards, the International Conference on Machine Learning is held annually. Although the area of Machine Learning has been multidisciplinary in nature from its very inception (Langley, 1986) the current state of Machine Learning research is radically different from that of earlier research (Drummond, 2006). As an engineering field, Machine Learning has become steadily more mathematical and more successful in applications over the past twenty years (Mjolsness & DeCoste, 2008). In fact, it is even argued that the increasing mathematical sophistication of Machine Learning in recent years has reached a level at which some premium conferences deter all but the most mathematically sophisticated researchers (Barber, 2008). Conversely, the state-of-the-art learning methods (algorithms) are based on complex and advanced concepts, e.g.: quadratic programming (Platt, 1999), probabilistic graphic models (Heckerman, 1997), hidden Markov models (Rabiner, 1989), and entropy measures (Quinlan, 1993). Moreover, the methods used for evaluating the performance of the learned models are often based on statistical re-sampling techniques such as cross-validation (Stone, 1974) and bootstrap (Efron, 1979), for which the underlying statistical assumptions can be quite complex and they are seldom included in the curriculum of introductory statistics courses.

In parallel to the increased mathematical sophistication of the field, the scientific methodology has also evolved. In 1988, it was reported that the Machine Learning community had become increasingly concerned about validating claims and demonstrating solid research results (Greiner et al., 1988). Evidently, most top conferences and journals in the field now require experiments to be reproducible[[1]](#footnote-1) and replicable[[2]](#footnote-2) to ensure that other researchers can validate the claims. In the eighties, many experiments featured small synthetic data sets and standard statistical tests, e.g., the t-test. Today’s experiments often feature large and complex real-world data sets and rigorous statistical testing, often involving non-parametric methods. Whether our prospective Machine Learning students are headed toward a post graduate education or the industry, the expectations on them are higher than ever.

In conclusion, the learning techniques and the theoretical foundations behind them are becoming more and more complex and so do the applications in which they are used. Thus, in order to understand Machine Learning, one must at the very least have a basic understanding of background subjects, e.g.: linear algebra, basic mathematics and calculus, statistics and probability, and programming. We argue that, without this proper background, the Machine Learning subject can only be understood at a very general and rather simplistic level.

*2.2 Machine Learning Education*

According to the Bologna process, the higher education is divided into three levels; basic, advanced, and research studies. Machine Learning courses are taught at various levels of education. However, they seem to be predominantly held at the advanced or research level of Computer Science (Barber, 2008). The prerequisites for admission to Master level Computer Science programs vary between different universities. At Blekinge Institute of Technology (BTH) in Sweden, the prerequisite is a Bachelor’s degree in Computer Science or a corresponding level of knowledge. The requirements for receiving a Bachelor of Science degree are: a total of 180 ECTS[[3]](#footnote-3) credit points, including 90 in computer science and at least 15 in mathematics. However, for the purpose of understanding this paper, it is sufficient to know that 1.5 ECTS credit points roughly correspond to one week of full-time studies (40 hours). Thus, the amount of 180 ECTS credit points represents three years of full-time studies. The majority of Computer Science courses at BTH are practically oriented. Thus, besides the theoretical foundations, most exercises and assignments include various forms of software design, documentation and programming. However, the majority of the Master students at BTH originates from outside Europe and tends to have a more theoretical background in Computer Science although experience tells us that this theoretical background, as well as learning strategies and study patterns, seems to vastly differ in comparison to those of the domestic students.

The Machine Learning course at BTH is given at the advanced level and is featured in a number of Computer Science Master Programs. The course comprises 7.5 ECTS credit points and corresponds roughly to five weeks of full-time studies. While the course has a strong focus towards Supervised Learning and Data Mining, the curriculum also includes Reinforcement Learning and Unsupervised Learning.

According to the aims and learning outcomes that are stated in the course descriptor, the student should be able to:

* Independently and thoroughly evaluate and compare the performance or, other qualities, of algorithms for typical learning problems,
* In a group, or independently, implement learning algorithms on the basis of algorithm pseudo code and scientific papers or books,
* Independently and thoroughly describe and compare different evaluation methods for learning algorithms,
* Independently and briefly describe and compare different machine learning paradigms,
* In a group, or independently, plan data mining experiments, apply data mining tools to run the experiment, and finally, gather information from the experimental run and present in a report,
* Independently and thoroughly perform a critical review of relevant techniques and methods found in literature in the fields of machine learning and data mining.

At BTH, the students are expected to learn about and make use of an open source Machine Learning workbench, called Weka (Witten & Frank, 2005), to conduct experiments and solve assignments. Basically, Weka is a piece of software that can be used to analyze data sets, perform machine learning and data mining experiments, and to analyze experimental results. However, Weka may also be used as an Application Programming Interface (API) to develop revised or new learning algorithms as well as complete applications. In order to use Weka as an API, the student has to have at least basic programming skills. The mandatory assignments of the BTH Machine Learning course include: performing an experiment using Weka, developing a simple supervised learning algorithm, and a reinforcement learning application.

**3. Method**

Our focus of study is a group of *n* = 11 respondents from a class of approximately 30 students enrolled in the Machine Learning course at Blekinge Institute of Technology. The aim of this case study is to investigate whether there is a correlation between prior knowledge of statistics, mathematics, and programming, and examination results. The case study comprises four different stages of data collection. During the fifth out of ten lectures in total, the students are asked if they would like to participate in taking a test for which the objective is to gather information that can be used to improve the learning of future students by modifying the presentation and contents of the course.

The students that do accept to take this test are given a list of five subjects for which they should rate their own level of knowledge. After completing the self assessment test, the students are given ten minutes to participate in a diagnostic test that features two elementary questions from each of the subjects. When the final written examination has been held and the course has officially ended, the results for the three assignments and the written examination are collected from the Student Documentation System[[4]](#footnote-4) in order to be used for analysis.

*3.1 Self Assessment*

At the self assessment stage, the students get to estimate their own level of knowledge of five subjects from 1 (no knowledge) to 9 (extensive knowledge). The featured subjects are: probability and statistics, basic mathematics and calculus, linear algebra, discrete mathematics, and programming. The rationale for selecting these particular subjects is that their theory and concepts form the basis of the state-of-the-art learning algorithms and are used in common machine learning textbooks (Mitchell, 1997; Witten & Frank, 2005) to explain learning theory and to describe algorithms.

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**4. Results**

The Machine Learning course is held once every fall at BTH and in 2008, the number of active students was 30 out of which roughly 50 per cent attended the lectures. From this group, 11 students participated in the self assessment and diagnostic tests. A total of 23 students handed in the first assignment on time. The subsequent assignments were handed in on time by 15 and 16 students, respectively. Moreover, 8 out of the 11 students participated in the final written examination held in January, 2009.

*4.1 Self Assessment Results*

In the self assessment test, the average test scores of the 11 respondents were above 5 for each of the featured subjects (see Table 1 for a summary of the results). Recall that, the ordinal scale of the test range from 1 (no knowledge) to 9 (extensive / very good knowledge). Thus, in general the students seem to perceive their own knowledge of the prerequisite subjects as above the level of an average understanding. According to the results, the students perceive themselves as having a good knowledge of basic mathematics and calculus, as well as of linear algebra. Not surprisingly, the students rate their knowledge about probability and statistics as just slightly above the average level of understanding.

**Table 1.** Self Assessment and Diagnostic Test Results

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| --- | --- | --- |
| Subject | Assessment Mean(SD) | Correct Answers |
| Probability and Statistics | 5.91(1.51) | .27 |
| Basic Mathematics & Calculus | 7.27(1.01) | .73 |
| Discrete Mathematics | 6.27(1.27) | .41 |
| Linear Algebra | 6.82(1.47) | .23 |
| Programming | 6.73(1.95) | .50 |

*The mean self assessment scores for the five included subjects and  
the overall ratio of correctly answered questions on the diagnostic test*

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**6. Conclusions**

This paper reports on a case study of an advanced level Machine Learning course at Blekinge Institute of Technology. In recent years, the number of applications to Computer Science programs has dropped dramatically. Moreover, the mathematical skills of undergraduates have been reported as low across Europe and in the United States. These factors make it difficult to teach advanced Computer Science courses, since the students in general might not have the prior knowledge needed in order to understand the content. We have studied the Machine Learning subject in particular and our aim is to investigate whether there is any correlation between prior knowledge and study results.

In this study we have given a class of students the opportunity to participate in a self assessment test in which the students were given the task of rating their own perceived level of prior knowledge in areas such as: statistics, mathematics, and programming. After submitting the test, the participants were also given a diagnostic test, which included questions about basic concepts in these subjects. We have investigated the relationship between the results of these two tests and the study results. We conclude that there is no obvious correlation between prior knowledge and study results, at least for the small group of students participating and when the prior knowledge is assessed through the featured self assessment and diagnostic tests. It is important to note, however, that self assessment tests have been proven, by large-scale studies in the United States, to accurately predict future study results in mathematics. In other words, the method of using a self assessment test to predict study results seems suitable but the self assessment test used in this study may be too limited to achieve accurate predictions.

For future work, we suggest the development of a self report, inspired by the Mathematics Science Inventory (MSI), but intended for Machine Learning students. Additionally, we intend to perform further investigations in order to fully understand the problem and to develop a practical guide aimed at improving the supervision of students during their work in solving the course assignments.

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2. Journal of Machine Learning, http://www.springer.com/computer/ artificial/journal/10994 [↑](#footnote-ref-2)
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4. Ladok, http://www.ladok.se/index.php?L=1 [↑](#footnote-ref-4)