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A MODEL OF CONCEPT LEARNING IN PHYSICS

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Abstract

Learning concepts in physics is difficult due to the often simultaneous presence of misconceptions. We have developed a dynamic model of concept learning, which includes the dynamics of misconceptions. In its simplest form the model simulates the learning of the concept and the unlearning of the misconception with a two-dimensional differential equation system. The major conclusion from our model simulations is that while teaching a concept, misconceptions should be intensively addressed. Rapid decay of concept knowledge observed in experiments after concept teaching is explained in our model with the persistent presence of a high level of misconception.

1. Introduction

Recently, exploring the time dependence of learning physics concepts has gathered increased attention (Bao 2008, Sayre 2009, Heckler 2010). The data about concept learning shows convincingly that the acquisition of concepts is a dynamic process. As a consequence the interpretation of quantities like the normalized gain, for example, requires great care since the results strongly depend on the time points when the data are recorded. Therefore a more thorough understanding of the dynamic process of learning is required. Heckler et al. (Heckler 2010) investigated concept learning of an introductory physics course at the university level. Data were collected from more than 1600 students. Every few days or every week 12 students (in the average) were asked to solve a set of multiple-choice questions concerning physics concepts. Students were asked before, while and after the topic was taught. The proportion of correct answers was then plotted against time. It turned out that the most effective learning event was the homework activity since the homework due time showed the highest level of concept knowledge.

The goal of this work is to construct a model, which is able to simulate the time course of concept learning. The model we present is based on previous work done by Lei Bao (Bao 2008). The major difference is that our model consists of two variables, one for the concept c and one for the misconception m. It distinguishes between not knowing the concept ($1 - c$) and the level of misconception m. The differential equation system we present to simulate concept learning has two stable fixed points, a concept fixed point and a misconception fixed point. Learning of concepts means in terms of our model, to move the system away from the misconception fixed point so that it relaxes on the concept fixed point after the learning phase.

The major conclusion from our model is that if misconceptions are not properly addressed in class, resulting in a reduced misconception level, teaching of concepts in physics will be almost futile. Student's concept knowledge rapidly decays, after the learning phase. Thus an initial unlearning phase of misconceptions is necessary (if misconceptions are initially present) to settle concept knowledge on the long run.

2. The Model

Our model of concept learning consists of two coupled differential equations, one for the concept c and one for the misconception m

$$dc/dt = \alpha\, c(1-c)\,(1 - m) - \gamma\, c\, m,$$

$$dm/dt = -\beta\, m\,(1-m)\, c + \mu\,(1-m).$$

The parameters α and γ are the coefficients for learning and unlearning of concepts. The misconception is learned with rate coefficient μ and unlearned with rate coefficient β. The levels of the concept and the misconception are in the interval [0, 1]. The variable c is defined as probability to solve a concept question correctly at the given time point. Although we call the variable m misconception level it summarizes all detrimental effects on the concept knowledge. Therefore m hampers the learning and promotes the unlearning of concepts. We assume that the learning of concepts is hard at the beginning and at the end. This justifies that the learning rate is proportional to $c(1-c)$. The most progress is made for concept learning of c = 0.5. The same argument also holds for the unlearning of misconceptions (unlearning is proportional to $m(1-m)$. However, learning of concepts does not only depend on the concept c but also on the level of misconception, m. Thus learning of concepts is easier the larger the factor $(1-m)$ is. The stronger the misconceptions are the slower is the learning of concepts. The unlearning of concepts is proportional to the product of the level of the concept and the misconception. If there is no concept there is no unlearning and the stronger the misconception the stronger the unlearning. The unlearning of misconception is amplified by the presence of a high concept level. Therefore we multiplied the misconception unlearning term $-\beta m(1-m)$ by c. Finally, misconceptions have a permanent learning term, $(1-m)$, due to everyday experience (for example: there is no real world experiment without friction) or due to intuitive perception (for example: adding a resistor to a circuit should increase the equivalent resistance).

3. Results

In order to find reasonable values for the learning and unlearning parameters we used the data provided by Heckler and Sayre (Heckler 2010). They applied multiple-choice questions to students in order to test their understanding of physics concepts in Mechanics and Electricity and Magnetism. A data point corresponds to the normalized answer of 12 students (average). At every time point a different representative sample of students was asked the same questions. The data points of the electric circuit problem are shown in Fig. 1.

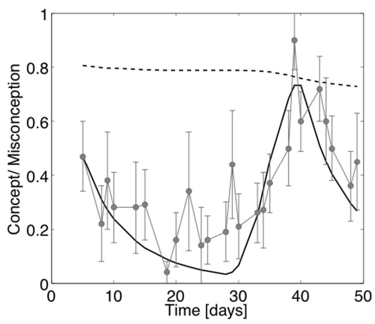

Figure 1: Fit of the model to the data provided by Heckler and Sayre (Heckler 2010) (electric circuit problem). The full line represents the concept knowledge and the dashed line the misconception level.

If a topic is taught directly by lectures, labwork or homework we increase α and assume an enhanced learning ability α_{enh}. To obtain the fit curve we used the procedure (*fminsearch*) provided by *Matlab*. The procedure was allowed to adjust the following parameters providing the results α = 0.4, α_{enh} = 3□44, β = 0.24, γ = 0.043, μ = 0.0015 and the initial value of the misconception level m_{init} = 0.8. The time points for the onset and the end of the enhanced learning phase were kept constant at t_1 = 28 days and t_2 = 39 days. These time points correspond to the onset and offset of the teaching period. We selected for the initial condition of the concept the first point of the measurement $c_{init} = c_5$ = 0.47 (circuit question). The fitted misconception level at the beginning is approximately m_{init} = 0.8 and seems to be rather high. The rate constant for enhanced learning is about 10 times higher α_{enh} = 3□44 than the basic coefficient α = 0.4. It is also remarkable that the rate for unlearning misconceptions is of one magnitude smaller than the rate of concept learning.

As a consequence, the unlearning of misconception has to be done in an efficient way in order to successfully teach concepts. If the misconception level is not substantially reduced (when starting at $m_{init} \cong 0.8$) during the learning phase, the concept level decays quite rapidly after the enhanced learning phase (see Fig. 1). Finally students end up in the misconception fixed point and all efforts to understand the concept were in vain. The long-term behavior of the system is shown in Fig. 2 (thin full line: concept; thin dashed line: misconception). It emphasis our point of view that we not only have to teach concepts, but we also have to unteach misconceptions.

What happens to the student knowledge if misconceptions are unlearned at the same time as the concept is taught is shown in Fig. 2. In order to do the corresponding simulations we introduced an enhanced unlearning coefficient for the misconception $\beta_{enh} = 0.37$ during the concept teaching period. Between days 28 and 39 we changed the misconception unlearning rate from β to β_{enh}. During this time period the misconception level drops markedly so that after the learning phase the system drives towards the concept fixed point.

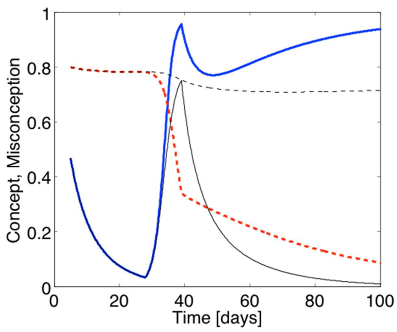

Figure 2: Simulation of unlearning misconceptions. The thick full line represents the concept knowledge and the thick dashed line is the level of misconception. The thin lines represent the simulation of the concept (full) and the misconception (dashed) due to the data shown in Fig. 1 for comparison.

4. Discussion

In order to provide a better understanding of the evolution of concept knowledge we have developed a new model, which allows for simulating the interaction between the concept and the misconception. Using the model we fit the data about concept knowledge recorded by Heckler and Sayre (Heckler 2010). In our model students start at a medium level of concept knowledge and at a strong misconception level. For the first 27 days the model moves towards the misconception fixed point. Between day 28 and 39 the learning activities take place leading to a change of the learning coefficient from α to α_{enh}. After day 39 the topic is assumed to change and without unteaching misconceptions the system moves back to the misconception fixed point. In contrast, if the misconceptions are properly addressed during the learning phase the misconception level drops substantially so that after the learning phase the system ends up in the concept fixed point on the long run.

References

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