Two-Dimensional Knowledge Model
for Learning Control
and Competence Mapping

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Abstract. The paper presents two-dimensional model for knowledge representation with volume as one variable and ability as another one. This makes possible describing current state of learner's abilities and integration for higher level parameters e.g. grading related to course or other entities. Both values are related to atomized knowledge elements (competences) with volume interpreted as credit units and ability levels are formed during learning with application of forgetting. This model makes possible characterization (grading) of knowledge based on real abilities independently of predeclared courses and for 'drop-outs'. So, on that bases one can obtain grade for some course if proper knowledge has been obtained in different courses and schools even when courses had not passed. Also this model helps to build connections between courses as using courses in the role of prerequisites becomes less usable. Not wasting knowledge obtained in MOOCs is another example with high drop-out levels where classical passed-failed model does not work.

Keywords: Competence-based learning · Credit units · Abilities · Automatic processing of solutions

1   Introduction

The drop-out rate for MOOCs is very high and in recent years a lot of studies have been conducted to explain the reasons behind the phenomena. Despite dropping out, those students who quit, have learned at least something and the question rises – how to get some recognition out of the work done. The solution might be that if student knows that completing even part of the course is beneficial then this might be additional motivation for the learner not to stop early in the course.

For example [1] investigates four week long course with following weekly completion rates: 21.5 %, 13.80 %, 10.24 %, and finally 8.50 % of 680 registered students. Instead of classifying 13 % of students (21.5 % after one week the start minus 8.5 % who finished) as drop-outs (zero credits) they could obtain a quarter tom three quarters of credits (with details about their knowledge). This could also be applied to any regular course and even to full curricula. Another analysis of large number of courses [2] shows similar completion rates (6.5 %). Therefore, it could be assumed that the productivity within the course for the drop-outs might be similar (may be 10 % for 25 % volume).

The idea of compiling credit units (or other information about learner's abilities) is becoming more acceptable. For example, IML [3] issues several types of qualifications. Collecting competences obtained in industry and education, including minor skills that might not be accompanied with certificate, into learning database is promising trend for life-long learning.

Two-dimensional model is in use but in a very limited manner: the first dimension – grading is measuring quality of learning and another one – credit units for evaluation of learning volume (time), for planning, and for calculating integrated measures (average grade). Unfortunately, both dimensions are not applied to learning control and serve as rather post-factum indicators. In this paper, we show how two-dimensional model can be used for learning control during whole learning cycle.

2   Competences

Key concept for this approach is low-level competence representing elementary unit that can be learned and usage of which can be measured.

There are many different definitions for the term 'competence'. Klarus has defined it as mix of skills, attitudes and knowledge that makes the employee or graduate successful in society and his/her profession [4]. Other definition states that by competence, we understand good performance in diverse, authentic contexts based on the integration and activation of knowledge, rules and standards, techniques, procedures, abilities and skills, attitudes and values [5]. We have defined competence-based learning as a knowledge based methodology which concentrates on measuring what a person can actually do as a result of learning [6]. In popular form, competence is explained as 'A competency, simply put, is something that a person or organization is competent in performing' [7] and 'Competence is the ability of an individual to do a job properly' [8]. All those (and other definitions) are very general, quite similar but do not help to implement learning environment directly.

Therefore, we prefer to use 'behavioural definition' stating that competency item must be usable in analysing outcomes of learner's activities so, that ability level related to every competence item can be measured (evaluated). Presumably, any of those items should appear in many actions combined with others. To avoid discussions concerning different definitions and interpretations of term 'competence', we shall use in this paper the word '**comp**'.

In other words, a comp is one item in learner's model which predicts reaction to specific action as input. Processes in feedback loops correct numerical data related to the comp (ability level, forgetting parameters). The model used is the following:

$$L(t) = L(t_0)f(\tau, p, t_0, t) \tag{1}$$

where L is ability level, τ is time constant, t is current time, t_0 is reference time, and p is forgetting rate. Currently, the power law [15, 16] is used:

$$f(\tau, p, t_0, t) = \left(1 + \left(\frac{t - t_0}{\tau}\right)\right)^{-p}. \tag{2}$$

All three parameters τ, p, t_0 are corrected after receiving learner's reactions.

3 Adaptive Control

Students tend to have very uneven background when they sign up for a courses in university, especially at higher levels of studies. Furthermore, during learning knowledge gaps may even increase because learning is a personal process. This will cause some students to pass courses really easy and on the other hand, some students are learning very slowly or dropping out. It is hard for the teacher to find suitable topics that would be manageable but still challenging for everyone in classic lecture format teaching. Therefore personal learning tracks become unavoidable to facilitate everyone's pace, state, and goals.

To facilitate personal learning and competence model, learner's state must be determined (measured) as precisely as possible. Number of levels in common grading systems (using 5 to 10 marks) is not sufficient to represent dynamics of learning. The learning environment we describe is functioning as follows. For every comp and for every student the following data referred in Eqs. (1) and (2) is recorded. Any action taken by the student that produces a recordable result is defined as task. All the results are analyzed automatically by the system evaluating which of the comps have been used when solving the task and how correct has been the usage [9]. Thereafter system modifies the state of corresponding comps. It is possible, in special case, that human (teacher) may be part of that process which usually causes time delays and less efficient operation of feedback loop.

There are several feedback loops in the system. Main difference from the classical closed-loop control is that the goal is not obtaining certain behavior of output signal but adjusting object to wanted behavior. The object (learner) is not simply reacting when input signals are applied but it is changing and our goal is to get wanted changes as efficiently as possible. In that sense, earning system is adaptive control (continuous identification) and model-based one as well. Ideas from both control theories are applicable but do not go into details in this paper.

In fact, two-dimensional model is used in education: abilities are measured by grades and volumes by credit units. However, those measures are applied to very large elements and credit unit has extremely high variation: usually, credit unit is related to average time but real personal time or amount of work differs at least 4–5 times for different students and courses. Our goals here is to introduce measurement units for both dimensions.

4 First Dimension – Ability

In order to model knowledge for personalized learning control, we use the ability as the first dimension of this model (ability comparable with that of Item Response Theory [10–12]).

To facilitate our detailed and desired granularity in the model, the assessment becomes complicated. For example, if the goal is to grade large object (e.g. the whole course) using very few available marks as formal education system expects is not proper for control. Better solution would be assess small parts of that large object independently where well-defined measures and rules could be used to achieve more precise feedback loops [13].

This model is simpler than for example IRT (Rasch model) which uses ability over scale of difficulty (probability of correct answer). In our model, only one numerical value is used which can be related to difficulty. IRT model parameters can be calculated form stored data but we are more interested in dynamics of learning and control.

Classical testing and also IRT assume that when knowledge is acquired it does not change with time. That, sadly, is not the case – if competence is not used over time, it starts to fade (forgetting). That should also be taken account in the model as otherwise, grading is simply snap-shot for certain time moment [14]. Using forgetting in the model enables learner to concentrate on relevant competences (new or forgotten) and avoid unnecessary efforts which do not improve knowledge.

The first dimension is produced in the system by processing learning action and expressing it with numeric value. It could be real number, for example in the range $0\ldots1$ (probabilities) or $-1\ldots+1$ to emphasize true and false by signs etc. Binary values are quite common as they allow simple analysis. However, in certain cases dichotomy is not the best choice (for example, when presence of measurement errors are unavoidable).

This outcome of the analysis is used as input for evaluation of ability levels (and forgetting parameters). Ability levels can also be mapped into different scales. From practical point of view integers are preferred because of easy interpretation by humans and also simpler processing (e.g. table functions). In our model half byte is used (values from 0 to 127). That gives us good variety of marks to use and is large enough scale to avoid loss of details.

Example. Let us consider an 'elementary' Ohm's law. In fact, application of this 'primitive' law assumes several knowledge elements/competences: Kirchhoff's laws, understanding direction of current, that voltage is difference of potentials, measurement units, and prefixes. One can make mistake in every aspect of the task and learners do so. Misconceptions are common. Practice is needed and it might take weeks of work before competence is achieved. When analyzing such a small task where the answer is one number (or number with a unit), several different outcomes can be detected. Corresponding competence states have to be changed accordingly.

Ability level for a competence is a dynamic value which is changing in time caused by two factors – (1) learning actions/tasks (rehearsing) and (2) forgetting.

5   Second Dimension – Volume (Credits, Difficulty)

There are many different scales for measuring volume (time) for learning. In education systems, usually it is assumed that credit level for a course has direct connection to time needed. For example, course with higher credits has more contact hours, requires more hours of independent work etc. Here we use as synonyms the terms volume, difficulty,

and credits emphasizing that they all represent the amount of work (in IRT the difficulty is comparable).

The role of this dimension is to close one feedback loop through integration (averaging) of abilities. One compulsory integrated value in formal education is official grade but even more important are such integrated values for motivating learners and control (selection) of actions. As this variable is used to calculation of integrated indicators, the most proper name would be 'weight'.

We need two types of weights:

- Difficulty levels assigned to learning actions/tasks which are solved by the learner during learning process
- Weights assigned to comps used.

Those two concepts are closely connected. For example, assume that the task T_i is based on (using) comps C_j. Denote by $WT(T_i)$ measure of difficulty for task T_i and by $WC(C_j)$ weight of competence C_j. Assume $WC(C_j)$ is assigned. Then we can assign difficulty $WT(T_i)$ to T_i integrating weights of related comps. Different measures can be applied for integration as average, mean square, min, max etc.

Several methods have been considered to determine the weights:

(1) Predefined by the author who created the learning object. This may be based on obvious parameters, for example, on volume of work to be done (number of components of answer).
(2) Processing elapsed time obtained from real process – more time, higher difficulty (volume).
(3) Average result from log files; in case on dichotomic model it is equivalent to the probability of correct answer.
(4) Adjusting difficulty levels to obtain uniform distribution over set of tasks;
(5) Combination of algorithms 1–4

All described approaches above have been tested and modified over years in real learning environment. First, predefined difficulties were assigned based on teacher's assumptions about complexity of tasks. Then when real results were collected, corrections were made to match the'rule of positivness' (3 dB rule): average score of positive answers should be at the level of −3 dB or approximately 7 solutions from 10 should be correct. It was assumed that in such case learning process will be motivating and this rule proved to be effective as the number of corrections needed according to logs once or twice per year was decreasing. In other words, this −3 dB level appeared to be rather stable (and is still so).

Then, in 2010, when comps were attached to tasks, comps obtained weights which were assigned to comps manually on the basis of experience. When more results were collected, 3 dB rule was applied to correct weights. The same comp is used in more than one course but its focus or importance for the course may vary. That caused comps to be assigned different weights for different course to reflect their part in that specific module. For this purpose, a scaling factor was associated with course.

Let's comment the methods shortly.

Method 1 – difficulty predefined by teacher (author of the tasks). This initial setting is needed to activate tasks at all. Analysis of log files showed that many assumptions (like 'smaller means simpler') were not correct. When analyzing records we have to keep in mind that recorded data are produced from closed-loop system and small task may appear more difficult as it appears when learner is just starting studying the topic. In real life, initial difficulty assignments had to be corrected sometimes substantially.

Method 2 – using elapsed time may be useful; however, analysis showed that correlation between elapsed time and correctness of answers is very weak (almost 0).

Method 3 – average results (averaging over all competences in all tasks). This method has proved to be rather stable to meet 3 dB law. As it has exhibited good stability, this method is considered as the most appropriate one.

Method 4 – assigning levels to the tasks so that tasks are distributed evenly between difficulty levels.

Current solution (as of spring semester 2015) is as follows:

1. For new tasks 3 dB level is assigned and levels are reviewed when at least 5 solutions appear. In case when evaluation of amount of work is possible, deviations from 3 dB levels are accepted.
2. When revising task levels, two operations are used: grouping tasks on the basis of calculated average results and leveling task numbers per level. To simplify control (selecting tasks) in the latest implementation tasks are grouped into only 4 levels.

6   Weighing Comps

To control personalized learning process, the system should find proper task for learner depending on his/her current state. Action is initiated by learner who can point to specific comp he or she wants to learn or, in automatic mode, task selection is based on specific algorithm which determines the most suitable task for the learner.

Average result may be considered as probability of correct answer (when scale 0 … 1 is used), then we introduce the following measure. Denote by *w99* average number of attempts needed to reach 99 % confidence that at least one correct result is achieved. This means that if average result is *A* then probability of correct answer in *w99* attempts is $P = 1-(1-A)^{w99}$. From this we have $w99 = log (P)/log (1-A)$ where $P = 0.99$ and *w99* is a real number. For very small values of *A* the number of attempts *w99* is proportional to *1/A* and may obtain large values. For example for $A = 0.1$ we have $w99 = 43.7$ which means that there is practically no chance to give correct answer. To avoid unreasonable behavior for such unlucky comp an upper limit is to be set and if the situation does not change this comp should be removed from usage.

The value w99 has been turned into basic weight for comps. For higher level items (including courses) scaling factor is applied which converts w99 values to credit units. In reality, this factor appears to be in the range from 15 to 25 and is set when course is compiled.

7   Connection to Formal Credits

Usually formal credit systems are based on evaluation of time to be used by student to pass the course. This may be correct when learning means only physical participation in lectures/labs and could be appropriate before IT era. Nowadays most of classical assumptions about prerequisites and ways of learning are not valid. Globalization has brought us to the situation where students starting learning in a course may have extremely varying background. In many cases, learning is supported by technology and therefore there are no regular classes, students can be from very different time zones, having different cultural background etc.

This has become very clear in case of MOOCs which combine those aspects and contradiction between classical concepts of courses and reality. Drop-outs have become a serious problem for MOOCs. It could be explained by the 'winner takes all' principle: one has passed a course (curriculum) or not, what a student has really learned is not represented in certificate. The situation in real life is different – for employer real abilities are becoming more important than list of units passed by an employee. Note that working experience – very important for employers – can also be integrated into competence map.

Formal education systems are based on credit systems and credit transfer processes are used to combine different studies. This means that a transformation from difficulty/weights to credits must be implemented. This may be simple linear transformation which uses different scales in different courses. Two-dimensional maps discussed have one benefit: every comp is unique for any higher-level competence even if it has been considered in several courses.

8   Example

This example visualizes learning process of a student in one course during spring semester 2014 (Fig. 1). Higher (thin) line shows credits learned and the lower (thick) one shows confirmed credits. In order to "confirm" that he/she did the learning, students have to attend on-campus test when tasks are selected by system and during those tests, students have some restrictions. It is clearly seen that the process is not conventional 'collecting points' as the volume is not monotonic.

Figure 2 shows learning graph with sum of credit units on the horizontal axis and integrated ability level on the vertical axis. Grade zones are also shown and student's final decision is marked by a dot at $V = 4.633$ and $L = 119$ which is located in the zone 4 (equivalent to grade B). Final grade is 'picked up' by student when his/her state reaches grade zones and the grade satisfies the student. Final (formal) grade is produced from skew zones representing grades from 1 to 5 (from E to A).

We can see from the figures that the student could get information about her state in any phase of learning. Minimal information would be credits and ability level. For example, on April 21, 2014 she could ask for certificate stating credits = 2.727 ECU at level $L = 120$. Competences forming that result could be included in that certificate.
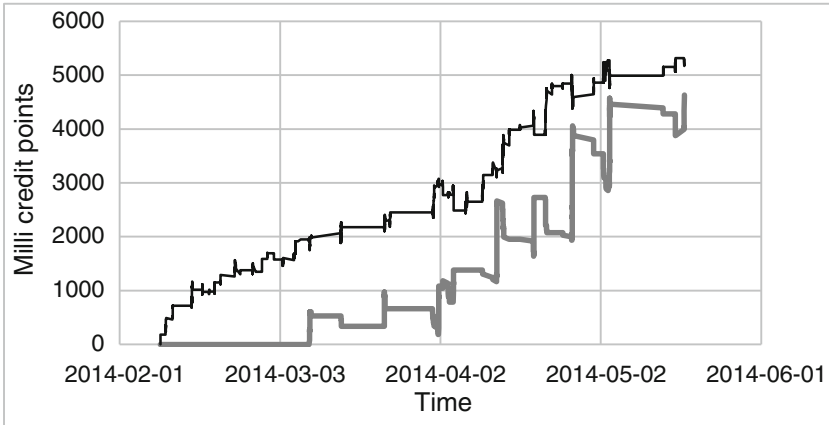
Fig. 1. Current credits and confirmed credits vs time. Credit units in mCU.
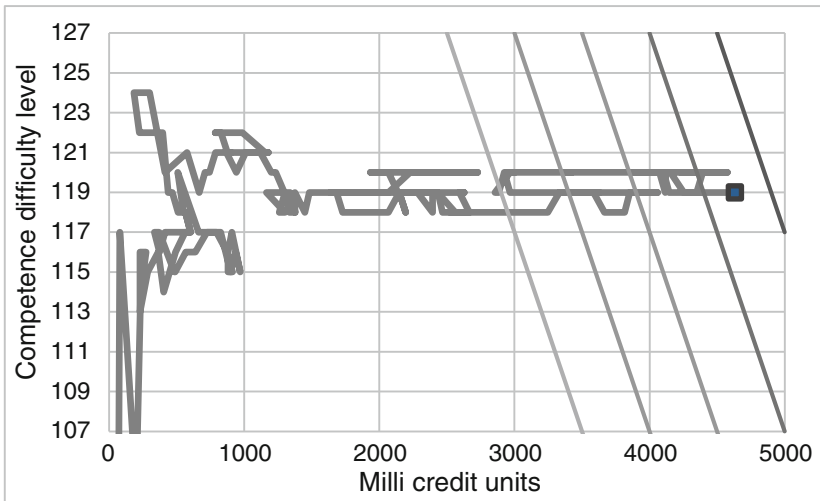

Fig. 2. Credits and corresponding competence levels at the final stage of learning the course. Final grade accepted by student is shown as a rectangular dot. It is in the zone of grade 4.

In electronic form, viewing tasks behind that certificate are possible and future states would be available. This particular student has lost very little in one year: on February 25, 2015 her credits had dropped from 4,633 to 4,589 and level from 119 to 118.

In Fig. 3 two tracks are shown: the narrow one represents everyday learning and the thick one represents confirmed units.
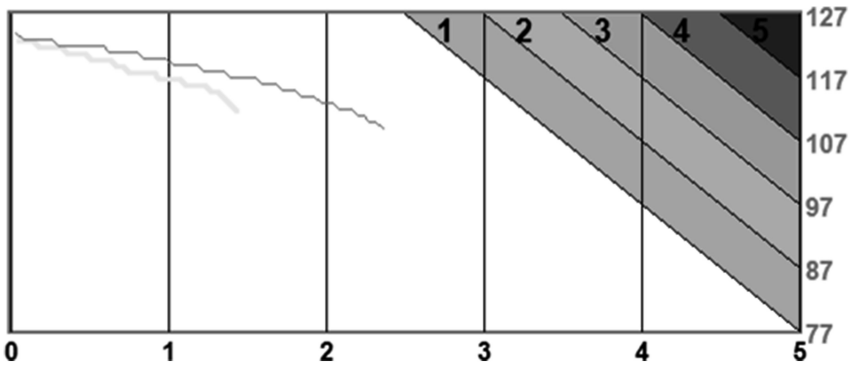
Fig. 3. Typical view of current state shown to student. Thin line is represents distribution of ordinary levels and thick line represents distribution of confirmed levels. On the right grading zones are seen.

9   Learning Control

System offers multiple options for personalized learning. The simplest (and quite popular) option is that student chooses a comp to activate (learn, test). The system determines the most proper selection for learner's state (controller in closed-loop system). The information used at that point is the current state and predicted state after 16 weeks. The system reacts by searching tasks which has proper difficulty level (for this competence) and ordering them by last usage of the task (this avoids too frequent appearance of the same task – students have stated that this annoys them very much).

System also offers higher level controls where student does not choose a specific lowest level comp but a group of comps from those which are set up in the system. Note that a comp may appear in several higher level items. Now the system makes the selection of a task based on learner's current state and contents of the competence item. This enables the system to be more sophisticated – better prediction of the result is possible.

The last learning control introduced in 2015 is based on the structure where higher level competences are formed from comps which have logical content and are supported by task set which is closed in this group. The structure is multilevel and regular course appears on the third level. Whole curriculum has not modelled so far but the fifth level could be the proper one. Such big joins are not appropriate to use in real learning but may be base for giving out certificates. A very important application is representing and analyzing relations between classical units like courses.

Graphical representation is based on using volume measures (from XXL to S) representing sum of w99-s involved in particular group (volume from more than 80 % to less than 20 %) and average ability levels shown in color code. In Fig. 4 second level competence from one course is shown and in Fig. 5 more deep case in another course where all 3 laws make separate competences is shown. It is nothing strange that even well-known laws of nature may have very different content depending upon what is included (deepness of knowledge). In these two cases substantial difference is in experimental base, i.e. which lab experiments are included.
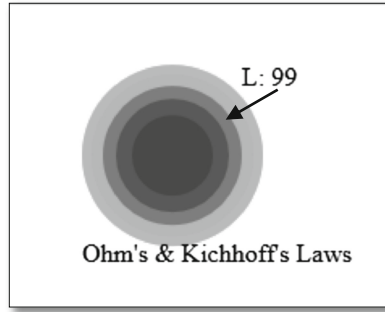
Fig. 4. Representation of one competence with selection of volume L which has ability level 99 (from 127). Clicking on the selected area opens task for this level.
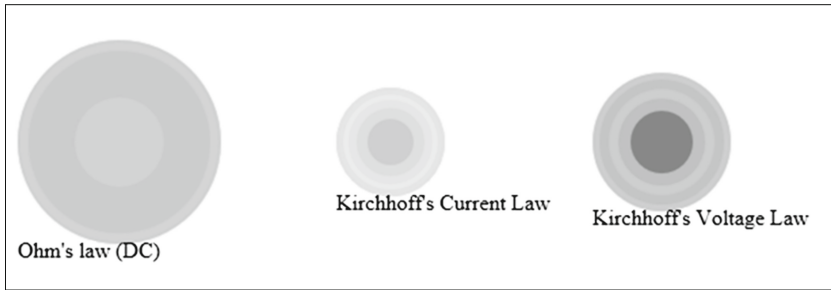

Fig. 5. Ohm's and Kirchhoff's laws as separate competences in another course. More low level abilities are covered here.

These diagrams can be used for learning (clicking causes activation of task) and examining (demonstration to somebody) when clicking shows which task could be proposed to the holder of that diagram. For example, in the examining mode clicking on different zones will pop-up the task from particular layer. Due to modelling forgetting, both levels and tasks which will be shown are changing in time.

Important note: this environment is never closed and a person can always activate any part for testing-learning. All parameters are changed as the result of actions. This is also true at course level: even when formal grade is assigned and transferred to formal system, the course as competence item will stay open forever.

10   Certificate

As well-known, the MOOCs have very high drop-out rate and unfortunately, only completed course results produce certificate. If the person has learned less, the work has not graded and formal result is zero. Now we demonstrate the possibility of certificate based on data for person whose learning process was shown on Fig. 2 (this is not real certificate).

> **We confirm that on Feb 26, 2015 20:00**
>
> the person identified as *Firstname Lastname* has the following competences:
>
> *Ohm's law* – level 85% of maximum for volume XXL and 95% for volume L
>
> *Norton and Thevenin circuits* – 80% for XL
>
> *Using multimeters* – 90% for XXL and …
>
> …

11   Conclusions

Two-dimensional mapping for learning results has been introduced where one axis represents acquired knowledge difficulty and another one – quality (ability level). Current state can be represented by a dot on the map or by curve(s) which show distribution of ability levels over difficulties (volumes). Difficulties can be connected to credit units and formal grades by mapping functions.

There are three main functions of using two-dimensional maps:

(1) showing current state of learning to students;
(2) saving knowledge obtained in course that has not been passed;
(3) using as prerequisites (initial state) for learning.

Using forgetting model is vital part of the model as degradation is natural process and for starting state old data may be misleading. Power law model [16] has been widely used for modelling of forgetting and it has been shown that it gives proper results in similar situations [17].

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