Automating Personalized Learning through Motivation

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Abstract. In this paper, we propose a model that personalises the learning experience of a student by automatically selecting the exercises that best suit the student's competences and that also maintain the student's motivation at a certain (high) level.

1 Motivation

Motivation is a big issue in learning theory and cognitive science [5,2,8,7]. It is known that motivation is a trigger for eagerness, close attention, cognitive development, personal growth and ultimately goal achievement. Most importantly, motivation is a key factor for keeping any learning experience pleasant independently of its speed or success. If an experience is rewarding or pleasurable, one most likely would want to repeat it, with the expectation to obtain more of that positive reward, and as we know, repetition and practice are very strongly linked to learning.

The relationship between rewards and learning has been studied extensively in fields such as psychology, neuroscience and pedagogy. Studies such as [3] show how the biological reward mechanism works in relation with reinforcement learning. It has been found that dopamine, which is a neurotransmitter associated with the reward system of the brain, plays an important role in learning, choice and belief formation.[1]

The reward prediction error hypothesis says that neurons release dopamine in proportion to the difference between a "predicted reward" and the actual "experienced reward" of a particular event. For instance, an unpredicted reward elicits activation (positive prediction error), a fully predicted reward elicits no response, and the omission of a predicted reward induces a depression (negative error). Reinforcement learning algorithms in computer science, where expected rewards can be estimated considering recently viewed rewards on sequential trials, are heavily inspired in these neuroscientific findings and behaviorist psychology approaches.

In this paper, we make the following analogy. Just like dopamine is released when reward is greater than expected leading to an increased desire or motivation towards the reward [1], we say when the mark a

[1] The relations between expectations, rewards and dopamine release has also been studied in music. [9] discusses how we get from the perception of sound patterns and the prediction of future sound pattenrs to reward and valuation. For instance, they state that when listening to a new musical piece, one can expect a certain set sounds to occur, based on one's history of listening to music.

student gets is greater that his self-assessment this leads to an increased desire or motivation towards the subject the student is learning. And as we have pointed out before, motivation is key for any learning experience. As a result of this analogy, we propose a model that personalises the learning experience of a student not only by selecting the exercises to suit the student's competences (as is currently common, e.g. knewton.com), but also to maintain the student's motivation at a certain (high) level.

2 eLearning and feedback expectations

In a learning scenario, we understand marks as rewards. Marks that a student receives can be viewed as positive/negative rewards. Whether the reward is positive or negative, as our analogy illustrates, depends on the difference between the *expected reward* of a student and the *actual reward* the student receives. In this paper, we want to estimate the level of reward, and personalise the learning experience to maintain a certain level of reward. To achieve this, we will estimate the *expected reward* and the *actual reward* for a given student and a given assignment.

We can think of *expected rewards* as self-assessments (what a student may expect in terms of marking) and *actual rewards* as the actual assessment the student received.The difference between these two values describes the level of reward obtained by the student. We refer to this difference as the student's *motivation* value. We say receiving a mark higher than expected results in a positive motivation value, whereas receiving a mark lower than expected results in a negative motivation value.

It is possible then to design a *sensor* for a class that would give us a hint of the motivational level of each student. We do not want students to stop making mistakes when solving assignments, of course, as mistakes are a necessary step in any learning process. What we are interested in, however, is to maintain a positive motivation level. In other words, we want the learning process to become a pleasurable experience (a dopamine release experience) which will motivate the student to repeat that experience, performing similar assignments to the one just performed. We believe that increasing the complexity of assignments while maintaining a good (positive) motivation level is the key to an optimal learning path. We say this criteria should be tailored to every student since each individual has a different learning pace and capacity which impacts his/her motivational level. That is, there is no one ideal assignment for all students. Some students might not feel challenged enough by an assignment and hence get bored, while others may find the same assignment too complicated and get discouraged.

As mentioned above, we want to design a sensor that can sense the motivation level of students. We can then take into account the individuality of students based on their history of motivation. The question that this paper tries to address is then: *Given a student and a selected assignment, what is the expected self-assessment and the expected actual assessment?* Based on these expectations, we then need to decide *how to optimise the learning path for a particular student.* In other words, what is the sequence of assignments that should be assigned to the student to maintain a good level of challenge and motivation?

3 Formal model

We assume there is a set of problems P to achieve an education competence c_P, a group G of students that have to achieve that capacity and a teacher t. Students solve problems from P and receive a mark in the range $E = [0, 10]$. Marks can be either self-assessed (when the student assess his own work) or externally assessed (e.g. by the teacher, colleagues, an automated software, etc.). We note by $se(\alpha, p_i) \in [0, 10]$ the self evaluation of student α over problem $p_i \in P$. Similarly, we note by $fe(\alpha, p_i) \in [0, 10]$ the final evaluation provided by some external entity (e.g. G's evaluation or t's evaluation) of α's performance over p_i. [2] When one of the problems is solved and a final mark is provided with a 10, we consider the student has achieved competence c_P.

We conceptualise the *motivation* that α obtains from solving a problem $p \in P$ as the difference between the final assessment and α's self assessment, that is: $fe(\alpha, p) - se(\alpha, p)$.

We assume there is a history of evaluations:
$H = \langle (se(\alpha, p), fe(\alpha, p)), (se(\beta, q), fe(\beta, q)), (se(\gamma, r), fe(\gamma, r)), \ldots \rangle$
that allows to compute expectations on se and fe via a learning procedure (e.g. via Bayesian inference [**?**]). That is, we assume we can compute for all $X \in P$ and $Y \in [0, 10]$, the following expectation (or probabilities):

- $P(se(\alpha, X) = Y|H)$
- $P(fe(\alpha, X) = Y|H)$

Given these expectations, we can define different learning strategies to select new assignments for student α. For instance, consider the following different learning strategy functions, noted as $New(\alpha, H) \in P$: [3]

MaxMotivation Maximise motivation, which is achieved by looking for an assignment that will maximise the difference between the expected self-assessment and the expected final assessment:
$New(\alpha, H) = \arg\max_p EMD(\mathbb{P}(fe(\alpha, p) = Y|H), \mathbb{P}(se(\alpha, p) = Y|H))$

MaxChallenge Maximise learning speed, which is achieved by looking for an assignment that will maximise the expected final assessment:
$New(\alpha, H) = \arg\max_p EMD(\mathbb{P}(fe(\alpha, p) = Y|H), Beta(1, 100)$

MaxSelfAssessment Maximise student self's opinion, which is achieved by looking for an assignment that will maximise the expected self-assessment:
$New(\alpha, H) = \arg\max_p EMD(\mathbb{P}(se(\alpha, p) = Y|H), Beta(1, 100)$

Balance Maximise the balance between motivation and learning speed, which essentially combines MaxMotivation and MaxChallenge:
$New(\alpha, H) = \arg\max_p EMD(\mathbb{P}(fe(\alpha, p) = Y|H), \mathbb{P}(se(\alpha, p) = Y|H))\cdot$
$EMD(\mathbb{P}(fe(\alpha, p) = Y|H), Beta(1, 100)$

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[2] For G's evaluation, where one essentially calculates the community's assessments, the COMAS algorithm can be used [4]. COMAS calculates the final assessment by aggregating peer assessments in such a way that more weight is given to those that are more trusted by the tutor. To calculate the tutor's trust in the students, a trust graph is built based on how similar are the students' assessments to the tutor.

[3] EMD stands for earth mover's distance [6]. $Beta$ stands for the beta distribution. $Beta(1, 100)$ is a distribution totally skewed towards 0.

4 Position

We conjecture that *learning strategies that aim at increasing motivation (e.g. our MaxMotivation and Balance strategies) result in more effective learning*. This conjecture is inspired by research results that highlight the importance of motivation in enhancing learning [5,2,8]. To increase motivation, the model presented in this paper is designed based on the evidence that, when a reward is greater than expected, the firing of certain dopamine neurons increases, which consequently increases reward-seeking behaviors and the desire or motivation towards the reward [1]. The model proposed in this paper assumes that *marks, in a learning environment, are a type of reward* and thus we interpret motivation as the difference between the expected mark of the student and the actual final mark the student receives. This conjecture will be put to test with an implementation of the idea and experiments with real students.

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