Deep Motivation Analysis in Students' Virtual Learning Environment Through Deep Learning

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Abstract

Virtual Learning Environment (VLE) is an Internet-based platform providing digital courses. Studies have shown the importance of motivation in the success of VLE experiences. This paper proposes a semi-supervised learning technique to predict the vector magnitude of three intrinsic indexes (achievement, affiliation, and power) and two extrinsic indexes (physical conditions and environment) using a neural network and non-linear mathematical modeling based on the Open University Learning Analytics Dataset (OULAD) and survey data. Our model can evaluate students' performance and determine effective practices in VLE.

Contents

1 Introduction

Virtual Learning Environment (VLE) is an online Internet-based platform for digital courses of study. VLE platforms including Coursera and Google Classroom are becoming increasingly popular among students. While their convenience can benefit students a lot when they lacked availability to traditional academic settings, VLE requires extremely strong self-motivation from students, since VLEs are generally characterized by a lack of supervision, guidance, and peer support.

This paper introduces a novel model for predicting VLE students' net motivation from five different indexes. These are three internal indexes by McClelland's Motivation theory: achievement (AC), affiliation (AF), and power (P), and two external indexes: physical conditions (PC) and environment (E). We further propose a neural network to learn how the intersections between the internal indexes affect each other in the process of modeling and preprocessing the inputs.

2 Related Works

Leino et al.[1] discovered a direct association between students' academic performance and stay-at-home environment in a random sample of 8 pupils. Specifically, they found a direct increase in students' performance when they are under the supervision of parents, providing them with an external force that stimulates their motivation to study.

Shuvaev et al.[2] proposed a neural network in an attempt to predict the reward and punishment mechanism of human basic needs, which are water, food, sleep and play. They used four 3x3 grids to represent the shift between the stages to account for the marginal costs and benefits. The reward and punishment are derived from calculations dependent on both the physical motivation and the net reward vectors (the Q function). According to their Q-learning model, the relationship between net reward and motivation is devised, shown in Equation 1.

$$\tilde{r} = \tilde{r}(\overrightarrow{r}, \overrightarrow{\mu}), \tag{1}$$

where $\overrightarrow{r}$ is the physical reward vector, $\overrightarrow{\mu}$ is the total motivation vector, and $\tilde{r}$ is the scalar reward value. The Q value (the total reward estimated for the future) is calculated as in Equation **??**.

$$Q(\overrightarrow{s_t}, a_t, \overrightarrow{u_t}) = \tilde{r}(\overrightarrow{s_t}, \overrightarrow{\mu_t}) + \gamma Q(\overrightarrow{s_{t+1}}, a_{t+1}, \overrightarrow{\mu_{t+1}}), \tag{2}$$

where γ is the discrepancy between expectation of long-term future rewards and short-term fixed rewards, $\overrightarrow{s_t}$ is the current state (environment) of the agent, a_t is a series of action, and $\overrightarrow{\mu_t}$ is the motivation vector at time t. In this work, we define students as motivated if the net reward vector exceeds the discrepancy γ.

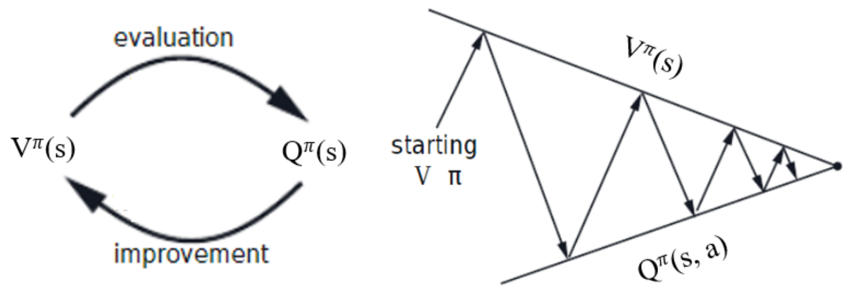

Figure 1: The convergence of V and Q states in a sequential progression of a series of actions a.

Other renowned learning techniques include the Markov decision process [3]. In Markov's view of motivations for decision, there are four main parameters, which are state space S, action space A, the probability of transforming into state s_{t+1} from s_t due to action a $(P(s_{t+1}|a, s_t))$ P_a, and the immediate reward $(R(s_{t+1}, s_t))$ R_a. A and S can be virtually infinite and can be represented using complex vectors. This theory is further developed by Otterlo and Wiering [4] using reinforcement learning. They propose using environment-agent pairs in sequential orders. As Figure 1 shows, under the decision policy π, the value of state s represented by $V(s)$ and the value after action a represented by $Q(s)$ converge with the variable time in reinforcement learning to the optimal solution.

The McClelland's theory of needs divides the human need into three main factors: achievement, affiliation, and power. All three factors influence each other and are based on both intrinsic and extrinsic parameters to the human brain function. In the work "How individual needs influence motivation effects:a neuroscientific study on McClelland's need theory," Rybnicek et al. [**?**] discovered that complex heterogeneous rewards activate different parts of the brain, including putamen or caudate, through an fMRI study. [5]'s research summary on flipped classrooms can also be applied, in which the authors implied the importance of engagement and freedom of students to be successful in VLE.

An overview published by Enyia [6] provides a comparison and critique of three main psychological motivation theories by Maslow, Herzberg, and McClelland. Maslow's hierarchy of needs is rather a primitive approach, while Herzberg weighs too much on the effect of hygiene environments on human behaviors. McClelland's theory of needs certainly fits the best into real-life scenarios, but McClelland also argued that the three factors are unconscious, making yielding a direct computational model of the theory difficult.

3 Dataset and Sampling

We use the Open University Learning Analytics Dataset (OULAD) and seven case studies conducted individually as our primary sources of data.

3.1 OULAD

The OULAD dataset is issued by the Open University, the British University with the largest student body. It contains information regarding students' attributes such as age, gender, disabilities, interaction times with the VLE platform, and scores. Each student's assessment information, VLE information, and course information is linked by their student's ID throughout several csv files.

3.1.1 Preprocessing

Our preprocessing of OULAD involves the matching of the following attributes into one single file according to the students' IDs. The following attributes are used in our study:

1. num_of_prev_attempts: the number of previous attempts before the final evaluation.
2. studied_credits: the credit of the course.
3. interact_times: the number of times of interaction of the VLE.
4. weight: the weight of the student.
5. date: $\text{date}_{\text{assessment}}$ - $\text{date}_{\text{start}}$.
6. score: the score of the student's assessment.
7. gender: the gender of the student; the dataset contains two genders: F and M.
8. highest_education: the highest education of the student; the dataset contains the following categories: A Level or Equivalent, HE Qualification, Lower Than A Level, No Formal quals, Post Graduate Qualification.
9. imd_band: the indices of multiple deprivations (IMD) is used to measure the relative deprivation of small areas; it is scaled from 0% to 100%.
10. age_band: the age of the student.
11. disability: whether the student is disabled or not; the dataset contains two categories: Y and N.
12. assessment_type: the type of assessment the student is taking; the dataset contains the following categories: CMA, Exam, and TMA.

Categorical variables in the dataset are changed to continuous variables through dummies.

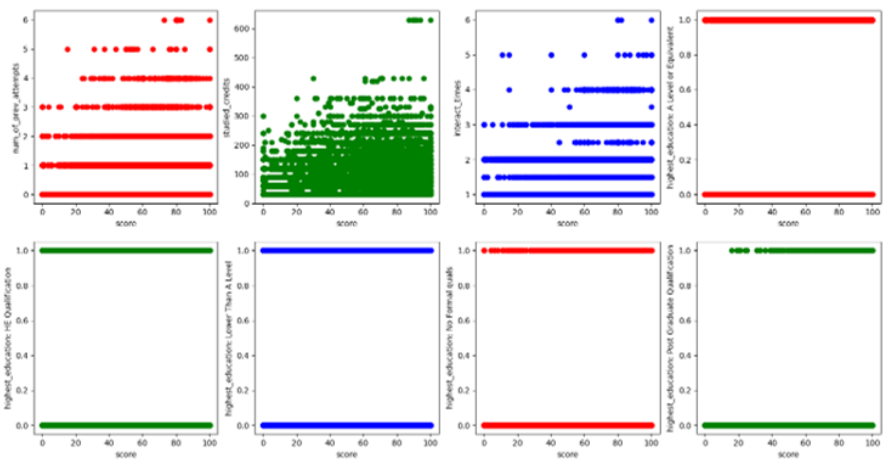

Figure 2: The plots of different variables about academic performance.

3.1.2 Exploratory Study

The analysis of some important variables is given below:

1. The covariance of num_of_prev_attempts, studied_credits, interact_times, highest_education, assessment_type, and score: These variables seem to have a strong variance with each other. Specifically, assessment_type and score have a strong association. Computer-marked examinations have a covariance of 2.117, while teacher-marked examinations have a covariance of -1.937. Figure 2 shows how each of the variables is correlated with the scores of the students. It appears that those with a low number of previous attempts, studied credits, times of interaction, and highest education can have scores varying from 0 to one hundred, but the distributions of scores on those with a larger value on these variables are centered at the higher end and are generally highly skewed to the left.

2. Physical and financial conditions have generally low correlation with the score of the students, which is used as a baseline to indicate a student's academic performance. The covariance between age and score is generally low, but there appears to be a moderate association between scoring high and being in the age band between 35 and 55 years old. The covariance of 2.930 between gender and score is also negligible.

Subject No./Gender/Age	Q1	Q2	Q3	Q4	Q5	Q6
0/M/20	Yes	5	4	(a)	(b)	(a)
1/M/8	Yes	7	8	(e)	(b)	(b)
2/F/15	Yes	5	5	(a), (d)	(a)	(a)
3/F/26	Yes	1	3	(a), (b), (c)	(a)	(a)
4/M/18	Yes	4	4	(d)	(b)	(a)
5/F/17	Yes	6	7	(e)	(a)	(b)
6/F/18	Yes	4	3	(b)	(b)	(b)

Table 1: Answers from each subject in the interviews

3.2 Case Study

In addition to the data gathered from OULAD, we conducted case studies on seven students whose ages range from 8 years old to 26 years old through interviews. Three of them have gender M and four of them have gender F. Each interview consists of the following questions.

1. Are you currently participating in VLE as your main source of education?
2. How would you rate your frequency of communication with others of your age offline on a scale of 1 to 10?
3. How would you rate your level of happiness on a scale of 1 to 10?
4. What would you say are your main sources of anxiety in academic life if any?
   (a) Lack of sports activities
   (b) Lack of encouragement/care from the similar-aged
   (c) Low scores
   (d) Pressures from your supervisors (mentors/parents)
   (e) None
5. Which of the following options best describes your studying environment?
   (a) Individual participant in online VLE platforms such as Coursera
   (b) Supervised online classroom by mentors/parents with classmates
6. Which of the following options best describes your situation?
   (a) Forced stay-at-home/lockdown in a small area
   (b) Voluntary VLE with an appropriate amount of free time

The results are summarized in Table 1 as they responded to each interview question. From the data, considering the fairly even distribution of categories between males and females in other columns, it also appears that there is no noticeable difference between the level of happiness and gender as the results of the exploratory analysis on OULAD. With a P-value of $0.6390 > \alpha = 0.05$, we failed to reject the null hypothesis that there is no difference between the mean level of happiness between M and F.

Age appears to have a positive correlation with the extent of happiness. The P-value of $0.0315 < \alpha = 0.05$. We reject the null hypothesis that there is no association between the level of happiness and age. As age becomes higher, the level of happiness tends to be lower.

Three out of four who are forced stay-at-home due to policies (i.e. COVID lockdown) reported a primary source of stress as "Lack of sports activities," and they are also the only three that reported lack of sports as one of their main sources of anxiety out of all subjects. They also claim that before they were forced to stay at home, they have participated in some level of sports activity before. Two of the three claim that they didn't play competitive sports nor did they frequently engage in sports hobbies, but they did have a habit to enjoy at least one to two hours of outdoor time per day. The other one played on the sports team at her school before the lockdown. It can be inferred that the drastic decrease in the amount of sports as compared to before can cause a decrease in happiness.

Another factor of anxiety that is negatively correlated with the happiness of the subjects is the lack of encouragement or care from the similar-aged groups. It can be inferred that there is a generally lower level of interaction offline and often online with a group of peers compared to traditional classroom teaching. Thus, encouragement or the frequency of engaging in dialogues with a community is also an important factor of the environmental influences on VLE students.

4 Ablation Experiments

4.1 Input Processing

Before the datum is passed on to the neural network, we first processed the raw datum from OULAD by grouping them into the following five groups, using the McClelland's Achievement Motivation Theory as a framework:

1. Physical Conditions (Extrinsic, p_c): The physical conditions that cannot be altered in short-term of the subject, including age, gender, weight, disability, financial IMD-band, and the frequency of physical exercises.

2. Environmental Conditions (Extrinsic, p_e): The environmental conditions of the subject in VLE. These are related to human interactions with the similar-aged or with mentors and the human-computer interaction frequency.

3. Achievement (Intrinsic, i_{ac}): A factor that measures the extent to which personal achievements (i.e. grades) motivates the subject. It can be attributed to the score, assessment type, the number of interactions with VLE, the highest education received by the subject, and the number of previous attempts.

4. Affiliation (Intrinsic, i_{af}): A factor that measures the extent to which the will to be connected or join a particular group or community motivates the subject. It can be attributed partially to the extrinsic environmental conditions, the date until the assessment, and the studied credit of the subject.

5. Power (Intrinsic, i_p): A factor that measures the extent to which the power to change the environment or community through the application of knowledge motivates the subject. It can be attributed to the extrinsic conditions, highest education received, and the grade which measures the academic performance of the subject.

From the exploratory analysis of OULAD, we derived the five groups from the attributes using the formulas:

1. $p_c = \alpha\cdot$ assessment_type $+ e^{\frac{||\text{imd\_band}||}{10}}$;
2. $p_e = e^{\text{age\_band}} + \frac{\text{age}\cdot\text{weight}}{100}$.
3. $i_{ac} = \beta\cdot$ score^2 - (interaction_times^2 + num_of_prev_attempts^2);
4. i_{af} = (ln(score+1) + ||imd_band||)/α + $\sigma(\alpha\cdot$num_of_prev_attempts) + $\sigma(\alpha\cdot$education);
5. i_p: $= (\frac{\text{studied\_credits}\cdot\text{education}}{\alpha} + e^{\frac{\text{imd\_band}}{10}})/\alpha + \ln(\text{education})$,

where α is the inflating coefficient set to 10^2 times the learning rate and β is the deflating coefficient set to 10^{-2} times.

4.2 Neural Network

We used a simple feed-forward network with three layers in total. The network architecture is shown in Figure 3.

The three convolution kernels are of sizes 5×128, 128×256, and 256×3 each. The input consists of a one-dimensional list of 5 factors: [p_c, p_e, i_{ac}, i_{af}, i_p].

The extrinsic factors, p_c and p_e, are fully connected with the first layer of the FNN, while the intrinsic factors, i_{ac}, i_{af}, and i_p, are connected with the last three rows only. This adds a recurrent feature to the first layer by adding them. The FNN expands the input values into vectors in 128 and 256 dimensional spaces and learn to minimize the proportional differences between the punishment and reward vectors.

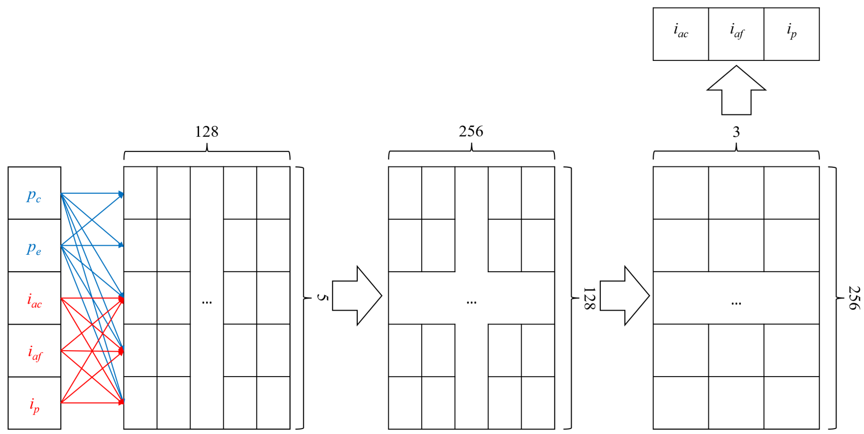

Figure 3: The network architecture

The importance of the neural network is that the three intrinsic psychological factors influence each other for an individual to maximize their reward and satisfaction [2]. Achievement can influence power, for instance, if one believes that they are more capable of making an impact, so they value the process of learning more, leading to higher motivation caused by i_p.

On the other hand, since the intrinsic factors are dependent on neutral extrinsic stimulus, the neural network is partially linked with the intrinsic factors, but fully connected with the extrinsic factors.

4.3 Loss Function

The cosine similarity loss of the vectors A and B is defined in Equation 3, so to minimize the angle between two vectors.

$$L(\overrightarrow{A}, \overrightarrow{B}) = \frac{\overrightarrow{A} \cdot \overrightarrow{B}}{|\overrightarrow{A}||\overrightarrow{B}|} \tag{3}$$

To start with, we define the following vectors:

1. Total intrinsic motivation (V_i), defined in Equation 4.

$$\overrightarrow{V_i} =< i_{ac}, i_{af}, i_p >; \tag{4}$$

2. Aggregate reward (r), defined in Equation 5. The aggregate reward vector measures how a student receives the desired stinulus in the VLE environment from the three intrinsic aspects. The physical factors are used as

a coefficient that determines the psychological multiplier effect of one's environment on their intrinsic factors.

$$\overrightarrow{r} \sim N(0,1) = \sigma((1 + \frac{p_c + p_e}{2}) \cdot V_i); \tag{5}$$

3. Aggregate punishment (p), defined in Equation 6. The aggregate punishment vector measures how a student receives undesired stimulus in the VLE environment from the three intrinsic aspects. These may include stress from overworking, loneliness from a lack of classroom setting, and inefficiency due to a lack of engagement [5]. The punishment vector can be modeled with a Laplace Transformed sawtooth function, with each period lengthening by the fraction of the previous period due to increasing endurance (decreasing slope every time of spontaneous recovery) [2]. Define f as in Equation 7. For simplicity, we assume intrinsic punishments are independent from extrinsic factors. Thus, the multiplier did not take place. In each punishment factor, the two other intrinsic factors are taken into account. Their product, representing the total motivation received from the two factors, simulates the punishment, or opportunity cost, or being motivated by the current factor. For instance, if a student experiences high affiliation, then the punishment results from low achievement and power, which in turn affects the will and confidence of one to attend in social activities inversely.

$$\overrightarrow{p} \sim N(0,1) =< f(i_{af} * i_p), f(i_{ac} * i_p), f(i_{ac} * i_{af}) >; \tag{6}$$

$$f(x) = \sqrt{x} - \lfloor \sqrt{x} \rfloor; \tag{7}$$

4. Net reward (r_{net}), defined in Equation 8. The vector is normalized to simulate a probabilistic Gaussian distribution.

$$\overrightarrow{r_{net}} = ||\overrightarrow{r} - \overrightarrow{p}||; \tag{8}$$

5. Total motivation vector (μ), defined in Equation 9.

$$\overrightarrow{\mu} = (\frac{\Omega}{\overrightarrow{r_{net}}}), \tag{9}$$

where $\Omega = \frac{i_{ac}+i_{af}+i_p}{3} \cdot \frac{p_c+p_e}{2}$. The Ω value is the product of the mean of intrinsic factors and the extrinsic multiplier, evaluating the total scalar reward gained. Dividing $\tilde{r}$ by the total reward vector $\overrightarrow{r_{net}}$, we receive the total motivation vector μ [2].

Our loss function is defined as in Equation 10, where $c = \frac{i_{ac} \cdot i_p}{i_{af}}$.

$$\text{Loss} = L(\overrightarrow{V_i}, \overrightarrow{\mu}) - c. \tag{10}$$

The loss function aim to put the total intrinsic motivation vector in proportional direction with the $\overrightarrow{\mu}$ vector. The discrepancy between the short-term

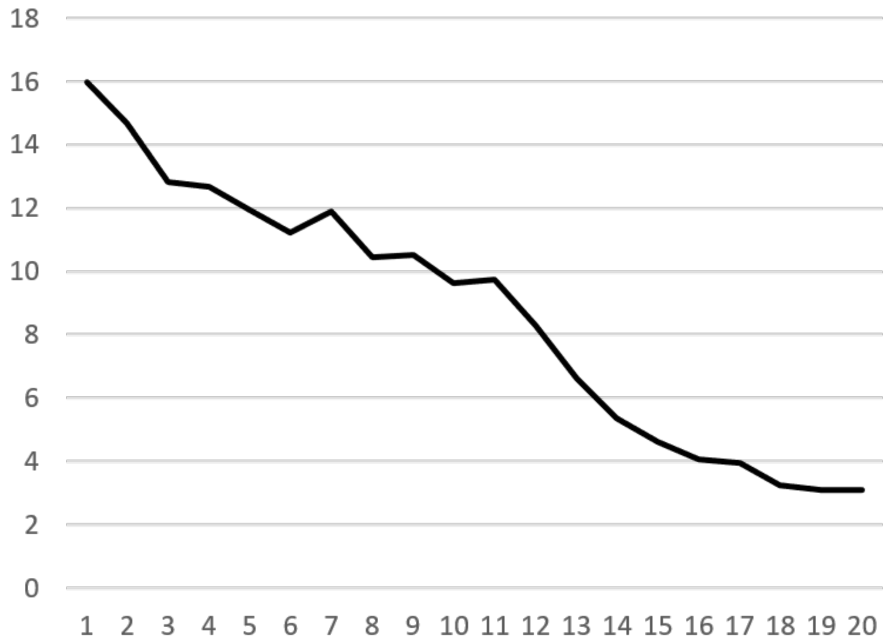

Figure 4: Decrease of loss function over each epoch during training phase

and long-term rewards is represented by θ, the angle between the short-term emotion-focused intrinsic reward $\overrightarrow{V_i}$ and the long-term self-controlled integrated motivation $\overrightarrow{\mu}$. Thus, we minimize the cosine similarity loss between the two vectors for students to find an optimal coping strategy for students in VLE situations.

On the other hand, the c value equates to the project of the achievement and power divided by the affiliation factor. From the grouping of attributes from OULAD, we found affiliation and power are directly positively correlated, while affiliation generally stayed low in VLE due to isolated environments. Since there is a tendency for students to rely on realistic evaluations of their ability and futuristic assessments of their works, they usually reward themselves from i_{ac} and i_p rather than i_{af}. Therefore, we simulate the learning processes of students by subtracting a constant coefficient from the cosine similarity loss function to compensate for such tendency.

4.4 Results

When trained using a batch size of 128 and a learning rate of 0.1, the loss function converges, as shown in Figure 4. In the validation phase, it is discovered that the loss stayed consistent. On average, the proportion of $\overrightarrow{\mu}$ is similar to that of the proportion of V_i, with a standard deviation of the difference in proportion of 2.3843. One interesting observation is that those originally with low affiliation has as an average multiplier around 2 (meaning their final long-term motivation vector is around two times the original $\overrightarrow{V_i}$), with a standard deviation of 1.6237. However, those originally with relatively higher affiliation had a generally lower multiplier of around 1.5, with a much scattered standard deviation of 3.2585.

5 Conclusion

Our work produces a model to simulate students' motivation from three aspects by the McClelland's theory of motivation: achievement, affiliation, and power. We also use two extrinsic factors, physical conditions and external environment. Each value is measured through the aggregation of multiple attributes in the OULAD and the conclusions seven case studies.

After we derive the values from the dataset and collected data, we feed each list of five factors to a three-layer FNN. The FNN's first layer is fully connected with the extrinsic factors, and partially connected with the three intrinsic factors. It is trained using a loss function that narrows down the discrepancy between students short-term and long-term reward vectors, taking an additional cost factor into consideration that accounts for the student's tendency to increase self-achievement and power recognition but lower affiliation.

The analysis and evaluation of individual cases are available on the website: www.gardensolution.cn.

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