A Talent Assessment Model based on Learning Behaviors and Patterns

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***Abstract*—Talent assessment is an important topic in various areas like enterprise management, education, and psychology. However, it is also a challenging topic as the conventional assessment methods and models are unsuitable for talent assessment due to the following two aspects: (i) domain-dependent. The assessment of talent is highly depended on a specific domain which requires a large volume of domain knowledge in the assessment model; and (ii) behavior-based (or pattern-based). The characteristics of talents are reflected by a wide range of factors like their behaviors (patterns), emotions, self-identities, and metacognition. In this paper, we propose a talent assessment model based on online learning behaviors and patterns by using fuzzy models. Specifically, we attempt to develop a talent assessment model by identifying their learning data as we believe that the learning behaviors in the online learning platforms like massive open online courses (MOOCs) can reflect some characteristics of talents. Furthermore, we discuss what are the data sources, the learning behaviors and the potential computational methods in this assessment model in details. In addition, the potential limitations and possible improvement plans are introduced.**

***Index Terms*—Talent Assessment, Learning Behavior, Learning Pattern, Fuzzy Model**

I. Introduction

With the explosion of knowledge and rapid development of technologies in 21st century, talent becomes the paramount factor of success for all different organizations. In an organization like government or enterprise, talent assessment is a very critical managerial issue "which involves using techniques to assess their mindsets, behaviors and skills" [6]. More generally, talent assessment is related to various areas like enterprise management, education, and psychology [3, 7, 9].

However, talent assessment is also a challenging topic as the conventional assessment methods, and models are unsuitable for talent assessment due to the following two aspects:

- **Domain-dependent.** The assessment of talent is highly depended on a specific domain which requires a large volume of domain knowledge in the assessment model [8]. The required skills and knowledge at talent levels will be significantly changed with the different industries, organizations or posts.
- **Behavior-based (or Pattern-based).** The characteristics of talents are reflected by a wide range of factors like their behaviors (patterns), emotions, mindsets, self-identities, and metacognition [6]. To the best of our knowledge, there is no standard framework for assessing talent in existing studies.

Therefore, this paper aims to fill this gap to some extends by developing a novel talent assessment model. To be specific, we propose a talent assessment model based on online learning behaviors and patterns by using fuzzy methods. Different from extant fuzzy models for talent assessment [10], we focus on adopting fuzzy methods to measure the degree of capacity in various criteria rather than adopting the Delphi method which involves opinions from experts for evaluation.

Concretely, we attempt to develop a talent assessment model by identifying their learning data as we believe that the learning behaviors in the online learning platforms like massive open online courses (MOOCs) can reflect some characteristics of talents. Furthermore, we discuss what are the data sources, the learning behaviors and the potential computational methods in this assessment model in details.

The remaining sections of this article will be organized as follows. Section 2 will discuss the detail model for talent assessment based on learning behaviors (or patterns). In Section 3, the potential limitations and possible improvement plans are introduced. In Section 4, we summarize the proposed model and findings in this study.

II. Related Work

There are many relevant studies on how to develop a talent assessment model. To provide an objective system for talent management in the organization, Huang et al. proposed "a fuzzy assessment model framework for talent management and understand the criteria for excellent managerial personnel" [9]. A later study by Huang et al. [10] improved their previous fuzzy assessment model by employing the Fuzzy Analytic Hierarchy Process to reduce the bias influenced by people. Talent assessment model was adopted in education. For example, Barry et al. [14] have proposed a talent assessment framework in elementary

978-1-7281-3388-1/19/$31.00 ©2019 IEEE
DOI 10.1109/ISET.2019.00011

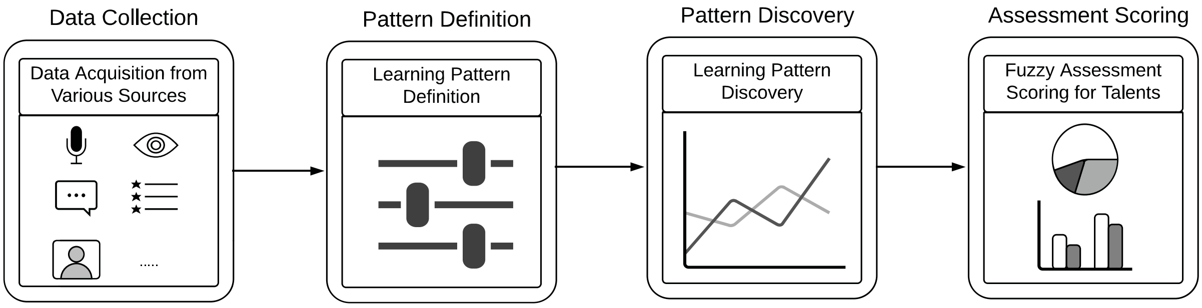

Fig. 1. The overall framework of the talent assessment model

schools to identify the talent in the dance, music, and theater. McCauley et al. [12] suggested that eight different methods including "Adopt a talent mindset", "Team up with HR", "Realize your management potential" and so on to be more involved in talent management. Sharma and Bhatnagar conducted a case study on a pharmaceutical organization in the Indian and revealed that "the talent mindset had helped the organization in recruiting the best talent" [16]. Tippins and Adler have discussed various issues including measurement, implementation, remotely delivered assessment, computerized adaptive tests and so on in technology-enhanced talent assessment [17]. Nijs et al. conducted a comprehensive review which "aims to contribute to the establishment of a stronger theoretical basis for talent-management by presenting a conceptual framework of talent in which the definition, operationalization, and measurement of talent and its relation to excellent performance is clarified" [13]. Davis et al. suggested a talent management strategy which "involves using techniques to assess their mindsets, behaviors, and skills and then providing effective training, development, and performance management interventions" [6]. More recently, the talent assessment for software development firms is investigated in their internal training process [2].

III. Methodology

In this section, the talent assessment model based on learning behaviors and patterns in the online learning platform will be introduced. The context of the proposed model is similar to a platform of massive open online courses (MOOCs) as it has been used as training in human resources of various organizations [15]. As shown in Figure 1, we adopt a computational method for establishing the talent assessment framework. To be specific, the framework can be divided into four sub-processes: (i) data collection; (ii)pattern definition; (iii) pattern discovery; and (iv) assessment scoring. The details of each sub-process will be introduced in the following subsections.

A. Data Collection

The data collection is to acquire data from various sources related to the talent to be assessed in the learning platform. As this study focuses on the learning behaviors, the collected data is relevant to learning activities in the platform. As a preliminary framework, the data sources like login lengths, login time, learning lengths, grades of assessment items, video watching lengths and so on are collected from the learning platform of MOOCs as shown in Table I. As these data are stored in the learning logs of the platform, a set of pre-defined parsers can extract these features from learning logs for further processing.

TABLE I
VARIOUS DATA SOURCES AND SYMBOLS

Symbols	Data Source Descriptions
t_x^i	Timestamp of x-th login of learner i
L_x^i	Length of x-th login of learner i
d_y^i	Timestamp of y-th learning activity of learner i
A_y^i	Length of y-th learning activity of learner i
N_i	Number of courses taken by learner i
$g_{a,c}^i$	Grade of assessment item a in a course c of learner i
T_c^v	Length of video v in a course c
$w_{v,c}^i$	Watching length of video v in a course c of learner i
$a_{v,c}^i$	Additional length of video v in a course c of learner i
$s_{v,c}^i$	Skipped length of video v in a course c of learner i

B. Pattern Definition

The definition of learning patterns will be crucial to the talent assessment framework as it is difficult to have a unified assessment criterion for defining which are the important learning patterns for talent assessment. In this study, we use an open-ended the solution to address this issue to some extends. Specifically, the framework can allow users to have self-defined assessment criteria for learning patterns. We can define a set of assessment criteria and their weights for assessing the talent based on the extracted features from various data sources. Formally, a pattern set can be defined as follows.

A learning pattern set P is a set of criteria for assessing the talent, the element in P is defined as

$$\{c_x(a) \to c_y(b), w_{c_x(a)\to c_y(b)} | a, b \in T, w \in [0,1]\} \quad (1)$$

where T is the set containing all elements in the feature Table I and possible results of their algebra operations, $c_x(a)$ is category of of the criteria a, and $w_{c_x(a)\to c_y(b)}$ is the weight of this pattern in the range of $[0, 1]$. The weight of criteria can be identified in various methods like Fuzzy Delphi Method [5]. Many patterns can be derived according to above definition. For example, patience has been considered as an important personal trait in [9]. One reasonable way of defining the degree of learning is the ratio of additional watching length to the length of all videos within a course. Formally, the learning patience can be denoted as

$$\theta_i = \frac{1}{1+e^{\beta_i}} \tag{2}$$

$$\beta_i = \frac{a^i_{v,c}}{\sum_{v\in c} T^v_c} \tag{3}$$

where $a^i_{v,c}$ is the additional length of video v in a course c of learner i, T^v_c is the length of video v in a course c, and equation (2) is a sigmoid function to normalized the degree of learning patience to the interval $[0,1]$. Further assume that there is a piecewise function for defining the category of the learning patience as follows.

$$c_x(\theta_i) = \begin{cases} low & 0 \le \theta_i < 0.3 \\ medium & 0.3 \le \theta_i < 0.6 \\ high & 0.6 \le \theta_i \end{cases} \tag{4}$$

If θ_i is relatively high and greater than 0.6, we can obtain the category is "high" learning patience. Similarly, we can define a score and obtain the category for the score. Suppose we have also obtained a "high" score for this learner. We can then have a pattern like "high learning patience $\rightarrow$ high score" for this learner i.

C. Pattern Discovery

The pattern we defined above is similar to the association rules in the data mining [1]. As the "support" is adapted to measure the strength of association rules, we propose a similar measurement called "strength" to discover the strong patterns. Formally, we define the following two kinds of strength.

The first one is the local strength, which is the ratio of the same patterns appeared for a single learner.

$$\epsilon^i_{c_x(a)\rightarrow c_y(b)} = \frac{f_i(c_x(a) \rightarrow c_y(b))}{M_i} \tag{5}$$

where $f_i(c_x(a) \rightarrow c_y(b))$ is the frequency of this patterns appeared in the all learning logs of this learner i, and M_i is the total number of learning patterns of the learner i. $\epsilon^i_{c_x(a)\rightarrow c_y(b)}$ represents how frequent the patterns appeared within a learner's behavioral data.

The second one is the global strength, which is the ratio of the number of learners have this pattern among all all users.

$$\varepsilon_{c_x(a)\rightarrow c_y(b)} = \frac{|I(c_x(a) \rightarrow c_y(b))|}{|I|} \tag{6}$$

where $|I(c_x(a) \rightarrow c_y(b))|$ is the number of learners have this pattern, and $|I|$ is the total number of learners. $\varepsilon_{c_x(a)\rightarrow c_y(b)}$ represents how frequent the patterns appeared within all learners' behavioral data.

We then set thresholds for both local and global strength to filter out some noisy and very infrequent learning patterns. The remaining patterns defined as a frequent learning pattern set F. For learner i, we can have a personal frequent learning pattern set F_i, which is a subset of F ($F_i \subseteq F$).

D. Assessment Scoring

The last step of this framework is to give the score on the learning patterns of a specific learner i. To measure how important a learning pattern to a learner, we use the idea of "Term Frequency and Inverse Document Frequency". Specifically, the "Term Frequency" is the local strength; "Inverse Document Frequency" is the inverse of the global strength. Therefore, the importance of a pattern $c_x(a) \rightarrow c_y(b)$ to learner i can be measured by two parts:

$$\gamma^i_{c_x(a)\rightarrow c_y(b)} = \epsilon^i_{c_x(a)\rightarrow c_y(b)} \times \eta_{c_x(a)\rightarrow c_y(b)} \tag{7}$$

$$\eta_{c_x(a)\rightarrow c_y(b)} = log\frac{1}{\varepsilon_{c_x(a)\rightarrow c_y(b)}} \tag{8}$$

where $\eta_{c_x(a)\rightarrow c_y(b)}$ is the normalized inverse of the global strength $\varepsilon_{c_x(a)\rightarrow c_y(b)}$.

In addition to the above importance factor $\gamma^i_{c_x(a)\rightarrow c_y(b)}$, we should consider $w_{c_x(a)\rightarrow c_y(b)}$ which is the importance for talent assessment as given in Equation (1). In an earlier research study [4], the fuzzy fusion method has been verified to be more effective than conventional weighted sum. Therefore, we adopt this fuzzy method to integrate two importance factors $\gamma^i_{c_x(a)\rightarrow c_y(b)}$ and $w_{c_x(a)\rightarrow c_y(b)}$ as follows.

$$\phi^i_{c_x(a)\rightarrow c_y(b)} = \frac{w_{c_x(a)\rightarrow c_y(b)}(1+\gamma^i_{c_x(a)\rightarrow c_y(b)})}{2} \tag{9}$$

$$\varphi_i = \sum_{c_x(a)\rightarrow c_y(b)\in F_i} \phi^i_{c_x(a)\rightarrow c_y(b)} \tag{10}$$

where ϕ_i is the scoring of each patterns of the learner i, and φ_i is the overall score of the learner i by taking all learning patterns.

IV. Discussion

The main limitations of this proposed framework are listed as follow.

- To decide the values of $w_{c_x(a)\rightarrow c_y(b)}$, the procedures involve experts' efforts, which are not scalable to a large pool of rules. If the total number of categories is $|C|$, there will be $|C|^2$ possible patterns which are a very large number. If the Fuzzy Delphi Method is adopted, the whole process will be unaffordable and extremely time-consuming.
- It is a challenging task to set the thresholds of global and local strength. If the thresholds are too small, there will be many noisy and useless patterns, whereas there will not be sufficient patterns if the thresholds are too large.

To address these limitations, it is necessary to adopt the machine learning models to automate the human involved processes. Concretely, we can use a supervised learning model to predict the value of $w_{c_x(a) \to c_y(b)}$ based on those patterns which have been assigned with weights. These assigned patterns will be treated as the training data to establish a predictive model based on machine learning models like deep neural networks [11]. For the threshold settings, an adaptive threshold can be trained with a similar model.

V. Conclusion

In this article, we have proposed a the talent assessment model based on learning behaviors and patterns in the online learning platform to fill the gap of measure behavioral data in talent assessment. The various aspects like what are the data sources, the learning behaviors and the potential computational methods in this assessment model have been covered. In addition, the limitation and the further improvement of the assessment model are discussed. For our future research, we will collect the data from real participants in a platform containing MOOCs and verify the effectiveness of the model through both simulation and survey studies.

Acknowledgment

The research in this paper was supported by the Innovation and Technology Fund (Project No. GHP/022/17GD) from the Innovation and Technology Commission of the Government of the Hong Kong Special Administrative Region, and the Science and Technology Planning Project of Guangdong Province (No.2016A030310423, 2017B050506004).

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