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Lo Pang-Yun TING
National Cheng Kung University

Shan Yun TENG
National Cheng Kung University

Kun Ta CHUANG
National Cheng Kung University

Ee-Peng LIM
Singapore Management University, eplim@smu.edu.sg

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Learning Personal Conscientiousness from Footprints in E-Learning Systems

Lo Pang-Yun Ting*, Shan-Yun Teng*, Kun-Ta Chuang*, and Ee-Peng Lim†,
* Dept. of Computer Science and Information Engineering, National Cheng Kung University, Taiwan
Emails: {lpyting, syteng}@netdb.csie.ncku.edu.tw, ktchuang@mail.ncku.edu.tw
† School of Information Systems, Singapore Management University, Singapore
Emails: eplim@smu.edu.sg

***Abstract*—Personality inference has received widespread attention for its potential to infer psychological well being, job satisfaction, romantic relationship success, and professional performance. In this research, we focus on *Conscientiousness*, one of the well studied Big Five personality traits, which determines if a person is self-disciplined, organized, and hard-working. Research has shown that *Conscientiousness* is related to a person's academic and workplace success. For an expert to evaluate a person's *Conscientiousness*, long-term observation of the person's behavior at work place or at home is usually required. To reduce this evaluation effort as well as to cope with the increasing trend of human behavior turning digital, there is a need to conduct the evaluation using digital traces of human behavior. In this paper, we propose a novel framework, called *HAPE*, to automatically infer an individual's *Conscientiousness* scores using his/her behavioral data in an E-learning system. We first determine how users learn in the E-learning system, and design a novel Pattern Relational Graph Embedding method to learn the representations of users, their learning actions, and learning situations. The interaction between users, learning actions and situations characterizes the learning style of a user. Through experimental studies on real data, we demonstrate that *HAPE* framework outperforms the baseline methods in the *Conscientiousness* inference task.**

I. Introduction

For industries, the recruitment of freshmen from schools generally refers to their explicit outcomes such as academic grades and professional activities in the campus. However, it is believed that an ideal candidate should not only behave with acceptable external performance but also with good internal characteristics, which is called personality in this paper. Personality can reflect people's characteristic patterns of thoughts, feelings, and behaviors. Due to its importance to the successful recruitment, personality inference has been recognized as a promising research area. According to the classic *Big Five personality theory* [1], the human personality traits can be organized as five factors: (1) *Openness to Experience*, (2) *Extroversion*, (3) *Agreeableness*, (4) *Neuroticism*, and (5) *Conscientiousness*. The first four traits, which are often investigated in previous works, can be easily found through having a short conversation with someone or getting along with somebody in a short time. For example, an interviewer can tell from an interviewee's speaking styles that whether he/she is anxious, outgoing or creative during a short talk. As compared to other traits, the last trait, namely *Conscientiousness*, is hard to be correctly ranked in a short time period. Note that *Conscientiousness* has been proved to be mostly related to academic outcome and workplace performance [2]. A person who has a high score of *Conscientiousness* represents that he/she is good at formulating goals, organizing problems, and working consistently to reach goals. Hence, the trait *Conscientiousness* is usually perceived as a representation of responsibility and reliability, and is the most important factor to predict the academic achievement and the working performance.

To find out whether a person is conscientious, it is necessary to understand how he/she usually acts (such as learning styles, working styles), and that is to say, we need to know a person's 'activity patterns'. The challenging points is that a person's activity patterns can only be detected through a long-term observation which is hard to be effectively recorded manually. Fortunately, the appearance of E-learning systems resolves this issue. In recent years, E-learning systems (e.g., Coursera, edX), which offer course videos and online assessments to users, have become more and more popular. In general, there are two kinds of teaching materials in an E-learning system: course videos and online assessments, and each video and assessment has its focusing concepts. Users can watch teaching videos or do assessments in more flexible and more effective ways. The user-generated traces on these platforms not only reflect users' preferences, sentiments, and characteristics of learning, but also represent users' long-term learning processes, which can help to infer users' scores of *Conscientiousness*.

A user's activity patterns in an E-learning systems mean that *what actions he/she usually performs* when *learning different teaching materials*. Specifically, the discovery of users' activity patterns from E-learning footprints could be challenging due to some reasons. First, there may exist hierarchical correlations between actions performed by users. For instance, if a user does an assessment, this action can be separated into two sub-actions 'with hint' and 'without hint' by considering if a user uses hints when doing an assessment or not. Therefore, two users' activity patterns will be more similar if they both do an assessment with hints than one user uses hints and another doesn't. Second, a user may have multiple activity patterns with different importance values, which means each activity pattern can only partially represent the way that a user learns.

To address these challenges, we propose a novel framework, called *HAPE*, to explore the action hierarchy and the importance of each activity pattern for *Conscientiousness* inference. The objective of *Conscientiousness* inference is to automatically infer users' scores of *Conscientiousness* by analyzing their activity logs in an E-learning system. In the *HAPE* framework, we consider two kinds of similarities as the major factors that affect how close users' scores of *Conscientiousness* are. The first one is the similarity of users' activity patterns. We design an embedding model based on the technique of knowledge graph embedding (KGE) to preserve two properties: (1) the hierarchical correlations between actions, and (2) the importance values of activity patterns for each user. The second one is the similarity of users' learning aptitudes since the scores of *Conscientiousness* have been proved to be correlated to users' abilities [3]. Hence, we consider both users' activity patterns and learning aptitudes to enhance the performance of *Conscientiousness* inference. To the best of our knowledge, there is no existing work investigating people's *Conscientiousness* through long-term learning data. The main contributions of our work are summarized as follow:

- We aim to automatically infer users' scores of *Conscientiousness* since *Conscientiousness* is the most important personality trait which is correlated with academic achievement and workplace performance.
- We device a novel *HAPE* framework, which incorporates users' activity patterns with their learning aptitudes, to model action hierarchy and the importance of each activity pattern which can help to enhance the performance of *Conscientiousness* inference.
- We perform experiments on real-world datasets to show that our *HAPE* can outperform other baselines, and we further discuss the performance of *HAPE* on users' persistence and activeness in an E-learning system.

This reminder of the thesis is organized as follows. Section 2 gives the introduction of related works. In Section 3 and Section 4, we formulate the problem and introduce the proposed framework. Section 5 presents data analysis and discusses the experimental results. Section 6 concludes the work.

II. Related Works

The design of our *HAPE* framework is closely related to two research fileds: (i) personality inference and (ii) knowledge graph embedding.

Personality Inference. Personality inference considers a broad spectrum of human generated data to automatically recognize people's personalities, including written texts[4], speaking styles [5], and so on. While most of personality inference works emphasize on inferring personality traits *Extraversion*, *Neuroticism* and *Openness to Experience*, our work aims to infer individual's scores of facets of *Conscientiousness*, which requires a long-term observation of one's learning or working styles rather than interaction skills.

Knowledge Graph Embedding. A knowledge graph (KG) is a multi-relational graph composed of entities (nodes) and relations (different types of edges). A typical KG can represent information about entities and relations in the form of a triple, which is defined as (h, r, t). In order to efficiently manipulate KGs due to the structure of such triples, knowledge graph embedding (KGE) has been proposed to project both entities and relations into a low dimensional vector space while preserving vector representation. TransE [6] assumes that the embedding of a tail entity $\mathbf{t}$ should be the nearest neighbor of $\mathbf{h} + \mathbf{r}$. The energy function is defined as follow:

$$E(h, r, t) = \|\mathbf{h} + \mathbf{r} - \mathbf{t}.\| \tag{1}$$

Besides TransE, TransR [7] and TransD [8] are also proposed to model more complicated relations. However, the above methods consider all entities and relations as the same level, which cannot be used to model the hierarchical information between triples. In addition, prior works do not consider the possibility of a triple to be a fact, which will be unable to know the importance of the information contained in an triple. Although TransF [9] models the similarity correlations between relations, it can only helps for the comparison between relations which are at the same level. While TKRL [10] considers that entities contain hierarchical types, the importance of different-level information is generally ignored. In our work, we fully explore the hierarchical information between triples and integrate the importance of each triple for a more practical embedding framework, which can successfully represent the similarities between users' learning styles in an E-learning system.

III. Problem Formulation

In this section, we will first give the description of the necessary symbols and definitions.

Definition 1 (Activity Log): Let $X^u = \{x_1^u, x_2^u, ...\}$ be an activity log set for a user u in an E-learning system, where each activity log x_t^u is the t-th activity for u. An activity represents a record of learning a teaching material. Each activity log contains a user ID, a teaching material ID, and the type of a teaching material (e.g., an assessment or a video).

In order to find out the important information from users' activity logs, we define action labels and situation labels, which are associated with each activity log.

Definition 2 (Action Label): In order to reveal the difference between actions performed by users, we classify actions by specificity. For example, the action *'Do an assessment'* can be classified into two sub-actions: '*With Hint*' and '*Without Hint*'. In our work, we regard each action or sub-action as an action label and organize all action labels into a hierarchical action structure. We assign the most general action labels to the first layer and the most specific action labels to the last layer. Figure 1 shows an example of a hierarchical action structure. Let z denote the number of layers in the hierarchical action structure. The m-layer action labels can be defined as $L_{A_m} = \{l_a^1, l_a^2, ...\}$, where each l_a^i is an action label and $1 \leq m \leq z$, and the set of all action labels in a hierarchical action structure is defined as $\mathbf{L}_A^z = L_{A_1} \cup L_{A_2} \cup ... \cup L_{A_z}$.

Definition 3 (Situation Label): Let $\mathbf{L}_K = \{l_k^1, l_k^2, ...\}$ be the situation label set, where each l_k^j is a situation label. To record actions that a user performs in different situations, we regard

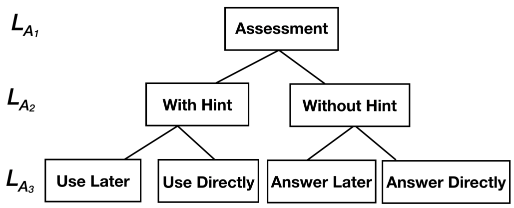

Fig. 1. Example of a hierarchical action structure

each side information in activity logs as a situation label. For instance, to record the number of times that a user encounter a teaching material, we can define two situation labels: '*First Time*' and '*N-th Time*'.

Definition 4 (Personality Facet): In our work, we mainly focus on the human characteristics related to the personality trait *Conscientiousness*. The Revised NEO Personality Inventory (NEO PI-R) [11] classifies *Conscientiousness* into six facets, namely, *Competence*, *Order*, *Dutifulness*, *Achievement Striving*, *Self-Discipline*, and *Deliberation*, which we denote as c_1, c_2, c_3, c_4, c_5, and c_6 respectively. We regard these six facets as our targeted personality facets $C = \{c_1, c_2, ..., c_6\}$ to be inferred.

Problem Statement: Given users $U = \{u_1, u_2, ...\}$, activity logs $\mathbf{X} = \{X^u | u \in U\}$, action labels $\mathbf{L}_A^z$, and situation labels $\mathbf{L}_K$, our goal is to infer scores of targeted personality facets C for all users. We aim to infer the scores $\mathbf{D} = \{D^u | u \in U\}$, where each $D^u = \{d^u_{c_1}, d^u_{c_2}, ..., d^u_{c_6}\}$ represents scores of six facets of a user u.

IV. Methodology

In this section, we present the *HAPE* (Hierarchical Activity Pattern Embedding) framework to automatically infer users' scores in six facets of *Conscientiousness* $\{D^u | u \in U\}$.

The *HAPE* framework includes three main phases. The goals of the three phases are to discover activity patterns, embed activity patterns, and compare similarities between activity patterns respectively. In the rest of the section, we will describe these phases in greater detail.

A. Activity Pattern Discovery

As mentioned previously, observing how a user learn from teaching materials in an E-learning system can help to understand his/her *Conscientiousness*. Hence, it is important to know what a user's activity patterns in an E-learning system. To find all users' activity patterns from the massive users' activity logs, we first label the important information in activity logs and mine these labeled logs to find each user's activity patterns.

1) Activity Logs Labeling: To find out useful information from massive users' activity logs, we utilize action labels and situation labels which are defined in Section 3. Here, we give an example and assume that situation labels $\mathbf{L}_K = \{$'*First Time*', '*N-th Time*'$\}$, and action labels $\mathbf{L}_A^3 = L_{A_1} \cup L_{A_2} \cup L_{A_3}$ which are designed in Figure 1. A subsequence s_t^u could look like this: $\{$'*Assessment*', '*With Hint*', '*Use Directly*', '*First Time*'$\}$. The first three labels are action labels and the last label is a situation label. This subsequence s_t^u represents that a user u has an activity log x_t^u of doing an assessment which u first encounters, and u uses a hint directly without consideration.

2) Activity Pattern Mining: In our method, we regard users' frequent patterns in E-learning systems as his/her activity patterns, which represent how a user usually learn. Given a user u's labeled sequences $\{s^u_{t_1}, s^u_{t_2}, ...\}$, an activity pattern set of a user u can be denoted as $\mathbf{P}^u = \{P^u_m | 1 \leq m \leq z\}$, and $P^u_m = \{p^1_m, p^2_m, ...\}$ represents the activity pattern set labeled by the m-layer action labels. Inspired by the well-known *FP-Growth* [12] algorithm, we retrieve users' activity patterns by the proposed mining algorithm. In each iteration, we discover activity patterns P^u_m which contains a specific layer m of action labels L_{A_m} in the hierarchical action structure.

Next, we will introduce how we embed this kind of structure and preserve the complicated information in activity patterns.

B. Activity Pattern Embedding

In our paper, we regard the similarities of users' activity patterns as the most important factor that affects how close users are in their *Conscientiousness* scores. In other words, if two users have more similar activity patterns, their scores of *Conscientiousness* should also be similar. However, it is difficult to conduct similarity comparison due to the complicated structure of activity patterns. Therefore, we first utilize all users' activity patterns to construct a multi-relational graph incorporating the action hierarchy and the importance of each activity pattern. Furthermore, to conduct similarity comparison of users, we design a novel embedding model based on KGE technique (Knowledge Graph Embedding) to project the graph into a low dimensional vector space while preserving the hierarchy and the importance information.

1) Pattern Relational Graph Construction: Inspired by the structure of knowledge graphs (KGs), we first convert all users' activity patterns into a specific multi-relational graph, called **pattern relational graph**, to model the complicated relations in activity patterns. To form the pattern relational graph, we formulate each activity pattern of a user u as a triple structure (u, a, k), where a is an action label and k is a set of situation label in an activity pattern. We regard users, situation labels, and action labels as head entities (nodes), tail entities (nodes), and relations (edges), respectively. The format of the pattern relational graph is defined as follow:

Definition 7 (Pattern Relational Graph): The pattern relational graph $G_p = \{U \cup K, A_{uk}\}$ is a directed graph which is constructed from all users' activity patterns, where U is the user set, K is the situation set, and A_{uk} is the edge set from users to situations. Each edge $a_{l,u_i \to k_j}$ in A_{uk} indicates that an action label was performed, where l represents the l-th layer an action label belongs to. Each triple $(u_i, a_{l,u_i \to k_j}, k_j)$ represents a l-th layer action performed by the user u_i when encountering the situation k_j.

From the pattern relational graph, we can clearly observe the similarity of users' actions when facing different situations. Next, to quantify the similarity between users, we develop a novel embedding method based on KGE for the pattern relational graph.

2) Pattern Relational Graph Embedding: Inspired by the technique of KGE (knowledge graph embedding), we propose a novel embedding model which can embed the pattern relational graph while preserving the hierarchy and importance information. As mentioned previously, we regard each activity pattern as a triple structure. Given a user u, an action label a, and a situation label k, the energy function we propose for a triple (u, a, k) is defined as $E(u, a, k) = \|\mathbf{u}_a + \mathbf{a} - \mathbf{k}_a\|$. We project users (head entities) and situation labels (tail entities) into relation spaces by utilizing proposed aggregated projection matrices $\mathcal{M}_{a,u}$ and $\mathcal{M}_{a,k}$ respectively, which are defined as $\mathbf{u}_a = \mathcal{M}_{a,u}\mathbf{u}$ and $\mathbf{k}_a = \mathcal{M}_{a,k}\mathbf{k}$.

Below we explain the design of aggregated projection matrices $\mathcal{M}_{a,u}$ and $\mathcal{M}_{a,k}$. During the procedure of embedding the pattern relational graph, we mainly consider two properties so as to preserve the action hierarchy in the embedding space. The first property is the importance of each layer of action labels, and the second property is the information inheritance in the hierarchical action structure. An action label belongs to a more specific layer is more important since it contains not only additional information but also original information inherited from its parent action labels. We design aggregated projection matrices $\mathcal{M}_{a,u}$ and $\mathcal{M}_{a,k}$, which combine original projection matrices of more general action labels, to map a user u and a situation k to the relation space of an action label a. To take the importance weight and inheritance information into account, an aggregated projection matrix is the weighted sum of original projection matrices of action labels which belong to more general layers. Hence, $\mathcal{M}_{a,u}$ and $\mathcal{M}_{a,k}$ are designed as follow:

$$\mathcal{M}_{a,u} = \sum_{i=1}^{\mathcal{L}_a} \alpha_i \mathbf{M}_{a^{(i)},u}, \quad \mathcal{M}_{a,k} = \sum_{i=1}^{\mathcal{L}_a} \alpha_i \mathbf{M}_{a^{(i)},k} \tag{2}$$

in which α_i is the importance weight of action labels belong to the i-th layer, $\mathcal{L}_a$ represents the order of the layer of an action label a, $a^{(i)}$ represents the i-th layer ancestor action label of a in the hierarchical action structure, and $\mathbf{M}_{a^{(i)},u}$, $\mathbf{M}_{a^{(i)},k}$ are original projection matrices for head entities and tail entities. The embedding result of an action label a can preserve the information from ancestor action labels, and the information from a more specific layer can gain more importance weight.

Furthermore, we also consider the importance of each triple (u, a, k), which represents an activity pattern in our paper. The importance of a triple means the probability of a triple to be a fact, that is to say, how often may a user u perform an action a when facing a situation k. In our paper, we set the importance value of a triple as its pattern frequency. Therefore, the objective function for the pattern relational graph embedding can be formulated as follow:

$$L = \sum_{(u,a,k)\in T} \sum_{(u',a',k')\in T'} c_{u,a,k}[E(u,a,k)+\gamma-E(u',a',k')]_+ \tag{3}$$

where $[x]_+$ denotes $max(0, x)$, $c_{u,a,k}$ is the importance of a triple (u, a, k), $E(\cdot)$ is the energy function, $\gamma > 0$ represents a hyperparameter of margin, T and T' represent the set of positive triples and negative triples respectively, which means T is a set of activity patterns and T' contains all combination of action labels and situation labels except for activity patterns. Finally, we can gain the embedding vector of all users, action labels and situation labels.

C. Similarity Comparison

In order to enhance the performance of *Conscientiousness* inference, we take users' learning aptitudes in an E-learning system into account since *Conscientiousness* are proved to be correlated to people's abilities [3]. We utilize a user's performance on teaching materials to construct a concept graph which can represent his/her learning aptitude. In order to compare users' activity patterns and learning aptitudes at the same time, we embed all users' concept graphs and design a similarity function to infer users' scores of six facets.

1) Concept Graph Embedding: As mentioned in Section I, each teaching material (an assessment or a video) has its main concept. To represent a user's learning aptitude, we construct a concept graph which reveals a user's performances on all concepts. A user u's concept graph is defined as $G_c^u = (V, E, F_V^u)$, which is directed and node-attributed. The node set V and the edge set E represent the main concepts of teaching materials (assessments or videos) and the progress relations between concepts respectively. If the edge $e_{v_i \to v_j}$ exists, concept v_i is the prerequisite of concept v_j. Each concept v_i has an attributed value $f_{v_i}^u$. An attributed value $f_{v_i}^u$ represents the average score a user u gains when learning teaching materials which belong to concept v_i. Note that V and E are the same in all users' concept graphs since the concept structure is the same in an E-learning system. In order to derive a detailed comparison of users' learning aptitudes, we perform the well known graph2vec [13] algorithm to embed all users' concept graphs. We take the collection of users' concept graphs $\mathbf{G}_c = \{G_c^u | u \in U\}$ as the input of graph2vec. Eventually, we generate embedding vectors of all users' concept graphs.

2) Similarity Function: We design a similarity function to choose the most similar neighbors for a specific user and infer a user u's scores of six facets based on these neighbors' score. The similarity function is designed as $Sim(u_1, u_2) = g(\bar{\mathcal{V}}_{A,K}^{u_1}, \bar{\mathcal{V}}_{A,K}^{u_2}) + g(\mathbf{V}_{G_c^{u_1}}, \mathbf{V}_{G_c^{u_2}})$, where $g(v_1, v_2)$ represents the cosine similarity of two vectors v_1 and v_2. $\mathbf{V}_{G_c^u}$ and $\bar{\mathcal{V}}_{A,K}^u$ represent a user u's the embedding vector of his/her concept graph and the average embedding of his/her all action labels vectors respectively. Based on this similarity function, we select the most n similar neighbors for a specific user. Finally, a specific user's scores of six facets can be inferred by averaging these n neighbors' scores.

V. Experiments

In this section, we conduct extensive experiments to evaluate the effectiveness of the proposed *HAPE* framework. We aim to answer the following research questions:

- Can *HAPE* outperform other baselines by considering users' activity patterns and learning aptitudes, and by modeling the action hierarchy in the task of inferring scores of six facets of *Conscientiousness*?
- How does the performance of *HAPE* vary with different parameter settings?

A. Dataset and Experimental Setup

For the purpose of this study, we apply a real data from a nonprofit-based E-learning service, Junyi online learning system[1], providing online videos and assessments for users. The Junyi academy platform is a Chinese online learning website. The collected data contains selected users' activity logs over a two-year period (2016-2018), including assessments answering records and videos watching records. We select 96 users who match three conditions: (i) have done at least 100 assessments within two years; (ii) have watched at least 100 videos within two years; (iii) have joined the E-learning system at least six months. Meanwhile, 12 teachers are recruited from different elementary to senior high schools. Each teacher is shown statistical information of 8 users' activity logs and is required to answer 24 questions (for per user) chosen from 120-item version of the Big Five personality Inventory (IPIP-NEO-120) [14]. These 24 questions are related to *Conscientiousness*, and each facet of *Conscientiousness* has 4 questions to derive a score from 1 to 5.

1) Baseline Methods: To demonstrate the effectiveness of proposed method, we compare *HAPE* with the baselines can be classified into three main groups: (i) Consider only users' activity patterns, (ii) Consider only users' learning aptitudes, and (iii) Consider both users' activity patterns and learning aptitudes. In our experiments, the minimum support δ of activity patterns mining is set as 0.05.

- **FP-n**: This method utilizes the FP-growth algorithm [12] to find the activity patterns. The activity patterns in this method are composed with situation labels and action labels which *only belong to the most specific layer* in the hierarchical actions structure, and the similarity comparison of two users' activity patterns is calculated by the jaccard similarity.
- **FP-h**: FP-h is the same as FP-n except that FP-h compares users' activity patterns which are composed with all action labels in the hierarchical actions structure.
- **TransR:** [7]: We utilize TransR to embed the pattern relational graph which is constructed with the same activity patterns as FP-h, while TransR embeds the pattern relational graph with relation projection matrices, which do not consider the action hierarchy and the importance of each activity pattern. The cosine similarity function is utilized to evaluate the similarity of two users' embedding results of action labels.
- **graph2vec:** [13]: This method compares two users' learning aptitudes by utilizing graph2vec to embed their concept graphs and evaluating the cosine similarity of their embedding results.

[1]Please refer to https://www.junyiacademy.org/ for the Junyi website.

- **TransR + graph2vec:** This method combines the similarity evaluation results of graph2vec.

The FP-n, FP-h and TransR methods mainly consider only users' activity patterns. While TransR derives the comparison by embedding the pattern relational graph, FP-n and FP-h simply evaluate the rate of the same activity patterns between two users to compare users' behaviors. Similar with our *HAPE*, TransR + graph2vec aggregates the comparison results of users' activity patterns and aptitudes, while this method does not consider the action hierarchy and the confidence of each triple.

2) Evaluation Settings: To quantitatively evaluate the proposed *HAPE* framework, the performance is evaluated for each user u in the testing dataset. In our work, *Mean absolute error* (MAE) and *Root mean squared error* (RMSE) are adopted to evaluated the correctness of inferred scores. The performance is the average of evaluation results of all users.

Finally, we randomly select 80% users' activity logs for training, and remaining 20% for testing. The performance of MAE and RMSE reported by 5-fold cross-validation is the average of MAE and RMSE computed in each training and testing phase.

B. **HAPE** *Performance*

To answer the first question, we compare *HAPE* with the above-mentioned baselines. The comparison results of *HAPE* and baselines are summarized in Table I and Table II. From the results of two tables, we have following observations:

- From the experimental results of FP-n, FP-h and TransR, which only focus on users' activity patterns, we derive three findings. The first one is while FP-h utilizes more complicated activity patterns than FP-n, it fails to perform well since it ignores properties of action labels which belong to different layers. The second one is that although FP-h and TransR use the same activity patterns, TransR gets a better result by utilizing embedding vectors of activity patterns to compare users' difference.
- By comparing the performances of graph2vec, TransR + graph2vec and *HAPE*, we can see that our *HAPE* framework can outperform than other baselines since *HAPE* models the action hierarchy and considers the importance of each activity pattern. In addition, from the experimental results, it can be seen that the facets of *Conscientiousness* cannot be inferred properly by only taking users' activity patterns (FP-n, FP-h, TransR) or learning aptitudes (graph2vec) into consideration.

C. Parameter Sensitivity Analysis

To answer the second question, we analyze the sensitivity of parameters which are utilized in the phase of pattern relational graph embedding. The embedding phase has a critical parameter: γ. The parameter γ controls the value of the importance weight of different layers in the hierarchical action structure. By varying γ as $\{0.1, 0.3, 0.5, 0.7, 0.9\}$, the results of different settings are shown in Figure 2. We can clearly see that, as the value of γ increases, the error value tends to decrease, and the

TABLE I

COMPARISON OF MAE PERFORMANCE. (NUMBERS INSIDE PARENTHESES DENOTE THE PERFORMANCE DIFFERENCE COMPARED TO *HAPE*.)

Model	c_1	c_2	c_3	c_4	c_5	c_6	Average Mean
FP-n	0.884(+0.266)	0.700(+0.102)	0.778(+0.184)	1.100(+0.350)	0.800(+0.154)	0.937(+0.201)	0.866(+0.209)
FP-h	0.893(+0.275)	0.825(+0.227)	0.728(+0.134)	1.059(+0.310)	0.840(+0.195)	0.978(+0.241)	0.887(+0.230)
TransR	0.770(+0.152)	0.609(+0.012)	0.670(+0.076)	0.954(+0.205)	0.875(+0.230)	1.012(+0.276)	0.815(+0.158)
graph2vec	0.736(+0.118)	0.600(+0.002)	0.663(+0.069)	0.851(+0.101)	0.752(+0.107)	0.826(+0.090)	0.738(+0.081)
TransR+graph2vec	0.745(+0.127)	**0.588(-0.008)**	0.665(+0.071)	0.807(+0.057)	0.720(+0.074)	0.791(+0.054)	0.719(+0.062)
HAPE	**0.618**	0.597	**0.594**	**0.749**	**0.645**	**0.736**	**0.656**

TABLE II

COMPARISON OF RMSE PERFORMANCE. (NUMBERS INSIDE PARENTHESES DENOTE THE PERFORMANCE DIFFERENCE COMPARED TO *HAPE*.)

Model	c_1	c_2	c_3	c_4	c_5	c_6	Average Mean
FP-n	1.194(+0.422)	1.003(+0.258)	1.038(+0.341)	1.337(+0.470)	1.022(+0.278)	1.207(+0.371)	1.134(+0.357)
FP-h	1.177(+0.405)	1.079(+0.334)	1.009(+0.312)	1.356(+0.488)	1.094(+0.350)	1.268(+0.431)	1.164(+0.387)
TransR	1.039(+0.267)	0.835(+0.090)	0.887(+0.191)	1.195(+0.327)	1.079(+0.334)	1.248(+0.411)	1.047(+0.270)
graph2vec	0.901(+0.129)	0.761(+0.016)	0.785(+0.089)	0.994(+0.126)	0.883(+0.139)	0.930(+0.093)	0.876(+0.099)
TransR+graph2vec	0.863(+0.091)	0.759(+0.014)	0.767(+0.070)	0.908(+0.040)	0.837(+0.093)	0.874(+0.038)	0.835(+0.058)
HAPE	**0.772**	**0.744**	**0.696**	**0.867**	**0.744**	**0.836**	**0.777**

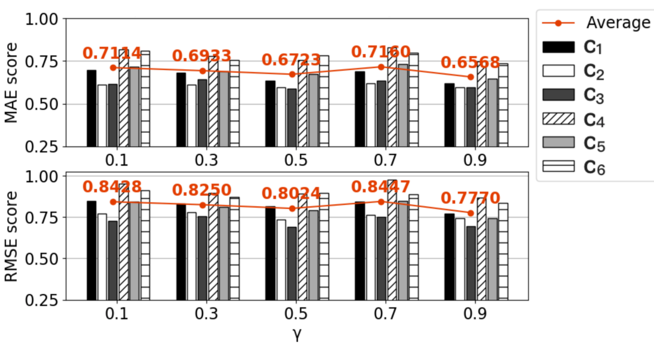

Fig. 2. Performance of varying γ.

result shows that we get the better performance when γ raises to 0.9. Note that the bigger γ represents that the more specific layers are more important, which means that considering the hierarchy of actions will actually enhance the correctness of *Conscientiousness* inference.

VI. CONCLUSIONS

In this paper, we investigate how to infer a user's scores of six facets for personality trait *Conscientiousness* based on his/her long-term learning data from an E-learning system. In the proposed *HAPE* framework, we take a user's activity patterns and learning aptitudes into consideration, and also consider the action hierarchy to enhance the performance of inferring facets. In addition, to consider the importance of an activity pattern, we define the adaptive confidence for each triple (activity pattern) in the pattern relational graph to represent the possibility of a specific triple to be a fact. The experimental results prove that our method can outperform other baselines. To sum up, we conduct extensive experiments on real E-learning dataset to show the robustness of our *HAPE* framework.

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