A Method of Enhancing User’s Motivation Using Experts’ Life Logs

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Abstract This paper describes a method of enhancing a user’s motivation to improve his/her skill level in a given field. Currently, the number of “expert” users, who record their knowledge and release it in the form of a life log in an attempt to achieve certain aims, is increasing. Users, who are affected by such experts and who also make efforts in achieving their own aims, are also increasing. We report on the development of a method of enhancing user’s motivation to begin making self-active efforts. The method should automatically select experts who can inspire users and be a good reference for them and present the experts’ life logs to the users. To achieve these functions, we propose a quantitative evaluation index between the life logs of experts and users. Through experiments we verify the possibility that the higher the proposed index of experts, the higher the rate of motivating users.

Keywords: learning technology systems, life log, experts, human motivation, upskilling support

1. Introduction

Because of the reduced size of various sensors and the advent of handheld devices using them, it is becoming easier to collect life logs in the real world such as those for GPS, acceleration data, and images. On the other hand, because of the popularity of blogs, social network services (SNSs), and Twitter, it is also becoming easier to collect life logs in cyberspace. At the same time, many experts’ records regarding knowledge and effort have been released as books and blogs. This increases the chance of using such records as life logs. We define “experts” as those who are at a higher skill level than general users in a certain subject of interest, or “field”. We define “life log” as information about the users’ past, including information that users record themselves. For “Learning foreign languages” (i.e., English in this case), there are experts who have achieved very high Test of English for International Communication (TOEIC) scores of 900 who have recorded their score transitions, lifestyle patterns, amount of effort (what effort they made to achieve their goal) on a daily basis, and the 1,000 hours of study they had done. For “Dieting”, there are experts who were able to reduce their weight by 50 kilograms in one year and they have recorded their weight transitions, as well as what and how much they ate. Moreover, ordinary users who are affected by experts and make an effort to achieve an aim by recording life logs are now on the increase. Research has also been done on attempts to provide logs compiled by experts to users in fields such as calligraphy, playing musical instruments, and sports.

As suggested above, the use of experts’ life logs is gradually increasing. However, the main approach in using them is simply to follow descriptions made by experts that users just happened to find. Moreover, a systematic and efficient method of enhancing a user’s motivation has not been established.

The purpose of our research was to establish a systematic and efficient method of enhancing a user’s motivation to improve his/her skill level by using life logs of both experts and users. We first considered the idea of stages in enhancing a user’s motivation. A useful model is the stages and processes involved in the making of self-change with regard to the habit of smoking. Although the stages reported there do not aim to achieve a certain skill level, they correspond to improvements in skill level and thus can be useful for developing a policy according to a user’s current stage. We therefore based the stages we set for enhancing user’s motivation on those given in the literature. The stages are shown in Figure 1.

In our work, we focused on getting users to advance from the “contemplation” stage to the “action” stage, encouraging them to start making an effort. There

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are two reasons for this. First, there are many people who are interested in a certain field but make little or no effort to immerse themselves in it. To illustrate this, we created a questionnaire for 5,550 men and women in their twenties to fifties who were interested in and felt the need to learn a foreign language (i.e., English). The results showed that 3,907 (70.4%) studied less than one hour per week. Second, users need to pass through the stages that result in their beginning to make an effort before sustaining it in the “maintenance” stage.

To get users to begin making self-active efforts by enhancing their motivation, it is necessary to provide them with something that will fascinate them as a result of their efforts and show them that it is possible for them to achieve good results. Therefore, we aimed to automatically select experts who could inspire users and be good references for them.

The rest of the paper is organized as follows. Section 2 describes previous work in this area and Section 3 proposes our method of presenting experts’ logs to users. In Section 4, we describe an experiment we conducted to evaluate the method’s validity. Section 5 concludes the paper with a brief summary of key points.

2. Previous Work

Some studies have been conducted on enhancing motivation in educational psychology. Specifically, these studies indicate that effective methods of enhancing motivation should enable positive verbal feedback and should teach the importance of studying and developing an organization strategy. However, in applying these methods, only teachers or counsellors can use them to support users (students), and these studies do not assume any systematic methods that can be implemented on a computer. Studies on enhancing motivation have also been done in information and communication technology (ICT) education. The authors of these studies insist that an effective way to enhance motivation is to teach using educational materials whose topics are broad-based and related to everyday life. Although teachers use computers or the Web in their teaching methods, educational materials they make themselves are required to enhance user motivation. Therefore, it is difficult to say that their systems are systematic.

There are also methods that systematically enhance users’ motivation by presenting life logs of other users. For example, there are published studies in which a user’s life log was matched with another user’s life log and both life logs were used in facilitating user efforts. Araki et al. conducted research on an instruction service regarding health club workouts. Their resulting system estimates the characteristics of users by using a daily record of their weight, the food they had eaten, and their physical activity. The system then recommends physical activities of other users who have similar characteristics. Wada et al. conducted research on a recommendation method regarding e-learning. Their resulting system estimates the number of times a user has accessed educational material by using the number of accesses of another user who has a similar access log. The system then recommends educational materials it predicts the user will access many times.

However, we need a more efficient method to achieve the aims of our work. As described above, the systems reported in the literature studies recommend physical activities or educational materials to users by matching the life logs of users who show similarities in terms of actions they have taken. These methods cannot, however, determine whether the first user is an expert who has succeeded in improving his/her skill.
level. Therefore, the recommended content may not be particularly interesting for the second user. In addition, it is doubtful that even following it would help improve the user’s skill level.

3. Matching Experts with Users

Our proposed method uses points of appeal in the expert’s life log and the similarity between the user’s life log and that of the expert (Figure 2). The expert in fact has made points of similarity between him/herself and the user into points that are likely to appeal to the user. The system implementing the method uses the vector sum between “Actually achieved” and “Similarity” to bring about the effect of making users think that they can improve their skill level. Moreover, by using the effects of “Points of appeal” and “Possible skill level improvement”, the system is able to help users begin to make efforts.

Figure 3 shows the system’s process flow. The process is executed on the user’s terminal, on the terminals of each expert, and on a matching server. The user’s life log and those of multiple experts are collected on the terminals of the user and each of the experts and stored in the database (DB) on the matching server. The format of life logs for both experts and the user is [date, skill level, attribute, life pattern], while the format for experts consists of only [date, time/amount of effort, content of effort]. The experts’ DB accumulates the life log of multiple experts over long periods (i.e., several months or several years), while the user’s DB accumulates the life log over short periods (several days or several weeks). After the matching process module receives the experts’ life logs and the user’s life log from the DBs, it matches the user with experts who can inspire and be good references for him/her. The user’s terminal receives the life log of experts matched by the module and presents it to the user. Of these process steps, we concentrate on the one that matches the user with experts because it is this step that helps users to begin making self-active efforts to improve their skill level.

3.1 Degree of gap matching

Here, we describe the degree of gap matching (DGM), a quantitative evaluation index we propose that is critical for matching an appropriate expert to a user based on a life log.

We propose the index based on two perspectives: “points of appeal” and “possible skill level improvement”. We formulate the index as follows:

$$DGM = \sum_{k=1}^{n} w_k L_k - \sum_{k=1}^{n} w_k X_k$$

(1)

where $L_k$ is the vector of skill level ($m$ is the number of skills), and $X_k$ is the feature quantity (the life log

Figure 2. Support in Starting Efforts.

Figure 3. System Process Flow.
which has the format [date, skill level, attribute, life pattern]) \((n)\) is the number of features. With regard to the suffixes of \(L \) and \(X\), \(E\) means “expert”, \(F\) “user”, \(c\) “current”, and \(p\) “past”. With regard to \(p\), we use \(p_{\text{max}}\) values that maximize \[
\sum_{k=1}^{n} w_x[k] \frac{|x_{p,c}[k] - x_{p}[k]|}{H} + 1
\]
in the set of past life logs stored in the expert’s DB. The term \(w\) is the weight of each element in its respective term. Qualifying exam classifications and test scores can be offered as examples of skill levels. We treat skill level as a (multiple dimension) vector. The learning of foreign languages includes aural comprehension and reading as separate skills. The category of physical training includes levels of instantaneous strength and endurance as “skills”. Since “feature quantity” is a life log which has the format [date, skill level, attribute, life pattern], it contains details on each of these features. To avoid dependence on a single field’s specific skill requirements, such as swinging posture in golf or pronunciation in learning a foreign language, we use the “attribute” feature to represent demographics (age, gender, origin, address, family size) and the “life pattern” feature as defined by the Japanese Ministry of Internal Affairs and Communications (number of holidays taken, overtime hours put in, time spent on commuting, time spent on TV/radio/newspapers/magazines, time spent on pastimes, time spent on playing sports). We set the value of \(w\) by giving a questionnaire to a few users in each field and analyzing the results (e.g. multiple regression analysis). In the questionnaire, we present information of multiple experts’ feature quantity to users and ask them how much the information enhances their motivation, as discussed in Section 4. When we run the system, we apply \(w\) set in the questionnaire for all users (many do not receive the questionnaire).

The greater the difference between the user’s current skill level and those of the experts, the higher the first term in Expression [1] becomes. This term makes it possible to determine an expert who has appeal to and can inspire a user. The more similar a user’s current feature quantity and an expert’s past feature quantity are, the higher the second term in Expression [1] becomes. This term enables users to find similarities between themselves and the expert and to believe that they can improve their skill levels. To illustrate this, if expert A’s DGM for a user is 0.5, expert B’s is 0.9, and expert C’s is 0.3, our system presents B’s life log ([date, skill level, attribute, life pattern] and [date, time/amount of effort, content of effort]) to the user since B’s DGM is the highest.

### 3.2 Modification of DGM

We gave a questionnaire to 74 participants in a company event to identify motivation-enhancing factors. The procedure was as follows. First, the participants listened to talks given by five experts with Ph.D.s. Then they were given information about the experts, including:

- Skill level (number of journals contributed to, number of international conferences attended)
- Attributes (age, gender, origin, address, family size)
- Life patterns (number of holidays taken, overtime hours put in, time spent on commuting, time spent on TV/radio/newspapers/magazines, time spent on pastimes, time spent on playing sports)
- Average monthly time spent on carrying out research toward a Ph.D.

Finally, the participants answered a questionnaire that asked them to choose from a list of factors that would most enhance their motivation to earn a Ph.D. on the basis of what they had heard from the experts.

The results are shown in Figure 4. Forty-four per-
cent of the participants chose “age similarity” or “environmental similarity” as the main factor. The remaining 56% chose either “minimal research time”, “short Ph.D. acquisition period”, or “overcoming hindrances”. Expression [1] takes into account the first two factors but not the last three.

On the basis of these findings, we added two indexes of expert’s properties to Expression [1]. The first index is about efficiency; the more the expert improves his/her skill level in a shorter amount of time, the higher the index becomes:

$$\sum_{k=1}^{m} w_p[k] \left( \frac{L_{Ec}[k] - L_{Ec,\text{max}}[k]}{t} \right)$$

where $t$ means the expert’s total effort time from past to present. The second index is about difficulty; if the expert has a feature quantity that is an obstacle to improving skill level, the index becomes higher:

$$\sum_{k=1}^{n} w_p[k] D[k]$$

where $D[n]$ means the expert’s difficulty in improving skill level in each feature quantity. With regard to age, for example, we use the relationship between aging and physical strength in fields that require physical activity and the relationship between aging and memory in fields that require mental activity\(^{17, 18}\). Figure 5 depicts the relationship between aging and physical strength and shows that people’s physical strength decreases with age. We form the idea that reduced physical strength due to aging makes it difficult to improve skill level because the reachable skill level is lowered. For example, with regard to weightlifting, if the same person has the same amount of training, it can be predicted that his/her reachable skill level at an older age is lower than at a younger age. We describe a method of using the relationship depicted in Figure 5 to derive the difficulty in improving skill level. First, we normalize the data of Figure 5 by dividing each value by a maximal value. We define these values as $\text{norm}(x)$ ($0 < \text{norm}(x) \leq 1$). We then set up $1 - \text{norm}(x)$ and define the value as difficulty in improving skill level. Figure 6 shows the derived difficulty in improving skill level. In fields that require mental activity, we define the value as difficulty regarding age in the same way as using the relationship between aging and memory. Considering the items in the “life pattern” feature that are related to time (e.g., time spent commuting, time spent on watching TV, and time spent on playing sports), we define the quantity “(life pattern item related to time) hours/24 hours” as the difficulty in improving skill level. This is because the more time people spend on doing things that are not related to making an effort in a given field, the harder it is for them to improve their skill level. For a feature quantity in which we cannot assume this difficulty, we ignore it (i.e., the difficulty of the feature quantity is set to 0).

These two indexes adapt to fields other than earning a Ph.D. The reason is that it is promising that these two indexes lower the barrier of “actually achieved” in Figure 2 by attaching the conditions of “achieving efficiently” and “achieving even in a difficult situation”; therefore, these two indexes enhance the effectiveness of “possible skill level improvement” in every field.

With the addition of these two indexes, the DGM becomes:

$$\text{DGM} = \sum_{k=1}^{m} w_p[k] (L_{Ec}[k] - L_{Ec}[k])$$

$$+ \sum_{k=1}^{n} \frac{w_p[k]}{X_{Ep,\text{max}}[k] - X_{Ep}[k] + 1}$$

$$+ \sum_{k=1}^{m} w_p[k] \left( \frac{L_{Ec}[k] - L_{Ec,\text{max}}[k]}{t} \right)$$

$$+ \sum_{k=1}^{n} w_p[k] D[k]$$

where $F_p$ and $D[k]$ are the feature quantity and difficulty index, respectively.

4. Evaluation

To evaluate the validity of the proposed method of
matching appropriate experts to users, we presented experts’ life logs to users and had the users answer a questionnaire about motivation.

4.1 Experimental objective

The experimental objectives were:
• To analyze the effective terms in DGM (Expression [2])
• To verify that the higher DGM an expert has, the more the user’s motivation is enhanced.

4.2 Experimental environment

We conducted an online questionnaire with the support of an Internet research firm. The experiment participants (hereafter “examinees”) were 155 men and women aged 20–60. For the fields in which efforts are made, we selected foreign language (English) and bookkeeping as “mental” fields and golf and dieting as “physical” fields. We selected these fields because many people are interested in them and because it is easy to quantify skill level. Each examinee answered one questionnaire in one field. The number of examinees in each field was as follows:
• Foreign language (English): 46
• Bookkeeping: 37
• Golf: 42
• Dieting: 30

The criteria for measuring the skill level in each field were as follows:
• Foreign language (English): TOEIC score (10–990)
• Bookkeeping: Bookkeeping exam level (levels 1–3)
• Golf: Golf score
• Diet: Amount of weight loss

We stipulated that all examinees had to be in the “contemplation” stage (Figure 1). They also had to have a skill level lower than a given threshold value (e.g., 600 TOEIC points) and fall under the “make little or no effort in the field” category (less than one hour per week).

4.3 Experimental procedure

The experimental procedure was as follows.
• We had the examinees fill in the “feature quantity input form” (Figure 7), the items of which include skill level, attribute (age, gender, origin, address, family size), and life pattern (number of holidays taken, overtime hours put in, time spent on commuting, time spent on TV/radio/newspapers/magazines, time spent on pastimes, time spent on playing sports).
• We created a virtual life log of 30 experts based on the examinees’ feature quantity forms and presented that virtual life log to one examinee. For 16 of the 30 virtual experts, we selected the following patterns. Compared with the examinee, (1) the skill level is [high/low], (2) the attributes are [similar/dissimilar], (3) the life pattern is [similar/dissimilar], and (4) the period during which efforts are made is [long/short]. We were careful to avoid dependency among feature quantity features by selecting not just two patterns but approximately six patterns for each feature quantity. For the other 14 virtual experts, we assigned typical feature quantities for various occupations.
• We asked each examinee the question, “Did the information you were given about the expert en-
hance your motivation to make an effort?" for each of the 30 experts (Figure 8). The answers are on a five-point scale: 1. Not at all/ 2. Only slightly/ 3. To some degree/ 4. Very much so/ 5. Extremely so.

4.4 Evaluation method

We conducted two main evaluations. In the first one, we analyzed effective terms in the DGM by using multiple regression analysis and Akaike’s information criteria (AIC). We set the questionnaire score as an objective variable, and each term in DGM as an explanatory variable. Questionnaire scores were in the form of points on a five-point scale. The terms in the DGM are the same as those in Expression [2]. Specifically, the first term in Expression [2] expresses the difference in skill level. The second term expresses the similarity among 12 feature quantities (skill level, age, gender, origin, address, family size, number of holidays taken, overtime hours put in, time spent commuting, time spent on TV/radio/newspapers/magazines, time spent on pastimes, and time spent on playing sports). It contains 12 sub-terms. The third term expresses efficiency. The fourth term expresses three difficulties (i.e., relevant to age, monthly overtime, and daily life patterns in terms of time spent). It contains three sub-terms. Therefore, we used 17 sub-terms (skill level and efficiency are regarded as one sub-term). Concerning multiple regression analysis and AIC, we conducted a hypothesis test toward a null hypothesis; that term’s weight was zero. Thus, we regarded terms for which the p-value<0.1 holds as effective. We used a t-value as a statistic of the hypothesis test. The t-value is the estimated term’s weight divided by the standard error. The p-value was calculated as follows because the t-value approximately follows the standard normal distribution (Z is a random variable following a standard normal distribution):

\[ p\text{-value} = \Pr(|Z| \geq |t\text{-value}|). \]

In the second evaluation, we analyzed the relationship between DGM set up using leave one out cross validation (LOOCV) and actual questionnaire scores. LOOCV is an analysis method that sets one out of n datasets as test data, sets the other data as training data, and then repeats learning n times.

4.5 Experimental results and discussion

Table 1 lists the effective term analysis results. Each circle means that the term is regarded as the effective term by the hypothesis test concerning multiple regression analysis and AIC. It can be seen that “age similarity” is effective in all fields. “Difference in level of skill”, “similarity in skill level”, and “efficiency” are effective in three of the four fields (except “dieting”). It should be noted that in the dieting field, comments were made such as “One cannot trust results showing a very high amount of weight loss” and “A result showing only a small amount of weight loss seems realistic and enhances my motivation.”

In this experiment, we set the top skill levels as follows:

- Foreign language (English): TOEIC score of about 900
- Bookkeeping: 1st (highest) level bookkeeping exam
- Golf: Golf score of about 80
- Diet: Amount of weight loss is about 50 kg

We discovered that the top skill level was set too high for the “dieting” field. Moreover, while it is good to make higher scores and attain higher categories, it is not good to lose a large amount of weight. Instead, it is good to achieve weight loss levels that are more appropriate. This led us to believe that the skill level in the dieting field is different in character from that in other fields. From Table 1, we see that “similarity (i.e., equality) of

![Figure 8. Questionnaire Form.](image-url)
gender” and “similarity in time spent on playing sports” are effective in the golf and dieting fields. It is thought that “gender” and “time spent on playing sports” are valued heavily in “physical” fields. Even though effective terms of similarity are more than those of difficulty, examinee comments indicate that some value difficulty more than similarity. Therefore, we verified the necessity of creating a separate model for each user.

Figure 9 shows the relationship between DGM calculated using LOOCV and actual questionnaire scores as a box-and-whisker plot. We conducted LOOCV by using data on all of the examinees in each field (for example, 46 examinees×30 experts in foreign language). The horizontal axis is the experts’ DGMs calculated using LOOCV, which sets the expert as test data, and the vertical axis is the questionnaire scores that each user gives each expert. From the results shown in Figure 9, we verified that a moderately positive correlation (>0.4) existed in all fields except dieting. Additionally, over 90% of the scores of experts whose DGM was over 3.1 were 3 (“enhanced to some degree”) or higher in the foreign language and golf fields. In the bookkeeping field, over 90% of the scores of experts whose DGM was over 3.3 were 3 or higher. This verifies the possibility that the higher the DGM of experts, the higher the rate of motivating users. We believe that the reason we did not obtain good results in the dieting field is that there is a problem in setting the skill level and that DGM is not well suited to this field.

For future research, we will mainly address the following points.

• Table 1 shows that efficiency is effective in three
fields; however, difficulty is not effective in every field. In particular, we believe that there was a problem with setting difficulty with regard to age. It is known that memory declines with age; however, crystallized intelligence does not decline with age\textsuperscript{18, 19}. We will consider the difficulty limited to applicable fields and take multiple factors of age into account.

- We will seek a way to apply our proposed method of enhancing a user's motivation to fields such as opponent-based games (e.g. chess, tennis) and art activities where the level of skill is difficult to digitize.
- Our proposed method uses virtual life logs of experts. In the future, we will use actual life logs of experts.
- We will address not only ways to advance from the “contemplation” stage to the “action” stage in Figure 1, but also ways to advance from the “action” stage to the “maintenance” stage. We will also seek a way to make further use of the efforts that experts have made.

5. Conclusion

We proposed a method for users to enhance their skill levels by encouraging them to begin making self-active efforts. This method should automatically select experts who can inspire users and be good references to them and it should present experts’ life log to users. To achieve these aims, we proposed DGM, a quantitative evaluation index between the life logs of experts and users from the viewpoint of similarity and difference. The greater the difference between a user’s and an expert’s current skill level and the greater the similarity between a user’s current feature quantity and an expert’s past feature quantity, the higher the DGM becomes. We also modified the DGM index by adding two indexes of experts’ properties (efficiency and difficulty). By conducting an experiment in which we presented experts’ life logs to users and showed how they could enhance user motivation, we found that the higher DGM of experts becomes, the higher the achievement rate to motivate users to begin self-active efforts.

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