Paper:

Proposal of Action Recommendation System Based on User Contexts in Daily Life

Hiroki Shibata[1], Yu Shirai, Yasufumi Takama[2]

Graduate School of System Design, Tokyo Metropolitan University, Japan
E-mail: 1; hshibata@tmu.ac.jp, 2; ytakama@tmu.ac.jp
[Received 00/00/00; accepted 00/00/00]

Abstract. This paper proposes a new combined system to recommend actions in daily life to users based on user context. Bandit algorithm is employed to choose an effective presentation of recommendation to both users and the system. Experiments are conducted on simulated environment using persona that models the typical Japanese people behavior. It shows the performance of the proposed system in supporting user's life.

Keywords: Recommendation, User context, Well-being, Bandit algorithm, life support system

1. Introduction

This paper proposes a new combined action recommendation system for the purpose of improving user's wellbeing. This study assumes that good life consists of not only physical health but also psychological (mental) status. As in common definition, this study also defines the wellbeing as the state people do well culturally beside in the traditional measure of health mentioned above.

In more detail, based on the definition in the literature [2], this study assumes the 3 conceptual factors of physical, psychological, environmental ones affect wellbeing. Based on these factors, the proposed system recommends actions to its user.

These 3 factors are modeled with real-valued quantities. These are called context in this study. In addition to these 3 factors, doers' rate [10] was used as part of the context. Experiments on a simulated environment with the persona method show that the proposed system can recommend acceptable actions to users and have the possibility to improve the wellbeing of a user in the real living environment.

2. Related work

2.1. Quality of life

There has been changes in the definition of the health. The traditional definition of the health is the good status of a person in physical and psychological aspects. The modern definition of the health is the comprehensive scale to measure the status of one's life in terms of physical, psychological, social, leisure activity, worthwhile of job, and living environment [1][6]. Especially, wellbeing related to the health in living environment is called Quality of Life (QOL) [8]. A conprehensive definition of components that consist of wellbeing is given in [2], in which mental, physical, environmental statuses are mensioned as the common factor in many literatures.

2.2. Recommendation

There is a number of frameworks in recommendation. One of them is item-recommendation that is used widely on the e-commerce sites. It aims to recommend an item to a user using user's activity history, item features and so on. The collaborative filtering is one of the successful methods in this domain [9]. As an action recommendation, App for Prediction by Partial Macthing (APPM) algorithm has been proposed [3]. It predicts the next appication that a user launches by employing a simple pattermaching method for strings as shown in [4] to the application usage history.

2.3. Bandit Algorithm

A bandit algorithm [5] solves the problem in which the optimal solution maximizes a payoff that is defined on a series of actions is obtained. In each step on the series, the algorithm must select so called an arm from the set of possible actions.

One of the successful method to solve this problem is Thompson sampling [7]. Thompson Sampling employs expectations of a bayesian model. This method selects an action in accordance with the distribution of the expectation. This method differs from the deterministic method like Upper Confidence Bound strategy, that is, it can avoid stucking in a state keeping selecting inappropriate arms by the effect of stochastic disturbance of the state.

3. Proposed system

To the best of our knowledge, there is no study to propose a practical recommendation system for daily life that supports multiple actions with restrictions in real life. To

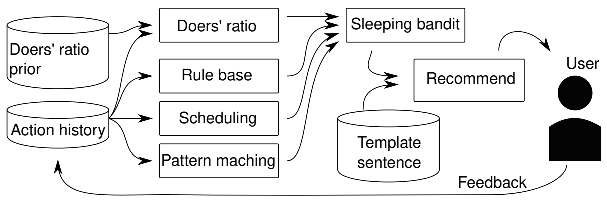

Fig. 1. Graphical image of the proposed system.

support practical use, the proposed system combines 3 action generating methods. Each of them is assigned an index m from the set $M = \{\mathrm{R}, \mathrm{S}, \mathrm{P}\}$. The following list shows the relations between their actual class of method.

- R: rule-based method (Sec. 3.4)
- S: schedule-based method (Sec. 3.3)
- P: pattern-based method (Sec. 3.2)

These methods are used to estimate a set of possible actions that is supplied to bandit algorithm to generate an action recommendation. The overall graphical image of this proposed system is described in Fig. 1.

The system interact with a user to present a recommendation and to obtain the feedback that is used to improve the future recommendation quality. For the sake of effective interaction, the proposed system employs bandit algorithm. By employing the bandit algorithm, each chance of recommendation is used effectively. Rest of this section is devoted to the formal description of this algorithm and needed defitions.

The finite set of possible actions is noted as A. Time interval that system dealt with is denoted as $T = [-t_\mathrm{c}, \infty)$. Negative offset t_c denotes a unit time length of life cycle period. This paper dealt with only periodic life cycle and such model. Actual time that system will run is $[0, \infty)$, however, for the general definition of the model this paper adds virtual interval $[-t_\mathrm{c}, 0)$ to it. By this formulation, prior information to avoid cold start problem can be incorporated (detail is given in Sec. 3.1.). Time periods at which the system may recommend are represented with a finite set of time points $\hat{T} \subset T$. The system interact with a user only on $\hat{T}$, however, it uses the context on T. The context is denoted as a series of family[1] $(x^t \in \mathbb{R}^V | t \in T)$, where V is an index set for each context dealt with in the system. The definition of the context is given in Sec. 3.1.

The procedure to obtain the state of each $t \in \hat{T} \wedge t \neq 0$ is disscussed. It is assumed that all state on $\tau < t, \tau \in T$ is given. Letting $\mathbf{r} \in [0,1]$ be a random value of reward (takes 1 if and only if a user accepts the recommendation.), $\mathbf{x} \in \mathbb{R}^V$ be a context, $\mathbf{s} \in \mathbb{R}^V$ be a parameter, and $\hat{T}_t = \left\{\tau | \tau < t \wedge \tau \in \hat{T}\right\}$, in the proposed method the distribution of $\mathbf{r}$ is defined as,

$$p(\mathbf{r}|\mathbf{x},\mathbf{s}) = \frac{\exp(\mathbf{r}\mathbf{s}\cdot\mathbf{x})}{1+\exp(\mathbf{s}\cdot\mathbf{x})}, \quad \ldots\ldots\ldots \quad (1)$$

1. General term of a tuple or multivariate variable in which indexes are not restricted to numbers. Each element can be referred with an index $v \in V$ in a way like x_v.

where $a \cdot b = \sum_{i \in V} a_i b_i$ is an inner product of $a \in \mathbb{R}^V$ and $b \in \mathbb{R}^V$. Prior distribution of $\mathbf{s}$ is defined as,

$$p(\mathbf{s}) = \mathrm{Norm}(\mathbf{s}|0, B), B \in \mathbb{R}^{V\times V}. \quad \ldots\ldots \quad (2)$$

where $\mathrm{Norm}(x|\mu,\Sigma)$ denotes the normal distribution of x with the average μ and covariance matrix Σ, and $\forall i, j \in V\, [i = j \Rightarrow B_{ij} = \beta, i \neq j \Rightarrow B_{ij} = 0]$. Introducing the series of reward $(r_\tau \in \{0,1\} | \tau \in \hat{T}^t)$, likelihood function is defined as,

$$L(r|x,\mathbf{s}) = \prod_{\tau\in\hat{T}^t} p(\mathbf{r} = r_\tau | \mathbf{x} = x^\tau, \mathbf{s}) \quad \ldots\ldots \quad (3)$$

Letting $\theta \in \mathbb{R}^V$ be the realization of $\mathbf{s}$, a negative logarithm of posterior distribution of $\mathbf{s}$ is then defined as,

$$l_t(\theta) = -\ln p(\mathbf{s} = \theta | r, x) = \frac{\theta\cdot\theta}{2\sigma^2} + \sum_{\tau\in\hat{T}^t} \ln(1+\exp(\theta\cdot x^\tau)) - \sum_{\tau\in\hat{T}^t} r_\tau \theta \cdot x^\tau + C \quad (4)$$

where C is a constant value independent of $\mathbf{s}$. The proposed method estimates $\hat{\theta}^t$ that holds,

$$l_t(\hat{\theta}^t) = \min\left\{l_t(\theta) | \theta \in \mathbb{R}^V\right\}, \quad \ldots\ldots\ldots \quad (5)$$

using Newton Raphson method approximately. The parameter θ^t is then sampled from the following distribution,

$$p\left(\theta^t | \hat{\theta}^t\right) = \mathrm{Norm}\left(\theta^t | \hat{\theta}^t, H^t\right), \quad \ldots\ldots \quad (6)$$

where $(\theta^t | t \in \hat{T}^v)$ is a series of parameter. Matrix $H^t \in \mathbb{R}^{V\times V}$ is a Hessian that is defined as,

$$H^t_{ij} = \frac{\partial^2 l_t}{\partial_{\theta_i}\partial_{\theta_j}}(\hat{\theta}^t), i, j \in V. \quad \ldots\ldots\ldots \quad (7)$$

Next the method selects an action from $a_t \in A$ that is recommended to the user. a_t is selected so that it satisfies the following equation,

$$f_t(a_t) = \max\{f_t(a) | a \in A\}, f_t(a) = \left(\hat{x}^t_a \cdot \theta^t\right)\eta^t_a, \quad (8)$$

where $\hat{x}^t_a \in \mathbb{R}^V$ is a temporal context that assuming a is recommended at t to a user. The rule to determine $\hat{x}^t$ is described in Sec. 3.1. Weight parameter $\eta^t_a \in [0,1]$ determines the importance of each action. $\eta^t_a = 0$ means a is unavailable at t. This is an optimization problem on the objective function f_t. θ^t is constant in this optimization, however, $\hat{x}^t_a$ and η^t_a have to be calculated for each $a \in A$. After this step, x^t is determined as,

$$\forall \tau \in (t_*, t]\left[x^\tau = \phi\left(\hat{x}^\tau_{a_t}\right)\right]., \quad \ldots\ldots\ldots \quad (9)$$

where $y \leq 0 \Rightarrow \phi(y) = 0, y \geq 1 \Rightarrow \phi(y) = 1, 0 < y < 1 \Rightarrow \phi(y) = y$. Note that actual context x is updated by a temporal context $\hat{x}$. t_* is the predecessor of t, which holds $\nexists \tau \in \hat{T}\,[t > \tau > t_*]$ formally. Letting $\Delta : A \to (0, \infty)$ be a function denotes a duration of actions, the following holds.

$$t - t_* = \Delta(a_t), \forall t \in \hat{T} \wedge t \neq 0. \quad \ldots\ldots\ldots \quad (10)$$

No recommendation is presented at the time $\tau \in (t_*, t)$, and recommendation is conducted at t_*. That is, this procedure determines the state in $(t_*, t]$ and assuming that the user keep taking the action a_t in $(t_*, t]$.

Weight η_a^t is determined by,

$$\eta_a^t = \rho_S^t(a) + (1 - \rho_S^t(a))\rho_R^t(a)\rho_P^t(a). \quad (11)$$

where ρ_S, ρ_R and ρ_P are determined by the module S, R, and P respectively. These are described in Sec. 3.3, Sec. 3.4, and Sec. 3.2 respectively.

3.1. Context

In the proposed system V has the following indexes.

- p: physical condition
- m: psychological condition
- e: environmental condition
- $a \in A$: prior probability of action a

We define $C = \{p, m, e\}$. Therefore, $V = C + A$. Indexes in C correspond to the 3 elements of wellbeing, physical, mental, environmental statuses that are mentioned in Sec. 2.1. In this study these 3 factors of wellbeing are employed. Elements on A are indexes for frequency of each action of A (Doers' rates).

Here after $\hat{x}^t$ in Eq. (8) is defined. For all $v \in A, \tau \in (t_*, t]$,

$$\hat{x}_{av}^{\tau} = \frac{x_v^{\tau - t_c} + \delta_{av}}{\sum_{v' \in A} x_{v'}^{\tau - t_c} + 1}. \quad (12)$$

Letting $w : V \times A \to \mathbb{R}$ be the function of variation rate of status caused by actions, for all $v \in C$ $(v \notin A), \tau \in (t_*, t]$,

$$\hat{x}_{av}^{\tau} = x_v^{t_*} + w(v, a)(\tau - t_*). \quad (13)$$

This is a model that represents the status related to each wellbeing component with a cumulative value with a piecewise linear function. For $\tau \in [-t_c, 0]$, x_v^{τ} denotes the initial condition that represents prior information about ordinal behavior of a user. Using this prior, it is supposed that the system can avoid the cold start problem. Letting $\mu^{-\tau}$ $\left(\in [0, 1^V], \sum_{v \in V} \mu_v^{-\tau} = 1\right)$ be the doers' rate at the time $-\tau$ in a life cycle like one weekday, such as given in [10] or estimated by the average in terms of many past users, the proposed method defines it as,

$$x_v^{\tau} = \mu_v^{-\tau}\omega, \quad (14)$$

where ω is a hyperparameter that adjusts the effect of prior information. For example, if μ is estimated using behavior history in some group of days (like weekdays), $-\tau$ can take from 0 AM to 24 PM in some time unit such as [s].

3.2. Pattern-based method

Pattern-based method generate candidates of recommended actions using APPM that is introduced in Sec. 2.2. In a way at random, the proposed system selects one of the candidates that have the maximum accuracy in the APPM prediction. Letting it be a^*, then for all $a \in A$, the following rule is applied.

$$a = a^* \Rightarrow \rho_P^t(a^*) = 0, a \neq a^* \Rightarrow \rho_P^t(a) = 1. \quad (15)$$

3.3. Schedule-based method

This method generates candidate actions that are needed to complete explicitely defined action chaines $G \in A^{\mathbb{N}}$. There are 2 types of scheduling. One of them is forward scheduling, and the other is backward one. Actions for foward scheduling, here A_f, are selected as,

$$A_f^t = \left\{a' \middle| \exists g \in G, n \in \mathbb{N}\left[g_n = a^{t_*} \wedge g_{n+1} = a'\right]\right\}. \quad (16)$$

Backward scheduling is used to lead a user to a future action. A future action is predicted by APPM. Letting it be c^t, then a set of backward scheduling A_b is defined as,

$$A_b^t = \left\{a' \middle| \exists g \in G, n \in \mathbb{N}\left[g_{n+1} = c^t \wedge g_n = a'\right]\right\}. \quad (17)$$

Letting $A_S^t = A_b^t \cup A_f^t$, for all $a \in A$, the following rule is applied.

$$a \in A_S^t \Rightarrow \rho_S^t(a) = 1, a \notin A_S^t \Rightarrow \rho_S^t(a) = 0 \quad (18)$$

3.4. Rule-based method

This method is more complicated than the other 2 methods. This method considers a set of rules, which is noted as $R \in A \times \mathbb{R}^{\{L,H\}} \times F$, where F is a set of classes to which a rule belongs. Therefore, each element of R is a tuple with 4 elements. In addition,

$$\forall r \in R\left[r_L \leq r_H\right]$$

holds. For a rule $r \in R$, r_L and r_H are lower and upper threshold within which r is applied. $r_1 \in A$ is the action corresponding to the rule r. The system consider 3 classes, that is, $F = \{\mathrm{i}, \mathrm{e}, \mathrm{t}\}$. Each element i, e, t means internal, external, and temporal factors respectively. For example, the rule $(\text{cleaning}, 0.1, 0.2, \mathrm{t})$ means the action cleaning has to be taken within a time interval $[0.1, 0.2]$. Note that $r_4 \in F$.

Letting R_t be a set of candidate actions from this method, it is defined as,

$$R^t = \left\{r \middle| r \in R, r_L \leq u_{r_4}^{t_*} \leq r_H\right\}. \quad (19)$$

where $(u_f^{\tau} | f \in F), t \in T$ is defined as,

$$u_\mathrm{i}^{\tau} = 1 - \min\left\{x_p^t, x_m^t\right\}, u_\mathrm{e}^{\tau} = 1 - x_e^t,$$
$$u_\mathrm{t}^{\tau} = t - t_c \max\left\{q \middle| q \in \mathbb{Z} \wedge q t_c \leq t\right\}. \quad (20)$$

In addition, the family $\left(v_f^{\tau} | f \in F\right), t \in T$ that holds

$$v_\mathrm{i}^t = u_\mathrm{i}^{t_*}, v_\mathrm{e}^t = u_\mathrm{e}^{t_*}, v_\mathrm{t}^t = \max\left\{\frac{u_\mathrm{t}^{t_*} - r_L}{r_H - r_L} \middle| r \in R^t\right\}, \quad (21)$$

is defined for the further modeling. Letting $y_1^t \leq y_2^t \leq y_3^t$ be the sorted series of v^t, Then ρ_R is determined as, $\forall a \in A$,

$$\nexists r \in R^t\left[a = r_1\right] \Rightarrow \rho_R^t(a) = 1 - y_2^t \quad (22)$$

$$\exists r \in R^t\left[a = r_1\right] \Rightarrow \rho_R^t(a) = \frac{\sum_{r \in R \wedge r_1 = a} v_{r_4}^t}{\sum_{f \in F} v_f^t N_{af}} \quad (23)$$

Fig. 2. The user interface used in an experiment. This is a scene that system recommend the user to have a dinner during the user is exploring the internet.

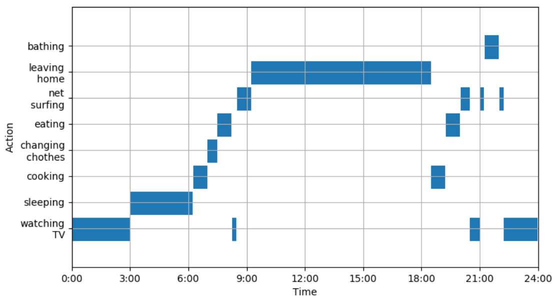

Fig. 3. Default actions for each time interval in a day that persona will take.

where N_{af} is the number of elements in $\{r|r \in R, r_1 = a, r_4 = f\}$.

3.5. Explanation text

The proposed system presents a user its recommendation with an explanation text. It intends so that users can grasp the reason of recommendation from the text qualitatively. The system employs template based text generation method, which generates a text like,

- As you are tired, it is recommended to {do the action}.

In {do an action}, the appropriate text is inserted. If the action is "taking a bath", then "take a bath" is inserted.

4. Experiments

This paper shows an experiment on a simulated environment to evaluate the proposed system. Persona method [11] is used to evaluate the validity of recommendation to a user. Participants are asked to act as the prepared persona and manipulate the system with the user interface provided by open source framework called RenGULAR[2]. A brief image of the user interface is shown in Fig. 2.

Participants have 14 days virtual life on the simulation. For each time after an action were taken, participants are asked whether they will accept an recommendation from the system or not before taking a new action. The system is configured to improves the quality of life of the persona. The only method can contribute this improvements is rule-based method described in Sec. 3.4. The other method just adjust its recommendations so that they are natural to the user.

This experiment is a simulation. Therefore, real effectiveness cannot be measured. However, the experiments can measure whether the recommendation is effective for the persona that is simulated by the participants knowledge or not. If the recommendations are not realistic, it is expected that participants will not accept them. As a result, QoL should not be improved.

2. https://rengular.js.org

QoL is measured by well-being components x^t_c $(t \in \hat{T}, c \in C)$. In detail, the following averaged cumulative value are used.

$$\bar{x_{cu}} = \frac{\sum_{t \in \hat{T}} x^t_{cu}}{|\hat{T}|}, c \in C. \qquad (24)$$

where U is a set of participants and index $u \in U$ denotes each participant. Notation $|X|$ represents the number of elements in a set X.

Participants are asked questionnaires after the experiments, about effectiveness of the proposed system.

4.1. Configurations

The persona has the following characteristics: 1) Age of 25 male, 2) Lives in Tokyo, Japan, 3) Mood maker and moody person, 4) single, 5) likes net-surfing and television, 6) Lives in a room with rental fee of 42000 Japanese Yen per month which is a dusty room because of many clothes. He is currently trying his best to change his lazy life. He wants to focus on his study, however, he often cannot help but watching TV, playing game, and exploring the internet. He wishes he could have regular life, like doing the dishes immediately after eating, waking up and going bed at the same time everyday. The default actions for each time period that persona will take if he reject a recommendation from the system is shown in Fig. 3. This plan is created based on doers' rate of [10]. It is modified so that the persona takes more lazy life cycle than ordinal people that can be estimated from [10].

Initial context $\mu^t_v, t \in [-t_c, 0), v \in A$ that appears in Eq. (14) is determined based on [10]. $\beta = 1$ for Eq. (2), and $\omega = 10^{-3}$ for Eq. (14) is used. These are selected considering results of prior experiments. From this prior experiments, prior for x did not contribute to solve the cold start problem, therefore, we set such small value like this to ω. Optimal value of β must be explored, however, at the time there is no enough experiments to discuss it. For the limitation of the writing space of the paper, we cannot show the action chains G mentioned in Sec. 3.3.

The rule bases are defined as in Table. 2. The list of each action $a \in A$ and its corresponding quantities $w(a, v)$ $(v \in C)$ in Eq. (13) and $\Delta(a)$ in Eq. (10) is shown

Table 1. Relation among $a \in A$ and $v \in C$, $w(a,v)$ in Eq. (13) with unit [/60 m], and $\Delta(a)$ in Eq. (10) with unit [m].

a $(\in A)$	$w(m,a)$	$w(p,a)$	$w(e,a)$	$\Delta(a)$
wake up	0.25	0.25	-0.25	15
go to bed	0.25	0.25	-0.25	240
leave home	-0.25	-2.00	-0.25	15
go home	-0.25	-2.00	-0.25	15
cook	0.00	-0.25	-0.25	15
eat	0.25	0.00	-0.25	30
wash	1.25	-0.50	2.50	15
change clothes	0.25	-0.25	-0.25	15
bath	7.50	7.50	-0.25	30
net surfing	0.25	0.25	-0.25	30
watch TV	0.25	0.25	-0.25	30
study	-1.25	0.25	-0.25	60
clean room	1.25	-0.75	18.75	30

Table 2. List of rules for $r \in R$. For $r_4 = $ t, that is, rules for time, threshold $(r_2, r_3 = r_{\mathrm{L}}, r_{\mathrm{H}})$ is written with unit of hours.

(clean room, 0, 0.3, e),	(net surfing, 0, 0.3, i)
(watch TV, 0, 0.3, i),	(bath, 0, 0.3, i)
(change clothes, 6, 8, t),	(eat (breakfast), 6, 8, t)
(clean room, 8, 16, t),	(eat (lunch), 11, 13, t)
(eat (dinner), 18, 20, t),	(bath, 18, 22, t)
(study, 19, 21, t),	(go to bed, 22, 24, t)
(go to bed, 0, 3, t)	

in this table. However, if a user reject the recommendation, $\Delta(a) = 15$ is applied regardless a. These configurations in Table. 2 and Table. 1 are determined based on authors' subjective knowledge.

4.2. Results

A set of participants is denoted as U in this section. Fig. 4 shows the acceptance rate of each participant $u \in U$. There is variation, however, most of participants have the acceptance rate higher than 0.5 while it does not reach 1.0. From this result, we suppose that recommendation was realistic at the some degree, that is, it seems that there were both acceptable and unacceptable recommendations to the persona. Table. 3 shows statistics obtained from the questionnaires. We can say that the proposed system worked well at some degree from this result as well. However, many participants answered that there were strange behavior from the system like recommending eating while sleeping, which is supposed to be the reason of the low values in the statistics on questions B and C.

Fig. 5, Fig. 6 and Fig. 7 show the context cumulative values $\bar{x_{cu}}$ defined in Eq. (24) of each participant $u \in U$ for $e, m, p \in C$ respectively in this order. Horizontal line in the figure denotes the baseline in which $\bar{x_{cu}}$ is calculated as a result when the user rejects all recommendations, that is, in which persona have taken the default actions all the time. From these results, it can be said that simulated wellbeing was improved. Additionally, with the moderate acceptance rate as shown in Fig. 4, it can be said that recommendations were effective. In other words, recommendations were not too strict in a level that the persona cannno accept but convincing to the persona by which he changes his behaviour.

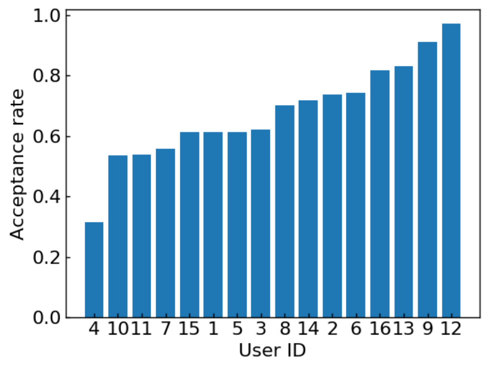

Fig. 4. Average acceptance rate of each participant.

Table 3. Statistics on Questionnaires: A) Effectiveness in improving wellbeing, B) Quality of recommendations, C) Usefulness of explanation at each recommendation, D) Suitability of recommendations frequency.

question	great	good	normal	bad	terrible
A	5	8	0	1	0
B	3	6	7	0	0
C	3	10	2	0	1
D	3	8	4	1	0

We investigate the quantities of these results next with Pearson correlation coefficient. Using the set of participant U, the coefficient is defined as,

$$r_c = \frac{\sum_{u \in U} \left(\bar{x}_{cu} - \bar{\bar{x}}_c\right)\left(A_u - \bar{A}\right)}{\sqrt{\sum_{u \in U} \left(\bar{x}_{cu} - \bar{\bar{x}}_c\right)^2 \sum_{u \in U} \left(A_u - \bar{A}\right)^2}}, c \in C, \quad (25)$$

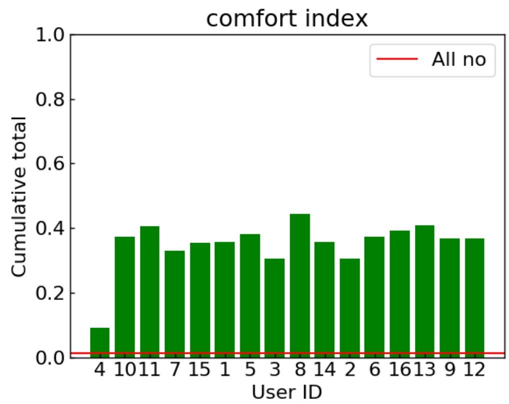

Fig. 5. Comparison in value of $\bar{x}_e$ in Eq. (24) for each user and all rejected case represented by the horizontal line.

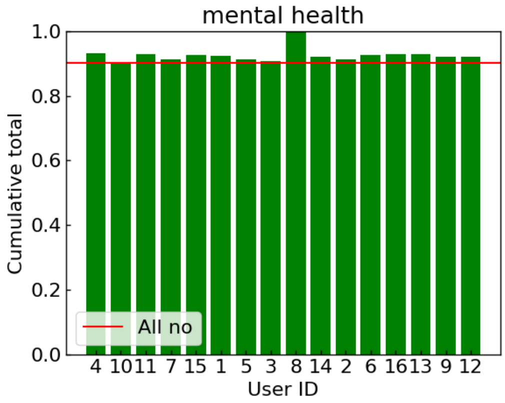

Fig. 6. Comparison in value of $\bar{x}_m$ in Eq. (24) for each user and all rejected case represented by the horizontal line.

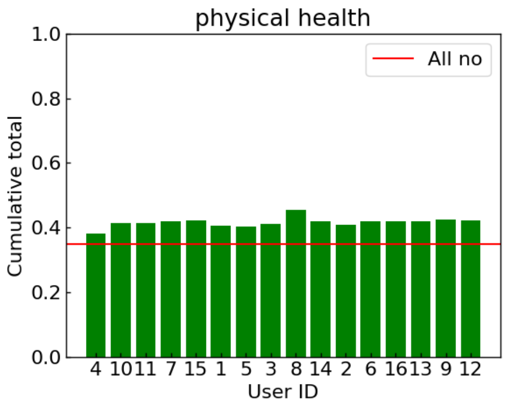

Fig. 7. Comparison in value of $\bar{x}_p$ in Eq. (24) for each user and all rejected case represented by the horizontal line.

where $A_u \in [0,1]$ is the acceptance rate of $u \in U$, and the others are defined as $\bar{A} = |U|^{-1} \sum_{u \in U} A_u, \overline{\bar{x}_c} = |U|^{-1} \sum_{u \in U} \bar{x}_{cu}$. Computing actual values, $r_p = 0.56, r_m = 0.06, r_e = 0.58$ was obtained. We can say that there is a positive correlation between physical status (p) and acceptance rate A. We can say the same things to environmental status (e) and A too. There is no correlation between mental status (m) and acceptance rate. It can be said that improvements were done in terms of physical and environmental status. These were demands of the persona described in the first paragraph of Sec. 4.1. As there was no demands to the persona in improving his mental status described, it is supposed that there was no improvement on the mental status (m) by accepting the recommendations. From these tendencies, we can also say recommendations were appropriate in order to improve the life of the persona.

We have taken questionnaires from participants. One participant answered, "there was strange recommendation. When the persona is sleeping, cooking was recommended." Another participant answered "Net surfing was recommended when eating. We cannot do net surfing while eating," and "Recommendation of cleaning was very effective. Repeated recommendation to clean the room motivated the participant to do it. However, recommendation of net surfing during study was not useful." It is supposed that these inappropriate recommendations are generated by the lack of consideration on $\Delta(a)$ when the user rejects the recommended action a. Number 4 participant who has low acceptance rate as in Fig. 4 answered the reason of this low value that, "I rejected recommendations many times because such a lazy person like this persona does not seems to accept the recommendation like cleaning room, going to the bed early time."

5. Conclusion

This paper proposed a action recommendation system in daily life based on user context. Multi-armed bandit algorithm was employed along with several sub-methods to produce the candidate actions (arms). The experiments on simulated environment with persona was conducted. Statistics from the questionnaires and interactive history of each participant showed the effectiveness of the proposed system.

The experiments were conducted on only a simulated environments. However, we could discovered the effectiveness and problems in the proposed system. In the future work, experiments in a real environment is needed, in addition to the improvements on the quality of recommendation system so that it does not produce inappropriate behavior like mentioned by the participants.

References:

[1] E. Diener, "Subjective Well-Being," Vol. 95, No. 3, pp. 542-575, 1984.

[2] G. Miller, L. Foster, "Critical synthesis of wellness literature," University of Victoria, Faculty of Human and Social Development and Department of Geography, 2010.

[3] A. Parate, M. Bohmer, D. Chu, D. Ganesan, B. M. Marlin, "Practical Prediction and Prefetch for Faster Access to Applications on Mobile Phones," Proceedings of the 2013 ACM International Joint Conference on Pervasive and Ubiquitous Computing, pp. 275-284, 2013.

[4] C. Shannon, "A Mathematical Theory of Communication," The Bell System Echnical Journal, Vol. 27, pp. 397-423, 623-656, 1984.

[5] S. Scott, "Multi-Armed Bandit Experiments in the Online Service Economy," Applied Stochastic Models in Business and Industry, Vol. 31, pp. 37-45, 2015.

[6] T. Adams, J. Bezner, M. Steinhardt, "The Conceptualization and Measurement of Perceived Wellness: Integrating Balance Across and Within Dimensions," Vol. 48, No. 4, pp. 165-173, 2010.

[7] W. Thompson, "On the Likelihood That one Unknown Probability Exceeds Another in View of the Evidence of Two Samples," Biometrika, Vol. 25, No.34, pp. 285-294, 1933.

[8] World Health Organization, "The World Health Organization quality of life (WHOQOL) - BREF," 2004.

[9] J. kawale, H. Bui, B. Kveton, L. Tran-Thanh, S. Chawla, "Efficient Thompson Sampling for Online Matrix-Factorization Recommendation," Advances in Neural Information Processing Systems 28, pp. 1297-1305, 2015.

[10] C. Sekine, Y. Watanabe, and M. Hayashida, "Decrease in Sleeping Time Stopped," Time Spent for Necessary Activities Increased: from the 2015 NHK Japanese time use survey, NHK (Japan Broadcasting Corporation), 2016, http://www.nhk.or.jp/bunken/english/reports/pdf/report 16071301.pdf [accessed Aug. 2021]

[11] M. Pérez-Montoro, L. Codina, "Designing User Experience," Navigation Design and SEO for Content-Intensive Websites, 2017.