HappyRec: Evaluation of a “Happy Spot” Recommendation System Aimed at Improving Mental Well-Being

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***Abstract*—In recent years, the number of people with depression has increased due to the COVID-19 pandemic. One of the activities which has been found to help in improving mental well-being and reducing stress is an exercise called the “three good things”. In this exercise, participants are asked to write down and reflect on three good things that happened to them each day every night before they sleep. However, for the people who suffer from conditions such as low self-esteem and depression, it is not easy for them to be aware of good things or small moments of happiness in their daily lives. To address this issue, we propose a happiness spot recommendation system to provide suggestions for nearby spots which might improve their positive affect using Google Maps. To verify the validity of our proposed method, we asked nine subjects to evaluate the proposed system and reported the happiness ranking accuracy of the recommended spots.**

***Index Terms*—Recommender System, Mobile Application, Geographical Information Systems, Psychological Well being**

I. Introduction

While the importance of health literacy for physical health is widely acknowledged, the area of mental health literacy has been comparatively neglected. In recent years, the number of people suffering from mental disorders has been increasing [1] [2]. In particular, the number of people with depression has increased substantially due to the pandemic of COVID-19 [3]. Thus, there has been much attention to study how perceived happiness might be improved. One existing mental health training method: an exercise called the “three good things” has been proven effective in improving mental well-being [4]. This exercise was developed by Seligman and colleagues [5], who are advocates of positive psychology. In this exercise, the participant is asked to remember and write down three good things that happened to them each day and reflect on them every night before they sleep. Participating in this exercise has been reported to help increase happiness, improve resilience and reduce depression. Similar results were also reported by Sekizawa and others in an experiment with Japanese subjects, indicating that this exercise is effective for users from non-Western cultural background as well [6].

However, the disadvantage of this exercise is that people need to remember all the good things during the day by themselves. In addition, it is not easy for people with low self-esteem or those who are in stressful and high anxiety situations to be aware of good things or the moments of happiness in their daily lives [7]. To address this problem, we develop a system that is able to recommend nearby ”happy spots” for clients based on their happiness profile which could provide opportunities for them to encounter more “good things” during stressful times. This approach can also help decrease the difficulty of recording happiness for the “three good things” exercise. Therefore, in this paper, we propose a happiness spot recommendation system to provide recommendations of nearby happy spots using Google Maps. To verify the validity of our proposed method, we carry out a small scale evaluation experiment and report the results.

II. Related Research

In recent years, research on spot (landscape) recommendation systems has attracted extensive attention due to their wide application. For example, in a previous study, Wang and others have developed a system to recommend green spaces to users, since green spaces have the capacity to improve the citizen’s health [8]. More recently, research has focused on user preference-aware recommendation systems, which are able to recommend locations based on an individual’s personal requirements [9] [10] [11]. However, such systems tend to focus more on leisure or commerce activities (recommending food venues/tourist or recreational locations) and were not specifically aimed at improving mental well-being. For example, the system proposed by Jia et al [8]

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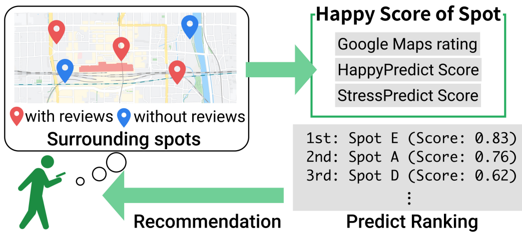

Fig. 1. The Overview of the Proposed System

only recommends green spaces and takes into account only summative metrics such as the overall the popularity and the sentiment of the location. Instead of the green spaces, our system can recommend all spot types based on the happiness characteristics of individual users with the aim of improving mental well-being.

When it comes to research aimed at improving mental well-being using information technology, Asai and colleagues built a database of happy moments [12]. This database is a collection of over 100,000 textual contents of happy moments which are annotated by European and American people with crowdsourcing, and it is a valuable database to measure what kind of moments make people feel happy. Another related study on happiness recommendation is the recommendation of subjective happiness activities proposed by Mohammed et al [13]. In this study, they applied SVM to classify the activities as positive or negative for subjective well-being and evaluated the accuracy of their method. However, the activities which are recommended are pre-prepared activities. In another study, Darius et al. [14] developed a smart phone application to support behavioural activation to treat depression which is usually performed by paper based approach in the previous research [15]. As a part of this application, the authors also described a system that recommends personalized activities. In comparison to the above studies, our proposed system can recommend physical locations in real-world based on their past entries, which could provide users for opportunities for positive affect in daily life.

III. Proposed Method

Unlike existing POI (Point of Interest) recommendation systems, the proposed system recommends locations which have the potential to provide users with positive affect based on past records of happiness in daily life (see Figure 1). Generally, user behavior/movement history and review information are utilized in a basic POI recommendation system. However, as each individual has their own unique pattern of experiences, feelings, thoughts and behaviors [16], it is difficult to match the personal happiness of users to a POI using a basic generalized approach without considering the happiness profile for each user based on their past happiness records. Therefore, we utilize the event information that users recorded when they "felt happy" in the "three good things" exercise for personalized recommendation. The "three good things" activity by itself has been proven to make users feel more positive [4]. Therefore, we believe that it is also possible to enhance users' sense of happiness in the process of collecting data. In addition, the logs provide more detailed longitudinal information about their personal happiness characteristics.

In this paper, we innovatively defined the "HappyPredict Score" and "StressPredict Score" to indicate whether a particular spot could result in positive affect for each user. The HappyPredict Score indicates the similarity between the user's past record of happiness based on the three good things activity and textual information available from user reviews. The StressPredict Score was created by applying a machine learning model which was trained on data from experts in psychology to confirm how useful a spot is in alleviating stress based on its name and type of the location. Moreover, we found that it is difficult to calculate and generate the score of happiness using HappyPredict Score only, when there are no reviews available for a particular spot on Google Maps. Hence, our proposed StressPredict Score was added to deal it. Using these scores, we can recommend unique spots to different users based on a combination of both scores.

To evaluate the performance of the proposed method, we also performed recommendation using only the popularity of spots as a baseline. In the related study [8], the authors used the number of geotagged tweets of a spot as a index to measure the popularity of the spot, however, since the number of tweets alone does not represent the quality of a place, we use the rating value registered in Google Maps[1] instead.

A. HappyPredict Score

This section describes how to calculate the HappyPredict Score which represents how likely a spot coincides with the users' happiness profile. The HappyPredict Score is defined as the similarity between the features of users (the vectors created from the recorded daily three good things activity) and the text review information of the spots posted on Google Maps.

We applied Word2Vec [17] for word embedding, and calculated the cosine similarity of each vectorized textual data. However, if we use all the words in three good things, the meaning of the vector will be diminished. Thus Bag of Words model (BoW) is utilized for the text data of three good things, and we only words with a high word frequency are used. Before the processing of the BoW, we also removed stop words. In addition, we use Surprise[2], a collaborative filtering library, to assign the value of the result of collaborative filtering to words with zero occurrences in the results of BoW. As a result, it is possible to recommend spots with words that the user has not experienced but could potentially be interested in. We extracted the review data of spots using the Google Maps API (the Google Maps API specification allows only five review data to be obtained) and vectorized all of the obtained text data.

B. StressPredict Score

In this section, we explain how to calculate the StressPredict Score, which predicts how much a spot could contribute to stress relief.

[1] http://maps.google.com/
[2] http://surpriselib.com/

When calculating the StressPredict Score, we applied a Random Forest model [18] to train the evaluation data of Google Maps. The data set is annotated by two psychologists who were asked to score 399 Google Maps spots on a scale of 1–7 to determine how appropriate each spots might contribute to stress relief.

We concatenated the word embedding results of the spots name and tag information registered in Google Maps into 396 dimensions vectors for training, and utilized the scored values (scaled 1-7) as the label. As a result, by inputting a spot name and tag information into our trained model, the output is the evaluation score of potential stress relief for that spot.

C. Aggregated Score

In our happy spot recommendation system, we propose three methods to calculate the "happy score". Firstly, we calculate the average of the HappyPredict Score (H_{score}) and StressPredict Score (S_{score}) as the overall score of the spot. Secondly, the average of Google Maps rating (G_{score}) and HappyPredict Score (H_{score}) is used as the overall score for another approach. Finally, we calculate the average of Google Maps rating (G_{score}), HappyPredict Score (H_{score}) and StressPredict Score (S_{score}) as the overall score. In addition, we use only the rating values G_{score} of Google Maps as a baseline.

$$Spot_{score} = \frac{\{(H_{score} \times 6) + 1\} + S_{score}}{2} \tag{1}$$

$$Spot_{score} = \frac{G_{score} + H_{score} \times 5}{2} \tag{2}$$

$$Spot_{score} = \frac{G_{score} + H_{score} \times 5 + (S_{score} - 1) \times 5/6}{3} \tag{3}$$

Where these scores are calculated and ranked for recommending surrounding spots to users.

IV. Evaluation Experiment

We conducted an evaluation experiment to verify whether the proposed system described in Section 3 can recommend spots that improve happiness during times of stress. Section 4.1 explains the experimental procedure, Section 4.2 explains the evaluation methods and Section 4.3 explains the experimental results.

A. Experimental Procedure

1) Records of "three good things": To collect textual data of daily good things for calculating the HappyPredict Score, we recruited nine university students as participants for our study. Participants were asked to perform the three good things on a smartphone application which we developed for two weeks. The smartphone application shown in Fig 2, which has been developed by Tanaka and others [19], was used for the recording process. When a good thing occurred, participants pressed the "RECORD" button on the smartphone screen to record the date, time, and location of the good thing. Before going to bed, the participants were asked to recall the good things based on the record they made during the day and recorded the reason why the event made them feel good. This

Fig. 2. HappyRec Application

recording process resulted in a total of 348 records from 9 people.

2) Recording the moments of unhappiness and stress: After the task of records three good things was completed, participants were asked to record the date, time, and location of three moments in their daily life when they felt stressed or unhappiness using a smartphone application.

The spots around the location where users felt stressed or unhappy that were recorded in this process were used to evaluate the usefulness of the locations proposed by our recommendation system. By using the location information where the user felt unhappy, we aim to determine if the recommended locations would be useful for users during a time when they felt stressed.

3) Creating a ranking of ground-truth answers: In the next stage, we compiled a ranking of the ground-truth answers to be used during the evaluation. The ground truth answers was obtained through a questionnaire that is given to the participants after they record their unhappiness. The questionnaire asked the participants to rank the 20 spots in the vicinity of the location that they indicated their unhappiness. Participants were asked to rank the spots based on how likely they feel these spots contained activities which they would enjoy and how likely it would be useful in alleviating their stress. This ranking was then used as the ground truth data in the evaluation.

B. Evaluation Methods

For the evaluation, we used nDCG to evaluate the ranking of locations using only Google Maps rating as the baseline in comparison to the four proposed methods. The size of the ranking to be evaluated could be less than 20 spots because there are spots where the Google Maps ratings/reviews do not exist. In approach 1) we evaluated the recommended locations using the average of the HappyPredict Score and the StressPredict Score. In this evaluation, spots which the HappyPredict Score could not be calculated due to the lack of reviews in Google Maps were ranked using only the StressPredict Score values. In approach 2), we evaluated the ranking using the average of the Google Maps rating and the

TABLE I
AVERAGE OF NDCG

Method	Average nDCG
Baseline	0.915
1) H_{score} + S_{score}	0.930
2) G_{score} + H_{score}	0.950
3) G_{score} + H_{score} + S_{score}	**0.970**
4) $G_{score} + H_{score} + S_{score}$ (all)	0.935

HappyPredict Score. In 3) we evaluated the ranking using the average of Google Maps rating in combination with the HappyPredict Score, and StressPredict Score. In 4) we created and evaluated rankings using only the StressPredict Score when reviews and ratings did not exist in Google Maps and the HappyPredict and StressPredict Score when they do.

C. Evaluation Results

To interpret the results, we applied nDCG to evaluate the total "happy score", and the average values of nDCG for each methods is shown in Table I. While the mean value of the baseline nDCG is 0.915, the mean value of the nDCG for each happiness score calculation method is higher. In addition, our proposed methods achieved better accuracy than the baseline even for spots that do not have reviews registered in Google Maps and are calculated using only the StressPredict Score.

V. CONCLUSION

In this paper, we proposed a "happy spot" recommendation system aimed at improving mental well-being. Our system applied Google Maps to recommend happy spots in the user's vicinity when they feel stressed or unhappy.

Two types of scores are utilized in our proposed system: 1) the HappyPredict Score, which is based on the similarity between the review information posted on Google Maps and the user's record of previous happiness events in the past (through the three good things exercise) 2) the StressPredict Score, which is based on a machine learning approach to determine how useful a spot is for stress relief based on the name and tag information that was trained using data from psychologist experts.

Nine subjects were asked to evaluate the ranking of the happy spots. We confirmed that the performance of the proposed method is better than the baseline method using Google Maps rating. In addition, the StressPredict Score can help solve the issue from previous studies which found it difficult to recommend spots which do not have ratings or reviews.

One limitation however is that in this experiment, the testers only created the correct ranking of the happiness level from the spots for the nDCG evaluation and did not visit the actual locations. In future research, we plan to design a recommendation user interface and then examine the effectiveness of the algorithm in a real-life setting through objective measures (i.e. by using the SRS-18 scale to determine if the system is able to successfully reduce user stress.) Our ultimate goal is to build an user friendly happy spot recommendation system, which could improve happiness during stressful moments.

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