SRM: Stress Recommendation system with Mobile sensor data

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Abstract

We are often stressed, and individual symptoms are different. For example, someone sweats, body temperature rises, and cell phone use increases rapidly. If we can accurately analyze these stress-causing factors, we can use them to recommend specific symptoms or activities to relieve stress. SRM(Stress Recommendation system with Mobile sensor data) uses mobile sensor data to identify personalized stressors. Through this, activities to prevent individual stress are recommended. Unlike previous recommendation systems using correlation and cosine similarity, SRM can more accurately identify and recommend factors that cause stress because it operates based on causal analysis using a counterfactual approach.

CCS Concepts: • **Computer systems organization → Embedded systems**; *Redundancy*; Robotics; • **Networks →** Network reliability.

Keywords: Recommendation system, Stress recognition, Mobile Sensor data, Physiological data

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1 Introduction

Over the past decades, smartphones and wearables have produced tons of live data every day which are collected via built-in sensors. These data are useful in monitoring the user's daily life and help better understand one's behavior. Analysis of the data could lead to designing an intervention system that suggests activities at opportune moments. We identify personalized stressors through the SRM(Stress Recommendation system with Mobile sensor data). If you can see in what situations you are stressed out by using individual mobile data, on the contrary, you can recommend what behavior to be careful about to relieve stress.

Since the existing recommendation system is not recommended using counterfactual-based analysis, it is difficult and ambiguous to determine whether the recommendation system actually caused a change. Xu, G. et al [6] said "How can make an intervention international action to enable the system to change the recommended items still remains an open question." For example, the moment a company advertises using the recommendation system, there are no moments when it does not advertise, so it is difficult to determine whether the actual increase in corporate sales is due to advertisement or not. Therefore, in this case, the advertising effect can be analyzed through Counterfactual-based causal analysis.

We developed a recommendation system using matching techniques for K-EmoPhone data consisting of emotional and mobile sensor variables. Matching makes pairs of comparisons that are similar in confounders but different in treatment levels. Therefore, unlike most recommended systems using correlation or cosine similarity, SRM recommends a method to analyze and alleviate stress factors using Counterfactual analysis methods. The contributions of this study are as follows.

- SRM was designed in a counterfactual way. Through this, the recommendation system can be approached based on causality, thereby enabling more accurate recommendations.
- We created a recommendation system based on human emotions. Through this, it proposes ways to avoid stress to people using mobile sensor data.

The rest of this paper is organized as follows. Section 2 reviews Review the study of emotion-based causal analysis. Section 3 summarizes the overall SRM system of causal analysis. Section 4 describes specific SRM system execution. Section 5 shows recommended mobile data for actual stress relief through case study. Finally, section 6 concludes the paper.

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2 Related Work

There have been prior studies that apply causal inference to sensor data. In [2], Mehrotra et al. developed an application that investigates the causality between emotional states and mobile phone interaction. Through this, the paper looked into what sensor data causes human emotions such as stress. Berkel et al. [5] suggested that the causality could be found from mobile data via CCM(Convergent Cross Mapping) since human mobile interaction might be interpreted as a dynamic system. Tsapeli, F. et al [4] insisted pure correlation analysis does not offer sufficient understanding of human behavior. Moreover, the author said causation analysis could allow scientists to identify factors that have a causal effect on health and well-being issues, such as obesity, stress, depression and so on and suggest actions to deal with them.

3 System Design

In this section, we describe the dataset used and the overall system of SRM.

3.1 Dataset

Here, we use a dataset "K-EmoPhone", which is composed of objective sensor data including motion, physiology, environment, and phone usage via an Android smartphone, Polar H10, and Microsoft Band 2 in a 1-week session per subject (n=81). Over three sets of 1-week data collections (Apr. 30~May 6, May 8~May 14, and May 16~May 22), 80 participants were recruited, and a total of 5,753 ESM responses were collected. The notification-initiated ESM requests were responded 43 times per person (SD = 20, MAX = 83, MIN = 0) on average.

Overall, more than 71 responses on average (SD = 17, MAX = 110, MIN = 20) were collected per participant. The average number of daily responses was 10.2 (SD = 0.3, MAX = 10.7, MIN = 9.7), so our goal of sampling at least 10 samples per person a day was met. However, we excluded invalid data from the entire set of samples, first by excluding ESM samples that were responded after the response expiry time (i.e., 10 minutes), and next by excluding ESM samples where wearable sensor data were missing. As a result, we used the remaining 2,227 ESM samples from 78 participants (23 females and 55 males)—two participants were removed due to a lack of valid samples. The participants in the final samples were 21.9 years old on average (SD = 3.8, MAX = 38, MIN = 17).

3.2 Overall System

Randomized Controlled Trial (RCT), one of the experimental studies, is a useful tool for examining the causal relationship. It compares the outcome from two or more different groups, which are called "control" and "treatment", and confirms the causality when there is a statistically significant difference in the outcome. It also randomly assigns the subjects to minimize the effect of confounders, variables that might affect both the treatment and outcome.

However, RCT may not be available due to ethical issues (e.g., harmful treatment), difficulties in recruiting subjects, etc. Sometimes, when we need to run the experiment in the real world and examine the efficacy of a certain intervention, we may choose an alternative option, "observational study" [3].

In observational studies, researchers could observe the effect of treatment, but it is not well determined who will be treated or not treated. In addition, confounders among the users are not controlled so that it may be difficult to conclude whether the treatment has efficacy in changing the outcome.

For instance, suppose we examine the efficacy of an intervention app for promoting physical activity. In this case, the users may be affected by other variables such as weather, emotions, or schedule, and the complex relationship among variables would make it difficult to prove that the app is effective. As there have been diverse health-related interventions such as "Digital Therapeutics", the causal inference is getting critical to examine the therapeutic efficacy with observational data.

Matching makes pairs of comparisons that are similar in confounders but different in treatment levels. Generally, the treatment is considered binary, but the matching could be extended to "non-bipartite matching" and support continuous values [1]. Matching applies distance techniques on minimizes distance measures of confounders (e.g., Mahalanobis distance, Propensity score, etc.) between pairs to minimize their influence when setting up the pairs of control/treatment groups. Causality then is estimated using the Average Treatment Effect (ATE).

Figure 1 overviews the overall system of SRM. We conducted causal analysis(Matching) for each user based on 79 mobile sensor data and presented what sensor data can relieve stress based on this.

Table 1. The questionnaire used in K-EmoPhone dataset. (Q1: Valence, Q2: Arousal, Q3: Attention level, Q4: Stress level, Q5: Emotion duration, Q6: Task disturbance level, Q7: Emotion change)

My emotion right before doing this survey was			
Q1. very negative (-3)	~	very positive (+3)	[ ]
Q2. very calm (-3)	~	very excited (+3)	[ ]
My attention level right before doing this survey could be rated as			
Q3. very bored (-3)	~	very engaged (+3)	[ ]
My stress level right before doing this survey was			
Q4. not stressed at all (-3)	~	very stressed (+3)	[ ]
My emotion that I answered above has not changed for recent __ minutes.			
Q5. [5, 10, 15, 20, 30, 60 min / I am not sure]			
Answering this survey disturbed my current activity			
Q6. entirely disagree (-3)	~	entirely agree (+3)	[ ]
How did your emotions change while you are answering the survey now?			
Q7. I felt more negative (-3)	~	I felt more positive (+3)	[ ]

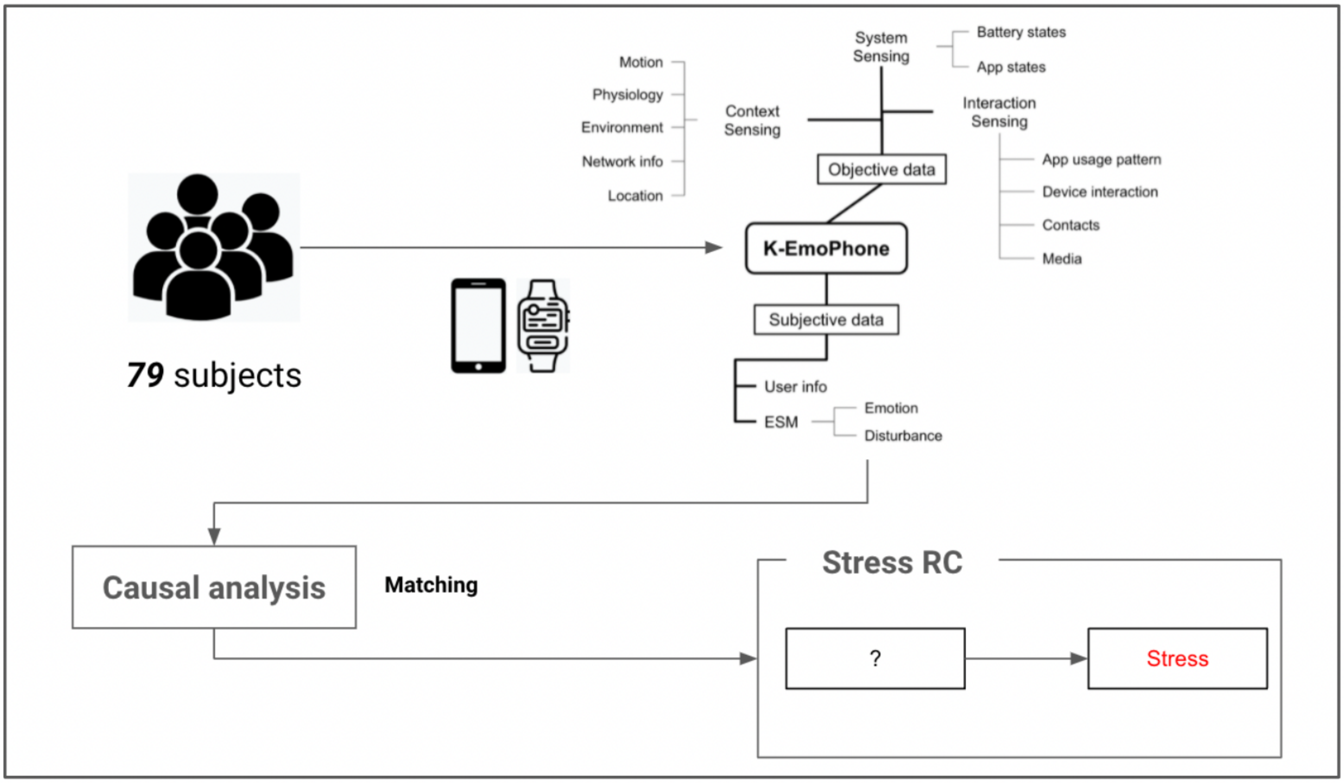

Figure 1. Overall system of the proposed SRM.

4 System Implementation

We conducted a causal analysis by treating all variables except stress in the K-EmoPhone dataset as causes and stress as results. This section introduces matching as an example of calorie consumption as the cause of steps. If you walk a lot, you are expected to burn calories, so if it works normally, steps should be the cause of calorie consumption.

In figure 2, We begin the matching by identifying potential confounders. The variables in K-EmoPhone (e.g., biosignal, environment, device usage patterns, etc.) are considered as candidates, and we conduct a correlation analysis to find which of them are significantly correlated with both treatment and outcome [2]. In our case study, four variables are shown to be confounders (e.g., location, battery usage, skin temperature, and heart rate). Next, the subjects are distributed into five ordinal groups so the first one includes subjects with the smallest steps while the last one has the largest steps. Note that we conduct a nonbipartite matching [1] since the treatment has continuous values.

We then calculate Mahalanobis distance(1) to take multiple confounders into account and pair the subjects in a way that minimizes the overall distance. In our case, we were able to reach the optimal matching (mean distance = 0.4306) with subjects having relatively high and low step counts in each pair.

$$Mahalanobis\ Distance = \sqrt{(\boldsymbol{X}-\boldsymbol{\mu})^{\top}\Sigma^{-1}(\boldsymbol{X}-\boldsymbol{\mu})} \quad (1)$$

Finally, we classify all the subjects into high and low treatment groups and used independent-samples t-test to check whether the confounders are well balanced for these two groups. We then calculate the ATE on the outcome (i.e., calories) for each group and conduct a Wilcoxon-signed rank test to see whether the difference is statistically significant. Our results show a significant difference between the groups ($p < .01$) with an effect size of 0.53. Therefore, by using matching methods, we could conclude steps cause calorie consumption.

Based on this causal analysis method, we conducted a causal analysis of stress for all variables as a result. Therefore, it is possible to analyze mobile sensor variables that causes stress for each user after executing SRM.

5 Result

Table 2 shows the results of ten randomly selected users out of 79 users. For example, user 3003 feels stressed when walking a lot, when the speed is fast, when the body temperature is low, when sweating a lot, when locking and unlocking the cell phone a lot, and when the battery temperature of the cell phone is high. Through this, SRM recommends that this person walk slowly to get less stress. It will also recommend

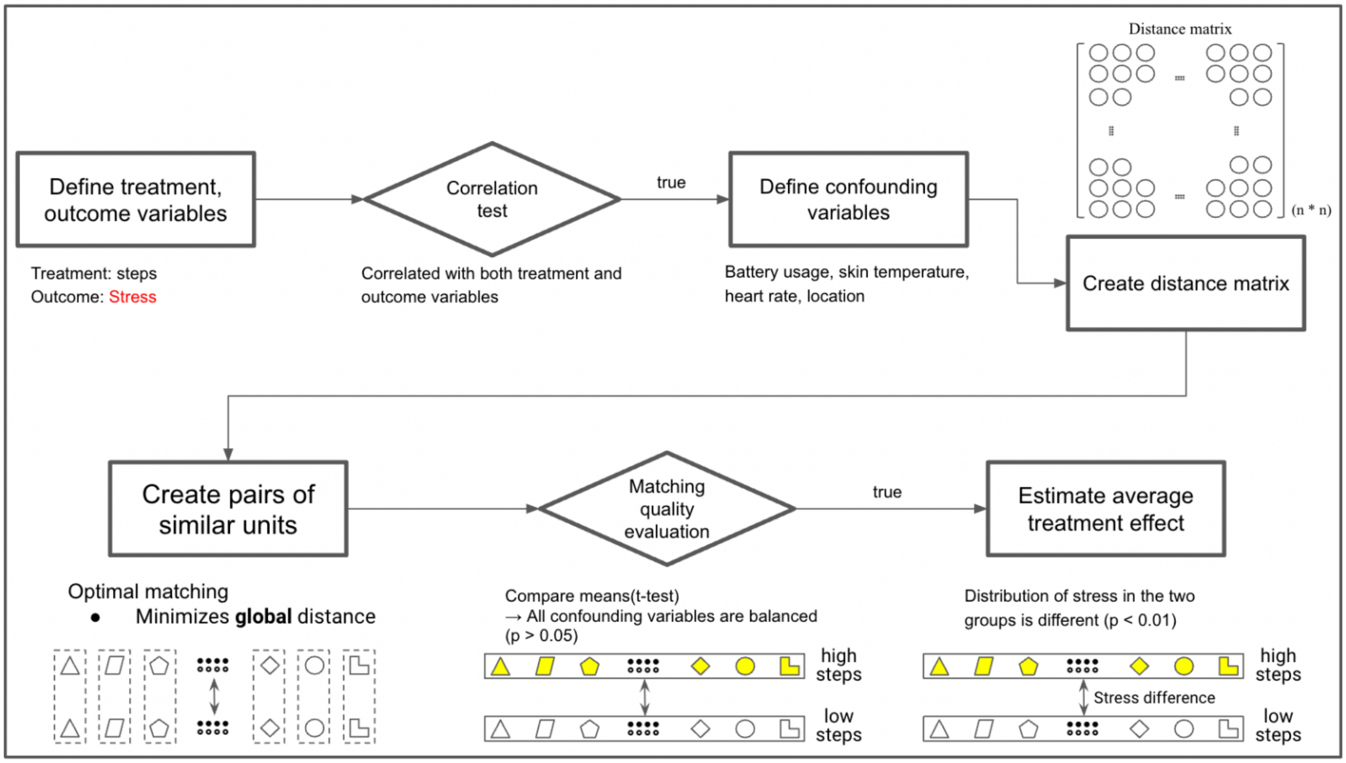

Figure 2. Matching process

this user to keep his body warm, avoid sweating a lot, and finally, not to use his cell phone too much.

Table 2. SRM result samples that cause stress

User ID	Stress factors
3003	Steps, Speed, Screen on/unlock, Skin-temperature, Gsr-resistance, Battery-temperature
3007	Ambient-light
3013	Valence
3016	Battery-level, RRinterval-interval
3018	Attention, Arousal, Valence
3022	Valence, Ambient-light
3025	Data-Traffic-rxKiloBytes
3028	Attention, Arousal, Valence, Ambient-light
3029	Attention, Valence
3041	Arousal, Valence

6 Conclusion

In this paper, we proposed a recommendation system that relieves human stress by utilizing mobile sensor data and emotional data. Unlike most recommended systems using correlation or cosine similarity, SRM recommends a method to analyze and alleviate stress factors using Counterfactual analysis methods.

However, there are also some limitations in this work. First, there is no correct answer to human emotions. Humans themselves often cannot clearly define their feelings. Therefore, it is practically impossible to quantitatively evaluate SRM. In addition, the K-EmoPhone dataset was collected in 2019. All personal identifiable information was deleted, so it was difficult to conduct qualitative evaluations such as interviews. Therefore, it's hard to find indicator for evaluating SRM.

Second, In the data preprocessing, we find that how to set the time window may affect the result of causal inference. Thus, we should choose the time window size carefully, considering the property of data, prior domain knowledge about them, or with iterative trials. Though there may not be a gold standard for the time window, we could set it which is (1) not too large to dilute small and temporary changes of data and (2) not too small to be failed in representing the data.

Third, when implementing the matching, covariate balance might not be perfectly done between the high and low treatment groups. For instance, if there is a high correlation between treatment and confounders, subjects within the same treatment group may show a similar level of confounders (e.g., subjects in the higher treatment also show high levels of covariates). Therefore, we may fail to match subjects with similar confounders coming from the different groups. Researchers should examine bias in the dataset and carefully perform confounder selection for balancing

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