

Data Analysis Techniques for Smart Nudging

Seshathiri Dhanasekaran*
seshathiri.dhanasekaran@uit.no
Institute of Informatikk
Tromso, Norway

Randi Karlsen
randi.karlsen@uit.no
Institute of Informatikk
Tromso, Norway

Anders Andersen
anders.andersen@uit.no
Institute of Informatikk
Tromso, Norway

Anne Håkansson
anne.hakansson@uit.no
Institute of Informatikk
Tromso, Norway

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1 BACKGROUND

Nudge principles and techniques are significant in communications, marketing, and groups' motivation to improve personal health, wealth, and well-being. We make numerous decisions in online situations [4]. People's health and well-being have garnered widespread interest and concern in this wearable's age. Smart nudging is defined as "digital nudging [6], where the guidance of user behavior is tailored to be relevant to the current situation of each user" [3]. Emerging digital devices such as smartwatches, smart bands, and smartphones will continuously capture and analyze your activity and health-related data from individuals and communities in their everyday environment [1][2]. Providing context-aware nudges in these digital health devices will help individuals identify and self-manage their health and physical activity.

2 OBJECTIVE

This study aims to provide data analysis techniques for smart nudging and examine its usability in developing a smart nudging system to provide context-based nudges that are more likely to succeed.

3 CONTRIBUTION OF THESIS

The thesis's major contribution is to develop machine learning models that can analyze physical activity with context data sources to predict user-preferred movement (Relevant Nudge) based on the data. The user's context refers to Location, Time, Weather, and User Preference here. We can use the nature of the data and analysis

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models to provide nudges for the people to keep them active and healthy without pushing them too much.

3.1 Data Collection

We recruited 30 people with privately owned apple activity trackers through online Facebook groups and forums worn before for user preference data collection. The inclusion criteria are owning an activity tracker from apple and being willing to share physical activity data. We conducted recruitment from October 2020 to May 2021. Participants gave informed consent by actively granting access to their data.

3.2 User Profiling and Classification

In data-intensive situations where the behavior of a heterogeneous mass of people must be understood or when computer-assisted decision-making is desired, user profiling and classification are critical responsibilities. A user profile includes activity data and preferences such as preferred activity, location, and time, essential for personalization. We are collecting the user profile data from the smartwatch health applications. We use the Support Vector Machine (SVM) algorithm to classify users based on their user profile. The classification of users based on User groups is to facilitate people who share similar interests and similar contexts. The user groups will be classified based on activity occurrence times. User profiling and classification of users will help us identify the context and nudge options available to people who share similar contexts. For example, E.g., People who are low activity and share similar contexts (owning a bicycle, proximity to running tracks) will help identify their context to nudge.

3.3 Activity Prediction

The purpose is to use smartwatch data to estimate future activity occurrence times and to develop a data-driven strategy for activity prediction [5]. Predicting activity helps deliver smart nudges. We plan to create a data analysis system for data collected from smartwatches to understand the context-aware activity to produce nudges. We propose Long Short Term Memory and Hidden Markov Model neural network models to understand user activity to design nudges. We plan to test at least two machine learning models to verify the efficiency of data analysis techniques on activity data to tailor smart nudges.

4 KEY CHALLENGES

Recruiting participants willing to share sensitive personal data (individual activity, location, weather, and calendar data) is a significant challenge in data collection. In addition, since the project is limited to test in the city of Tromsø, participants' selection criteria are very much narrow and restricted. After the Covid-19 outbreak in March 2020, people's activity patterns and preferences are widely changing and significantly less.

Due to the limitation of data, we have limited choices of machine learning techniques to build our model. Since the sample size and participant size are minimal, we are limited to choosing machine learning models compatible with this project.

5 PROJECT STATUS AND TIMELINE

We are currently working on classification models to classify the user based on their capability and preference.

We developed a Python parser to extract data from Apple and Fitbit smartwatches proprietary health applications. In addition, we developed a personal dashboard monitoring and visualization for individual users with Kibana and Python. We plan to work on user profiling and classification to be finished by 2022 January. We plan

to work on nudge design modeling with two models, preferably LSTM and HMM. We plan to build models to predict user-preferred activity based on the user preference with context data and publish results.

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