Predicting the Quality of User Experiences to Improve Productivity and Wellness

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Introduction

College students often struggle to balance their work with personal wellness. In part, this occurs because students work when they are unable to focus. While there are many successful scheduling agents deployed worldwide (Berry et al. 2011; Pollack 2005), these applications require users to predict and specify their own schedules and preferences, which, due to the cognitive load placed on the user, is an inherent source of inaccuracies when characterizing productivity.

An alternative approach to increasing both productivity and wellness is to help users achieve flow. Flow is a state in which people feel focused, motivated, and fully immersed in their activity, resulting in feelings of satisfaction and even joy (Csikszentmihalyi 1991). The Experience Sampling Method (ESM), in which users are randomly surveyed throughout the day about their experiences, is a well-studied mechanism for characterizing flow (Hektner, Schmidt, and Csikszentmihalyi 2007).

We hypothesize that we can adapt ESM to build a model of users' efficacy and predict when they will be most likely to experience flow. We also hypothesize that we can present this information effectively to users, allowing them to understand when they are most likely to achieve flow. Instead of creating a full schedule, we strive to inform users about their own work habits so they can schedule their activities more effectively. In order to test these hypotheses, we introduce the Productivity and Wellness Pal (PaWPal), a smartphone-based application that seeks to make users aware of their efficacy at various tasks as well as which courses of action are likely to lead to immersive experiences.

Refining Our Hypothesis Using ESM

To understand the factors influencing student productivity and wellness, we conducted a weeklong study at Harvey Mudd College in April 2014. Using the ESM app PACO (Evans 2012), we surveyed twenty-five participants at eight randomly selected times each day about contextual and situational information informing their current experience.

Our study resulted in three takeaways about how PaWPal could improve users' decision making processes. First, users reported that smartphone-based ESM surveys did not disrupt them during immersive experiences. Second, we found that participants enjoyed becoming more self aware by responding to ESM surveys, but that surveys were sometimes overly invasive or occurred when users could not respond (for example, during class). This information led us to hypothesize that using an *adaptive* ESM notification scheme that adapts to a user's calendar as part of PaWPal would allow users to train the application without being excessively interrupted. Finally, we learned that there are easily identifiable features such as time of day, day of the week, location, and interaction with others that are correlated with flow, leading us to hypothesize that we can accurately predict user efficacy.

PaWPal's Design

PaWPal's current design as an Android application reflects our takeaways from the ESM study. The application incorporates adaptive ESM and learns on collected data to make predictions about a user's efficacy.

Adaptive ESM

Currently, PaWPal uses Google Calendar data to analyze when a user is free or busy. Then, it randomly schedules survey notifications during users' free time or, if the user does not have enough free time, randomly throughout the day in a classic ESM style. The number of notifications is initially set to six, reduced from our preliminary ESM study due to the shorter sampling window. The eventual goal is that once PaWPal collects enough data about a particular individual, it can intelligently issue notifications only in moments where it needs more information. Although users may fill out their calendars inaccurately, we hope to additionally use inference and location-based methods to improve data accuracy.

Predicting Users' Experiences

PaWPal uses Support Vector Regression to predict a user's efficacy at four different activity types: curricular, extracurricular, social, and restorative. To do this, PaWPal trains three regression models which predict effectiveness, immersion, and emotional state. High levels of each of these qualities produce a state where the user is more likely to work quickly without being easily distracted or emotionally strained—in other words, a state of flow. The advantage of using SVR is that the technique is easily extensible, allowing

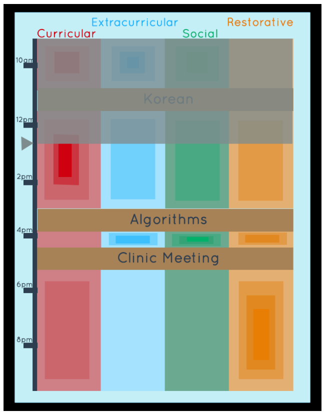

Figure 1: PaWPal's heat map homepage. Each unscheduled block of time is shaded based on a user's predicted efficacy.

us to add new features simply by eliciting them and labeling new and old data with them. Using this model of efficacy, where the overall effectiveness is the average of the scores produced by these models, we are able to help the user decide when they would be most successful at a given activity.

Preliminary user testing led us to present this information in the heat map-style visualization shown in Figure 1. The heat map displays each of our four activity types in a different column. Scheduled events pulled from the user's calendar partition the day into unscheduled blocks of time. Each unscheduled block of time is then shaded with concentric boxes of increasing saturation based on how effective we predict the user will be at the corresponding activity.

Preliminary Evaluation

To test the quality of our predictions, we ran our SVR on data obtained during the ESM study. We hand-tagged this data using several temporal features (e.g., the time of day and day of the week) along with contextual data from users' calendars (e.g., whether the data point fell in a scheduled block of time). When deployed, we expect that PaWPal will be able to collect *at least* this amount of data from users.

In one test, we ran cross-validation with three different types of models. The first model was an SVR trained using a coarse grid search over parameters. The second was a naïve classifier that simply predicted the mode of its training data as the label for all testing data. We chose this mode-based model for comparison as users often picked "3" as their response to 4-point "forced choice" Likert questions in our ESM study. The third classifier was similar to the second except that it used the mean of its training data. For each model type, we ran the cross-validation ten times and noted the mean absolute error of the efficacy predictions when compared to the efficacy the user reported for that data point as part of the ESM study. As shown in Figure 2, we found that our regression model performed significantly better than both naïve models.

Our tests show encouraging results, and we have many reasons to believe that PaWPal's performance can be even better. We expect the final version of PaWPal to use individualized data for predictions instead of predicting across

	Imm	**Eff**	**Em**
Our SVR Classifier	0.63	0.57	0.53
Mode Classifier	0.79	0.83	0.59
Mean Classifier	0.78	0.67	0.62

Figure 2: Using SVR and the ESM data, we trained models to predict the user's immersion (Imm), effectiveness (Eff), and emotional state (Em) while performing a given task. This figure shows the mean absolute error from running cross-validation on our regression model, a naïve "mode-picking" classifier, and a naïve "mean-picking" classifier.

all users. Additionally, the final version will analyze a larger dataset than our preliminary SVRs, as it will be used over a long period of time, and incorporate more features than our preliminary SVRs. These changes should improve the predictive power of PaWPal. We hypothesize that we can further improve predictions by adding non-temporal features such as location or interaction with others, which were correlated with immersion, effectiveness, or emotion in the ESM study.

Conclusions

In this paper, we have presented a new smartphone application called PaWPal that seeks to make users aware of their efficacy at various tasks using a combination of adaptive ESM and SVR classification. PaWPal shows promise in learning and contextualizing a user's experiences within their schedule, helping them choose activities that maximize their opportunities for productivity, wellness, and flow. We plan to conduct a user-study of the full application in the spring of 2015, which will include additional contextual features such as location and current level of interaction. We hope that this will increase the accuracy of PaWPal's predictions. With these additional features, we believe that PaWPal will provide users with reliable information about their work habits and support their personal wellness.

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