Mobile Sensing and Support for People with Depression

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Depression is a common, burdensome, often recurring mental health disorder with high prevalence. Even in developed countries, patients have to wait for several months to receive adequate treatment. In many parts of the world there is only one mental health care professional for over 200.000 people [1]. Smartphones are ubiquitous and have an increasingly large complement of sensors that can potentially be useful in monitoring behavioral patterns that might be indicative of depressive symptoms and providing context sensitive intervention support [2,3].

The objective of this study was two fold, first to explore the detection of daily-life behavior based on smart phone sensor information to identify subjects with a clinically meaningful depression level, second to explore the potential of context sensitive intervention delivery to provide in-situ support for people with depressive symptoms.

Proxies for social [4] and physical [5] behavior derived from smartphone sensor data was successfully deployed to deliver context sensitive and personalized interventions to people with depressive symptoms. Subjects who used the application for an extended period of time showed significant reduction in self-reported symptom severity.

Non-linear classification models trained on features extracted from smartphone sensor data including Wifi, accelerometer, GPS and phone use, demonstrated a proof of concept for the detection of depression with reasonable accuracy. While findings of effectiveness must be reproduced in a RCT to proof causation, they pave the way for a new generation of personalized digital health interventions leveraging smartphone sensors to provide context sensitive information for in-situ support and unobtrusive monitoring of critical mental health states.

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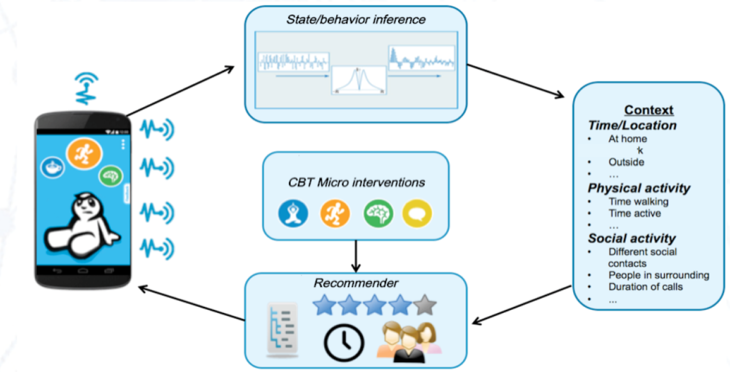
Depression: the leading cause of disability worldwide

In October 2012, the world health organization (WHO) estimated that 350 million people worldwide suffer from depression [1]. It is expected that depression will be the world's largest medical burden on health by 2020 [2]. Traditionally, depression is treated with medication and/or face to face psychotherapy utilizing methods such as cognitive-behavioral therapy (CBT) which has been proven to be effective [3]. Yet, for 50% of the world's population there is only one mental health expert responsible for 200.000 or more people [2].

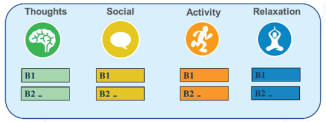
Personalised Just-in-time interventions: a scalable therapy solution ?

In recent years, this problem led to the rise of digital versions of CBT in the form of educational interactive websites and smart phone applications [4]. Many of these solutions presented reasonable effects [5], sometimes even on a par with face to face therapy [6]. However, a recent review revealed an array of shortcomings still present in most of the approaches, for example, the lack of personalization and missing in-situ support [7]. A key to the solution could lie in personalised digital health interventions offered through modern smart phones and their sensors. By 2016, the number of global smartphone users is estimated to reach 2.16 billion [8]. Smartphone based learning systems could adapt to subject's individual needs by interpreting feedback and treatment success [9] and could provide important context information for adequate in-situ support, see for example [10] and [11], in the form of interactive interventions and further infer a subject's condition state.

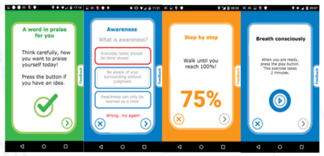
The aim of the present work therefore was, to explore the potential and feasibility of context sensitive intervention delivery based on smart phone sensors, to provide in-situ support for people with depressive symptoms, and to explore the detection of daily-life behavior based on smart phone sensor information to identify subjects with a clinically meaningful depression level.



- 100+ crafted interactive interventions with multimedia content
- Established techniques from behavioral therapy for depression
- Grouped into baskets with similar focus



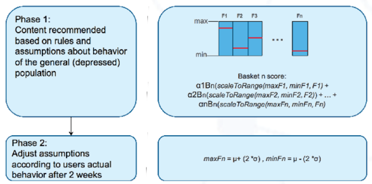
The following screenshots show examples of interactive interventions. From left to right, the first one shows a mindfulness exercise where the user has to check a box after a small thinking task, the second shows a psychoeducational multiple choice intervention, the third shows a real time activity tracking intervention showing the progress of a ditsance the user should walk and the forth shows a multimedia, audio intervention playing a breathing exercise.



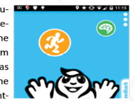
For transparency, at any time the user is able to have a look at the collected usage data over different periods of times. The screenshots on the right show tracked data from social, phone usage and physical activities (from left to right)

Recommendation of grouped interventions depends on:
- The behavior of the user during the last 24 hours represented by contextual features potentially related to depression computed from sensor and phone usage spanning:
- Walking time (Accelerometer)
- General activity (Accelerometer)
- Time at home (estimated using WiFi hotspots)
- Phone usage
- Movement in space (GPS statistics, number of different hotspots)
- Social activity (incoming/outgoing calls, number of text messages)
- Number of calendar events

And a set of static rules spanning:
- Time of the day (discretized)
- Location (Home, Outside)
- User Preference (Past rating of content, completion rate, ...)



Where αmBn is the weight of feature m on basket n, Fn is the value of feature n over the last 24 hours, scaleToRange() is a function to calculate the fraction of Fn reached of the range between defined small and large values of Fn. The baskets with the highest scores were presented to the subject in the form of touchable circles on the application's home screen as shown on the right. The size of the circles indicated the recommendation score and the unique icons represented the type of the domain the basket belongs to. The screenshot on the right shows an example where a basket with physical exercises received the highest score (orange circle), followed by a basket of the domain mindfulness (green circle).



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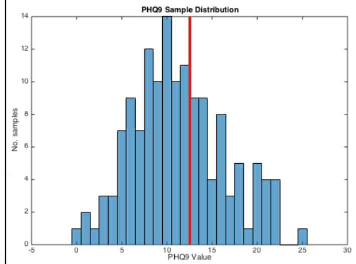
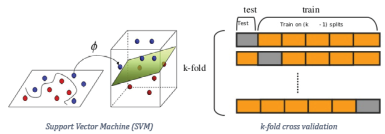
Analysis: Sensing

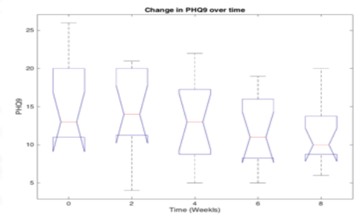




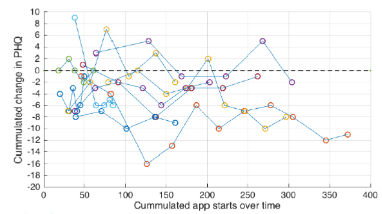
PHQ-9≥11 vs. PHQ-9≤10 classification performance	SVM, RBF kernel gamma=13.53, C=2.78
Accuracy	72.7
Sensitivity	65.9
Specificity	79.7

Every two weeks, subjects were asked to answer PHQ-9 questionnaires computing a depression score between 0 and 30. The goal was, to resemble the PHQ-9 score based on the behavior of the subject over the course of the preceding two weeks. Behavior is represented by 120 features computes from statistics over the preceding two weeks of each context dimension. We approached this as a supervised machine learning task with binary classes to distinguish between samples representing a PHQ-9≥11 and PHQ-9≤10. To approximate generalizability, we conducted a 10-fold cross validation on 143 samples of 36 subjects using a SVM. Hyper parameters were optimized using grid search on the mean cross validation scores.

Analysis: Support



Boxplot of PHQ-9 score progression of subjects with PHQ ≥11 at t0 over time



Scatter plot of cumulated app starts per subject over time and cumulated change in PHQ-9 values. Note: The development of PHQ-9 scores of individual subjects is indicated by connected points of the same color.

PHQ-9 score	tn, median PHQ9 (IQR)	t0, median PHQ9 (IQR)	N	z^a	P
t2, median (IQR)	14.00 (11.25-20.00)	13.00(11.00-20.00)	12	0.283	.77
t4, median (IQR)	13.00 (8.75-17.25)	13.00(11.00-20.00)	12	1.216	.22
t6, median (IQR)	11.00 (8.25-16.00)	13.00(11.00-20.00)	12	2.013	.04*
t8, median (IQR)	10.00(8.75-13.75)	13.00(11.00-20.00)	12	2.479	.01*

Wilcoxon sign-rank test results between t0 and tn, Note: ^{a}Wilcoxon sign-rank test

We conducted a spearman correlation analysis between total app starts and change in PHQ-9 from t0 to tn of the 12 subjects classified as clinically depressed at t0 and with a system adherence of at least 4 weeks. We observed a negative correlation with rho=-.498 and p=.099.

Limitations

The clinical study carried out is based on a non-randomized, uncontrolled single-arm study design, which rules out the possibility to proof any causation. Additionally, to lower the inhibition threshold, subjects were not asked to provide information about control variables such as other current treatments to rule out their impact on treatment outcome. Furthermore, although research has shown that the PHQ-9 is strongly correlated with depression, not everyone with an elevated PHQ-9 is certain to have a depression. Moreover, in this first pilot we did not quantify the efficacy of the proposed recommendation algorithm. This would involve detailed feedback from participants in order to judge appropriateness of context related intervention recommendations.

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