Personalized Learned Model to Predict Being Under the Influence

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Abstract—**This paper focuses on the personalization of a mobile application called *RU Influenced*. This personalization will allow us to measure whether the user is under the influence of alcohol or other drugs like marijuana. The Android platform provides a set of sensor technologies that we can use to estimate a blood-alcohol concentration equivalent influence factor. The structure of this application includes two mobile-based cognitive tests called the Digital Symbol Substitution Test (DSST) and STROOP Test and a reaction time test called the Stop Light Test. This application will provide a set of tools for self-monitoring where users can self-quantify their state and avoid being charged with Driving Under the Influence (DUI).**

Index Terms—**DSST test, STROOP test, Stop Light Test, Machine Learning, Drunk Driving, driving under the influence.**

I. Introduction

This paper describes an effort intended to create a powerful tool for end-users to assess their level of impairment and avoid driving and other dangerous activities when they are under the influence. According to the National Highway Traffic Safety Administration (NHTSA), nearly 40% of the drivers killed in fatal crashes are under a high-level of influence [1]. Moreover, the socioeconomic impact of driving under the influence is staggering, with a 2006 study estimating it at $129.7 billion in the U.S. Currently, the most common methods used by police units include NHSTA-standardized field sobriety tests and a breath-alcohol test. However, breathalyzers are too expensive for most people to own. For these reasons, we want to provide tools that can decrease these numbers radically and can also easily be obtained by the users.

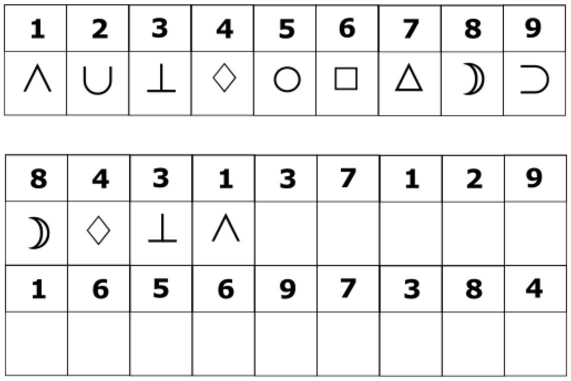
Currently, twenty-one states including Colorado and the District of Columbia have laws legalizing marijuana in some form. Drugs such as marijuana have no easy field test; most of these drugs require blood-based analysis. Therefore, it is necessary to come up with new methods to identify if an individual is under the influence of these drugs. With a personalized model, we expect to increase the chance that impairment can be accurately determined.

II. Previous Work

Several studies have shown that the DSST and STROOP tests are measures of cognitive functions correlated with levels of impairments or intoxication [2] [3]. However, we are the first group to research the concept of individualized baselines for DSST and STROOP testing. To do this, we have personalized an application called *RU Influenced* that includes both of these cognitive tests. The Stop Light test, a test measuring reaction time, is also included in this application.

A. The Digital Symbol Substitution Test (DSST)

The DSST is frequently used to measure associative abilities [4]. This test is normally administered as a paper-and-pencil task where an individual is given numbers between one and nine and a symbol below each number. On the same page, the subject is given a series of random numbers from one to nine and below each number, there is a blank space where the subject draws the symbol appropriate for each digit, see Figure 1. The subject needs to correctly complete a fixed number of questions as fast as he/she can.



1	2	3	4	5	6	7	8	9
∧	∪	⊥	◇	○	□	△	☽	⊃

8	4	3	1	3	7	1	2	9
☽	◇	⊥	∧					
1	6	5	6	9	7	3	8	4

Fig. 1. DSST: Paper-and-pencil task

B. The STROOP Test

The STROOP effect is a demonstration of interference in the reaction time of a task [5]. This test consists of a list of colors printed with a different ink color not denoted by the name. For example, the word ‘pink’ is printed in blue ink, see Figure 2. It has been shown that naming the color of the word takes longer and is more prone to errors if the name of the color is not printed in the color denoted by the word [5]. Another study has shown that intoxicated people need more time to complete the whole series of words than people who are not under the influence [6].

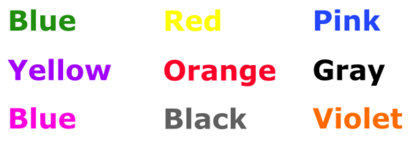


Fig. 2. STROOP Test: List of colors

C. Stop Light Test

The Stop Light Test is a driving response test which measures response times to a range of driving-relevant signs, e.g., stop light colors, randomly appearing signs, and obstacles. There are no studies at the moment that show a relation between this test and level of impairment or intoxication. However, we decided to study and measure this test with respect to the others. For our implementation of this test, we are only considering change in stop light colors, see Figure 3.

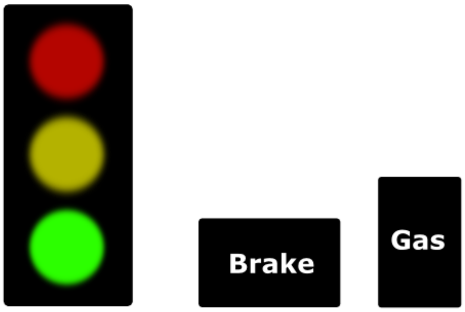


Fig. 3. Stop Light Test: Change in stop light colors

III. Problem Statement

The main goal of this project is to use the *RU Influenced* application to gather enough data to be able to build a personalized model that can predict the level of influence of a user. One of our long-term goals is to be able to correlate this level of influence with a blood alcohol level. There are many variables that we need to consider with respect to the data. For example, one day the subject might perform poorly on one of the tests, but on a subsequent day, he can get much better. This is called *learning effect*. On the other hand, let's say that we are testing the application with a 20-year-old man and a 60-year-old woman. There is a high probability that the 20-year-old man will exhibit a better reaction time than the 60-year-old woman, but that does not mean that the woman is under the influence. These are some difficulties that we need to overcome.

IV. Android Implementation

It is widely known fact that the number of Android users is growing exponentially [7]. The Android platform provides a set of features and technologies very useful for this study. For these reasons, we decided to implement this application using the Android platform. The general framework of *RU Influenced* consists of six main screens: add or select user, user state, start screen, DSST Implementation, STROOP Test Implementation and Stop Light Test Implementation, see Figure 4.

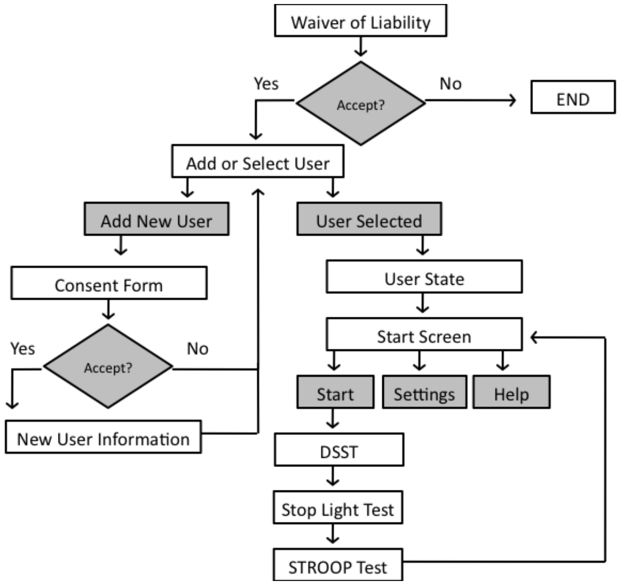


Fig. 4. General Framework

A. Add and Select User

After the user accepts a waiver of liability, a screen will appear asking to select an existing user account or add a new one, see Figure 5. If the user decides to add a new user account, a consent form will appear providing all the necessary information and purposes of this study. The users can either accept or decline this form. If the consent form is accepted, a new screen will appear with a few text fields asking for a username, age and gender. The username is asked to provide the users with a list of user accounts and will not be used for data collection, as all data will be completely anonymous. Users can also delete user accounts from this screen. If the user selects an existing user account, the *user state screen* will appear.

B. User State

In this particular screen, the user is asked a few questions to determine what sort of state the user's mind is in. This helps associate the data with a particular state. For the purposes of this study, we expect the subjects to be sober, but we cannot guarantee that they will in fact be sober. For these reasons, we decided to include an area where the user can specify if he/she has been drinking or if he/she has been using marijuana, see Figure 6. After the user provides all the necessary information the *start screen* will appear.

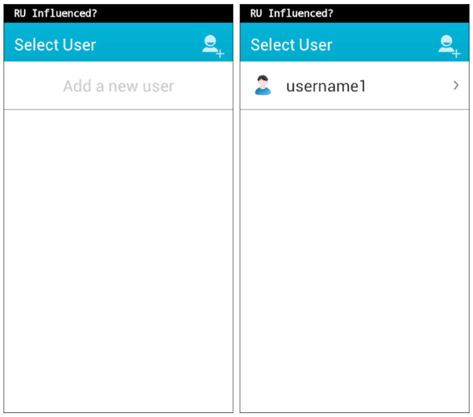
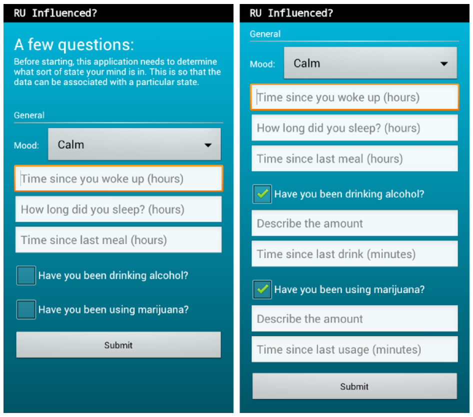


Fig. 5. Add and Select User Screen



A few questions:

Before starting, this application needs to determine what sort of state your mind is in. This is so that the data can be associated with a particular state.

General

Mood: Calm

Time since you woke up (hours)

How long did you sleep? (hours)

Time since last meal (hours)

☐ Have you been drinking alcohol?

☐ Have you been using marijuana?

Submit

General

Mood: Calm

Time since you woke up (hours)

How long did you sleep? (hours)

Time since last meal (hours)

☑ Have you been drinking alcohol?

Describe the amount

Time since last drink (minutes)

☑ Have you been using marijuana?

Describe the amount

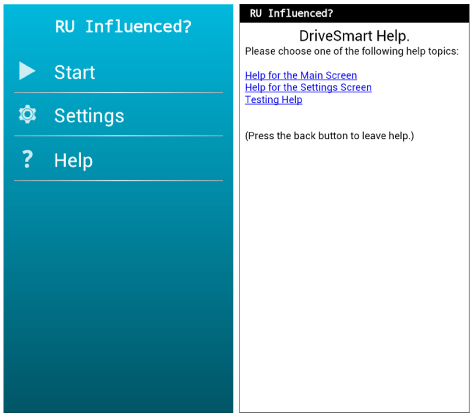
Time since last usage (minutes)

Submit

Fig. 6. User State Screen

C. Start Screen

The start screen contains a few options: *start*, *settings* and *help*. If the user selects start, the Digital Symbol Substitution Test will begin, followed by the Stop Light Test and the STROOP Test. On the other hand, if the user selects help, an HTML view containing instructions on how to perform the tests will appear, see Figure 7.



DriveSmart Help.

Please choose one of the following help topics:

Help for the Main Screen
Help for the Settings Screen
Testing Help

(Press the back button to leave help.)

Fig. 7. Start and Help Screens

D. DSST Implementation

As mentioned above, this test is normally used as a paper-and-pencil task; however, there are many ways of implementing a mobile-based version of this test. For this study, we decided to use the *match-nomatch* approach. The program presents the user with two rows of random symbols. Each column of symbols are “matching.” Two symbols from that set will appear in the center of the screen. If they are in the same column, the user has to press the match button; otherwise the user has to press the “no match” button. The objective is to press the correct button as fast as possible, see Figure 8. After this test is completed, the Stop Light Test will begin.

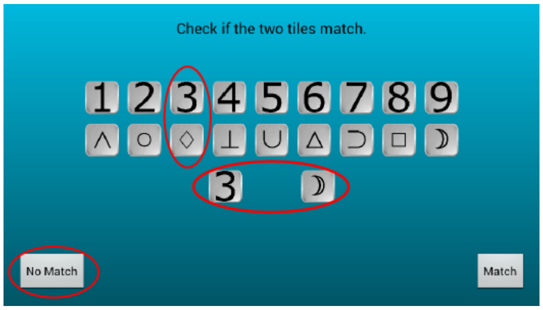

Check if the two tiles match.

Fig. 8. DSST Implementation

E. Stop Light Test Implementation

In this screen, a stop light will change color each time the user presses a button. The yellow light will be lit when changing from the green color, but it will not necessarily change from yellow to red because this will be predictable for users. Instead, the light colors change randomly. The subject needs to press the accelerate button when the green light is on and the brake button when the red light is on, see Figure 9. After this test is completed, the STROOP Test will begin.

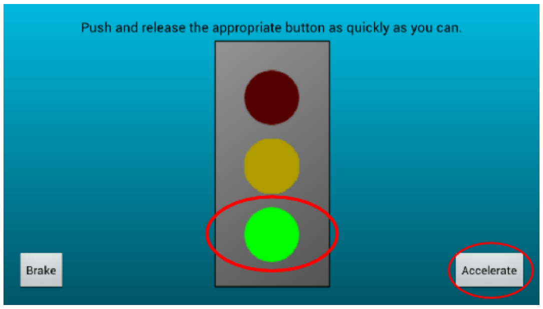
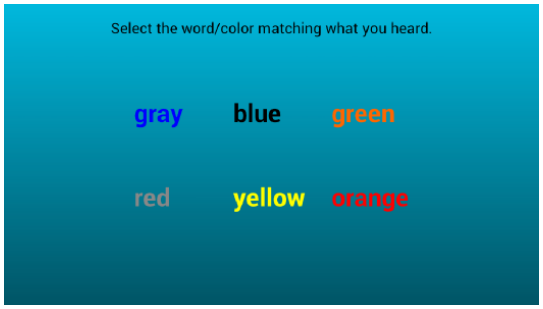

Push and release the appropriate button as quickly as you can.

Fig. 9. Stop Light Test Implementation

F. STROOP Test Implementation

For this test, we were able to implement a mobile-based system where the user hears the words/colors and has to select them on the screen, see Figure 10. After this test is completed, the application proceeds to store the data and goes back to the start screen, where users can perform the tests again or simply close the application.



Select the word/color matching what you heard.

Fig. 10. STROOP Test Implementation

V. Data Storage

To be able to collect the data, we need to use a database system. The Android platform does not interact directly with remote databases but instead uses an SQLite database unique to each application and which can only be accessed inside that application. For the purpose of this study, this will not be very useful since we need to access the collected data outside the application to be able to apply machine learning algorithms to it. Therefore, it is necessary to use a remote database. To achieve this, we use PHP scripts. Through PHP scripts, it is possible to establish a connection between an Android application and a remote MySQL database. The Android platform uses HTTP requests to connect with the PHP scripts, and the PHP scripts are able to send and receive data from the remote database.

VI. Experiments

For this study, we were able to collect data from participants between the ages of 19 and 22. The *RU Influenced* application was downloaded into their Android devices in order to collect data for a period of two weeks. As mentioned above, all participants were encouraged to be sober when taking the tests, this is because one of our goals is to build a personalized model that can learn a user's characteristics when he/she is sober. For the data collection, we used the process described in the *Data Storage* section. The measured time and accuracy of the results (among other features such as age, gender, mood, last time he/she ate, last time he/she slept, how long did he/she sleep, time of the day, date, trial number, etc.) were stored in a remote database. Four more questions were asked to the participants in case they were drinking alcohol or using marijuana, however, since they were all sober, all these questions had a value of zero. All results were stored anonymously.

VII. Technical Approach

The essential function of this application is to predict a level of influence of a user. In other words, we need a numeric value that can be correlated with the level of influence that we want to find. For this reason, a supervised learning algorithm such as multiple linear regression [8] seems like a good approach for this problem.

A. Multiple Linear Regression

In order to perform multiple linear regression in our data, we first need to establish our attributes and our dependent variable. Since the data that we have is not completely numeric, we first changed some attributes from nominal to numeric, e.g., gender, and mood. For our dependent variable we are using a combination of the results denoted as *score*.

$$\text{score} = 100\frac{(\alpha_1+\alpha_2+\alpha_3)}{3} - 10\frac{(\tau_1+\tau_2+\tau_3)}{3}$$

The α- and τ-values are the accuracy and time average of each test, respectively. Using multiple linear regression will allow us to obtain a predicted score value of a new instance.

$$\hat{y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k$$

So far we are assuming that the relation between the attributes and the dependent variable is completely linear. In real practice this is not true. One of this research questions is how the results change with respect to time. We will see these effects in the *Results* section. However, we first need to find an implementation that can produce the weight of each attribute in order to predict a new score value.

B. Implementation

It is known for a fact that regression coefficients can be obtained from the equation

$$b = (X'X)^{-1}X'Y$$

where X, Y, and b are matrices of the attributes values, class values, and the coefficients values, respectively. However, there are different ways or methods that can be used to obtain these coefficients [9] [10]. For the purposes of this project and taking into account that the models will be build on an Android device, we decided to use Singular Value Decompostion (SVD). It has been proven that SVD is a very useful technique for a number of applications including regression [10]. To simplify this problem and take advantage of the technologies that are available, we are using OpenCV (Open Source Computer Vision) for Android [11]. This library contains different functions of performing SVD that allow us to obtain the regression coefficients of a model very quickly.

C. Main Idea

After we have our model, we are going to be able to predict the score of a new instance. Now, when a user performs the tests we will obtain two different scores, the real score and the score predicted by the model. The next stage of this project is to observe the difference between these two values and relate this difference with a level of influence. To be able to do this we will need to collect data from participants that are under the influence. This stage of the project will be carried out as future work.

The goal of building a individualized model is to be able to apply *domain adaptation* [12]. This technique consists of taking a learned model that was trained with a lot of data from one source domain and adapt it to a different target domain. In other words, we want to analyze smaller groups of people, calculate separate models for each group or clusters, and then map new users into an appropriate cluster.

VIII. Results

There are two main questions that we expect to answer with these results. The first is something that we mentioned earlier, the *learning effect*. As expected, we can observe that this effect exists in our data, see Figure 11.

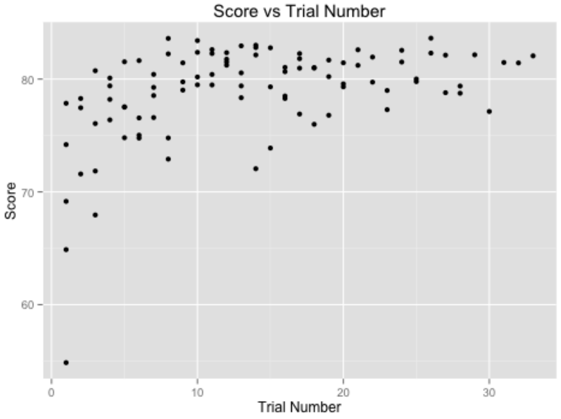


Fig. 11. Learning Effect

From this figure we can infer that the relation between the trial number and the score is not linear but logarithmic. This means that our model is no longer linear regression, we need to add some non-linear elements, making it a non-linear regression model. However, after a certain number of attempts the data behaves constant.

The second questions that we expect to answer is how these results vary according to time of the day. Again, by plotting the data, see Figure 12 we can see that in fact the results vary according to time of the day. For this reason, we are using a third order polynomial in our time data to take into account this daily variation.

It is important to mention that according to the data that we have so far, we cannot infer that the results vary according to the mood of a person, see Figure 13. From this figure, we can observe that there is no significant difference in the results between people who are tired or sleepy and people who are happy or calm. However, we will need more data to conclude that this feature is not relevant for our study.

By adding non-linear elements to our data we have improved our model; however, we still need more data for training and testing. In terms of performance, the SVD libraries of OpenCV seem like the best approach to solve this kind of regression problems on an Android device.

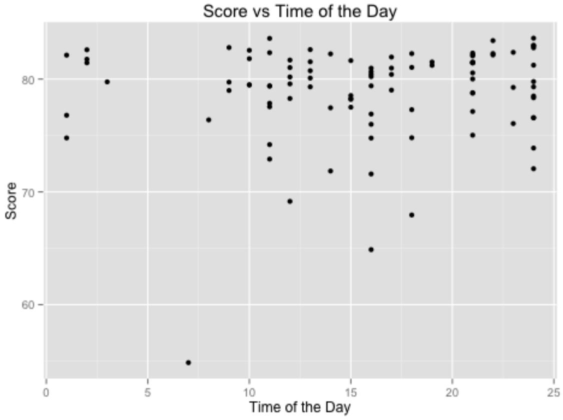


Fig. 12. Daily Variation

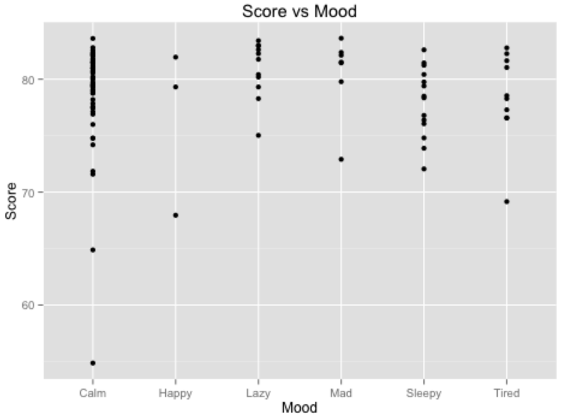


Fig. 13. Mood Variation

IX. Future Work

This application is intended to have a fourth test. This test will be an automated gaze analysis: specifically, the well-known and widely used Horizontal Gaze Nystagmus (HGN) [13]. Irregular motion while tracking at off-angle gazes is an uncontrollable motor reflex when someone is intoxicated, causing the eye to jitter when tracking an object. For this reason, we strongly believe that a phone-based version of this test will be very useful for end-users. One longer-term goal of this application is to be potentially used by third parties, e.g. police officials.

X. Conclusion

In general, *RU Influenced* will allow users to have an idea of their level of influence. After we collect data from users that are under the influence we will be able to give the user an estimate of their level of influence. When we collect this additional data, we expect to observe a significant difference between users who are sober and users who are not. However, from the results obtained so far we can infer many things. As we mentioned in the *Results* section we were able to prove that the *learning effect* exists in our data as well as daily variation of the scores obtained by the users.

Acknowledgment

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