UNIVERSITY OF OULU

FACULTY OF INFORMATION TECHNOLOGY AND ELECTRICAL ENGINEERING

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INDOOR OUTDOOR DETECTION

Master's Thesis
Degree Programme in Computer Science and Engineering
May 2019

García Hurtado J. (2019) Indoor Outdoor Detection. University of Oulu, Degree Programme in Computer Science and Engineering, 46 p.

ABSTRACT

This thesis shows a viable machine learning model that detects Indoor or Outdoor on smartphones. The model was designed as a classification problem and it was trained with data collected from several smartphone sensors by participants of a field trial conducted. The data collected was labeled manually either indoor or outdoor by the participants themselves. The model was then iterated over to lower the energy consumption by utilizing feature selection techniques and subsampling techniques. The model which uses all of the data achieved a 99 % prediction accuracy, while the energy efficient model achieved 92.91 %. This work provides the tools for researchers to quantify environmental exposure using smartphones.

Keywords: Environmental exposure, smartphone instrumentation, machine learning, classification model, energy efficiency, battery consumption, context aware applications, smartphones.

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FOREWORD

The aim of the thesis is to assess the viability of an energy efficient model to predict environmental exposure using smartphone instrumentation. The process was to first understand the state of the art, then design an experiment, collect data, transform it and use it to produce a machine learning classification model to predict either indoor or outdoor environments. Afterwards, energy efficiency was taken into account, so measurements of battery consumption of the different sources of information was collected and later used to iterate over the created model and design a new one which was accurate and energy efficient. Lastly, the robustness of the model was tested using data collected on extreme cases, and the results were analyzed comparing them to previous attempts, available in the literature, to predict environmental exposure.

This thesis is partially funded by the Academy of Finland (Grants 276786-AWARE, 286386-CPDSS, 285459- iSCIENCE, 304925-CARE), the European Commission (Grant 6AIKA-A71143-AKAI), and Marie Skłodowska-Curie Actions (645706-GRAGE). As a result of this thesis and the work of Theodoros Anagnostopoulos, Jorge Goncalves, Denzil Ferreira, Simo Hosio and Vassilis Kostakos, the paper "Environmental exposure assessment using indoor/outdoor detection on smartphones"[1] was published in the journal "Personal and Ubiquitous Computing" in 2017.

Special thanks to Denzil Ferreira for all the support as the supervisor, as well as to Zhanna Sarsenbayeva and Julio Mendoza who helped during the data collection phase.

Helsinki, 22nd May, 2019

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LIST OF ABBREVIATIONS AND SYMBOLS

AP	Access Point
API	Application Programming Interface
APIs	Application Programming Interfaces
GPS	Global Positioning System
GSM	Global System for Mobile communications
NA	Not Applicable
RF	Radio Frequency
RFID	Radio Frequency Identification
RSS	Received Signal Strength
SVM	Support Vector Machine

asu	asu. Unit to measure GSM signal strength.
km	kilometer. Unit to measure distance.
lx	lux. Unit to measure luminance.
mbar	millibar. Unit to measure atmospheric pressure.
min	minutes. Unit of time.
mW	milliWatt. Unit of power.

1. INTRODUCTION

As the smart cities initiative grows, more data is available about what is happening where, historic data is readily available, and hence, better decision making can happen[2]. Sensors allow to record more information about the conditions of cities as well as about the behaviour of the population, and even individuals. Due to ethical reasons[3], the idea of this big data collection is to avoid individual people tracking. And even if ethical reasons are discarded, a complex algorithm that takes multiple inputs of data would need to be created to get information about a specific individual. For the general purposes, having information about a specific person is not very relevant, but, for medical reasons, having accurate information of a patient can result in better outcomes [4]. Now a days, not only cities are full of sensors, but smartphones are equipped with a wide array of sensors that can get context information of an individual at a relatively low cost. What this means, is that by leveraging these sensors, a more accurate picture can be created and used, for example, for a better health care.

Indoor outdoor detection is a topic which is specially important for health sciences usually related to patients' environmental exposure [5]. Combining the information of when and where a patient has been outdoors with the information of the cities pollution could greatly benefit the analysis of Asthma and other allergic diseases cases [6, 7]. Other areas of study which could benefit of this kind of information focus on better understanding the link between pregnant women exposure to pollution and birth size [8], infant intelligence [9], cognitive development [10], and the advancement of puberty [11].

Studies that have tried to create models of environmental exposure have been usually done from self-reported questionnaires, which may be unreliable and inconsistent. An automated study, which is more reliable, could be carried out by using the smartphones people carry on a daily basis [12], and the quantification of environmental exposure could be greatly improved.

In this thesis, the viability of an energy efficient Indoor Outdoor detection algorithm is assessed. The algorithm takes advantage of the sensors in smartphones, and does not rely on instrumentation of the environment, like installing beacons or tags, or on previous mapping of the environment. To create the algorithm, sensor data was collected by several participants while ground-truth of indoor and outdoor labels was tagged. The indoor outdoor detection was achieved using a classification problem, and the trade off between power consumption and prediction accuracy was analyzed.

2. LITERATURE SURVEY

Not a lot of research has been done on environmental exposure using smartphones, but there are several papers that can be used as a start. Localization techniques for mobile technologies and how to use them in indoor and outdoor settings has substantial literature [13]. Even though this is not strictly addressing environmental exposure, characterizing the locations as indoor or outdoor would be one way to close the gap.

Other related research is activity recognition techniques. These can be extrapolated to environmental exposure if the activities can be classified into indoor and outdoor. Some of them will be pretty straight forward, for example "brushing teeth" is likely to be an indoor activity, but some others will be harder or impossible to classify, like "walking". Location-based services is another area of investigation that could be used to identify environmental exposure.

In all of these techniques, energy efficiency is an important topic to consider when discussing smartphones. One way to improve this is by using periodic sampling instead of continuous sensing, another is by using the sensors that are less energy draining.

2.1. Localization

Several localizations techniques exist. Some use fingerprinting locations, while others rely on calculating the distance to already known locations. Some fingerprinting techniques use RFID (Radio Frequency Identification) [14] to identify tags that are placed before hand in specific locations. Identification of these tags gives the possibility to identify the fingerprinted location which then also identifies the position of the user. Other methods use similar fingerprinting techniques, but instead of using RFID tags they use Bluetooth tags [15], while others use RSS (Received Signal Strength) to identify a location [16, 17, 18, 19]. For example, WiFi RSS for outdoor localization using fingerprinting has been shown to work [20] and other methods, like the LocataNet system, show how to extend the existing GPS (Global Positioning System) RSS locating method to difficult environments by the use of additional hardware that broadcasts the constellation information [21]. If a mapping between the fingerprinted location and indoor and outdoor characteristics exist, then the environmental exposure could be extrapolated.

Even though some localizations techniques try to replace the use of GPS, often, indoor localization techniques still rely on GPS when available. A design of a wireless mobile indoor/outdoor tracking system uses GPS when available, and RF (Radio Frequency) [22] when not. Indoor location tracking is achieved by uLocate by mixing WiFi and GPS data of elderly people [23].

When GPS is not used, WiFi is a very common system to rely on, but some locations have sparse WiFi signal. Research has shown that by using sensors that change due to user movement, like the accelerometer, the magnetometer and the gyroscope, a robust localization algorithm that estimates the direction of the movement of users can be created [24]. Aside from the classic additional hardware, like RFID or Bluetooth tags, other approaches have been studied, like one using smartphones and synchronized acoustic beacons that emit non-invasive audio [25].

Other systems that could be used to calculate the environmental exposure are indoor navigation systems. It has been shown that using accelerometer, gyroscope, magnetometer and WiFi, a reliable real time indoor navigation system using smartphones can be created [26]. To achieve this, the system uses WiFi and geomagnetic fingerprints of the area. In this environments, the use of a barometer can also be used to give information about the elevation [27].

2.2. Activity recognition

As mentioned before, activity recognition could be used to extrapolate environmental exposure, as long as a reliable conversion between activity and environmental exposure can be detected.

Several algorithms have been created to investigate the viability of activity recognition. For example, the system SurroundSense leveraged the microphone and camera of the user's smartphone to measure sound, light and color, and infer the activity using an SVM (Support Vector Machine) [28] classifier. Another approach was shown by the Jigsaw sensing engine, which used continuous sensing of the accelerometer and microphone and periodic GPS sensing to infer the activity by classifying the data with a J48 tree based classifier [29].

Semi-supervised machine learning models have also been used for activity recognition by classifying cell signal, light and magnetic field data [30]. The model uses a Naive Bayes classifier which was efficient on accuracy and energy consumption. In this system, GPS was avoided to reduce the energy cost, but it is not the only system to take energy cost into consideration. The SenseLess system uses a dynamic approach by choosing the most energy efficient smartphone sensors for activity recognition [31].

2.3. Location-based services

Location-based services literature is extensive, and as long as a reliable match between a specific service and its environmental exposure associated exists, then it would be possible to use them to extrapolate environmental exposure.

For example, a system using ultrasonic signal acquisition was proposed for indoor location based services [32]. The system is based on ultrasonic beacons placed in the ceilings of buildings. Another example, was a system for location recognition and prediction designed to be used for location based services [33]. This system uses data gathered from smartphones' GPS and WiFi sensors, and combines it with machine learning techniques, leveraging k-Nearest Neighbors and Decision Trees classifiers, to recognize the user's location, and Markov models to predict the the destination of the user.

2.4. Environmental exposure

The methods mentioned above already researched have not directly tried to quantify environmental exposure using smartphones, and hence they are not ideal since they require either environment instrumentation, like installing beacons, or a mapping of the environment. There is some literature that has tried to calculate the environmental exposure and react to the user being either indoors or outdoors. For example, an indoor and outdoor activity recognition system was attempted by using the availability of GPS signal, assuming when GPS signal is available the user is outdoors [34]. There is no detailed accuracy assessment, but environments that might contradict the assumption are indoor environments with glass ceilings.

Another approach to indoor outdoor detection was a lifelog system that used user's position, activity, and experience to predict the user behaviour and switch between indoor or outdoor activity detection based on the availability of GPS and Bluetooth beacons that were previously installed [35].

Environmental exposure using smartphones has been explicitly addressed by IODetector [36]. This system uses an Android application that classifies the environment, with a model with a prediction accuracy of 85%, by using the light sensor, magnetometer and cell tower signal strength. Since GPS was not used, the system is relatively energy efficient. Other models have used GPS to predict environmental exposure and have shown that by adding a light sensor [37] or a magnetometer [38], the accuracy can be improved.

A GPS only system has also been designed to infer environmental exposure, but instead of using the number of satellites or the location accuracy given by the satellites, the system plots the visible satellites on the sky and the not visible but expected satellites, and based on this plot, tries to determine the reason why the satellites are not visible. For example, indoors is usually classified as no satellites at the top but some satellites in the horizon [39].

Even though environmental exposure has been studied, energy efficiency has been taken into account lightly. For example, it has been shown that a more energy efficient model can be created by relying on lightweight smartphone sensors or by reducing the duty cycle of them [40], but there is no analysis of the trade off with the accuracy of the environmental exposure calculation.

Something important to mention about all the research that tried to asses environmental exposure, is that the labeling of the data collected (indoor or outdoor) is done in the same phone that is sensing the environment, which is problematic since the act of labeling can affect the collected data and result in a biased analysis.

To summarize, indoor activity recognition generally uses lightweight sensors and avoids GPS, while activity recognition in both indoor and outdoor settings uses GPS to detect which environment setting the user is on, which results in a high power consumption. Some methods to save power have been subsampling, but they have been adopted without feature selection, which then results in a lower performance of the classifiers used. This thesis tries to detect indoor and outdoor settings with a high accuracy and a low energy requirement, by selecting a subset of sensors that optimize the requirements.

3. EXPERIMENT DESIGN

To create an energy efficient indoor outdoor detection algorithm is a complex problem. Following a deterministic approach, with fixed boundaries to classify data, to design a classifier would be a very difficult process, that most probably is not viable. Since it is not clear how to directly infer environmental exposure from data available by the smartphone a user carries, a machine learning approach was chosen.

To create a machine learning model a big amount of data is required to train the algorithm. This data is composed of features that are extracted from the information available by the target user's device. A wide variety of information can be obtained from a smartphone, but not all of it is related to the context the user is on, and not all of the context related information will be necessarily helpful to infer environmental exposure. The method how the features are extracted is by prepocessing the available information into variables that can more easily be included in a machine learning algorithm. After all the data is collected and preprocessed, the machine learning model can be trained, and evaluated. An overview of the whole system of data collection is available in Appendix 2.

3.1. Information sources

The information chosen for the machine learning model can be divided into two groups. The first one is information coming from physical sensors in the device that could be influenced by the environment. The second group is information that comes either from external APIs (Application Programming Interfaces) that could give relevant context of the user, or from the device's status that can relate to the current actions of the user or the physical state of the device. In the following sections the sources of information used and why they were used are explained.

3.1.1. Physical sensors

The following sensors are the ones chosen to collect data that might be related to the environmental exposure of the user.

Light sensor: The light perceived by the smartphone can be used to infer the availability of natural light versus artificial light. The sun provides around 110 000 lx (lux, measurement of light) when it's shining fully [41], compared to between 300 lx to 750 lx emitted by indoor lighting [42, 43], and between 0.27 lx to 1.0 lx provided by the moon under a clear sky [41]. Since this values mentioned are in ideal conditions, additional information is needed to make the light information more useful.

First, the phone might be in the pocket of the user, which would mean the light sensor is obstructed and no light measurement is available. For this scenario, the proximity sensor was also included, and the idea is to determine when the information of the light sensor is reliable.

Secondly, the clouds can significantly affect the amount of light received from the sun. To address this issue, information about the weather was included. The cloud coverage would correlate to how much light passes through the atmosphere and can be used to compensate the light sensor's readings.

Lastly, the sun is not available 24 hours a day. This changes depending on the time and place the user is. To further improve the possibility to infer information from the light sensor, information about the part of the day was collected. Even though a simple approach would be to divide the day in 2, daytime and nighttime, in places away from the equator there are seasons that can change the division between nighttime and daytime in a matter of days. For this reason, it was decided to divide the day in 3 parts of similar expected light: day, night and twilight. As shown in Figure 1 twilight was used for both sunrise and sunset, since the amount of light is the same.

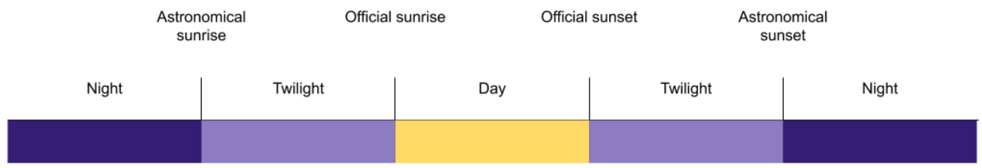

Figure 1. Classification of part of the day

To calculate the section of the day the user was at, the date and location of the user was gathered and the algorithm by the Almanac for Computers [44, 45] was used to infer the astronomical sunrise and sunset as well as the official sunrise and sunset. Before and after the astronomical sunrise and sunset respectively, no light from the sun is perceivable in the atmosphere, which would mean that any light perceived by the light sensor is artificial light or moon light. Between the official sunrise and sunset the sun light is direct, which would help the model to understand the light values better.

GSM (Global System for Mobile communications) antenna: GSM signals are affected by structures, and crossing from an outdoor to an indoor environment comes with a decrease in signal strength [36].

Accelerometer: With this sensor, information about the velocity of the user can be calculated. Velocity can help determine the transportation and hence extrapolate to an indoor or outdoor environment.

Magnetometer: The magnetometer is one of the main sensors used for indoor navigation. This sensor is designed to measure the Earth's magnetic field to calculate the true north, which is useful in navigation applications. The magnetometer is sensitive to disturbances caused by electronics, magnets and metals [46], and hence, the magnetometer variance is a good indication of nearby structures and electronics, which happen mostly in an indoor environment.

Microphone: Sound acoustics are significantly different between indoor and outdoor environments, so the decibel level and the frequency can be a good extra data point to infer the environmental exposure.

GPS antenna: Even though GPS is the sensor with most energy consumption, it is still a reliable sensor when it comes to differentiate between indoor and outdoor environments. Since GPS needs to have a direct line of sight between the satellite and the phone's antenna, a smartphone inside an indoor environment will have a harder time discovering satellites. The sensor was used to find the number of satellites, but it was also used to find the location of the user to query the weather as mentioned in the light sensor section.

WiFi antenna: Similar to the GPS train of thought, WiFi AP (access points) are more prominent in indoor environments and the amount of them differ from outdoor environments. Even though this might be changing with smart cities development, it is worth investigating if the combination of the data provided by the WiFi antenna with the other information collected might have a good enough understanding of the context to infer the environmental exposure.

Barometer: Barometric pressure is a parameter that buildings with controlled environments usually regulate to be either positive or negative depending on the season of the year and the height of the building. For example, maintaining a positive pressure would mean that less air comes in the building, which would make the building cleaner and less contaminated.

Proximity: The proximity sensor, as mentioned earlier in the light sensor section, was used as a helper sensor to give the machine learning model a better chance to understand when the light sensor information is relevant and when it is not.

3.1.2. Other sources

The following sources of information are the ones chosen to collect data that can give extra information to extrapolate environmental exposure.

Activity of the user: Google's Activity Recognition API (Application Programming Interface) was used to obtain the activity. The activity the user is doing is greatly correlated with the environment. For example, biking is most probably an outdoor activity, while commuting in a bus or a car is, depending on the definition of indoor and outdoor, an indoor activity.

Screen status: Screen status correlates to the usage of the smartphone, which could also be related to the environmental exposure of the user itself.

If there is a difference between the screen status between indoor and outdoor environments, then it could be used in combination with the other data to infer the environmental exposure.

Weather: Even though weather is of great influence to humans behaviour, in this case there is no intention of using it directly to infer environmental exposure, but more of a helper data point to use in combination with other data collected by the light sensor and the GPS antenna, as mentioned in the previous section.

Time of day: As weather, this information is not used directly to infer environmental exposure, even though for example, most people are indoors at night, but mostly as a helper data point for the light sensor as mentioned before.

3.2. Data collection

3.2.1. Data specification

The data collected all came from the information sources mentioned previously. Some of the sources provided multiple variables, and all of the data collected was labeled with the context of the user based on manual input explained in the next section. In Table 1, the variables collected with their respective sources, possible values, units and frequency of collection are shown.

Some clarification is in order regarding what data and how the data was collected. To avoid battery consumption, the information sources, activity of the user, weather, time of day, microphone, GPS antenna and WiFi antenna, which have a high battery impact were collected at a lower frequency.

The GSM signal strength and the neighbouring towers signal strength have different units due to how the sensor's API is implemented. It is relevant to note that the relationship between asu and dBm is

$$1\,\mathrm{dBm} = -113 + 2 * \mathrm{asu}, \tag{1}$$

which means that 0 asu is equivalent to −121 dBm or less, and 31 asu is −51 dBm or more.

Regarding the accelerometer data, the values collected do not include the force of gravity, which allows easier manipulation of the data in data processing. The magnetometer data was collected on each axis (x, y, z) of the device. With respect to the microphone, data was collected for 30 s and then processed with the Ambient Noise Plugin from the AWARE platform [47], and the WiFi antenna's scan functionality was used to count how many AP were visible from the phone.

GPS data was a concern, since this sensor is the heaviest consumer of battery. As mentioned in Table 1, the data was collected every 5 minutes. When the time to collect data came, the GPS antenna was switched on for a minimum of 20 s and a maximum of 40 s. This was done to guarantee enough time to calculated the location of the user with enough accuracy even on cloudy days, but avoiding having the sensor on for too long. When a fix was acquired within the time

Table 1. Data collected specifications

Variable	Source	Range	Units	Frequency
Activity	Google Activity Recognition API	in vehicle bicycle on foot still unknown tilting	NA[1]	5 min
Barometric pressure	Barometer	NA[2]	mbar	5 Hz
Ambient luminance	Light sensor	0 to 100 000	lx	5 Hz
Proximity	Proximity sensor	0 and 1	NA	On change[3]
Cloud coverage	Weather API	0 to 100	%	5 min
Part of day	Time of day	night twilight day unknown	NA	5 min
GSM signal strength	GSM antenna	0 to 31	asu[4]	On change[5]
GSM neighbouring towers signal strength	GSM antenna	−121 to 10	dBm	On change[6]
Acceleration	Accelerometer	NA[7]	m/s^2	5 Hz
Magnetic field	Magnetometer	NA[8]	µT	5 Hz
Ambient noise	Microphone	NA	dB	5 min
Noise frequency	Microphone	>= 0	Hz	5 min
Active satellites	GPS antenna	>= 0	NA	5 min
Screen status	Screen status	off on locked unlocked	NA	On change
WiFi AP	WiFi antenna	>= 0	NA	5 min

1) NA (Not applicable).

2) The range of the barometer varied from sensor to sensor.

3) Whenever the value of the proximity sensor changes, the value is recorded.

4) asu (Arbitrary Strength Unit).

5, 6) Whenever the GSM antenna connected to a new GSM tower the value was recorded.

7) The range of the accelerometer varied from sensor to sensor.

8) The range of the magnetometer varied from sensor to sensor.

parameters, the number of satellites used for the fix was stored and the location was used to calculate the weather and the part of day information. If no location was available then the number of satellites recorded was 0 and the part of day and weather kept the previous recording. It is important to note that the location of the user was never stored.

3.2.2. Procedure

The goal of the data collection procedure was to collect data from several participants, avoiding human error when labelling the data. To do this, the AWARE framework was used [47]. This framework contains a method to create user studies and gather the data remotely, as well as allow changes to the study on the fly. Additionally it provides several ready made plugins to collect certain data, and also allows the creation of additional plugins for the study. For this user study, the AWARE plugins Ambient noise, Google Fused Location and Google Activity Recognition and the sensor collection framework for aware were used as the information source. Furthermore, 2 extra plugins and an android application were created to complete the information sources and allow the labeling of the data.

Application development

The plugin for Indoor Outdoor collection was created as an additional source of information needed for some data not present in the existing AWARE plugins. This plugin did not require any user interaction aside from the installation process, and it was in charge of being the information source for weather, time of day, GSM antenna, GPS antenna, screen status and WiFi antenna. The Indoor Outdoor collection plugin went through 9 iterations until it worked as expected. All the other information was collected using AWARE.

Aside from the Indoor Outdoor collection plugin created specifically for this study, another generic plugin was created to collect user traces. This Traces Collector plugin was used to remove possible tampering of data when the user wanted to label the information provided. How the plugin works, is it connects via Bluetooth to another Bluetooth device which will provide information about the traces. It requires user interaction after the installation. Initially it shows the user a notification seen in Figure 2.

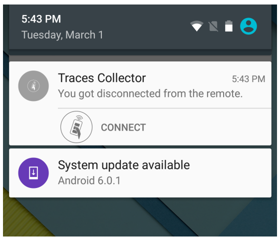

Figure 2. Traces Collector plugin notification

Then the user starts the connection process and accepts the pairing as Figure 3 illustrates.

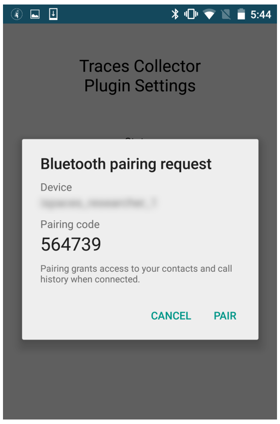

Figure 3. Traces Collector plugin pairing process

Afterwards, the plugin is in functional state and shows a permanent notification with the current state of the connection to the remote device and provides a full screen view of the status of the connection, shown in Figure 4.

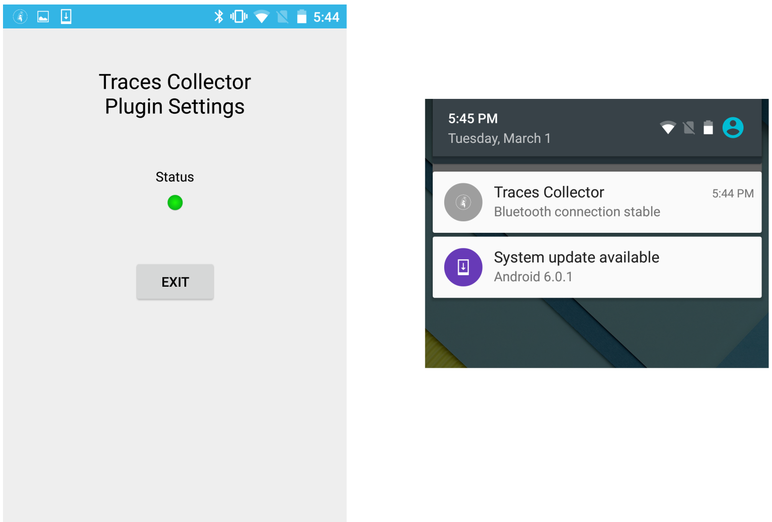

Figure 4. Traces Collector plugin status notification and full view

A trial of the study was conducted, and it was clear that Bluetooth was not as stable as expected. Due to this the functionality to reconnect automatically to the remote device was added to the Traces Collector plugin. The creation of this plugin went through 9 iterations until it was reliable for a real experiment.

Regarding the external device which connected via Bluetooth to the Traces Collector plugin, a second smartphone was used. An Indoor Outdoor Remote application was developed that provided a simple interface for the users to interact with. It contained a setup screen visible in Figure 5 and a remote screen to change the current environment between indoor and outdoor.

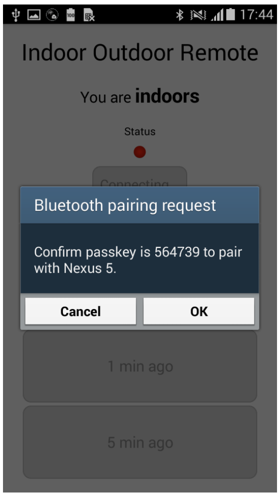

Figure 5. Indoor Outdoor Remote setup

As seen in Figure 6 the remote view contained 3 options instead of just a switch. This was implemented in one of the iterations since it was clear that participants would forget to interact with the device. In this case the options of Now, 1 minute ago and 5 minutes ago were implemented to give flexibility.

This was afterwards taken into account when the debriefing of the participants happened and when the data analysis happened. The remote application always showed a notification to remind the user to interact with it, and for convenience, as shown by Figure 7, the notification contained actions so the user did not have to open the application to change environments but could do it directly from the notification screen.

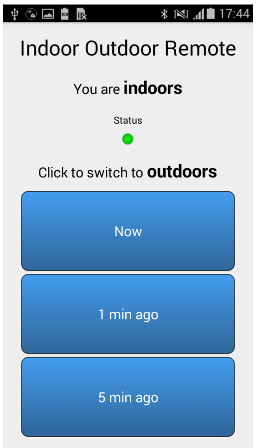

Figure 6. Indoor Outdoor Remote options

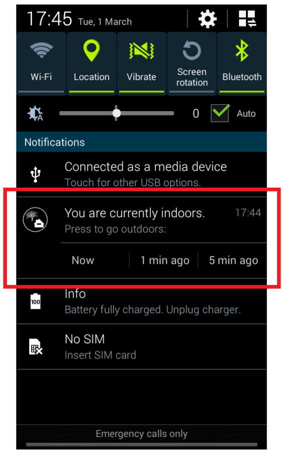

Figure 7. Indoor Outdoor Remote convenience notification

It is important to note that the use of a secondary device was to avoid tampering of the data collected by the main device. Movements like taking the phone out of the pocket, shifting its orientation, or unlocking it would impact the data collected, which could then be a trigger for the machine learning model to train on.

Participants' process

The participants of the study with whom a meeting could be agreed upon were given verbal instructions on how to collect the data, and all the initial setup was done by the researcher, other participants received a set of instructions available in Appendix 1. In all the cases, the initial phase was the setup of the devices, which required the installation of the AWARE framework application in the user's smartphone, followed by the joining of the study, which required the additional installation of the plugins mentioned earlier. Then the installation on the second device, the remote to label the data, was handled, as well as the connection via Bluetooth between the user's device and the remote device.

Some clarification was necessary for the participants to label the data in a uniform manner. This included explanations of several situations which could be unclear to them. Since one of the main motivations to do this study is to provide context for health sciences, one of the parameters taken into consideration to classify places was the relative quality of air. For this reason, places like inside a bus or a car were considered indoors, while open ended tunnels or balconies were considered outdoors. Other situations that were unclear for some participants were inner yards, which were classified as outdoors when no ceiling existed. Aside from this pre-identified ambiguous locations, the participants were told to label ambiguous places in a consistent manner.

Afterwards, the participants were instructed to label the transitions as soon as they happened and to keep a log of forgotten labeling that was later used to either re label the data collected or to remove data points which were unreliable. When the data collection finished, the participants had a debriefing, where information about their whereabouts as well as their activities was recorded in case it was needed in the data processing and analysis.

3.2.3. Extreme cases

Aside from the data collected from participants in normal day to day conditions, another data set was collected to test the machine learning model in extreme cases to verify how robust it was. The model is expected to not work well on this cases since it has not been trained to understand them. The cases were the following:

Windowless basement: The basement had no GPS signal, no natural light and no network signal.

Indoor location near a big window and glass walls: This meant there was a high quantity of natural light as well as easy line of sight of GPS satellites.

Urban canyon: This was an inner yard that was outdoors and surrounded by tall walls. This meant only the satellites at the top would be visible by the GPS antenna but none of the ones in the horizon would be. It would also have a similar structure than an indoors environment, which would mean similar readings for the magnetometer sensor.

Constant transitions: Frequent transitions between indoors and outdoors with 30 seconds in between each transition.

Completely different environment: Data from a different country which would mean a very different environment. For example, different atmospheric pressure, earth's magnetic field, structures and materials of buildings, and others.

From all except the different country, the data was collected half of the time with the main device in the pocket and half the time with the main device in the hand. The total time of data collection for each scenario was 30 minutes, except for constant transitions and completely different environment. The data from a different country was collected for 1 normal day (afternoon to afternoon) from the participant, which included phone calls with a headset and without, frequent outdoors biking, walking and commuting in a bus.

3.2.4. Energy consumption

Since one of the main goals of the project is to create an energy efficient model that can predict the environmental exposure, data about how much energy do the different information sources consume was necessary to collect. Qualcomm's Trepn Power Profiler [48, 49] was used to estimate the energy consumption values. An LG Nexus 5, which was fully supported by Trepn's hardware instrumentation, was used as the measurement device for all the information sources to avoid hardware variation bias. Data was collected during a 20 minute window with a sampling rate of 100 milliseconds for each information source. During the profiling phase, the device was without human interaction to reduce the variability of tasks the smartphone had to do, and hence, try to capture the battery consumption of the information source instead of other tasks. Data about the information source turned off was also collected.

4. DATA ANALYSIS

4.1. Data processing

The data collected needed to be transformed before it could be analyzed and used in the creation of the machine learning models. It was processed as follows:

Activity: Coded as: 0 (in vehicle), 1 (bicycle), 2 (on foot), 3 (still), 4 (unknown), and 5 (tilting).
Barometric pressure: No processing.
Ambient luminance: No processing.
Proximity: Coded as: 0 (obscured) and 1 (not obscured).
Cloud coverage: When no data was possible to collect, this feature was 0 %. This happened when no last known location of the user was available.
Part of day: Coded as: 1 (twilight), 2 (night), 3 (day), and -1 (unknown). Unknown happened when no last known location of the user was available.
GSM signal strength: No processing.
GSM neighboring towers signal strength: The signal strength of all neighboring towers visible by the smartphone were averaged.
Acceleration: No processing.
Magnetic field: The variance from the data collected in each axis was calculated for an 18-second sliding window [36]. The total variance was also calculated by summing each axis.
Ambient noise: No processing.
Noise frequency: No processing.
Active satellites: No processing.
Screen status: Coded as: 0 (off), 1 (on), 2 (locked), and 3 (unlocked).
WiFi AP: No processing.
Indoor/Outdoor labels: Coded as: 0 (indoor) and 1 (outdoor).

All the data was either upsampled or downsampled to 1 Hz to create the models based on this. Upsampling was achieved by replicating the last known value, while downsampling was achieved by averaging the values. Additionally, all the labels of indoor and outdoor were moved in time depending of the button pressed by the users. "1 minute ago" was moved back 1 minute while "5 minutes ago" was moved 5 minutes back in time. For the cases of "5 minutes ago", during debriefing, the participants were asked to explain the situation to identify possible errors logging the data, and when more than 5 minutes had elapsed, the data was corrected accordingly.

4.2. Data summary

4.2.1. Indoor outdoor data

Data from 11 participants recruited, averaging 27 years of age, was collected. All participants were from Oulu, Finland. The whole data set contained 388 hours of data with 97 498 data points. The area covered spanned 81 km^2. The participants did 214 transitions between Indoor and Outdoor environments. The transition labels were divided between 156 "now", 36 "1 minute ago" and 22 "5 minutes ago". The summary of the collected data after processing can be seen in Table 2.

Table 2. Data collected summary

Variable	Range	Units	Type
Activity	0, 1, 2, 3, 4 and 5	Net number	Categorical
Barometric pressure	997 to 1009	mbar	Continuous
Ambient luminance	0 to 10 000	lx	Continuous
Proximity	0 and 1	Net number	Categorical
Cloud coverage	0 to 100	%	Discreet
Part of day	−1, 1, 2 and 3	Net number	Categorical
GSM signal strength	0 to 31	asu	Discreet
GSM neighbouring	−121 to 10	dBm	Continuous
Acceleration	0.01 to 10.67	$m\,s^{-2}$	Continuous
Magnetic Variance	1 to 9000	μT^2	Continuous
Ambient Noise	13 to 56	dB	Continuous
Noise frequency	8 to 310	Hz	Discreet
Active satellites	0 to 13	Net number	Discreet
Screen status	0, 1, 2 and 3	Net number	Categorical
WiFi AP	0 to 22	Net number	Discreet

4.2.2. Battery analysis

Two sets of data were collected, the consumption of battery when the information source was idle, and the consumption when it was active. Subtracting the active measurement from the idle one would give the battery consumption of the information source. The data collected can be seen in Table 3.

Table 3. Power consumption of collecting each variable

Variable	Power consumption (mW)
Activity	61.74
Barometric pressure	96.48
Ambient luminance	15.30
Proximity	14.10
Cloud coverage	67.39
Part of day	40.85
GSM signal strength	25.42
GSM neighbouring	25.42
Acceleration	86.31
Magnetic field	77.49
Ambient noise	40.37
Noise frequency	40.37
Active satellites	59.18
Screen status	0.75
WiFi AP	33.64

4.3. Machine learning model creation

Since what needed to be done was determine if the user is indoor or outdoor, it made sense to treat the problem as a classification problem. The plan would be to classify the environmental context of the user. The initial input would be the features seen in Table 2, and for subsequent iterations, the features would be selected. The output of the model would be either indoor or outdoor.

To create the models, the measurement of performance was the prediction accuracy p which is

$$p = (t_p + t_n)/(t_p + t_n + f_p + f_n), \qquad (2)$$

where the variables are

t_p = true positives,

t_n = true negatives,

f_p = false positives, and
f_n = false negatives.

Using a binomial test, a confidence interval for p was also calculated.

To create the models, Weka Machine Learning Toolbox in R was used. They were built using the data set at a sampling rate of 1 Hz but their accuracy was measured for the full range of sampling rates to see the effect on accuracy of subsampling, which is a good technique to reduce energy consumption. The subsampling was done using steps of 2 to 100. For example, subsampling of 10 means only 1 record every 10 seconds is retained.

4.3.1. Model 1. Indoor outdoor classification

Since it is not possible to know *a priori* the best model for the data set collected, some experimentation was in order. After trying several machine learning models, J48[1] outperformed other models. Using J48, Model 1 was created using all the features collected. It was validated using a 10-fold cross validation test. In Figure 8, a prediction accuracy of 99 % without subsampling can be seen, while after subsampling, the accuracy can drop to less than 40 %.

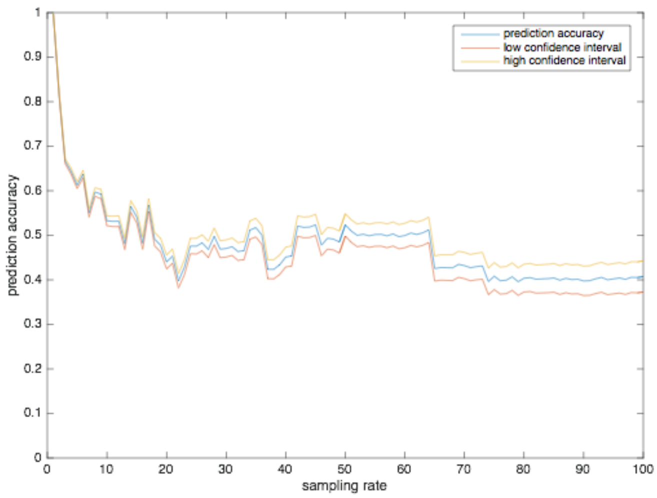

Figure 8. Prediction accuracy for Model 1

4.3.2. Model 2. Feature selection

Even though Model 1 performed very well, it uses all of the features collected. It is important to remember, this features were selected base on literature review and on reasoning of expected changes due to the environment, but it does not mean they are actually useful for the model to determine the environmental exposure.

[1]A Weka implementation of C4.5.

Moreover, the previous model is the model with highest energy consumption possible.

Since one of the goals of this project is to include the battery impact in the model created, multiple Weka feature selection algorithms were experimented with to try to reduce the number of features to use, and potentially reduce power consumption. The best results were achieved with the Consistency Subset Evaluation model, with Genetic Search, and the features selected were: Activity, Barometric pressure, Ambient luminance, Accelerometer, Magnetic variance and Number of WiFi AP (6 out of 15).

As expected, this model is comparable in accuracy to Model 1. It was also validated using a 10-fold cross validation test, and also subsampling was applied to calculate the prediction accuracy on several sampling rates. Prediction accuracy, shown in Figure 9, is 98.44 % without subsampling, and as Model 1, it can drop to less than 40 % after subsampling.

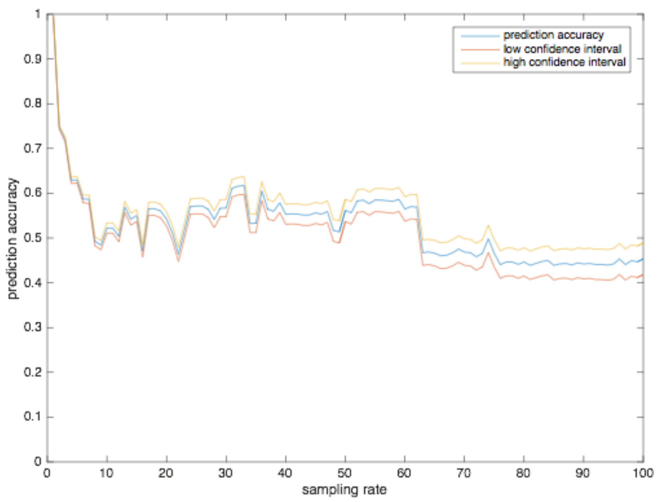

Figure 9. Prediction accuracy for Model 2

4.3.3. Model 3. Energy efficient features

The model 2 also performed very well, and it uses a subset of the measured features, which should decrease the energy consumption. However, the features were selected to maximize prediction accuracy instead of reduce energy consumption.

After experimenting further with the model, while trying to optimize for both low energy consumption and prediction accuracy, Model 3 was created. The parameters used to make decisions on which attributes to use were based on Table 3's power consumption of each variable and on the importance of each feature on the prediction accuracy. The attributes used for the model were Activity, Ambient luminance, and Number of WiFi AP (3 out of 15). As with the other models, 10-fold cross validation was done, and prediction accuracy was estimated for different levels of sampling rates.

As Figure 10 shows, the accuracy of the model is comparable to Model 1 and Model 2. The prediction accuracy without subsampling is 92.91 %, and after subsampling the accuracy could drop lower than 60 %.

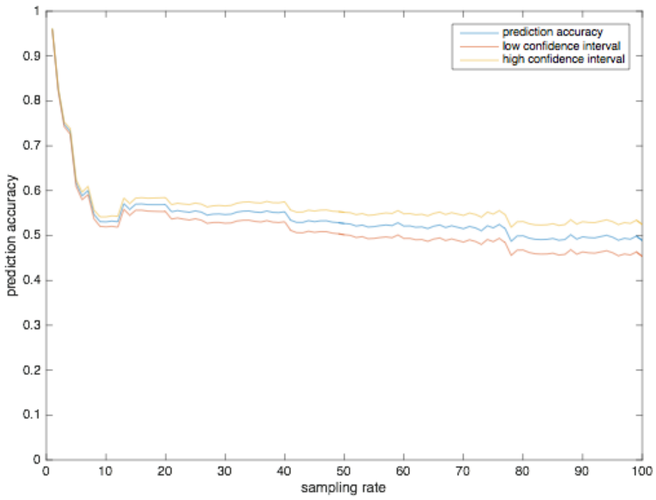

Figure 10. Prediction accuracy for Model 3

4.4. Model results

As mentioned in the previous section, all 3 models created performed similarly, as seen in Figure 11, but they used different attributes to train on. They all present the expected result of lower prediction accuracy as subsampling happens.

4.4.1. Energy consumption

Models 2 and 3 were designed to reduce the energy consumption of the model, but the data collected on energy consumption was based on the frequency of data collected instead of the range of sampling rates shown in the prediction accuracy results. To address this, Qualcomm's Trepn Power Profiler [48, 49] was used again to collect data on all different sampling rates.

As the previous battery consumption data collection, this one also had a 100 ms profiling rate, and the measurements were taken following the best practices recommended [48]. Multiple versions of the collection software were created, so that the sensors used were the ones needed by each model. Additionally, the software turned on and off the sensors according to the full range of sampling rates, from 1 Hz to 100 Hz, and it stayed in each sampling rate for 5 minutes.

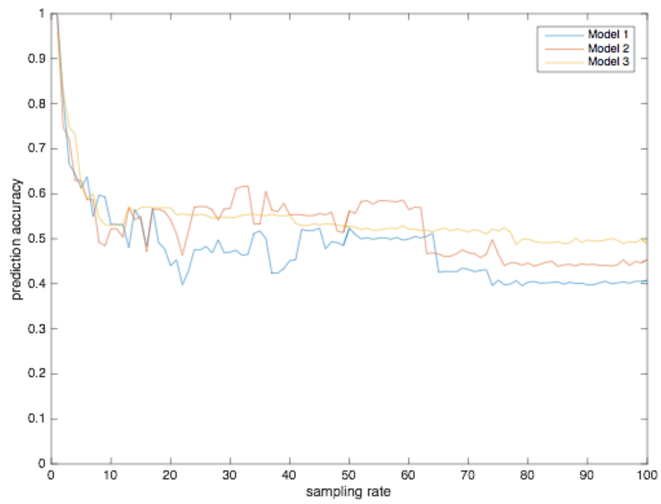

Figure 11. Prediction accuracy of all models

Figure 12 shows the results of power consumption of each model at all the sampling rates used for prediction accuracy.

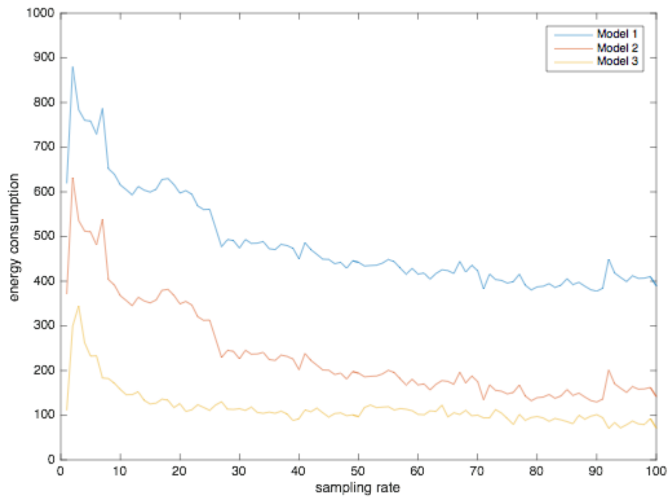

Figure 12. Models' battery consumption at varying sampling rates

For Model 1, the power profiling was done on a version of the application that collected simultaneously the barometric pressure, ambient luminance, acceleration and magnetic variance. The processing of the data was done locally on the device to take into account the extra processing power required. Since the magnetic variance was created using an 18-second sliding window, the magnetometer was only collected for sampling rates greater than 18. Since the remaining sensors were only collected every 5 minutes, there was no need to measure their consumption again, since the frequency is lower than 1 Hz, and we already had their respective values in Table 3.

Regarding Model 2, the same process was followed as for Model 1. Since the sensors used that required a higher frequency than 5 minutes were the same as Model 2, the previous measurement was used as a baseline, but only the additional variables used for this model were added to the power consumption from Table 3.

Finally, Model 3 required a different set of measurements. The only measurement required was for ambient luminance. The rest of the battery consumption came from Table 3.

4.4.2. Robustness

Since Model 3 had similar good results as the other models, but had a significantly lower battery consumption, this is the model chosen to quantify environmental exposure. Using the extreme cases data set collected earlier, the robustness of the model was assessed. Important to note is that the model was not trained using the data set, and as expected and shown in Table 4, the results were poor. But the good news was that this extreme cases are not impossible to recognize, since after training the model with the extreme cases data set and doing a 10-fold cross validation test, the prediction accuracy greatly improved.

Table 4. Robustness results for Model 3

Environment	Phone position	Prediction accuracy (%)	
		Without training	With training
Windowless basement	Pocket	24.86	100
	Hand	43.55	93.33
Near big windows	Pocket	34.96	100
	Hand	14.09	91.23
Urban canyon	Pocket	81.68	98.99
	Hand	100	100
Constant transitions	Pocket	52.41	62.89
	Hand	47.22	88.35
Different country	Mixed	42.22	95.30

4.4.3. Comparison with other models

After analyzing the results of all the proposed models, it is necessary to compare them with the models available in literature. Table 5 shows the prediction accuracy without subsampling of the different models. There is also an estimated energy consumption of the models based on the sensors they used[2]. Additionally, to give perspective of the predictive accuracy, the amount of time in a year (in days) where a bad prediction would happen for each model, assuming 365 days per year, was also calculated and shown.

Table 5. Comparison between models' results

Model	Accuracy (%)	Error (days/year)	Energy (mW)	Information Sources
Model 1	99	0.8	680.76	All in Table 3
Model 2	98.44	1.0	370.96	Activity Barometric pressure Ambient luminance Acceleration Magnetic variance WiFi AP
Model 3	92.91	14.2	110.68	Activity Ambient luminance WiFi AP
[36]	85	54.6	218.62	Acceleration Proximity Ambient luminance GSM signal strength Magnetic variance
[38]	86.1 to 96.5	12.8 to 50.8	136.67	GPS Magnetic variance
[37]	90	36.5	> 211	GPS Camera[1] Ambient luminance WiFi GSM signal strength Magnetic variance

1) Battery consumption for the Camera sensor was not taken, hence the greater than sign in the Energy column.

[2] The energy consumption information was taken from Table 3

5. DISCUSSION

The goal was to create a method to quantify environmental exposure of users using smartphones, while considering accuracy and energy efficiency. Three models were designed, initially giving priority to prediction accuracy, and then iterated by adding more weight to the energy efficiency by using less energy hungry sources as well as taking subsampling into account.

Assessment of the models has been done using the prediction accuracy which allows comparison to other models in the literature, since it is a common measurement in a priori work. Nevertheless, one of the motivations for this thesis was to provide a model useful for health sciences, reason why confidence intervals of the prediction accuracy were estimated using binomial experiment tests. An overview of how the indoor outdoor detection would work is visible in Appendix 3.

5.0.1. Smartphone-based environmental exposure assessment

Even though the literature shows it has been challenging to create environmental exposure detection due to the large quantity of work in this area [36, 35, 38, 34, 37], some methods have been created. Unfortunately, all of this methods propose a solution that depend on unrealistic conditions that do not scale well. For example, instrumentation of the environment or a priori mapping might be useful in small environments, but a wider deployment does not seem viable.

Smartphones are now part of most people's day to day life [12] and they contain a wide array of sensors and capabilities which can be used to create an environmental exposure detector with an accurate prediction rate. Thanks to their ubiquity, scientist can now quantify environmental exposure using an affordable method for longitudinal studies. In addition, cellular service providers and scientist studying human mobility patterns could greatly benefit of this or similar methods [36].

Having a meta sensor for indoor outdoor detection in most smartphones can benefit users by increasing the possibilities of location-based services. Developers will be able to come up with nice and useful ideas to take advantage of this new context information.

5.0.2. Energy efficient machine learning models using smartphones

Traditional machine learning techniques deal with feature selection and prediction accuracy, but it is important to take into account the expense of the data needed for the prediction. One clear expense is battery, in the case of smartphones, and Model 3 was created using a heuristic based on measurements of energy consumption, taking into account that the sources of information can be turned on and off. Further research should investigate the possibility of hybrid models that sometimes receive data from all the possible information sources and at others only a subset of those, as well as use different sampling rates to optimize for battery life. As an example, information about the battery status could easily be used to determine when all sensors can be switched on (battery charging and above a certain threshold) and when only key sensors should be turned on. Other techniques to decrease battery life is piggy backing data collection and network connections to other apps the user is already using, that way reducing the impact the environment exposure inference has on the user's battery. Sampling rate could also be dynamic depending not only on the battery status but also on key sensors data that might indicate no change of environment. For example, reaching an activity of "still" means the previous prediction should not change until the user's activity changes to something indicating movement, and during this period all other information sources could be switched off.

5.0.3. Limitations

The results for the extreme cases data set results show that a robust model that performs under any condition seems not viable yet. The models were trained with parts of the collected data sets and tested on the rest, and they performed pretty well, which means some training would be required for each user that uses this indoor outdoor detection method. This is probably due to differences in users' behaviour, which can easily be solved with an initial calibration, but also due to a different environment which definitely affected the results. Moreover, device sensors themselves are a variable not taken into account. Can training a model in one device for a user and environment apply to the same user in the same environment but a different device? This are all interesting aspects to take into account in future work.

6. CONCLUSIONS

An indoor outdoor detection model was proven to be viable by utilizing smartphones. The model was created as a classification machine learning model. The inputs of the model were several features that change with the user's context, and the output was the indoor or outdoor label of the current context. Additionally the model's design took into account battery consumption, so it was optimized for a high prediction accuracy as well as a low battery consumption. Three models were designed, all using different features to assess their results based on these metrics. They were also analyzed when subsampling was taken into account to further decrease the battery consumption. There is a definite relation between prediction accuracy and power consumption, and further work needs to be done to improve the prediction at lower power consumption rates. The most energy efficient model was tested against extreme cases to assess its robustness, and it was clear that to provide an accurate model, an initial training phase to the future circumstances of the user is necessary for now.

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[48] Trepn power profiler - qualcomm developer network. URL: `https://developer.qualcomm.com/software/trepn-power-profiler`.

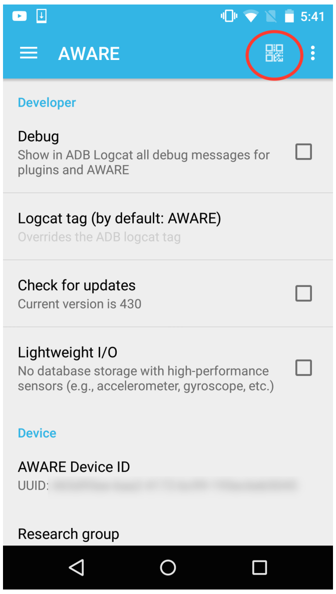
[49] Trepn profiler - android. URL: `https://play.google.com/store/apps/details?id=com.quicinc.trepn`.

8. APPENDICES

Appendix 1	Instructions for participants
Appendix 2	Architecture diagram of the data collection system
Appendix 3	Architecture diagram of the Indoor Outdoor detection system

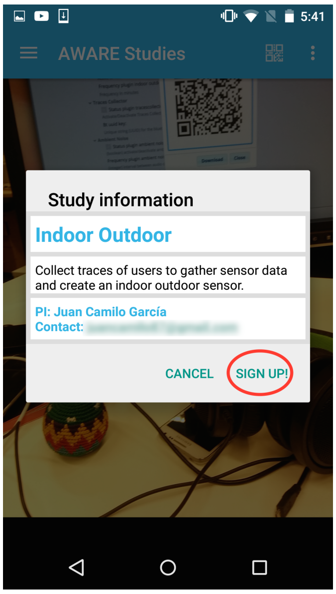
Instructions for participants

Follow this instructions to join the Indoor Outdoor data collection study. If a step is unclear, please contact us.
1. Install on the second phone the .apk file named "Indoor Outdoor Remote.apk".
2. Install on your personal phone the .apk file named "Aware Framework".
3. On your personal phone open the application "Aware"
4. Click here:

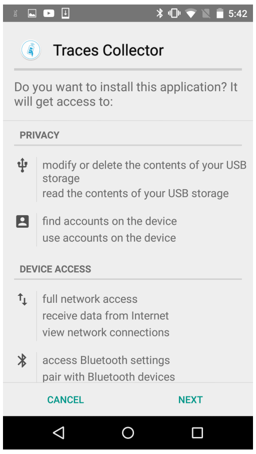


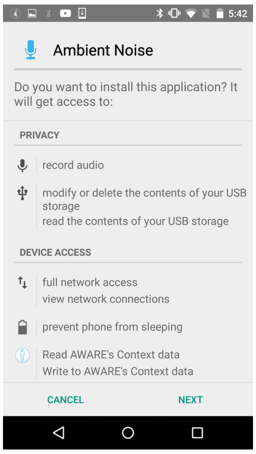
5. Scan this QR code:

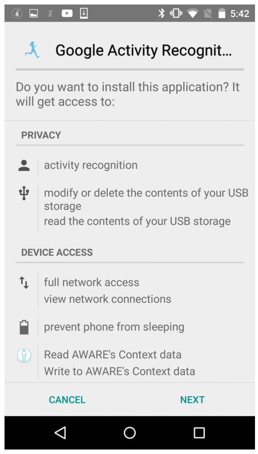
6. Click here:

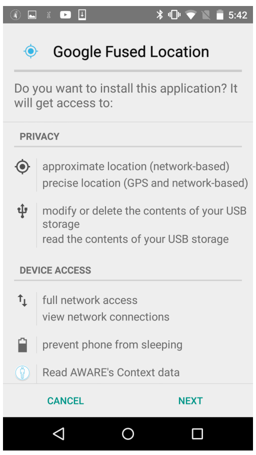


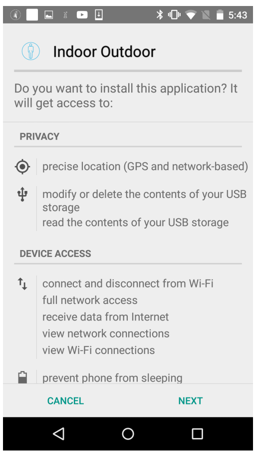
7. Wait. The application will close and it will start downloading 5 other applications which will be running in the background collecting data. During the download of the applications acceptance to install the applications will appear. It will also request to turn on Bluetooth. Accept all the dialogs. This are the screenshots of the installations.



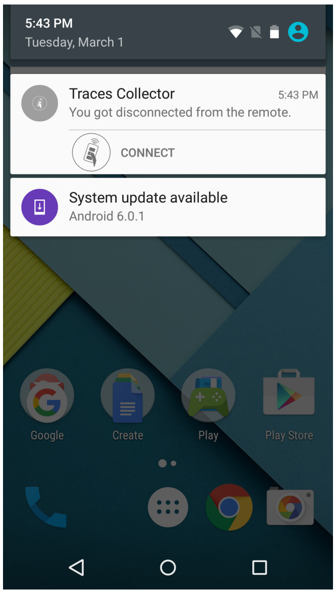




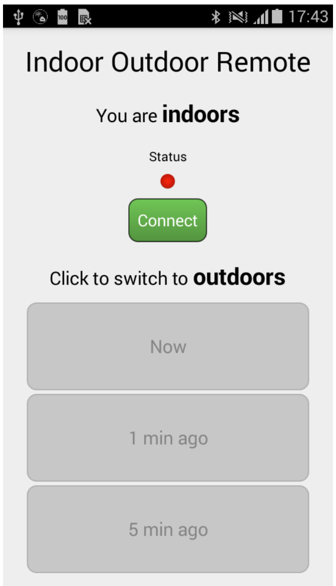




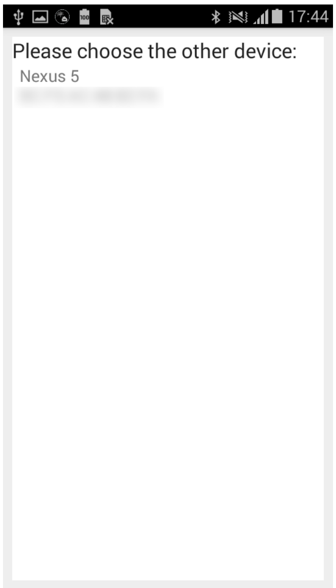
8. When everything is installed, the notification will appear in the notification bar. This notification will be permanent during the whole duration of the study.



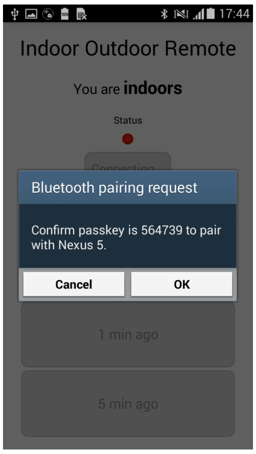
9. Click the notification (NOT the "Connect" button).
10. The second device will also have a notification, open it. The following screen will appear:

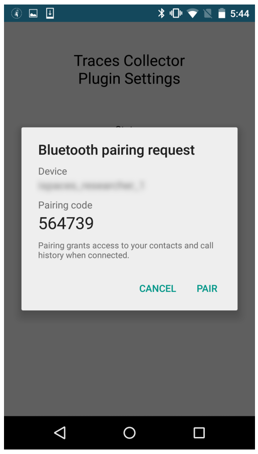


11. Click connect on your personal phone. It will request to enable discoverable mode.
12. Click connect on the second phone. A screen similar to the following should appear on your personal phone.

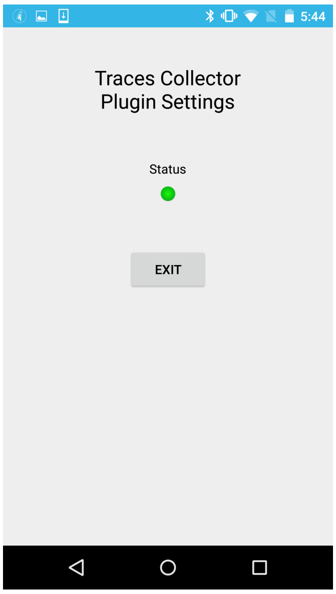


13. Click the device of the list. The pair messages of Bluetooth paring should appear. Follow the pairing instructions on the devices.

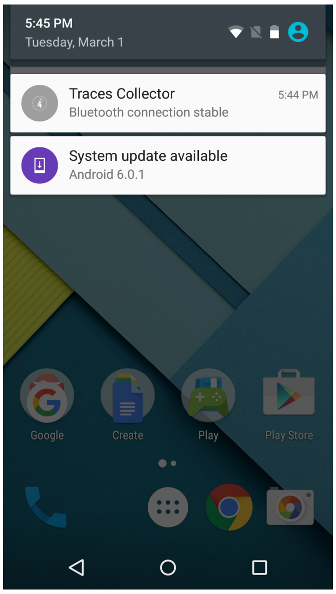




14. The devices should be connected at this stage. On your personal device, click Exit.

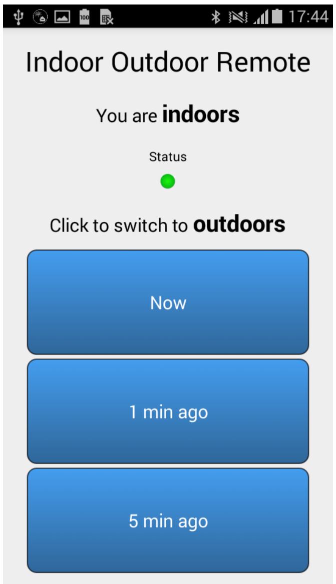


A permanent notification should appear saying "Bluetooth connection stable".

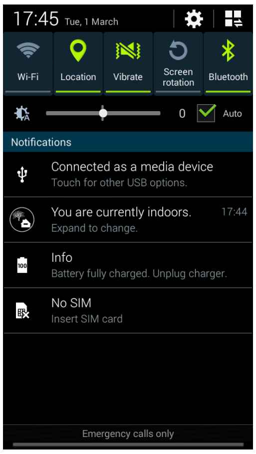


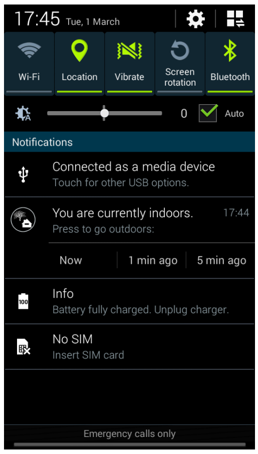
When the devices get disconnected, the notification will change. The devices will try to reconnect automatically, but in case of failure, you will need to connect them again following the previous process.

15. Now the data collection begins. When you go outdoors or go indoors, the corresponding buttons should be clicked. Based on the following image, if you are indoors and are going outdoors, click the button "Now". If you forget, and you estimate it was around a minute ago, press "1 min ago", or if you estimate 5 minutes then "5 min ago". If it was longer than 5 minutes, press "5 min ago" and write down in a log the time of pressing the button as well as the time the real transition occurred.



The previous process can also be done directly from the notification in the second device.

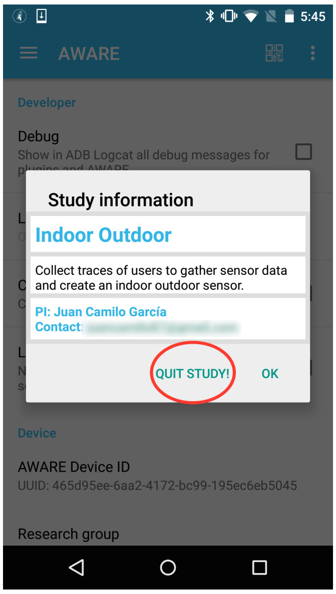




Notes: Since many sensors will be turned on, you might experience a faster battery drain than usual, so please be prepared to charge your phone.

When the study finishes:

1. Open Aware on your personal phone and click here:



2. If you have a debriefing session, bring both phones to the debriefing. If you do not have a debriefing, follow the next steps.

3. Extract the files from your personal phone located in the following folders.
- /sdcard/Android/data/com.aware/files/Documents/AWARE/
- /sdcard/Android/data/com.aware.plugin.ambient_noise/files/Documents/AWARE/
- /sdcard/Android/data/com.aware.plugin.google.activity_recognition/files/Documents/AWARE/
- /sdcard/Android/data/com.aware.plugin.google.fused_location/files/Documents/AWARE/
- /sdcard/Android/data/com.aware.plugin.indoutdoor/files/Documents/AWARE/

- /sdcard/Android/data/com.aware.plugin.tracescollector/files/
Documents/AWARE/

4. Extract the following file from the second phone:
- /sdcard/Queue_Estimation/traces.csv

5. Uninstall Aware from your personal phone.

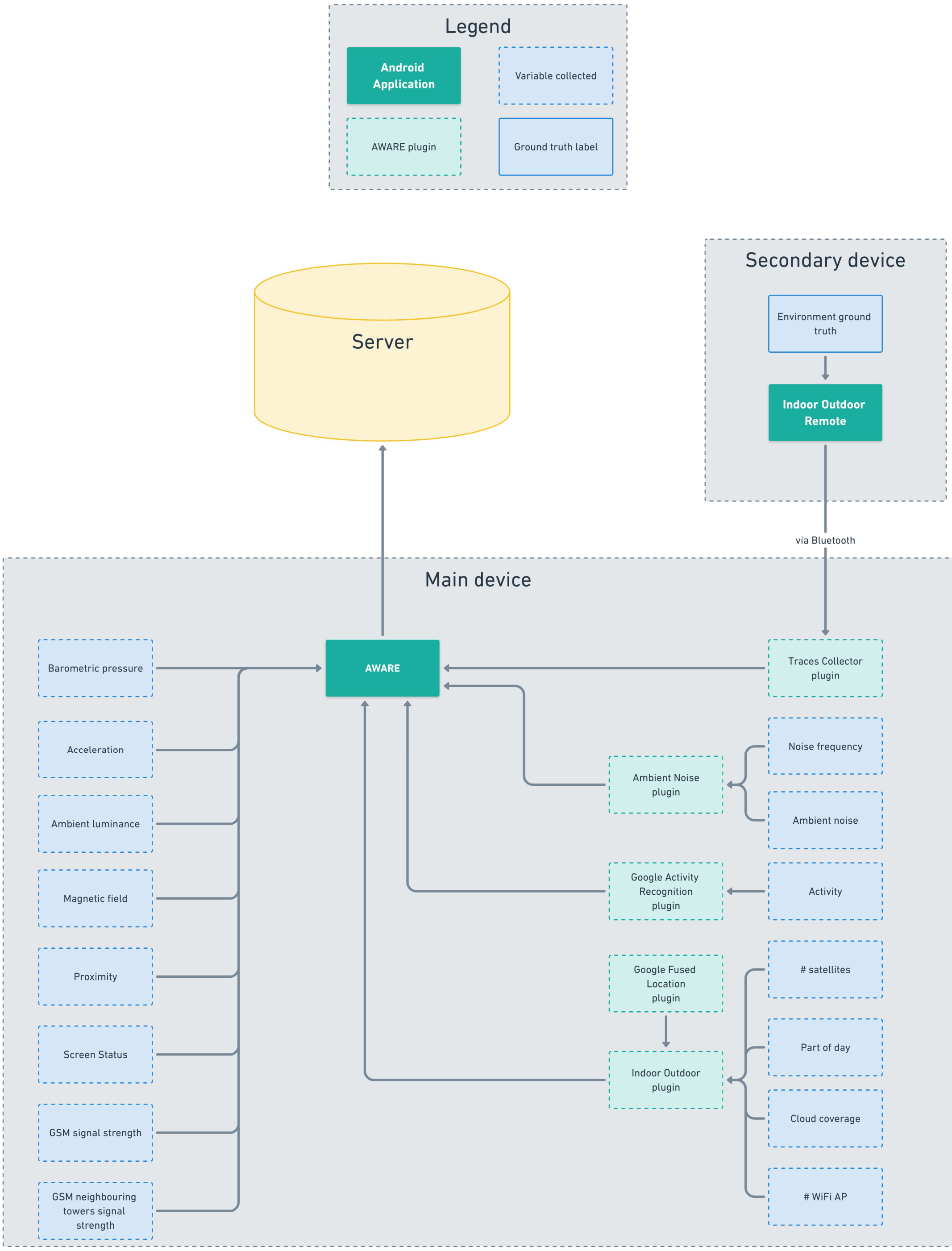
6. On your personal phone, go to settings, applications and uninstall the following applications.

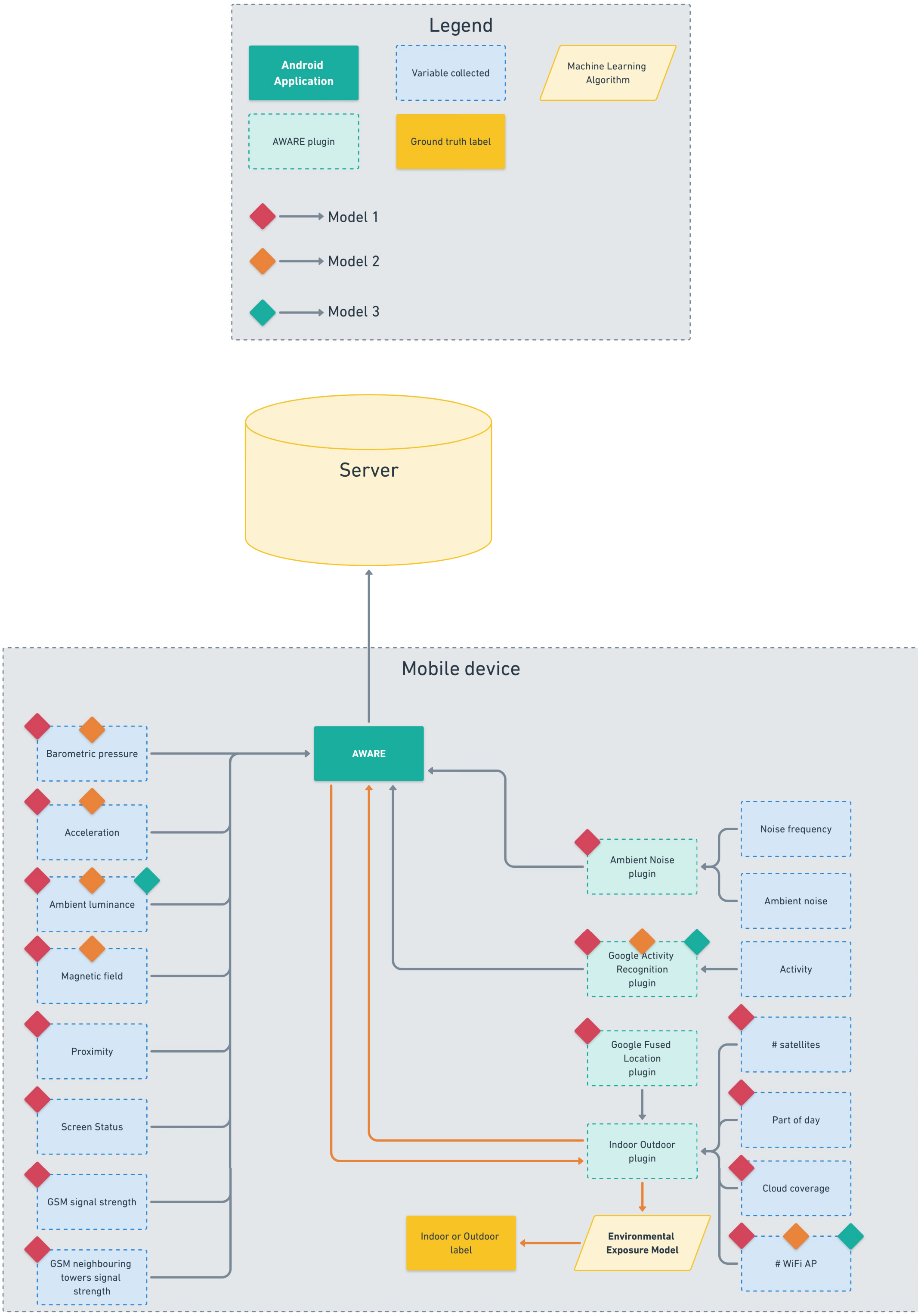
- Ambient Noise
- Google Activity Recognition
- Google Fused Location
- Indoor Outdoor
- Traces Collector

7. Uninstall the application "Indoor Outdoor Remote" from the second phone.

8. Send us the log you wrote about the transitions and wait for our confirmation and additional questions.

Thank you for your participation in the study.


Legend
Android Application
Variable collected
AWARE plugin
Ground truth label
Secondary device
Environment ground truth
Indoor Outdoor Remote
Server
via Bluetooth
Main device
Barometric pressure
AWARE
Traces Collector plugin
Acceleration
Noise frequency
Ambient Noise plugin
Ambient luminance
Ambient noise
Magnetic field
Google Activity Recognition plugin
Activity
Proximity
Google Fused Location plugin
satellites
Screen Status
Part of day
Indoor Outdoor plugin
Cloud coverage
GSM signal strength
GSM neighbouring towers signal strength
WiFi AP


Legend
Android Application
Variable collected
Machine Learning Algorithm
AWARE plugin
Ground truth label
Model 1
Model 2
Model 3
Server
Mobile device
AWARE
Barometric pressure
Acceleration
Ambient luminance
Magnetic field
Proximity
Screen Status
GSM signal strength
GSM neighbouring towers signal strength
Ambient Noise plugin
Noise frequency
Ambient noise
Google Activity Recognition plugin
Activity
Google Fused Location plugin
satellites
Part of day
Indoor Outdoor plugin
Cloud coverage
WiFi AP
Indoor or Outdoor label
Environmental Exposure Model