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Data Sharing in Participatory Social Sensing

Master Thesis

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Abstract

Data from citizens needs to be collected and analysed to create or improve current services in society. Data collected from them, in general, reveals information about their behaviour and choices. In addition, it can also reveal sensitive information, that they might not be comfortable with. To preserve the privacy of citizens is where data privacy comes into play. One of the methods to maintain data privacy is by letting citizens choose how much data to share. The lesser data that is shared or higher the privacy that is chosen, the more concealed the data is. Given the choice, citizens would generally choose the highest privacy level. At times, less concealed data is needed while solving problems that need data with less errors. To help citizens reduce the level of privacy of the data when needed, different kinds of incentives can be used, such as monetary incentives. From a fixed budget on the demand side, rewards(incentives) are handed out to citizens to incite them to give less privatized data, yet maintaining a minimum level of privacy. The goal of the Thesis is to understand the social dynamics of privacy and information sharing. Existing data can be used or data can be collected for the purpose of the analysis.

Today, smartphones that are being carried by billions of people have inbuilt sensors like the location, accelerometer and gyroscope. The interconnected network of smartphones where users can share large volumes of data about their behavioural and social aspects is called participatory social sensing.

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Chapter 1

Introduction

In today's world, almost everybody owns a smartphone. Information collected from a large number of interconnected smartphones equipped with multiple number of sensors each can aid to accumulate large volumes of data which is heterogeneous and autonomous in nature. This large amounts of data in any form is called Big Data¹ and it is the stepping stone to large scale data analytics and Deep learning to understand the complexities in our society.

Currently, a lot of the data collected in mobile applications² and on the web³ is done in a manner where users are unaware of the collection of their data. This process not only lacks transparency but also does not give users control over their data. Users should be able to make informed decisions about what data to share or not. Additionally, since no privacy algorithms are implemented on the data collected, user privacies are at risk. Paul Ohm in his paper [17] explains that it can be shown that anonymized data can be de-anonymized surprisingly easily. In this dissertation, focus is not given on the attacks such as hacking and any other methods but concentrated on the threats to the information in the data collected.

The aim is to setup a fair way to collect data by setting up a platform over a participatory sensing network where users can trade their data for some incentives to stakeholders who approach them. Incentives can be money, vouchers or anything else. Stakeholders inform users about the date, duration for which data is collected, who will use the data and what will it be used for. Additionally, users have the possibility to share data with some added levels of privacy. To achieve this goal, it is first essential to understand the relationship between incentives and mobile sensor data sharing. In this

¹Date:23-08-2016 https://en.wikipedia.org/wiki/Big_data

²Date:23-08-2016 http://www.theregister.co.uk/2014/02/21/appthority_app_privacy_study

³Date:23-08-2016 <http://www.techlicious.com/blog/whos-gathering-your-personal-information>

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dissertation, a survey and social experiment is designed where a platform is created and users can trade and view their data in a transparent manner. Data from user inputs and decisions is collected and later analysed to throw light on user decision of their sensor data.

Chapter 2

Related Work

Participatory social sensing is the active participation of users with their mobile phones and any other sensory devices to form a network that enables the collection and analysis of data. The ubiquity of mobile devices and cellular infrastructure makes it a possibility to obtain data over a large area for no incremental cost. Burke et al introduce the concept [4] and talk about the potential benefits and propose an initial architecture. Collecting data from various sensors is important for Big data analysis and to find answers to complex social questions such as sentiment evolution and the spread of epidemics ???. Lei Song et al [21] performed an extensive survey on the sensory devices for the purpose of health sensing and found that different sensor combinations is the pillar to obtaining meaningful signals. Giannotti et al [12] propose the *Planetary Nervous System* to collect data from connected sensors and use that data to do big data analysis with privacy awareness.

Some applications of participatory sensing are LiveCompare, TraficSense and CenseMe mobile applications. LiveCompare is introduced by Linda Deng et al [11] where the widespread availability of mobile phones is made use of to find cheap groceries making use of the camera for barcode decoding and location to find the stores. TraficSense by Prashanth Mohan et al [16] is a concept aimed to keep track of traffic on the road with a mixture of traffic and vehicle types. It collects a variety of sensor data such as the accelerometer and the location but not limited to them. CenseMe created by Emiliano Miluzzol et al [15] where friends in social networks can share their status in terms of their mood, activity, surrounding and habit. This includes physical and virtual sensors that can capture the online life of a person.

Participatory sensing is needed for a fairer system to trade data due to the fact that many mobile applications take data away from users without their knowledge. Jinyan Zang et al [22] did a study using 110 Android and iOS apps to find the ones that share personal information, behavioural information and location data with third parties. This also revealed that collecting

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user information does not require a notification from the application. They also found that paid applications still shared sensitive information to third parties.

Ashwini Rao et al [20] examined the behavioural profiles formed by Google and Yahoo. Participants were surprised and concerned that data has been collected from them. Additionally, the profiles formed were found to be in some aspects inaccurate and had excess of information, that the profiles did not seem to be anonymous anymore. Further, a survey was created asking participants questions about the behavioural profiles and was launched on Amazon Turk. Participants found the profiles formed to be not easily accessible and also complained that they wanted to know more about who is going to use their data and for what it will be used. Overall, the impression of participants is that the whole process of collecting data lacked transparency. This shows that there is a need for more privacy and control of data from the user side.

Studies have been done to investigate the relationship of users and their data. Alesandro Acquisti et al [1] created a survey to observe the privacy concerns in e-commerce preferences and masking of location data. They found that users do not make reckless decisions, rather they make decisions based on what information they have, how much they care and what they believe the effect of their actions will be. This leans on the fact that with sufficient information users can make rational choices about the privacy of their data.

Rebecca Balebacco et al [2] study through surveys and an experiment that users do not remember the sensors accessed by each application, shown during installation of the mobile application and proposes to inform users during the use of the application itself before collecting the sensor data. Similarly, Lin Jialiu et al [14] examines through crowdsourcing the perception of users to the data collection from mobile applications. The main takeaway from here is that users felt more comfortable if the purpose of a resource access was stated.

Additionally, studies have been done on assessing sensor data sharing in mobile phones. George Danezis et al [10] did a study to assess how much people value their location data using auction technique. They found that the median bid was 43\$ a period of one month, but this varied a lot on whether the person was a student, the relationship status and their travelling habits. Dan Cvreck et al [9] also examines the value of location privacy with over 1200 people and varied demographics. In this case the users were told fake goals in order not to be biased about their data privacy. Contradictions were found to the study [10] about the change in value due to travelling habits, but the median bid was found to be the same. There was also differences in results among the uses with different demographics. This shows that one

incentive does not fit to all users.

Delphine Christine et al [8] perform an extention of the study in the paper of George Danezis et al [10]. It is attempted to analyse how various factors can affect data sharing such as demographics, incentives and spatio-temporal elements vary the importance users have on their data for various sensors. Other aspects such as the purpose for which data is shared and to whom the data is shared is also studied. It is found that younger people and people with affiliations with buyers of their data tend to share more information. They also found that users claimed more rewards to corporations. The work by Camp Jean [5] has mentioned that the participants of the surveys may not tell the truth despite of financial rewards. The later only ensures that the users successfully complete the survey.

Other than the surveys, there are studies done on the mobile phones themselves. Brush et al [3] collect the location data of 32 users for a period of 2 months. Users have five privacy options they can choose from:

- Deleting near home
- Mixing to provide k anonymity
- Randomizing
- Discretizing
- Subsampling

At the end of the two months, users were shown visualizations of their data. The authors mentioned that the user interface was not intuitive and that users might have been biased to the location data due to the experimental setup. Additionally, it was found that users were not consistent with privacy decisions and with whom they shared data. It was concluded that users need to be properly informed about every detail to enable them to make rational choices.

Haksoo Choi et al [6] is a framework that provides sharing of sensor data based on rules along with the possibility of applying obfuscation algorithms. They found that users share data with a purpose and hence the purpose of data sharing should be included in the rules. Additionally, Eiji Hayashi et al [13] with 20 participants examine the sensor data sharing with all or no options. It is found that all or no options are a poor fit for user preferences and sharing of partial sensor information should also be provided.

Various algorithms can be used to protect the privacy of users while providing various amounts of data sharing possibilities. Pournaras et al [19] propose a scheme where users have the possibility to share various amounts of data. Users supply data to the data aggregators who buy data. The incentives that are received depend on the quality of the data that is shared and

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the quality required by the data aggregators. If the data shared is of lower quality then the errors in data processing increase. Similarly, with higher quality the data processing tasks will give lesser errors. The process of manipulating the quality of sensor data is called summarization. The errors in the data has the possibility to be mitigated if there is a large population of users participating in the data sharing tasks. Summarization concerns algorithms from simple arithmetic functions to clustering algorithms.

In this dissertation the following drawbacks have been addressed:

- **Transparency of data collection** - users are informed about the process, time, duration of data collection
- **Easier data accessibility** - users can access data collected using a web application directly from the mobile application
- **Provide more information about data collection** - users are informed about what data is being collected, who is collecting their data and the purpose of the collection
- **User control over their data** - users have the possibility to choose the quality of data to share instead of all or no options
- **Personalized incentives** - each data request is assigned incentives based on the individual user profiles

Delphine Christine et al [7] conclude their paper on the challenges for the future, the following points have been addressed [18]:

- Including the participants in the privacy equation
- Providing composable privacy solutions
- Trade-offs between privacy, performance and data fidelity
- Making privacy measurable
- Defining standards for privacy research
- Holistic architecture blueprints

Chapter 3

Computational Model

3.1 Introduction

A data request is a request to users to trade their mobile sensor data. The aim is to create a computational model that is able to assign personalized rewards to each data request for every user. Each user is associated with a privacy intrusion profile. The model uses the user profiles to assign each data request a maximum achievable reward. The model attempts to identify the data requests where users might not be inclined to share mobile sensor data. These data requests are assigned a higher maximum obtainable reward. Similarly, the data requests where the users would want to share more mobile sensor data are assigned a lower maximum obtainable reward. This permits to see whether incentives do indeed make a difference in mobile sensor data sharing. The model aims to identify the amount of data each user would share for a data request and assign maximum obtainable rewards accordingly.

3.2 Model

The sections below explain the various building blocks of the computational model. The Figure 3.1 provides an overview of the flow of the model.

3.2.1 Collecting User Information

To begin with the model, user information is collected. The information collected consists of but is not limited to :

- Gender
- Year of birth
- Country

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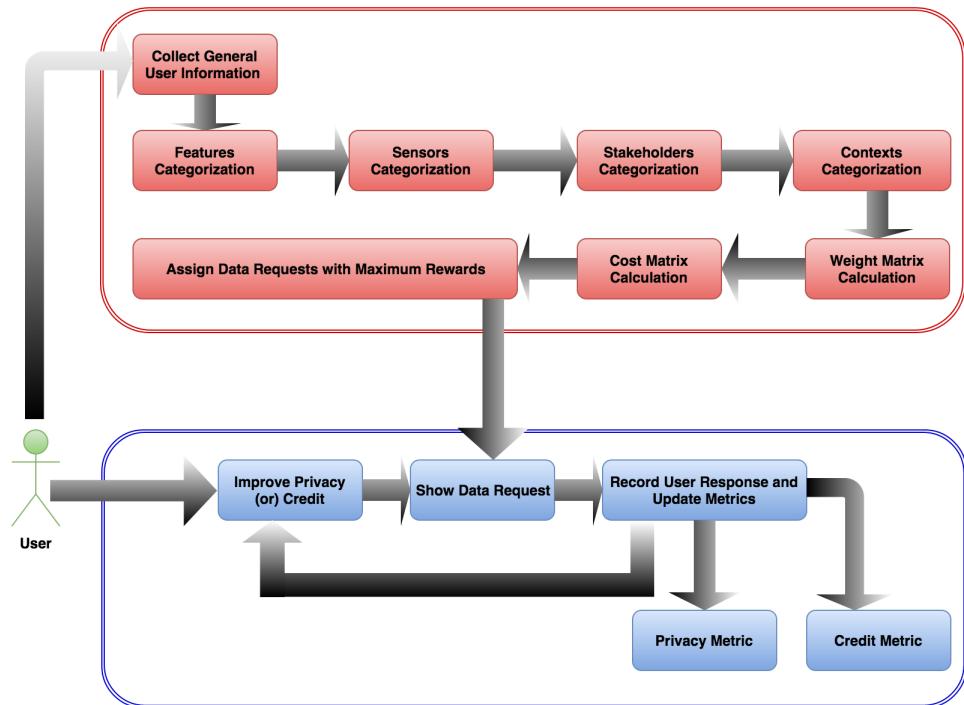


Figure 3.1: Computational Model Flow Chart

- Education Level
- Occupation
- Frequency of mobile phone use per day
- List of different mobile applications present on the users phones

3.2.2 Categorization of the Features

Features are the elements that govern the data sharing decision. A feature can be one of the following:

- **Sensors** : They consist of the sensors in the mobile phone that users can trade for a data request
- **Stakeholders** : They consist of any entity that requests users for mobile sensor data
- **Contexts** : They consist of the purpose for which a stakeholder would like to obtain the user's mobile sensor data

Features are placed in categories according to how privacy intrusive they are. Features are the three dimensions that form a data request. A data

request is defined as a stakeholder asking users to share their mobile sensor data for a particular context. Users are asked to categorize the features into one of the five categories:

1. Very low privacy intrusion
2. Low privacy intrusion
3. Medium privacy intrusion
4. High privacy intrusion
5. Very high privacy intrusion

Categories are linearly scaled and equally spaced. As indicated by the numbers on the left of the categories, these range from 1 to 5 and users can place each of the features in a category according to their perceived intrusion level. Category 1 represents that the feature does not at all contribute to the data sharing decision. Similarly, category 5 represents that the feature contributes to the maximum possible for the user's data sharing decision. It represents that users are reluctant to give away their sensor data for this feature. More than one feature can be placed in the same category.

Let the variable n_{cat} represent the number of categories, which here are five. Additionally, let the category assigned to the sensors be represented by the variable a , the category assigned to the stakeholders be represented by the variable b and the category assigned to the contexts be represented by the variable c .

Once users have categorized the sensors, stakeholders and the contexts into the respective categories reflecting the importance of each of the features in the data sharing decision, each feature is assigned a weight. Let the respective weights of sensors, stakeholders and contexts be represented by the variables, w_a , w_b and w_c and calculated as follows:

$$w_a = \frac{a}{a + b + c} \quad (3.1)$$

$$w_b = \frac{b}{a + b + c} \quad (3.2)$$

$$w_c = \frac{c}{a + b + c} \quad (3.3)$$

3.2.3 Categorization of the Sub-Features

Once the features have been categorized and their weights calculated as above, sub-features are to be categorized. A sub-feature is defined as one type of a feature. In other words, sub-features are the different types of features that appear during data request to the user. The following are examples of sub-features for each feature :

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- Sensors :
 - Accelerometer
 - Battery
 - Gyroscope
- Stakeholders :
 - Corporation
 - Government
 - Educational Institution
- Contexts :
 - Education
 - Navigation
 - Gaming

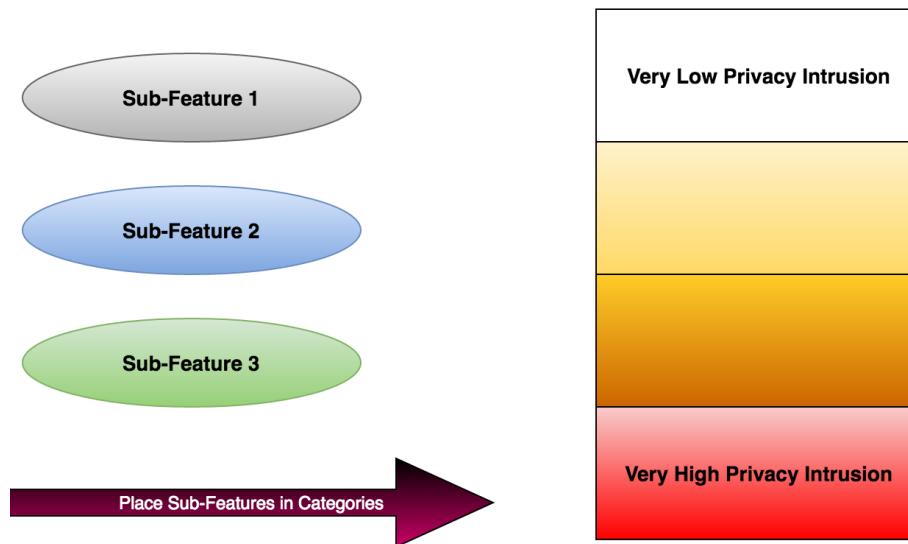


Figure 3.2: Categorizing Sub-Features according to the perceived Intrusion Level

Each of the above are different kinds or sub-features of the respective features. For each of the available features, the respective sub-features need to be in turn categorized in the same categories mentioned in section 3.2.2. The

categories are the same as mentioned in the previous section. Let n_{sf} be the number of sub-features each feature has.

As seen in the conceptual diagram which is shown in the figure 3.2, users place each of the sub-features available for every feature in the given categories.

Let every sub-feature be represented by unique indices within its feature. For example, in the list of sub features provided above, accelerometer is the first sub-feature of sensors, corporation is the first sub-feature of stakeholders and education is the first sub-feature of contexts. For each of the sub-features of sensors, categories they are placed in by users is represented by a_i and i is the index of the sub-feature. Similarly, categories assigned to sub features of features stakeholders and contexts respectively are represented by b_j and c_k , where j and k are the identifiers of the sub-features categorized.

3.2.4 Weight Matrix Calculation

Each data request to users consists of the three above mentioned features in them. Each of the features each have n_{sf} sub-features that can appear in turns in a data request assuming that each feature has the same number of sub-features. The total number of possible data requests are $n_{dr} = n_{sf}^3$.

Let W be a matrix with three dimensions $n_{sf} \times n_{sf} \times n_{sf}$. We call this the weight matrix. Each cell of W , that is $W_{i,j,k}$ represents a data request which involves the sensors sub-feature with identifier i , stakeholders sub-feature with identifier j , and the contexts sub-feature with identifier k . That is, each cell of W represents the weight of a data request to the users. The aim of the weight matrix is to use the information collected from the user categorizations, to assign weights to each data requests. Intuitively, the process examines the data requests where the user is least likely to trade data and assigns higher weights to those data requests. This process is seen in Section 3.3 with examples. As mentioned before, each cell of the matrix W represents the weight of a data request with a unique sensor sub-feature i , stakeholder sub-feature j and context sub-feature k . To calculate the weight of a data request :

$$W_{i,j,k} = (a * a_i) + (b * b_j) + (c * c_k) \quad (3.4)$$

Applying this formula for every possible values of i, j and k gives the weight matrix W .

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3.2.5 Cost Matrix Calculation

The aim is now to assign a maximum obtainable rewards to each data request. This reward is the maximum credit users can receive for a particular data request. Let C be the cost matrix with the three dimensions $n_{sf} \times n_{sf} \times n_{sf}$. Let it be assumed to have a budget of B for a day, where B can be in an actual currency or any virtual credits. In this thesis the budget will be referred to with the unit credits. Each cell of the cost matrix will represent the amount of rewards allocated for a particular data request for one day. To begin with, we calculate the sum of all the cells of the weight matrix W :

$$s_W = \sum_{i=1}^{n_{sf}} \sum_{j=1}^{n_{sf}} \sum_{k=1}^{n_{sf}} W_{i,j,k} \quad (3.5)$$

where the function s_W gives the sum of a matrix, in this case the weight matrix. Let $C_{i,j,k}$ represent the credit allocated for the data request which involves the sensor's sub-feature with identifier i , stakeholder's sub-feature with identifier j , and the context's sub-feature with identifier k . To calculate one cell of the cost matrix :

$$C_{i,j,k} = \frac{W_{i,j,k} * b}{s_W} \quad (3.6)$$

Repeating the above for every cell of C , the entire cost matrix can be calculated. Now, all the maximum obtainable rewards have been allocated per day for every data request.

3.2.6 Cost and Privacy Metrics

Every data request has been assigned a reward. This is the maximum reward that a user can obtain for that data request. The cost metric is the amount of rewards the user has obtained by trading sensor data for each data requests. Similarly, the privacy metric is the amount of privacy percentage obtained while trading data for requests. It intuitively quantifies the amount of data the user has refused to share hence implying privacy. The cost and privacy metrics are inversely proportional to each other, in the sense that when the cost increases the privacy decreases and vice versa.

In each data request one chooses how much data is to be shared, from the maximum amount of data to no data at all. The possible responses to a data request are called options. Each option corresponds to a summarization level explained in detail in section 3.2.8. The reward assignment to each option is linearly scaled according to the reward assigned to each data request. Let us assume there are options for a data request ranging from 1

to m (numeric options), where 1 corresponds to the option where the users give all their data for a request and m to where the users choose not to give any data for a request. Therefore there are a total of m options for every data request. Each option in a data request has the following:

- The amount of credit change if this particular option for a data request is chosen
- The amount of privacy change if this particular option for a data request is chosen

While assigning rewards to data requests there are two scenarios to consider:

- Assigning option rewards without a participation reward. Users are not rewarded for responding to data requests
- Assigning option rewards inclusive of a participation reward. Users are rewarded for responding to data requests irrespective of the option chosen

Let us examine the first scenario. Let the option rewards be calculated for the data request with sensor sub-feature i , stakeholder sub-feature j and context sub-feature k . The assigned reward for any option numbered h of this data request is calculated as follows:

$$r_h = \frac{C_{i,j,k} * (m - h)}{m - 1} \quad (3.7)$$

Applying this formula by replacing h by the option numbers from 1 to m gives the reward the user can receive for each option. Similarly, if a participation reward is assigned to each option, it would mean that even though the user does not share data, they still receive rewards for answering the data request. This concept can be implemented to ensure user participation in the experiment. Let x be a fraction of the total budget B that is dedicated for user participation. Using a geometric progression with $a = 1$ and $z = \sqrt[m-1]{x}$, we can calculate the fraction of the maximum reward obtainable from a data request f_h , an option numbered h gets:

$$f_h = a * z^{h-1} \quad (3.8)$$

The fraction of the rewards an option h can be assigned has been calculated, to get the rewards r_h of option h for the data request with sensor sub-feature i , stakeholder sub-feature j and context sub-feature k :

$$r_h = f_h * C_{i,j,k} \quad (3.9)$$

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This assigns rewards to each option, taking into consideration a participation rewards that the user gets even if data is not shared for that data request.

Privacy percentage p_h is linearly scaled between the first to the m^{th} option between 0 and 1 as follows:

$$p_h = \frac{(h - 1)}{m - 1} \quad (3.10)$$

The total cost and privacy is the sum and arithmetic average of all the rewards and privacy respectively, obtained from every answered data request. If a data request is left unanswered, a maximum privacy of 1 and minimum cost of 0 credit is assumed.

3.2.7 Improving the Metrics

Users can choose to improve the privacy or credit metric. If one chooses to improve their credit, the data request where maximum rewards can be obtained is fetched from the database. Otherwise, if users want to improve their privacy the data request which can maximize the privacy is fetched from the database. Additionally, options that can improve the metrics are indicated.

3.2.8 Summarization of Collected Data

Each data request has the possibility to have m number of options the user can choose from for every data request. These options range from 1, which indicates that the user would like to give all his data, to option number m , which indicates that the user does not want to give any data to this data request.

Summarization is a privacy algorithm that modifies the quality of data to provide less information than in its original form [19]. A higher summarization level gives data with a lower quality. A lower summarization level gives data with a higher quality. In this model, sensor data is collected for a period of d hours every y seconds for every data request. If the data is summarized, according to the option chosen, the data is collected either every y seconds or less.

Data is collected for the d hour period, and at the end of this period according to the option chosen by the user, it is summarized. Summarization can be linearly assigned to each option. The highest privacy option m corresponds to the highest summarization level. The first option corresponds to the lowest summarization level. An example of assigning the summarization level l_h for an option h for a data request has the possibility of the following :

$$l_h = y * h \text{ where } h \neq m \quad (3.11)$$

This gives the frequency of sensor data collection for every option of a data request.

3.3 Analysis of the Model

In this section, three different examples are explained in order witness some properties of the weight and cost matrices.

3.3.1 Setup

In the following examples, the following features and sub-feature are considered:

1. Sensors
 - a) Accelerometer
 - b) Noise
 - c) Location
2. Stakeholders
 - a) Corporation
 - b) Government
 - c) Educational Institution
3. Contexts
 - a) Navigation
 - b) Environment
 - c) Social Media

Numbers indicated to the left of the sub-features are the corresponding unique indices. This uniquely identifies a sub-feature of a feature. There are in total $num_{sf} = 3$ sub-features for each feature. Each user will receive a number of

$$num_{sf}^3 = 27$$

data requests in total. The number of categories available to categorize is $cat = 5$ as explained in 3.2.2. Additionally, it is assumed that a budget $b = 100$ Chf per day is available. The input to the model are the user choices during the categorization of the features and sub-features.

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3.3.2 Examples

To make reference easier to the graphs, instead of sub-feature names, numeric indices are used. From now on each feature and sub-feature will be referred to by its index such as feature 1 for sensors and sub-feature 2 of feature 1 for the noise sensor. The tuple (a,b,c) represents a data request with:

1. a - Sensor's sub-feature a
2. b - Stakeholder's sub-feature b
3. c - Context's sub-feature c

where a, b and c are all numbers from one to three.

If features and sub-features have all been given the same categories respectively by users, then all data requests should be assigned equal weights and rewards. In example 1, users choose categories for the features and sub-features as shown in the Table 3.1. From this input, the formulation of the weight matrix is shown in Figure 3.3a, and the cost matrix is shown in Figure 3.3b. For each data request indicated as a tuple of (sensors, stakeholders, contexts) in the x-axis of Figures 3.3a and 3.3b, all have identical weights and rewards. This is due to the fact that the users find all the features and sub-features equally intrusive so all the data requests are weighted equally.

Table 3.1: Categorization for Example 1

Feature	Sub-Feature ID = 1	Sub-Feature ID = 2	Sub-Feature ID = 3
Sensors	Accelerometer	Noise	Location
1	3	3	3
Stakeholders	Corporation	Government	Educational Institution
1	3	3	3
Contexts	Navigation	Environment	Social Media
1	3	3	3

It is concluded that if the users perceive the features and respective sub-features in an equally intrusive way, then all the data requests will receive the same weight and reward assignments.

In example 2, it is attempted to test if data requests containing sub-features with higher intrusion levels are assigned higher weights and rewards. Table 3.2 indicates the user input. As it can be seen, all features have equal categories, and all sub-features have the categories of 3 with an exception the sensor sub-features. The sensor sub-features with indices 1,2 and 3 have respectively categories 1,3 and 5. This means that requests with sensor sub-

3.3. Analysis of the Model

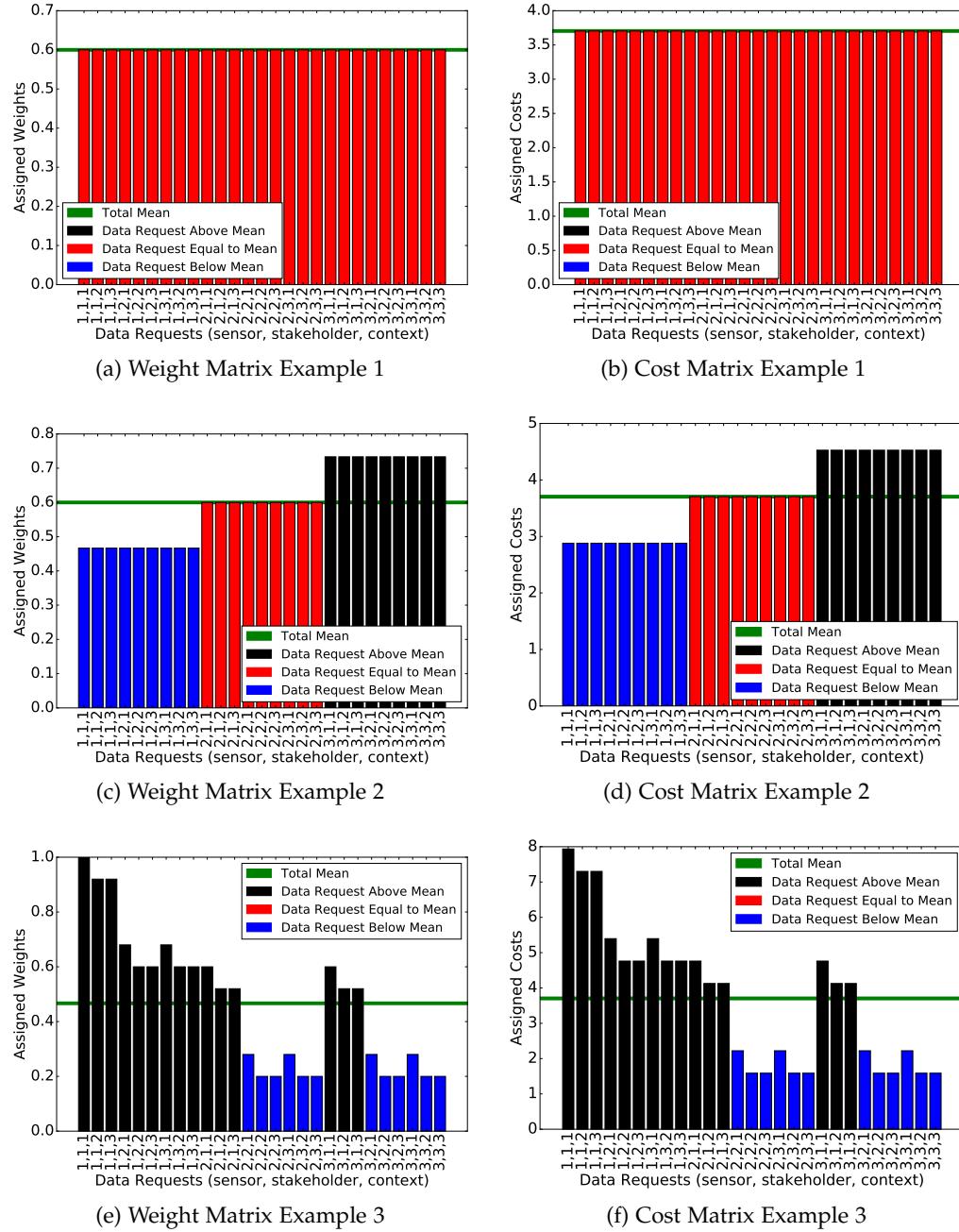


Figure 3.3: Values Assigned to Matrices

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feature 1 will be assigned a lesser weight in comparison to the other sensor sub-features.

Similarly, the data requests with sensors sub-feature 2 will have a higher weight assigned than sensor sub-feature 1 because of its higher category, but lower than sensor sub-feature 3. Lastly, data requests with sensor sub-feature 3 will have a highest weight compared to the others, due to the category being 5. The weight and cost matrices can be seen in Figures 3.3c and 3.3d respectively.

Table 3.2: Categorization for Example 2

Feature	Sub-Feature ID = 1	Sub-Feature ID = 2	Sub-Feature ID = 3
Sensors 3	Accelerometer 1	Noise 3	Location 5
Stakeholders 3	Corporation 3	Government 3	Educational Institution 3
Contexts 3	Navigation 3	Environment 3	Social Media 3

From the above inputs and graphs, it is concluded that the model assigns a higher weigh to data requests with sub-features that users find more intrusive compared to the others.

For example 3, the feature and sub-feature categories are both assigned different values, to show how varying their values together affects the assignments of the weight and cost matrix. Table 3.3 is the user input. All the features have different categories assigned from 3 to 5. Additionally, the sub-feature 1 of each feature has a category of 5, higher than the other sub-features which are all categorized as 1. The weight and cost matrices generated are shown in Figures 3.3e and 3.3f respectively.

Table 3.3: Categorization for Example 3

Feature	Sub-Feature ID = 1	Sub-Feature ID = 2	Sub-Feature ID = 3
Sensors 5	Accelerometer 5	Noise 1	Location 1
Stakeholders 4	Corporation 5	Government 1	Educational Institution 1
Contexts 3	Navigation 5	Environment 1	Social Media 1

3.3. Analysis of the Model

As it is observed in both figures, the data request with the highest weight is the one with the tuple (1,1,1). This tuple indicates that the data request involves all sub-features 1 of each feature. This happens because all of the sub-features 1 are assigned a category of 5. The feature sensor and its sub-feature 1 are categorized as 5, so all the data requests with tuple (1,*,*), where * is all the other possible sub-features from other features, are all above average as seen in Figures 3.3e, irrespective of the categories of the other feature sub-features. This shows that assigning a higher category to a feature can lead to higher data request rewards.

The green horizontal line in the graph indicates the mean value of the weights and rewards. In general due to sub-features categorized as 5, those data requests receive a higher weight and reward. In some cases, the data requests still receive a lower weight such as tuple (2,2,1), (2,3,1),(3,2,1) and (3,3,1) tough context sub-feature 1 has a category of 5. This is due to the fact that sensor and stakeholder feature have a higher category of 5 and 4 respectively than the context feature. Since their sub-features are assigned a lower privacy intrusion category than the context sub-features, the weight of the data requests is lower. This shows that even tough a sub-feature may be regarded as very intrusive, it's weight increasing changing ability depends on the category of the feature it belongs to.

Additionally, it is noted that data requests with at least two sub-features 1 are all above average. We can witness the property of the model, which puts more emphasis on the perception of the features than the sub-features themselves. As seen in the figure, all the features with higher intrusion categorizations have weights and rewards that are well above average.

It can be concluded that the model assigns weights to data requests, by emphasizing on the feature's weights. A feature with a high category has the ability to assign higher rewards with a highly categorized sub-feature. It also has the ability to lower the weight of a data request with a sub-feature lowly categorized. Features with lower categories contribute lesser to the weight assignments, irrespective of their sub-feature categories.

Chapter 4

Experiment Methodology

In the previous chapter, the computational model has been explained in detail. This model has been implemented as a mobile application for the Android platform and is used to collect real data from users. This application will help collect information that will aid to see the influence of incentives on the data sharing decision. In this chapter some of the work and decisions that are taken before and after the start of the experiment are explained. It is then proceeded to explain how the experiment is carried out along with detailed instructions to the usage of the mobile application created.

4.1 Preparatory Phase

4.1.1 Pre-Survey

The pre-survey¹ is a survey created that runs before the deployment of the social experiment. This survey was made in order to study the perception of users on the three features to be studied which are explained in detail in section 4.2.2. Figure 4.1² depicts the features and their sub-features visually.

As shown in the figure, there were a lot of sub-features to choose from each feature. Increasing the number of sub-features for each feature in the experiment in turn increases the number of data requests posed to the user. Additionally, we wanted to gain insight into the perception of users on the three features. Hence the survey was prepared to understand all of the above. Additionally, it can help redesign some of the aspects of the experiment based on the ambiguities found and user feedback. The participants pool consists of both people who are aware and unaware of data privacy and sensors. Participants were not paid for filling out the survey. Till now, 199 entries have been recorded.

¹https://descil.eu.qualtrics.com/SE/?SID=SV_0xGS6kfmr8GtQd7

²Figure made by Athina Voulgari

4. EXPERIMENT METHODOLOGY



Figure 4.1: The Three Features Examined

4.1.2 Sub-Features

Figures 4.2a, 4.2b and 4.2c, each show the average intrusion level of each possible sub-feature for the sensors, stakeholders and contexts. For the experiment, it was decided to choose for each feature two non-intrusive and two intrusive sub-features each. The minimum privacy intrusion level is one which indicates this sub-feature to not be intrusive, and the maximum is five which means that the sub-feature is very privacy intrusive.

For the sensors feature, it can be observed that the sub-features GPS and microphone are found to be have an intrusion of 4.2 and 3.8 on a scale of five, which means users find these sensors on average very intrusive. On the other hand, sub-features light and accelerometer are found to be lower in intrusion with values of 2.2 and 2.3 on a scale of five, which means that users find these sensors non-intrusive in general. The average of all sensors intrusion values is 2.8 as indicated by the blue line.

Similarly, looking at the stakeholder feature graph 4.2b, it is seen that sub-features corporation and government are found to be intrusive by the users with levels 3.8 and 3.6 on a scale of five. On the other hand, sub-features

4.1. Preparatory Phase

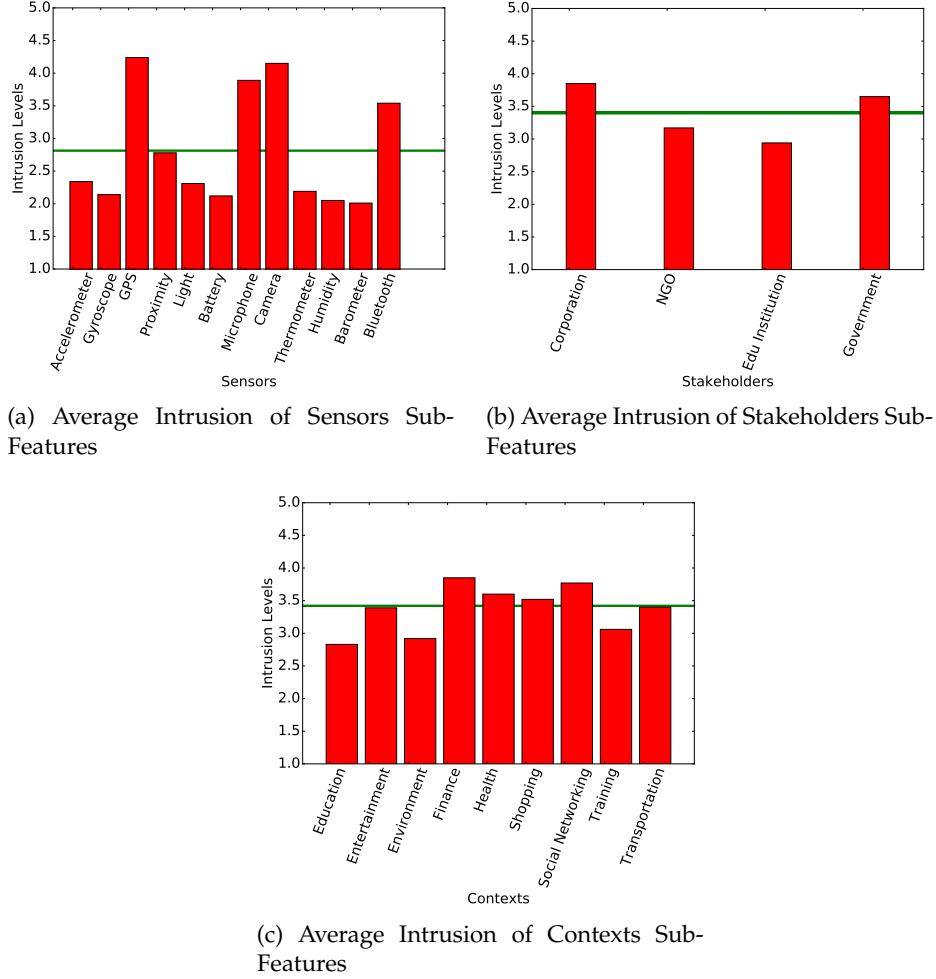


Figure 4.2

educational institution and non governmental organization are found to be relatively less intrusive by the users with values of 3.2 and 2.95. For intrusion levels of contexts feature in graph 4.2c, it is observed that sub-features social-networking and health are found to be intrusive by the users with values 3.8 and 3.6 on a scale of five. Sub-features environment and transportation are regarded as less intrusive by user with values of 2.9 and 3.3 on a scale of five. The above mentioned sub-features for every feature have been chosen for the experiment.

4.1.3 Privacy Options

Each data request is accompanied with privacy options ranging from 1 to 5 as explained in section 3.2.6. Option one indicates that the users would

4. EXPERIMENT METHODOLOGY

like to share their raw data without any sort of summarization or reduction in information. Option number 5 indicates that the users would not like to share their data for this data request. The options in between have linearly scaled summarization levels assigned to them ranging from least privacy (1) to most privacy (5). For more information on the summarization levels for each option please refer to section 3.2.8.

4.1.4 Question Structure

A data request is when a stakeholder asks users mobile sensor data for a particular context or purpose. Each data request to the user is posed in the form of a question with the following template :

"Please choose the amount of X sensor type data shared with Y stakeholder for use in a Z context app"

where Sensors X can be :

1. Accelerometer
2. Light
3. Noise
4. Location

where Stakeholders Y can be:

1. Corporation
2. Non Governmental Organization
3. Government
4. Educational Institution

and where Contexts Z can be:

1. Social Networking
2. Environment
3. Navigation
4. Health/Fitness

In total this makes 64 data requests to the user. From now on, we will refer to mobile sensor data as just data.

4.1.5 Budget and Experiment Duration

The experiment is set to run for a total of two days, excluding the time taken for the entry phase and exit phase. The budget set for the core phase

of the experiment is $b = 35$ Chf and is excluding the cost of participation in the entry and exit phase. Participants are paid 10 Chf for coming to the Entry Phase, and 15 Chf for participating in it. Similarly for the Exit Phase, participants are given 10 Chf for showing up, and 5 Chf for participating in it. Out of the budget B , $\frac{1}{7}$ is given away for the participation of the users in the core phase.

4.2 Entry Phase

The entry phase denotes the first day of the experiment. Users are asked to install the application from the PlayStore.

4.2.1 Collecting General User Information

As the figure 4.3 shows, the users are asked to answer some personal non-intrusive questions. The following is asked from the users:

1. Gender
2. Employment Status
3. Education Level
4. Year of birth
5. Country where user has lived most of his life
6. How many time a day do you check your Mobile phone per day.
7. Kind of applications the user has in the mobile phone.

The users may go back and re-answer the questions, but once the submit button is pressed on the screen 4.4b, the data is sent to the server and hence cannot be changed. Users cannot navigate to the next pages without filling out all the questions.

4.2.2 Categorization of Features

As described in chapter 3, the users are asked to categorize the features sensors, stakeholders and contexts. As shown in figure 4.4a, each of the features are indicated followed by a drop down list of privacy options ranging from "*very low privacy intrusion*" to "*very high privacy intrusion*". The option "*very low privacy intrusion*" means that the feature does not affect the users mobile sensor data sharing decision, whereas "*very high privacy intrusion*" refers to a feature that very much affects the sharing of mobile sensor data.

Users need to click on the drop down menu to choose one of the privacy intrusion options. All the options are compulsory, and no default option is

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(a) User Information Screen 1

Gender

Male Female

Year Of Birth

Education Level

How Concerned are you about the privacy of your mobile sensor data?

Not at all	Extremely			
<input type="radio"/> 1	<input type="radio"/> 2	<input type="radio"/> 3	<input type="radio"/> 4	<input type="radio"/> 5

SUBMIT

(b) User Information Screen 2

Employment Status

Full Time Part Time Not Looking for Work
 Looking for Work Retired Student Disabled

In what country did you spend most of your life?

How often do you check your mobile phone a day?

<35 36-70 71-100 101-135 >135

SUBMIT

Figure 4.3: User Information Screens

provided. Users cannot navigate to the next page without filling out all of the questions.

4.2.3 Categorization of Sub-Features

For each of the features categorized in the previous sub-section, their sub-features need to be categorized in a similar fashion. Once again, the privacy options range from "*very low privacy intrusion*" to "*very high privacy intrusion*" like in section 4.2.2 . The users are first presented with the categorization of Sensors sub-features as shown in figure 4.5a.

Below each sensor is a drop down menu where the user has the possibility to choose how much each of the sensors would affect the mobile sensor data sharing. Once all the sensors have been associated with a privacy intrusion level, the user can click the green submit button and is directed to the next page where the sub-features of stakeholders need to be in turn categorized in a similar fashion. This is depicted in figure 4.5b.

4.2. Entry Phase

(a) Categorizing Features (b) User Information Screen 3

Figure 4.4: Categorization and User Information Screens

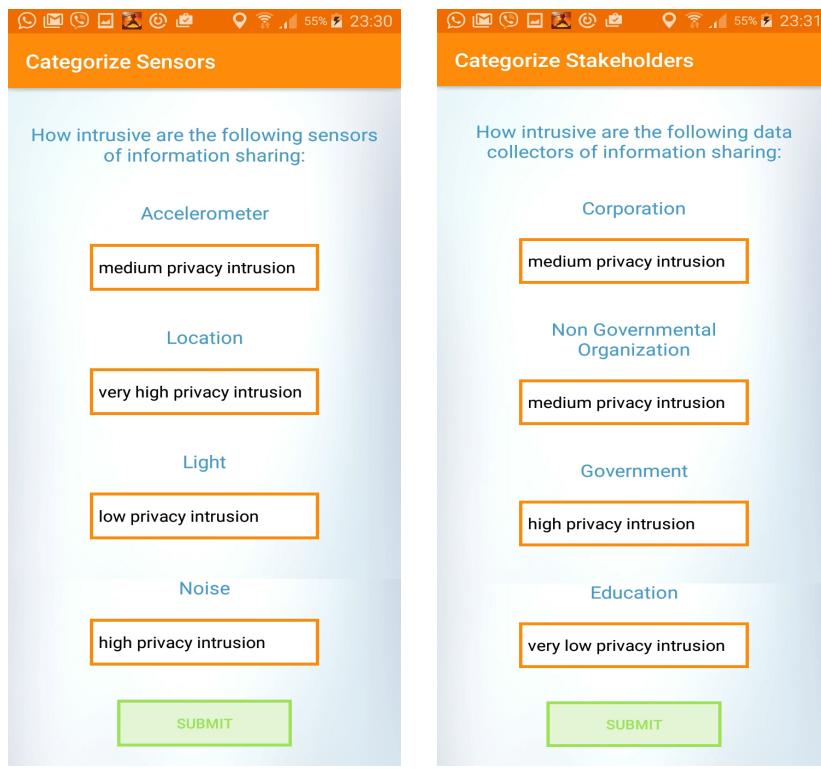
Each stakeholder type has a drop down menu each where the user can once again classify how much each of them affect data sharing. Once the user has finished entering the privacy intrusion level for stakeholders sub-features, the user has the possibility to click the green submit button and is directed to the next page.

On this page, the users are asked to categorize how much each of the contexts sub-features affect mobile sensor data sharing. This is depicted in figure 4.6. Each context has a drop down menu below, where the user can rate each context. Once this has been done the user can click on the green submit button. The user will be redirected to the next page only if all the drop down boxes have been filled out. All questions are compulsory there is no default choice.

4.2.4 Answering Questions with No Incentives

After the categorization questions are answered and user answers are recorded, users will be presented with 64 questions. Each of these questions is a mo-

4. EXPERIMENT METHODOLOGY



The figure consists of two side-by-side screenshots of a mobile application. Both screens have a header bar at the top showing various icons and the time '23:30'. The left screen is titled 'Categorize Sensors' and asks 'How intrusive are the following sensors of information sharing?'. It lists five sensors: Accelerometer, Location, Light, Noise, and a fifth one whose name is partially visible. Each sensor has a corresponding orange rectangular button below it with a privacy intrusion level: 'medium privacy intrusion' for Accelerometer, 'very high privacy intrusion' for Location, 'low privacy intrusion' for Light, and 'high privacy intrusion' for Noise. The fifth sensor's button is also orange. At the bottom of this screen is a green 'SUBMIT' button. The right screen is titled 'Categorize Stakeholders' and asks 'How intrusive are the following data collectors of information sharing?'. It lists four data collectors: Corporation, Non Governmental Organization, Government, and Education. Each collector has a corresponding orange rectangular button below it with a privacy intrusion level: 'medium privacy intrusion' for Corporation, 'medium privacy intrusion' for Non Governmental Organization, 'high privacy intrusion' for Government, and 'very low privacy intrusion' for Education. At the bottom of this screen is a green 'SUBMIT' button.

(a) Categorizing Sensors
(b) Categorizing Stakeholders

Figure 4.5: Categorization of Sensors and Stakeholders Screen

bile sensor data request to the users. Users have the possibility to choose from the available five privacy options mentioned in section 4.1.3. The options are indicated as a measure of how much data users can give, ranging from maximum data to least data. The higher the privacy of the option, the less information about the sensor data is given away for that request and vice versa. Users can change the answers for a data request until the green submit button on top of the options that appears is clicked. The screen with the data request is shown in figure 4.7a.

After the users choose an option for the data request, a green submit button appears which is shown in figure 4.7b. Clicking on the submit button sends the response to the data request to the server and cannot be changed. At this stage, no indications of credit gained or privacy improvements are indicated.

Once all the questions have been answered, the user goes to the core phase of the experiment, which starts at day number two. In the experiment, day number one is the entry phase, the core phase is day number two and three.

4.3. Core Phase

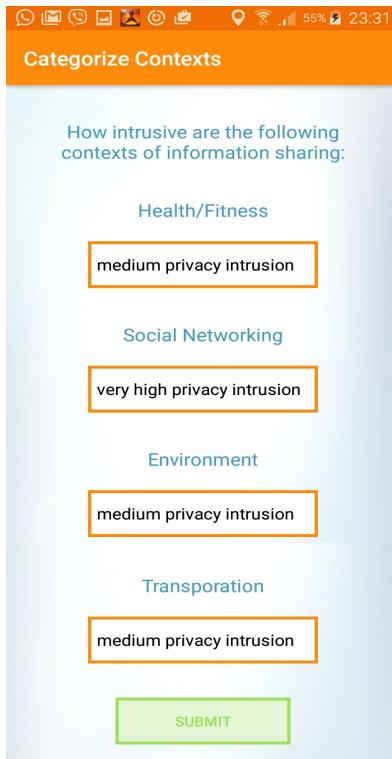


Figure 4.6: Categorization of Contexts Screen

4.3 Core Phase

Once the entry phase is done, the user is presented with the screen shown in figure 4.8. The "*i*" button at the bottom right of the screen denoted by the number 9 is clickable. This takes the users to the FairDataShare portal. Figure 4.9 shows the homepage of the portal. Users can then click on the data generator registration section of the website where they can signup with their:

1. Username
2. Password
3. Email
4. Unique Identifier

The unique identifier is located at the bottom of the application screen is an alphanumeric sequence denoted by number 8. If it is long pressed the user can select the identifier, then copy and paste it in the textbox asking for the unique identifier in the portal. Figure ?? shows what the registration page looks like. The users can use this website to see all the data collected from

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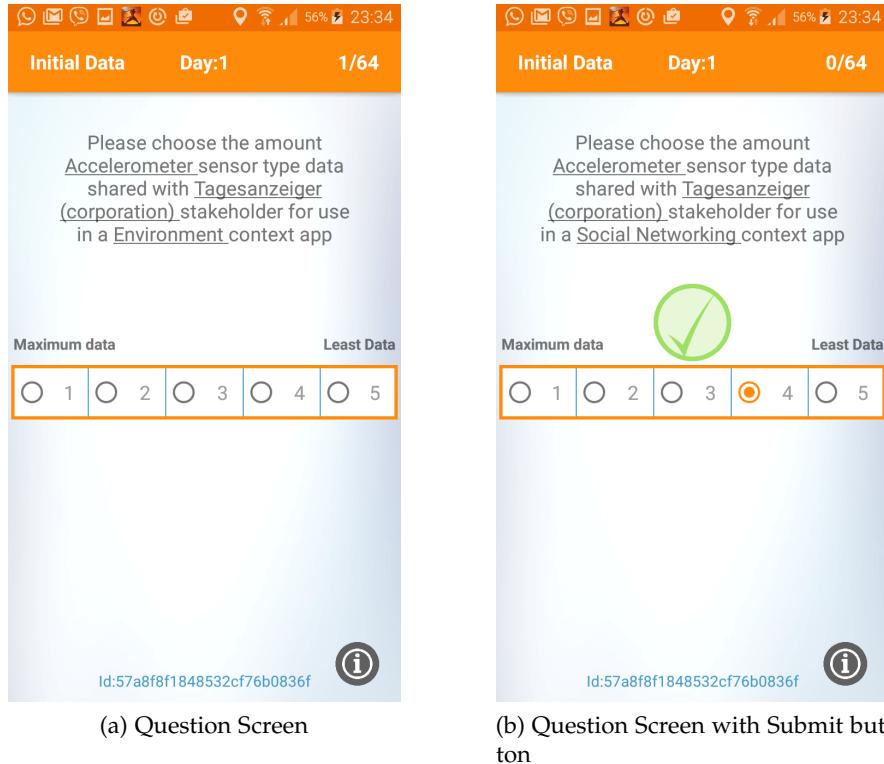


Figure 4.7: First Day Screen

them for all the mobile sensors. More details about the FairDataShare portal refer to the section 4.5.

The user have the possibility to login into the portal after a minimum of 24 hours after the start of the core phase to see the data that has been collected and shared with the stakeholders.

In the task-bar, the user can see the bidding day number and how many questions have been answered from the total available shown by numbers 1 and 2 in the figure 4.8a. Day number one corresponds to the day where users answer questions with no incentives of any kind and was presented in the previous sub-section. The screen presented after the entry phase is over is what is called the "*improvement screen*". The button numbered 3 represents "improve privacy" and the button numbered 4 represents "improve credit" respectively. The items numbered 6 and 5 represent the privacy percentage and credit obtained by the user respectively. Privacy is measured in terms of the percentage of mobile sensor data not traded to the stakeholders. Credit is measured in terms of the currency Swiss Francs obtained for trading data to the stakeholders.

4.3. Core Phase

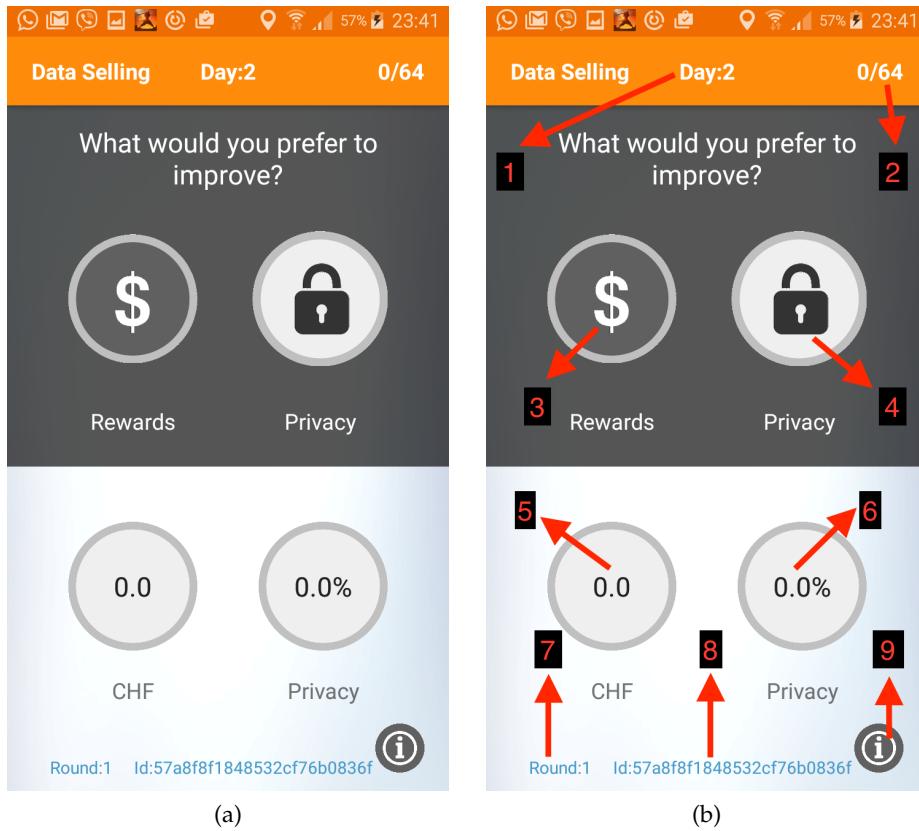


Figure 4.8: Improvement screen

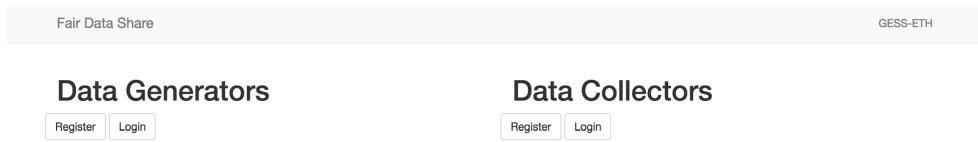


Figure 4.9: FairDataShare Homepage

The item numbered 7 is the round number which indicates the number of times the user has answered all the data requests. The item numbered 2 is the number of questions the user has answered in the current round. Item number 1 indicates the experiment day number.

There are a total of 64 data requests, hence after all the 64 have been answered, the number of questions answered is reset and the number of rounds answered increases by one. This indicates all the data requests that have been answered and how many are left unanswered. Each question will have 5 options to choose from, ranging from maximum data sharing to least data

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Data Generators

Check the code provided in the App

Register

Enter Username
Enter Password
Enter Email
Enter App Code

Register Cancel

Figure 4.10: Data Generators Registration Page

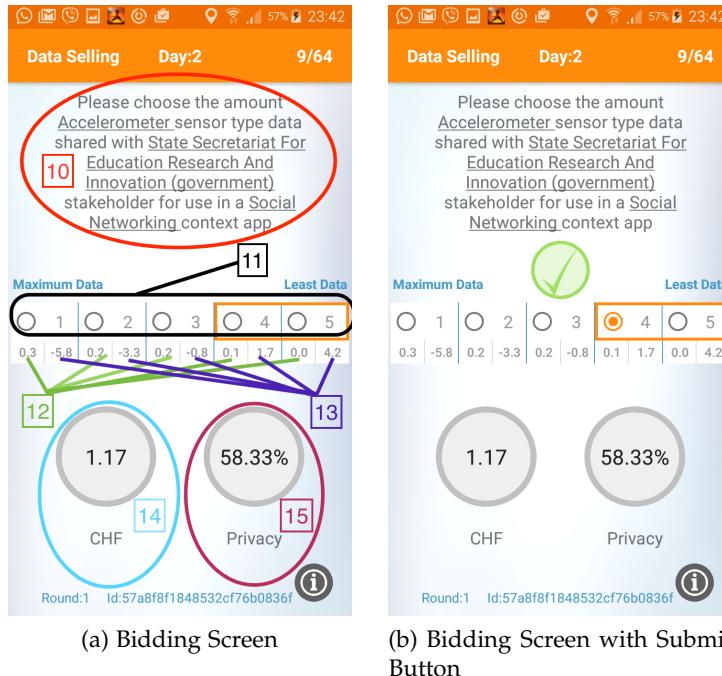


Figure 4.11: FairDataShare Portal

sharing.

From the starting time of the core phase till 24 hours later marks one bidding day. Once 24 hours is over, another bidding day starts where the privacy and credit metrics are reset. The day number in the task bar is incremented by one. The user has to answer all the data requests again for this new bidding day. Previous responses to data requests are not carried over to the next

day. If a data request is not answered, it is considered that the user does not want to trade mobile sensor data for that request. Additionally, each data request carries a participation fee, this is irrespective of the amount of mobile sensor data shared, by not participating in a data request the user foregoes this credit gain. The core phase goes on for a period of 48 hours.

4.3.1 Improve Privacy or Credit

The improvement screen shown in figure 4.8 is where users can choose whether they would like to improve the privacy or the credit. The elements of this screen have been explained in the previous section 4.3. The improve credit button should be chosen if the user is interested in maximizing the amount of credit obtainable. This uses an algorithm that uses the previous user answers to put forth a data request that can increase the credit to the maximum explained in section 5.2.3. The credit improvement button is represented by the item number 5. Similarly, the improve privacy button is used to further improve the privacy that has been obtained. This puts forth a data request that can further increase the user privacy. It needs to be noted that the ultimate change in the privacy or credit metrics depends on the option chosen by the user for the data request. The privacy improvement button is represented by the number 6.

Scenario examples for each button is given in the next section after introducing the next screen in the application. For example, if a user chooses to improve the privacy, then clicks on improve privacy button and gets a data request. The user still chooses option one with maximum data sharing (least privacy) for the data request, this may not improve his privacy but decrease it. This is because option 1 indicates that the user trades all the data for this request without filtering the sensor information. Trading all data gives the user more credit, but decreases the privacy metric.

Similarly, if a user chooses to improve the credit obtainable, the user clicks on the improve credit button and gets a data request. Then the user chooses the option five with least data sharing (maximum privacy) which indicates that no data is traded for this request. This response counters the initial desire to improve the credit obtainable. Trading no data increases one's privacy, but does not increase the credit to the maximum. Therefore, an actual improvement in the chosen metric depends on the chosen improvement button chosen and the choice of the appropriate option for that data request.

4.3.2 Answering Questions with Incentives

After choosing a metric to improve, a screen is presented as shown in figure 4.11a. This screen is called the "bidding screen". This screen is very similar to the screen 4.8 presented in the entry phase, except that the user is aware

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of the amount of privacy and credit obtained as indicated by items 14 and 15 respectively. Additionally, the user can see information about how the privacy and credit will increase or decrease for each privacy option of a data request. The items numbered 11 are the privacy options ranging from one to five.

The items numbered 12 are the improvement in privacy for each possible option of the current data request shown as item numbered 10. The items numbered 13 are the improvements in credit for each possible options of the current data request. Once the user decides on which options to choose according to how much data wants to be traded, the users can click on the radio option as explained in section 4.1.3 and then click again on the green submit button that pops up shown in 4.11b to confirm the answer. Once the green button has been clicked on, answers cannot be changed. The user has the possibility to go back to the improve screen from the bidding screen using the back button. Using the back button in the improve screen leads the user out of the application.

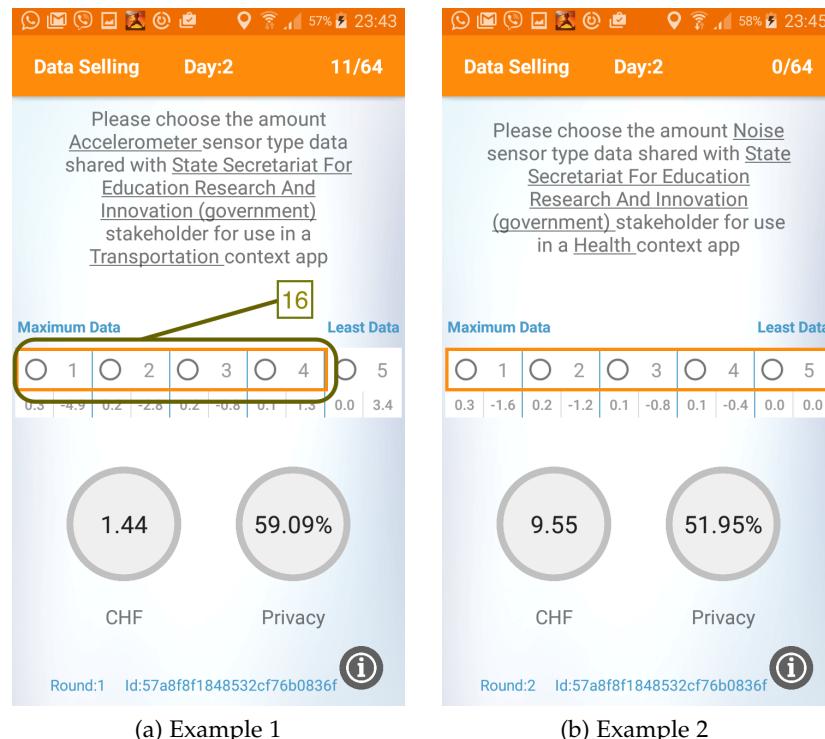


Figure 4.12: Recommendation Box

Additionally, for every question there is an orange recommendation box surrounding some options. This recommendation is highlighted by the number

16 in figure 4.12a. This gives an indication to the user as to which options can improve the privacy or the credit compared to the previous time the user has answered this data request. For example, if the user has previously answered option 4 to a data request and has clicked on improve credit, the system puts an orange box around options 1,2,3 and 4. Similarly, if the user clicked on improve privacy button, and the users previous answer was option 1, the system would recommend the options 1,2,3,4 and 5. Two examples of this are provided in figures 4.12.

It needs to be noted that the orange box does not necessarily provide an improvement of the particular metric chosen, it is meant to indicate improvements compared to the previous time the data request was answered to.

4.4 Exit Phase

After the end of the core phase, the participants are asked to fill up a survey based on their experience in the experiment. Some questions are about the rewards received, the privacy and credit metrics, design of the application, and how the experiment was conducted. The survey³ is linked to the user using the unique identifier assigned in the application. Once the survey is filled, the users receive their money for the entry phase, core phase and exit phase together, but only if they did not have their phones switched off throughout the experiment and participated in the core phase. This is done by checking the data collected on the server.

4.5 FairDataShare Web Portal

The FairDataShare portal⁴ is a website where users can view the data collected from them during the core phase of the experiment. Below is an explanation of how users and stakeholders can view mobile sensor data.

4.5.1 Data Generator's Portal

Once the users are registered which was explained in section 4.3, they can come back to the portal after a 24 hours period or later to view their mobile sensor data collected in the server. The data portal login page is shown in figure 4.13. Since the users are already registered from the mobile phone in the entry phase, they can go to the portal from their computers and this time login instead of register. Users should enter their:

1. Username

³https://descil.eu.qualtrics.com/SE/?SID=SV_3P0ySMqNe006v5j

⁴<http://fair-data-share.inn.ac/>

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2. Password

Once this is done, users will be redirected to the data collection page shown in figure 4.14 with the following options in the task-bar to choose from:

1. Accelerometer
2. Light
3. Noise
4. Location

Users can choose the sensor from the task-bar whose data they want to see by clicking on it. The data displayed includes the following columns :

1. Timestamp
2. Bidding day
3. Sensor Values

Figures 4.15, 4.16, 4.17 and 4.18 show examples of the data that can be seen for the location, light, accelerometer and noise sensor.

Data Generators

The screenshot shows a 'Login' form with the following structure:
- A title 'Login' at the top.
- Two input fields: 'Enter Username' and 'Enter Password'.
- Two buttons at the bottom: 'Login' and 'Cancel'.
The entire form is contained within a light gray border.

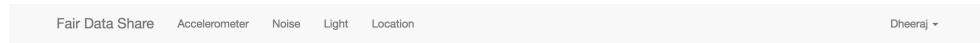
Figure 4.13: Login Page

The screenshot shows a 'Welcome' page with the following structure:
- A title 'Welcome Dheeraj' at the top.
- Below it, the text 'Email: dheerajsudhakar@gmail.com' and 'User ID: 578e91e778f2511711cfb9f5'.
- A horizontal navigation bar with links: 'Fair Data Share', 'Accelerometer', 'Noise', 'Light', and 'Location'.
The entire page is contained within a light gray border.

Figure 4.14: Welcome Page

Users first register as data generators as indicated in the section 4.2.4.

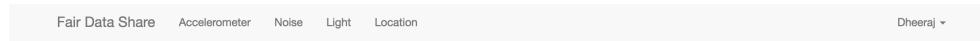
4.5. FairDataShare Web Portal



GPS

Day	Timestamp	Longitude	Latitude
2	1469013765330	48.963470458984375	9.13031005859375
2	1469013795336	48.963470458984375	9.13031005859375
2	1469013825352	48.963470458984375	9.13031005859375
2	1469013839928	48.963470458984375	9.13031005859375
2	1469013869930	48.963470458984375	9.13031005859375
2	1469013899934	48.963470458984375	9.13031005859375
2	1469013929937	48.963470458984375	9.13031005859375
2	1469013959940	48.963470458984375	9.13031005859375
2	1469013989944	48.963470458984375	9.13031005859375
2	1469014019949	48.963470458984375	9.13031005859375
2	1469014049954	48.963470458984375	9.13031005859375
2	1469014079958	48.963470458984375	9.13031005859375
2	1469014123960	48.963470458984375	9.13031005859375
2	1469014153964	48.963470458984375	9.13031005859375

Figure 4.15: Location Data



Light

Day	Timestamp	Value
2	1469013775346	126
2	1469013805526	161
2	1469013835527	127
2	1469013840127	130
2	1469013870325	145
2	1469013900326	186
2	1469013930525	190
2	1469013960725	182
2	1469013990726	0
2	1469014020727	0
2	1469014050729	0
2	1469014080929	0
2	1469014111127	0
2	1469014141327	0

Figure 4.16: Light Data

4.5.2 Stakeholder's Portal

For a stakeholder to view data, they need to register in the portal shown in figure 4.9 by clicking register. Once that is done, the page in figure 4.19 is shown asking for the following details :

1. Company Name

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Fair Data Share	Accelerometer	Noise	Light	Location	Dheeraj ▾
-----------------	---------------	-------	-------	----------	-----------

Accelerometer

Day	Timestamp	x	y	z
2	1469013775479	-0.5650315880775452	7.220912456512451	6.789956092834473
2	1469013805528	-0.10534487664689554	8.101978302001953	6.531382083892822
2	1469013835557	0.3830725704193115	6.368576526641846	7.5848307609558105
2	1469013839977	0.3734954595565796	6.196194171905518	7.785943984985352
2	1469013870007	-0.038307227194309235	6.339846134185791	7.422025203704834
2	1469013900047	-0.05746084079146385	10.141838073730469	-0.13407529890537262
2	1469013930077	0.009576806798577308	10.141838073730469	-0.15322890877723694
2	1469013960107	0.028730420395731926	10.170568466186523	-0.14365209639072418
2	1469013990180	-6.847416877746582	-6.119579315185547	-3.246537446975708
2	1469014020378	-6.89530086517334	-6.100425720214844	-3.265691041946411
2	1469014050578	-7.268796443939209	-6.244078159332275	-1.6376339197158613
2	1469014080579	-7.39329481248779	-6.205770969390869	-1.3503297567367554
2	1469014110779	-7.2113356590271	-6.358999729156494	-1.1300631761550903
2	1469014140798	-7.364564418792725	-6.224925464361572	-0.61294156351089478

Figure 4.17: Accelerometer Data

Fair Data Share	Accelerometer	Noise	Light	Location	Dheeraj ▾
-----------------	---------------	-------	-------	----------	-----------

Noise

Day	Timestamp	Rms	Spl	Bands
2	1469013765685	146.42578125	65.35355377197266	0.0,2.4057037E-5,6.9086714E-6,6.0710937E-7,2.9846692E-7,3.0724346E-5,2.7675502E-5,6.437194E-4,6.671106E-5
2	1469013795661	126.37060546875	64.0741195678711	0.0,1.7532275E-5,7.1945624E-6,5.1027865E-7,1.262046E-7,1.1799247E-5,3.324563E-5,5.093394E-4,4.5384477E-5,
2	1469013825662	241.427001953125	69.69691467285156	0.0,1.9904654E-5,6.4675687E-6,5.0418254E-7,3.6831852E-7,4.132275E-5,1.20294404E-4,2.49995E-4,2.0823021E-4
2	1469013840254	503.76220703125	76.08570861816406	4.2.1346188E-5,
2	1469013885667	524.6171875	76.43804931640625	0.0,2.13898E-5,2.8374447E-5,3.0414352E-5,3.4566263E-5,9.557794E-5,0.0050782408,0.0015603136,0.0013168416,
2	1469013915660	172.947021484375	66.7994613647461	5.3.2593807E-6,
2	1469013945661	278.451171875	70.9361801147461	0.0,3.054911E-5,5.686226E-6,4.36027E-7,1.0158309E-6,4.9987982E-5,4.676138E-5,0.0017947021,9.102744E-4,2.33
2	1469013975678	1768.630615234375	86.99394226074219	0.0,2.2745946E-5,2.0635262E-5,2.6642087E-5,2.901498E-5,9.767513E-5,3.8286814E-4,0.002663158,0.13813451,0.
2	1469014005674	182.28271484375	67.25611114501953	5,
2	1469014035678	116.080810546875	63.33640670776367	0.0,2.0691217E-5,5.0631206E-6,5.293276E-7,5.824385E-7,3.2161366E-5,2.3359193E-5,1.09764966E-4,2.6371961E-

Figure 4.18: Noise Data

2. Email

3. Stakeholder Category

4. Company Website

The stakeholder category is the type the stakeholder comes under such as :

1. Corporation
2. Educational Institution
3. Government
4. Non-Governmental Organization

Once these details have been filled in, the stakeholder can click on the register button. Once registered, the stakeholder can login like shown in figure 4.20. When access is granted the stakeholder is redirected to the page shown in figure 4.21. The stakeholder can choose from each of the available drop down lists :

1. A sensor
2. A context
3. An anonymous user
4. A bidding day number

Once this is entered, the stakeholder can see the data for that user with the privacy level decided by the anonymous user. If the stakeholder does not see any data, it means the user did not share data for this particular request. Stakeholders can view the sensor data in a similar fashion to users as seen in the previous figures. Data is available to the stakeholders 24 hours after the start of the core phase.

Data Collectors



The screenshot shows a registration form titled "Register". It contains the following fields:

- Enter Username
- Enter Password
- Enter Email
- Enter website URL
- Corporation (dropdown menu)

At the bottom are two buttons: "Register" and "Cancel".

Figure 4.19: Registration Page

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Data Collectors

The screenshot shows a simple login interface. At the top, it says "Login". Below that are two input fields: one labeled "Enter Username" and another labeled "Enter Password". At the bottom are two buttons: "Login" on the left and "Cancel" on the right.

Figure 4.20: Login Page

The screenshot shows a horizontal row of five dropdown menus and one "Ok" button. From left to right, the labels are: "Sensor" (set to "Accelerometer"), "Context" (set to "Social networking"), "Day" (set to "1"), "User" (set to "578de2af67a73d18562e2936"), and "Ok".

Figure 4.21: Data Collectors Data Retreiving Page

Chapter 5

Explanation of the Mobile Application

This chapter explains the details behind the making of the mobile application environment. First an overview is given, followed by a detailed explanation of the main components of the Android mobile application. This includes the architecture, database schemas and algorithms. Next, the server business logic and storage of the application is presented.

5.1 The Building Blocks

The following sections will explain integral parts of the server and client of the mobile application. A gist of the architecture is shown in the figure 5.1. It shows the mobile application represents the user participating in the experiment. As the experiment goes on, mobile sensor data and responses to the data requests which are collected are periodically sent to the Kinvey Data Store.

The users can login into the FairDataShare Portal from their computer or the mobile application. Once the user is authenticated, the user requests are sent from the FairDataShare server to the Kinvey Data Store¹. Kinvey in turn fetches the appropriate data and gives it back to the FairDataShare Server. This in turn structures the data so it can be readable, and pushes it to the user to see on the portal. The concept is similar for the Stakeholders, except they can only access the portal through the computer and not the mobile application.

¹<https://kinvey.com>

5. EXPLANATION OF THE MOBILE APPLICATION

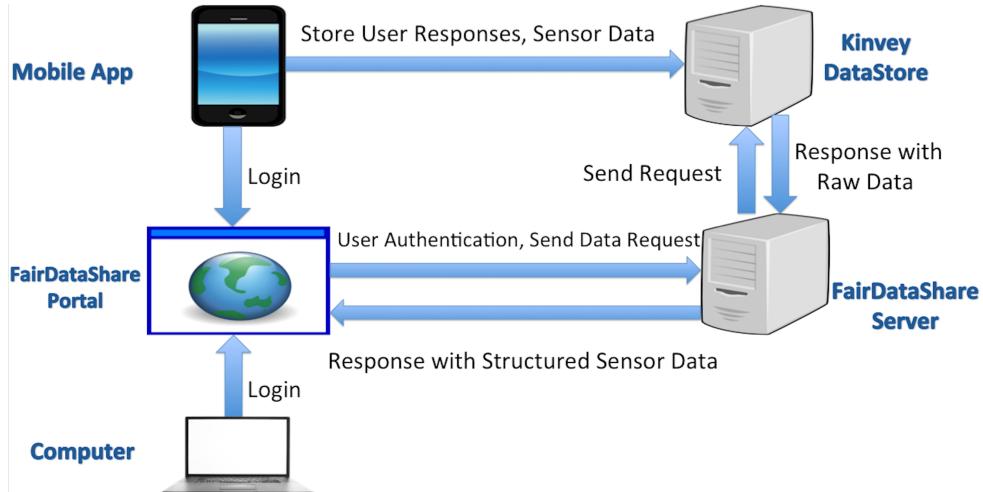


Figure 5.1: Conceptual Diagram of Mobile Application Architecture

5.2 The Mobile Application

The mobile application was developed for the Android platform with phones having API above level 17². Phones are assumed to have internet connectivity and sufficient storage space of at least 100 Mb. Below is an explanation of some of the tasks that take place in the application. A block diagram of the interaction of each of the components in the application is depicted in figure 5.2.

5.2.1 Local Storage

The local storage is an integral part of the application. The database used is SQLite³ and is the default database for the Android environment. Small sized unrelated data pieces are stored in preference files (as key value pairs), whereas larger related data is stored in the database. The following paragraphs will explain each table present in this application followed with their function and schema. All tables explained here are pertaining to the user using the mobile application and not the server.

Figure 5.3a shows the **QUESTION_STORE**'s table schema. This table stores each possible data request with its features such as with its sensor **SENSOR**, stakeholder **STAKEHOLDER** and context **CONTEXT**. Each of these are represented by an integer, for example sensor 0 stands for accelerometer sensor. Each data request is accompanied by an unique question identifier **QID**,

²<https://developer.android.com/guide/topics/manifest/uses-sdk-element.html>

³<https://developer.android.com/reference/android/database/sqlite/package-summary.html>

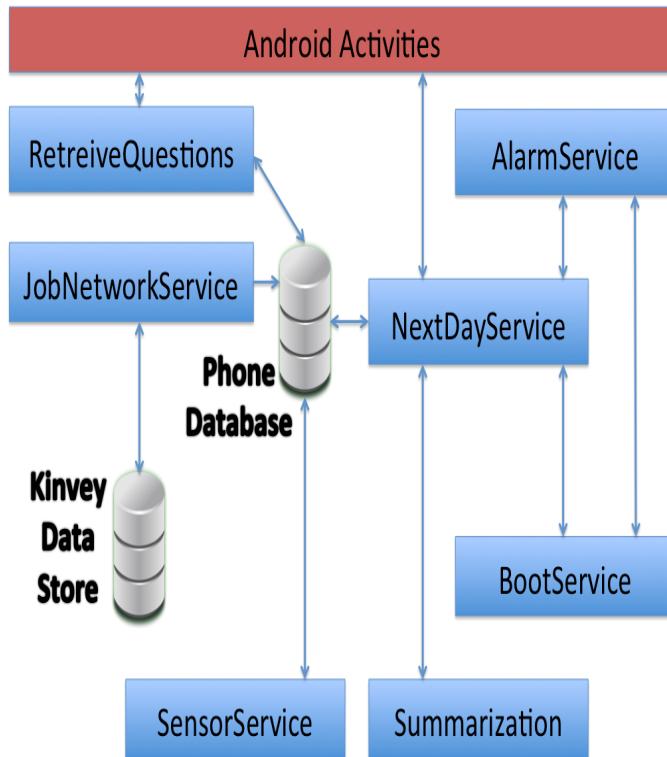


Figure 5.2: Interaction of Components of Mobile Application

weight assigned *WEIGHT* and the cost assigned *COST*. This data is not sent to the server.

Figure 5.3b depicts the table *WHICH_ANSWERS*'s table schema. This stores the questions identifier *QID* of each data request that has been answered by the user for each round. This is helpful while fetching data requests, so as not to fetch the request twice in the same round. It makes sure that all questions are answered before answering them for a second time. This data is not sent to the server.

Figure 5.4a explains the schema of *STORE_ANSWERS* table. This table is used to store the data request identifier *QID* with the corresponding user responses *LEVEL*, along with the increase or decrease in credit obtained *COST_OBT*. The total cost is calculated by adding all the costs in this table. Similarly, the total privacy is calculated by averaging of all the user responses stored in this table. Only the most recent responses are stored in this table. The content of the table is not sent over to the server.

Figure 5.4b denotes the schema of *STORE_POINTS* table. This table is used to store the credit and privacy obtained for each bidding day. This information

5. EXPLANATION OF THE MOBILE APPLICATION

QUESTION_STORE	WHICH_ANSWERED
<ul style="list-style-type: none"> ⌚ Q_ID: INTEGER ⌚ SENSOR: INTEGER ⌚ STAKEHOLDER: INTEGER ⌚ CONTEXT: INTEGER ⌚ COST: REAL ⌚ WEIGHT: REAL 	<ul style="list-style-type: none"> ⌚ Q_ID: INTEGER

(a) Table Schema of QUESTION_STORE (b) Table Schema of WHICH_ANSWERED

Figure 5.3: Table Schemas

STORE_ANSWERS	STORE_POINTS
<ul style="list-style-type: none"> ⌚ Q_ID: INTEGER ⌚ LEVEL: INTEGER ⌚ DAY: INTEGER ⌚ COST_OBT: REAL 	<ul style="list-style-type: none"> ⌚ DAY: INTEGER ⌚ PRI: REAL ⌚ COST: REAL

(a) Table Schema of STORE_ANSWERS (b) Table Schema of STORE_POINTS

Figure 5.4: Table Schemas

is sent to the server as soon one bidding day is over.

Figure 5.5 depicts the USERRESPONSE_CACHE table's schema. This table stores a unique key *KEY* for each user response, followed by a flag *ISSENT*, which is 1 if the response is not sent to the server, and 0 if it is sent. The user response saved consists of the following entries :

1. User Identifier
2. Timestamp of the response
3. Sensor Identifier
4. Stakeholder Identifier
5. Context Identifier
6. Privacy Level response for this data request

5.2. The Mobile Application

USERRESPONSE_CACHE	
KEY:	INTEGER
UR:	VARBINARY(2000)
IS_SENT:	INTEGER

Figure 5.5: Table USERRESPONSE_CACHE Schema

7. Cost obtained for this data request
8. Current Total Privacy of the user
9. Current Total Credit of the user
10. Maximum Obtainable Credit for this data request in this round
11. Metric Chosen to Improve (Improve Privacy or Improve Credit)

All of the above fields are packed into the field *ur* shown in 5.5. The data in this table is sent to the server. Once the entry is sent to the server, the *ISSENT* field is changed to 0 and deleted locally. The unique keys *KEY* are useful for deleting sent entries. Figure 5.6 and 5.7 show the table schemas for data storage of the following sensors:

1. Accelerometer in the STORE_ACCELEROMETER table
2. Noise in the STORE_NOISE
3. Location in the STORE_LOCATION
4. Light in the STORE_LIGHT

The general schema for all the sensor tables is the following :

1. *KEY* - Uniquely identifies each sensor entry
2. *TIMESTAMP* - The time the sensor value was collected
3. *ISSENT* - Denotes whether the sensor entry has been sent to the server or not
4. The other columns are specific to each sensor and represent the actual sensor values collected

5. EXPLANATION OF THE MOBILE APPLICATION

STORE_ACCELEROMETER	STORE_NOISE
<p>KEY: INTEGER</p> <p>X: REAL</p> <p>Y: REAL</p> <p>Z: REAL</p> <p>TIMESTAMP: NUMERIC(15,0)</p> <p>IS_SENT: BOOLEAN</p>	<p>KEY: INTEGER</p> <p>RMS: REAL</p> <p>SPL: REAL</p> <p>BANDS: CHARACTER(20)</p> <p>TIMESTAMP: NUMERIC(15,0)</p> <p>IS_SENT: BOOLEAN</p>

(a) Table Schema of STORE_ACCELEROMETER (b) Table Schema of STORE_NOISE

Figure 5.6: Table Schemas for Sensor Data

STORE_LOCATION	STORE_LIGHT
<p>KEY: INTEGER</p> <p>LAT: REAL</p> <p>LONG: REAL</p> <p>TIMESTAMP: NUMERIC(15,0)</p> <p>IS_SENT: BOOLEAN</p>	<p>KEY: INTEGER</p> <p>X: REAL</p> <p>TIMESTAMP: NUMERIC(15,0)</p> <p>IS_SENT: BOOLEAN</p>

(a) Table Schema of STORE_LOCATION (b) Table Schema of STORE_LIGHT

Figure 5.7: Table Schemas for Sensor Data

5.2.2 Alarms and Notifications

Every bidding day where the user answers data requests lasts for a period of 24 hours. After one bidding day is over, the system needs to be informed in a timely manner to perform some application critical functions. The functions performed are explained in detail in section 5.2.2. To inform the system of such an event Android provides the functionality in the form of alarms.

Alarms can be set to go off just once or in a repeated fashion to trigger tasks. Unfortunately, the alarms provided by Android are not exact for some versions ⁴, in the sense that they are triggered around that time set but not exactly at that time to optimize the battery, and can be delayed upto 24 hours. Hence, it is decided to set the repeating alarms manually.

⁴<https://developer.android.com/training/scheduling/alarms.html>

The first time the application opens the alarm is set to ring in exactly 24 hours, but things change when the phone is switched off. One of the conditions of the experiment is not to have the phone switched off at any time. Nevertheless, it is taken into account the scenario where the phone is kept switched off for a period of time. There are various things that can happen:

1. The phone is rebooted.
2. The phone is switched off, during this time an alarm is missed.
3. The phone is switched off for a period greater than 24 hours. One or more alarms can be missed.

Once the phone is switched off, all alarms are erased from memory⁵. Alarms do not execute when the phone is switched off. Hence, when the phone switches on, BootReceiver service of the application is triggered with pseudocode shown in 1. This checks whether an alarm has been missed, if it has been missed 200 seconds is given for the phone to stabilize after boot before triggering tasks. Otherwise, a new alarm is set using the pseudocode shown in 2. To set an alarm we need the time difference between now and when the alarm should ring. After that is calculated, the alarm is set.

Algorithm 1 BootService Algorithm

```
1: procedure BOOTSERVICE
2:   now ← current timestamp
3:   i ← timestamp of last triggered alarm
4:   if now – i < 86400 then
5:     Call SetAlarmLater()
6:   else
7:     Set alarm in 200 seconds
```

Algorithm 2 Alarm Algorithm

```
1: procedure SETALARMLATER
2:   now ← current timestamp
3:   i ← timestamp of last triggered alarm
4:   latertime ← i + 86400
5:   latergap ← latertime – now
6:   Set Alarm in latergap seconds
```

⁵<https://developer.android.com/reference/android/app/AlarmManager.html>

5. EXPLANATION OF THE MOBILE APPLICATION

Going to the Next Data Sharing Day

Once the alarm rings, it marks the end of a bidding day. Once a bidding day ends a number of tasks need to be executed and for this the NextDayService is triggered, which is described in pseudocode shown in 5. To start with the privacy and credit is sent to the server and stored locally in the STORE_POINTS table. *Privacy* which is the total privacy obtained, *Credit* is the total credit obtained, *Round* which is the number of times the user answered all the questions and *CurrentQuestion* which is the current question the user is answering is all reset to zero. The *Day* corresponds to the current day number is incremented by one to denote the next bidding day.

Algorithm 3 NextDayService Algorithm

```
1: procedure NEXTDAYSERVICE
2:   Store Privacy, Credit, Day in STOREPOINTS
3:   Send Privacy, Credit, Day to Server
4:   Privacy, Credit, Round, CurrentQuestion  $\leftarrow$  0
5:   Day  $\leftarrow$  Day + 1
6:   Store current time
7:   Call Summarization()
8:   if Day > End then
9:     End experiment
10:   else
11:     Update user interface elements
```

The current time of executing the alarm is saved in case the phone is rebooted or switched off. After that, the sensor data which is saved locally needs to be summarized, the corresponding method is called and is explained in pseudocode shown in 4. Finally it needs to be checked if the experiment is over or not and update the user interface accordingly. This means either the various metrics on the improvement and bidding screens (which ever is currently active) are updated, or the end of experiment screen is shown.

5.2.3 Fetching Data Requests

A data requests need to be fetched from the database in two scenarios :

1. After a question has been answered in the first bidding day (entry phase)
2. After the privacy or credit improvement button has been clicked (core phase)

In the first bidding day, once a data request has been answered the next one

is fetched sequentially from the database. This just requires knowing the current data request number and fetching the next data request from table QUESTION_STORE. For the other bidding days, fetching of the data requests depends on the improvement button chosen. According to the choice, the following is done:

1. **Improve Privacy** - Obtain data request from table STORE_ANSWERS where user has answered with lowest privacy
2. **Improve Credit** - Obtain data request from table STORE_ANSWERS where user has answered with highest privacy

In addition to sending the data request to the user interface, it is needed to show how choosing each option of the data request will affect the total privacy and total credit metrics. To do this for the total cost, the computation *last – possible* is output, where *last* stands for the credit obtained the last time the data request was answered. *possible* stands for the maximum amount of credit that can be obtained for this option (each data request has five privacy options 3.2.6). The possible total cost changes are shown under the options. For more detail on how credits are split among options in a data request refer 4.1.3.

Every option of a data request has an associated percentage of data that is given away as described in 3.2.6. According to the percentage of data given away, the total privacy is calculated for each possible option. The difference between the current privacy and each possible total privacy is calculated and indicated under each option. This gives an indication to the user as to what each option will do to the metrics.

5.2.4 Recording User Choices

The figure 5.5 describes the table USERRESPONSE_CACHE. Each time a user enters a response to a data request, all the fields mentioned in section 5.2.1 are recorded and stored in a class object. This object is transformed into a byte array so as to be stored easily in the table as is without transformation. When the JobNetworkService described in 5.2.6 is called, the class object is sent as it is to the server after converting it back to an object.

5.2.5 Sensor Data Collection and Summarization

Sensor data is collected from the following sensors :

1. Accelerometer sensor
2. Noise sensor
3. Location sensor
4. Light sensor

5. EXPLANATION OF THE MOBILE APPLICATION

A sensor service is triggered when the application is installed and is stopped when the experiment is over. This collects data from every sensor every 30 seconds and stores it in the appropriate tables mentioned in section 5.2.1. At the end of a bidding day, sensor data needs to be summarized according to the wishes of the user. This starts by first finding out the lowest privacy level for each sensor. Privacy levels range from one to five, that is from the lowest to highest privacy levels. Using this level summarization is done as shown in pseudocode 4. Every privacy level corresponds to an action:

1. 1- All data is sent to the server
2. 2- Send 75% of the data
3. 3- Send 50% of the data
4. 4- Send 25% of the data
5. 5- Do not send any data

Initially all the sensor data has a field *ISSENT* with value of zero. Data that should be sent to the server is set with *ISSENT* = 1, and all others that have value *ISSENT* = 0 are ignored.

Algorithm 4 Summarization Algorithm

```
1: procedure SUMMARIZATION
2:   for each sensor do
3:     Fetch sensor data from sensor table
4:     level  $\leftarrow$  Fetch user privacy level
5:     if level  $\leftarrow$  1 then
6:       Set all ISSENT  $\leftarrow$  1
7:     else if level  $\leftarrow$  2 then
8:       for 3 out of every 4 records do
9:         ISSENT  $\leftarrow$  1
10:    else if level  $\leftarrow$  3 then
11:      for 1 out of every 2 records do
12:        ISSENT  $\leftarrow$  1
13:    else if level  $\leftarrow$  4 then
14:      for 1 out of every 4 records do
15:        ISSENT  $\leftarrow$  1
16:    Delete all entries with ISSENT  $\leftarrow$  0
17:    Update Database
```

5.2.6 Server Synchronization

User responses and sensor data need to be sent to the server. This is done periodically every 5000 seconds in order to free up space on the phone when-

ever the internet is available. It is triggered first when the application is started for the first time. Data is fetched from the tables in the database. Data with fields marked as $ISSENT = 1$ is data that is ready and that has not been sent yet to the server. Such data is sent, and when an acknowledgement is received from the server, this data is deleted from the table.

Algorithm 5 JobNetworkService Algorithm

```
1: procedure NETWORKSERVICE
2:   Fecth data from USERRESPONSECACHE
3:   for each record do
4:     if ISSENT == 1 then
5:       Send record to Server
6:       if SUCCESS then
7:         Delete record
8:       for each sensor do
9:         Fecth data from sensor table
10:        for each record do
11:          if ISSENT == 1 then
12:            Send record to Server
13:            if SUCCESS then
14:              Delete record
```

5.3 The Server

5.3.1 Kinvey Data Storage

Kinvey⁶ is a mobile backend as a service which provides a platform for mobile phones to link applications to a backend cloud storage⁷. For the purpose of this application the backend has been used to store data and for some business logic implementations in javascript.

Security

All communications from the application to the server is encrypted using TLS/SSL encryption⁸ to communicate with the backend service. This is automatically provided and done by the Kinvey SDK.

⁶<http://kinvey.com/>

⁷https://en.wikipedia.org/wiki/Mobile_backend_as_a_service

⁸Kinvey white paper : KINVEY CLOUD SERVICE: SECURITY OVERVIEW 2014

5. EXPLANATION OF THE MOBILE APPLICATION

Collection Store

Locally, all information is stored in SQLite which is a relational database. The database used in Kinvey is MongoDB so instead we have collections on the server. When the user starts the application, general personal information is entered as explained in 5.2.1. This data is stored in the collection UserInformation with the schema shown in the screen shots A.1 and A.2.

Once this is done, users have to categorize the various Features, Sensors, Stakeholders and then the various Contexts. This information is sent to the server in collections named Features, Sensors, Stakeholders and Contexts. Schema is shown in A.3, A.4, A.5 and A.6 respectively.

All the data stored locally on the mobile phone which is sent by the JobNetworkService explained in section 5.2.6 is received by Kinvey. User responses are stored in the collection UserResponse shown in A.7 and A.8.

The sensor data sent by the JobNetworkService is stored in collections named after the sensors themselves. The schema of the tables is shown in figures A.9, A.10, A.12 and A.11.

To keep track of all the existing users in the experiment, the collection Users stores all unique user identification strings of participants. The schema is shown in A.13.

Finally, the collection Score shown in A.14 stores the total privacy, total credit obtained by the user for each bidding day.

Bussiness Logic

Most of the bussiness logic used for the FairDataShare portal is present in Kinvey. There are two main scripts stored in Kinvey are:

1. Script to find the privacy preferences of the users
2. Script to perform data summarization 4

The stakeholders make a request for data on the FairDataShare portal giving the following details:

1. Bidding day number
2. Anonymous user
3. Sensor
4. Context

Given this input plus the category of the stakeholder (which is known from their registration), we look into the UserResponse Collection trying to find the most recent record that fits this criteria and extract the privacy level.

Once the privacy level is known, summarization on user data is performed. Data has been taken from the user with a certain summarization, and if the summarization level is lower than the privacy level extracted, further summarization needs to be done. The pseudocode is shown in 6.

Algorithm 6 Server Summarization Algorithm

```
1: procedure SUMMARIZATION
2:   data  $\leftarrow$  sensor data from collection
3:   if summarizationlevel == privacylevel then
4:     Return data
5:   else
6:     skip  $\leftarrow$  summarizationlevel - privacylevel + 1
7:     for every skipnumber records out of 4 do
8:       Delete record from data
9:   Return data to portal
```

5.3.2 FairDataShare Web Portal

The FairDataShare portal makes use of a server at ETH Zurich other than the Kinvey Data Store to safely store the usernames, passwords of the users and the stakeholders in a collection. The database technology used is MongoDB. The language used to interact with Kinvey is Express.js, which is based on Node.js. Most of the data portal business logic is on Kinvey as described in section 5.3.1. The webpage was constructed using simple Html and css. All screenshots of the portal including detailed information is provided in chapter 4.

Chapter 6

Experimental Findings

The following chapter will give an overview of the data obtained from the survey, which was conducted before running the experiment. Later, an overview of the data obtained from the experiment is explained along with feedback received from the participants.

6.1 Findings from the Pre-Survey Data

The survey had 199 participants. Participants were not given any incentives to participate. After filtering out spurious and half-filled entries 189 entries are used for the data analysis. In the following paragraphs information obtained in the survey will be introduced.

Out of the total participants 63.64% are male and 36.36% are female. The mean birth year was found to be 1985. The demographics of the participants is explained in Table B.1. On the education level 2.53% have not completed high school, 9.60% have completed high school, 5.05% have gone to some college, 28.79% have obtained their bachelors degree, 39.90% have obtained their masters degrees and 14.14% have obtained their Phds. About the employment of the participants 51.52% are full time employees, 6.06% are part time employed, 6.06% are unemployed and looking for work, 1.52% are unemployed and not looking for work, 0.51% are retired and 41.92% are students. None of the participants are disabled.

Figure 6.1a depicts the various kinds of applications the population has on their mobile phones. As seen, the most popular applications are social networking, transportation and music applications. Figure 6.1c shows the frequency of mobile usage among the population. It is observed that the majority of the people use their phones 36-70 times a day.

Figure 6.1a depicts the percentage of users who have different applications shown in the figure's x-axis installed on their phones. Is it observed that

6. EXPERIMENTAL FINDINGS

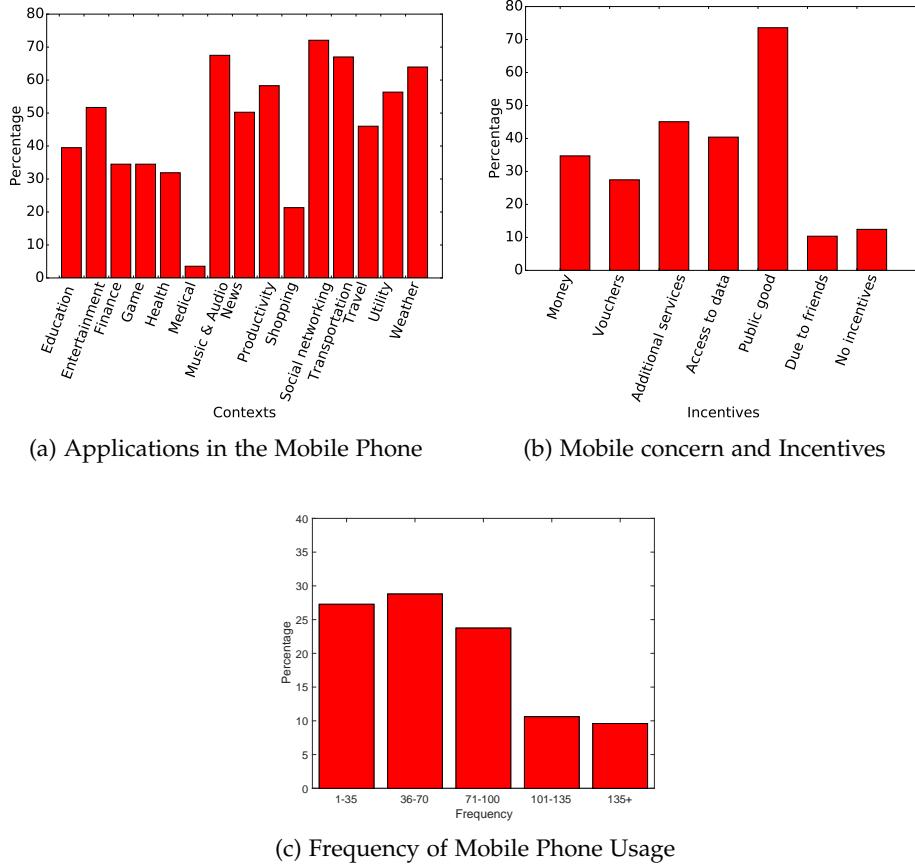


Figure 6.1: Table Schemas

the applications which are installed the most are music and audio, social networking, transportation and weathers applications with 67.51%, 72.08%, 67.01% and 63.96% of users having them installed respectively.

Figure ?? shows the percentage of users who would give data for each incentive indicated. As it can be observed, 73.58% of users would give data for public good which is the most chosen option. The least popular reasons to share data are “*Due to friends*” and “*No incentives*”. 34.72% of users would accept “*Money*” as an incentive, 27.46% would accept “*Vouchers*”, 45.08% would accept “*Additional services*”, 40.41% would accept “*Free access to data*”. This shows that money is possibly not the only incentive that can be used to incentivize users to share more data.

Figure 6.2a depicts the percentage of users who have different levels of concern for the privacy of their mobile sensor data. Level 1 corresponds to “*Not at all concerned*” and level 5 to “*Extremely concerned*”. As seen, 77.5% of users are concerned to a level of 3 and above and 22.5% of users are concerned to a

6.1. Findings from the Pre-Survey Data

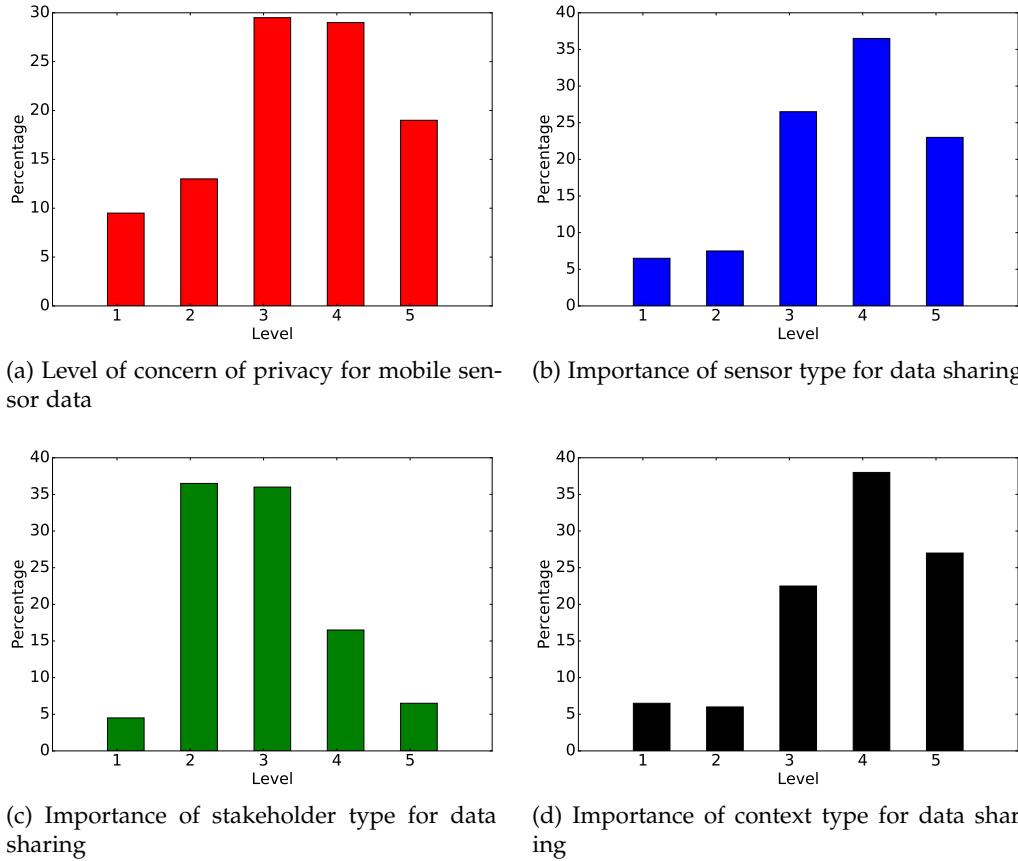


Figure 6.2: fgdgg

level of 1 and 2 together. This shows that most users are at least moderately concerned about the privacy of their mobile sensor data.

Figure 6.2b depicts the importance of the sensor type for who mobile sensor data is shared. Level 1 corresponds to "*Not at all important*" and level 5 to "*Extremely important*". As seen, 36.5% of users care to a level of 4 and 86% of users care to a level of 3 and above. Similarly, Figure 6.2c depicts the importance of the stakeholder type from which data is shared. 36% and 36.50% of users find the stakeholder important to a level of 4 and 5 respectively and 89% of users find the importance of stakeholder to a level 3 and above. Figure 6.2d shows the importance of the context of application type for which mobile sensor data is shared. 38% of users find the importance of the context of application to a level of 4 and 87.5% of users find the importance of the context of application to be of level 3 and above.

Figure 6.3a indicates the level of privacy intrusion for all the sensors indicated in the x-axis labels. Privacy intrusion level 1 corresponds to "*Very*

6. EXPERIMENTAL FINDINGS

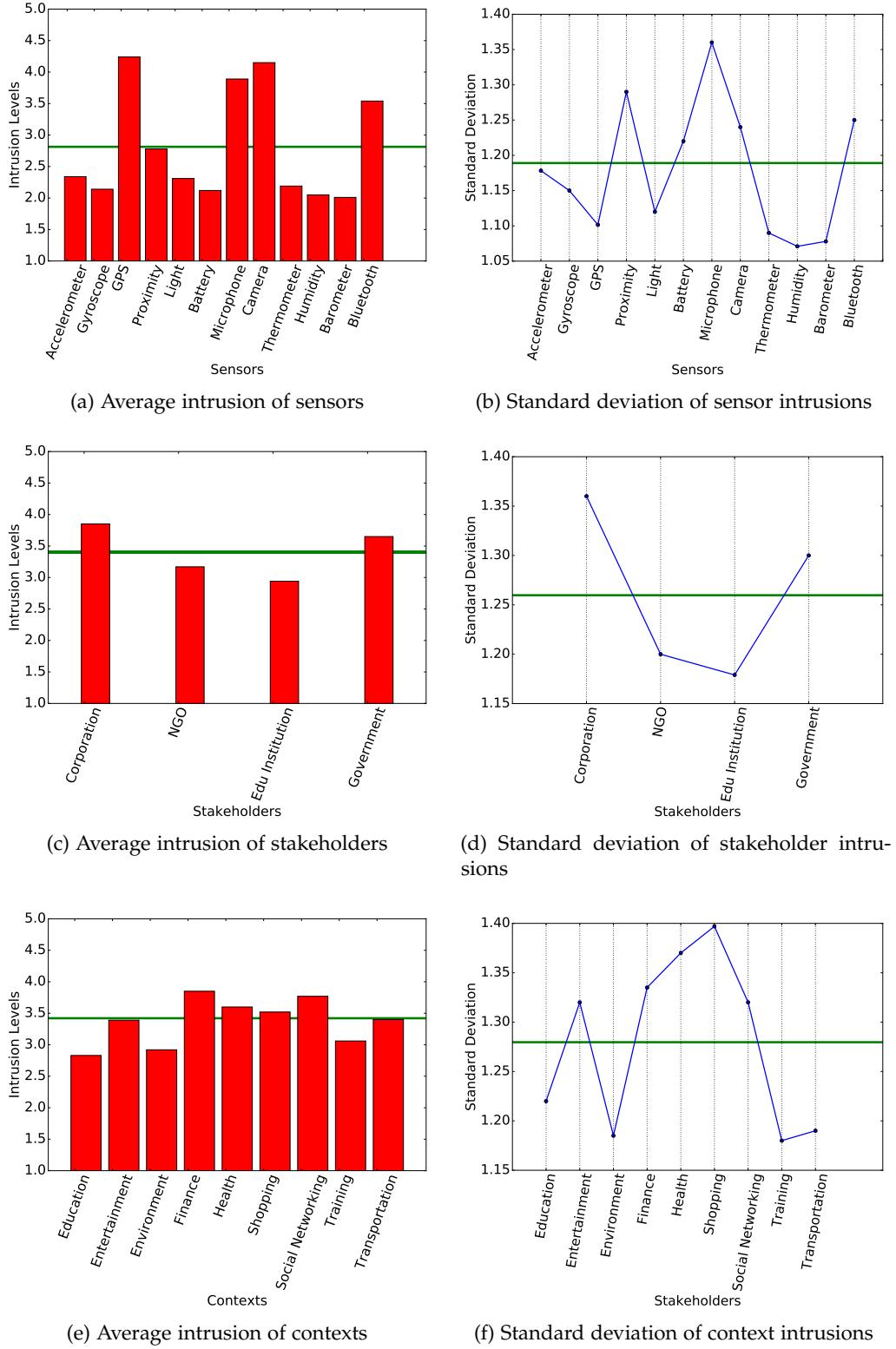


Figure 6.3: Table Schemas

6.2. Findings from the Experiment Data

low privacy intrusion" and level 5 to "*Very high privacy intrusion*". As seen in the figure, the location, camera, microphone and bluetooth sensors are found to be most privacy intrusive with levels of 4.23, 4.14, 4.14 and 3.52 respectively. The gyroscope, battery, humidity and barometer are found to be least privacy intrusive with privacy intrusion levels of 2.13, 2.11, 2.04 and 2.00 respectively. The accelerometer, proximity, light and thermometer are found moderately intrusive with privacy intrusion levels of 2.33, 2.79, 2.31 and 2.19 respectively. Figure 6.3b shows the standard deviation around the mean privacy intrusion of each sensor. Among all sensors proximity, battery, microphone, camera and bluetooth the privacy intrusion levels assigned by users has a higher spread around the mean than the rest.

Figure 6.3c indicates the level of privacy intrusion for all the stakeholders indicated in the x-axis labels. Privacy intrusion level 1 corresponds to "*Very low privacy intrusion*" and level 5 to "*Very high privacy intrusion*". As seen in the figure, the most intrusive stakeholders are corporation and government with privacy intrusion levels of 3.84 and 3.64 respectively. Stakeholders NGO and educational institution have privacy intrusion levels of 3.17 and 2.94 respectively and have less than average privacy intrusion levels. Figure 6.3d shows the standard deviation around the mean privacy intrusion level for each stakeholder. As observed, stakeholder corporation and government have a higher spread of privacy intrusion levels around the mean compared to the NGO and educational institution.

Figure 6.2c indicates the level of privacy intrusion for all the contexts of applications. Privacy intrusion level 1 corresponds to "*Very low privacy intrusion*" and level 5 to "*Very high privacy intrusion*". As seen in the figure, the most privacy intrusive contexts are health, finance, shopping and social networking with levels of 3.60, 3.85, 3.50 and 3.75 respectively. The less than average privacy intrusive contexts are training, environment, entertainment, transportation and education with privacy intrusion levels of 3.06, 2.92, 3.39, 3.38 and 2.83 respectively. Figure 6.3f shows the standard deviation of the privacy intrusion levels for every context of applications. As observed, there is a higher spread of privacy intrusion levels around the mean for contexts entertainment, finance, health, shopping and social networking.

6.2 Findings from the Experiment Data

An emulation of the social experiment explained in Chapter 4 was held with 9 participants. This was done in order to test the working of the mobile application and receive user feedback before the actual experiment run that will be officially held with the ETH Decision Laboratory.

The experiment was held for a period of 3 days. Out of the total number of days, 3 participants did not answer requests on day 2 and day 3. Participants

6. EXPERIMENTAL FINDINGS

were not monetarily incentivized for the emulation of the experiment, but were asked to think of the incentives indicated in the application as real incentives they will receive. This might cause a deviation from the ideal scenario where users are paid for their participation while examining the results. The mobile application ran successfully on all participant's phones even after being switched off. All data was successfully recorded on the server. Using the data collected on the server, the relationship between data sharing and incentives is examined.

Table 6.1: Average Score Obtained in the Experiment

Day	Privacy	Credit
1	56.43%	7.75
2	40.17%	9.29
3	47.97%	8.80

Table 6.1 shows the average privacy and credit obtained by the users for each day of the experiment. It is observed that the privacy metric is higher on the first day than on day 2 and 3. Furthermore it is also observed that the cost metric is higher on day 2 and day 3 than day 1. It can be inferred that users have decreased their privacy in order to obtain credit on day 2 and 3.

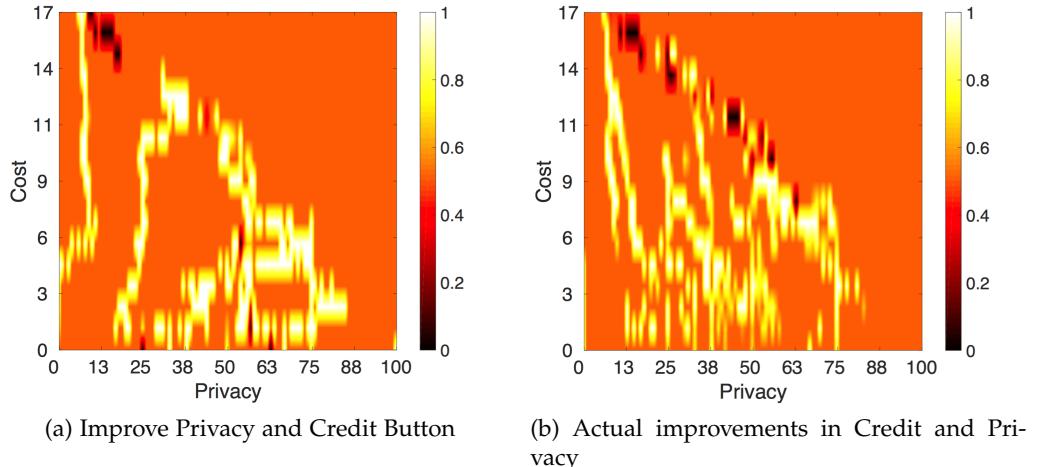


Figure 6.4: Table Schemas

Figure 6.4a depicts the probability of the user clicking on the improve privacy or improve credit button for every possible cost and privacy metric value obtained in the experiment from all participants. Probability values

6.2. Findings from the Experiment Data

closer to 1 depicts that the user probability of clicking on the improve credit button is highest. Similarly, probability value of 0 depicts that the user probability of clicking on the improve privacy button is highest. The figure depicts that users have higher probabilities of clicking on the improve privacy button when they have a high cost metric and a low privacy metric.

Figure 6.4b depicts the probability of an increment in the cost or privacy metric for every possible cost and privacy metric value obtained in the experiment from all participants. Probability values closer to 1 depicts that the user's probability of choosing an option for a data request that will increase the cost metric. Similarly, probability value of 0 depicts that the user's probability of choosing an option for a data request that will increase the privacy metric. When Figures 6.4a and 6.4b are observed together, it is seen that most of the times when the probability that users click on the improve credit button is high, users clicking on an option for a data request that improves their cost metric is also high. It is also observed that in some areas where the probability of clicking on the improve button is high, Figure 6.4b shows that users have a high probability of clicking on an option for a data request that improves their privacy metric. It could be due to the fact that even tough users have more intentions to improve their cost metric as seen before, the ultimate decision could lie on the data request presented whether they will click on an option that will increase the cost or privacy metric.

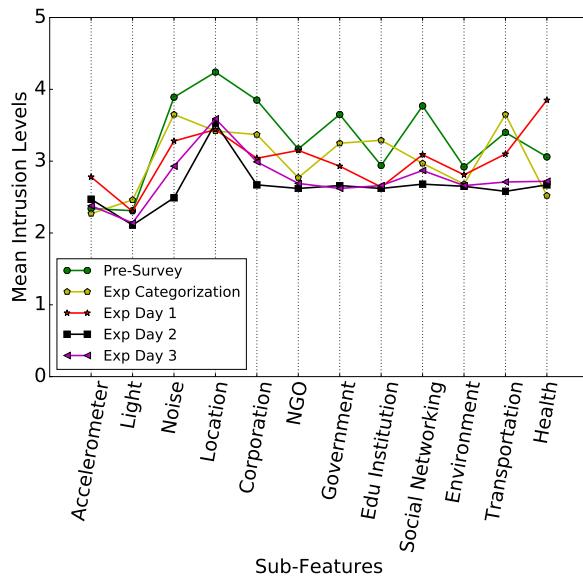


Figure 6.5: Mean Privacy Intrusion Levels for Sub-Features

The figure 6.5 depicts the mean of privacy intrusion levels assigned to the

6. EXPERIMENTAL FINDINGS

sub-features in the pre-survey, experiment categorization. It also depicts how much data was shared for each sub-feature during the experiment on day 1, day 2 and day 3. As it can be seen, there is a difference in the mean privacy intrusion levels assigned during the pre-survey and during the experiment categorization for some sub-features. This is perhaps due to the low number of participants in the experiment.

Additionally, it is observed that for all sub-features, the privacy level chosen for data requests during the experiment day 1 is much higher than on day 2 and day 3. This is indicated by the day 1 line being much higher than the lines day 2 and day 3. This shows that users have chosen to improve their cost metric on day 2 and day 3.

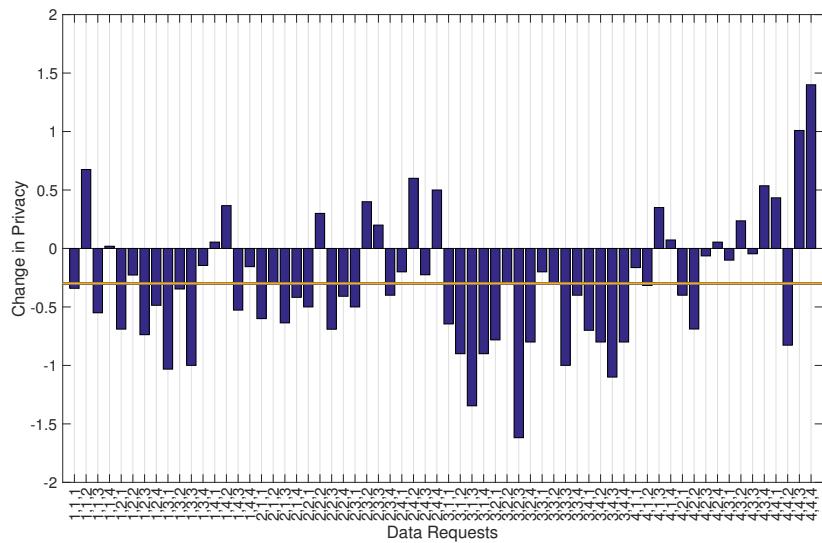


Figure 6.6: Gain in Privacy Between Day 2 and Day 1

Figure 6.6 depicts the gain in privacy for every data request in the experiment between day 2 and day 1. This was obtained by subtracting the responses to data requests on day 2 from the responses to data requests on day 1. If the bars are on the positive side, it indicates that users chose a higher privacy option for that data request on day 2 than on day 1. If the bars are on the negative side, it means that users chose a lower privacy option for that data request on day 2 than on day 1.

It is observed that there are a lot of bars on the negative side of the graph, indicating that users in general have chosen to decrease their privacy to increase the cost metric. The horizontal line in the graph indicates the mean gain in privacy between day 2 and day 1 for all data requests. The line is on the negative side indicating that users have overall chosen to decrease their

6.2. Findings from the Experiment Data

privacy and opt to improve the cost metric.

There are some data requests for which the user has not decreased the privacy such as the data request involving the location sensor, stakeholder education and context transportation. This is perhaps because location sensor is categorized with a privacy intrusion level of 3.42 which is the second most intrusive sensor. Additionally, the context transportation is also categorized with a privacy intrusion level of 3.65 which is the most intrusive context. The stakeholder education is categorized with a privacy intrusion level of 3.29. From the Figure 6.5 it can be seen that for day 1, users have already given more data on average for educational institutions. Hence it could be that they were not incentivized enough to give even more data for this stakeholder than they already had. Putting all the points above together could be the reason why data request (4,4,4) has a bar on the positive side of the figure. Similar reasonings can be applied to other data request with an increase in privacy rather than decrease.

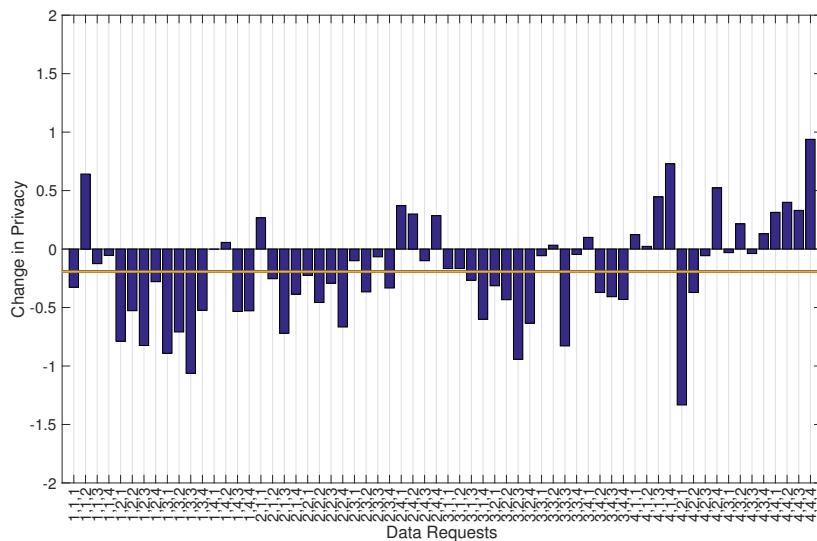


Figure 6.7: Gain in Privacy Between Day 3 and Day 1

Figure 6.7 depicts the gain in privacy for every data request in the experiment between day 3 and day 1. This was obtained by subtracting the responses to data requests on day 3 from the responses to data requests on day 1. If the bars are on the positive side, it indicates that users chose a higher privacy option for that data request on day 3 than on day 1. If the bars are on the negative side, it means that users chose a lower privacy option for that data request on day 3 than on day 1.

It is observed that there are more bars on the negative side than the positive

6. EXPERIMENTAL FINDINGS

side hence this means that users have shared more data on day 3 than day 1 which means they chose to improve their cost metric over the privacy metric. The horizontal line shown in the figure depicts the average gain in privacy which is on the negative side. This shows that overall they have decreased their privacy level for data requests on day 3 compared to day 1. There are some data requests for which users have shared less data than on day 1, this could be due to the fact that users were not incentivized enough for these data requests.

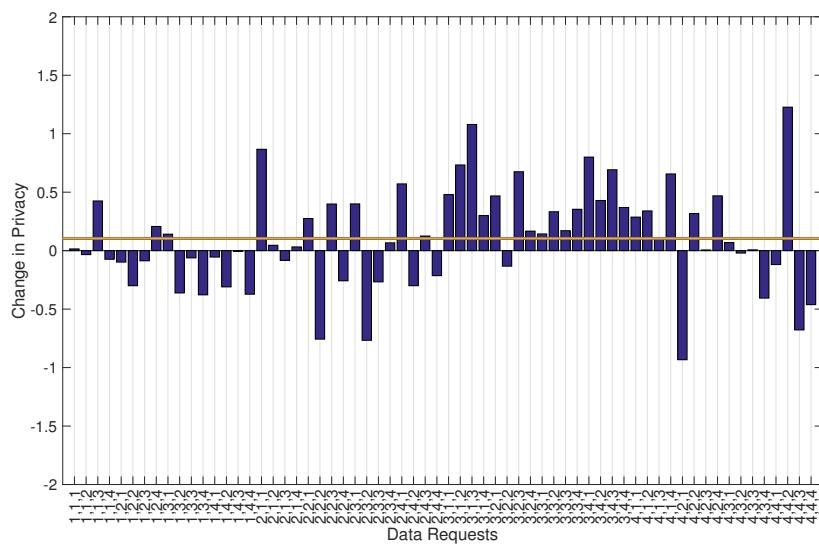


Figure 6.8: Gain in Privacy Between Day 3 and Day 2

Figure 6.8 depicts the gain in privacy for every data request in the experiment between day 3 and day 2. This was obtained by subtracting the responses to data requests on day 3 from the responses to data requests on day 2. If the bars are on the positive side, it indicates that users chose a higher privacy option for that data request on day 3 than on day 2. If the bars are on the negative side, it means that users chose a lower privacy option for that data request on day 3 than on day 2.

As it is observed, the horizontal line which indicates the average gain in privacy is on the positive side which means that users have on average increased their privacy on day 3 compared to day 2. Additionally, it can be seen that there are more bars on the positive side. This could be due to the fact that users expected more rewards on day 3, or that they became more privacy aware as they used the application due to the privacy metric.

Chapter 7

Conclusion and Future Work

In this dissertation, a survey was deployed to understand the perception of users on mobile sensors, stakeholders and contexts. This information was analysed and used in fine tuning the parameters of the mobile application. The mobile application developed has a computational model inbuilt that automatically assigns incentives to data requests according to the user profiles. A data request consists various features such as the sensor type to collect, stakeholder who is collecting the data and the purpose of data collection. The model assigns higher incentives to data requests which are considered intrusive and lesser incentives to data requests that are found less intrusive. The application collects all user input data plus mobile sensor data shared with the summarization chosen by the user. This data is sent to the cloud server and is accessed by both the user and the stakeholder in a transparent manner. Interrelationships within features are examined and the data obtained from the mobile application is analysed. Results to reinforce the need for the computational model are obtained. Additionally, an increased amount of data sharing is obtained after users are compensated with incentives.

In future, the social experiment can be held with a larger more representative pool of people who are actually awarded the incentives indicated in the mobile application. More work can be done to analyse the data obtained to find inter-relationships between features and relate the data to the user information provided. Deeper comparisons of the pre survey and experiment data can also be done. Furthermore, the model could incorporate machine learning algorithms to predict the sequence of user choices based on previous ones to put up appropriate incentives for each data request.

Appendix A

Appendix A

birth_year	check_mobile_frequency	country	education	education_background	education_level	employment_status	entertainment	finance
1994	3	"France"	0	0	3	6	0	1
1924	3	"Arménie"	0	0	4	4	0	0
1923	3	"Armenia"	0	0	4	2	0	0
1922	3	"Aruba"	0	0	3	2	0	0
1992	1	"France"	0	0	4	6	0	0
1991	1	"France"	0	0	5	6	0	0
1924	3	"Argentin...	0	0	3	2	0	0
1921	3	"Andorre"	0	0	2	1	0	0
1923	3	"Argentin...	0	0	2	2	0	0
1922	3	"Antigua-...	0	0	2	1	0	0
1922	3	"Anguilla"	0	0	2	2	0	0
1922	3	"Anguilla"	0	0	2	1	0	0
1923	3	"Angola"	0	0	2	2	0	0
1926	2	"Angola"	0	0	4	6	0	0
1924	3	"Andorre"	0	0	3	5	0	0
1924	3	"Angola"	0	0	4	6	0	0
1920	5	"Fiji"	0	0	1	3	0	0

Figure A.1: Screenshot of Collection UserInformation Part 1

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gender	health	medical	mobile_sensor_privacy	music	user_id	navigation	news	productivity	shopping	social_network
2	1	0	3	1	"57a8f8f1848532cf7...	0	0	0	1	1
2	0	0	3	0	"579a148f352257bc0...	0	0	0	0	0
2	0	0	3	1	"57975541e813f9973...	0	0	0	0	0
2	0	0	2	0	"57975159890927b61...	0	0	0	0	0
2	0	0	3	1	"57935b55a67b0ba32...	1	0	0	0	0
2	1	0	3	1	"579357faa67b0ba32...	1	0	0	0	1
2	1	0	3	0	"579357faa67b0ba32...	0	0	0	0	0
1	0	0	3	0	"57931cad866a46bd5...	1	0	0	0	0
2	1	0	3	0	"57930d55837af5db6...	0	0	0	0	0
1	1	0	3	0	"5792471c493006891...	0	0	0	0	0
2	1	0	3	0	"57923fbfc3d7cee30...	0	0	0	0	0
2	1	0	3	0	"57923946c3d7cee30...	0	0	0	0	0
2	0	0	3	0	"5792373d3692318e3...	1	0	0	0	0
2	0	0	4	1	"57922e1afb5591741...	0	0	0	0	0
2	1	0	3	0	"57922a329bb316492...	0	1	0	0	0
2	0	0	3	1	"579224ffba4636590...	0	0	0	0	0
2	0	0	1	0	"5791d082bb71b5202...	0	0	0	0	0
1	1	0	4	1	"578e91e778f251171...	1	1	0	0	1

Figure A.2: Screenshot of Collection UserInformation Part 2

user_id	context	data_collector	sensor
"57a8f8f1848532cf7...	1	3	5
"579a148f352257bc0...	2	3	3
"57975541e813f9973...	4	5	1
"57975159890927b61...	4	3	1
"57935b55a67b0ba32...	1	3	5
"579357faa67b0ba32...	1	3	5
"57931cad866a46bd5...	3	2	2
"57930d55837af5db6...	4	1	2
"5792471c493006891...	4	2	2
"57923fbfc3d7cee30...	4	1	2
"57923946c3d7cee30...	3	1	2
"5792373d3692318e3...	4	1	2
"57922e1afb5591741...	4	2	2
"57922a329bb316492...	3	2	4
"579224ffba4636590...	4	2	2
"578e91e778f251171...	3	5	4
"578e28687d1cdd1b6...	4	3	2

Figure A.3: Screenshot of Collection Features

user_id	acc	gps	light	noise
"57a8f8f1848532cf76b0836f"	3	5	2	4
"57a8f8f1848532cf76b0836f"	3	5	2	4
"579a148f352257bc0612c70b"	2	2	4	3
"57975541e813f99735dd0598"	2	4	3	3
"57975159890927b613d0f49f"	1	3	5	3
"57935b55a67b0ba32f81eeac"	3	5	1	5
"579357faa67b0ba32f81e724"	3	5	1	5
"57931cad866a46bd554a1896"	2	2	3	4
"57930d55837af5db6734a438"	2	1	2	4
"5792471c493006891e4e0c2b"	2	2	3	4
"57923fbfc3d7cee306b50957"	2	3	3	4
"57923946c3d7cee306b4fb44"	2	4	2	4
"5792373d3692318e3ba9e929"	2	1	2	4
"57922e1afb55917415770d44"	2	3	4	4
"57922a329bb316492f70242b"	2	1	2	4
"579224ffba46365901e66e78"	2	2	2	4
"578e91e778f2511711cfb9f5"	1	5	1	3

Figure A.4: Screenshot of Collection Sensors

user_id	corp	edu	gov	ngo
"57a8f8f1848532cf76b0836f"	3	1	4	3
"579a148f352257bc0612c70b"	3	3	4	2
"57975541e813f99735dd0598"	1	4	1	3
"57975159890927b613d0f49f"	2	4	4	5
"57935b55a67b0ba32f81eeac"	5	3	5	5
"579357faa67b0ba32f81e724"	5	3	5	5
"57931cad866a46bd554a1896"	2	4	4	1
"57930d55837af5db6734a438"	3	3	1	2
"5792471c493006891e4e0c2b"	2	4	1	1
"57923fbfc3d7cee306b50957"	3	4	3	2
"57923946c3d7cee306b4fb44"	3	3	3	3
"5792373d3692318e3ba9e929"	3	3	2	2
"5792373d3692318e3ba9e929"	3	3	2	2
"57922e1afb55917415770d44"	4	3	2	1
"57922a329bb316492f70242b"	2	4	2	1
"579224ffba46365901e66e78"	2	4	2	1
"578e91e778f2511711cfb9f5"	5	2	5	4

Figure A.5: Screenshot of Collection Stakeholders

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user_id	environment	health	social_networking	transportation
"57a8f8f1848532cf76b0836f"	3	3	5	3
"579a148f352257bc0612c70b"	4	2	2	2
"57975541e813f99735dd0598"	2	2	4	2
"57975159890927b613d0f49f"	3	1	5	5
"57975159890927b613d0f49f"	3	1	5	5
"57975159890927b613d0f49f"	3	1	5	5
"57935b55a67b0ba32f81eeac"	1	1	1	1
"579357faa67b0ba32f81e724"	3	1	5	3
"57931cad866a46bd554a1896"	3	3	3	5
"57930d55837af5db6734a438"	3	2	1	3
"5792471c493006891e4e0c2b"	1	2	1	3
"57923fbfc3d7cee306b50957"	3	3	2	5
"57923946c3d7cee306b4fb44"	3	2	3	3
"5792373d3692318e3ba9e929"	2	3	1	3
"5792373d3692318e3ba9e929"	2	3	1	3
"5792373d3692318e3ba9e929"	3	3	1	3
"5792373d3692318e3ba9e929"	3	3	2	4

Figure A.6: Screenshot of Collection Contexts

contexts	credit	credit_can_be	credit_gain	credit_question	data_collectors	timestamp	day_no
0	6.510009765625	0	-0.07690429687499994	0.17944335937499994	0	"2016-07-25 11:51:57.234"	3
1	6.436767578125	0.3002929687499994	0	0.35034179687499994	2	"2016-07-25 10:19:00.938"	3
0	6.436767578125	0.3002929687499994	0	0.35034179687499994	2	"2016-07-24 14:53:15.508"	3
2	6.436767578125	0.3002929687499994	0	0.35034179687499994	1	"2016-07-24 14:53:04.694"	3
3	6.436767578125	0.3002929687499994	0	0.35034179687499994	1	"2016-07-24 14:53:13.376"	3
1	6.436767578125	0.3002929687499994	0	0.35034179687499994	1	"2016-07-24 14:52:55.396"	3
0	6.436767578125	0.3002929687499994	0	0.35034179687499994	1	"2016-07-24 14:52:41.651"	3
2	6.436767578125	0.3002929687499994	0	0.35034179687499994	0	"2016-07-24 14:52:37.05"	3
3	6.436767578125	0.3002929687499994	0	0.35034179687499994	0	"2016-07-24 14:52:39.684"	3
1	6.25732421875	0.17944335937499994	0.17944335937499994	0.17944335937499994	2	"2016-07-24 14:23:08.071"	3
3	6.436767578125	0.17944335937499994	0.17944335937499994	0.17944335937499994	2	"2016-07-24 14:23:09.255"	3
1	6.436767578125	0.3002929687499994	0	0.35034179687499994	0	"2016-07-24 14:52:34.802"	3
0	6.436767578125	0.3002929687499994	0	0.35034179687499994	0	"2016-07-24 14:52:20.038"	3
0	6.077880859375	0.17944335937499994	0.17944335937499994	0.17944335937499994	2	"2016-07-24 14:23:07.005"	3
1	5.53955078125	0.17944335937499994	0.17944335937499994	0.17944335937499994	1	"2016-07-24 14:23:02.056"	3
3	5.8984375	0.17944335937499994	0.17944335937499994	0.17944335937499994	1	"2016-07-24 14:23:04.974"	3
2	5.718994140625	0.17944335937499994	0.17944335937499994	0.17944335937499994	1	"2016-07-24 14:23:03.856"	3

Figure A.7: Screenshot of Collection UserResponse Part 1

user_id	improve	privacy_can_be	privacy_gain	privacy_level	privacy_percentage	sensors
"57935b55a67b0ba32f81eeac"	1	1.5625	0.78125	3	63.28125	1
"57935b55a67b0ba32f81eeac"	2	0	0	5	63.28125	2
"57935b55a67b0ba32f81eeac"	2	0	0	5	63.28125	2
"57935b55a67b0ba32f81eeac"	2	0	0	5	63.28125	2
"57935b55a67b0ba32f81eeac"	2	0	0	5	63.28125	2
"57935b55a67b0ba32f81eeac"	2	0	0	5	63.28125	2
"57935b55a67b0ba32f81eeac"	2	0	0	5	63.28125	2
"57935b55a67b0ba32f81eeac"	2	0	0	5	63.28125	2
"57935b55a67b0ba32f81eeac"	2	0	0	5	63.28125	2
"57935b55a67b0ba32f81eeac"	2	0	0	5	63.28125	2
"57935b55a67b0ba32f81eeac"	2	0	0	5	63.28125	2
"57935b55a67b0ba32f81eeac"	2	0.5504352278545781	-1.036866359...	1	64.28571428571429	1
"57935b55a67b0ba32f81eeac"	2	0.5580357142857082	-1.004464285...	1	63.28125	1
"57935b55a67b0ba32f81eeac"	2	0	0	5	63.28125	2
"57935b55a67b0ba32f81eeac"	2	0	0	5	63.28125	2
"57935b55a67b0ba32f81eeac"	2	0.542041248016929	-1.070861977...	1	65.3225806451613	1
"57935b55a67b0ba32f81eeac"	2	0.5113968439509051	-1.183518410...	1	68.64406779661017	1
"57935b55a67b0ba32f81eeac"	2	0.5327868852458977	-1.106557377...	1	66.39344262295081	1
"57935b55a67b0ba32f81eeac"	2	0.5225988700564983	-1.144067796...	1	67.5	1

Figure A.8: Screenshot of Collection UserResponse Part 2

day_no	user_id	lat	long	summarization	timestamp
3	"578e91e778f2511711cfb9f5"	47.419864654541016	8.502890586853027	1	1469186498206
3	"578e91e778f2511711cfb9f5"	47.419864654541016	8.502890586853027	1	1469186468203
3	"578e91e778f2511711cfb9f5"	47.419864654541016	8.502890586853027	1	1469186408196
3	"578e91e778f2511711cfb9f5"	47.419864654541016	8.502890586853027	1	1469186438200
3	"578e91e778f2511711cfb9f5"	47.419864654541016	8.502890586853027	1	1469186378192
3	"578e91e778f2511711cfb9f5"	47.419864654541016	8.502890586853027	1	1469186288183
3	"578e91e778f2511711cfb9f5"	47.419864654541016	8.502890586853027	1	1469186348189
3	"578e91e778f2511711cfb9f5"	47.419864654541016	8.502890586853027	1	1469186258180
3	"578e91e778f2511711cfb9f5"	47.419864654541016	8.502890586853027	1	1469186228177
3	"578e91e778f2511711cfb9f5"	47.419864654541016	8.502890586853027	1	1469186318186
3	"578e91e778f2511711cfb9f5"	47.419864654541016	8.502890586853027	1	1469186198171
3	"578e91e778f2511711cfb9f5"	47.419864654541016	8.502890586853027	1	1469186168166
3	"578e91e778f2511711cfb9f5"	47.419864654541016	8.502890586853027	1	1469186138163
3	"578e91e778f2511711cfb9f5"	47.419864654541016	8.502890586853027	1	1469186108160
3	"578e91e778f2511711cfb9f5"	47.419864654541016	8.502890586853027	1	1469186078154
3	"578e91e778f2511711cfb9f5"	47.419864654541016	8.502890586853027	1	1469186018145
3	"578e91e778f2511711cfb9f5"	47.419864654541016	8.502890586853027	1	1469186048150

Figure A.9: Screenshot of Collection Location

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day_no	summarization	timestamp	user_id	x	y	z
3	1	1469186493918	"578e91e778f251171...	0.0191536135971546...	-0.143652096390724...	10.15141487121582
3	1	1469186463719	"578e91e778f251171...	0.0191536135971546...	-0.143652096390724...	10.15141487121582
3	1	1469186373308	"578e91e778f251171...	0.0191536135971546...	-0.124498486518859...	10.180145263671875
3	1	1469186433709	"578e91e778f251171...	0.0287304203957319...	-0.134075298905372...	10.15141487121582
3	1	1469186343108	"578e91e778f251171...	0.0287304203957319...	-0.134075298905372...	10.15141487121582
3	1	1469186403508	"578e91e778f251171...	0.0191536135971546...	-0.134075298905372...	10.15141487121582
3	1	1469186282709	"578e91e778f251171...	0.0191536135971546...	-0.143652096390724...	10.15141487121582
3	1	1469186222308	"578e91e778f251171...	0.0287304203957319...	-0.105344876646995...	10.20887565612793
3	1	1469186252509	"578e91e778f251171...	0.0287304203957319...	-0.143652096390724...	10.160991668701172
3	1	1469186312909	"578e91e778f251171...	0.0287304203957319...	-0.143652096390724...	10.15141487121582
3	1	1469186131909	"578e91e778f251171...	0.0191536135971546...	-0.143652096390724...	10.160991668701172
3	1	1469186192307	"578e91e778f251171...	0.0287304203957319...	-0.134075298905372...	10.160991668701172
3	1	1469186162108	"578e91e778f251171...	0.0191536135971546...	-0.143652096390724...	10.160991668701172
3	1	1469186101709	"578e91e778f251171...	0.0287304203957319...	-0.143652096390724...	10.15141487121582
3	1	1469186011488	"578e91e778f251171...	0.0191536135971546...	-0.143652096390724...	10.132261276245117
3	1	1469185981478	"578e91e778f251171...	0.0287304203957319...	-0.143652096390724...	10.160991668701172
3	1	1469186071708	"578e91e778f251171...	0.0191536135971546...	-0.143652096390724...	10.15141487121582

Figure A.10: Screenshot of Collection Accelerometer

bands	user_id	day_no	rms	spl	summarization	timestamp
"0,0,1.9080862E-5,...	"578e91e778f251171cfb9f5"	3	107.31494140625	62.65440368652344	1	1469186468205
"0,0,1.5665331E-5,...	"578e91e778f251171cfb9f5"	3	88.882568359375	61.01753234863281	1	1469186498214
"0,0,1.952634E-5,5...	"578e91e778f251171cfb9f5"	3	100.1298828125	62.05247497558594	1	1469186438208
"0,0,2.1573624E-5,...	"578e91e778f251171cfb9f5"	3	47.744140625	55.61960220336914	1	1469186408210
"0,0,2.0647063E-5,...	"578e91e778f251171cfb9f5"	3	73.727294921875	59.39376449584961	1	1469186378210
"0,0,2.1016425E-5,...	"578e91e778f251171cfb9f5"	3	71.015380859375	59.0682487487793	1	1469186348202
"0,0,2.062715E-5,6...	"578e91e778f251171cfb9f5"	3	96.7724609375	61.7562370300293	1	1469186258193
"0,0,2.1374477E-5,...	"578e91e778f251171cfb9f5"	3	67.723876953125	58.656036376953125	1	1469186168186
"0,0,1.7658736E-5,...	"578e91e778f251171cfb9f5"	3	106.538818359375	62.59135818481445	1	1469186198197
"0,0,1.8755187E-5,...	"578e91e778f251171cfb9f5"	3	40.89111328125	54.27377700805664	1	1469186318192
"0,0,1.429928E-5,4...	"578e91e778f251171cfb9f5"	3	21.7080078125	48.773597717285156	1	1469186078184
"0,0,1.9742341E-5,...	"578e91e778f251171cfb9f5"	3	85.58349609375	60.68899917602539	1	1469186138189
"0,0,2.134739E-5,5...	"578e91e778f251171cfb9f5"	3	78.437744140625	59.93170166015625	1	1469186108185
"0,0,2.007436E-5,5...	"578e91e778f251171cfb9f5"	3	82.403076171875	60.360069274902344	1	1469186048176
"0,0,2.0650641E-5,...	"578e91e778f251171cfb9f5"	3	76.4638671875	59.71032333740234	1	1469185958181
"0,0,1.4806586E-5,...	"578e91e778f251171cfb9f5"	3	21.33837890625	48.624427795410156	1	1469186018178
"0,0,2.0179677E-5,...	"578e91e778f251171cfb9f5"	3	101.021484375	62.12947463989258	1	1469185988177

Figure A.11: Screenshot of Collection Noise

day_no	summarization	timestamp	user_id	x
3	3	1469447239362	"57935b55a67b0ba32...	47
3	3	1469447109437	"57935b55a67b0ba32...	54
3	3	1469447319071	"57935b55a67b0ba32...	39
3	3	1469446323286	"57935b55a67b0ba32...	109
3	3	1469446998112	"57935b55a67b0ba32...	180
3	3	1469446812605	"57935b55a67b0ba32...	165
3	3	1469446228120	"57935b55a67b0ba32...	83
3	3	1469445977205	"57935b55a67b0ba32...	96
3	3	1469445805362	"57935b55a67b0ba32...	156
3	3	1469445621109	"57935b55a67b0ba32...	157
3	3	1469445343373	"57935b55a67b0ba32...	136
3	3	1469445541953	"57935b55a67b0ba32...	143
3	3	1469445255903	"57935b55a67b0ba32...	150
3	3	1469444855996	"57935b55a67b0ba32...	127
3	3	1469444963549	"57935b55a67b0ba32...	127
3	3	1469445171668	"57935b55a67b0ba32...	100

Figure A.12: Screenshot of Collection Light

user_id
"57a8f8f1848532cf76b0836f"
"579a148f352257bc0612c70b"
"57975541e813f99735dd0598"
"57975159890927b613d0f49f"
"57935b55a67b0ba32f81eeac"
"579357faa67b0ba32f81e724"
"57931cad866a46bd554a1896"
"57930d55837af5db6734a438"
"5792471c493006891e4e0c2b"
"57923fbfc3d7cee306b50957"
"57923946c3d7cee306b4fb44"
"5792373d3692318e3ba9e929"
"5792373d3692318e3ba9e929"
"57922e1afb55917415770d44"
"57922a329bb316492f70242b"
"579224ffba46365901e66e78"
"578e91e778f2511711cfb9f5"

Figure A.13: Screenshot of Collection Users

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timestamp	user_id	credit	day_no	privacy
"2016-08-08 23:35:20.788"	"57a8f8f1848532cf76b0836f"	6.310096153846153	1	74.609375
"2016-07-28 16:23:21.687"	"579a148f352257bc0612c70b"	9.030898876404493	1	56.25
"2016-07-26 14:22:12.236"	"57975541e813f99735dd0598"	9.01900773195876	1	57.03125
"2016-07-26 14:09:18.367"	"57975159890927b613d0f49f"	8.850940265486726	1	58.203125
"2016-07-26 14:00:00.565"	"57935b55a67b0ba32f81eeac"	0	4	0
"2016-07-25 13:59:00.084"	"57935b55a67b0ba32f81eeac"	6.510009765625	3	63.28125
"2016-07-24 13:59:31.599"	"57935b55a67b0ba32f81eeac"	8.8885498046875	2	50.390625
"2016-07-23 13:59:31.382"	"57935b55a67b0ba32f81eeac"	5.90576171875	1	67.1875
"2016-07-23 09:31:59.106"	"57931cad866a46bd554a1896"	1.2409156976744176	1	55
"2016-07-23 08:36:40.373"	"57930d55837af5db6734a438"	8.348214285714286	1	60.9375
"2016-07-22 18:18:33.16"	"5792471c493006891e4e0c2b"	1.2428977272727268	1	52.5
"2016-07-22 17:48:06.151"	"57923fbfc3d7cee306b50957"	1.253551136363636	1	55
"2016-07-22 17:19:40.016"	"57923946c3d7cee306b4fb44"	9.385190217391308	1	53.125
"2016-07-22 16:32:46.545"	"57922e1afb55917415770d44"	7.999999999999998	1	63.28125
"2016-07-22 16:22:07.321"	"57922a329bb316492f70242b"	8.459821428571429	1	60.9375
"2016-07-22 13:22:00.152"	"578e91e778f2511711cfb9f5"	14.11313657407408	3	18.359375

Figure A.14: Screenshot of Collection Score

Appendix B

Appendix B

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Table B.1: Demographics of Population in the Survey

Country	Percentage
United States of America	1.01%
United Arab Emirates	0.51%
The former Yugoslav Republic of Macedonia	0.51%
Syrian Arab Republic	0.51%
Switzerland	20.71%
Spain	1.01%
Slovakia	0.51%
Serbia	5.05%
Russian Federation	0.51%
Netherlands	1.52%
Italy	2.02%
Iran	1.01%
India	14.65%
Hungary	0.51%
Greece	29.29%
Germany	10.61%
France	1.52%
Czech Republic	1.01%
Costa Rica	0.51%
China	0.51%
Columbia	0.51%
Canada	0.51%
Bolivia	0.51%
Brazil	1.52%
Bahrain	0.51%
Argentina	0.51%
Austria	2.02%

Table B.2: Employment Classification of Groups For Sensors

Occupation	1	2	3	4	5
Employed full time	4.90%	6.86%	26.47%	38.24%	23.53%
Employed part time	8.33%	16.67%	33.33%	16.67%	25.00%
Unemployed and looking for work	8.33%	16.67%	16.67%	25.00%	33.33%
Unemployed and not looking for work	0.00%	0.00%	0.00%	66.67%	33.33%
Retired	0.00%	0.00%	100.00%	0.00%	0.00%
Student	7.23%	4.82%	26.51%	39.76%	21.69%
Disabled	0.00%	0.00%	0.00%	0.00%	0.00%

Table B.3: Gender Classification of Groups For Sensors

Gender	1	2	3	4	5
Female	5.56%	4.17%	33.33%	30.56%	26.39%
Male	7.14%	9.52%	22.22%	39.68%	21.43%

Table B.4: Average Birth Year of Groups For Sensors

1	2	3	4	5
1989	1979	1986	1986	1983

Table B.5: Education Classification of Groups For Sensors

Education	1	2	3	4	5
Less than high school	20.00%	20.00%	20.00%	40.00%	0.00%
High school	10.53%	0.00%	52.63%	31.58%	5.26%
Some college	10.00%	20.00%	30.00%	20.00%	20.00%
Bachelors degree	7.02%	10.53%	24.56%	42.11%	15.79%
Masters degree	3.80%	5.06%	24.05%	35.44%	31.65%
PhD degree	7.14%	7.14%	17.86%	35.71%	32.14%

Table B.6: Employment Classification of Groups For Stakeholders

Occupation	1	2	3	4	5
Employed full time	3.92%	4.90%	16.67%	33.33%	41.18%
Employed part time	16.67%	16.67%	8.33%	50.00%	8.33%
Unemployed, looking for work	8.33%	8.33%	16.67%	16.67%	50.00%
Unemployed, not looking for work	0.00%	0.00%	0.00%	33.33%	66.67%
Retired	0.00%	0.00%	0.00%	100.00%	0.00%
Student	4.82%	7.23%	15.66%	37.35%	34.94%
Disabled	0.00%	0.00%	0.00%	0.00%	0.00%

Table B.7: Gender Classification of Groups For Stakeholders

Gender	1	2	3	4	5
Female	5.56%	6.94%	23.61%	36.11%	27.78%
Male	3.97%	6.35%	11.90%	35.71%	42.06%

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Table B.8: Average Birth Year of Groups For Stakeholders

1	2	3	4	5
1986	1989	1984	1985	1984

Table B.9: Education Classification of Groups For Stakeholders

Education	1	2	3	4	5
Less than high school	20.00%	20.00%	0.00%	60.00%	0.00%
High school	15.79%	5.26%	21.05%	31.58%	26.32%
Some college	0.00%	10.00%	20.00%	40.00%	30.00%
Bachelors degree	1.75%	12.28%	15.79%	35.09%	35.09%
Masters degree	5.06%	1.27%	13.92%	37.97%	41.77%
PhD degree	0.00%	7.14%	21.43%	28.57%	42.86%

Table B.10: Employment Classification of Groups For Contexts

Occupation	1	2	3	4	5
Employed full time	4.90%	3.92%	23.53%	36.27%	31.37%
Employed part time	16.67%	8.33%	25.00%	25.00%	25.00%
Unemployed, looking for work	8.33%	16.67%	25.00%	25.00%	25.00%
Unemployed, not looking for work	0.00%	0.00%	0.00%	66.67%	33.33%
Retired	0.00%	0.00%	0.00%	100.00%	0.00%
Student	7.23%	6.02%	20.48%	44.58%	21.69%
Disabled	0.00%	0.00%	0.00%	0.00%	0.00%

Table B.11: Gender Classification of Groups For Contexts

Gender	1	2	3	4	5
Male	7.14%	6.35%	23.02%	38.10%	25.40%
Female	5.56%	5.56%	19.44%	38.89%	30.56%

Table B.12: Average Birth Year of Groups For Contexts

1	2	3	4	5
1986	1986	1986	1985	1983

Table B.13: Education Classification of Groups For Contexts

Education	1	2	3	4	5
Less than high school	20.00%	0.00%	0.00%	80.00%	0.00%
High school	10.53%	10.53%	31.58%	36.84%	10.53%
Some college 1	0.00%	0.00%	40.00%	30.00%	20.00%
Bachelors degree	7.02%	8.77%	24.56%	35.09%	24.56%
Masters degree	6.33%	3.80%	17.72%	40.51%	31.65%
PhD degree	0.00%	7.14%	17.86%	35.71% 3	9.29%

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