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Detecting User Reading Behaviour Using Smartphone Sensors

Bachelor Thesis (12 EAP)

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Abstract

Smartphones have become very widespread. 15% of total internet traffic consisted of mobile traffic in 2013. Mobile traffic has been growing 1.5 times annually over the course of last 5 years and the trend is likely to continue or even accelerate. Smartphones have claimed an important role in the way people are accessing information. Mobile application analytics sessions do not have to rely only on what is seen on the screen or hits, but can take advantage of other features built-in to smartphones such as gyroscope and accelerometer. In this paper a solution for classifying reading activity on smartphones is proposed. This involves activity recognition from smartphone accelerometer and gyroscope data. An artificial neural network was trained on training data. Results show that classifying reading activity on smartphone in that way is feasible.

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Introduction

Nowadays smartphones have become extremely popular. According to The Cisco Visual Networking Index (VNI) Global Mobile Data Traffic Forecast, mobile traffic in 2013 was nearly 18 times the size of the whole internet in year 2000. Average smartphone usage grew 50 percent in 2013. Smartphones will reach 66 percent of mobile data traffic by 2018. Global mobile devices and connections in 2013 grew to 7 billion from 6.5 billion in 2012. Smartphones accounted 77% of that growth.(5)

Smartphones play big role in how information is being accessed. Therefore it is important to analyze mobile usage. Analyzing usage helps to understand the perception of the user regarding to the content displayed by a smartphone app. Hence, a lot of research is going on in mobile analytics. Current state of the art mobile analytics tools rely on events defined by developers for example screen views or user demographics. (6)(7)(8)

However, smartphones are equipped with different embedded sensors. Access to sensor data enables devices to recognize different activities. Activity recognition tries to classify physical activities carried out by a person. Recognition can be accomplished using data retrieved from inertial sensors such as accelerometers or gyroscopes.(9) We believe, that sensor information can be used to enhance mobile analytic process to understand the user motives.

This work attempts to propose a new way how sensor data would enrich mobile analytic process. To prove the concept a framework was built. Experiments discussed in this paper were conducted to introduce sensor information to the analytics process to provide more meaningful insights about user. According to the results it is possible to detect user reading activity with more than 90% accuracy.

1.1 Outline

This paper is structured the following way: Chapter 2 gives an overview of the state of the art about content rating, mobile analytics and activity recognition. Chapter 3 states the research problem. Chapter 4 gives overview of the methodology how the problem is solved. Chapter 5 draws conclusions. Chapter 6 gives overview of related works in the field of activity recognition. Chapter 7 concludes the thesis with future research directions.

2

State of the Art

2.1 Content rating

Content rating refers to the process of determining quality of the content. Following section discusses most common strategies to rate content.

2.1.1 Explicit user feedback

Explicit feedback refers to user taking action on his/her side and giving active feedback by pressing buttons or giving stars etc.

2.1.1.1 One-dimensional feedback

The simplest technique to get user feedback about content is to add simple one-click button. Examples include:

- Facebook Like button
- Google "+1" button
- simple thumbs up button
- Heart or favorite button
- "flag as inappropriate"
- "mark as helpful"

Using one-click button is easy for the user. It allows person to give feedback about a product/content while spending very small amount of time.

2.1.1.2 Two-dimensional feedback

Two-dimensional feedback is a method that allows to give feedback on two levels: positive and negative. Most common example is YouTube thumbs up and thumbs down button. This method provides only pure black and white scale for rating content. The user either has to like it or dislike it.

2.1.1.3 Multi-dimensional: 3 stars and more

Multi-dimensional rating is usually represented with a five star rating scale. This is most common for e-commerce sites. 5 star rating scale has become very popular for product reviews. The advantage of this model is that customer feedback could be displayed as an average across ratings and also a small bar graph could show the distribution between responses.

2.1.2 Implicit feedback - mobile application analytics

Lately, many mobile analytic tools have been developed to collect and track data about user behaviour. Developers integrate the analytics program code in to their application. The analytics code will collect information and send it to the server. The developers can then track their application usage. Current analytics tools calculate session lengths or screenview lengths using custom events that developer defines programmatically. Mostly a screenview is counted, when a new screen is loaded or a button pressed etc.

2.1.2.1 Flurry analytics session length

Flurry session length is defined as the length of time between the start application event and the end application event. The length of the session can vary based on how the developer integrates the SDK into the application.(7)

2.1.2.2 Flurry custom timed events

Developer calls event logger to start logging an event. When event is over, the developer calls stop event timing function. Yet developer can't assess whether user is reading the content or not.(6)

2.1.2.3 Google Analytics session length

By default Google Analytics will group hits that are received within 30 minutes of one another into the same session. Developers can manually start a new session by sending a hit to Google Analytics.(10)

2.1.2.4 Google Analytics screen view

Screens represent content users are viewing within application. The equivalent concept in web analytics is a pageview. Measuring screen views allows to see how users are navigating between different pieces of content.(11)

2.2 Activity recognition

Activity recognition is a process in which actor's behaviour along his/her environment are monitored and analysed to detect ongoing activities. It involves different tasks: activity modelling, behaviour and environment monitoring, data processing and pattern recognition. (12) To facilitate activity recognition it is necessary to:

1. Create computational activity models, to allow systems conduct reasoning and manipulation

2. Monitor and capture user behaviour

3. Process information through aggregation and fusion for generating high level abstraction of situation.

4. Decide algorithms to use for activity recognition

5. Carry out pattern recognition

Currently there are two main activity recognition approaches; vision-based and sensor-based activity recognition. (12)

2.2.1 Vision-based activity recognition

Vision-based activity recognition uses of computer vision techniques to analyse visual observations to recognize patterns. Researchers have used different devices such as single camera, stereo and infra-red. Since visual real world representation is often times complex, vision-based activity recognition approaches have problems related to reusability and scalability. The invasiveness of this approach has prevented massive usage in some applications, because cameras are usually used as recording devices. (12) Furthermore, using vision based activity recognition systems is undesired on smartphones, because vision based applications would drain battery.

2.2.2 Sensor based human activity recognition

Sensor-based approach uses sensors embedded to the smartphone. The sensor data which is being collected is usually analysed by data mining and machine learning techniques, to provide models for pattern recognition. Wearable sensors are attached to humans. Commonly inertial measurement devices e.g. accelerometers, gyroscopes, magnetometers are being used. Wearable sensor-based approach is relatively inexpensive for data acquisition to recognize human physical movements.(12)

2.3 Machine learning and pattern recognition

Machine learning solves the problem of identifying patterns and trends in data. As a result, machine learning techniques play important role in many fields e.g. speech recognition, image, or text classification. Tackling nontrivial problems using handcrafted rules or heuristics would be too complex and provide poor results. Better results can be reached by adopting a machine learning approach in which a large set of samples called a training set is used to fine-tune the parameters of an adaptive model. The categories of samples in training set is known in advance, commonly by handlabelling them individually. The result of running a machine learning algorithm can be expressed as function of $y(x)$ which takes new sample x as input and generates an output vector y. Exact form of $y(x)$ is determined during training phase (aka learning phase). Once the model has been trained, it can then classify new samples.(14)

2.3.1 Neural Network

Neural network(15) is an information processing paradigm, which is evolved during attempts to construct mathematical representation of information processing in biological systems. Neural networks have an ability to detect patterns and trends from data, where it would be too complex to be noticed by humans or other computer techniques.

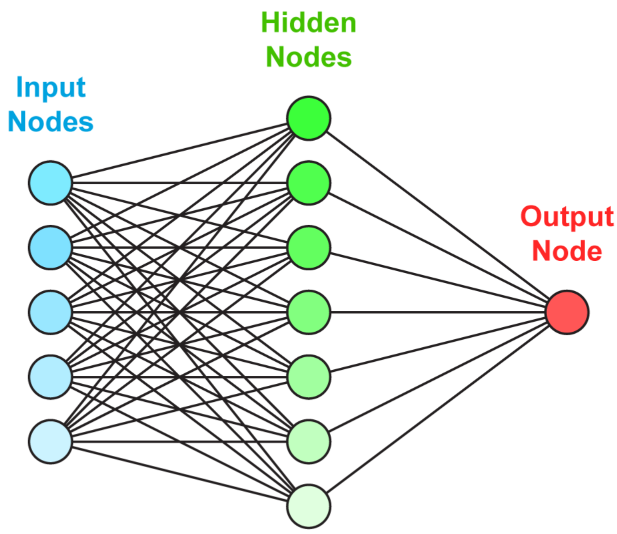

Figure 2.1: Artificial neural network (1)

Conventionally an algorithmic approach is used to solve problems i.e. computer takes specific steps that are pre-coded. This limits computer problem solving capability to problems that we already know how to solve. Neural networks are able to learn how to do tasks based on initial training data. The downside is that because the network finds out how to solve the problem independently, its operations might be unpredictable.

Figure 2.1 shows that the nodes represent neurons in different layers. Each neuron has inputs from previous layer. The output of each neuron is decided by the activation function and weights of the edges.

2.3.2 K-nearest neighbor algorithm

Using K-nearest neighbor algorithm does not include any learning process. Prediction is based on voting the k-nearest neighbors to the test data point. Sample under prediction will be classified as the majority of k-nearest training set points. To determine the nearest neighbors a distance metric is used. In most cases Eucledian distance is used as the distance metric.(16)

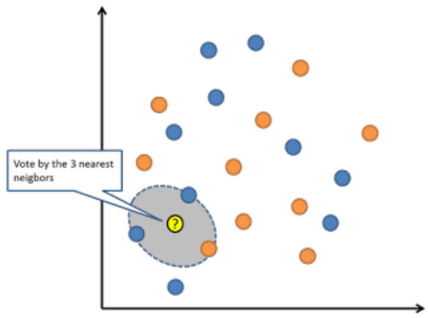

Figure 2.2: K nearest neighbor algorithm(2)

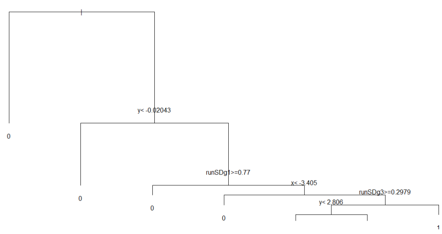

Figure 2.3: Decision tree algorithm

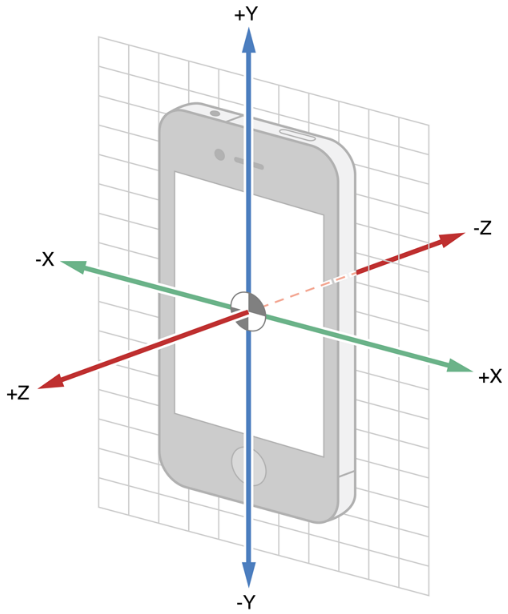

Figure 2.4: Phone accelerometer (3)

2.3.3 Decision tree

The main idea of a decision tree is to divide data recursively into different groups based on some division criteria. During training various criteria is used. Usually less than or greater than relation is used as a decision boundary.(16)

2.4 Sensors for data acquisition

2.4.1 Accelerometer

A triaxial accelerometer is a sensor measuring acceleration caused by movement or gravitation. It returns real valued estimate of acceleration along the x, y, z axis. This means, accelerometer can measure the movement of object it is attached to. Most of the smartphones have accelerometer in them. In the context of this research, movement of hand was measured, while person was reading text on a smartphone. By sensing the amount of acceleration it is possible to determine the devices position and movement in 3-dimensional space.(17)

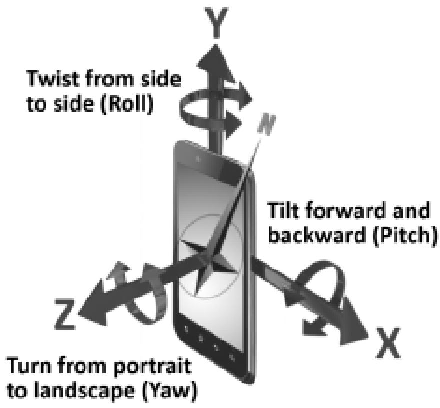

Figure 2.5: Phone gyroscope(4)

2.4.2 Gyroscope

Gyroscope is a device, that measures orientation. It measures roll, pitch and yaw of the device. The combination of accelerometer and gyroscope data, makes it possible to have a total of 6-axis motion sensing, which is more precise than accelerometer or gyroscope alone.

2.5 Summary

There are many ways for ranking data: flagging content, thumbs up/down rating methods, giving stars or points etc. There are analytics platforms on developers side that provide different metrics about content usage. Various machine learning methods are available to classify data and recognize patterns.

3

Problem Statement

The recent improvements in mobile technologies are fostering the emergence of ubiquitous environments in which the user is able to access, create and share information at any location with considerable ease. (18) It is possible to use the data collected through the handset to personalize content for the user to enrich his/her mobile experience. However, the enhancement of the system should not rely only on user provided explicit feedback. Explicit feedback requires engagement from user i.e. button press, writing reviews, sharing etc.

While humans are considered motivated enough to give feedback by pressing a "like" button, it does not reflect a complete understanding in how interested the users are in the information presented in mobile screen. This suggests, that there could be relevant information for the user, which is not ranked due to inactive user participation. There are strategies to induce active participation of the mobile user to rank content. For example, users in social media networks are collecting "likes" on their page to win competitions. Often times, the user pressing the like button is not even reading the content. Current strategies have limitations as the user participation is optional. Therefore, solutions that could provide implicit feedback about each users behaviour should be encouraged.

Motivation to write this thesis comes from the possibility to build a content rating framework, which would be based on implicit feedback. Implicit feedback enables to recognize user preferences to aspects in mobile applications e.g. content or layout without requiring active participation from the user. Implicit feedback enables to collect feedback also from passive users. Feedback from passive users may increase the overall user engagement by increasing content relevance.

Since implicit feedback depends on many different variables, reliable implicit feedback is complex to achieve. Current analytics tools are not able to provide information how much attention particular content got from the user. For example, Google mobile analytics session expires in 30 minutes by default.(19) This time frame is too long to assess whether particular content is really receiving attention from the user or not. On mobile applications the amount of attention content gets is hard to asses, because mobile application analytics rely on screenviews.

3.1 Research Question

Mobile devices allow capturing the environment using their embedded sensors (light sensor, GPS, accelerometer, gyroscope, microphone). Therefore it is possible to track and find patterns from sensor data. The challenge is to implement and develop accurate pattern recognition mechanisms, that would allow devices to determine specific actions e.g. reading.

Chapter 6 will give overview of many works done to classify activities based on accelerometer data. Various authors have classified running, walking, ascending and descending stairs, laying and sitting etc. Also reading books has been classified.(20) Previous works don't take advantage of the fact that modern phones have also embedded gyroscopes. More sensors provide more data. More data makes easier for pattern recognition algorithms to recognise patterns. Using gyroscope data enhances activity recognition, as gyroscope can stabilize the collected data to recognize the activity more accurately.

This work proposes a new metric for rating content and analysing user behaviour on smartphone applications by *classifying reading activity on smartphone based on accelerometer and gyroscope data.* Classifying reading activity helps recommender systems provide more relevant content to the user. Based on applications usage, it is possible to estimate user interest in the content displayed on mobile screen. The work answers following question: *Can reading activity on smartphones be detected or not?* To answer the question an activity recognition experiment was conducted. Details about the framework are discussed in next chapter.

3.2 Summary

Introducing sensor information in the mobile analytic process would help to provide more accurate implicit feedback about smartphone user behaviour. The following thesis attempts to answer stated question. Details are provided in Chapter 4.

4

Contributions

In this section the ideas about introducing sensor data in the analytic process are being explored. As proof of concept, a framework is built and evaluated. The rest of the chapter provides detailed information about building the framework and evaluating its performance.

4.1 Proposed system: Implementation and Configuration

Figure 4.1 shows data collection system consisting of 2 applications for Android OS. While test subject is reading a news article, application 1 saves accelerometer and gyroscope readings into SQL database. Table 4.1 shows a database entry made by data collection application. Application 2 in figure 4.1 runs simultaneously on a separate phone and takes pictures of test subject reading the article. Pictures were taken to facilitate subsequent data labelling. Applications were exchanging data over Bluetooth. Figure 4.2 shows more detailed program flow of data collection and camera application. There was also a third application, that was designed to make picture labelling by hand easier.

4.1.1 Sensor data collection application

Sensor data collection application displayed a web-page in WebView with a news article for subjects to read. The article was the same for each subject. While subject was reading the article, application saved accelerometer and gyroscope readings over one second interval into SQL database on phones internal memory. Time stamp of the

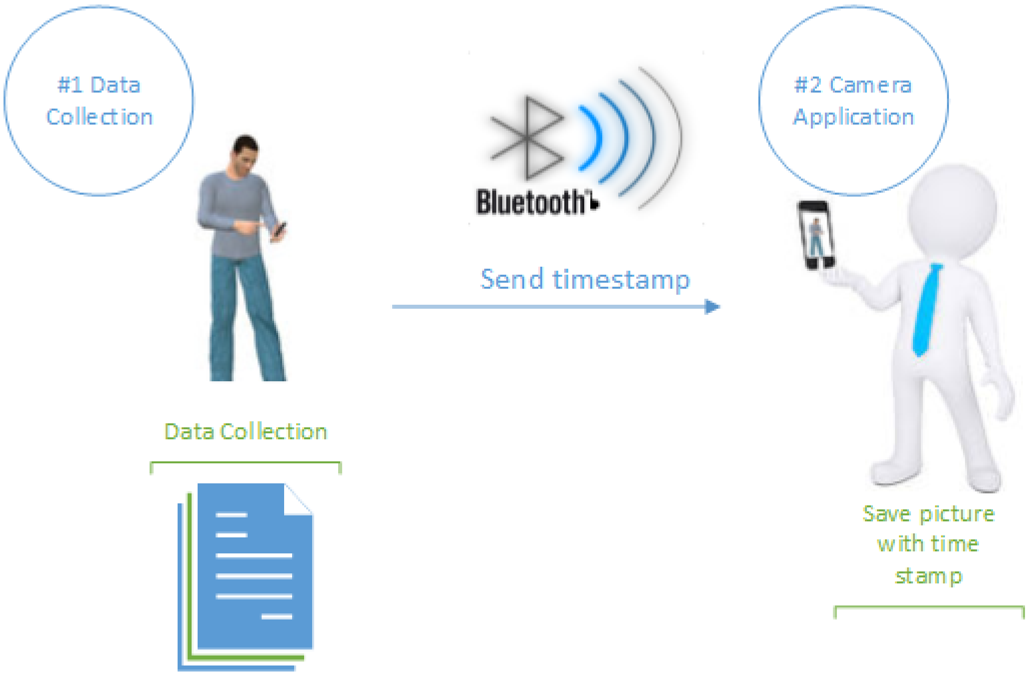

Figure 4.1: Data collection system

database entry was sent over Bluetooth to camera application running on the second phone. 1 Hertz frequency was selected to reduce resource consumption, as the classification model will be used in mobile applications. Application was run on Samsung Galaxy S2 smartphone.

4.1.2 Camera application

To facilitate data labelling each subject was photographed synchronously with the data collection. On Bluetooth message received event the Camera application on second

time stamp	x	y	z	g1	g2	g3
2014_04_02_09_42_26_147	-0.12	2.15	9.79	0.08	0.00	0.00
2014_04_02_09_42_27_127	0.54	1.54	9.15	0.00	-0.29	0.88
2014_04_02_09_42_28_127	0.26	1.46	10.07	0.00	-0.04	0.12
2014_04_02_09_42_29_163	-0.29	1.27	10.05	0.00	0.04	0.00

Table 4.1: A sample of raw data collected from test subject

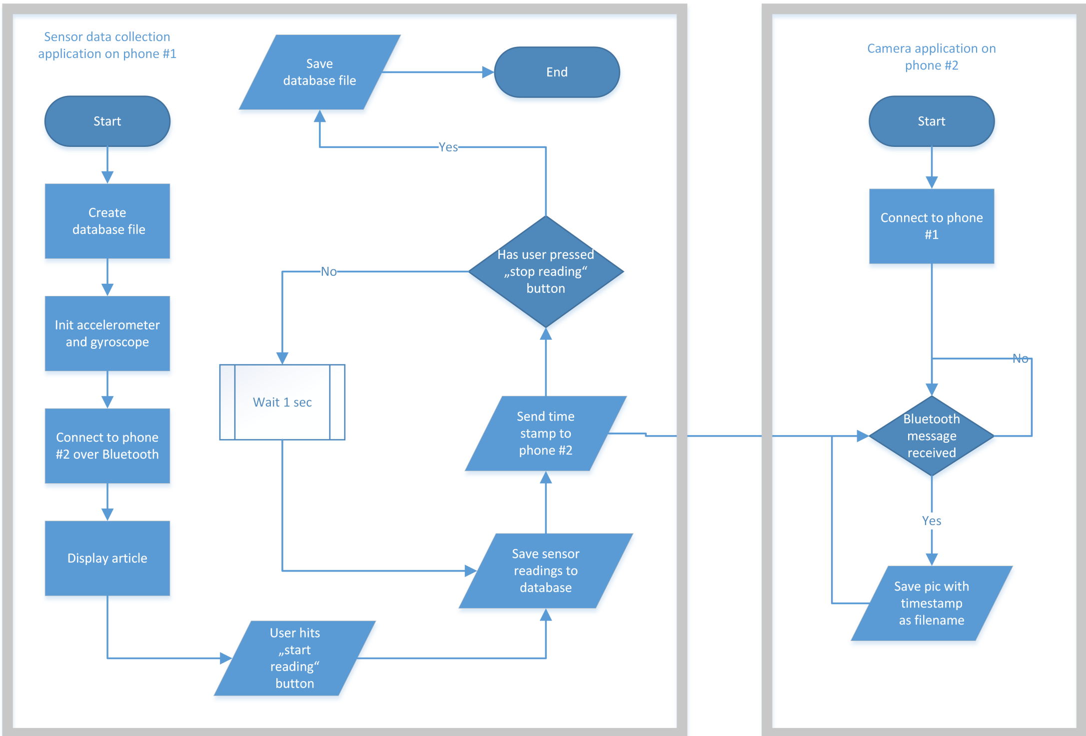

Figure 4.2: Data collection system program flow chart

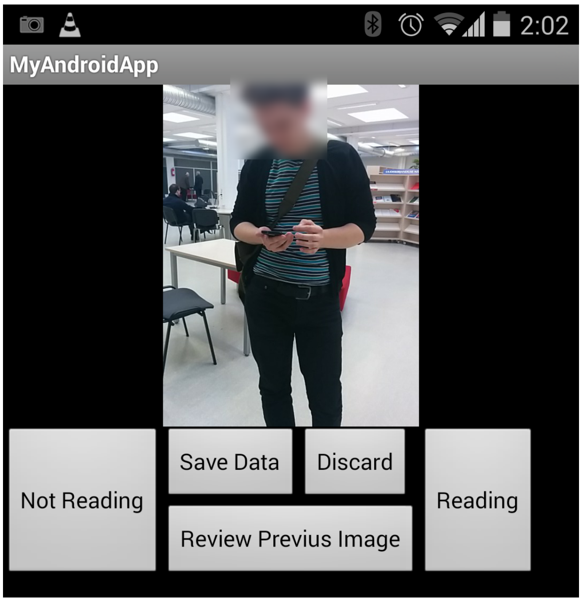

Figure 4.3: Application for data labelling

phone captured photo of the subject performing assigned task and saved the photo to phones internal memory with the received time stamp as the file name. Camera application was running on Google Nexus 5 smartphone.

4.2 Data collection

Three days experiment was conducted. Data was collected from 35 different subjects in different common situations where users are usually reading content from their smartphones e.g. walking on the street, standing, sitting, during a bus ride (standing and sitting). Also data was collected in different situations where users were not reading something on their device e.g walking and holding device in hand, having the device in their chest pocket or jeans pocket while sitting or walking.

4.3 Data labelling

Figure 4.3 shows layout of labelling application that was developed to go over pictures and assess them easily. Labelling application read and displayed photos captured by camera application. User labelling the data assessed whether subject on the photo

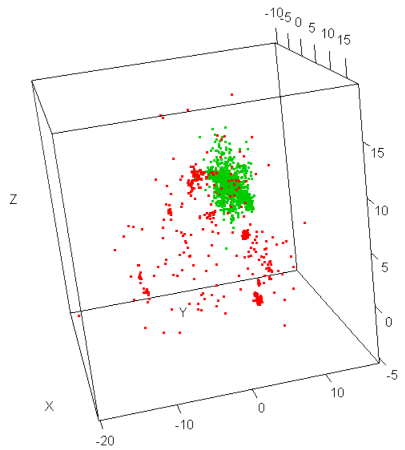

Figure 4.4: Accelerometer readings

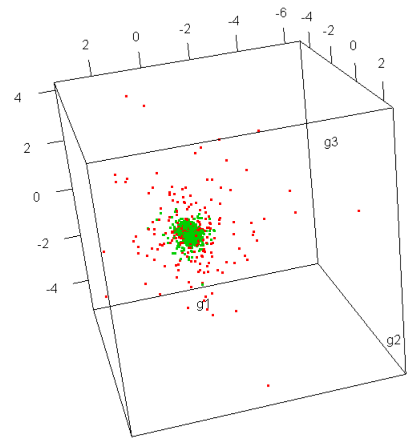

Figure 4.5: Gyroscope readings

was reading or not and labeled the time stamp accordingly by pressing corresponding buttons.

Using statistical computing environment R[1], accelerometer and gyroscope readings were joined with data labels using previously recorded time stamp as key.

4.4 Plots

Collected data was visualized using statistical computing environment R. Visualizations are shown on figures 4.4,4.5, 4.6 and 4.7. Data points are coloured by labels. The green points represent training samples where user was reading and red points represent training samples where user was not reading.

4.5 Cleaning/preparing data

Each subject generated dataset was joined into one big dataset. Initial plots indicated, that reading position is relatively stable position. Since data was organised sequentially, a 5 second sliding window standard deviation calculation was run over each subject data. This led to discarding 4 first samples from every subject readings.

[1] http://www.r-project.org

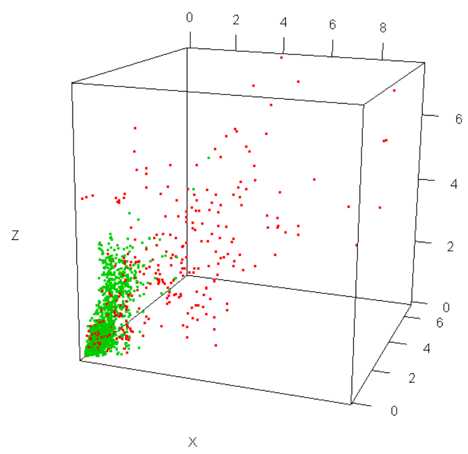

Figure 4.6: Accelerometer readings sliding window standard deviation

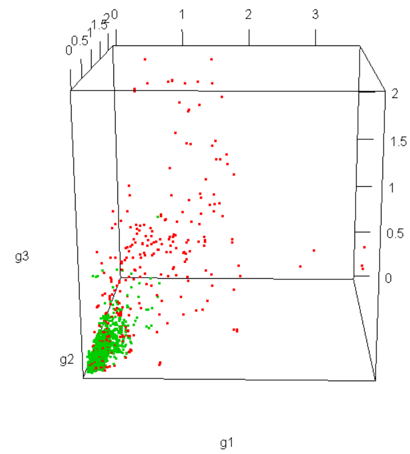

Figure 4.7: Gyroscope readings sliding window standard deviation

Initially there were approximately 5000 data samples. After cleaning data from not suitable samples there were 4577 samples left. 3829 samples were labelled as positive reading examples and 748 samples were labelled as negative not reading examples. Dataset was randomly split into training, validation and test set by 80% 15% and 5% respectively.

4.6 Selection of learning algorithm

As observed from figures 4.4,4.5, 4.6 and 4.7 the classification problem is not trivial. Neural network has many advantages over k-nearest neighbour or decision tree algorithm in the context of this research.

- Using decision tree could cause the problem of over fitting the data, which would cause poor generalization of the learning algorithm.
- For k-nearest neighbours it would be necessary to keep all the training data in phone memory for real time prediction. Prediction would be also computationally expensive, unless training data points are not organized into a k-dimensional tree. Latter would significantly increase application loading time on phone.

Table 4.2: Neural Network Average Accuracy on Test Set

Accelerometer only	Accelerometer and gyroscope	Accelerometer, gyroscope and standard deviations
93.378%	93.649%	95.045%

- Neural network advantage over logistic regression algorithm is that neural network itself is able to come up with more complex and non-linear hypothesis than logistic regression alone. In order to find complex enough features for logistic regression, a high-order polynomial has to be calculated.

4.7 Neural network and its performance

For this research neural network was used with a sigmoid function as activation function of each neuron.

A neural network with 12 inputs and one hidden layer with 2 hidden units was trained on 80% i.e. 3549 samples of cleaned data. Inputs were raw data from 3 accelerometer and 3 gyroscope axes, sliding window standard deviation of 5 seconds of all axes. Reading position is a stable posture. As seen from table 4.2 adding sliding window standard deviation improved average classification accuracy by 1%. On average neural network then classified reading activity with 95% accuracy on test set. Neural network was trained 10 times to get average result. Cost function was minimized for 30 iterations. Back propagation algorithm was used for training process. Algorithm1 shows pseudo code for training the neural network.(21)

```
Data: ProblemSize,InputPatterns, iterations, learningRate
Result: Network
Network=ConstructNetworkLayers();
NetworkWeigths=InitializeWeigths(Network,ProblemSize);
for i=1 to iterations do
    Pattern.i=SelectInputPattern(InputPatterns);
    Output.i=ForwardPropagate(Pattern,Network);
    BackwardPropagateError(Pattern.i,Output.i,Network);
    UpdateWeigths(Pattern.i,Output.i,Network,learningRate);
end
return Network;
```

Algorithm 1: Neural network back propagation algorithm

4.8 Summary

To demonstrate how sensor data can enhance mobile analytic process an Android based data collection and labelling system was developed.

Three days experiment was conducted. Data sets from different subjects were cleaned and joined into one big data set by using statistical computing environment R. Neural network with 12 input units and one hidden layer with 5 units was trained on 80% of cleaned data. The neural network classified reading activity with 95% accuracy on average.

5

Conclusions

There are many different ways to rate mobile content in the form of various explicit user feedback e.g. like buttons, thumbs up and thumbs down, star ratings as well as there are ways to analyse usage statistics of applications on using mobile analytics tools. Implicit feedback enables to collect more data for getting better insight of content usage and user behaviour. In recent years many works have been conducted in order to classify activities using smartphones. Previous works have shown that sensor-based activity recognition on smartphones is feasible. Yet previous works have not classified reading activity on smartphones. This work proposes one possible way to classify this activity with high accuracy. Classifying reading activity provides possibility to have more precise estimates on mobile content usage statistics, by utilizing sensor- and visual-based activity recognition techniques. A set of mobile applications was developed to facilitate data collection and labelling. Accelerometer and gyroscope data was collected from 35 different subjects, after cleaning data 4438 sample readings were left. A neural network was trained on 80% of data and 94% accuracy was reached on classifying reading activity using a smartphone. The results show that classifying reading activity using accelerometer and gyroscope data is possible with high degree of accuracy. We provide Android application source code along with neural network training implementation accompanied by training data in a Git repository [1].

[1] https://github.com/taavitaavi/detect-smartphone-reading

6

Related Work

One of the most cited work, when it comes to activity recognition is (22). Bao and Intille used 5 biaxial accelerometers. Using decision tree classifiers, recognition accuracy of over 80% on a variety of 20 everyday activities was achieved. For this leave-one-subject-out-validation was used on data acquired without researcher supervision from 20 subjects. They found that user-specific training is not necessary to recognize activities.

In (23) Kwapisz, Weiss and Moore showed that smartphone can be used to perform activity recognition by simply keeping it in ones pocket. Furthermore, they showed that activity recognition can be highly accurate, with most activities being recognized correctly over 90% of the time. Additionally, activities can be recognized quickly, since each example was generated from 10 seconds of data.(23)

In (24) Anquita classified a set of physical activites (standing, walking, laying, walking upstairs and walking downstairs) using supervised machine learning techniques for processing inertial body signals. Anquita made use of hardware friendly support vector machine and a Samsung Galaxy S2 smartphone. The same phone was also used for this research. They found that smartphone only has to be enough for activity recognition, since usually people would not be likely to wear many sensors. Also collecting data using smartphone is easy and not restraining for the subject as opposed to using various sensors attached to the subject. Activities were video taped in order to facilitate data labelling. (24)

In (25) a reduction in the number of sensors necessary for activity recognition was proposed to take advantage of the wide usage of smartphones. This would allow to facilitate the development of applications usable by millions of people. Six activities (sitting, standing, walking, running, ascending stairs and descending stairs) were classified with following assumptions: 1) The mobile phone will be located inside the user's pocket 2) Frequency of sensing will be one second. Machine learning algorithms such as K-Nearest Neighbor, C4.5 and RIPPER were used to classify activities. Performance of algorithms was compared and 3-NN algorithm was performing the best. In (26) a concept description of mobile application analytics tool was developed. One of the highest valued features for companies CEO-s was to know how long the users spend on each screen.

When it comes to applications developed for the smartphone industry, there is Samsung "Smart Stay" feature. Samsung has developed "Smart Stay" feature for its devices, to avoid screen dimming while user is looking at the phone and save battery by dimming the display, while user is not looking at the device. Samsung's "Smart Stay" feature is based on front facing camera and eye detection. Samsung's solution falls short in poor lighting conditions, because the phone can not "see" the user, and fails to detect eyes from front camera image. The feature might get users paranoid, because of the feeling, that phone is "watching" the user.(13) In(27) a personal content ranking system is proposed. Although many works have been conducted to classify various activities, most of them use only accelerometer data. None of the cited works have tried to classify reading behaviour on smartphones.

7

Future Research Directions

One application of the proposed solution lies in the rating of content effectiveness and analysing user statistics on mobile applications. Solution to stated problem will also raise context awareness of mobile devices. Being able to sense reading activity would also propose the possibility to enhance battery life by switching off the display when user is not reading. Solution proposed in this paper could complement Samsung "Smart Stay" feature.

In this research tablet PCs were not included as data collection device. Further research should be done using also tablet PCs for collecting data. Adding more features as inputs to machine learning algorithms might enhance the classification rate such as eye detection from front camera image. One plausible feature might be the ratio of characters displayed to time from last scroll. Research how amount of time that user spends for reading content reflects users interest could be also done. Interest of the user is a cognitive state that may change due to many factors. We are interested on exploring how emotions can influence user behaviour in the future. That would help recommender systems provide more relevant shopping suggestions.

8

Sisukokkuvõte

15% kogu internetiliiklusest aastal 2013 moodustas nutiseadmete andmeside. Mobiilse andmeside maht on viimase 5 aasta jooksul kasvanud 1.5 korda aastas ning see trend on tõenäoliselt jätkumas kui mitte kiirenemaski. Nutiseadmed mängivad olulist rolli inimeste harjumustes infot otsida. Nutiseadmete laialdase levikuga on tekkinud uus vajadus pakkuda nutiseadmetest lähtuvale liiklusele analüütikat. Nutiseadmete kasutust puudutav analüütika ei pea põhinema ainult ekraanil kuvataval, vaid võib kasutada ka güroskoobilt ja akseleromeetrilt saadavat informatsiooni. Käesolev töö pakub lahenduse lugemise klassifitseerimiseks nutiseadmetel läbi tegevustuvastuse. Selleks õpetatakse välja tehislik neuronvõrk. Tulemused näitavad, et lugemistegevuse tuvastamine sellisel viisil on võimalik.

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