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UNIVERSITÉ DE MONTRÉAL

DATA ANALYSIS FROM AN INTERNET OF THINGS SYSTEM IN A GAS STATION CONVENIENCE STORE

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Ce mémoire intitulé :

DATA ANALYSIS FROM AN INTERNET OF THINGS SYSTEM IN A GAS STATION CONVENIENCE STORE

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en vue de l'obtention du diplôme de : Maîtrise ès sciences appliquées

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DEDICATION

Dédié à ma famille qui a été mon support durant tous mes années d'éducation.

RÉSUMÉ

Le numérique est de plus en plus populaire et peut être appliquée à plusieurs industries et entreprises afin d'améliorer la productivité et extraire des informations de marketing. Ce travail de recherche s'adresse sur le potentiel des applications d'exploration de données dans un magasin numérisé de vente au détail traditionnel. L'objectif est de démontrer que grâce à un système IoT, des informations peuvent être extraites à partir des données collectées à l'aide des méthodes appropriées, tel que les méthodes d'exploration de données. Nos objectifs ont été réalisés en installant des capteurs Bluetooth dans un dépanneur de station d'essence dans la ville de Laval et en recueillant des données provenant des appareils Bluetooth des clients. Ces appareils incluent tous les téléphones intelligents et les montres intelligentes équipés de la technologie Bluetooth. Une collecte automatisée a été faite sur une durée de une semaine. À partir des données collectées, une première analyse a été effectué pour trouver une corrélation entre le RSSI et les distances réelles dans le but de tracer le mouvement des clients dans le magasin. Ces analyses ont montré que la précision des capteurs n'est pas assez forte pour démontrer un mouvement précis des clients. Pour s'adapter au manque de précision observé, la prochaine étape a été de regarder les données des capteurs comme des événements de présences ou absences dans les zones autours de chaque capteur. Avec les présences identifiées, une proportion de volume d'activité dans chaque zone a été établi comme donnée pour être utilisée avec les rapports de ventes du magasin pour en construire un arbre de décision. Nos résultats ont démontré que des informations peuvent être extraites à partir de la construction de ces arbres de décision qui contiennent des données venant d'un système IoT bien mis en place dans un environnement de vente au détail traditionnel.

ABSTRACT

Digitalization is increasingly popular and can be applied to multiple industries and businesses to improve productivity and extract marketing insights. This research work looks at the potential of data mining applications in a digitalized traditional retail store. The goal is to demonstrate that through the means of an IoT system, insight can be extracted from the collected data with the proper tools, such as data mining methods. This has been done by installing Bluetooth beacons in a gas station convenience store in the city of Laval and collecting data coming from the customers Bluetooth devices. These devices include all smartphones and smart watches equipped with Bluetooth. An automated collection of data was done for a duration of one week. From the collected data, a first analysis was done to find a correlation between the RSSI and real distances to trace customers pathways within the store. These analysis showed us that the sensors precisions are not high enough to show a precise client pathway within the store. To adapt to this lack of precision, the next step was to look at the data from the sensors as events of presences or absences in the zones around each sensor. With each presence identified, a proportion of volume of activity in each zone has been established as data to be used with the store's sales report to build a decision tree. Our results have showed that useful information can be extracted from a properly constructed decision tree with data coming from an IoT system put in place in a traditional retail environment.

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LIST OF SYMBOLS AND ABBREVIATIONS

ARAT	Active Reader Active Tag
ARPT	Active Reader Passive Tags
BLE	Bluetooth Low Energy
CART	Classification and Regression Trees
IoT	Internet of Things
ISO	International Organization for Standardization
GPS	Global Positioning System
M2M	Machine to Machine
MAC	Media Access Control
NFC	Near Field Communication
PRAT	Passive Reader Active Tag
RFID	Radio Frequency Identification
RSSI	Received Signal Strength Indicator
V2V	Vehicle to Vehicle Communication

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CHAPTER 1 INTRODUCTION

Technology is now at the forefront of all business innovations and retail stores must adapt to that reality. IoT applications are increasingly popular and can lead to significant revenue improvements when properly implemented. This research project will attempt to further advance methods to work towards that new reality. The Internet of Things (IoT) and data mining are concepts we hear more and more about but are not always well understood. The technical definition for IoT, as defined in *The Internet of Things: A survey*, consists of a "pervasive presence around us of a variety of things or objects […] which are able to interact with each other and cooperate with their neighbours to reach common goals" (Atzori et al., 2010). These interactions are done through means of wireless communications technologies such as Radio-Frequency Identification. In practical terms, connected objects can constantly communicate with each other sending all sorts of information such as physical position, transactions information and other (Atzori et al., 2010). Data mining, which will be explored furthermore in this research paper, can be briefly defined as "the discovery of interesting, unexpected or valuable structures in large datasets" as defined by Hand (2007). These two concepts of IoT and data mining are closely interlinked together. With well-designed IoT systems, we can have useful data mining applications. These can be adopted in the context of the retail industry to dramatically revolutionize the way the merchant and customers interact with each other in a brick and mortar store.

According to a web page article from Forbes[1], 70% of retail executives say that they are ready to adopt IoT for a better customer experience and 73% agree that proper management of that data is critical to their operations (Columbus, 2017). These implementations can be on applied on various facets of the industry such as brick and mortar store layouts or a customer in-store personalized experience amongst other applications. That same article also highlights retailer readiness with a statistic showing that 79% of retailers will be ready by 2021 to offer each unique customer a personalized in store experience using IoT technologies (Columbus, 2017).

Articles published by technology and management consulting firms Accenture and McKinsey highlights the disruption potential the IoT will have in the retail industry (Gregory, 2014). Several

[1]https://www.forbes.com/sites/louiscolumbus/2017/03/19/internet-of-things-will-revolutionize-retail/%20-%2056d24b785e58

areas where there is room for improvements are identified, but for the scope of this project, our research project will focus on improving customer experience. Some degree of personalized marketing already widely exists. For example, when shopping for a baby chair on Amazon, ads of baby cradles and other baby related furniture will start appearing on the user's Facebook account. The Internet of Things is identified as taking a step further, where with object interconnectivity the business can predict the consumers' needs by observing their habits, and collecting and analysing several data points coming from consumer's smartphones or smart wearables (Gregory, 2014). IoT has the potential to improve customer relationship management tools by building a real-time and personalized profile on each consumer, solely using technology with no human objectivity. For example, a customer that walks into the store is identified by his phone and then notified to an in-store promotion which is only directed towards him based on his browsing history, or from any other source of data collected (Manyika et al., 2015). Another identified IoT application is the optimization of the store layout based on consumers' location. For example, high margin products can be placed in areas where a high flow of traffic is recorded from the sensors (Gregory, 2014).

Data collected from IoT devices comes to little use as it is without any proper analytics tool. Data mining serves as a tool to make sense of structured and unstructured data. Aligned with this research project, data mining is frequently used to analyse customer's habits for marketing purposes by using methods such as classification, clustering and decision trees. It is important to note that the literature stresses the point that an effective data mining process does not solely rest in the data mining method, but firstly in a proper judgement of the business application of the data (Radhakrishnan et al., 2013).

This project is done in partnership with a gas station convenience store based in Laval, Quebec, which is looking to explore how IoT applications can improve its business operations. The focus of this project will not be on the conceptual system required for IoT implementation, but instead on demonstrating how data coming from a properly implemented system can be exploited to bring useful insights for operational and marketing purposes. To be able to extract useful information from the IoT system, data mining will be used for the data analysis. Data mining methods, which will be explored in more depth in chapter 2, permit us to easily analyse large datasets which would otherwise be difficult to interpret.

1.1 Thesis structure

This thesis is structured as follows. Chapter 2 presents a literature review of IoT, more precisely the definition of IoT, its technologies, its use in brick and mortar retail and its challenges. We will also discuss in chapter 2 some data mining techniques which are pertinent to IoT systems and marketing. Chapter 3 will present the research objectives in depth as well as the methods that have been used to conduct the experimentations. The methods include store and technology identification, data collection steps and data analysis methods. Chapter 4 will present a detailed analysis and discussion of the results obtained from the data collection done in this research. Chapter 5 will present conclusions and recommendations for future advancements in this research and discuss limitations.

CHAPTER 2 IOT AND DATA MINING OVERVIEW

This research project will involve setting up an IoT system within a retail store environment and perform pertinent data analysis on the collected data. Before doing so, this chapter will start with presenting a literature review on the work done related to IoT systems and their technologies, as well as their applications and challenges. The second part of this literature review will look at the data mining methods which are pertinent to be applied on the collected data coming from customers at a convenience store.

2.1 Internet of Things (IoT)

2.1.1 Definition

One of the first mentions of internet of things originated from Kevin Ashton back in 1999 (Ashton, 2009). He points out the overwhelming presence of data sources which are limited by one major limitation: the human factor in the capturing process. From there was born the idea of IoT, computers that would replace bar code scanners and such capture a continuous and complete set of data. Technologies RFID (Radio Frequency Identification) and sensors have permitted IoT to develop.

IoT is a vast term which can vary in definition, but essentially converges to a fundamental definition where it consists of a connected system of smart objects, which work together and with little to no human interventions, to supply us with information that we want (Perera, Zaslavsky, Christen, & Georgakopoulos, 2014).

Amongst the definitions of IoT, we find in literature some definitions that focus on the “Things”, some that focus on the “Internet” and some on the semantics of the “Internet of Things”.

The definition that focuses on the “Things” studies the integration of objects into a network by the use of technologies such as RFID (Bandyopadhyay & Sen, 2011). To be a “thing” in an IoT system, that device must have the capacity to collect data without any human interventions (Gubbi, Buyya, Marusic, & Palaniswami, 2013). Further in the literature review in section 2.1.4.2 some characteristics of these smart objects will be discussed in greater details.

The other focus is on the “Internet” which is on a higher-level approach that looks at the network and not at the individual objects (Bandyopadhyay & Sen, 2011).

The third focus is on the semantics of the “Internet of Things. This approach aims to consolidate the various challenges pertaining to data collected in this IoT network. These challenges include the collection of data, storage and analysis amongst others (Bandyopadhyay & Sen, 2011).

2.1.2 Technologies

As it will be seen a bit later in this research paper in

Table 2.1, for an IoT system to be effective, the smart objects within it must be process-aware objects, that is, objects that can discern activities in relation to location and time (Palumbo, Barsocchi, Chessa, & Augusto, 2015).

Indoor localization has its own set of challenges which is not present in outdoor localization technologies such as GPS. Some challenges include indoor obstructions that would disrupt Bluetooth signal. Other challenges are the interference with other wireless signals in an indoor space that might interfere with signal strengths (Chawathe, 2008).

IoT technologies can be found in literature under categories such as RFID, NFC (Near Field Communication), M2M (Machine to Machine) and V2V (Vehicle to Vehicle Communication). RFID works with the use of electronic tags attached to the tracked items which communicate with the receivers through radio frequency electromagnetic fields. The tags can either be PRAT (Passive Reader Active Tags), ARPT (Active Reader Passive Tags) or ARAT (Active Reader Active Tag). NFC technologies comprise RFID technologies but are found within mobile phones to enable communications between them. These technologies work on very short range and can only transfer a small amount of data. The next category is M2M and enables communication between a variety of electronics such as computers, smart phones and sensors. The functioning of M2M is described as the ability of the device to send requested information to other devices. This is done through technologies such as Bluetooth and WIFI (Network based) amongst others. The last category is V2V and comprises applications which are long range. The nodes in a V2V network can communicate to each other’s within a range of 100m. This is done with an Ad-Hoc network comprised of connected sensors (Shah & Yaqoob, 2016).

For this research project, the category of interest is M2M technologies which are the most readily accessible, hence this literature review will focus on Bluetooth and WIFI sensors as they are the most easily purchasable for our research.

2.1.2.1 Bluetooth Sensors

Bluetooth was conceived in 1994 and serves as a mean of device short range communications without the need of physical cables. It works with a radio system and is present in many electronic devices such as computers or printers (Ferro & Potorti, 2005).

Since this wireless mean of communication has started in 1994, Bluetooth technologies have evolved in a significant way to become highly effective in indoor localization applications. The emergence of BLE from standard Bluetooth is enabling low-powered short range communication and faster transmission of data. It has been implemented since its evolution in the majority of smart devices (Gomez, Oller, & Paradells, 2012). BLE technology also has many practical advantages such as not requiring a large setup space, compatible with multiple Bluetooth enabled devices and highly power efficient (Zhuang, Yang, Li, Qi, & El-Sheimy, 2016). An experimental setup was found in the literature where the experiment was set up in an office space with eight BLE devices to validate the use of this technology. The sensors were placed at a level 3 m above ground level in a 6x6 m office. The sensors being place at a high level were unobstructed by office objects such as desks or cubicles. A localization method was established using the sensor's RSSI (Received Signal Strength Indicator), which is simply the measure strength of the captured signal in decibels, and a logarithmic function determined by equation (1) (Palumbo et al., 2015).

$$RSSI = -(10n \cdot log_{10}d - A) \quad (1)$$

Where n is the slope distance/RSSI, A is the intersection in RSSI and d is the distance. The data collection was done with a person walking with a phone put 1.5 m above ground level, and stopping five seconds at marked locations. After using the above formula to establish a correlation between RSSI and distance, results found that 75% of the calculated distances versus real ones were within 1.8 m of reality (Palumbo et al., 2015).

Some advantages of Bluetooth technology will be discussed. Among the strength of BLE enumerated in the beginning of this section, that technology is energy efficient and highly compatible with multiple devices. This advantages permits BLE sensors to be installed with batteries, instead of being hardwired, increasing their mobility (Zhuang et al., 2016).

BLE does come with some disadvantages. One of them is the range is limited, resulting in having to deploy multiple sensors to achieve a complete coverage of a larger space. Although literature

also describes it as a potential advantage in some situations. With a limited range, if a device is captured on the sensor we are guaranteed that it is in an area at a proximity of the BLE beacon. Another disadvantage is the time it takes for a Bluetooth device to be discovered. In an experimentation done by Chawathe, it was found that it took on average a time of 10.24 seconds for BLE sensor to successfully capture the presence of a Bluetooth device (Chawathe, 2008).

2.1.2.2 WIFI Sensors

Another technology with big potential in indoor localization applications are WIFI enabled sensors.

WIFI has many advantages, such as the technology already being implemented in most mobile devices and now even in larger electronics such as smart TVs and cars. To add more advantages, WIFI devices are also not power hungry. Although, WIFI equipped beacons require more energy than their BLE counterparts making them less versatile. An advantage of WIFI technologies is identification. WIFI protocols are more accurate in identifying the scanned device then Bluetooth technologies (Saloni & Hegde, 2016).

Other characteristics of WIFI have also been found in literature which explains the technologies popularity in IoT systems. WIFI enabled sensors have the ability to transfer a high amount of data at very high speeds which is essential for data collection. It has also been identified as having a high coverage area of about 300 m outdoors and 100 m indoors. The technology can also accommodate a growing system since it is easily scalable. Finally, another interesting aspect of WIFI is the reliability of its signal (Li, Xiaoguang, Ke, & Ketai, 2011).

An important aspect of WIFI technology is in relation with a device's MAC Address. A MAC Address is a unique identifier which is seen by the network the device is connected on. A WIFI connected device will have a unique MAC Address which permits unique identification. This means that in an IoT system a particular device can be identified and studied over time (Cunche, 2014).

2.1.3 Applications in Brick & Mortar Retail

IoT applications in brick and mortar retail stores are still relatively new since sensors have only become recently affordable and the adoption of this technology is recent. Literature is scarce on

the subject but there are still some research applications done in a brick and mortar retail environment like it is the case of this research project.

An interesting application identified in literature consists of tracking customer's movements in store to adapt specific promotions according to the data collected (Hagberg, Jonsson, & Egels-Zandén, 2017). A study was done in a South Korean retail store to observe customers' behavior for marketing purposes (Hwang & Jang, 2017). Their movements were tracked by using IoT sensors which interact with the customer's smartphones WIFI antennas, revealing their semi-precise physical location inside the store. The precision of this technology varies with the quality of devices which interact with each other and the WIFI antenna signal strength. This leads to a certain margin of error in the data analysis. Each customer is identified by his unique "Mac Address" from his smartphone allowing each data point to be linked to a recurrent customer. The data is also temporal having a time stamp associated with each data point. With the data collected, an analysis was made to observe how the customers interact with different store items and what their general routine is. This led to a conclusion showing how varying the location of different displays in store can lead to an optimized layout for sales. An important remark done by the authors of the experiment is that although a change of sales and traffic volume was observed after applying the optimized layout, there is no guarantee that it is the sole cause for that change. Furthermore, other variables were not taken into effect such as interactions with staff members or cash counter interactions (Hwang & Jang, 2017).

Another research paper was found with experimentations using NFC equipment. In that study, the store products as well as its clients are both NFC equipped to start a link between the consumers and the shop. That link brings forth the possibility of targeted presentations to customers. For example, a sport loving shopper would see a football game display on the television screen he is looking at. Another application is to provide a complete shopping package. A customer would insert his items in his virtual basket within a physical store and in consequence the sales associate can provide a personalized package related to the items chosen by the customer. This package would be done automatically using IoT analytics and not simply a subjective assessment (Longo, Kovacs, Franke, & Martin, 2013).

A study was also found evaluating customer's behaviors in a digitalized grocery store. The article explores the potential of embedding the store with smart objects by integrating cell phones with

smart equipped baskets, store shelves and products. The study involved sending a sample of 60 people to shop for a BBQ grocery list. Specifically for the salmon, different promotions would show up on the shoppers' cell phones to evaluate their decisions to get fresh salmon or not based on the promotions they see. Since this is all connected to an IoT network, these promotions are customizable and given in real-time. The conclusion of the study was that according to the promotion displayed, there was a correlation between the customers decision to purchase fresh salmon or not (Fagerstrøm, Eriksson, & Sigurðsson, 2017).

Applications in brick and mortar can go beyond the direct customer service experience but also indirectly by being more efficient in store operations. An example shown in literature describes a situation where a refrigerator would be part of an IoT network. That refrigerator would have sensors capable of detecting whether it's performing at its full capacity. If that device is faulty, an alert would be sent to store staff in order to service it (Lee & Lee, 2015).

2.1.4 Challenges

The Internet of Things is still a relatively new concept and many challenges are present in its adoption. Amongst these obstacles lies the lack of standardization for an IoT infrastructure as well as implementation challenges.

2.1.4.1 Standardization

With a growing number of adoptions of IoT, basic tasks such as data generation and storage have a need for a standardized model. Per Banafa's article, four dependant categories are identified in the process of standardizing IoT practices: platform, connectivity, business model and killer applications (Banafa, 2016).

First, a platform which can handle data with the use of the appropriate analytical tools. The platform also englobes user experience such as the interface design and it should have the capability to be scaled for larger applications (Banafa, 2016).

Secondly, the need for a standardized connectivity baseline should be established for a proper stream of data and interaction with the established platforms. Connectivity includes aspects such as how the data is connected. For example, the use of smart wearable devices, smart homes or on a much larger scale, smart cities (Banafa, 2016).

Thirdly, a robust business model. This is important to have all the players involved in an IoT infrastructure to be invested in the created ecosystem (Banafa, 2016).

The last point mentioned in the article is “killer applications”. Simply put, killer applications represent the tangible outcome from the collected data and its analysis (Banafa, 2016).

2.1.4.2 Implementation

The other aspect of IoT challenges lies in its implementation.

The concept of IoT is a complex one and it includes a multiple of inter-related systems that need to properly work with each other. The systems mentioned by Banafa (2016) include sensors, networks, standards, intelligent analysis and intelligent actions. Sensors are the driving force of an IoT system. Recent technology advances in that domain have led to much more affordable IoT equipment making the implementation affordable for smaller players. Networks define how the sensors interact with each other and the collecting database. Same as with sensors, advances in technology has allowed for cheaper network maintenance and much faster speeds. Another implementation step involves looking at standards. Standards are important to regulate how data is handled over the network and how it is stored. All three of the first processes of implementations face similar challenges. Security is of the upmost importance given the fact that there is an extremely huge amount of data being sent and processed across networks. Other challenges include regulatory issues and optimizing the power consumption of an IoT system. The other aspects of implementation which are strongly inter-related with each other are intelligent analysis and intelligent actions. These steps include transforming the collected data into useful and easy to understand business knowledge and transitioning that knowledge into tangible actions. The challenges in these implementations are the proper applications of data analytics on IoT data as well as updating these systems to support a large flux of incoming real-time data (Banafa, 2016).

Other aspects of implementation challenges are also discussed in Kortuem’s et al. (2010) article. The research question in their article is focused on the interaction between human users and the smart objects themselves, which are suggested to have these three fundamental characteristics: activity-aware objects, policy-aware objects and process-aware objects.

Table 2.1 summarizes the article’s description of these characteristics (Kortuem, Kawsar, Fitton, & Sundramoorthy, 2010).

Table 2.1: Smart Objects

Smart Objects	**Description**
Activity-Aware Objects	They can discern different activities and the order in which they are performed. These objects are simply for data gathering.
Policy-Aware Objects	They can understand activities in the scope of the policy that has been programed for the IoT system. Mainly for compliance.
Process-Aware Objects	They can discern different activities with relation to the location they are performed and the time they are performed at.

Another challenge is implementing smart objects while considering the human interactions. Smart objects by themselves have little added value, but smart objects that are well integrated into an ecosystem where they interact not only with each other, but also consider the human inputs, and there lies the implementation challenge (Kortuem et al., 2010).

2.1.4.3 Ethical Issues

Connecting IoT sensors to people's personally devices brings with it ethical questions. Does the user still have his privacy? How is that privacy protected with all the data gathering that happens in an IoT system?

In BLE technologies, one of the reason of its popularity is because it is not invasive of a person's personal device. In order to detect a presence, a BLE beacon only needs to detect a Bluetooth transmission being made without connecting to the device, which would then be intrusive to one's privacy (Chawathe, 2008). However, if a device owner's actions can be linked to another activity whose identity is disclosed, for example, using a credit card or using a loyalty card (e.g. Petro-points), that could allow identify the device owner. It should not be done without the informed consent of the subject. Therefore, when designing an IoT system to collect information about people's trends and habits, close attention must be payed to whether the system has potential privacy risks.

The ethical issue is much more prominent in WIFI driven IoT systems. As previously discussed in the literature review, we found that WIFI can identify a device's unique Mac Address. This means

that the monitored device owner is being watched and can be profiled and potentially reveals the person's personal identity. Another issue is the possibility of linking various WIFI devices to the same owner which can lead to greater data collection and in return a greater invasion of privacy (Cunche, Kaafar, & Boreli, 2014).

2.1.4.4 ISO Standardization

To overcome the challenges enumerated in sections 2.1.4.1 and 2.1.4.2, the International Organization for Standardization published ISO 30141. This standard serves the purpose to provide the necessary tools for all IoT systems to work with. It helps to overcome the mentioned challenges by setting the following objectives as stated by the standard: "to enable the production of a coherent set of international standards for IoT", "to provide a technology-neutral reference point for defining standards for IoT" and "to encourage openness and transparency in the development of a target IoT system architecture and in the implementation of the IoT system" (ISO, 2018).

2.2 Data Mining Methods

Once a proper IoT setup has been done in our gas station convenience store, data mining methods are going to be used to properly analyze the data collected. The following section will present the data mining methods which are pertinent to the type of data that we will be collecting for our research project.

The use of data analytics goes hand in hand with an IoT system. Without these tools, the insight that can be extracted from the sheer volume of data is very limited (Radhakrishnan et al., 2013).

Data mining methods are plentiful and an extensive literary review can be done on this subject but for our research project we will focus solely on learning methods. Learning methods can be separated into two categories: supervised learning and unsupervised learning. Supervised learning methods consist in predicting an output variable based on input variables. This is done with the use of training and testing datasets. Supervised learning is separated into classification methods and regression methods. Unsupervised learning methods consist in having only input variables with no studied output data. This serves the purpose of figuring out how the data is distributed and categorized. Unsupervised learning is separated into clustering and association methods (Brownlee, 2016).

The focus of our research is to demonstrate the possibility of useful data analysis from an IoT system. The discussed methods in this literature review section will be on supervised learning methods as they are the most pertinent for the type of data we will be gathering in our research.

2.2.1 Classification and Regression Methods

Classification methods are used to classify output variables into pre-defined groups or classes of attributes. The purpose is to correctly predict to what class or group a studied variable, based on its attributes, will belong to (Kesavaraj & Sukumaran, 2013). Regression methods are very similar to clustering methods, with the only difference that the output variables are not pre-defined classes or categories but real values instead (example: sales amounts in dollars) (Brownlee, 2016).

Classification and regression methods all follow the same two fundamental steps. The first step is the supervised learning part, where a training dataset is used to create classifying rules. The second step is the applications of these rules to a testing dataset. The methods used are decision trees, rule-based methods, memory based learning, neural networks and Bayesian networks (Kesavaraj & Sukumaran, 2013). For our research, we will focus on decision tree methods.

Decision trees represent a classification model in the form of a tree composed of nodes which look at an attribute, a decision branch which looks at the value of the attribute and leaf nodes which are the classification (Kesavaraj & Sukumaran, 2013). For example, a node can be: Exercises a minimum of 4 times a week, and its subsequent decision branch would be true or false. A leaf node in that decision tree could be "Healthy". An example of a decision tree is shown in Figure 2-1.

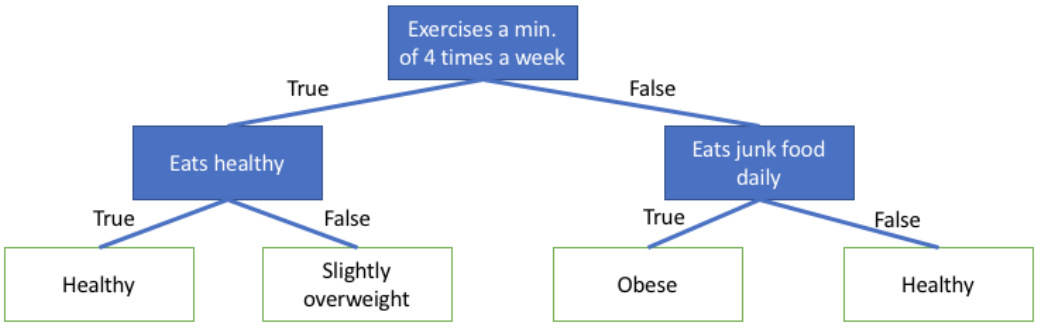

Figure 2-1: Decision Tree Example

Decision trees are constructed by looking over attributes of a training dataset. The first step looks at all data at the node. If all variables can be assigned to one class, then it becomes a homogenous

leaf node. If not, then a partition is created per attribute. This process repeats until all data are put in a homogeneous leaf node or there are no more attributes to keep dividing into more nodes. Pruning methods can also be applied which serve to remove nodes that have little added classifying relevance to the decision tree (Kesavaraj & Sukumaran, 2013).

The quality of each class, which is the ratio of right decisions/classification over the total sample number at the node, can be measured in various ways per the decision algorithm used. Some commonly used algorithms are the CART method or C4.5 method (Kesavaraj & Sukumaran, 2013).

The CART method, which stands for Classification and Association Regression Tree, is used to construct binary trees, meaning each node splits into two binary decisions true and false. The split is done based on the twoing criteria, which is a measure of class purity. The subsequent tree is then pruned using the cost-complexity pruning method. Some advantages of the CART method are that it can easily handle both regression and classification tasks, it can easily determine which variables are most significant and prune less useful variables. Some disadvantages are that the CART method can only split one variable at a time at each node and if wrong modifications are done to the training dataset, it could lead to an unstable tree (Singh & Gupta, 2014).

The C4.5 method starts by finding from all possible splitting tests the one that gives the best result using the information gain criteria. An important difference between C4.5 and the CART method is the ability for C4.5 to create a decision tree which contains both discrete and continuous values. When sorting discrete attributes, a test is used to generate possible outcomes based on the number of unique attributes for the value at the node. For continuous attributes, the data is split using binary cuts and the information gain criteria is applied to produce the next node of the decision tree, similarly to discrete values. C4.5 also allows for pruning by using an error based pruning method. An advantage of this method includes the ability to sort through both discrete and continuous attributes. Another advantage is for the method's capability to leave marked unknown attributes which will not be calculated in the information gain. A disadvantage of this method is the frequent generation of nodes with zero or near zero values. This leads to a noisier decision tree with confusing rules generation (Singh & Gupta, 2014).

An example of supervised learning in literature was found where a study was done in the banking industry. The article shows how classification analysis can be used to identify the success factors in direct marketing campaigns. The conclusion of the study was that the duration of the calls and

the month of the year the call was made where the biggest contributors to a successful marketing campaign. This was obtained by applying classification methods on the studied dataset (Moro, Laureano, & Cortez, 2011).

2.3 Literary Review Conclusion

Chapter 2 presented an overview of the IoT technologies that can be used for remote identification, such as BLE or WIFI, as well as some applications in retail stores. It also presented the challenges facing IoT system such as ethical issues that might arise form one. The chapter also presented data mining concepts which are needed to reveal hidden patterns from the data collected from an IoT system. These concepts had to be reviewed to understand the objectives which will be listed in the next chapter.

CHAPTER 3 MATERIALS AND METHODS

3.1 Objectives

The objective of this research project is to demonstrate that through the means of an IoT system, insight can be extracted from the collected data with the proper tools, such as data mining methods.

We built a database which includes Bluetooth devices addresses, RSSI, device classification and sales figures. This was done using of BLE sensors, tracking the positional and temporal data from Bluetooth devices and the sales report data coming from the store management.

Using the above data as inputs and studied variables, we will be working towards an analysis for:

- Defining a correlation between device signal strength and physical location of the device to establish a customer pathway and the amount of customer activity in defined zones.
- Establishing a correlation between the data collected with the IoT sensors and the sales data using data mining techniques.

The next section will present the methods and experimental procedure used to accomplish the objectives set above. This research was done in cooperation with Marques' (2018) research. Marques' project focuses on the implementation and conception of an IoT system, whereas this research focuses on the applications from the data generated. The methodology is separated in three sections. The first section presents the IoT system setup which was done in cooperation with Marques. The second section presents the RSSI to real distances triangulation methods used for customer pathway tracing. The third section presents the data mining method used to analyse the data coming from the implemented IoT system and the sales report from the convenience store.

3.2 IoT system setup

This sub section presents the store and technology identification for our IoT system setup as well as the location of our sensors and a description of the products contained in their surrounding areas.

3.2.1 Store Identification

The first step towards accomplishing the goals of this research project is to identify a convenience store to work with to install sensors and collect data from. Our aim was to find a gas station which

has a constant client flow and a regular customer base. This rules out gas stations on the highway which would include a larger proportion of people traveling. We settled on a convenience store located in the suburbs of Montreal which is known to have regular customers that go weekly at the gas station. It is also not by a highway so the proportion of irregular travelers is small.

3.2.2 Technology Identification

As seen in the literature review, many technologies exist for the sake of IoT data collection. For our experimental setup, we have adopted the solution developed by the Montreal startup reelyActive[2], which provides Bluetooth beacons that continuously collect data from any detected Bluetooth source. The company also provides an online platform (Pareto), which offers tools to monitor the status of the beacons and to consolidate data collection. Figure 3-1 shows a Print Screen from Pareto.

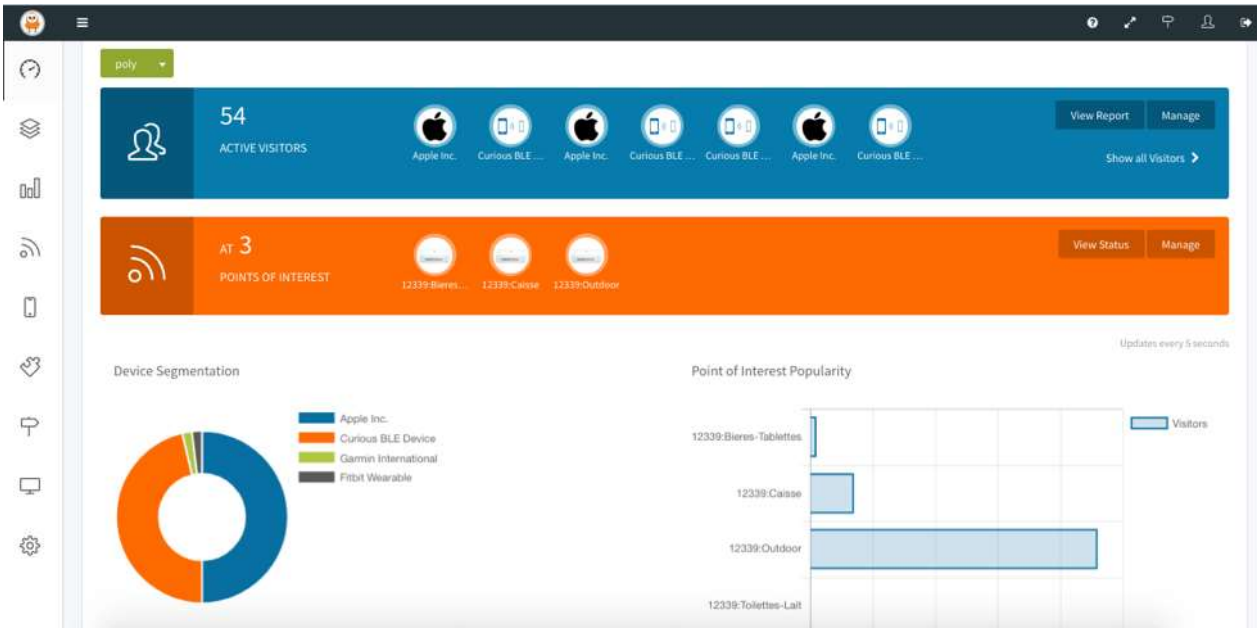

Figure 3-1: Pareto Main Page User Interface

As previously discussed, Bluetooth is a cheap and easy way to collect data from customers while simultaneously preserving their privacy, and it fitted the modest budget we had for this pilot project. To stress the ethical question around data collection from personal devices, as discussed

[2] http://www.reelyactive.com/

in section 2.1.4.3, the data collected was not linked with any identification method such as payments at the cash or association with a customer's loyalty card. The company we worked with also did not disclose any customer information to us. Given these facts, the data we collected was completely untraceable to any customer. For this reason, we have purchased four Pareto beacons and a trial subscription of Pareto to access all data collected by the sensors. Costs cannot be disclosed in this paper to respect the ReelyActive company's confidential pricing plan given to us.

3.2.3 Sensors Setup

To maximise the quality of the data, zones of interest were identified to insert the RFID beacons in. These four zones contain products of interest for a data analysis. A detailed description of the zone contents is shown in

Table 2.1. The sensors located on a scaled map of the store floor are shown on Figure 3-2. The dark grey bands at the bottom of Figure 3-2 are the store counters.

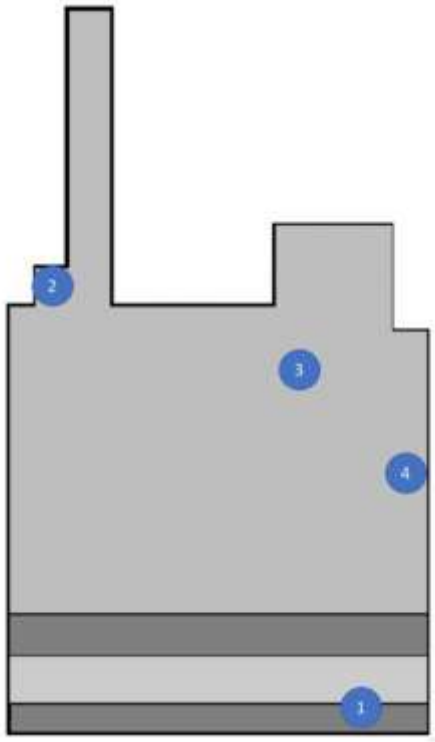

Figure 3-2: RFID Sensors Locations

Table 3.1: Sensor Zones Description

Sensor	Label	Zone Contains
1	Cash	Cash, gum, sweets, tobacco
2	Washroom	Lottery, milk, restroom, energy drinks, dairy products, soft drinks
3	Liquor	Alcohol, small electronics, beef jerky, chips, chocolate bags, mixed nuts
4	Outdoor	Ice cream, cold non-alcoholic drinks

As seen in the literature review, ideally the sensors should have been installed high up on the ceiling to not have signal interference coming from the shelves, but due to store limitations and other concerns such as theft, the sensors had to be installed in locations that were not free of all obstructions. Another limitation we had with sensor location was that they had to be placed out of sight. This was because the company did not want their customers to think that they were in partnership with the beacon provider ReelyActive. Sensor 1 was installed atop a television facing the cash. Sensor 2 was installed behind the lottery booth. Sensor 3 was installed on a shelf corner. Sensor 4 was installed behind a wine fridge. Due to the mentioned limitations, these sensors all had physical obstructions such as sensor 1 having a TV in the way, or sensor 3 having the lottery booth in the way.

3.3 RSSI To Real Distances Triangulation Methods

This section presents the data collection performed from the previously set up IoT system as well as the methods used to find a correlation between measure RSSI values and real physical distances.

3.3.1 Data Collection

A total of three automated data collections as well as one manual data collection were performed to collect the data for our experimentations.

3.3.1.1 First Raw Data Run

The first raw data run was done for a week using a JavaScript code provided from Pareto. The collection was done for the duration of one full week. A total of 917493 lines of data were collected

during this week. The raw data was stored in an Excel file in CSV format. The pertinent raw data collected included:

- Timestamp (Epoch format)
- Session duration (milliseconds)
- Device Bluetooth ID
- Device tag
- Strongest RSSI captured with the beacon identified

The code can be found in Appendix A, first section. A sample of the first raw data run can be found in Appendix B, first section.

After considering the data collected in this data run, we concluded that we would need signal strengths from each of the beacon at the same time to define zones to trace a customer pathway. No further analysis was done with this first data run.

3.3.1.2 Second Raw Data Run

A second raw data run was done to include the RSSI captured from each beacon to define more precise zones by finding the intersecting zone between the four beacon RSSI strengths. The collection was done for the duration of one full week. A total of 937245 lines of data were collected during this week. The pertinent data collected is the same as section 3.3.1.1.

The code can be found in Appendix A, second section. A sample of the first raw data run can be found in Appendix B, second section.

3.3.1.3 Manual Data Run for zone Delimitations

To establish the limits of the store as well as collecting data for the RSSI to physical distances correlation methods, a manual data run was performed at the convenience store. The RSSI values at the points identified in Figure 3-3 were collected.

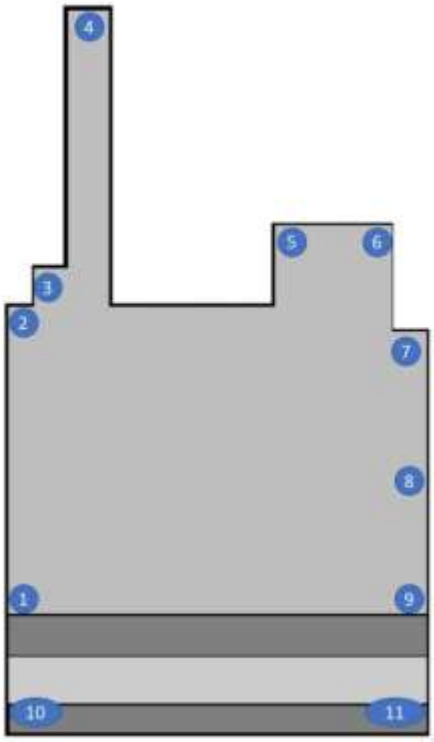

Figure 3-3: Zone Delimitation Captures

Using a Fitbit Bluetooth wearable device, trademark of Fitbit Inc., the manual collect was done by using the Pareto interface and standing for at least 1 min at each of the map positions to stabilize the RSSI. One run was done with the Fitbit not on a wrist but left sitting on a high object in the store (Fitbit not on body). Another run was done with the Fitbit on the wrist. Another run was done with an iPhone X, trademark of Apple Inc., in the front pocket and finally a fourth run was done with the same phone in the back pocket. The RSSI recorded for each of the four runs is shown in Table 3.2, Table 3.3, Table 3.4 and Table 3.5. In these tables, the numbers are in RSSI. A higher RSSI means a closer distance from the beacon and a lower RSSI distance means a further distance from the beacon. The highest value that was recorded was an RSSI of 182 when a device was placed directly on a beacon. This value of 182 was found using the online Pareto interface.

Table 3.2: RSSI Signals, Fitbit Not on Body [dB]

	Sensors (RSSI)			
Map Points	**Cash**	**Outdoor**	**Washroom**	**Liquor**
1	148	147	167	159
2	160	151	177	157
3	145	150	182	168
4	140	143	164	162
5	167	151	160	159
6	163	156	160	173
7	148	168	162	165
8	144	167	163	168
9	159	161	168	165
10	152	158	163	157
11	162	156	159	156

Table 3.3: RSSI Signals, Fitbit on Wrist [dB]

	Sensors (RSSI)			
Map Points	**Cash**	**Outdoor**	**Washroom**	**Liquor**
1	150	152	161	155
2	144	150	161	159
3	152	145	178	160
4	139	148	154	137
5	148	154	152	158
6	150	148	153	161
7	148	158	146	158
8	155	164	156	152
9	167	149	153	160
10	151	144	156	158
11	166	155	156	159

Table 3.4: RSSI Signals, iPhone X in Front Pocket [dB]

	Sensors (RSSI)			
Map Points	**Cash**	**Outdoor**	**Washroom**	**Liquor**
1	155	164	0	152
2	163	147	179	167
3	158	152	181	165
4	140	143	161	149
5	160	150	150	162
6	157	154	149	166
7	153	172	156	157
8	164	155	157	162
9	157	153	152	156
10	169	151	151	153
11	164	159	165	160

Table 3.5: RSSI Signals, iPhone X in Back Pocket [dB]

	Sensors (RSSI)			
Map Points	**Cash**	**Outdoor**	**Washroom**	**Liquor**
1	157	157	166	162
2	160	158	172	166
3	144	155	178	168
4	148	148	168	153
5	161	164	164	170
6	160	159	156	168
7	156	176	159	162
8	166	169	159	167
9	158	147	149	161
10	170	155	149	159
11	160	162	164	157

3.3.1.4 Third Raw Data Run for RSSI to distance validation

For validation purposes, another collect was done using the Pareto code and the Fitbit device. Referring to Figure 3-3, a path starting from point 1 through point 11 and ending at point 10 was taken. The Fitbit device was placed at each point for at least 1 min to ensure the RSSI signal was detected and stabilized. We will refer to this validation run further in sections 4.1.1.1 and 4.1.1.2.

3.3.2 Zone Definition Triangulation Methods

Amongst our objectives, we want to establish a customer pathway within the convenience store. To do so, the RSSI signal coming from the Bluetooth devices captured by the beacons must be converted in measured distances. To find a correlation, two methods are tried in our research project. The first method involves using a linear correlation and the second method involves using a logarithmic correlation found in the literature.

3.3.2.1 Linear Correlation Method

From the manual data run, collections were done using a Fitbit and an iPhone X devices to establish a correlation between the RSSI and physical distances. To find that correlation, the data found with the Fitbit was chosen. This was done after discussion with the subject matter expert and Founder of Pareto devices who recommended us with the higher precision of using a Fitbit. The data found with the iPhone X will be used for validation.

The first step in the analysis is to measure the distance between each point on the map (Figure 3-3) and each beacon. These measurements were taken using a laser measuring tool for a high level of precision. The measured distances are shown in Table 3.6.

Table 3.6: Distances Between Each Delimitation Point and Beacon [m]

	Meters			
Map Points	**Cash**	**Outdoor**	**Washroom**	**Liquor**
1	8.2	10.4	7.4	7.3
2	12.4	10.0	0.8	5.4
3	12.7	9.6	0.3	5.0
4	17.8	12.5	6.3	9.2
5	11.7	5.6	6.1	3.5
6	11.7	4.7	8.2	4.6
7	9.2	2.0	9.1	4.1
8	5.0	2.3	10.6	5.5
9	3.6	4.0	11.7	6.7
10	7.7	11.3	9.3	8.8
11	2.0	6.0	12.9	8.3

The next step is finding the linear correlation between RSSI and distance using the equation (3).

$$RSSI = -d * n + A \quad (3)$$

Where d is the distance in meters, n is the slope m/RSSI and A is the intercept in RSSI which is in units of decibels. The formula with the distance isolated and the slope isolated gives us:

$$d = -\frac{(RSSI - A)}{n} \quad (4)$$

$$n = -\frac{RSSI - A}{d} \quad (5)$$

The next step was to find the slope n between each map point and beacon. This is done by using equation 5. For the RSSI signals, the values used are the averages from the "Fitbit not on body" and "Fitbit on the wrist" data coming from Table 3.2 and Table 3.3. The value for "d" is the measured distances shown in Table 3.6. To find the Intercept A, it is the RSSI recorded when the distance of a Bluetooth device is at 0 m, hence the max RSSI that can be achieved. While performing the tests, we took the Fitbit device and stuck it on one of the beacons and monitored the RSSI that was recorded on the online Pareto interface which was 182. Hence A = 182. The slope was then computed for each map point and is shown in Table 3.7.

Table 3.7: Linear Method Slopes [m/RSSI]

	Slope (n)			
Map Points	**Cash**	**Outdoor**	**Washroom**	**Liquor**
1	4.0328	3.1396	2.4384	3.4159
2	2.4248	3.1615	16.5725	4.4488
3	2.6453	3.5957	6.6058	3.6012
4	2.3940	2.9306	3.6285	3.5512
5	2.1014	5.3112	4.2284	6.6651
6	2.1845	6.4304	3.1184	3.2381
7	3.6765	9.3159	3.0921	4.9953
8	6.4489	7.2488	2.1183	3.9707
9	5.3223	6.7420	1.8432	2.9060
10	3.9534	2.7384	2.4243	2.7704
11	8.8256	4.4307	1.8955	2.9348

The next step was to consider each beacon as having its distinct hardware characteristics, which means that each beacon has its own slope. For each beacon the average slope was taken.

Cash: n = 4.00, Outdoor: n = 5.00, Washroom: n = 4.36, Liquor: n = 3.86

3.3.2.2 Logarithmic Correlation Method

The steps in this section are similar to the previous section, but instead we use a logarithmic correlation found in literature (Palumbo et al., 2015).

The equation used is repeated below for reference.

$$RSSI = -(10n * log_{10}d - A) \tag{6}$$

Where d is the distance in meters, n is the slope m/RSSI and A is the intercept in RSSI. The formula with the distance isolated and the slope isolated gives us:

$$d = 10^{(\frac{RSSI-A}{-10n})} \tag{7}$$

$$n = \frac{-RSSI + A}{10 * log_{10}d} \tag{8}$$

The value of A is the same as the one in the previous section, being the max RSSI recorded of 182.

Using equation 8 and the same methodology as the linear correlation, the slope for a logarithmic correlation was found for each point and computed in Table 3.8.

Table 3.8: Logarithmic Method Slopes [m/RSSI]

	Slope (n)			
Map Points	**Cash**	**Outdoor**	**Washroom**	**Liquor**
1	1.1329	1.0779	0.6276	0.8728
2	0.9701	1.0506	0.6862	0.8785
3	1.0798	1.1569	0.1350	0.6670
4	1.3080	1.1792	0.8208	1.0974
5	0.7989	1.0748	0.9323	0.9226
6	0.8314	1.1241	0.8755	0.5627
7	1.1463	0.8227	0.9469	0.7845
8	1.2026	0.7000	0.7435	0.8019
9	0.7443	1.0374	0.7010	0.6898
10	1.0563	1.0151	0.7582	0.8315
11	0.7794	0.9543	0.7874	0.8386

For each beacon, the average slope is computed to be:

Cash: n = 1.00, Outdoor: n = 1.02, Washroom: n = 0.73, Liquor: n = 0.81

3.4 Sales Data Mining Setup

The third method used in this research project involves using presences at beacons and sales reports as input data for a data mining method. The data for presences was taken from the collect done in section 3.3.1.2. From these presences and sales reports, the purpose is to observe trends that will lead to predictive conclusions. To get to these conclusions, data mining will be used as an analysis tool.

The data mining method that will be used for this research is the CART method. This is done using python programming language and the built in "DecisionTreeClassifier" class from the Sklearn library (Scikit-learn, 2018).

The CART method works through ways of recursive partitioning. The steps to construct the decision tree are enumerated below and found in literature (Rutkowski, Jaworski, Pietruczuk, & Duda, 2014).

1. A top node at the beginning of the tree is created and uses all data and possible attributes.
2. From that node, the attribute that produces the greatest separation is selected as the first split. The sample is then separated into two other nodes where for one node the attribute is true and for the other node the attribute is false.
3. Step 2 is then repeated on each new created node.
4. The process ends when all data is put in a homogeneous leaf node or there are no more possible attributes for separation.

To decide which attribute produces the greatest separation in step 3, the CART method used in the Sklearn library does not use the traditional twoing criteria (Singh & Gupta, 2014) but instead is a modified version of the algorithm which uses the Gini coefficient to measure impurity[3], which is a ratio between 0 and 1. A value of 0 would mean a perfect separation of the data for the given

[3] http://scikit-learn.org/stable/modules/tree.html#tree-algorithms-id3-c4-5-c5-0-and-cart

attribute. As the value increases towards 1, the impurity also increases. The Gini coefficient is measured using equation 9 (Rutkowski et al., 2014).

$$Gini(S_q) = 1 - \sum_{k=1}^{k} (P_{k,q})^2 \quad (9)$$

Where S_q is a subset of the training set, k is a class and $P_{k,q}$ represents the fraction of all elements in subset S_q that belong to the class K.

For example, if all items of subset S_q belong to class k, then $P_{k,q}$ is equal to 1 and the Gini coefficient is 0 indicating a homogenous class.

3.5 Methods Conclusion

In the methods chapter, we have presented the steps taken to reach our objectives. An IoT implementation was done within the convenience store with the Bluetooth beacons set up in specific zones. Once the system was set up, data collections were performed. The automated collection with RSSI strengths coming from all four sensors was done for a full week and a manual collection was done to gather data to be used for a correlation between RSSI values and physical distances. The correlation methods described were both linear and logarithmic. Both methods produced an equation that converts the RSSI values into physical meters. The last part of the methods present the data mining method that will be used in the analysis section which uses data from beacon presences and sales report to construct a decision tree.

CHAPTER 4 RESULTS AND DISCUSSION

The following chapter presents the analysis done with the collected data from our IoT implementation. The first section consists of analysing the data to transform captured RSSI values into distances or presences in defined zones. The second section consists of using the detected presences from the beacons as well as sales reports to be applied in data mining algorithms.

4.1 Zone Definition

One of the objectives of this project is to trace customer's pathways within the store to extract useful information out of it. To achieve that, a correlation should be found between the RSSI collected and the actual distance within the store. The first part of the zone definition is done by using triangulation methods between all four beacons. The second part of the analysis is done by analysing only the area around each individual beacon.

4.1.1 Four-Sensor Triangulation Methods

Using the beacons to evaluation distances, two methods have been tried to find a correlation between RSSI and physical distance. The first method is by presuming that the RSSI has a linear correlation with the distance between the Bluetooth device and the beacons. The linear method is described in section 3.3.2.1. The second method is a logarithmic correlation and is described in section 3.3.2.2.

The correlations are then to be used to locate customer activities within zones. The store was divided in 12 different zones of 3.4 x 3.4 meters with the 13^{th} zone being anything outside the walls of the store. These zones are shown in Figure 4-1. On the figure, the black dots are the manual points collected in section 3.3.1.3 and the red ovals are the beacons.

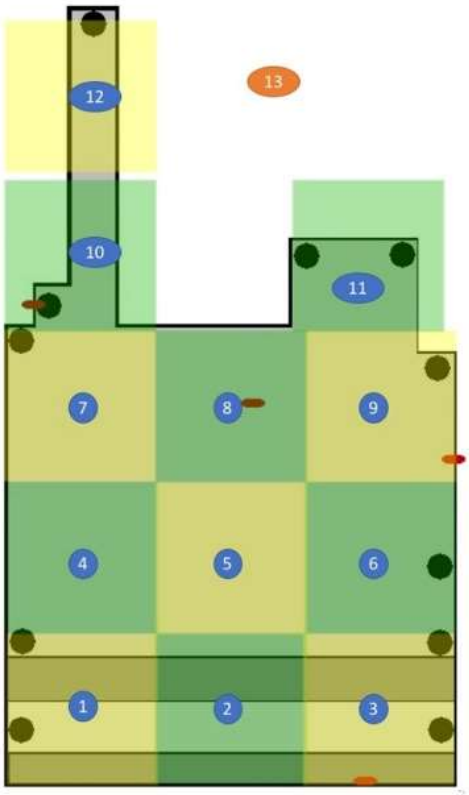

Figure 4-1: Defined Zones for Pathway Tracing

4.1.1.1 Linear Correlation Discussion

The first validation of the linear correlation method described in section 3.3.2.1 was done using the average data collected with the iPhone X both in the front pocket and back pocket from Table 3.4 and Table 3.5.

Using equation 4 with the value of A and the slopes of each beacon found in section 3.3.2.1, computations were made to verify the validity of the linear correlation method. .

Table 4.1

Table 4.1 shows the computed the distance with equation 4, and Table 4.2 shows the computed error percentage using equation 6. For the error percentage, we have capped values to a maximum of 100% error for ease of comprehension.

$$\%Error = \left|\frac{Experimental - Theoretical}{Theoretical}\right| * 100 \quad (10)$$

Table 4.1: iPhone X Calculated Distances from Beacons Using Linear Method [m]

	Calculated Distances (m)			
Map Points	**Cash**	**Outdoor**	**Washroom**	**Liquor**
1	6.50	4.30	22.70	6.47
2	5.12	5.90	1.49	4.01
3	7.75	5.70	0.57	4.01
4	9.50	7.29	4.01	8.02
5	5.37	5.00	5.73	4.14
6	5.87	5.10	6.77	3.88
7	6.87	1.60	5.62	5.82
8	4.25	4.00	5.50	4.53
9	6.12	6.39	7.22	6.08
10	3.12	5.80	7.34	6.73
11	5.00	4.30	4.01	6.08

Table 4.2: iPhone X Distances Experimental Errors with Linear Method

	Calculated Distances Error (Percentage)			
Map Points	**Cash**	**Outdoor**	**Washroom**	**Liquor**
1	20.6%	58.5%	100.0%	11.6%
2	58.6%	40.8%	90.0%	25.6%
3	38.8%	40.6%	89.4%	19.7%
4	46.5%	41.4%	36.7%	12.3%
5	53.9%	10.1%	6.8%	17.5%
6	49.7%	9.2%	17.3%	16.2%
7	25.7%	21.6%	38.0%	41.9%
8	15.7%	75.6%	48.2%	18.2%
9	71.5%	59.7%	38.1%	9.4%
10	59.5%	48.8%	20.9%	23.9%
11	100.0%	28.2%	68.9%	27.1%
Average	**49.1%**	**39.5%**	**50.4%**	**20.3%**

By looking at the error percentages, the precision using a linear correlation with our iPhone X data is not very high. Looking at the cash and washroom beacons, an error percentage of around 50% is calculated. The beacons were obstructed by obstacles such as a television and a lottery machine

which could affect the accuracy of the RSSI readings. Another conclusion that could be extracted is that the relationship between RSSI values and measured distance cannot be modeled linearly.

The next validation test consists of tracing a pathway within the store to compare with the theoretical path shown in Figure 4-2. The starting position is the blue circle. The data collected in section 3.3.1.4, which contains captured RSSI values from a Fitbit device, was used to trace a theoretical path. The RSSI to distance conversion was done similarly as with the iPhone X validation test by using equation 4 and the found values of A and n.

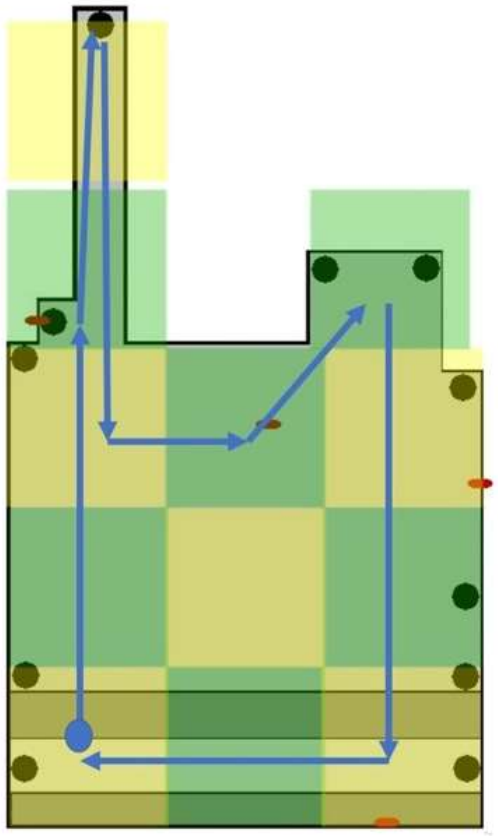

Figure 4-2: Actual Pathway Taken with The Fitbit

Figure 4-3 visually shows how the RSSI limits of each zone was determined. The blue arrow is the inner limit of zone 5 captured by the cash beacon and the orange arrow is the upper limit. The physical distance found is then converted to an RSSI upper and lower limit using equation 3. The same method was used for each zone and each beacon. The values obtained are shown in Table 4.3.

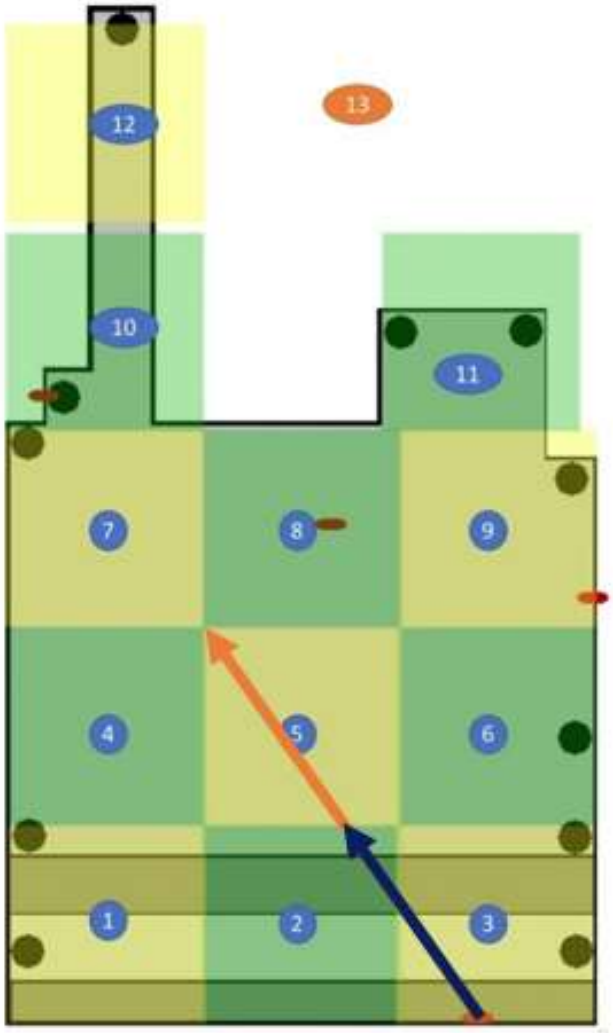

Figure 4-3: Demonstration of RSSI Limit per Zone

Table 4.3: Linear Formula Zone Limits in RSSI

cash_zone	outdoor_zone	washroom_zone	liquor_zone	limit	Zone
145.9	119.5	131.4	141.7	Lower	1
166.4	145.1	153.7	161.5	Upper	1
158.9	132.3	126.7	145.7	Lower	2
179.4	157.9	149.0	165.5	Upper	2
165.8	140.0	119.0	143.2	Lower	3
186.3	165.6	141.3	163.0	Upper	3
140.0	126.4	145.0	151.7	Lower	4
160.5	152.0	167.4	171.5	Upper	4
149.0	142.6	139.4	158.2	Lower	5
169.4	168.2	161.7	178.0	Upper	5
152.3	154.7	128.6	154.2	Lower	6
172.7	180.3	150.9	174.0	Upper	6
130.2	127.6	160.0	157.5	Lower	7
150.7	153.2	182.4	177.3	Upper	7
137.3	144.1	148.8	170.1	Lower	8
157.8	169.7	171.1	189.9	Upper	8
139.2	160.9	134.8	160.6	Lower	9
159.6	186.5	157.2	180.4	Upper	9
118.8	122.8	164.0	153.3	Lower	10
139.3	148.4	186.3	173.1	Upper	10
128.0	147.8	140.4	158.9	Lower	11
148.5	173.5	162.7	178.7	Upper	11
106.0	112.0	149.7	142.4	Lower	12
126.5	137.7	172.0	162.2	Upper	12

The RSSI limits shown in Table 4.3 and the data collected in section 3.3.1.4 containing the Fitbit captures were then loaded into a python script for analysis. The script, along with its output, can be found in Appendix C. The python script analyses the dataset to establish at which zone, using the limits of Table 4.3, and at which time the device was captured. The output from the python script then permits us to trace a theoretical pathway from the captured data and is visually shown in Figure 4-4.

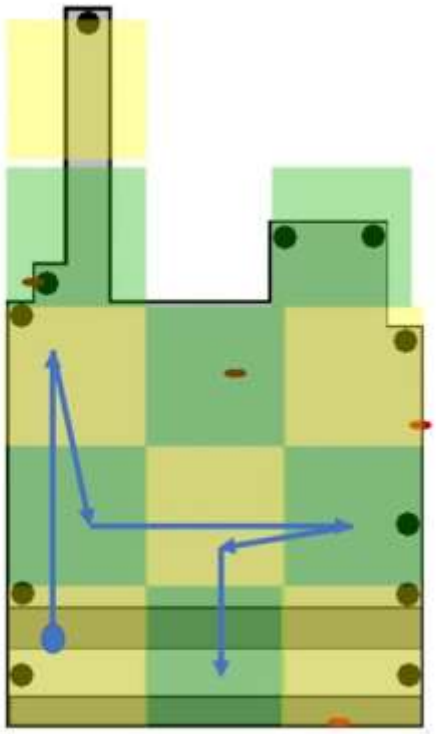

Figure 4-4: Pathway Detected Using Linear Correlation

Comparing the paths between Figure 4-2 and Figure 4-4, even a device with a higher capture precision such as the Fitbit does not yield precise results with the linear method. The pathway seems to start accurately but quickly deviates from the theoretical path before passing through the washroom beacon.

4.1.1.2 Logarithmic Correlation Discussion

Using the same validation test as the linear correlation method with the iPhone X, but on the logarithmic correlation described in section 3.3.2.2 instead, we get the results shown in Table 4.4 and Table 4.5 for calculated distances and experimental errors.

Table 4.4: iPhone X Calculated Distances from Beacons Using Log Method [m]

	Calculated Distances (m)			
Map Points	**Cash**	**Outdoor**	**Washroom**	**Liquor**
1	5.575	3.523	nan	6.983
2	3.876	5.629	5.204	3.337
3	7.758	5.309	1.886	3.337
4	12.322	8.483	84.856	11.133
5	4.141	4.325	569.197	3.469
6	4.726	4.453	1783.239	3.209
7	6.156	1.598	501.368	5.750
8	3.076	3.227	441.623	3.898
9	5.049	6.517	2962.309	6.214
10	2.284	5.467	3363.068	7.548
11	3.750	3.523	84.856	6.214

Table 4.5: iPhone X Distances Experimental Errors with Log Method

	Calculated Distances Error (Percentage)			
Map Points	**Cash**	**Outdoor**	**Washroom**	**Liquor**
1	32%	66%	nan	5%
2	69%	44%	100%	38%
3	39%	45%	100%	33%
4	31%	32%	100%	22%
5	64%	22%	100%	2%
6	60%	5%	100%	31%
7	33%	22%	100%	40%
8	39%	42%	100%	30%
9	41%	63%	100%	7%
10	70%	52%	100%	15%
11	84%	41%	100%	26%
Average:	**51%**	**39%**	**100%**	**22%**

By looking at the error percentages, the precision using a logarithmic correlation with our iPhone X data is not very high. Looking at the cash an error percentage of around 50% is calculated and the washroom beacon is completely off with 100% error. Similarly to the linear correlation, the cash beacon obstructed by the television also affects the logarithmic correlation. The washroom beacon obstructed by the lottery machine is even more greatly affected and does not yield any accurate result.

The next validation is the pathway test. Below are calculated in the same way as the linear method the upper and lower RSSI limits of each zone, but by using equation 6 with the logarithmic slopes.

Table 4.6: Logarithmic Formula Zone Limits

cash_zone	outdoor_zone	washroom_zone	liquor_zone	limit	chosen_zone
161.4	147.9	174.6	160.5	Upper	1
148.7	138.9	172.3	151.8	Lower	1
188.3	155.2	174.0	163.3	Upper	2
155.5	142.8	172.0	153.2	Lower	2
236.4	161.7	173.2	161.5	Upper	3
160.9	145.7	171.5	152.3	Lower	3
156.6	151.4	177.2	169.1	Upper	4
146.4	140.9	173.6	155.5	Lower	4
164.7	164.7	175.9	181.4	Upper	5
150.1	146.8	173.0	158.6	Lower	5
169.3	200.9	174.3	172.7	Upper	6
151.7	153.1	172.1	156.6	Lower	6
150.9	152.1	196.2	179.5	Upper	7
143.3	141.3	175.6	158.3	Lower	7
154.7	166.7	178.4	228.2	Upper	8
145.5	147.4	174.0	167.5	Lower	8
156.0	243.3	175.1	193.4	Upper	9
146.1	157.5	172.6	160.0	Lower	9
146.2	149.5	196.2	171.2	Upper	10
140.2	139.8	176.4	156.2	Lower	10
149.9	172.9	176.1	184.0	Upper	11
142.6	149.2	173.1	159.0	Lower	11
142.2	144.8	178.7	161.0	Upper	12
137.5	137.0	174.1	152.1	Lower	12

The next step is loading the data into python as previously described and tracing the pathway obtained with the logarithmic correlation.

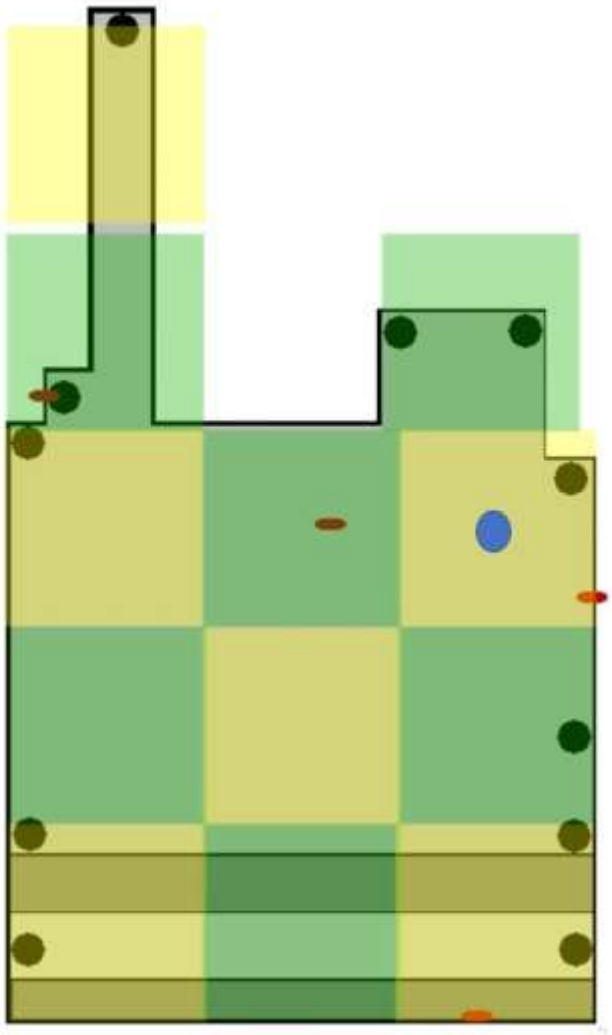

Figure 4-5: Pathway Detected Using Logarithmic Correlation

Comparing the paths between Figure 4-2 and Figure 4-5, it can be observed that the logarithmic correlation does not yield a precision high enough to use to trace a customer's pathway.

4.1.1.3 RSSI to Distances Correlations General Conclusions

The results found for both the linear or logarithmic correlations were found to be problematic to trace an indoor pathway taken by customers. In both cases, the validation test with the iPhone X was consistently high in error percentage when converting from RSSI to a distance. The same can be said for the pathway tracing using the Fitbit testing device which is supposed to have a higher Bluetooth signal precision than an iPhone X. In both cases, the calculated pathway deviated

significantly from the theoretical pathway. The greatest error was observed in the logarithmic correlation method, where a stationary location was detected instead of a pathway.

After discovering the low precision of the results, we setup a meeting with the beacon provider to better understand the outcomes. After discussion, these points were raised. First off, looking at the excerpt of raw data collected for the validation run in Appendix B, we can observe that most points collected did not have an RSSI collected at each of the beacons, which would automatically place that point in zone 13. This is due to Bluetooth technology limitations where it takes a certain amount of time for a sensor to be captured and can be easily obstructed by obstructions such as a shelf in the way or other wireless devices interference. Another issue with this approach is the size of the experimental store. The experimental zone measures a size of roughly 64 m^2 which is quite small for a space with 4 beacons.

Our findings in this section are in agreement with the discussion points we have seen in literature about BLE devices and indoor localization, where successful experiments were conducted in large spaces and the sensors were unobstructed. (Palumbo et al., 2015)

Our findings also showed that a more complex system including both BLE and WIFI beacons should be put in place to obtain more precise results. We have found within literature research which collaborate with our findings on precision. In the research found, the initial problem was that WIFI sensors on their own were not precise enough. By combining them with BLE sensors, the median accuracy of the results increased by 23% (Kriz, Maly, & Kozel, 2016).

In our next experiment, we will be using smaller study zones to simply capture presences or absences at single sensors instead to remedy for the lack of granularity from the sensors setup.

4.1.2 Single Sensor Zoning

With the inconclusive results obtained in the previous section, which attempted to trace a customer pathway with the beacon collection, we will now attempt to extract useful information with the knowledge of having lower localization precision from the beacons. In the next experiment, we observe the activity happening at a single beacon instead of using triangulation methods from data coming from all four sensors.

The first steps of this analysis are computed using python and the code can be found in Appendix C as the single sensor zoning code and output.

The dataset used for the single sensor zoning method is the one from section 3.2.4.2 collected for a full week from April 9th to the 16th.

The first step was to identify the size of the zones of interests around each beacon. This was done manually by using the Pareto interface and the FitBit device by setting the device at the limits of the zones of interest and waiting a considerable time to settle to a RSSI. The limits that were found are presented in the Table 4.7 and showed approximately in Figure 4-6.

Table 4.7: Single Sensors Zoning Limits

Beacon	Limit	Explanation
Cash	168	Area where customers stand in line to pay
Cash	172	Area behind cash counter (employees)
Outdoor	166	Delimited area around fridge
Outdoor	350	Exagarated max RSSI for 0m distance
Washroom	178	Area where customers fill lotto tickets
Washroom	350	Exagarated max RSSI for 0m distance
Liquor	170	Area where the liquor fridge is located
Liquor	350	Exagarated max RSSI for 0m distance

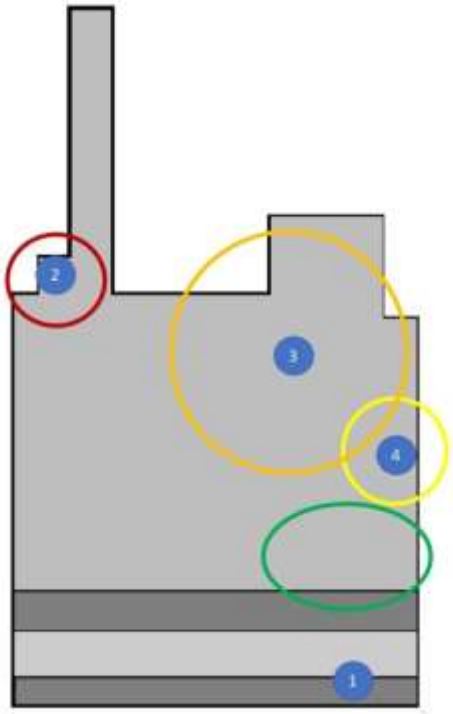

Figure 4-6: Single Sensors Zoning

In Figure 4-6, the green circle is the zone captured by beacon #1 which corresponds to the cash area, the red circle is the zone captured by beacon #2 which corresponds to the washroom area, the orange circle is captured by beacon #3 which corresponds to the liquor area and the yellow circle is captured by beacon #4, which corresponds to the outdoor area.

The next step was to separate the raw data into each day of the week. The timestamp was given in Unix epoch format which is the number of milliseconds since Jan 1, 1970. To separate the data, an online converter was used to identify the limits of each day of the week. For example, Monday April 9th 2018 12:00:00 AM is 1523246400000 in Unix epoch.

After separating in days, some data pre-processing had to be performed on the raw CSV values. First we removed all beacon captures as Bluetooth devices from the collection. This was done by removing from the python dataframe all entries where the "DeviceTags" was described as a beacon of any kind. Then other irrelevant devices were removed from the collection such as Bluetooth coming from objects being transported in cars such as an Apple TV, a camera, or any other non-wearable or smartphone device. This was also done by filtering the "DeviceTags". Finally, the last cleanup was done by removing employee or store Bluetooth devices data from the collection. This was done by checking the amount of time a certain Bluetooth device ID was captured. On average, most captures were collected between 1 to 40 times. Then there was a discrepancy were a few were captured over 1000 times. Having removed device IDs which appeared a significant amount of times more than the majority of captures being captured 1 to 40 times, we can say with high confidence that employee devices have been removed in this pre-processing step. These discrepancies were removed from the data collection to obtain only customer data.

Finally, the code was run to identify the number of unique Bluetooth devices presences, hence unique customers, per beacon per day. The returned output is summarized in Table 4.8.

Table 4.8: Number of Presences Per Beacon

	Presence at Beacons			
Day	**Cash**	**Outdoor**	**Washroom**	**Liquor**
Monday	46	39	13	18
Tuesday	25	27	16	12
Wednesday	30	23	8	16
Thursday	37	30	18	20
Friday	40	31	14	14
Saturday	41	31	10	21
Sunday	30	24	14	9

The next step involves finding a scale to separate the data into quiet, normal and busy for the data analysis portion. The logic used to separate the data is shown in Table 4.9. The value of a "range" corresponds to the maximum value minus the minimum value. Values lesser than "average – range/count" are considered as quiet and values greater than "average + range/count" are considered busy. The colour formatting shown in Table 4.9 is applied on all beacons and sales data tables (section 4.2) to visually show the classification.

Table 4.9: Classification Logic for Sales Proportions and Beacon Activity

Logic	Colour	Classification
Less than (Average-Range/Count)		Quiet
Average - Range/Count		Normal
Average		Normal
Average + Range/Count		Normal
Greater than (Average+Range/Count)		Busy

In Table 4.10, Table 4.11 and Table 4.12, proportions are presented to discuss potential insights that can be extracted from this data. Table 4.10 shows the absolute activity proportions for each given day, Table 4.11 shows the activity proportions for each given beacon for all days and Table 4.12 shows the relative activity all beacons for each given day. The relative activity was found by comparing each beacon activity per day with the average of the whole week. For example, on Monday the cash relative proportion is calculated as such: 46/(average of the week) = 18%. Thick lines were added to the tables to visually clarify when the rows or columns are being compared for proportions.

Table 4.10: Presence at Beacons (Per Day Proportions)

	Presence at Beacons (Per day proportions)			
Day	Cash	Outdoor	Washroom	Liquor
Monday	46	39	13	18
Tuesday	25	27	16	12
Wednesday	30	23	8	16
Thursday	37	30	18	20
Friday	40	31	14	14
Saturday	41	31	10	21
Sunday	30	24	14	9

Table 4.11: Presence at Beacons (Per Beacon Proportions)

	Presence at Beacons (Per beacon proportions)			
Day	Cash	Outdoor	Washroom	Liquor
Monday	46	39	13	18
Tuesday	25	27	16	12
Wednesday	30	23	8	16
Thursday	37	30	18	20
Friday	40	31	14	14
Saturday	41	31	10	21
Sunday	30	24	14	9

Table 4.12: Presence at Beacons (Per Day Relative Proportions)

	Presence at Beacons (Per day relative proportions)			
Day	Cash	Outdoor	Washroom	Liquor
Monday	18%	19%	14%	16%
Tuesday	10%	13%	17%	11%
Wednesday	12%	11%	9%	15%
Thursday	15%	15%	19%	18%
Friday	16%	15%	15%	13%
Saturday	16%	15%	11%	19%
Sunday	12%	12%	15%	8%

From Table 4.10, some information can be extracted. We can observe that the cash is always the busiest area among the 3 zones, which would be the expected result from a gas station convenience store. To clarify that the cashier is not part of the count, looking back at Figure 4-6, the cashier

stands behind the counter and the zone delimited by RSSI signal does not include the cashier position hence the data contains only customers waiting at the cash. This also does confirm a certain level of accuracy in the data extracted as the cash beacon is what would be expected as the busiest one at all days. Another interesting information that can be extracted is the consistent higher proportions of presence at the "Outdoor" zone (which consists of mostly cold non-alcoholic drinks) versus the "Washroom" (Lottery) and "Liquor" zones. This can lead to interesting applications for the store manager such as displaying promotions in that area knowing that customer traffic is higher. In section 4.2 we will go more in depth into comparing these results with the sales reports for that same week using a decision tree to validate further the accuracy of the results from the beacons. Table 4.11 is showing more varying data when looking at the activity for a beacon throughout the whole week. It is harder to extract useful information by simple analysing it visually. Table 4.12 can also potentially show us useful information, where relative activity is compared. Also with a visual inspection it is harder to analyze, and same as Table 4.11, it will be explored more in details in section 4.2.

Comparing with the results from the four-sensor triangulation method, the data is more reliable when using a single sensor for general positioning information on customer activity. This is because in section 4.1.2 we bypass the issue of precision by not looking at a precise pathway but simply a presence or not of a device within the zone.

4.2 Sales & Beacons Data Analysis

In this section, we will be attempting to perform a data analysis on the sales data in correlation with the single sensor zoning data collected from the previous section 4.1.2. The purpose is to prove that there is a correlation between customer's physical activities within the store and the sales generated. This correlation will show that the data collected from an IoT system can be used to study and improve store sales. For the sales data, we were given access by the convenience store to all the cash register history for the given week of data collection from section 3.3.1.2. The categories chosen to be included in the analysis are all products that can be found around the studied beacons. Non-alcoholic drinks are found around the outdoor beacon, sweets and tobacco products are found around the cash beacon, alcoholic drinks and salty snacks are found around the liquor beacon. For confidentiality reasons, the raw sales data cannot be attached to this research project, but proportions will be shown. In Table 4.13, the sales proportions of each category calculated was

taken relative to the whole week (for example, on Monday 11.6% of the weekly non-alcoholic drinks were made).

Table 4.13: Sales Proportions Per Category (For the Week)

	Categories (Sales Proportions Percentage)					
Day	Non-Alcoholic Drinks	Sweets	Alcoholic Drinks	Lottery	Salty Snacks	Tabacco
Monday	11.6%	12.9%	7.4%	11.7%	12.2%	15.6%
Tuesday	15.2%	15.8%	13.4%	12.9%	12.9%	14.3%
Wednesday	14.8%	12.1%	9.4%	17.5%	10.7%	13.7%
Thursday	19.4%	18.8%	16.6%	17.1%	17.6%	17.3%
Friday	19.1%	15.3%	19.3%	16.7%	23.2%	15.6%
Saturday	12.5%	18.7%	20.4%	12.8%	16.7%	12.4%
Sunday	7.3%	6.4%	13.5%	11.3%	6.7%	11.1%

With the classification logic that was explained in Table 4.9, two different proportions were compared for the sales data. The first comparison, found in Table 4.14, shows the sales proportions for each category over a week. The second comparison is done in Table 4.15, where it shows the sales proportions of each day over all categories. The colour coding and logic is the same as shown in Table 4.9.

Table 4.14: Sales Proportions Relative to The Week

	Categories (Sales Proportions percentage over days)					
Day	Non-Alcoholic Drinks	Sweets	Alcoholic Drinks	Lottery	Salty Snacks	Tabacco
Monday	11.6%	12.9%	7.4%	11.7%	12.2%	15.6%
Tuesday	15.2%	15.8%	13.4%	12.9%	12.9%	14.3%
Wednesday	14.8%	12.1%	9.4%	17.5%	10.7%	13.7%
Thursday	19.4%	18.8%	16.6%	17.1%	17.6%	17.3%
Friday	19.1%	15.3%	19.3%	16.7%	23.2%	15.6%
Saturday	12.5%	18.7%	20.4%	12.8%	16.7%	12.4%
Sunday	7.3%	6.4%	13.5%	11.3%	6.7%	11.1%

Table 4.15: Sales Proportions Relative to The Categories

	Categories (Normalized sales proportions percentage over categories)					
Day	Non-Alcoholic Drinks	Sweets	Alcoholic Drinks	Lottery	Salty Snacks	Tabacco
Monday	11.6%	12.9%	7.4%	11.7%	12.2%	15.6%
Tuesday	15.2%	15.8%	13.4%	12.9%	12.9%	14.3%
Wednesday	14.8%	12.1%	9.4%	17.5%	10.7%	13.7%
Thursday	19.4%	18.8%	16.6%	17.1%	17.6%	17.3%
Friday	19.1%	15.3%	19.3%	16.7%	23.2%	15.6%
Saturday	12.5%	18.7%	20.4%	12.8%	16.7%	12.4%
Sunday	7.3%	6.4%	13.5%	11.3%	6.7%	11.1%

We then proceed to using a decision tree data mining method to demonstrate the potential utilities of an IoT system to a brick and mortar retail environment. The decision tree algorithm used is presented in section 3.4.

For this experimentation, four different datasets were used. The used data involved the activity of each beacon from section 4.1.2 combined with the sales proportions from this section. The first dataset consists of Table 4.11 and Table 4.14, the second dataset consists of Table 4.11 and Table 4.15, the third dataset consists of Table 4.12 and Table 4.14 and finally the fourth dataset consists of Table 4.12 and Table 4.15. These table combinations consist of different combos of activity comparisons that are either spread over a week or over all beacons as previously discussed. This is done to find the most accurate combination per the decision tree algorithm. Datasets can be seen in Table 4.16 to Table 4.19.

Table 4.16: Dataset 1 Using Table 4.11 and Table 4.14

Day	Cash_B	Outdoor_B	Washroom_B	Liquor_B	Non_Alcoholic_Drinks	Sweets	Alcoholic_ Drinks	Lottery	Salty_Snacks	Tabacco
Sunday	Busy	Busy	Normal	Busy	Quiet	Normal	Quiet	Quiet	Normal	Normal
Monday	Quiet	Normal	Busy	Quiet	Normal	Normal	Normal	Normal	Normal	Normal
Tuesday	Quiet	Quiet	Quiet	Normal	Normal	Normal	Quiet	Busy	Normal	Normal
Wednesday	Normal	Normal	Busy	Busy	Busy	Busy	Busy	Busy	Normal	Busy
Thursday	Busy	Normal	Normal	Quiet	Busy	Normal	Busy	Busy	Busy	Normal
Friday	Busy	Normal	Quiet	Busy	Normal	Busy	Busy	Normal	Normal	Quiet
Saturday	Normal	Quiet	Normal	Quiet	Quiet	Quiet	Normal	Quiet	Quiet	Quiet

Table 4.17: Dataset 2 Using Table 4.11 And Table 4.15

Day	Cash_B	Outdoor_B	Washroom_B	Liquor_B	Non_Alcoholic_Drinks	Sweets	Alcoholic_ Drinks	Lottery	Salty_Snacks	Tabacco
Sunday	Busy	Busy	Normal	Busy	Normal	Normal	Quiet	Normal	Normal	Busy
Monday	Quiet	Normal	Busy	Quiet	Busy	Busy	Quiet	Quiet	Quiet	Normal
Tuesday	Quiet	Quiet	Quiet	Normal	Normal	Normal	Quiet	Busy	Quiet	Normal
Wednesday	Normal	Normal	Busy	Busy	Busy	Busy	Quiet	Normal	Normal	Normal
Thursday	Busy	Normal	Normal	Quiet	Normal	Quiet	Normal	Normal	Busy	Quiet
Friday	Busy	Normal	Quiet	Busy	Quiet	Busy	Busy	Quiet	Normal	Quiet
Saturday	Normal	Quiet	Normal	Quiet	Quiet	Quiet	Busy	Normal	Quiet	Normal

Table 4.18: Dataset 3 Using Table 4.12 Table 4.14

Day	Cash_B	Outdoor_B	Washroom_B	Liquor_B	Non_Alcoholic_Drinks	Sweets	Alcoholic_ Drinks	Lottery	Salty_Snacks	Tabacco
Sunday	Busy	Busy	Quiet	Normal	Quiet	Normal	Quiet	Quiet	Normal	Normal
Monday	Quiet	Normal	Busy	Quiet	Normal	Normal	Normal	Normal	Normal	Normal
Tuesday	Normal	Normal	Quiet	Busy	Normal	Normal	Quiet	Busy	Normal	Normal
Wednesday	Quiet	Quiet	Busy	Busy	Busy	Busy	Busy	Busy	Normal	Busy
Thursday	Busy	Normal	Normal	Quiet	Busy	Normal	Busy	Busy	Busy	Normal
Friday	Normal	Normal	Quiet	Busy	Normal	Busy	Busy	Normal	Normal	Quiet
Saturday	Normal	Normal	Busy	Quiet	Quiet	Quiet	Normal	Quiet	Quiet	Quiet

Table 4.19: Dataset 4 Using Table 4.12 Table 4.15

Day	Cash_B	Outdoor_B	Washroom_B	Liquor_B	Non_Alcoholic_Drinks	Sweets	Alcoholic_ Drinks	Lottery	Salty_Snacks	Tabacco
Sunday	Busy	Busy	Quiet	Normal	Normal	Normal	Quiet	Normal	Normal	Busy
Monday	Quiet	Normal	Busy	Quiet	Busy	Busy	Quiet	Quiet	Quiet	Normal
Tuesday	Normal	Normal	Quiet	Busy	Normal	Normal	Quiet	Busy	Quiet	Normal
Wednesday	Quiet	Quiet	Busy	Busy	Busy	Busy	Quiet	Normal	Normal	Normal
Thursday	Busy	Normal	Normal	Quiet	Normal	Quiet	Normal	Normal	Busy	Quiet
Friday	Normal	Normal	Quiet	Busy	Quiet	Busy	Busy	Quiet	Normal	Quiet
Saturday	Normal	Normal	Busy	Quiet	Quiet	Quiet	Busy	Normal	Quiet	Normal

Each one of the four datasets were then loaded in individual python scripts. The structure of each script is the same. The first step within the script was to define which variables are used as predictor variables and which ones as outcome variables. Days and beacon activity were chosen for this study as our predictor variable and each sales category individually as our outcome variable. The second step is to define the training size and the test size for the decision tree. It was chosen that the test size sample would be 25% and the training size sample would be 75% of the dataset. The third step consists of applying the CART algorithm with the pre-compiled method and exporting it visually to PDF files to create visual decision trees. The last step involves applying the created decision tree on each category and evaluating its accuracy. The accuracy of each dataset and each category is shown in Table 4.20 to Table 4.22. Accuracy is simply calculated by the python script by computing how many real predictions are done over the total testing sample. The complete python script can be found in appendix C with a sample output for dataset 1.

Table 4.20: Dataset 1 Prediction Accuracy

Dataset 1	
Category	**Accuracy**
Non-Alcoholic Drinks	50%
Sweets	50%
Alcoholic Drinks	0%
Lottery	0%
Salty Snacks	50%
Tabacco	25%

Table 4.21: Dataset 2 Prediction Accuracy

Dataset 2	
Category	**Accuracy**
Non-Alcoholic Drinks	50%
Sweets	0%
Alcoholic Drinks	0%
Lottery	50%
Salty Snacks	0%
Tabacco	25%

Table 4.22: Dataset 3 Prediction Accuracy

Dataset 3	
Category	**Accuracy**
Non-Alcoholic Drinks	50%
Sweets	0%
Alcoholic Drinks	0%
Lottery	0%
Salty Snacks	50%
Tabacco	25%

Table 4.23: Dataset 4 Prediction Accuracy

Dataset 4	
Category	**Accuracy**
Non-Alcoholic Drinks	50%
Sweets	0%
Alcoholic Drinks	100%
Lottery	0%
Salty Snacks	0%
Tabacco	50%

Analyzing the accuracy results, we can see that there is potential for a correlation between the customer's physical locations within the store and sales data. This section will examine more closely the decision tree in Figure 4-7 that was formed from dataset 4, shown in a classified form in Table 4.25, and using alcoholic drinks as the outcome variables. All decision trees produced can be found in appendix E.

Table 4.24 shows a legend of the values used in the decision trees. The python script works better with numbers so the days of the week and the activity classification terms were transformed into integers.

Table 4.24: Decision Tree Legend

Legend	
Sunday	1
Monday	2
Tuesday	3
Wednesday	4
Thursday	5
Friday	6
Saturday	7
Quiet	1
Normal	2
Busy	3

Table 4.25: Dataset 4 Classified Values

Day	Cash_B	Outdoor_B	Washroom_B	Liquor_B	Non_Alcoholic_Drinks	Sweets	Alcoholic_ Drinks	Lottery	Salty_Snacks	Tabacco
Sunday	Busy	Busy	Quiet	Normal	Normal	Normal	Quiet	Normal	Normal	Busy
Monday	Quiet	Normal	Busy	Quiet	Busy	Busy	Quiet	Quiet	Quiet	Normal
Tuesday	Normal	Normal	Quiet	Busy	Normal	Normal	Quiet	Busy	Quiet	Normal
Wednesday	Quiet	Quiet	Busy	Busy	Busy	Busy	Quiet	Normal	Normal	Normal
Thursday	Busy	Normal	Normal	Quiet	Normal	Quiet	Normal	Normal	Busy	Quiet
Friday	Normal	Normal	Quiet	Busy	Quiet	Busy	Busy	Quiet	Normal	Quiet
Saturday	Normal	Normal	Busy	Quiet	Quiet	Quiet	Busy	Normal	Quiet	Normal

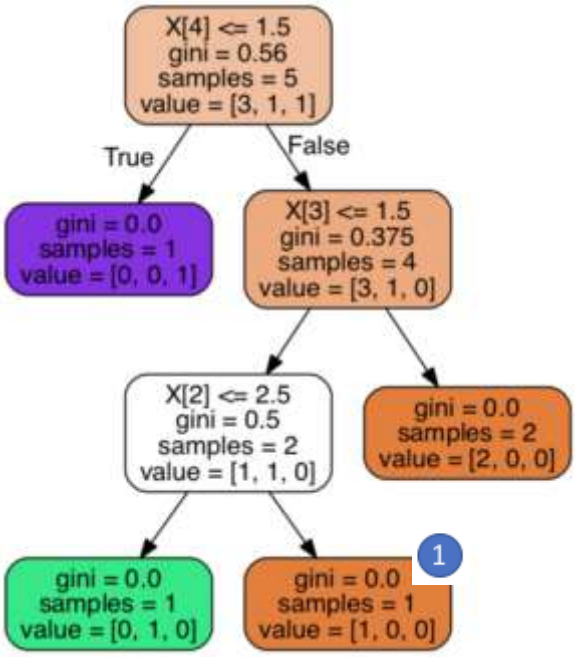

Figure 4-7: Alcoholic Drinks from Dataset 4 Decision Tree

This decision tree was chosen to be examined more closely because it returned a 100% accuracy when tested in the python script. The colour coding is done automatically by the python script and is not relevant for any analysis. The decision tree will be examined closely in the next paragraph. While looking at the results of this decision tree, it is important to keep in mind that this research is done on an exploratory basis, hence the amount of data collected represents an idea of what a lengthy implementation could lead to. For this research, we have a week of data collection which means that our total sample size is 7, which includes a training sample size of 5 and a test sample size of 2.

Analyzing the decision tree, first thing is to clarify what each line represents. The first line, which contains possible values of X[1] to X[5], represents the column where an attribute is observed. By cross-referencing with Table 4.25, X[1] represents the day column, X[2] represents the cash beacon column, X[3] represents the outdoor beacon column, X[4] represents the washroom beacon column and X[5] represents the liquor beacon column. As for the value of the attribute, by cross referencing with

Table 4.24, 1 means quiet, 2 means normal and 3 means busy. On the next line of the decision tree, we find the Gini impurity value. As previously discussed, a lower value is optimal meaning that the separation puts most of the samples in the same class. In the case of this decision trees, the

similarities are based on sales activity being quiet, normal or busy. On the next line, the sample size represents the number of samples that are on the node. Finally, on the last line, the value with the three numbers represent the outcome of the output variable on that node where the first number is the number of outcomes with quiet, the second number is the number of outcomes with normal and the last number is the number of outcomes with busy.

If we follow the path with the circle label 1, it means that if the washroom beacon is not quiet (relative to the week), the outdoor beacon is quiet and the cash beacon is busy, then the expected alcoholic drinks sales should be quiet (relative to other categories).

These findings are interesting and show that the customer's behaviors have a correlation with the store sales. A store manager could extract practical applications out of this decision tree. First we will clarify which products can be found at the mentioned beacons by cross-referencing with

Table 3.1 and Figure 4-6 for the single sensor zoning limits. At the washroom beacon, the products within that zone are lottery tickets, for the outdoor beacon we can find cold non-alcoholic drinks and at the cash beacon we find the cash register lineup as well as gum, sweets and tobacco products. This would mean that by looking at outcome of point 1 pathway, if for that day there is low activity at both lottery tickets and cold non-alcoholic drinks, but while having a busy cash lineup, then the store manager can also expect low alcoholic drink sales. An example of a practical marketing application could be as such; an automatic alert is set up to trigger on the manager's smart phone when the conditions of decision tree pathway 1 are satisfied. This alert could recommend setting up special promotions for the rest of the day on alcoholic products to boost sales if inventory needs to be cleared on that day or week.

Such decision trees can also help store owners better understand when some products are expected to sell more, which can lead to operational decisions such as showcasing new products during the times and zones when and where sales are expected to be higher. Those are just some applications amongst others that can come out of an IoT system.

CHAPTER 5 CONCLUSION

This research was meant to demonstrate, from a first experimental IoT system setup in a traditional retail store, that data analytics methods can be applied to extract useful information and insights to improve store operations. The applications of most interest did not come from tracing precise paths coming from the Bluetooth devices but became more useful when the IoT system was observed from a less granular point of view. This led to showcase more practical possibilities to exploit the data with data mining methods. From less precise information, more useful applications came out of it such as smart alerts when a certain pattern is detected from the IoT system. This same information can also potentially help understand business owners the behavior of their sales when it comes to products, days or zones of interest within the store.

After performing a collection from the Bluetooth beacons and applying a first data analysis which traces each unique customer's pathway inside the store, we encountered the first limitation to the system, which is the Bluetooth precision. Due to this limitation, our findings were that a precise pathway could not be traced with the current setup put in place and by using the linear or logarithmic correlation methods. However, readings based on single sensors provided much more reliable results which were used for the sales data analysis. In the recommendations below we discuss what should be done instead to receive data with better granularity in future work.

The second demonstration of this research project was to show a correlation between more general positional data, which in our case was the activity proportions at different beacons, and the sales numbers classified per categories. We have indeed showed, in an exploratory basis, that it is possible to find correlations between BLE-sensed customer activity and sales activities, by applying a decision tree CART method, which could be used to predict the sales of different categories of items depending on the activity at different zones.

Recommendations for further experimentations would be to include an integrated Bluetooth and WIFI IoT system instead to increase locational precision from customer's smart devices; in that case, a more careful attention would be required to the ethical and social issues that the research may arise, especially if a field data collection with real customers is attempted. Another recommendation would be to perform these experimentations in a larger zone, preferably spanning over multiple floors as that is when the sensor technology will work best. Finally, we also

recommend to perform the data collection over multiple weeks and applying decision tree algorithms now that we know from this pilot project of its potential.

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APPENDIX A – PARETO DATA COLLECTION CODES

Non matrix Pareto data collection code

```
const fs = require('fs');
const socketioClient = require('socket.io-client');

const PARETO_TOKEN = '';
const PARETO_URL = 'https://pareto.reelyactive.com';
const DEFAULT_LOGFILE_NAME = 'eventlog';
const DEFAULT_LOGFILE_EXTENSION = '.csv';
const HEADER =
    'time,event,sessionId,sessionDuration,deviceId,deviceTags,deviceUrl,rssi,receiverI
    d,receiverTags,receiverDirectory,receiverUrl,position,isPerson'

process.env.PARETO_TOKEN = PARETO_TOKEN;
var socket = socketioClient(PARETO_URL, { query: { token: PARETO_TOKEN } });
var filename = DEFAULT_LOGFILE_NAME + '-' + getLocalTwelveDigitString() +
DEFAULT_LOGFILE_EXTENSION

console.log('Logging events to file', filename, '  Press Ctrl-C to terminate.');
fs.appendFile(filename, HEADER + '\r\n', null);

socket.on('appearance', logEvent);
socket.on('displacement', logEvent);
socket.on('keep-alive', logEvent);


function logEvent(event) {
fs.appendFile(filename, toCSVString(event) + '\r\n', null);
}


function getLocalTwelveDigitString() {
var date = new Date();
var output = '';
output += date.getFullYear().toString().slice(-2);
output += ('0' + (date.getMonth() + 1)).slice(-2);
output += ('0' + date.getDate()).slice(-2);
output += ('0' + date.getHours()).slice(-2);
output += ('0' + date.getMinutes()).slice(-2);
output += ('0' + date.getSeconds()).slice(-2);
return output;
};
```

Matrix Pareto data collection code

```
const fs = require('fs');
const socketioClient = require('socket.io-client');


const PARETO_TOKEN = '';
const RECEIVER_IDS = [ '001bc50940820011', '001bc50940820012',
                       '001bc50940820014', '001bc50940820015' ];
const PARETO_URL = 'https://pareto.reelyactive.com';
const DEFAULT_LOGFILE_NAME = 'eventlog';
const DEFAULT_LOGFILE_EXTENSION = '.csv';
const HEADER =
    'time,event,sessionId,sessionDuration,deviceId,deviceTags,deviceUrl,rssi,receiverId,receiverTa
    gs,receiverDirectory,receiverUrl,position,isPerson'

process.env.PARETO_TOKEN = PARETO_TOKEN;
var socket = socketioClient(PARETO_URL, { query: { token: PARETO_TOKEN } });
var filename = DEFAULT_LOGFILE_NAME + '-' + getLocalTwelveDigitString() +
DEFAULT_LOGFILE_EXTENSION

console.log('Logging events to file', filename, '  Press Ctrl-C to terminate.');
fs.appendFile(filename, HEADER + '\r\n', null);

socket.on('appearance', logEvent);
socket.on('displacement', logEvent);
socket.on('keep-alive', logEvent);


function logEvent(event) {
    fs.appendFile(filename, toCSVString(event) + '\r\n', null);
}


function getLocalTwelveDigitString() {
    var date = new Date();
    var output = '';
    output += date.getFullYear().toString().slice(-2);
    output += ('0' + (date.getMonth() + 1)).slice(-2);
    output += ('0' + date.getDate()).slice(-2);
    output += ('0' + date.getHours()).slice(-2);
    output += ('0' + date.getMinutes()).slice(-2);
    output += ('0' + date.getSeconds()).slice(-2);
    return output;
};


function toCSVString(event) {
    var output = event.time;
    output += ',' + event.event;
    output += ',' + event.sessionId;
    output += ',' + event.sessionDuration;
    output += ',' + event.deviceId;
    output += ',' + event.deviceTags.toString().replace(',', ' | ');
    output += ',' + event.deviceUrl;
    output += ',' + event.rssi;
    output += ',' + event.receiverId;
    output += ',' + event.receiverTags.toString().replace(',', ' | ');
    output += ',' + event.receiverDirectory;
    output += ',' + event.receiverUrl;
    output += ',' + event.position.toString().replace(',', ' | ');
    output += ',' + event.isPerson;
    for(var cReceiver = 0; cReceiver < RECEIVER_IDS.length; cReceiver++) {
        var receiverId = RECEIVER_IDS[cReceiver];
        output += ',';
        if(event.rssiSignature.hasOwnProperty(receiverId)) {
            output += event.rssiSignature[receiverId];
        }
    }
    return output;
}

```

APPENDIX B – RAW DATA

Non-Matrix Form Raw Data Excerpt

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	time	event	sessionId	sessionDurat	deviceId	deviceTags	deviceUrl	rssi	receiverId	receiverTags	receiverDire	receiverUrl	position	isPerson
2	1519447816801	displacemen	7265656c-00	4722050	2091484bb4	indoorpositic	https://sniffy	156	001bc50940	Owl-in-one	poly:12339:T	undefined	-73.729433	no
3	1519447816745	keep-alive	7265656c-00	15546584	2091484bb4	indoorpositic	https://sniffy	164	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729287	no
4	1519447817981	keep-alive	7265656c-00	21198643	2091484bb4	indoorpositic	https://sniffy	157	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729215	no
5	1519447818822	displacemen	7265656c-00	4723888	2091484bb4	indoorpositic	https://sniffy	156	001bc50940	Owl-in-one	poly:12339:T	undefined	-73.729433	no
6	1519447819737	keep-alive	7265656c-00	39072	628576152d	dmp	https://sniffy	143	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729287	no
7	1519447820933	keep-alive	7265656c-00	114924284	ac233fa0034	temperature	https://www	160	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729287	unlikely
8	1519447822501	keep-alive	7265656c-00	15552166	2091484bb4	indoorpositic	https://sniffy	164	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729215	no
9	1519447823688	keep-alive	7265656c-00	4729113	2091484bb4	indoorpositic	https://sniffy	156	001bc50940	Owl-in-one	poly:12339:T	undefined	-73.729433	no
10	1519447823688	keep-alive	7265656c-00	21204368	2091484bb4	indoorpositic	https://sniffy	157	001bc50940	Owl-in-one	poly:12339:T	undefined	-73.729433	no
11	1519447825748	keep-alive	7265656c-00	45256	628576152d	dmp	https://sniffy	142	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729287	no
12	1519447825961	keep-alive	7265656c-00	114929313	ac233fa0034	temperature	https://www	159	001bc50940	Owl-in-one	poly:12339:E	undefined	-73.729383	unlikely
13	1519447828529	keep-alive	7265656c-00	15558031	2091484bb4	indoorpositic	https://sniffy	164	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729287	no
14	1519447828861	keep-alive	7265656c-00	4734103	2091484bb4	indoorpositic	https://sniffy	156	001bc50940	Owl-in-one	poly:12339:T	undefined	-73.729433	no
15	1519447829796	keep-alive	7265656c-00	21210457	2091484bb4	indoorpositic	https://sniffy	157	001bc50940	Owl-in-one	poly:12339:T	undefined	-73.729433	no
16	1519447830875	displacemen	7265656c-00	114934225	ac233fa0034	temperature	https://www	165	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729215	unlikely
17	1519447831755	keep-alive	7265656c-00	51096	628576152d	dmp	https://sniffy	142	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729287	no
18	1519447833254	appearance	7265656c-00	114936880	2091484bb3	indoorpositic	https://sniffy	151	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729287	no
19	1519447833888	keep-alive	7265656c-00	4739140	2091484bb4	indoorpositic	https://sniffy	156	001bc50940	Owl-in-one	poly:12339:T	undefined	-73.729433	no
20	1519447834567	keep-alive	7265656c-00	15564239	2091484bb4	indoorpositic	https://sniffy	164	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729287	no
21	1519447835714	keep-alive	7265656c-00	21216368	2091484bb4	indoorpositic	https://sniffy	157	001bc50940	Owl-in-one	poly:12339:T	undefined	-73.729433	no
22	1519447836388	keep-alive	7265656c-00	114939733	ac233fa0034	temperature	https://www	165	001bc50940	Owl-in-one	poly:12339:T	undefined	-73.729433	unlikely
23	1519447836948	keep-alive	7265656c-00	56292	628576152d	dmp	https://sniffy	142	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729287	no
24	1519447838734	keep-alive	7265656c-00	4744156	2091484bb4	indoorpositic	https://sniffy	156	001bc50940	Owl-in-one	poly:12339:T	undefined	-73.729433	no
25	1519447839608	keep-alive	7265656c-00	15569286	2091484bb4	indoorpositic	https://sniffy	164	001bc50940	Owl-in-one	poly:12339:E	undefined	-73.729383	no
26	1519447841734	displacemen	7265656c-00	4747151	2091484bb4	indoorpositic	https://sniffy	156	001bc50940	Owl-in-one	poly:12339:T	undefined	-73.729433	no
27	1519447841734	keep-alive	7265656c-00	21222567	2091484bb4	indoorpositic	https://sniffy	158	001bc50940	Owl-in-one	poly:12339:T	undefined	-73.729433	no
28	1519447842408	keep-alive	7265656c-00	114945756	ac233fa0034	temperature	https://www	165	001bc50940	Owl-in-one	poly:12339:T	undefined	-73.729433	unlikely
29	1519447842968	keep-alive	7265656c-00	62306	628576152d	dmp	https://sniffy	142	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729287	no
30	1519447843908	displacemen	7265656c-00	4749006	2091484bb4	indoorpositic	https://sniffy	156	001bc50940	Owl-in-one	poly:12339:T	undefined	-73.729433	no
31	1519447845507	keep-alive	7265656c-00	15575023	2091484bb4	indoorpositic	https://sniffy	164	001bc50940	Owl-in-one	poly:12339:E	undefined	-73.729383	no

Matrix Form Raw Data Excerpt

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
1	time	event	sessionId	sessionDurat	deviceId	deviceTags	receiverId	receiverTags	receiverDire	receiverUrl	position	isPerson	cash	outdoor	washroom	liquor
2	1523320274582	keep-alive	7265656c-00	8891750	c869cded303	AppleTV	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729287	no	0	138	0	0
3	1523320274582	keep-alive	7265656c-00	40145895	ac233fa0034	temperature	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729215	unlikely	160	162	158	154
4	1523320277582	keep-alive	7265656c-00	1912326	2091484bb4	indoorpositic	001bc50940	Owl-in-one	poly:12339:E	undefined	-73.729383	no	156	0	151	154
5	1523320278590	keep-alive	7265656c-00	40149866	2091484bb3	indoorpositic	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729287	no	154	154	167	0
6	1523320279602	keep-alive	7265656c-00	40150892	ac233fa0034	temperature	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729215	unlikely	160	162	157	154
7	1523320279514	keep-alive	7265656c-00	40151216	2091484bb4	indoorpositic	001bc50940	Owl-in-one	poly:12339:T	undefined	-73.729433	no	0	156	159	153
8	1523320280074	keep-alive	7265656c-00	40152102	2c41a12608f	audio	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729287	no	0	140	0	0
9	1523320280594	appearance	7265656c-00	3	463b660565	curious	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729287	possibly	0	146	0	0
10	1523320281574	keep-alive	7265656c-00	8898718	c869cded303	AppleTV	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729287	no	0	139	0	0
11	1523320283614	keep-alive	7265656c-00	1918309	2091484bb4	indoorpositic	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729215	no	157	0	151	154
12	1523320283614	keep-alive	7265656c-00	40154880	2091484bb3	indoorpositic	001bc50940	Owl-in-one	poly:12339:T	undefined	-73.729433	no	154	155	167	0
13	1523320284033	keep-alive	7265656c-00	276083	69ab626c72	iOS | fb?	001bc50940	Owl-in-one	poly:12339:E	undefined	-73.729383	yes	0	0	0	137
14	1523320284514	displacemen	7265656c-00	276500	69ab626c72	iOS | fb?	001bc50940	Owl-in-one	poly:12339:T	undefined	-73.729433	yes	0	0	137	137
15	1523320284802	keep-alive	7265656c-00	40156081	2091484bb4	indoorpositic	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729287	no	0	157	159	154
16	1523320285666	displacemen	7265656c-00	277689	69ab626c72	iOS | fb?	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729287	yes	0	144	137	137
17	1523320285829	keep-alive	7265656c-00	40157137	ac233fa0034	temperature	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729287	unlikely	161	163	157	154
18	1523320286914	keep-alive	7265656c-00	40159060	2c41a12608f	audio	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729287	no	0	140	0	0
19	1523320287321	keep-alive	7265656c-00	8904565	c869cded303	AppleTV	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729287	no	0	138	0	0
20	1523320288633	keep-alive	7265656c-00	1923532	2091484bb4	indoorpositic	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729215	no	158	0	151	155
21	1523320289434	appearance	7265656c-00	23926	57239d8743	curious	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729287	possibly	0	147	0	0
22	1523320290534	keep-alive	7265656c-00	40161924	2091484bb4	indoorpositic	001bc50940	Owl-in-one	poly:12339:T	undefined	-73.729433	no	0	157	160	153
23	1523320290534	keep-alive	7265656c-00	40161946	2091484bb3	indoorpositic	001bc50940	Owl-in-one	poly:12339:T	undefined	-73.729433	no	154	156	167	0
24	1523320290934	keep-alive	7265656c-00	282987	69ab626c72	iOS	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729287	possibly	0	144	137	137
25	1523320291134	appearance	7265656c-00	1	64f01ab2015	dmp	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729215	no	136	0	0	0
26	1523320291853	keep-alive	7265656c-00	40162969	ac233fa0034	temperature	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729287	unlikely	162	163	157	0
27	1523320291853	keep-alive	7265656c-00	40164109	2c41a12608f	audio	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729287	no	0	141	0	0
28	1523320293962	keep-alive	7265656c-00	8911126	c869cded303	AppleTV	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729287	no	0	138	0	0
29	1523320294162	appearance	7265656c-00	39318251	2091484bb4	indoorpositic	001bc50940	Owl-in-one	poly:12339:E	undefined	-73.729383	no	0	0	0	166
30	1523320294554	keep-alive	7265656c-00	1929520	2091484bb4	indoorpositic	001bc50940	Owl-in-one	poly:12339:T	undefined	-73.729433	no	158	0	153	154
31	1523320295954	keep-alive	7265656c-00	288014	69ab626c72	iOS	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729287	possibly	0	146	0	0

Fitbit Validation Raw Data Excerpt & Defined Zone Using Linear Function

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q
1	time	event	sessionId	sessionDurat	deviceId	deviceTags	receiverId	receiverTags	receiverDire	receiverUrl	position	isPerson	cash	outdoor	washroom	liquor	Zone
2	1525019982819	displacemen	7265656c-00	10041	2c41a15996	audio	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729215	no	143	143	0	0	13
3	1525019982819	keep-alive	7265656c-00	9027	2c41a159b5	audio	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729215	no	143	0	0	0	13
4	1525019982554	keep-alive	7265656c-00	207220874	2091484bb4	indoorpositic	001bc50940	Owl-in-one	poly:12339:E	undefined	-73.729383	no	0	152	161	159	13
5	1525019982949	keep-alive	7265656c-00	335110031	ac233fa0034	temperature	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729287	unlikely	0	157	153	0	13
6	1525019984952	keep-alive	7265656c-00	335112224	2091484bb3	indoorpositic	001bc50940	Owl-in-one	poly:12339:T	undefined	-73.729433	no	160	159	165	0	13
7	1525019985963	keep-alive	7265656c-00	11058	69214b785d57		001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729287	unlikely	137	144	140	142	13
8	1525019985566	displacemen	7265656c-00	207223949	2091484bb4	indoorpositic	001bc50940	Owl-in-one	poly:12339:E	undefined	-73.729383	no	0	152	0	159	13
9	1525019985566	keep-alive	7265656c-00	8594725	2091484bb4	indoorpositic	001bc50940	Owl-in-one	poly:12339:E	undefined	-73.729383	no	162	144	0	164	13
10	1525019985566	keep-alive	7265656c-00	168799	7802b7225f58		001bc50940	Owl-in-one	poly:12339:E	undefined	-73.729383	unlikely	163	0	166	160	13
11	1525019986976	keep-alive	7265656c-00	72551869	2c41a12608	audio	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729287	no	139	149	0	0	13
12	1525019986587	keep-alive	7265656c-00	23227905	2091484bb4	indoorpositic	001bc50940	Owl-in-one	poly:12339:E	undefined	-73.729383	no	153	0	143	159	13
13	1525019987865	keep-alive	7265656c-00	223625	5f517696778	dmp	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729215	no	138	140	0	0	13
14	1525019987952	displacemen	7265656c-00	13045	69214b785d57		001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729287	unlikely	0	143	140	143	13
15	1525019988387	keep-alive	7265656c-00	335115461	ac233fa0034	temperature	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729215	unlikely	156	156	153	148	13
16	1525019989380	displacemen	7265656c-00	14469	69214b785d57		001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729215	unlikely	138	143	140	143	13
17	1525019989968	keep-alive	7265656c-00	335117253	2091484bb3	indoorpositic	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729287	no	160	159	165	0	13
18	1525019990609	keep-alive	7265656c-00	8599359	2091484bb4	indoorpositic	001bc50940	Owl-in-one	poly:12339:E	undefined	-73.729383	no	0	0	0	165	13
19	1525019990964	keep-alive	7265656c-00	173708	7802b7225f58		001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729287	unlikely	161	148	0	161	13
20	1525019991609	keep-alive	7265656c-00	207229623	2091484bb4	indoorpositic	001bc50940	Owl-in-one	poly:12339:E	undefined	-73.729383	no	0	152	0	159	13
21	1525019991609	keep-alive	7265656c-00	23232489	2091484bb4	indoorpositic	001bc50940	Owl-in-one	poly:12339:E	undefined	-73.729383	no	153	0	0	159	13
22	1525019991879	displacemen	7265656c-00	174625	7802b7225f58		001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729215	unlikely	159	148	0	161	13
23	1525019991974	displacemen	7265656c-00	17063	69214b785d57		001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729287	unlikely	139	141	0	141	13
24	1525019992887	keep-alive	7265656c-00	72557754	2c41a12608	audio	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729215	no	138	148	0	0	13
25	1525019992980	keep-alive	7265656c-00	228718	5f517696778	dmp	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729287	no	138	140	0	0	13
26	1525019992980	displacemen	7265656c-00	18076	69214b785d57		001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729287	unlikely	139	141	0	0	13
27	1525019993512	displacemen	7265656c-00	176470	7802b7225f58		001bc50940	Owl-in-one	poly:12339:T	undefined	-73.729433	unlikely	158	147	163	161	4
28	1525019993512	displacemen	7265656c-00	207231681	2091484bb4	indoorpositic	001bc50940	Owl-in-one	poly:12339:T	undefined	-73.729433	no	0	152	161	159	13
29	1525019994521	keep-alive	7265656c-00	335122018	ac233fa0034	temperature	001bc50940	Owl-in-one	poly:12339:T	undefined	-73.729433	unlikely	156	156	152	148	13
30	1525019995022	keep-alive	7265656c-00	335122294	2091484bb3	indoorpositic	001bc50940	Owl-in-one	poly:12339:T	undefined	-73.729433	no	160	159	166	0	13
31	1525019996551	displacemen	7265656c-00	335123724	ac233fa0034	temperature	001bc50940	Owl-in-one	poly:12339:T	undefined	-73.729433	unlikely	156	156	152	149	13

Fitbit Validation Raw Data Excerpt & Defined Zone Using Log Function

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q
1	time	event	sessionId	sessionDurat	deviceId	deviceTags	receiverId	receiverTags	receiverDire	receiverUrl	position	isPerson	cash	outdoor	washroom	liquor	Zone
2	1525019982819	displacemen	7265656c-00	10041	2c41a15996	audio	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729215	no	143	143	0	0	13
3	1525019982819	keep-alive	7265656c-00	9027	2c41a159b5	audio	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729215	no	143	0	0	0	13
4	1525019982554	keep-alive	7265656c-00	207220874	2091484bb4	indoorpositic	001bc50940	Owl-in-one	poly:12339:E	undefined	-73.729383	no	0	152	161	159	13
5	1525019982949	keep-alive	7265656c-00	335110031	ac233fa0034	temperature	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729287	unlikely	0	157	153	0	13
6	1525019984952	keep-alive	7265656c-00	335112224	2091484bb3	indoorpositic	001bc50940	Owl-in-one	poly:12339:T	undefined	-73.729433	no	160	159	165	0	13
7	1525019985963	keep-alive	7265656c-00	11058	69214b785d57		001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729287	unlikely	137	144	140	142	13
8	1525019985566	displacemen	7265656c-00	207223949	2091484bb4	indoorpositic	001bc50940	Owl-in-one	poly:12339:E	undefined	-73.729383	no	0	152	0	159	13
9	1525019985566	keep-alive	7265656c-00	8594725	2091484bb4	indoorpositic	001bc50940	Owl-in-one	poly:12339:E	undefined	-73.729383	no	162	144	0	164	13
10	1525019985566	keep-alive	7265656c-00	168799	7802b7225f58		001bc50940	Owl-in-one	poly:12339:E	undefined	-73.729383	unlikely	163	0	166	160	13
11	1525019986976	keep-alive	7265656c-00	72551869	2c41a12608	audio	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729287	no	139	149	0	0	13
12	1525019986587	keep-alive	7265656c-00	23227905	2091484bb4	indoorpositic	001bc50940	Owl-in-one	poly:12339:E	undefined	-73.729383	no	153	0	143	159	13
13	1525019987865	keep-alive	7265656c-00	223625	5f51769677	dmp	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729215	no	138	140	0	0	13
14	1525019987952	displacemen	7265656c-00	13045	69214b785d57		001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729287	unlikely	0	143	140	143	13
15	1525019988387	keep-alive	7265656c-00	335115461	ac233fa0034	temperature	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729215	unlikely	156	156	153	148	13
16	1525019989380	displacemen	7265656c-00	14469	69214b785d57		001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729215	unlikely	138	143	140	143	13
17	1525019989968	keep-alive	7265656c-00	335117253	2091484bb3	indoorpositic	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729287	no	160	159	165	0	13
18	1525019990609	keep-alive	7265656c-00	8599359	2091484bb4	indoorpositic	001bc50940	Owl-in-one	poly:12339:E	undefined	-73.729383	no	0	0	0	165	13
19	1525019990964	keep-alive	7265656c-00	173708	7802b7225f58		001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729287	unlikely	161	148	0	161	13
20	1525019991609	keep-alive	7265656c-00	207229623	2091484bb4	indoorpositic	001bc50940	Owl-in-one	poly:12339:E	undefined	-73.729383	no	0	152	0	159	13
21	1525019991609	keep-alive	7265656c-00	23232489	2091484bb4	indoorpositic	001bc50940	Owl-in-one	poly:12339:E	undefined	-73.729383	no	153	0	0	159	13
22	1525019991879	displacemen	7265656c-00	174625	7802b7225f58		001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729215	unlikely	159	148	0	161	13
23	1525019991974	displacemen	7265656c-00	17063	69214b785d57		001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729287	unlikely	139	141	0	141	13
24	1525019992887	keep-alive	7265656c-00	72557754	2c41a12608	audio	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729215	no	138	148	0	0	13
25	1525019992980	keep-alive	7265656c-00	228718	5f51769677	dmp	001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729287	no	138	140	0	0	13
26	1525019992980	displacemen	7265656c-00	18076	69214b785d57		001bc50940	Owl-in-one	poly:12339:C	undefined	-73.729287	unlikely	139	141	0	0	13
27	1525019993512	displacemen	7265656c-00	176470	7802b7225f58		001bc50940	Owl-in-one	poly:12339:T	undefined	-73.729433	unlikely	158	147	163	161	13
28	1525019993512	displacemen	7265656c-00	207231681	2091484bb4	indoorpositic	001bc50940	Owl-in-one	poly:12339:T	undefined	-73.729433	no	0	152	161	159	13
29	1525019994521	keep-alive	7265656c-00	335122018	ac233fa0034	temperature	001bc50940	Owl-in-one	poly:12339:T	undefined	-73.729433	unlikely	156	156	152	148	13
30	1525019995022	keep-alive	7265656c-00	335122294	2091484bb3	indoorpositic	001bc50940	Owl-in-one	poly:12339:T	undefined	-73.729433	no	160	159	166	0	13
31	1525019996551	displacemen	7265656c-00	335123724	ac233fa0034	temperature	001bc50940	Owl-in-one	poly:12339:T	undefined	-73.729433	unlikely	156	156	152	149	13

APPENDIX C – PYTHON CODES

Pathway Tracing Code

```
import pandas  as pd

#-------------------------------------------------------------------------#
#      Data Loading                                                       #
#-------------------------------------------------------------------------#

data_dir = '/Data_Collection/April_29/'
linear_data_file = 'eventlog-180429123943.csv'
log_data_file = 'eventlog-180429123943_log.csv'

linear_df = pd.read_csv(data_dir + linear_data_file,
                dtype={"time" : long,
                       "event" : str,
                       "sessionId" : str,
                       "sessionDuration" : float,
                       "deviceId" : str,
                       "deviceTags" : str,
                       "receiverId" : str,
                       "receiverTags" : str,
                       "receiverDirectory": str,
                       "receiverUrl": str,
                       "position" : str,
                       "isPerson" : str,
                       "cash" : int,
                       "outdoor" : int,
                       "washroom" : int,
                       "liquor" : int,
                       "Zone" : int})

log_df = pd.read_csv(data_dir + log_data_file,
                dtype={"time" : long,
                       "event" : str,
                       "sessionId" : str,
                       "sessionDuration" : float,
                       "deviceId" : str,
                       "deviceTags" : str,
                       "receiverId" : str,
                       "receiverTags" : str,
                       "receiverDirectory": str,
                       "receiverUrl": str,
                       "position" : str,
                       "isPerson" : str,
```

```
                    "cash" : int,
                    "outdoor" : int,
                    "washroom" : int,
                    "liquor" : int,
                    "Zone" : int})

#-------------------------------------------------------------------------#
#    Linear Data Pre-Processing                                           #
#-------------------------------------------------------------------------#

# Add new column:
# Purpose: Identifying fitbit testing device
# Query: Fitbit testing device, Device ID: 7802b7225f58

deviceID = '7802b7225f58'

isTestingDevice = []

for row in linear_df['deviceId']:
    if deviceID in row:
        isTestingDevice.append(True)
    else:
        isTestingDevice.append(False)

linear_df['isTestingDevice'] = isTestingDevice

# Create new dataframe
# Content: Data points containing only testing device

linear_testing_device_df = linear_df.query('isTestingDevice == True')

#-------------------------------------------------------------------------#
#    Log Data Pre-Processing                                              #
#-------------------------------------------------------------------------#

# Add new column:
# Purpose: Identifying fitbit testing device
# Query: Fitbit testing device, Device ID: 7802b7225f58

deviceID = '7802b7225f58'

isTestingDevice = []

for row in log_df['deviceId']:
    if deviceID in row:
        isTestingDevice.append(True)
    else:
```

```
        isTestingDevice.append(False)

log_df['isTestingDevice'] = isTestingDevice

# Create new dataframe
# Content: Data points containing only testing device

log_testing_device_df = log_df.query('isTestingDevice == True')

#-------------------------------------------------------------------------#
#      Linear Result validations                                          #
#-------------------------------------------------------------------------#

# Dataframe where all points gathered are not outside (zone 13)
linear_inside_df = linear_testing_device_df.query('Zone != 13')

# Zones during complete testing time: 12:39:00 PM to 12:52:00 PM
print('Linear complete testing time')
print(linear_inside_df.query('time >= 1525019940000 & time <= 1525020720000'))
# Actual Zones Pathway: 1(4)->4->7->10->12->10->8->11->9->6->3->1
# Returned Zones Pathway: 4->7->4->5->6->5->2

#-------------------------------------------------------------------------#
#      Log Result validations                                             #
#-------------------------------------------------------------------------#

# Dataframe where all points gathered are not outside (zone 13)
log_inside_df = log_testing_device_df.query('Zone != 13')

# Zones during complete testing time: 12:39:00 PM to 12:52:00 PM
print('Log complete testing time')
print(log_inside_df.query('time >= 1525019940000 & time <= 1525020720000'))
# Actual Zones Pathway: 1(4)->4->7->10->12->10->8->11->9->6->3->1
# Returned Zones Pathway: 9
```

Pathway Tracing Code Output

```
Linear complete testing time
            time         event                             sessionId  \
25    1525019993512  displacement  7265656c-0000-4000-8048-7802b7225f58
36    1525019999905    keep-alive  7265656c-0000-4000-8048-7802b7225f58
487   1525020222802  displacement  7265656c-0000-4000-8048-7802b7225f58
502   1525020228639    keep-alive  7265656c-0000-4000-8048-7802b7225f58
521   1525020237746  displacement  7265656c-0000-4000-8048-7802b7225f58
538   1525020243731    keep-alive  7265656c-0000-4000-8048-7802b7225f58
599   1525020272832    keep-alive  7265656c-0000-4000-8048-7802b7225f58
```

```
611   1525020278652    keep-alive  7265656c-0000-4000-8048-7802b7225f58
637   1525020290500    keep-alive  7265656c-0000-4000-8048-7802b7225f58
651   1525020296934    keep-alive  7265656c-0000-4000-8048-7802b7225f58
660   1525020302619    keep-alive  7265656c-0000-4000-8048-7802b7225f58
671   1525020308603    keep-alive  7265656c-0000-4000-8048-7802b7225f58
686   1525020316521  displacement  7265656c-0000-4000-8048-7802b7225f58
720   1525020332683    keep-alive  7265656c-0000-4000-8048-7802b7225f58
752   1525020349570    keep-alive  7265656c-0000-4000-8048-7802b7225f58
761   1525020354935    keep-alive  7265656c-0000-4000-8048-7802b7225f58
783   1525020365676    keep-alive  7265656c-0000-4000-8048-7802b7225f58
948   1525020447640    keep-alive  7265656c-0000-4000-8048-7802b7225f58
959   1525020453514    keep-alive  7265656c-0000-4000-8048-7802b7225f58
969   1525020459625    keep-alive  7265656c-0000-4000-8048-7802b7225f58
975   1525020465546    keep-alive  7265656c-0000-4000-8048-7802b7225f58
1018  1525020491887  displacement  7265656c-0000-4000-8048-7802b7225f58
1026  1525020497650    keep-alive  7265656c-0000-4000-8048-7802b7225f58
1079  1525020526551    keep-alive  7265656c-0000-4000-8048-7802b7225f58
1090  1525020532134    keep-alive  7265656c-0000-4000-8048-7802b7225f58
1150  1525020562735  displacement  7265656c-0000-4000-8048-7802b7225f58
1270  1525020627823    keep-alive  7265656c-0000-4000-8048-7802b7225f58
1386  1525020690022    keep-alive  7265656c-0000-4000-8048-7802b7225f58

     sessionDuration      deviceId deviceTags        receiverId receiverTags  \
25          176470.0  7802b7225f58        NaN  001bc50940820014   Owl-in-one
36          182661.0  7802b7225f58        NaN  001bc50940820014   Owl-in-one
487         405560.0  7802b7225f58        NaN  001bc50940820014   Owl-in-one
502         411735.0  7802b7225f58        NaN  001bc50940820014   Owl-in-one
521         420512.0  7802b7225f58        NaN  001bc50940820014   Owl-in-one
538         426537.0  7802b7225f58        NaN  001bc50940820014   Owl-in-one
599         455590.0  7802b7225f58        NaN  001bc50940820014   Owl-in-one
611         462008.0  7802b7225f58        NaN  001bc50940820014   Owl-in-one
637         473287.0  7802b7225f58        NaN  001bc50940820014   Owl-in-one
651         479686.0  7802b7225f58        NaN  001bc50940820014   Owl-in-one
660         485397.0  7802b7225f58        NaN  001bc50940820014   Owl-in-one
671         491448.0  7802b7225f58        NaN  001bc50940820014   Owl-in-one
686         499314.0  7802b7225f58        NaN  001bc50940820015   Owl-in-one
720         515510.0  7802b7225f58        NaN  001bc50940820015   Owl-in-one
752         532596.0  7802b7225f58        NaN  001bc50940820015   Owl-in-one
761         537694.0  7802b7225f58        NaN  001bc50940820015   Owl-in-one
783         548617.0  7802b7225f58        NaN  001bc50940820015   Owl-in-one
948         630796.0  7802b7225f58        NaN  001bc50940820015   Owl-in-one
959         636425.0  7802b7225f58        NaN  001bc50940820015   Owl-in-one
969         642586.0  7802b7225f58        NaN  001bc50940820015   Owl-in-one
975         648590.0  7802b7225f58        NaN  001bc50940820015   Owl-in-one
1018        674679.0  7802b7225f58        NaN  001bc50940820015   Owl-in-one
1026        680646.0  7802b7225f58        NaN  001bc50940820015   Owl-in-one
1079        709520.0  7802b7225f58        NaN  001bc50940820011   Owl-in-one
```

```
1090       714885.0  7802b7225f58       NaN  001bc50940820011   Owl-in-one
1150       745486.0  7802b7225f58       NaN  001bc50940820011   Owl-in-one
1270       810578.0  7802b7225f58       NaN  001bc50940820011   Owl-in-one
1386       872773.0  7802b7225f58       NaN  001bc50940820011   Owl-in-one

            receiverDirectory receiverUrl              position  \
25     poly:12339:Toilettes-Lait   undefined  -73.729433 | 45.603054
36            poly:12339:Caisse   undefined  -73.729215 | 45.603003
487    poly:12339:Toilettes-Lait   undefined  -73.729433 | 45.603054
502   poly:12339:Bieres-Tablettes   undefined  -73.729383 | 45.603081
521    poly:12339:Toilettes-Lait   undefined  -73.729433 | 45.603054
538    poly:12339:Toilettes-Lait   undefined  -73.729433 | 45.603054
599    poly:12339:Toilettes-Lait   undefined  -73.729433 | 45.603054
611   poly:12339:Bieres-Tablettes   undefined  -73.729383 | 45.603081
637           poly:12339:Caisse   undefined  -73.729215 | 45.603003
651    poly:12339:Toilettes-Lait   undefined  -73.729433 | 45.603054
660          poly:12339:Outdoor   undefined   -73.729287 | 45.60309
671           poly:12339:Caisse   undefined  -73.729215 | 45.603003
686    poly:12339:Toilettes-Lait   undefined  -73.729433 | 45.603054
720          poly:12339:Outdoor   undefined   -73.729287 | 45.60309
752          poly:12339:Outdoor   undefined   -73.729287 | 45.60309
761   poly:12339:Bieres-Tablettes   undefined  -73.729383 | 45.603081
783    poly:12339:Toilettes-Lait   undefined  -73.729433 | 45.603054
948           poly:12339:Caisse   undefined  -73.729215 | 45.603003
959    poly:12339:Toilettes-Lait   undefined  -73.729433 | 45.603054
969          poly:12339:Outdoor   undefined   -73.729287 | 45.60309
975    poly:12339:Toilettes-Lait   undefined  -73.729433 | 45.603054
1018  poly:12339:Bieres-Tablettes   undefined  -73.729383 | 45.603081
1026   poly:12339:Toilettes-Lait   undefined  -73.729433 | 45.603054
1079  poly:12339:Bieres-Tablettes   undefined  -73.729383 | 45.603081
1090         poly:12339:Outdoor   undefined   -73.729287 | 45.60309
1150         poly:12339:Outdoor   undefined   -73.729287 | 45.60309
1270   poly:12339:Toilettes-Lait   undefined  -73.729433 | 45.603054
1386         poly:12339:Outdoor   undefined   -73.729287 | 45.60309

     isPerson  cash  outdoor  washroom  liquor  Zone  isTestingDevice
25    unlikely   158      147       163     161     4             True
36    unlikely   159      150       163     159     4             True
487   unlikely   151      151       172     164     7             True
502   unlikely   153      152       172     164     7             True
521   unlikely   152      150       173     164     7             True
538   unlikely   152      149       173     164     7             True
599   unlikely   152      150       173     164     7             True
611   unlikely   152      150       173     164     7             True
637   unlikely   153      150       173     164     7             True
651   unlikely   153      150       172     164     7             True
660   unlikely   153      149       172     163     7             True
```

```
671   unlikely   152     149      166     157    4          True
686   unlikely   154     145      163     165    4          True
720   unlikely   160     166      164     168    5          True
752   unlikely   160     166      164     168    5          True
761   unlikely   161     166      164     168    5          True
783   unlikely   160     166      164     169    5          True
948   unlikely   158     161      159     165    5          True
959   unlikely   160     161      163     170    5          True
969   unlikely   162     162      163     171    5          True
975   unlikely   161     161      164     170    5          True
1018  unlikely   162     163      164     170    5          True
1026  unlikely   160     163      160     170    5          True
1079  unlikely   166     163      155     164    6          True
1090  unlikely   166     164      155     164    6          True
1150  unlikely   165     164      158     164    5          True
1270  unlikely   167     155      156     157    2          True
1386  unlikely   170     146      154     154    2          True
Log complete testing time
            time       event                        sessionId  \
1128  1525020000000  keep-alive  7265656c-0000-4000-8048-7802b7225f58

     sessionDuration      deviceId deviceTags        receiverId receiverTags  \
1128        734567.0  7802b7225f58        NaN  001bc50940820012   Owl-in-one

      receiverDirectory receiverUrl              position  isPerson  cash  \
1128  poly:12339:Outdoor   undefined  -73.729287 | 45.60309  unlikely   158

     outdoor  washroom  liquor  Zone  isTestingDevice
1128      165       146     162     9            True
```

Single Sensor Zoning Code

```
import pandas  as pd
import numpy   as np

#-------------------------------------------------------------------------#
#      Data Loading                                                       #
#-------------------------------------------------------------------------#

data_dir = '/Users/Georges/Google Drive/Education/ResearchProject/Store/Collection/'
data_file = 'eventlog-180409203116.csv'

df = pd.read_csv(data_dir + data_file,
                 dtype={"time" : long,
                        "event" : str,
                        "sessionId" : str,
                        "sessionDuration" : float,
                        "deviceId" : str,
                        "deviceTags" : str,
                        "receiverId" : str,
                        "receiverTags" : str,
                        "receiverDirectory": str,
                        "receiverUrl": str,
                        "position" : str,
                        "isPerson" : str,
                        "cash" : int,
                        "outdoor" : int,
                        "washroom" : int,
                        "liquor" : int,
                        "Zone" : int})

#-------------------------------------------------------------------------#
#      Limit Definition                                                   #
#-------------------------------------------------------------------------#

# Delimited zones found during testing on May 13th
cashLowerLimit      = 168 # Area where customers stand in line to pay
cashHigherLimit     = 172 # Area behind cash counter (employees)
outdoorLowerLimit   = 166 # Delimited area around fridge
outdoorHigherLimit  = 350 # Exagarated max RSSI for 0m distance
washroomLowerLimit  = 178 # Area where customers fill lotto tickets
washroomHigherLimit = 350 # Exagarated max RSSI for 0m distance
liquorLowerLimit    = 170 # Area where the liqor fridge is located
liquorHigherLimit   = 350 # Exagarated max RSSI for 0m distance

# Day delimitation for a 1 week sample (April 9-16, 2018)
'''
```

```
Online epoch to human date converter used
Source: https://www.epochconverter.com/
'''
firstMondayLowerLimit  = 1523246400000
firstMondayUpperLimit  = 1523332799000
secondMondayLowerLimit = 1523851200000
secondMondayUpperLimit = 1523937599000
tuesdayLowerLimit      = 1523332800000
tuesdayUpperLimit      = 1523419199000
wednesdayLowerLimit    = 1523419200000
wednesdayUpperLimit    = 1523505599000
thursdayLowerLimit     = 1523505600000
thursdayUpperLimit     = 1523591999000
fridayLowerLimit       = 1523592000000
fridayUpperLimit       = 1523678399000
saturdayLowerLimit     = 1523678400000
saturdayUpperLimit     = 1523764799000
sundayLowerLimit       = 1523764800000
sundayUpperLimit       = 1523851199000

#-------------------------------------------------------------------------#
#      Data Pre-Processing                                                #
#-------------------------------------------------------------------------#

# Remove beacon data from collection
df.query("deviceTags != 'beacon | indoorpositioning' ", inplace=True)
df.query("deviceTags != 'beacon' ", inplace=True)
df.query("deviceTags != 'track | beacon' ", inplace=True)
df.query("deviceTags != 'iBeacon' ", inplace=True)

# Remove irrelevant devices from collection using device tags
# Removed device tags: AppleTV, smarthome, camera
df.query("deviceTags != 'AppleTV' ", inplace=True)
df.query("deviceTags != 'smarthome' ", inplace=True)
df.query("deviceTags != 'camera' ", inplace=True)

# Remove device ID's that appear over 1000 times in the dataframe
# These devices skew the data and could be employees cell phones
# or other bluetooth devices installed inside the store.
# Method used to identify devices: df.deviceId.value_counts()
# Removed device IDs: ac233fa00341, 2091484bb4ce, 2091484bb3fe,
#                     2091484bb4bf, 2091484bb4c7, 2c41a12608f4,
#                     883d240b4861
df.query("deviceId != 'ac233fa00341' ", inplace=True)
df.query("deviceId != '2091484bb4ce' ", inplace=True)
df.query("deviceId != '2091484bb3fe' ", inplace=True)
df.query("deviceId != '2091484bb4bf' ", inplace=True)
```

```
df.query("deviceId != '2091484bb4c7' ", inplace=True)
df.query("deviceId != '2c41a12608f4' ", inplace=True)
df.query("deviceId != '883d240b4861' ", inplace=True)

# Detect presence in defined beacon zones
presenceAtCash     = []
presenceAtOutdoor  = []
presenceAtWashroom = []
presenceAtLiquor   = []

for row in df['cash']:
   if row > cashLowerLimit and row < cashHigherLimit:
      presenceAtCash.append(True)
   else:
      presenceAtCash.append(False)

for row in df['outdoor']:
   if row > cashLowerLimit and row < cashHigherLimit:
      presenceAtOutdoor.append(True)
   else:
      presenceAtOutdoor.append(False)

for row in df['washroom']:
   if row > cashLowerLimit and row < cashHigherLimit:
      presenceAtWashroom.append(True)
   else:
      presenceAtWashroom.append(False)

for row in df['liquor']:
   if row > cashLowerLimit and row < cashHigherLimit:
      presenceAtLiquor.append(True)
   else:
      presenceAtLiquor.append(False)

df['presenceAtCash']     = presenceAtCash
df['presenceAtOutdoor']  = presenceAtOutdoor
df['presenceAtWashroom'] = presenceAtWashroom
df['presenceAtLiquor']   = presenceAtLiquor

# Remove data with no presence at any beacon
df.query('presenceAtCash == True or \
          presenceAtOutdoor == True or \
          presenceAtWashroom == True or \
          presenceAtLiquor == True', inplace=True)

# Create new days column
day = []
```

```
for row in df['time']:
    if (row > firstMondayLowerLimit and row < firstMondayUpperLimit) \
    or (row > secondMondayLowerLimit and row < secondMondayUpperLimit):
        day.append('Monday')

    elif row > tuesdayLowerLimit and row < tuesdayUpperLimit:
        day.append('Tuesday')

    elif row > wednesdayLowerLimit and row < wednesdayUpperLimit:
        day.append('Wednesday')

    elif row > thursdayLowerLimit and row < thursdayUpperLimit:
        day.append('Thursday')

    elif row > fridayLowerLimit and row < fridayUpperLimit:
        day.append('Friday')

    elif row > saturdayLowerLimit and row < saturdayUpperLimit:
        day.append('Saturday')

    elif row > sundayLowerLimit and row < sundayUpperLimit:
        day.append('Sunday')

df['day'] = day

#-------------------------------------------------------------------------#
#     Data Analysis                                                       #
#-------------------------------------------------------------------------#

# Traffic per day, per beacon zone
# Printed values shown below
print('Monday: ')
print('cash: ')
print(df.query("day == 'Monday' and presenceAtCash == True").deviceId.nunique())
print('outdoor: ')
print(df.query("day == 'Monday' and presenceAtOutdoor == True").deviceId.nunique())
print('washroom: ')
print(df.query("day == 'Monday' and presenceAtWashroom == True").deviceId.nunique())
print('liquor: ')
print(df.query("day == 'Monday' and presenceAtLiquor == True").deviceId.nunique())
print('Tuesday: ')
print('cash: ')
print(df.query("day == 'Tuesday' and presenceAtCash == True").deviceId.nunique())
print('outdoor: ')
print(df.query("day == 'Tuesday' and presenceAtOutdoor == True").deviceId.nunique())
print('washroom: ')
```

```
print(df.query("day == 'Tuesday' and presenceAtWashroom == True").deviceId.nunique())
print('liquor: ')
print(df.query("day == 'Tuesday' and presenceAtLiquor == True").deviceId.nunique())
print('Wednesday: ')
print('cash: ')
print(df.query("day == 'Wednesday' and presenceAtCash == True").deviceId.nunique())
print('outdoor: ')
print(df.query("day == 'Wednesday' and presenceAtOutdoor == True").deviceId.nunique())
print('washroom: ')
print(df.query("day == 'Wednesday' and presenceAtWashroom == True").deviceId.nunique())
print('liquor: ')
print(df.query("day == 'Wednesday' and presenceAtLiquor == True").deviceId.nunique())
print('Thursday: ')
print('cash: ')
print(df.query("day == 'Thursday' and presenceAtCash == True").deviceId.nunique())
print('outdoor: ')
print(df.query("day == 'Thursday' and presenceAtOutdoor == True").deviceId.nunique())
print('washroom: ')
print(df.query("day == 'Thursday' and presenceAtWashroom == True").deviceId.nunique())
print('liquor: ')
print(df.query("day == 'Thursday' and presenceAtLiquor == True").deviceId.nunique())
print('Friday: ')
print('cash: ')
print(df.query("day == 'Friday' and presenceAtCash == True").deviceId.nunique())
print('outdoor: ')
print(df.query("day == 'Friday' and presenceAtOutdoor == True").deviceId.nunique())
print('washroom: ')
print(df.query("day == 'Friday' and presenceAtWashroom == True").deviceId.nunique())
print('liquor: ')
print(df.query("day == 'Friday' and presenceAtLiquor == True").deviceId.nunique())
print('Saturday: ')
print('cash: ')
print(df.query("day == 'Saturday' and presenceAtCash == True").deviceId.nunique())
print('outdoor: ')
print(df.query("day == 'Saturday' and presenceAtOutdoor == True").deviceId.nunique())
print('washroom: ')
print(df.query("day == 'Saturday' and presenceAtWashroom == True").deviceId.nunique())
print('liquor: ')
print(df.query("day == 'Saturday' and presenceAtLiquor == True").deviceId.nunique())
print('Sunday: ')
print('cash: ')
print(df.query("day == 'Sunday' and presenceAtCash == True").deviceId.nunique())
print('outdoor: ')
print(df.query("day == 'Sunday' and presenceAtOutdoor == True").deviceId.nunique())
print('washroom: ')
print(df.query("day == 'Sunday' and presenceAtWashroom == True").deviceId.nunique())
print('liquor: ')
```

```
print(df.query("day == 'Sunday' and presenceAtLiquor == True").deviceId.nunique())
```

Single Sensor Zoning Code Output

```
Monday:
cash:
46
outdoor:
39
washroom:
13
liquor:
18
Tuesday:
cash:
25
outdoor:
27
washroom:
16
liquor:
12
Wednesday:
cash:
30
outdoor:
23
washroom:
8
liquor:
16
Thursday:
cash:
37
outdoor:
30
washroom:
18
liquor:
20
Friday:
cash:
40
outdoor:
31
```

```
washroom:
14
liquor:
14
Saturday:
cash:
41
outdoor:
31
washroom:
10
liquor:
21
Sunday:
cash:
30
outdoor:
24
washroom:
14
liquor:
9
```

Sales Data Mining Dataset 1 Script

```
import pandas as pd
from   sklearn.model_selection  import train_test_split
from   sklearn.tree            import DecisionTreeClassifier, export_graphviz
from   sklearn.metrics          import accuracy_score
from   graphviz                import Source

#-------------------------------------------------------------------------#
# Loading Datasets                                                        #
#-------------------------------------------------------------------------#

# Dataset naming description

data_dir='/Users/Georges/GoogleDrive/Education/ResearchProject/DataAnalysis/DataMiningDat
aset/'
data_file = 'DataSet1.csv'

df = pd.read_csv(data_dir + data_file)

#-------------------------------------------------------------------------#
# Data slicing                                                            #
#-------------------------------------------------------------------------#
```

```
# Beacon activity as predictor variables
x = df.values[:, 1:6] # Predictor variables (1st column to 5th)

# Non alcoholic drinks as outcome variable and train/test split
y1 = df.values[:, 5] # Outcome variables (5th column)

x1_train, x1_test, y1_train, y1_test = train_test_split(x, y1, test_size=0.25,\
                                       random_state=1)

# Sweets as outcome variable and train/test split
y2 = df.values[:, 6] # Outcome variables (6th column)

x2_train, x2_test, y2_train, y2_test = train_test_split(x, y2, test_size=0.25,\
                                       random_state=1)

# Alcoholic drinks as outcome variable and train/test split
y3 = df.values[:, 7] # Outcome variables (7th column)

x3_train, x3_test, y3_train, y3_test = train_test_split(x, y3, test_size=0.25,\
                                       random_state=1)

# Lottery as outcome variable and train/test split
y4 = df.values[:, 8] # Outcome variables (8th column)

x4_train, x4_test, y4_train, y4_test = train_test_split(x, y4, test_size=0.25,\
                                       random_state=1)

# Salty snacks as outcome variable and train/test split
y5 = df.values[:, 9] # Outcome variables (9th column)

x5_train, x5_test, y5_train, y5_test = train_test_split(x, y5, test_size=0.25,\
                                       random_state=1)

# Tabacco as outcome variable and train/test split
y6 = df.values[:, 10] # Outcome variables (10th column)

x6_train, x6_test, y6_train, y6_test = train_test_split(x, y6, test_size=4,\
                                       random_state=1)

#------------------------------------------------------------------------#
# Decision tree training - Gini                                          #
#------------------------------------------------------------------------#

# Non alcoholic drinks
y1 = DecisionTreeClassifier(random_state=1, max_depth=None, min_samples_leaf=2)
y1.fit(x1_train, y1_train)
```

```
# Sweets
y2 = DecisionTreeClassifier(random_state=1, max_depth=None, min_samples_leaf=1)
y2.fit(x2_train, y2_train)

# Alcoholic drinks
y3 = DecisionTreeClassifier(random_state=1, max_depth=None, min_samples_leaf=1)
y3.fit(x3_train, y3_train)

# Lottery
y4 = DecisionTreeClassifier(random_state=1, max_depth=None, min_samples_leaf=1)
y4.fit(x4_train, y4_train)

# Salty Snacks
y5 = DecisionTreeClassifier(random_state=1, max_depth=None, min_samples_leaf=1)
y5.fit(x5_train, y5_train)

# Tabacco
y6 = DecisionTreeClassifier(random_state=1, max_depth=None, min_samples_leaf=1)
y6.fit(x6_train, y6_train)

#-------------------------------------------------------------------------#
# Decision tree plotting - Gini                                           #
#-------------------------------------------------------------------------#

# Export to .dot format with graphviz method
y1_data = export_graphviz(y1, out_file=None, filled=True, rounded=True)
y1_graph = Source(y1_data)
y2_data = export_graphviz(y2, out_file=None, filled=True, rounded=True)
y2_graph = Source(y2_data)
y3_data = export_graphviz(y3, out_file=None, filled=True, rounded=True)
y3_graph = Source(y3_data)
y4_data = export_graphviz(y4, out_file=None, filled=True, rounded=True)
y4_graph = Source(y4_data)
y5_data = export_graphviz(y5, out_file=None, filled=True, rounded=True)
y5_graph = Source(y5_data)
y6_data = export_graphviz(y6, out_file=None, filled=True, rounded=True)
y6_graph = Source(y6_data)

# Render into PDF
y1_graph.render(filename='gini_non_alcoholic_drinks')
y2_graph.render(filename='gini_sweets')
y3_graph.render(filename='gini_alcoholic_drinks')
y4_graph.render(filename='gini_lottery')
y5_graph.render(filename='gini_salty_snacks')
y6_graph.render(filename='gini_tabacco')

#-------------------------------------------------------------------------#
```

```
# Prediction                                                                  #
#-----------------------------------------------------------------------------#

# Test
y1.predict([[3, 1, 2, 1, 3]])
y2.predict([[5, 1, 1, 1, 2]])
y3.predict([[3, 2, 1, 3, 1]])
y4.predict([[1, 2, 2, 1, 1]])
y5.predict([[4, 1, 3, 3, 1]])
y6.predict([[6, 2, 2, 2, 2]])

# Store predictions of test set
y1_pred    = y1.predict(x1_test)
y2_pred    = y2.predict(x2_test)
y3_pred    = y3.predict(x3_test)
y4_pred    = y4.predict(x4_test)
y5_pred    = y5.predict(x5_test)
y6_pred    = y6.predict(x6_test)

#-----------------------------------------------------------------------------#
# Accuracy                                                                    #
#-----------------------------------------------------------------------------#

y1_accuracy = accuracy_score(y1_test, y1_pred) * 100
y2_accuracy = accuracy_score(y2_test, y2_pred) * 100
y3_accuracy = accuracy_score(y3_test, y3_pred) * 100
y4_accuracy = accuracy_score(y4_test, y4_pred) * 100
y5_accuracy = accuracy_score(y5_test, y5_pred) * 100
y6_accuracy = accuracy_score(y6_test, y6_pred) * 100

print('Non Alcoholic Drinks accuracy: ', y1_accuracy)
print('Sweets accuracy: ',              y2_accuracy)
print('Alcoholic Drinks accuracy: ',    y3_accuracy)
print('Lottery accuracy: ',             y4_accuracy)
print('Salty Snacks accuracy: ',        y5_accuracy)
print('Tabacco accuracy: ',             y6_accuracy)
```

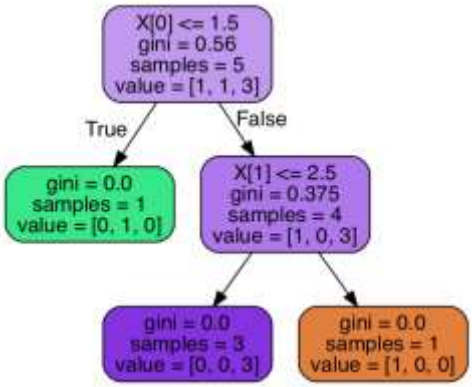
Sales data mining dataset 1 output

```
('Non Alcoholic Drinks accuracy: ', 50.0)
('Sweets accuracy: ', 50.0)
('Alcoholic Drinks accuracy: ', 0.0)
('Lottery accuracy: ', 0.0)
('Salty Snacks accuracy: ', 50.0)
('Tabacco accuracy: ', 25.0
```

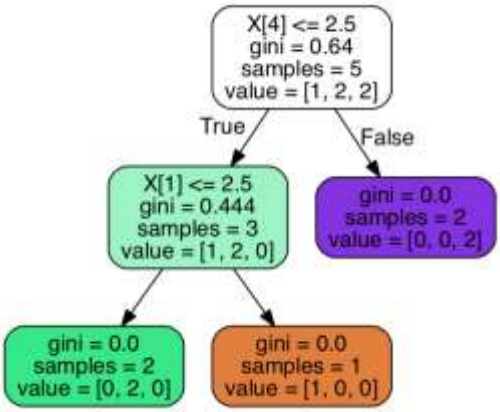
APPENDIX D – DECISION TREES

Decision trees from tables 21 & 25 dataset

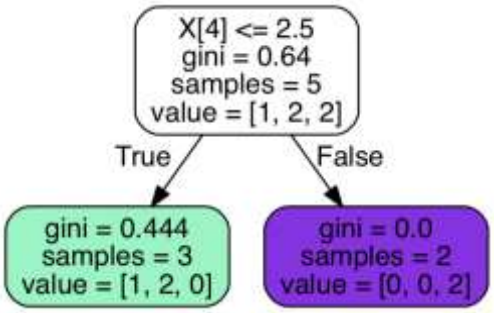
Alcoholic drinks



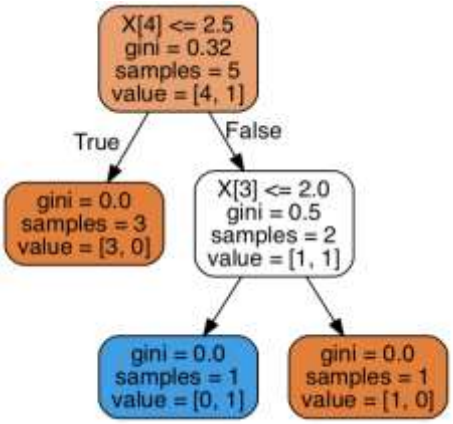
Lottery



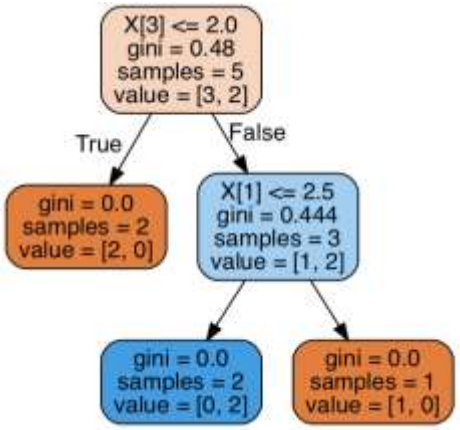
Non-alcoholic drinks



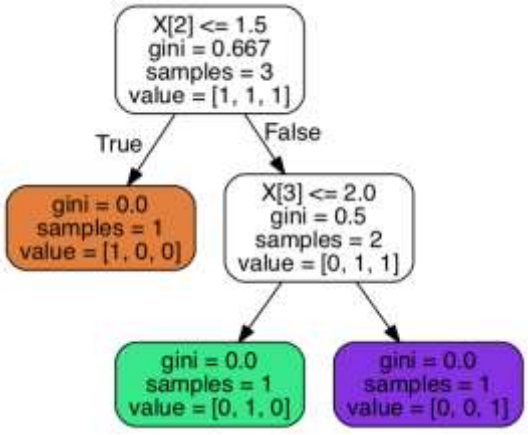
Salty Snacks



Sweets

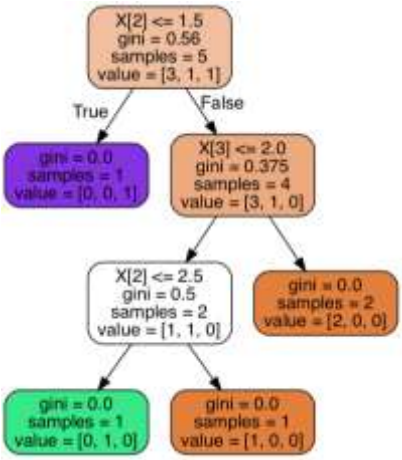


Tabaco

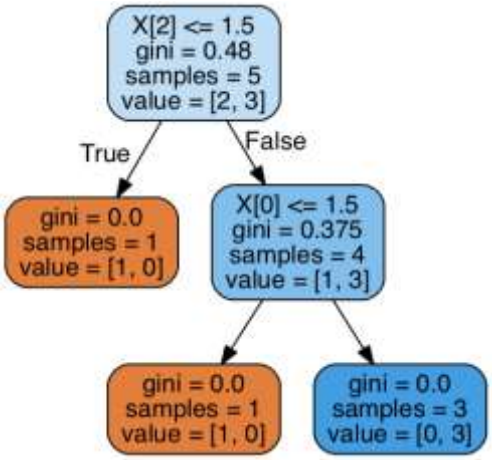


Decision trees from tables 21 & 26 dataset

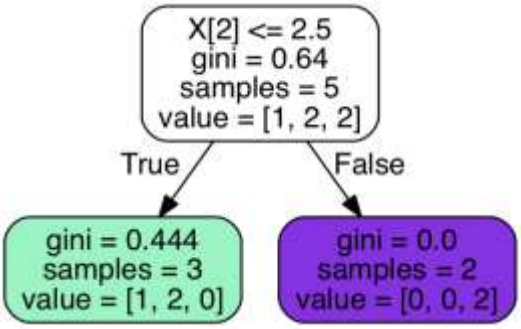
Alcoholic drinks



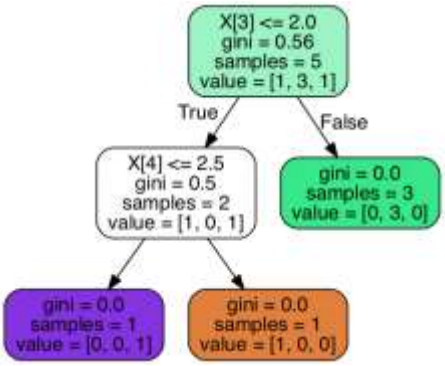
Lottery



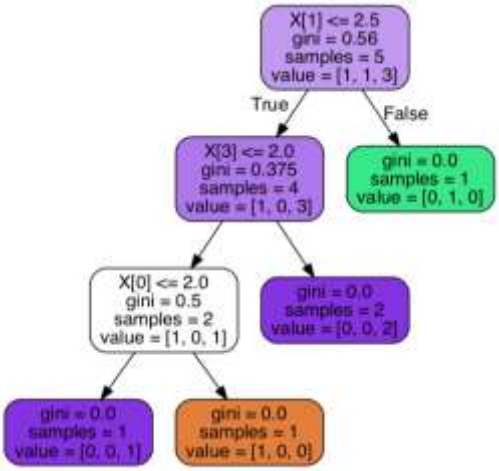
Non-alcoholic drinks



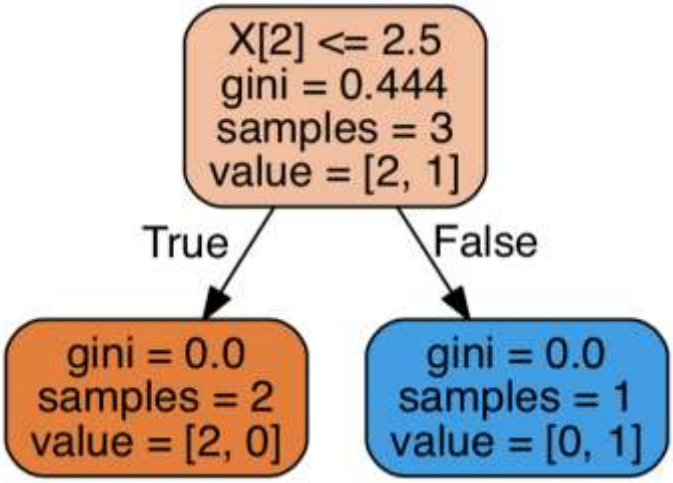
Salty Snacks



Sweets

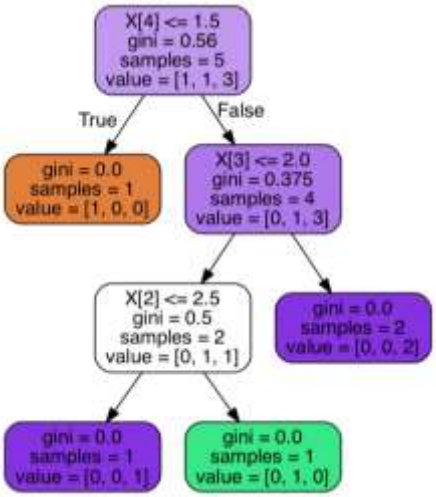


Tabaco

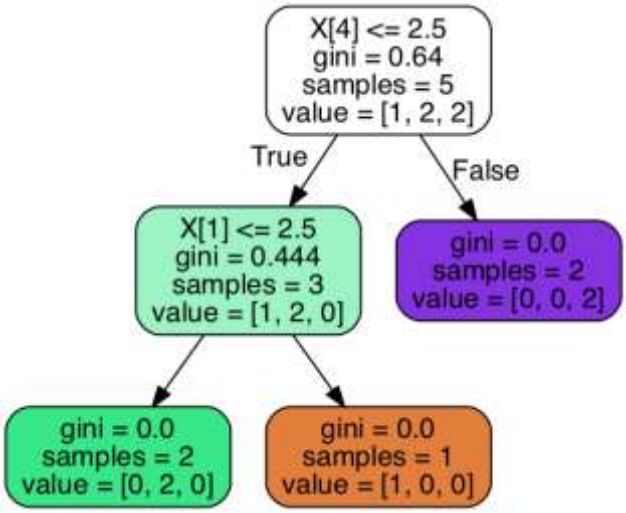


Decision trees from tables 22 & 25 dataset

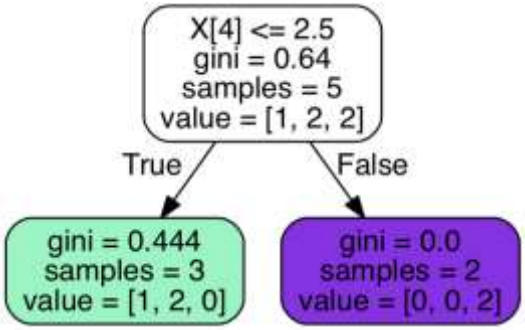
Alcoholic drinks



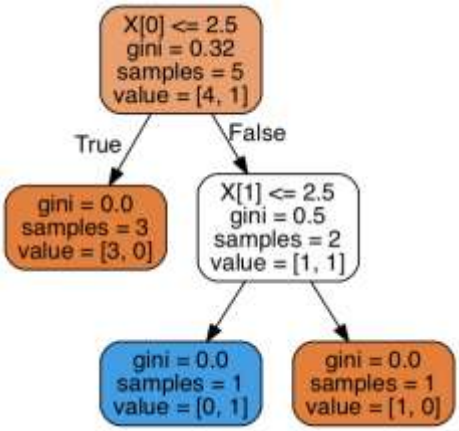
Lottery



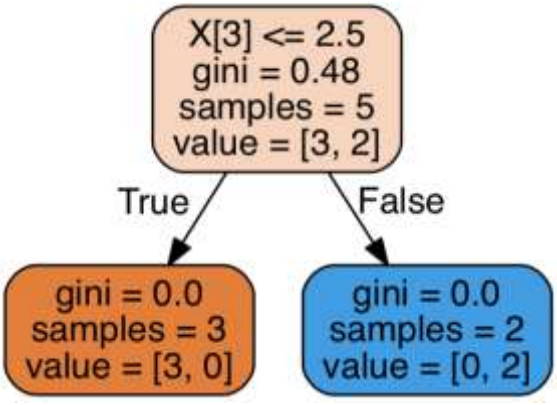
Non-alcoholic drinks



Salty Snacks



Sweets



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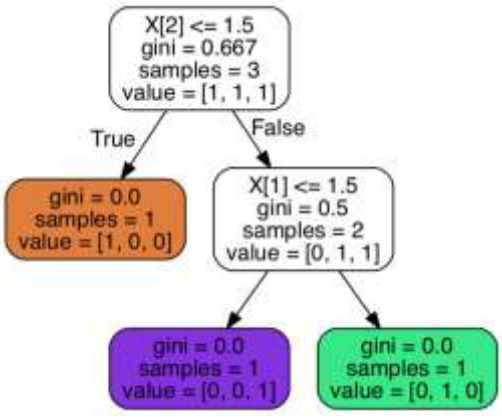
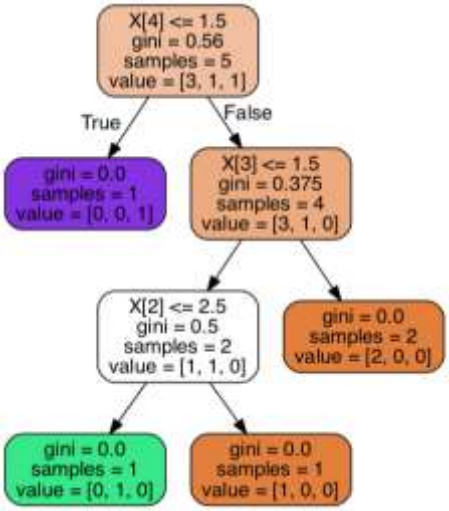
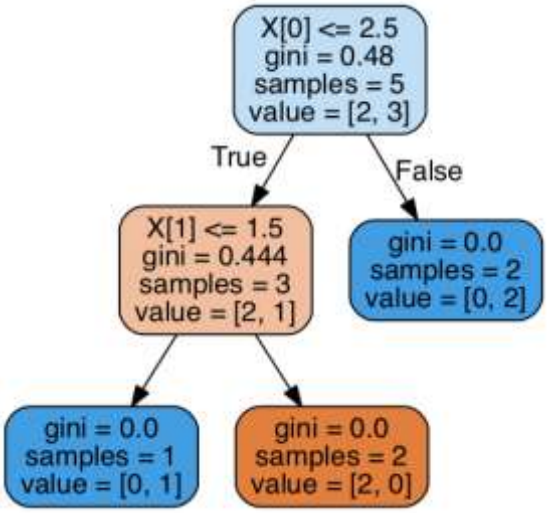


Decision trees from tables 22 & 26 dataset

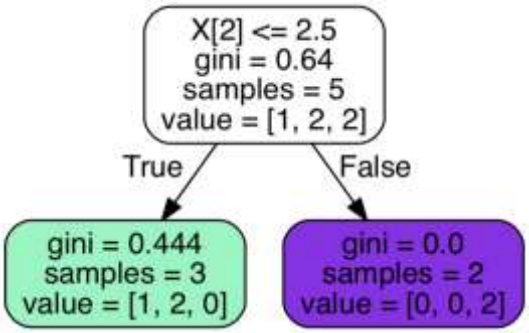
Alcoholic drinks



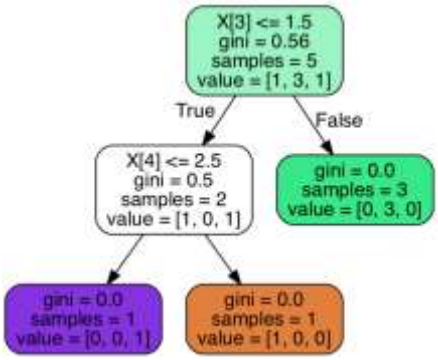
Lottery



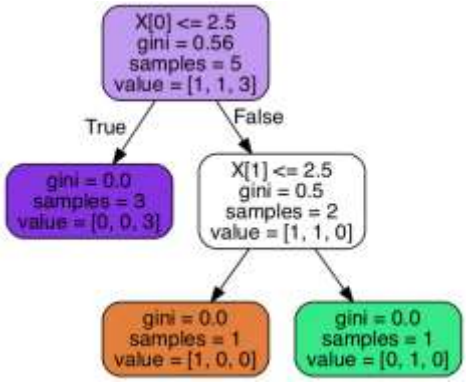
Non-alcoholic drinks



Salty Snacks



Sweets



Tabaco