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Creating Human Digital Memories with the Aid of Pervasive Mobile Devices

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Abstract

The abundance of mobile and sensing devices, within our environment, has led to a society in which any object, embedded with sensors, is capable of providing us with information. A human digital memory, created with the data from these pervasive devices, produces a more dynamic and data rich memory. Information such as how you felt, where you were and the context of the environment can be established. This paper presents the DigMem system, which utilizes distributed mobile services, linked data and machine learning to create such memories. Along with the design of the system, a prototype has also been developed, and two case studies have been undertaken, which successfully creates memories. As well as demonstrating how memories are created; a key concern in human digital memory research relates to the amount of data that is generated, and stored. In particular, searching this set of big data is a key challenge. In response to this, the paper evaluates the use of machine learning algorithms, as an alternative to SPARQL, and treats searching as a classification problem. In particular, supervised machine learning algorithms are used to find information in semantic annotations, based on probabilistic reasoning. Our approach produces good results with 100% sensitivity, 93% specificity, 93% positive predicted value, 100% negative predicted value, and an overall accuracy of 97%.

Keywords: Human Digital Memory, Lifelogging, Sensor Networks, Ubiquitous Computing, Linked Data, Supervised Machine Learning

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1. Introduction

Memories influence every aspect of our lives. It is considered to be the most basic and important operation of the brain, with very few cognitive processes (recognition, language, planning, etc.) being able to operate effectively without a contribution from it [1]. They are a significant part of our existence that can be shared anywhere and at any time. Reminiscing, over past experiences, is a substantial part of our lives. It is a practice that has been performed over thousands of years and is what makes us who we are. However, losing the ability to recollect memories is not only disadvantageous, but can prove quite detrimental, particularly to many older people [2]. Nevertheless, recent advances in technology can alleviate this problem, to a certain extent. As technology advances, computing devices have now taken a more central role in our lives. They have shifted in reliance from just being seen as "glorified calculators" [3], to devices that are capable of capturing and storing our entire lives. As such, this shift has resulted in the area of creating and managing human digital memories, being declared a grand challenge in computing research [4].

In today's society, the proliferation of "smart" mobile devices is becoming more abundant. Currently, 81.6 million mobile subscriptions are held in the UK [5]. By 2016, Cisco predicts that there will be more than 10 billion mobile Internet-connected devices, which exceeds the worlds projected population, at that time, of 7.3 billion [6]. Devices are now smarter, smaller, easier to transport and able to capture a variety of data, such as photos, location and videos. Body sensors are also becoming more widespread, as people develop an interest in monitoring their health. These devices are capable of capturing physiological data, such as sweat rates, body temperature and heart rate, whilst environmental sensors can gather temperature, humidity and atmospheric readings. As these devices become more prevalent, within our environment, a vast array of information about us and our surroundings can be captured and utilised. Storage capacities are also increasing, and a lifetime of data can be saved; resulting in an increasing amount of content being captured, stored and shared. The explosion of mobile computing and ubiquitous content sharing has enabled users to create and distribute data instantly.

As mobile devices become more widespread, and sophisticated, this has led to a generation of users who capture more content, ubiquitously, than previously seen. For example, in relation to YouTube, traffic from mobile devices tripled in 2011 and over 4 billion hours of video are watched each month, with more than 20% of global views coming from such devices [7]. This shift in ubiquitously capturing and sharing

content has led to people creating extensive digital collections and reflection of those items has become an active part of people's lives [8]. Taking the concept of capturing personal content one step further, the practise of 'lifelogging' refers to the process of automatically recording aspects of one's life in digital form [9]. As described by Dodge and Kitchin [10], "*A life-log is conceived as a form of pervasive computing consisting of a unified digital record of the totality of an individual's experiences, captured multimodally through digital sensors and stored permanently as a personal multimedia archive*". Whilst the process of recording this information is known as lifelogging, the outcome is often referred to as a human digital memory (HDM). As defined by Kelly [11], "*A HDM is typically a combination of many types of media, audio, video, images, and many texts of textual content*". These personal archives are constructed from a wide range of data sources, across various media types [12]. As technology advances and sensors become more prevalent within our environment, the range of data that we have access to is increasing. Therefore, a greater level of detail can be incorporated into the creation of a HDM. New possibilities will allow content about us, and family and friends to be clustered and linked together, based upon a multitude of factors. This will include information from mobile and physiological computing. This data provides a richer understanding about aspects of our health, level of activity and physical wellbeing. Even, providing information on how we made others feel at that time. However, whilst we have access to many data sources, capturing and collating all of this information is a challenge. The vision, and one of the challenges, of Memories for Life is to help people manage and use their digital memories across their entire lifetime [4]. This work illustrates how data, from pervasive devices, can be used to create a more vivid HDM and how this data can be captured and utilised for an extensive amount of time.

This paper explores how HDMs can be created, using pervasive devices, and is an extension of previous work [13]. In this work, the DigMem system is presented, which creates rich and interactive HDMs, utilizing devices in the user's present environment. In order to create these dynamic memories, a new method is being proposed. The approach creates an ad-hoc peer-to-peer (P2P) network and obtains data, from ubiquitous devices. Utilizing linked data, and machine learning, these various pieces of information are brought together, to form a HDM. Whilst each device generates many specific pieces of data, these individual data sets are not suitable, on their own, for representing a HDM, as the level of detail is very low. In order to overcome this, memory boxes are created by semantically linking all the related data and turning it into visual items of events. Previous work [13] focused on creating the P2P network that

is used to obtain information, from a number of device-specific services. In this paper, the idea is extended into a fully functional system that takes the gathered information and constructs it into a HDM. This is achieved using machine learning and semantic web technologies. In this sense, the system is capable of creating HDMs that take advantage of the user's current environment. This is beneficial as DigMem provides a standardized method that enables the user to create an ad-hoc P2P network and obtain information, from devices prevalent within their environment. This approach eliminates the need to purchase specialist equipment and allows a more dynamic memory to be created, as a number of different services can be brought together to produce a richer HDM. The approach also benefits from being flexible enough to collect and use HDM data over an extensive period.

In order to demonstrate the applicability of the design, a prototype has been developed. To validate the implementation, two case studies have also been undertaken. A key concern in human digital memory research relates to the amount of data that is generated, and stored. In particular, searching this set of big data is a key challenge. In response to this, the paper evaluates the use of machine learning algorithms, as an alternative to SPARQL, and treats searching as a classification problem. Based on probabilistic reasoning, supervised machine learning algorithms are evaluated to find information, in semantic annotations.

2. Related Works

Capturing memories is an activity that all of us do regularly. From taking photos and videos to inadvertently saving emails and texts, our lives can be reconstructed from our digital artefacts. Nowadays, these moments are less likely to be captured on "traditional" cameras and camcorders but increasingly on mobile devices and sensor equipment. This increasing trend of capturing content, ubiquitously, is one that will only strengthen over time, thus presenting us with new and novel ways in which data can be obtained. This shift has resulted in the effortful selective capturing of moments being replaced with digital lifelogging, which seeks to be effortless and all-encompassing, in terms of data capture [14]. Content is being captured constantly and with minimal user involvement (i.e. with the use of automatic, wearable, devices). Mobile devices and sensor equipment are now able to capture a more comprehensive record of everyday life, more or less as and when it happens [14]. These devices, offer an innovative, and less obtrusive, method for capturing content ubiquitously and are able to document our entire lives. A vast collection of information can be recorded about ourselves, at any time. Automatically recording this data,

and quantifying how a given aspect of our body changes over time, provides an insight into our underlying behaviours [9], [15]. This increasing trend is one that will only strengthen over time; presenting us with new and novel ways in which the data that can be obtained.

2.1 Wearable Lifelogging Systems

A revolutionary lifelogging tool is Microsoft's *SenseCam* [16], a small wearable device that triggers, automatically, to capture photos. It contains a digital camera and multiple sensors, including sensors to detect changes in light levels, an accelerometer to detect motion, a thermometer to detect ambient temperature, and a passive infrared sensor to detect the presence of people [17]. The *SenseCam* has been used in various studies [9], [17–24] to monitor behaviour and capture memories. For example, Lee *et al.* [17] use the technology as a memory aid to capture the user's daily routine. The images recorded are then presented in a timeline format, similar to the approach used in Microsoft's *MyLifeBits* [25] project. In contrast, the *SenseCam* has also been used within the area of travel research. One such approach is Kelly *et al.*'s [22] study that uses the device to measure its effectiveness of tracking sedentary behaviour. Their initial results indicate that the over–reporting of self–reported journeys was common. In order to track this type of behaviour the *SenseCam* was a useful tool.

The *SenseCam* is seen as the leading technology in capturing memories. However, other projects have also been undertaken for the purposes of lifelogging and monitoring behaviour. Blum *et al.*'s [26] *inSense* is one such system. It uses acceleration, audio and visual sensing equipment, to perform real–time context recognition. While Belimpasakis *et al.* [27] have implemented a "*client–server platform that enables life logging, via mobile context collection, and processes the data so that meaningful higher-level context can be derived*". Meanwhile, *MemoryLane* [8], [28], "*allows people to capture, actively organize and reflect on digital representations of mementos relating to people, places and objects*". This work centred on distributing a Sony visual IC recorder/camera, which took photos and recorded audio, to 31 participants. For 3 days, the users then captured any pictures and audio narratives about significant people, places and objects in their lives [8]. This study illustrated that HDMs are important for reflection and that people are interested in reflecting upon their digital artefacts. However, the system relies on the user actively taking pictures and recording audio data. In order to construct a truly reflective digital memory this data, along with other pieces of information, needs to be collected with as little user interaction as possible.

As well as recording audio data, researchers have also been focusing on collecting physiological information, via the use of sensing technologies. The *activPAL* system uses a single–axis accelerometer [29] that can identify sitting or lying, standing, and walking transitions. The *activPAL* accelerometer has also been used to determine habitual behaviour, whilst also determining the interplay between sedentary behaviour and periods of physical activity [30]. However, the limitation of this system is its inability to recognise slow steps, due to the small amount of amplitudes that are produced. In terms of creating memories, this system can be used to illustrate the movements of a user throughout the day. Nevertheless, the context in which those movements occurred is unknown, without the use of a visual aid.

Armbands have also been developed that house several sensors within the device so that a variety of physiological data can be collected. The *SenseWear Armband (SWA)* collects data from a bi-axial accelerometer, galvanic skin resistance (sweat rates), heat flux (heat dissipated from the body), and skin and near body temperature, to estimate energy expenditure (EE) and step count [31]. The device has been used within Dwyer *et al.*'s [31] work to determine its accuracy for estimating energy expenditure (EE) and step count during treadmill walking in cystic fibrosis (CF) patients, compared to healthy adults. In this instance, the *SWA* provided a reasonably accurate measure of step count compared to manual counting during tread mill walking and diagnosis of CF didn't affect its accuracy [31]. The *SWA* has also been used to monitor adherence in women with rheumatoid arthritis in a similar way to measuring decreases in sedentary behaviour [32]. The results from this study concluded with an 89% adherence rate and that the *SWA* is a viable method of quantifying physical activity and may be useful to monitor effectiveness of interventions to increase activity in people with rheumatoid arthritis [32]. In relation to creating memories, this system can also be used to illustrate the movements of a user throughout the day. However, like the *activPAL* system [29], the context in which those movements occurred is unknown, without the use of a visual aid.

Whilst the technologies and methods discussed are a useful starting point, within the area of lifelogging, novel solutions are needed that include much richer data capturing capabilities and require a less obtrusive and expensive, approach. Although the *SenseCam* has been hailed as a "*revolutionary pervasive device*" [2] it has its limitations. One drawback is that the data that is captured is limited, as only photos and a very small amount of sensor data are recorded. Whilst photos are a good place to start, memories are made up of so much more than that. Emotions and environmental factors also contribute to

the composition of memories. These important issues need to be factored into creating an accurate HDM. Another drawback is in relation to accessing the data. *SenseCam* images have to be manually uploaded periodically, which can be very time-consuming and mundane for the user. The device is also very expensive. Exploiting the services of devices, already present within our environment, is a far less-costly approach. These are important points to consider, and ones that will be propelling the research forward. Mobile and peer-to-peer (P2P) technologies can be seen as a way to alleviate these problems. The explosion of mobile computing and the sharing of content ubiquitously have enabled users to create and share memories instantly. Access to different data sources, such as location, movement, and physiology, has helped to create a data rich society where new and enhanced memories will form part of everyday life. P2P systems have also increased in popularity, over the years, due to their ad hoc and decentralized nature. As mobile devices become increasingly part of P2P systems, a completely new dimension for capturing, sharing and interacting with enhanced human digital memories is forming.

2.2 The Use of Mobile Devices in Creating HDMs

Memories are often impulsive events and are better suited to being captured and shared on a portable device. These devices are compact and easy to carry, making them ideal for sharing content amongst users. Olsson *et al.* [33] state that "*Mobile phones offer natural opportunities for collecting instant digital pictures and videos because of their immediate availability to users*". Mobile computing, along with P2P networking, and the notion of collecting digital life memories, has begun to generate a great deal of interest.

One such approach is *JMobiPeer*, a P2P middleware for mobile ad hoc networks (MANETs). It has been designed to work on the Java 2 Mobile Platform Micro Edition (J2ME) and is compatible with the JXTA (Juxtapose) P2P protocols [34]. The *JMobiPeer* system has obtained good results, in relation to the discovery time and bytes exchanged. However, as Wang and Motzfeldt [35] observe, it "*has only been tested on emulators on standard PCs. This is likely due to high requirements on CPU and memory from running the framework*". Therefore, real world testing on actual mobile devices would be required to determine whether the application could be executed on devices that are far less capable.

Taking an opposing view, Tsai *et al.* [36] created a *Mobile Social Software (MoSoSo)* application that runs on mobile devices. The application "*allows users to discover, communicate and share resources with each other*". It is a P2P social networking application in which users can view friends, share files, message each other and edit their own profiles. Taking a similar approach, Park and Cho [37] discuss how

a mobile social network can be constructed by obtaining the life–logs of users and how this network can be used to share information. In this work, lifelogs were collected using a Samsung smart phone and a mobile social network was built with semantic relations using a Bayesian network model [37].

Meanwhile, Palazzi *et al*. [38] created the *P2PBluetooth* platform, a "*proof–of–concept file sharing application for mobile phones that works through Bluetooth connectivity*" [38]. In particular, their work focuses on creating a P2P network using J2ME. An interesting aspect to their work is file sharing and the idea of proximity. However, this work is limited to very short distances, since Bluetooth has a limited range. Our work aims to be less restrictive, by creating connections using JXTA to support different proximity requirements. In other works, Ismail *et al.* [39] have designed a framework to identify personal memories, through photo image analysis and a reporting system. Their system uses the JXTA P2P networking architecture to create a virtual network of peers who share their serendipitous moments among themselves [40]. This work is particularly interesting as JXTA is a platform that is currently being explored for the system.

In other works, Hamm *et al.* [41] have implemented "*a system for automatic annotation of daily experience from multisensory streams on smartphones*". At regular time intervals, an Android-based smartphone collects images, audio, location and accelerometer data. Using multiple annotations tags, daily logs can be reviewed and segmented into meaningful events. After this, the *bag-of-words representation*, along with state-of-the-art classifiers, can be used to predict the tags. The model is trained, using 41 days of data, and finally used to predict the remaining one day. This process is repeated 42 times, with a different day being held out each time [41]. This work is interesting; however, a considerable time is spent on manually annotating the information. Whilst the information was eventually learnt, the time it takes to physically segment and tag the data is a major drawback of the system.

In terms of capturing data, mobile devices fit well with our natural ability to move within our environment. These tools and standards provide mechanisms for interconnecting device functionality as independent network discoverable services. However, this alone does not support the memory structures required. There is a need to build additional middleware services to achieve this. Memories are not isolated static events, but rather a continuous sequence of experiences contextually linked and created within and across different geographical areas within the environments, we occupy. This is a key requirement in our work. Once data has been captured, it needs to be effectively searched, so that information can be brought

together, to form a HDM. However, due to the phenomenal amount of material that is generated, and stored, searching this set of big data is a key challenge, within this area.

2.3 Machine Learning Algorithms For Searching HDM Data

Computer algorithms, and visualization techniques, are fundamental in supporting the analysis of datasets, commonly referred to as *Big Data* [42]. More recently, the medical domain has been using such techniques, extensively. One example of this is the Common Spatial Patterns (*CSP*) algorithm. This was proposed by Woon *et al.* and has been successfully used to study Alzheimer's [43]. In other studies, Latchoumane *et al.*, analyse electroencephalogram (*EEG*) signals, using Multi-way Array Decomposition (*MAD*). This is a supervised learning process for evaluating multidimensional and multivariate data [44].

Multi-Layer Perceptrons (*MLP*) [45] and Probabilistic Neural Networks (*PNNs*) [46] have featured widely in research to process and analyse medical datasets. *MLPs* are feed-forward networks that work with back-propagation learning rules. *PNNs* are similar to *MLPs*, in this way, and consist of three layers; an input layer, radial basis layer, and a competitive layer. This type of feed-forward network operates using the Parzen's Probabilistic Density Function (*PDF*) [47]. In terms of overall performance, *PNN* networks perform slightly better than *PML* networks [48].

The primary goal of such algorithms is to extract meaning from potentially huge amounts of data. Their association with particular data characterizes these features, such as datasets that contain data about neurodegenerative diseases. This has led to a great deal of work in feature extraction, within datasets. One example of this is the Discrete Cosine Transform (*DCT*) [49] algorithm that decreases the number of features and the computation time when processing signals. *DCT* is used to calculate the trapped zone, under the curve, in special bands [50].

Using *Decision Trees* [51], *Naïve Bayes* [52] and *Neural Networks* [46], similar algorithms have been used to predict heart disease. In Palaniappan and Awang's study [53], the results indicate that, using the lift chart for prediction and non-prediction, the *Naïve Bayes* algorithm predicted more heart disease patients than both the *Neural Network* and *Decision Tree* approaches. Using data, collected from patients suffering with Alzheimer's, Joshi *et al.*, were able to identify the various stages of Alzheimer's. This was achieved using *neural networks*, *multilayer perceptrons*, including the coactive neuro-fuzzy inference system (*CANFIS*) and *Genetic Algorithms* [54]. The results showed that *CANFIS* produced the best classification accuracy result (99.55%), as compared to C4.5 (a decision tree algorithm).

Other algorithms, such as dissimilarity based classification techniques, have proven to be very useful for analysing datasets. For example, the classification of seismic signals has been extensively explored using algorithms such as the k-nearest neighbour classifier (*k-NN*), and *Linear* and *Quadratic* normal density based classifiers [55]. Nonetheless, when there are a large number of prototypes, the results have shown that Bayesian (normal density based) classifiers outperform the *k-NN* classifier.

Within the medical domain, dealing with big datasets is common. For example, in pharmocogentics 5Tb files are often used. In terms of creating HDMs, very little work exists that brings these two areas together, and is one aspect of this work that makes it unique. As big data becomes part of everyday life, dealing with it will become a significant challenge.

This paper expands on the technologies and ideas, described above, in order to create varied and dynamic HDMs, which emerge through the analysis of features. The limitation of current systems is that they are restricted in relation to the amount of data that is captured and how searching is performed. Human memories are not made up of a finite set of criteria. There are many dimensions to a memory. Creating HDMs should take the same approach. This is a very important aspect to consider and one that is directly comparable to our current work. The services that can be accessed are not limited, and the user is not "locked-down" to only capturing a restricted set of data items. To form a better snapshot of our lives various technologies need to work together, so that we can visually recap our experiences and the feelings and changes our bodies were going through when these events were occurring. Current work aims to address these limitations by automatically gathering a variety of data, from distributed data sources. This data is then semantically linked and, using supervised machine learning algorithms, it is searched. Information is found based on probabilistic reasoning, and not by defining specific keywords or complicated queries. This information is then used to form a memory box, of a particular time. In this perspective, a memory box contains a number of items, including photos and location information, as well as physiological sensor readings. Over an extensive period, an endless stream of memories can be searched.

3. The DigMem System

As we have seen, several technologies can be used to capture a variety of data. These include, *SenseCam* for automatically capturing photos [16], the *SWA* for calculating physiological signals [31], and *activPAL* for detecting body positions [29]. These technologies are used to capture data about a user's activities and to access information about the physical characteristics of people. In addition, mobile devices

are also an important vehicle for capturing data and for disseminating information, with several applications being developed in this area. These include the *Mobile Social Software (MoSoSo)* application for resource sharing [36] and the *JMobiPeer* middleware for creating a mobile P2P platform; that's interoperable with JXTA [34]. However, whilst such systems have been successful, each platform is proprietary in nature. Nevertheless, it is appropriate to build on these advances. Using P2P networks, pervasive devices, cloud computing, semantic web technologies and machine learning, the DigMem system is presented that details how HDMs can be created, using a variety of devices and technologies. The system developed in Dobbins *et al.* [13] is extended in this paper and demonstrates how previously obtained information is transformed into memory boxes of events.

The system is composed of three components – Mobile DigMem (MoDM), the DigMem Server and DigMem web application. In order to create a memory box, the Mobile DigMem (MoDM) middleware [13] first seeks out and discovers various services that pervasive devices, within the P2P network, have to offer. For example, these can include camera services that obtain photographs, location services that relay location information or heat sensors that transmit temperature readings. The data that is obtained is semantically linked, searched, using the DigMem Server aspect of the system, and then visually depicted, as a memory box, within the DigMem web application. In this way, a variety of information can be queried and brought together, to form a snapshot of a particular time. For example, in the case of a smart home, various sensors are embedded in devices, to record a range of information. Figure 1, below, illustrates an example of such a layout.

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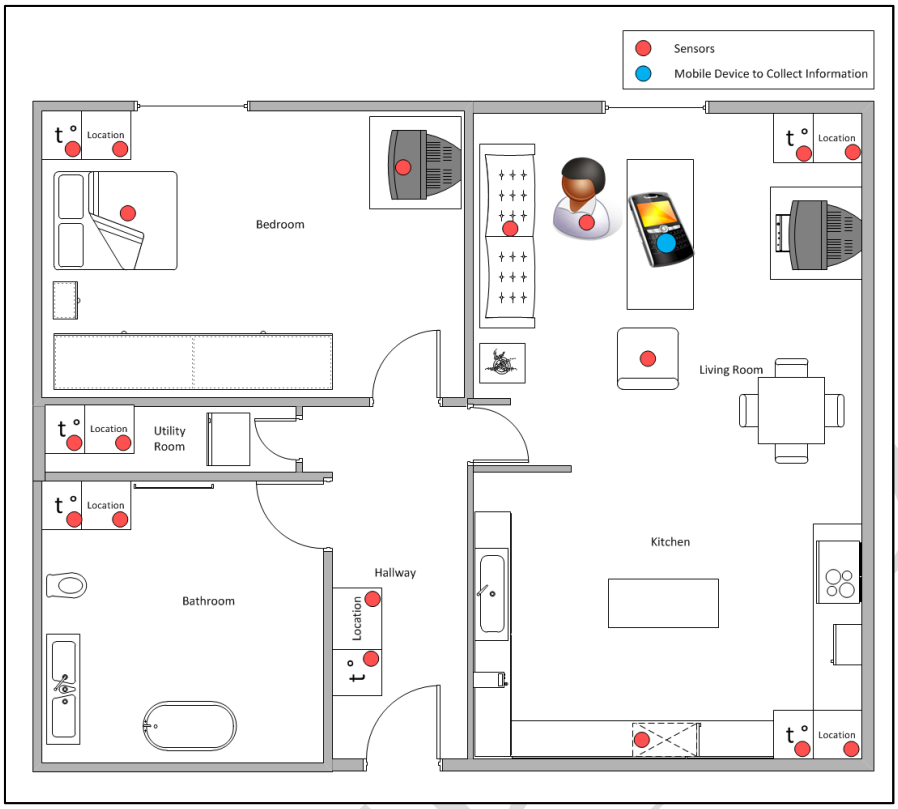

Fig. 1 Example of How DigMem Collects Information in a Smart Home Environment

In this example, sensors in the bed can monitor sleeping patterns; smart TVs can store viewing information; smart fridges can determine food consumption and sensors in sofas and chairs can determine sedentary behaviour and even measure and report on your weight. In addition, room temperature can be recorded and the indoor location, of the user, determined. As well as sensors in the environment, body sensors are also capable of recording a range of physiological data. Each of these devices would need to be DigMem compatible. When the user enters the environment, their mobile device, which is also DigMem compatible, sends out a broadcast, looking for information. An ad-hoc P2P network is then created, between the devices in the user's current environment and their mobile device. Once this has been created, another message is sent, from the mobile device, to the sensor devices, to request information. Each device then responds to this request and sends their data back to the mobile device. Once the information is received, it is automatically transferred to cloud storage. At this point, further processing can turn the information into a memory box.

When the user queries this particular time, all of these pieces of separate information are brought together to form a memory box. This memory can be used to determine a number of behaviours. For instance, body sensor, couch and TV information can be used to establish how long the user has been sitting

down watching TV. When the user leaves this environment and, for example, goes into the city centre to have coffee with friends, a different number of services will be utilized for this memory. Their mobile device can be used to capture photo and location data, whilst also seeking out devices that are prevalent within this setting, such as other cameras, their friend's devices and building information. The two memories, which have been created, are different and reflective of the user's surroundings, at that time. In this sense, we are able to create memories in a range of environments. The system is adaptive enough to seek out devices and their services and to incorporate this data into our memories, resulting in a more detailed memory of an event. By not being "tied-down" to what information can be obtained, the system is able to create individual and specific memories; a feature that has not been seen before in this area. HDMs evolve with the individual. As smart environments slowly become a reality, and with all of this data available, harnessing it into a HDM presents us with a unique opportunity.

3.1 Design Specification

Creating human digital memories, using pervasive devices, within the user's environment, has the potential to revolutionise how lifelogging is performed. Specialist equipment would no longer be needed, and a more personalized HDM can be created. Current work aims to create memory boxes that are composed of a variety of data, from distributed sources. These HDMs contain vivid structures, and varied information sources emerge, through the semantic clustering of content and other memories. By combining, and linking, information, from various devices together, a memory, composed of a "mash up" of information, is created and a greater level of detail achieved. These reasons are propelling the research forward, so that an open, extensible and fully functional solution can be achieved. The principal requirements of the DigMem system are as follows.

1. To use an open, cost-effective and extensible platform, capable of obtaining a wide range of data.
2. Develop a framework that is flexible and extensible so that any number of data sources can be used in the creation of memory boxes.
3. Build additional middleware services, to achieve the memory structures required. Thus, enabling a plug-and-play platform for memory data sources that can be exploited by any digital life memory middleware service.
4. Enable this large amount of data to be efficiently searched so that it can be concisely represented as a memory box.

5. Provide a method that is as unobtrusive as possible and that is capable of obtaining and using data over an extensive period of time.

The system requirements have been formulated to address some of the limitations of current methods and to address one of the goals of the Memories for Life Grand Challenge [4], which is to ensure that, "*Data is still accessible in 50 years time, despite inevitable changes in software, hardware and formats*". As we have seen, specialist equipment (e.g. *SenseCam*) is needed in order capture continuous information about the user. However, this approach is costly, proprietary and requires the user to upload their captured images/data each day. In addition, only photos and a small amount of sensor readings are recorded. HDMs are composed of much more information than this. The DigMem system aims to address these issues by building on the nomadic nature of people so that HDMs are reflective of the user's current environment. These memories are unique and are not "tied-down" to only featuring a limited amount of information. Nevertheless, it is still appropriate to build on these existing technologies to address these limitations.

3.2 System Architecture

As previously stated, the DigMem system is composed of three components, Mobile DigMem (MoDM), the DigMem Server and DigMem web application (see Fig. 2). A full description of the system is presented below.

In order to start collecting data, all MoDM [13] compliant devices advertise, to the P2P network, the services that they can offer to other devices. They then wait for connection requests. As the user enters the device's environment, they launch MoDM, on their mobile device. The MoDM interface then displays all the services that DigMem supports. Currently this is limited to photographic, location and physiological information. However, as the system matures more data types will be added. Upon selection of a service(s), the user's device (UD) sends out a request to all peers, within the network, in order to obtain the use of their service(s). The device(s) respond to this request, connect to the UD and send their data, via bidirectional pipes. After the user has selected the service(s) that they want, the application continues to collect data, without any more user intervention.

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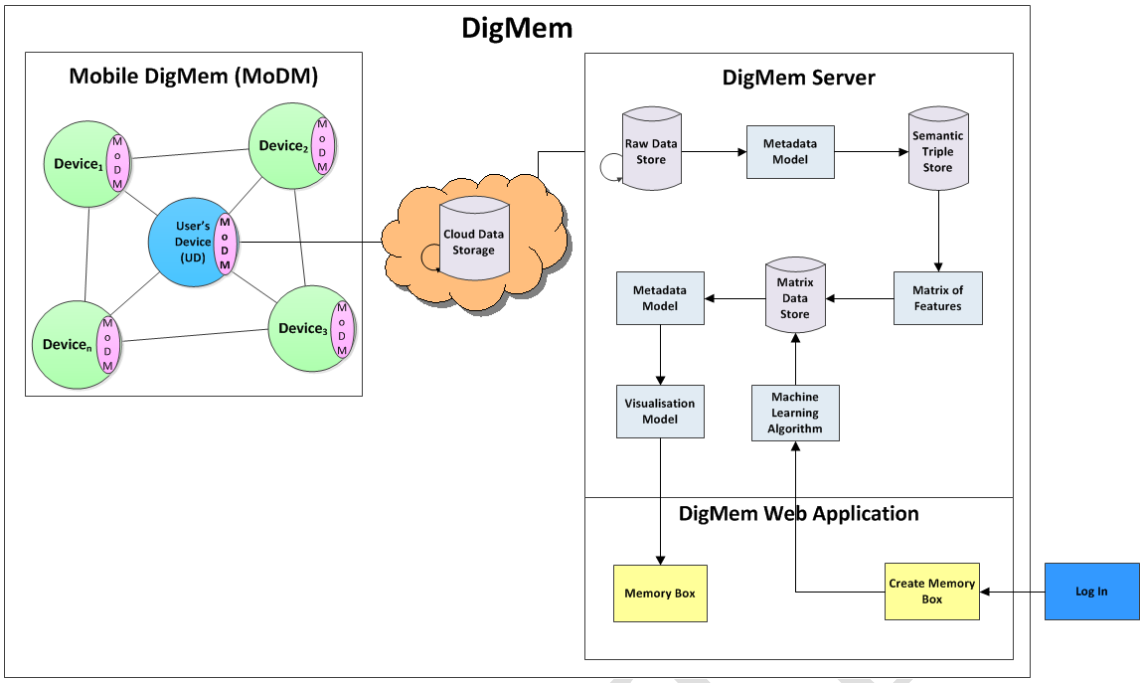

Fig. 2 DigMem System Design

On the UD, a local, cloud-connected, directory stores all information that is collected. This data is then transferred, periodically, from the cloud, to the Raw Data Store. From this point, the DigMem Server side of the system is utilised. Each user is assigned a unique ID to which their raw data is indexed with. The assignment of this ID enables each user to keep track of their data. Using the cloud bridges the gap between MoDM and the DigMem Server. The benefit of using this service is that information can be accessed anywhere and at any time. It also eliminates the need for the user to upload their data onto the system. By periodically transferring the collected data, free space is created on the mobile device. This is very important, since the storage capacities of these devices are limited. This automated approach to data collection is also far less intrusive, than previous lifelogging methods, and is unique. Once the MoDM application is started, it collects raw data from the previously mentioned services that DigMem supports, saves this in the cloud, transfers this information into the Raw Data Store and frees up space on the UD, all without user intervention.

Once raw data has been transferred to the Raw Data Store, extraction and transformation of the raw information, into a metadata model, occurs. These metadata models enable the raw information to be structured into a formal representation of the data. These models are then saved, in the Sematic Triple Store. Periodically, these models are converted, using the *Matrix of Features (MoF)* algorithm [56]. The development of this algorithm converts the metadata tuples into a matrix representation. Memory boxes

themselves are temporal and transitory. This matrix contains every data item that has been collected. When new information is obtained, this data follows the same path and is transformed from its raw form into the metadata model then, using the *MoF* algorithm, is added to the matrix. This matrix is stored within the Matrix Data Store. As time passes this element grows with the user. When memory boxes are created, this HDM space is the element this is searched.

When the user wants to retrieve a memory, they first log into the DigMem web application. After logging in, the searching of these documents is treated as a classification problem, based on features, for example, time, locations or heartbeat, which are defined in the vector object. The retrieval of information occurs by using a supervised machine learning algorithm to explore the dataset. This process is beneficial as explicit queries do not have to be defined, as is the approach for other searching methods (e.g. SPARQL [57]). A wider range of information can be included in the memory; the user is not limited to specifically setting out what information they require. A much richer and more-detailed memory is created, than previously seen.

Once the data has been retrieved, it is converted back into the metadata model. The reason behind converting the data back into this model is for flexibility. This model enables the manipulation, and transformation, of the data, into any other format, for further analysis. The metadata model is then transformed into a visualisation model. This model enables the data to be transferred from the DigMem Server to the DigMem web application, and displayed within the web browser. The model is then loaded into the DigMem web application, and a memory box is created and displays all of the information, as graphical items. This is opposed to just listing the raw information, for example; location coordinates, file locations of photos or physiological readings, which do not hold as much meaning, perhaps as photographs or a map would. Figure 3, below, illustrates an overview of the process of capturing data and creating a memory box, and is based on the system design from Figure 2.

Dobbins, C., Merabti, M., Fergus, P., & Llewellyn-Jones, D. (2014). Creating Human Digital Memories with the Aid of Pervasive Mobile Devices. Pervasive and Mobile Computing, 12, 160–178. doi:10.1016/j.pmcj.2013.10.009

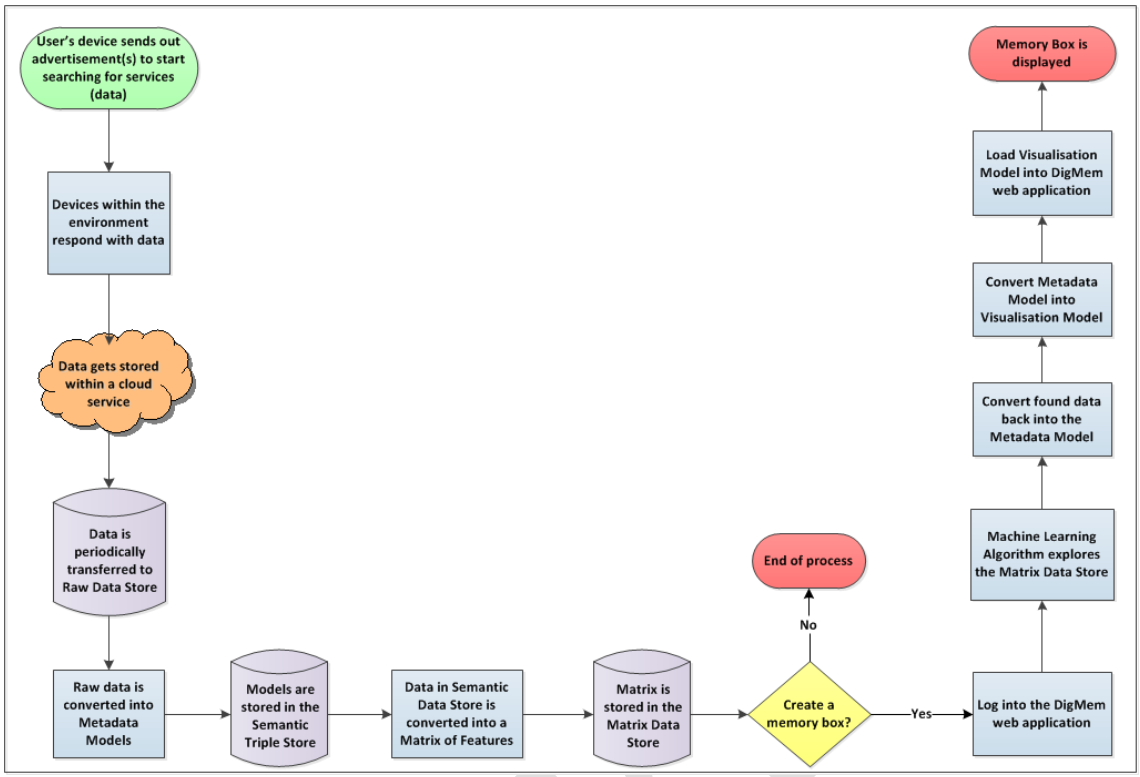

Fig. 3 Overview of Creating a Memory Box.

Using this configuration, more dynamic and detailed human digital memories can be created. The use of pervasive devices, linked data and machine learning are central to the system, and are what make it unique. By incorporating data from outside sources, as well as from body sensors, a better understanding of ourselves can be retrieved and reasoned over. DigMem is flexible enough to grow with the user and allows an entire lifetime to be digitally captured.

4. Implementation

So far, the ways in which memory data can be captured and how this information can be searched and connected, have been discussed. Additionally, the design of the DigMem system has been presented. Currently, systems, such as *SenseCam* and the *SWA*, have been used to capture an explicit set of results. *SenseCam* captures photos and limited sensor data, whilst the *SWA* captures physiological data, such as sweat rates and energy expenditure. Whilst these systems are useful, within their specific areas, they are not a practical solution in creating human digital memories, over a lifetime. Buying expensive, specialist, equipment and using such closed systems are not a viable option. A new system is required, which can be deployed on everyday devices, and can be adapted to the surrounding environment. In the next section, the

DigMem implementation is presented, which moves towards the goal of creating rich human digital memories, using pervasive devices, linked data and machine learning.

4.1 Technical Description

The prototype that has been developed, in this work, is used to demonstrate the DigMem Server and Web Application aspect of the system, to create a new memory box. For further information on the Mobile DigMem (MoDM) middleware platform, please refer to [13].

The prototype uses a Samsung Galaxy Tablet to collect a variety of data. For the purpose of this demonstration, the development of two android services collects photos, every 30 seconds, and GPS data, when a new location has been sensed. NeXus-10 body sensors [58] are also used to collect physiological information. In order to gather this data, a C-sharp application was developed. This application connects a laptop to the body sensors, via Bluetooth, and collects Electrocardiography (ECG) data. It should be noted that these services have been used purely as a demonstration tool to illustrate how memory boxes are created. As stated previously, as the system matures many more data types will be added. However, these specific services were chosen because, when combined, they are capable of illustrating the user's movements, interactions and biological changes.

Once the data has been collected it is stored locally, on the user's mobile devices, in the users Dropbox Cloud [59] folder. When the devices are connected to Wi-Fi, the data is automatically synced with their cloud directory. This information is available on any other device that the user is registered, via Dropbox, to receive data on. The development of a number of python scripts then enables the information to be transferred from the Dropbox directory to a MySQL database (Raw Data Store). This data store is located on a secure server. Dropbox has a limited amount of storage space. Therefore, by moving the data space is automatically created, for incoming information. This is a very simple and effective way of using Cloud Computing technology to send data, via the Internet, to different locations [60].

Once the data has been transferred, into the Raw Data Store, the DigMem Server aspect of the system is used. This part of the system is able to transform these fragmented pieces of collected information into a memory box. In order to do this, another application service was developed that extracts the information, from the Raw Data Store, and transforms it into Resource Description Framework (RDF) models (metadata model). This RDF information is saved in the Semantic Data Store. Then, using the *Matrix of Features (MoF)* [56] algorithm, the RDF data is transformed into a universal matrix of features. This algorithm is

able to transform any number of RDF files into its own vector of features, which describes that file. Once the RDF files have been processed, they are all merged into a single file. This file is used to form a single dataset. This dataset is then saved, in the Matrix Data Store.

The matrix representations, of all the digital memories, are combined to create a single search space. The searching of HDMs is treated as a classification problem. Following an analysis of the literature, simple, yet powerful algorithms, which give good results, have been selected. The classifiers considered in this study include the linear discriminant classifier (*LDC*), quadratic discriminant classifier (*QDC*), uncorrelated normal density based classifier (*UDC*), polynomial classifier (*POLYC*), logistic classifier (*LOGLC*), k-nearest neighbour, (*k-NNC*), decision tree (*TREEC*), parzen classifier (*PARZENC*), support vector classifier (*SVC*) and Naive Bayes classifier (*NAIVEBC*) [61]. The linear, quadratic and uncorrelated normal density-based classifiers are all density-based classifiers. The *LDC* is particularly useful when two classes are not normally distributed, and where monotonic transformations, of posterior probabilities, helps to generate discriminant functions. The *QDC* assumes that the classes are normally distributed with class specific covariance matrices, thus allowing a set of optimal discriminant functions to be obtained. The *UDC* works in a similar way to the *QDC* classifier but computation of a quadratic classifier between the classes by assume normal densities with uncorrelated features. The *QDC* takes decisions by assuming different normal distribution of data that leads to quadratic decision boundaries. The *NAIVEBC* classifier greatly simplifies learning by assuming that features are independent given class [62].

The polynomial and logistic classifiers are linear-based classifiers, which predict class labels based on weighted, linear combination of features or the variables of the objects. The *LOGLC* computes the classification of a dataset by maximizing the likelihood criterion, using the logistic (sigmoid) function. The *POLYC* adds polynomial features to the datasets in order to run the untrained classifier. It is possible to construct second order terms, using this classifier. The parzen, decision tree, support vector, and k-nearest neighbour classifiers are nonlinear classifiers. Nonlinear classifiers compute the optimum smoothing parameter between classes in the datasets. Using smoothing parameters without any learning process, produces discrimination. Smoothing parameters may be a scalar, a vector or a matrix with objects and their features. The *TREEC* classifier uses binary splitting and classes are decided upon the basis of a sequence of decision rules. Quadratic programming optimises the *SVC*, and non-linearity is determined by the kernel. If an *SVM* model, uses the sigmoid kernel then it behaves more or less like a two-layer, perceptron neural

network. There are four basic kernels, linear, polynomial, radial basis function and sigmoid. In this type of classification, functions map training sets into a higher dimensional space in this type of classifier. It finds a linear separating hyperplane, with the maximum margin in the higher dimensional space. The *KNNC* and *PARZENC* are similar in the sense that their build-up classifiers still use the training dataset and their parameters, while *KNNC* classifies the object in a feature space with the nearest training parameters.

The PRTools pattern recognition toolbox has then been used to implement the classification algorithms. Each classifier is evaluated to determine its overall performance, and accuracy, in finding information in HDM datasets. *Sensitivity*, (true positives), *specificity* (true negatives), *positive predicted values* and *negative predicted values* are used as the performance evaluation techniques. A Receiver Operator Curve (*ROC*) is then used to summarise the classifier's performances. This standard technique is based on trade-offs between true positive and true negative error rates [63].

Once the related information has been found, the data is converted back into RDF. As stated previously, converting the data into RDF enables greater flexibility in the ways it can be processed. In order to display the collected information, the data is transformed, again, into the JavaScript Object Notation (JSON) format (visualisation model). Once the information is in this format, a web interface was constructed. This interface displays the memory boxes. Using the newly created JSON file, the information is exhibited, as a memory box. In order to demonstrate the system, the query "What was I doing on 17th July 2012 at 8:35pm?" has been executed. Based on the results from the classification algorithm, the memory box, from that time, has been constructed and is displayed in Figure 4. Each input (Location, Photos and Heartbeat), and examples of potential other input devices that can provide information, are displayed in the memory box (see Fig. 4a)). It should be noted that these inputs are just examples of the type of information that can be gathered. When an input is clicked a separate window opens, and a more in-depth illustration of the data is seen. Figure 4 b) illustrates the photos that were collected on 17th July 2012 at 8:35pm. Figure 4 c), illustrates the user's location, at that time, whilst Figure 4 d) illustrates the ECG data that was obtained. It should also be noted that the graph in Figure 4 d) is not intended to be a representation of an ECG signal, but rather it is illustrating an average reading every 30 seconds.

As it can be seen, the results from the various input devices are now visually displayed. The memory box illustrates that on the 17th July 2012 at 8:35pm the user was walking around Liverpool. The results also

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indicate that they may have slowed down or taken a break, as their heart rate had dropped slightly during their walk.

Fig. 4 DigMem Memory Box (a), DigMem Photo Data (b), DigMem GPS Data (c) and DigMem ECG Data (d)

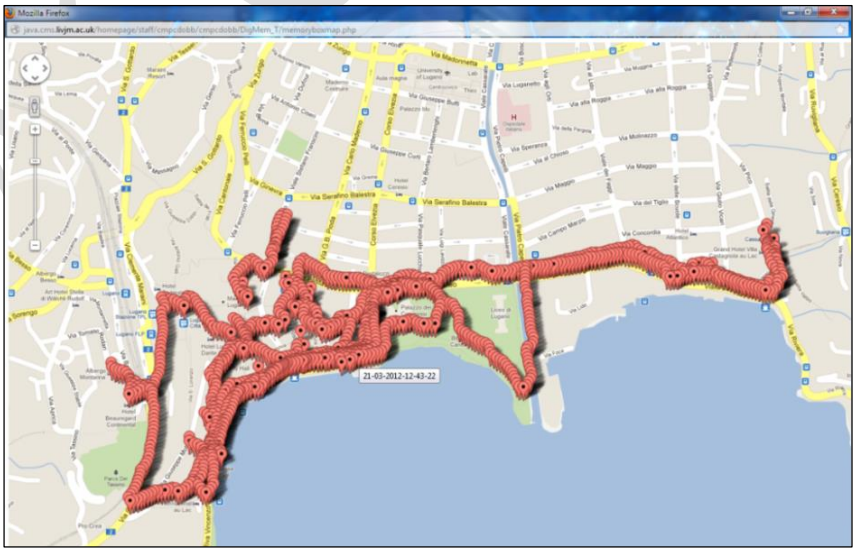
Compared to other systems, this method offers a much broader range of information that can be retrieved. Other systems, such as Microsoft's *MyLifeBits* [25], are considered to be one-dimensional. Searching is done based on keywords. The DigMem system enables users to explore their data without defining specific keywords or needing a pre-existing knowledge of the data, to create queries (SPARQL).

By clustering the data by a timestamp all of the related information can be extracted from the dataset. The user doesn't have to know what they are looking for, just the date of an event. Various pieces of information can be brought together so that a greater level of detail can be achieved. The system also does not rely on particular pieces of hardware to create a memory. Any pervasive device that can provide information, and running the MoDM middleware, can contribute to the memory. This plug-and-play platform enables the system to maintain flexibility and allows memories to be created across many different environments.

4.2 Case Studies

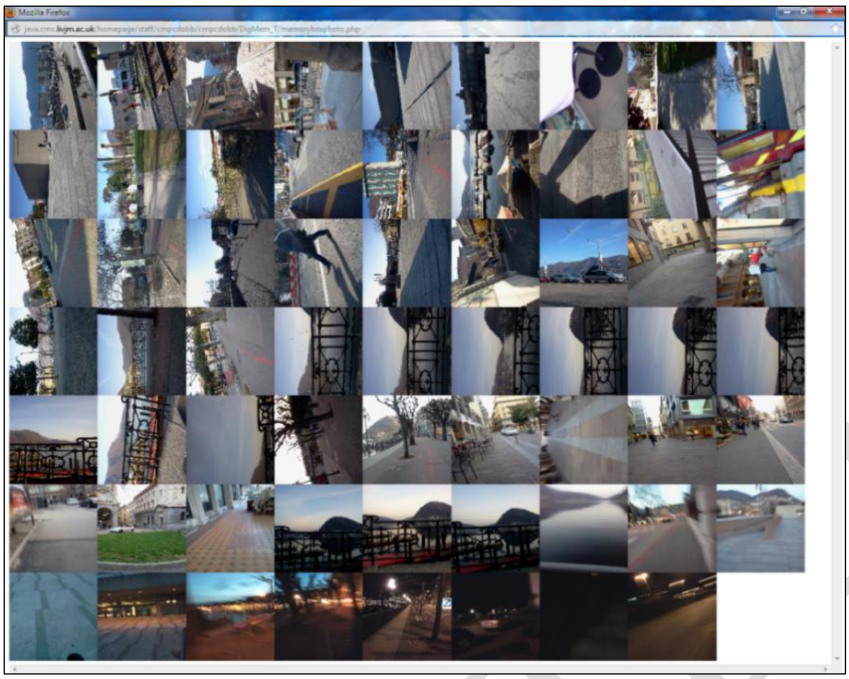
In order to demonstrate the system, two short case studies have been undertaken that have used the DigMem system to record the movements of a user and build a memory of a particular time. The first study lasted for five days and involved the user carrying around the tablet device. During this time, whenever the user was outside, photo and GPS services were deployed to collect data. The reason behind only documenting these journeys was due to the limitations of GPS. Location data was recorded whenever a new position was sensed, and photos were collected every 5 minutes. During the deployment phase, 181 photos and 4,221 pieces of GPS data were collected.

In order to create a memory box, of a particular time, during that week, the query, "What was I doing on 21st March 2012?" has been successfully executed (see Fig. 5). The location data from that time is displayed in Figure 5 a), whilst Figure 5 b) displays the photos that were collected. The results from the query indicate that the user was by lake Lugano, Switzerland, walking around.



(a)

Dobbins, C., Merabti, M., Fergus, P., & Llewellyn-Jones, D. (2014). Creating Human Digital Memories with the Aid of Pervasive Mobile Devices. Pervasive and Mobile Computing, 12, 160–178. doi:10.1016/j.pmcj.2013.10.009



(b)

Fig. 5 DigMem Memory Box Data from 21st March 2012 – GPS (a) and Photo Data (b)

The second use of the system involved the user carrying around the Samsung Galaxy tablet, whilst the ECG (NeXus) body sensors were attached to their body. Photos were collected every 30 seconds and GPS coordinates were saved every time a new location was received.

During the deployment phase of this study, the body sensors collected an extraordinary amount of information. Within 5 minutes, 613,301 pieces of ECG data (approximately 2044 samples per second) were gathered. In order to process this information the ECG data had to be normalised, and an average value for each minute was calculated. These values were then transformed into RDF and used to plot the users ECG information, within the memory box. Again, the plotted graph is not intended to be a representation of an ECG signal, but rather an illustration of the normalised values.

The query, "Where was I, what was I doing and how did I feel on 6th August 2012, between 11:30am and 12:00pm?" was then successfully executed (see Fig. 6). The location data, from that time, is presented in Figure 6 a), whilst Figure 6 b) displays the photos that were collected from that time. Figure 6 c) also illustrates the ECG data that was obtained. By searching the RDF data, of a variety of pervasive devices, and linking these various pieces of information together, it has been established that the user was walking around Liverpool John Moores University. The photos give a visual illustration of their journey, whilst the plotted GPS coordinates give an indication of their location. The ECG data also illustrates that the user was

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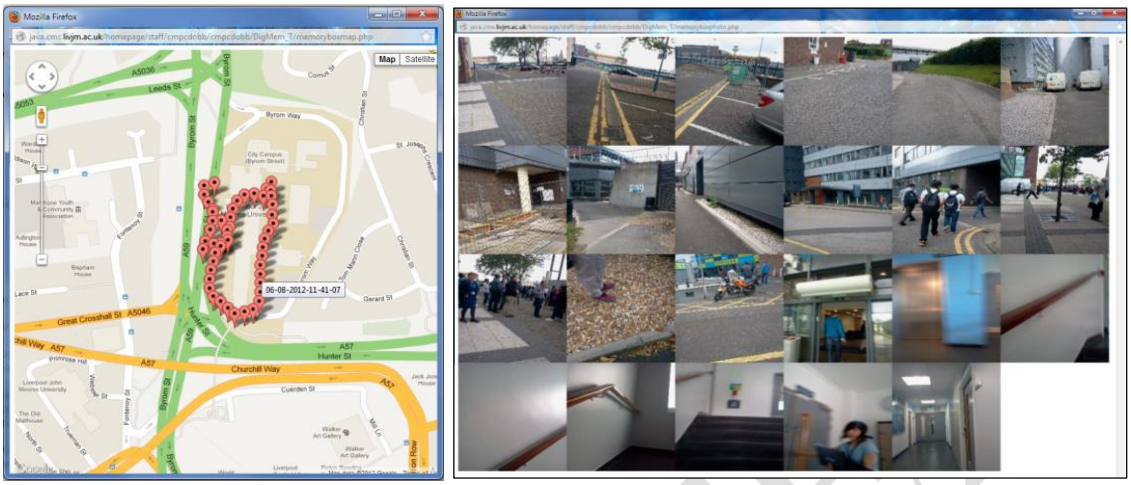
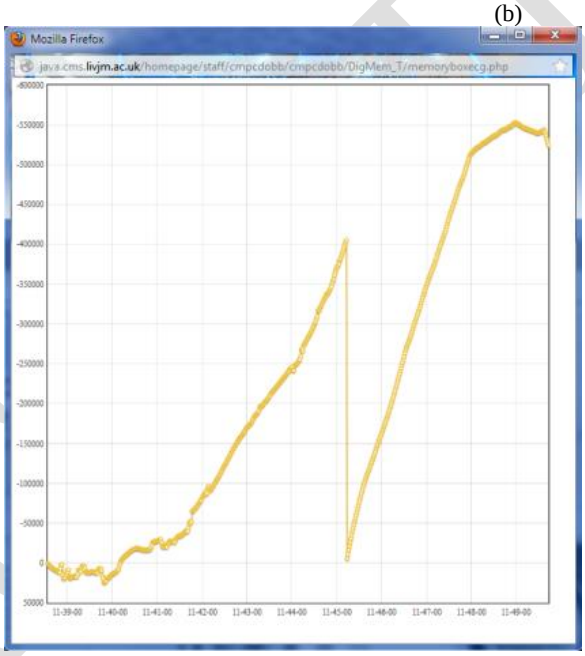
walking around (as their heart rate was not particularly high) before it suddenly increased, at the end of the journey. From the photographs, we know that this was due to them climbing the stairs.



(a) (b)



(c)

Fig. 6 DigMem Memory Box Data from 6th August 2012 – GPS (a), (b) Photo Data and (c) ECG

As it can be seen, the results, from these studies, are encouraging and do validate the design, and idea, that human digital memories can be created using every day, pervasive, devices and linked data. Memories created in this way offer a new insight into the composition of a memory and how data can be reasoned over. The use of linked data enables any item, embedded with a sensor, to be capable of being included in the memory. Memories can be created from data that has been accumulated over a lifetime and as our human memories develop and grow so will their digital counterpart. Interaction with our memories

is also fundamental and is what makes the work unique. By enabling users to be able to "go into" their memories and to see various information, such as temperature, location and emotions, could lead to the augmentation of group memories and has the advantage of benefiting numerous aspects of people's lives. Although the system has only been used to track journeys, this is just one aspect of how it can be used. Whether it enhances social groups and interactions, aids in the health and recovery of memory–related illness or used to reduce sedentary behaviour, the possibilities are endless.

5. Evaluation

This section presents the results for searching human digital memories using, the previously discussed, supervised machine-learning algorithms. The HDM dataset (containing *time*, *gps*, *ecg* and *photograph locations*) is considered, using a 50% *holdout* technique and *k-fold* cross-validation. The primary focus is to find an alternative way of searching big data (the continuous collection of data we accumulate throughout our life), based on probability. Rather than using very specific query languages, like SPARQL, we treat the searching of human digital memory data as a classification problem. In this way, we describe the features of a memory and use probabilistic reasoning to filter data (memory boxes) that contain similar features to those described.

5.1 Searching Human Digital Memory Data

The HDM memory blocks consist of the features *time*, *gps*, *ecg* and *photograph location*. These features have been chosen because, when combined, they provide enough information to illustrate the user's movements, interactions and heartbeat. Using the previously described classifiers, their performances have been evaluated, against the memory blocks, to determine the *sensitivity*, *specificity*, and *positive* and *negative predicted values* they produce, when separating different memory blocks. The 57 record HDM dataset is split using a *holdout cross-validation* method (50% for training and 50% for testing). In order to estimate the *sensitivities*, *specificities*, *positive* and *negative predicted values* and *error rate* the classifiers are repeated 30 times. This number is considered, by statisticians, to be an adequate number of iterations to obtain an average [64]. This method provides a *mean error rate* and *standard deviation*, for each of the classifiers used. It also ensures that randomly generated records, while maintaining the same proportion of records in the training and test sets, provides a combined mean error, using different record configurations. In other words, it allows for generalised classification, rather than specific instances.

5.1.1 Classifier Performance

To evaluate the performance, of each classifier, the *classperf* function is used. Table 1, below, illustrates the averages obtained for the *sensitivity*, *specificity*, and the *positive* and *negative predicted values*.

	Sensitivity	**Specificity**	**Positive Predicted Value**	**Negative Predicted Value**
Classifier	*HDM*	*HDM*	*HDM*	*HDM*
LDC	0.9230	0.8571	0.8571	0.9230
QDC	0.6923	0.9287	0.9000	0.7647
UDC	1.0000	0.9285	0.9285	1.0000
POLYC	0.9230	0.8571	0.8571	0.9230
LOGLC	0.6923	0.9285	0.9000	0.7647
KNNC	1.0000	0.0000	0.4814	NaN
TREEC	0.9230	1.0000	1.0000	0.9333
PARZENC	0.7690	1.0000	1.0000	0.5384
SVC	1.0000	0.8571	0.8666	1.0000
NAIVEBC	0.8461	0.7857	0.7857	0.8461

Table 1: Classifier Performance

In order to determine the accuracy of the classifiers, the *k-fold* cross-validation technique has also been used. This was performed using the *crossval* function, in PRTools, to determine whether the results, obtained from the 50% *holdout* method, could be improved. The results, using the *crossval* function with 1 and 6 repetitions, obtained better results, as shown in Table 2.

	50% Holdout: 30 Repetitions		**Cross Val, 5 Folds, 1 Repetitions**	**Cross Val, 5 Folds, 6 Repetitions**	
Classifiers	*Mean Err*	*SD*	*Mean Err*	*Mean Err*	*SD*
LDC	0.1950	0.0062	0.1824	0.1634	0.0288
QDC	0.0914	0.0430	0.0679	0.0693	0.0247
UDC	0.0568	0.0281	0.0380	0.0445	0.0257
POLYC	0.1950	0.0000	0.1824	0.1634	0.0288
LOGLC	0.0864	0.0041	0.0333	0.0701	0.0292
KNNC	0.5179	0.0468	0.4440	0.4639	0.0362
TREEC	0.0284	0.0541	0.0161	0.0206	0.0080
PARZENC	0.4795	0.0000	0.4887	0.4962	0.0419

SVC	0.0716	0.0000	0.0161	0.0473	0.0323
NAIVEBC	0.2568	0.0345	0.1818	0.2029	0.0475

Table 2: Classifier Performance

Overall, the results show that several of the classifiers performed particularly well. In particular, the *UDC* and *TREEC* classifiers performed remarkably well. The *UDC* classifier provided the best results with 100% *sensitivity*, 93% for *specificity*, 93% for *positive predictive value*, and 100% for *negative predictive value* and an overall accuracy of 97%. The *TREEC* classifier provided 92% for *sensitivity*, 100% for *specificity*, 100% for *positive predicted value*, and 93% for *negative predicted value* and an overall accuracy of 96%, were achieved. Several other classifiers also produced good results. The *SVC* classifier had an overall accuracy of 93%, while the *LDC* classifier had an overall accuracy of 89%.

5.1.2 Model Selection

Figure 7, below, shows the *ROC* curve and the cut-off values for the false negative and false positive rates, for each of the classifiers used. Utilizing the HDM dataset, Figure 7 illustrates that several of the classifiers used performed very well. This dataset contained 57 records and two classes (1 for one memory box and 2 for a second memory box).

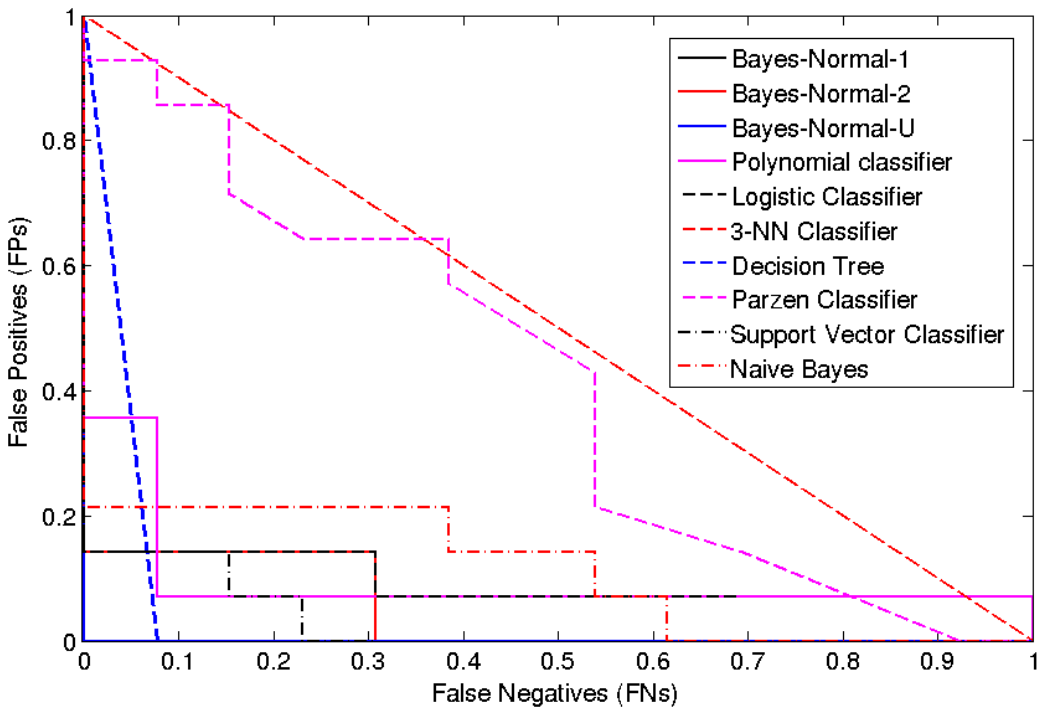


Fig. 7 Receiver Operator Curve for the HDM dataset

As it can be seen from the *ROC* curve, the results are very good for several of the classifiers, such as the *UDC*. However, for others, such as the *KNNC*, the results are poor. The results indicate that the use of machine learning techniques is encouraging. Memory-related data is composed of such a vast array of items. Simply searching this data with specific queries, or keyword searches, does not produce the level of detail that is required. As demonstrated, machine learning algorithms are able to treat the challenge of searching this data as a classification problem and to retrieve information based on features.

6. Discussion

This paper successfully demonstrates the implemented DigMem system and builds on previous work in [13]. It provides a flexible solution that embraces the use of pervasive mobile devices, cloud computing, P2P networking, linked data and machine learning. The system provides a method of creating HDMs in any environment, using any DigMem compliant devices. This has many advantages over other systems. Systems, such as [9], [17–19], use Microsoft's *SenseCam* to create memory browsers or within lifelogging research, whilst [29–32] use the *activPAL* and *SWA* devices to monitor behaviour. The disadvantage of these systems is that specialist, and expensive equipment are often needed and the data is quite limited. However, the DigMem system overcomes these shortcomings by using any DigMem compliant device, for data collection. The system is not limited to collecting photos; any number of services can be included in a memory. Table 3 provides a comparison between the state-of-the-art lifelogging devices and DigMem.

	Data Collected	Automatic Upload of Data	Searching	Expensive	Extendable	Adaptive	Storage	Open Source Platform
DigMem	Unlimited from ad-hoc services*	Yes	Probabilistic	No	Yes	Yes	Cloud (unlimited)	Yes
SenseCam	Photos	No	Keyword	Yes	No	No	8GB Flash Memory - 20,000 images (8 days of data approx.)	No
SenseWear Armband (SWA)	Motion, Step Count, Sweat Rates, Skin Temperature, Body Heat	No	Time-Based	Yes	No	No	28 days worth of data (data rate is 32 times/second)	No
ActivPAL	Activity Data (Sitting, Standing, Walking), Step Count, Transitions, Energy Expenditure	No	Time-Based	Yes	No	No	4MB	No

*Any device that supports DigMem can be used for data collection, thus not limiting the data that is collected

Table 3: Comparison of DigMem against the state-of-the-art lifelogging devices

As it can be seen, DigMem offers a number of advantages over current systems. The data collected is not limited, it is automatically uploaded to the cloud and searching is probabilistic, based on the

description of features. Memory boxes, resembling those features, are extracted with a probabilistic confidence value that the search features, and the features in the memory block, are similar. It is also able to run on any Android (open source) device, thus expensive equipment is not needed. Its plug-and-play middleware is also extendable and when services aren't available, replacement devices are found. The use of cloud storage also provides an unlimited amount of space, depending on which service is used. Memories are created in an unobtrusive manner and are formed from environment specific devices, instead of being device specific (e.g. only using a *SenseCam* to collect photos), which is a novel aspect of the work. Data, collected over a lifetime, is semantically linked and any instance of our lives can be re-constructed. This has profound implications in the use of such a system and, currently, it is being used to investigate its effectiveness in monitoring and measuring sedentary behaviour [65].

In terms of capturing data, there are several notable features that make this system a viable alternative. Most notably, the data-gathering platform, on the tablet device, as well as the previously implemented MoDM middleware [13], are built using the open-source Android operating system. This allows the hardware features of devices to be freely accessed, whilst the data is not encoded in a proprietary format. Regarding the physiological platform, this has been developed in C-sharp and enables a connection, to the NeXus-10 body sensors, to be established, via Bluetooth. As well as providing this connection, the programme collects various physiological signals and stores the data as a time-stamped .csv file. This is beneficial as the data, again, is not encoded in a proprietary format. Data from both platforms are freely accessible. This is very important as the information can be manipulated at a later time.

In terms of the architecture of MoDM, P2P was chosen, in contrast to a client-server model, for a variety of reasons. Most notably because it is a scalable solution, as more peers join the network, its capability increases and strengthens [66]. Furthermore, as peers exit the network this also does not affect a peer's ability to exchange information. If one peer is unavailable, then another one, with similar capabilities, can provide the same information, or service. This fits in well with creating HDMs, as memories constructed in various environments will require the use of different services. Being "tied-down" to a set number of services does not fit in with the diverse composition of memories. HDMs are not composed of a fixed number of items, as we move through different environments; the requirements of a HDM will change. As Parameswaran *et al.* states, "*A client-server scenario like the Web depends on a single server storing information and distributing it to clients in response to their requests. The information repository remains*

essentially static, centralized at the server, and subject only to updates by the provider. Users assume a passive role in that they receive, but do not contribute, information. A P2P network, on the other hand, considers all nodes equal in their capacity for sharing information with other network members" [67]. The idea of HDMS does not fit in well with a client-server situation. Users need to be able to gather and share information equally.

In addition, the DigMem system is able to provide adequate flexibility, in a number of environments, and allows for any number of ad-hoc services (AHS_1, AHS_2, AHS_3….AHS_n) to be used, for gathering information for the HDM. The devices that are accessed shape the memories. Devices present in one environment will differ to those of another, thus altering the information that is available. A P2P network can handle this dynamically changing set of peers. This P2P architecture is used to gain access to the services that devices have to offer. The system is also adaptive to accommodate the fall-out of peers. For example, if a camera suddenly becomes unavailable, e.g. if it is placed inside a bag or pocket or runs out of battery, then another camera service is chosen. For instance, a CCTV camera in the city centre would be recording images continually. If the original camera service has become unavailable, then the CCTV camera, if it was DigMem compliant, could be used instead. With recent advances within the field of facial recognition [68–70], this idea could soon be a possibility. In the future, this technology could be used, within DigMem, so that the system knows what its users look like. If CCTV images were being used, then DigMem would be able to gather these images, identify the user, match the captured images to their profile and add the images to their record. The original service, which is now rendered useless, is replaced with another that is available. By retrieving data from these pervasive devices, memories are richer in detail. Information is incorporated into the memory that necessarily would not have been available otherwise. For example, a mobile phone would not be able to take the temperature reading of the room; however, by connecting to the thermostat this information could be retrieved and sent back, to enhance the memory.

In terms of storing the information that the devices collect, the Dropbox Cloud software [59] was chosen as it is a free (for a certain amount of space) service that is compatible with most mobile devices and operating systems. It is also a very effective and unobtrusive way to transfer data to many devices and locations. This method of data transfer eliminates the need for the user to manually upload their content, which is the current method used in other systems. Regarding the storage of the raw data, the decision to

store this information in a MySQL database allows developers the freedom to choose the data processing tools that they require, i.e. Excel, SPSS, or Matlab.

In order to create memory boxes the raw data needs to be transformed into RDF. By transforming the data, into this model, information from different schemas can be merged and, more importantly; RDF also supports the evolution of schemas over time, without requiring all the data to be changed [71]. This feature is very important, and one of the main reasons to transform the data into RDF. Any HDM system needs to be flexible enough to withstand the evolution of technology and to enable people to use and create memories "*across their entire lifetime*" [4]. Through the use of RDF, as new standards and devices become available their data, as well as data collected 10 years ago, for instance, can all still be used in the creation of HDMs. This is another unique aspect of the system.

Once the information is transformed into RDF it is converted into a matrix, using the *MoF* [56] algorithm. The reasoning behind using this newly developed algorithm is so that the data can be classified, based on the features of the dataset, instead of being searched with explicit queries. This algorithm is able to take any number of RDF documents and turn them into a universal dataset of features. This is beneficial and overcomes the limitations of searching RDF data with SPARQL, the query language for RDF [72]. SPARQL is a complex language that relies on the user understanding the domain before queries can be constructed. However, if the user is unfamiliar with the underlying RDF, then finding information can almost be impossible. Furthermore, navigating SPARQL's complex labyrinth of syntax is a difficult task entirely. In order to overcome this challenge the *MoF* algorithm is able to facilitate information extraction from semantic metadata. Instead of creating complex queries, to search the RDF, the information is instead transformed into a matrix of object instances, with associated features. This approach enables probabilistic searches to be performed. The metadata serializations provide rich semantic data structures that describe information.

This dataset is then explored using several well-known, yet simple, classification algorithms. This is in contrast to other approaches, where data is searched using keyword searches or complex queries. As it can be seen, from the results obtained in the previous section, using machine-learning algorithms for searching large data sets (the memories that we accumulate over a lifetime) yields some positive and interesting results. By transforming the obtained information back into RDF, enables the data to be manipulated and serialised in a number of different ways. This is a very important, and useful, feature as

the same results can be easily be transformed into a variety of formats, without too much trouble. In this case, the data has been converted into JSON. This format was chosen, to display the data on the web, because it is compatible with AJAX, is faster and easier as opposed to XML and is self-describing [73]. These semantic web principles and machine learning algorithms were chosen because they are able to support the evolution of data over an extensive period of time and are able to extract information from large datasets.

The purpose of this research is to illustrate how pervasive mobile devices, linked data and machine learning can be used to search HDM data and create human digital memories. Arguably, the time that the system was run for was limited. Nonetheless, the results do support the use of these devices, and these various technologies, in creating HDMs. Memories are composed of much more information than merely photos and location. As the amount of data increases so does the difficulty in searching it. This is reiterated by Fuller *et al.* [74], who states, "*HDM data is highly heterogeneous and unstructured, therefore, it is difficult to form search queries*". However, the use of RDF and machine learning can alleviate this problem. The *MoF* and machine learning algorithms are capable of transforming and analysing large sets of data. Instead of focusing on producing queries to search this enormous set of "*heterogeneous and unstructured"* [74] data this method focuses on treating the searches as a classification problem. Therefore, using the DigMem system, this mass amount of varied data can be easily explored. This method enables much richer and more-detailed memories to be created, than previously seen. Memories can be created as the user moves through their environment, a novel feature of the system.

A great deal can be learnt from this development. Firstly, the implementation illustrates that the MoDM middleware platform, and the use of pervasive mobile devices, can support the memory structures required. This is achieved by enabling a plug-and-play platform, for memory data sources, which can be exploited by the DigMem application. Secondly, the use of RDF enables data to be incorporated into a memory, irrespective of its format. This feature is especially useful because, as Fitzgibbon and Reiter [4] question, in their report on the Memories for Life Grand Challenge, "*How can we ensure that data is still accessible in 50 years time, despite inevitable changes in software, hardware and formats?*". As demonstrated in this work, the use of RDF is seen as a way to address this question. As time goes on and new devices and formats emerge; they can still be incorporated into the memory box. This is reiterated by the W3C [71], who comment that, "*RDF has features that facilitate data merging even if the underlying*

schemas differ, and it specifically supports the evolution of schemas over time without requiring all the data consumers to be changed". Thirdly, the use of machine learning algorithms illustrates a new way to explore HDM data. Collecting data over an extensive period of time (e.g. over a lifetime) yields an unprecedented amount of information. This increase in both the volume and the variety of data requires advances in methodology to automatically understand, process, and summarize the data [75]. Keyword searching is no longer a viable option for rich information The *MoF* algorithm converts RDF data into a matrix of features and, using machine-learning algorithms, the queries are treated as a classification problem. Therefore, the user does not have to explicitly define what information they require. Given any timestamp, data from around that period can be extracted. This is a unique aspect of the system that re-defines how HDM data is searched.

The memory boxes that are created from this data can also be used to reason over behaviour. The DigMem system illustrates that by incorporating data from any pervasive device a greater level of detail is achieved. For example, the data from smart fridges can be used to quantify dietary habits, whilst the human body provides us with physiological data. Any object can become a data source and their information used in a memory. This is particularly important because a richer level of detail is achieved and can be used to reason over behaviour and help us to understand aspects about our health, level of activity and physical wellbeing. Questions about ourselves will begin to emerge, such as "How was I feeling at *x* point in my life?" "What factors made me feel like this?" and "How were others around me feeling at the same time?" RDF, linked data and machine learning makes these queries possible to execute. Any time, throughout our lives, can be reconstructed and our feelings, from those times, reasoned over. This is a very powerful feature of the system as any point in our lives can be reconstructed and reasoned over.

7. Summary and Future Work

Memories link past experiences with the future and are a very powerful tool that people have at their disposal. Digitizing this process enables a whole new way in which interaction with technology can occur. Currently, a wide variety of data is accessible; however, there has been very little development in bringing these items together, for the purpose of building HDMs. The DigMem system addresses this issue by seeking out and using any device's specific service, for the task of creating a memory, and exploring this data, using RDF and machine learning algorithms. Therefore, memories created in this manner are not "locked-down" to a particular device. Any device can be used, thus providing a flexible and low-cost

solution. The use of RDF also enables data, collected over a long period of time, to still be usable in a memory box. This aspect allows the system's longevity to be increased and sustained over a very long time.

This work paves the way for creating fully interactive HDMs, which can be reasoned over and augmented with group memories. Our digital memories will grow alongside their human counterparts. This paper is an extension of [13], with current work building on the initial prototype and idea of creating HDMs, with data obtained from ubiquitous mobile devices. In previous work, only photos were captured. The system has progressed with the addition of the GPS and NeXus body sensor services, as well as the incorporation of cloud services and data-storage areas. The main progression has been in relation to how memory-related data is able to be effectively searched and brought together to create memory boxes. Fragmented pieces of data are now semantically linked and transformed into visual items. This work provides exciting results in terms of how fully interactive HDMs can be created and how such a system can be used to influence various aspects of our lives.

While the results, from the machine learning algorithms, were encouraging, the dataset used was small. One two-memory boxes were used, which were consecutive, in terms of time periods. Future work would consider a far larger dataset. This would need to contain many human digital memories, over a much bigger time span, for example, a months' worth of data, rather than days or hours. Furthermore, given that only two classes were utilized, it was sufficient to use supervised learning, to make classifications between the two. However, searching human digital memories is perhaps more of a clustering problem, i.e. finding clusters based on a set of features. The reason being that the targets of memories are likely to be incremental values, as a person traverses through time (this could be time and data or an ID representing a memory box ID). This means that we do not have sensible target values or if we do, the range of possibilities continually grows, as we progress through time. Therefore, instead of asking the algorithms to predict Y based on our data X, we are rather asking it what can you tell us about the data. In our future work, algorithms such as *k-means* will be explored.

Furthermore, collecting a lifetime's worth of information undoubtedly produces a vast amount of data. Securing this collection becomes harder as it grows in size. In any system that records personal information, privacy becomes an issue. In comparison to how much data can be captured, over a lifetime, the demonstrated system collects a small amount of information, which is retained in secure data stores. However, the issue of privacy will need to be addressed as the amount of data, and users, increases. Private

areas will need to be established for each user, where they can store their information and choose what memories to share with others. Another issue, regarding privacy, relates to identity theft. If devices are stolen, and false memories created, then this affects the user's entire HDM store. Whilst this is a problem, it is out of the scope of this research. Future work aims to look further into the issues regarding security so that memory data can be collected, and stored, safely. These key questions will be propelling the research, into this, area forward.

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