project desAIner

An exploration of a design process that focuses on "Big Data" gathered from smart physical devices as the future of design decision making.

Yuri Klebanov

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Innovation Design Engineering

Royal College of Art
Postgraduate Art and Design

Imperial College London

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Executive summary

This project revolves around the question: How can designers cope with the stream of Big Data in the IoT era? It is an exploration of the future of the product design process in the upcoming age of smart connected devices. The aim of this project is to understand the implications of the growing trend of the Internet of Things (IoT) on the way we will be designing in the future. During this project I was trying to identify novel and useful trends and insights and predict how will they affect designers work in the future. Building on those insights I am also trying to suggest some new tools that will be essential for the future IoT product designer.

In this thesis I propose that the future designer can maintain a rapid feedback cycle with his users, but will therefore need automated tools to extract product insights from the stream of Big-Data generated by the IoT devices he has launched.

To prove the feasibility of this vision, I decided to test the proposed design process, and build working prototypes of the tools necessary to make this vision a reality. I chose a set of headphones as my showcase product and built the story and the vision around those headphones as an example. Later in this this report I will also describe how the same tools and principles can be applied to almost any other physical product design process.

A key concept in the IoT world is Big Data, therefore a major focus of this project is looking at the potential impact of Big Data on designers and how could they benefit from it. A main goal of this project was to understand and demonstrate five key waypoints in the envisioned process:

1. Data collection
2. Encoding the key semantic features
3. Data analysis and interpretation
4. The interface and the outputs of the system
5. The impact on design decision making and the way it affects
6. The actual physical end product

The final outputs include several physical, working prototypes of "smart" headphones that evolved along the project based on insights collected from those prototypes and other data sources. Another output is a dataset gathered from several users and an algorithm that analyses it. On top of the algorithm, I designed an interface to present the output of the algorithm in a clear meaningful way to the designer. To demonstrate the relevance of the project to a wider range of products beyond headphones, a chart outlining several other sample scenarios was produced.

I believe that building on the research, the hardware and the software prototypes developed during this project, could lead to a scalable real market product providing meaningful tools for designers in the near and far futures of the IoT era.

Table of Content

Statement of originality

This is statement is to certify that as far as I know, the content of this document is my own original work. I claim full responsibility for the contents of this paper.

I declare the work presented in the following thesis was written entirely by me and no other sources besides the ones mentioned in the references appendix were used.

All oral sources of advice used for the benefit of this project and it's research are mentioned in the acknowledgements section.

Acknowledgements

I would like say great thank you to Dr. Michael Fink (Head of the Computer Science and Design Program in Bezalel Design Academy and the Hebrew University), who served as an advisor and mentor during this project. Dr.Fink was of great help and contributed a major portion of his time, knowledge and experience to bring the project to its current level of insights and functionality.

I would like to acknowledge other professionals and experts whom I consulted during my research: Jeremy Gow, Christian Guckelsberger, Guido Hermans, Antonios Liapis and David Arenburg.

I would also like to thank all the staff and tutors at the Innovation Design Engineering programme at the Royal College of Art and Imperial College London, who provided feedback during the many tutorials and gateways and kept challenging me again and again throughout the whe whole process.

Introduction

The main goal behind this project was to understand how can I, as a designer, benefit from the IoT era? I decided to explore the hypothesis that the Big Data provided by devices and products in the IoT era can be used to bring radical change to the product design, decision making processes and manufacturing flows conducted by product designers and companies focused on physical products.

"6.4 billion connected things will be in use worldwide in 2016, up 30 percent from 2015, and will reach 20.8 billion by 2020. In 2016, 5.5 million new things will get connected every day." — Gartner Inc. [1]

As described in Gartner's prediction the IoT revolution suggests that with time more and more devices will become 'smarter' and almost every "thing" will have sensors embedded in it. Those sensors will provide tremendous amounts of data regarding how those products are used. Such data can be invaluable for designers who wish to better understand how their products are actually being used and how they might improve the future generations of those products. Nowadays most product designers rely on manual user surveys, which cover only small percent of the users and deliver biased results in many cases. My vision it that in the IoT era the data about how users interact with the product will be streamed live from the product users, analyzed and served to the designer and other decision makers in the the product manufacturing process, continuously throughout the entire life of the product. Similar systems already exist in the software world, where developers and designers have analytics systems attached to their products, providing them with live data analysis of how people interact with their product. Those analytics tools enable developers and designers to receive live feedback from their users and almost immediately understand the pros and cons of their software usability.

Early adoptions of such concepts in the physical world can already be seen among large manufacturers in heavy duty systems and high end industry products. In his interview to Computing.co.uk, Bill Ruh, VP of global software services at GM said: *"If I could do the analytics without IoT, I would, but I can't because I need the machine data and machines are chatty. So for us, the IoT is necessary but it's not the most interesting part. The analytics, the insight you gain: that's where the value is. It's just that you need the data in order to gain the insight."* [2]

GM use the Internet of Things to monitor equipment on their factories, manage and repair their jet engines by detecting minor faults before they turn into major issues that might risk lives. Another example is OnStar - "*OnStar is an opt-in service that allows GM to monitor certain aspects of your vehicle's status as well as provide various types of assistance: navigation, music, roadside service, emergency service, and so forth.*"[3] GM use the same principles of fault detection in cars as they use in jet engines. This allows GM more efficient maintenance and significant life extension for their product, as well as increasing client satisfaction with the quality of the products and the services provided to support and maintain them.

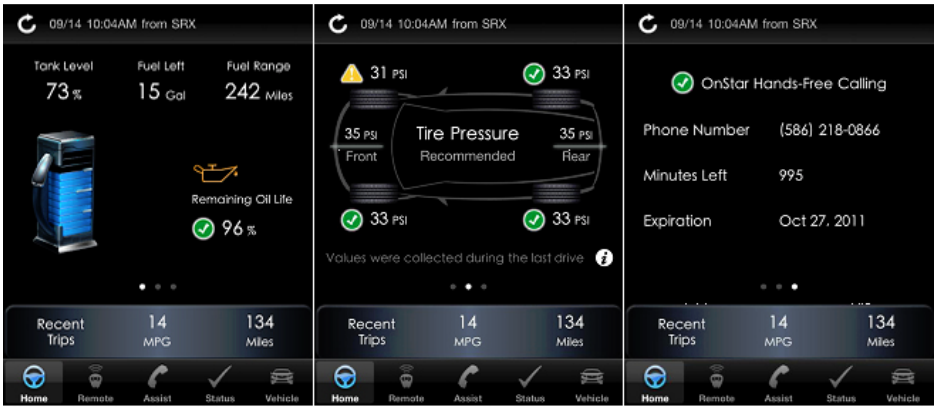

Fig 1: OnStar app screenshots

As I mentioned above I envision that such analytics tools and principles will be applied in the near future to the majority of physical mass consumer products, and will become a critical component in the designer's toolkit in the IoT era. Today, most designers have little understanding of Big Data and almost the same level of interaction with it, as an average mass consumer. There are very few professional tools that make Big Data accessible and beneficial for designers in their daily jobs. Designers working on physical IoT products have little or no expertise and awareness of working with analytics systems. At the same time companies providing analytics platforms for IoT products seldom identify designers as their target audience.

Fig 2: ubidots.com - a cloud sensor data capture service, dashboard screenshot

"For product developers, IoT provides invaluable new pointers to needed improvements. These pointers will find their way into the product's intellectual property and the myriad databases… Requirements for the new products are extracted from these data stashes. Thus, the IoT offers a better way to design quality and to ensure a better user experience… the IoT offers unprecedented advantages in making tomorrow's versions of today's products more competitive—anything and everything from apparel to armaments."
— Stanley Przybylinski [4]

In this project I explore and demonstrate how the future IoT designer tools might look like and what key functionality they might offer. I achieve this goal by undergoing the process of designing a showcase of evolving IoT product prototypes alongside with the software and hardware tools needed for such a process.

In this report I will go through analyzing the existing software analytics systems and explain how, in my opinion, they might be improved and adapted to be used with hardware sensors and physical products. I will then describe the process and the logic behind the hardware and the software prototypes and tools I developed during this project. I would then suggest possible ways to realise this project to to market. I will discuss the sustainability and privacy issues, go through the background research that took place prior to the main phase of the project and explain my personal learning objectives and aspirations that lead me to this adventure.

Disrupting the Designer-User Feedback Loop

The industrial revolution is responsible for the majority of physical waste accumulated today. Similarly, the data revolution is responsible for endless amounts of digital garbage which floods the internet and leads to a constant increase of storage. Our goal is to convert this digital waste into meaningful insights for the designer. Specifically, I'd like to make the data accessible to designers who do not have an analytical background, by telling the story of how representative users and user groups are experiencing their product. I believe that the power to tap into these insights should be democratized and available to all, including "indie designers" (and not only large corporate who can afford to hire a Big Data analytics group).

The proposed system would be of greater value for designers and other decision makers within a product company if they provide rich insights about specific user groups interact with the the product. Such novel insights could be generated by combining data insight from other aspects of the user life and not just from his interaction with the specific product. What if instead of showing charts of how many interaction a certain feature had, the main focus of the system was to show who are the personas interacting with it?

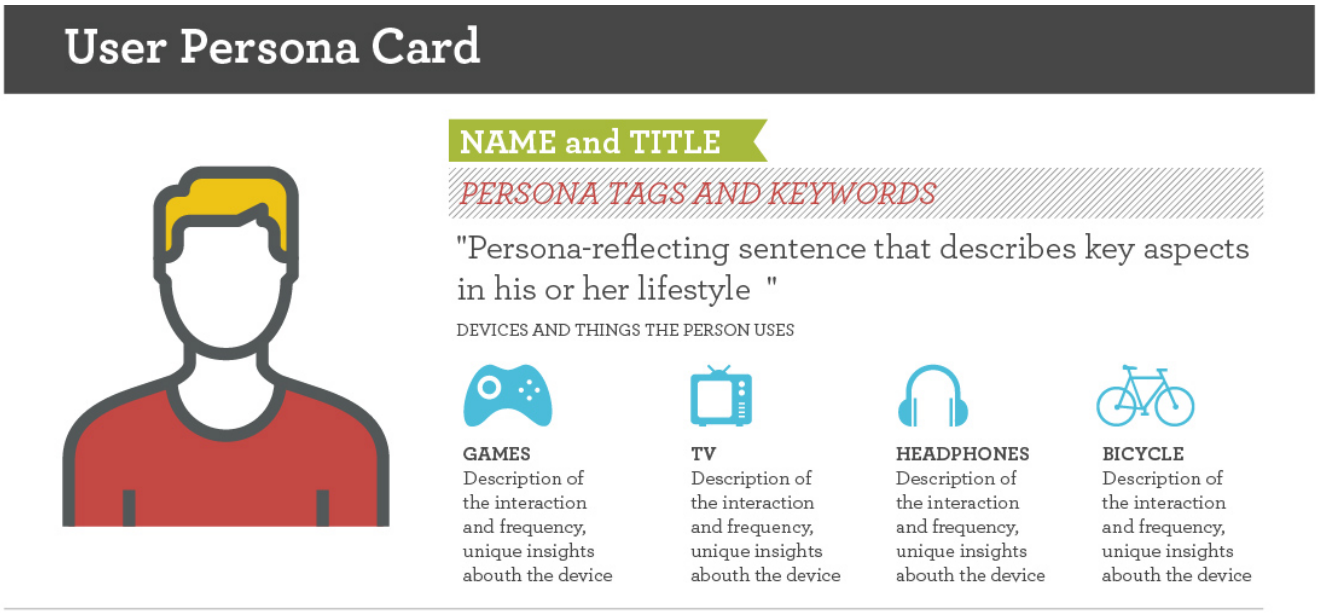

Fig 3: User persona card template

Currently, the task of generating user scenarios and personas is tedious and time consuming. Large companies that can afford such research send agents across the world to manually interview the users, and then spend a long time putting all the data collected together to generate insights that might have some value. Often, most of those insights are believed to be biased and suffer from low reliability. I suggest that in the era of smart devices, systems like the one presented in this project will simplify the process of data collection and analysis, reduce its cost and will deliver more objective insights. I also believe that by collecting data from several related products and not just the product in task, we will be able to gain a richer insight and better understanding of the different user personas. I believe that in the era of big Data new, surprising and previously unnoticed insights will emerge. We will be able to gain those insights only by processing Big Data and understanding how usability of one product affects another. For example understanding how a certain user eating habits (data extracted from a smart fridge) affect the way he rides his bike and the garments he is wearing. By using machine learning and clustering algorithms the analytics systems will be able to recognize behavioural trends among groups of users and make them accessible to the designer, who in turn will be able to make informed decisions when designing the next generation of the product.

"Products will evolve to evolve. A new generation of products is being designed to grow alongside the user, to develop new features, and adjust their behavior to better serve the user. There are hints of this happening, but the full impact of this trend may take more time to build… Today, a design team delivers a production-ready thing, something finished and ready for manufacturing and consumption. Tomorrow's designer must be prepared to ride "shotgun" with the customer and the product for the life of that product, perhaps helping to grow and adapt the product over time." - Mark Rolston [5].

In addition to important insights, I believe AI algorithms could be trained to make actual design suggestions as well. For example:

- After finding different user clusters it might suggestsplitting the product line into sub-products.
- Identify product functionality that is not in use and suggestit is redundant or should be made more accessible.

Project Plan

As I mentioned in the the introduction, the m09ain focus of this project is to explore the future design process and understand in depth the meaning of each step in that process. In my future vision this design process will involve a central system of data collection and analysis. I believe such system could become a key element in the future toolkit of the IoT product designers. In my vision, the future product design process will include the following steps:

1. A first generation of a smart product is designed and manufactured. In this phase designers and product leads decide on which key semantic interactions they wish to monitor
2. The product is introduced to the users and being used over X amount of time. During this time sensors inside the product collect data about key semantic interactions by different users
3. The data is combined with insights from other smart devices the user was interacting with. This information analyzed by an algorithm which identifies and highlights major usability patterns and divides the users into clusters by their behaviour patterns.
4. A new generation of product is designed based on the insights in stage 3

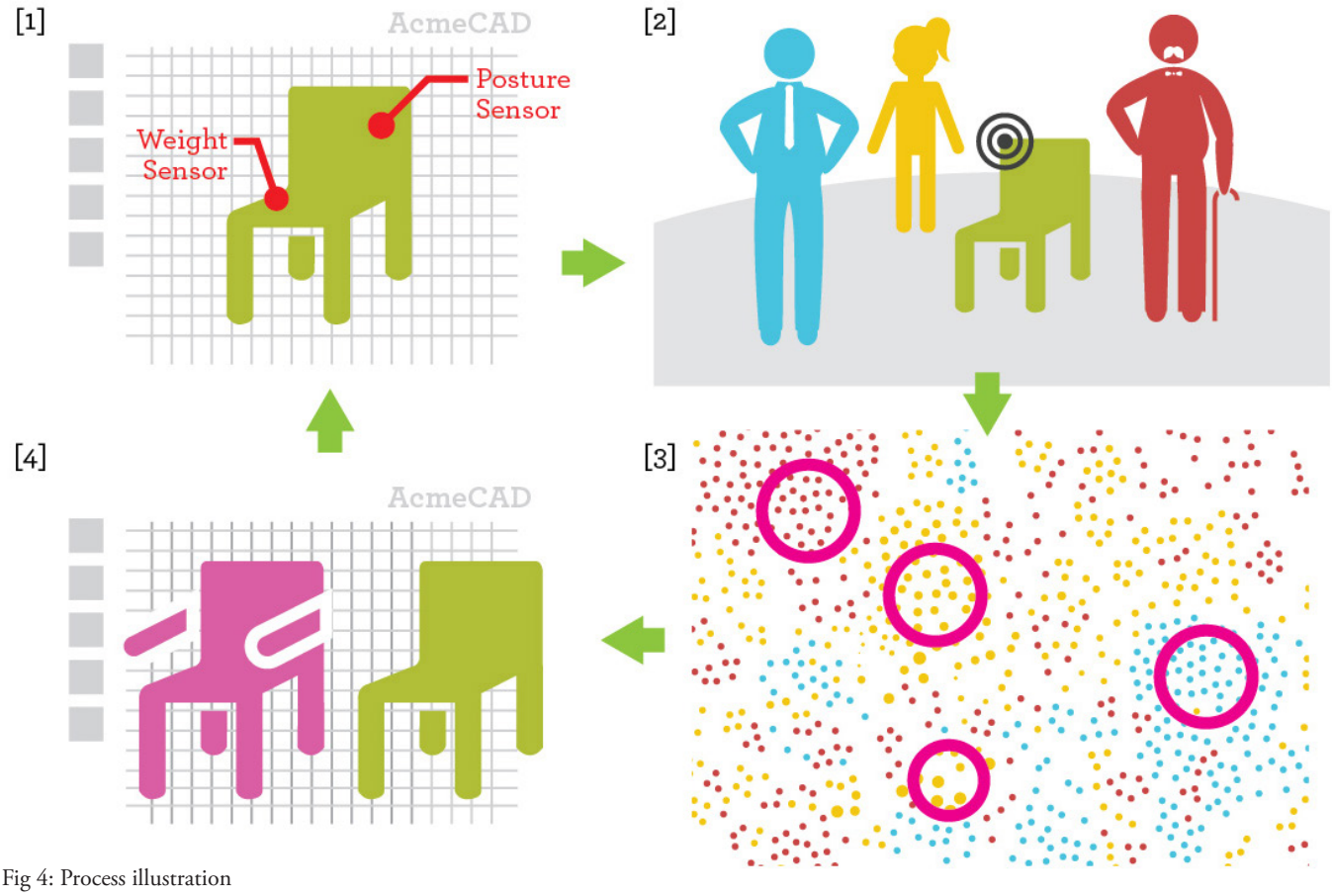

Fig 4: Process illustration

A key concept in this flow is the definition of the "Key Semantic Interactions". Typically an IoT device will log many raw data streams such as accelerometer, GPS location, temperature etc. However, the designer and product leads are interested in a higher level of information such as "the user is biking" or "running" and his location is "Home" or "Work". Therefore, it is critical to aggregate the low level raw data logging into these higher level "Semantic Interactions". This process can be done using standard machine learning techniques.

From this higher level data stream I wish to extract meaningful insights that can assist in generating the future versions of a product. For example, the process described has the potential to lead to three types of outcomes:

1. Highly Personalized products: specially tailored for the user
2. Adaptive Products that include features that allow one product fit different users (such as chair height handle)
3. Genetic Modular Products (Ikea/Lego): have core features similar among all users but some features will be highly personalized

Fig 5: 3 Types of products: Highly Personalized, Adaptive and Genetic Modular

To gain the best understanding of how each one of the above steps will work I made several physical product prototypes and software tools relevant for each step. Those included sensor embedded, data logging and cloud connected physical prototypes, basic machine learning and data analysis algorithms as well as an interface to present the outputs of those algorithms in a meaningful way for designers. The algorithms that were used are:

1. K-Nearest Neighbours (KNN) - a pattern recognition algorithm used to recognize patterns of untagged data within a dataset of tagged patterns
2. K-Means - a clustering algorithm that separates a certain amount of data points (which are represented by several vectors) into 'K' amount of clusters.
3. Principal component analysis (PCA) - this algorithm used to convert multi dimensional data points to a smaller amount of dimensions to make it possible to represent them on a 2 or 3D charts.

The process and the work done is described in the following chapter.

Process Overview

The first step was to identify what products would best showcase the insight extraction process. As a quick exploration in creating an IoT device, I built a computer mouse with 12 copper tape electrodes (integrated into the inner part of the mouse) that were used as capacitive sensors to identify how different users hold the mouse, by logging the touch points between the mouse and the user's hand thus collecting data about the ergonomic performance of the product.

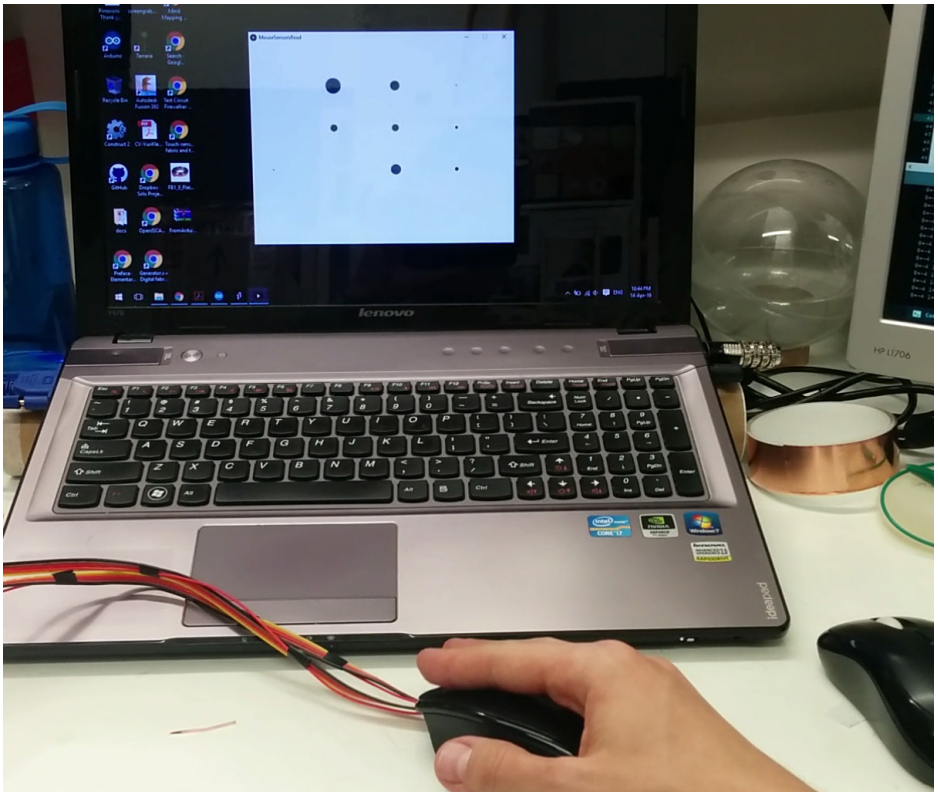

Fig 6: Touch points logging mouse prototype

After I saw I can properly build and log data from an IoT device, the next experiments were carried out to prove the feasibility of a system that could be used to generate specific design insights. My goal was to automatically identify users by their behaviour patterns based on the Key Semantic Interactions extracted from raw sensor data that was gathered from a "smart" physical product (headphones in our case). Once a database of users was created the next goal was successfully cluster them into groups that could be represented by coherent user profiles.

I decided to use headphones as my showcase product. The main reasons for choosing headphones were the wide range of design opportunities as well as the fact that people use them in a many different scenarios. Therefore I believe it is a good showcase product which will allow me to gain many interesting insights about a wide range of personas and usability scenarios which I could apply to interesting design outcomes. In the future I'm hoping to apply the methods described below to other types of products, to prove their relevance and scalability.

Step 1: Physical implementation
A prototype was built embeded with 6 sensors that track 10 raw data parameters:
- Temperature and Humidity inside the ear
- Two pressure sensors - measuring the pressure on the user's head
- An accelerometer to measure movements along X,Y and Z axes
- A gyroscope to measure rotation along X, Y and Z axes

A "Particle Photon" prototyping kit was used to enable internet connectivity and uploading the sensor samples directly to a cloud data logging service, thus proving the feasibility of creating a wireless cloud connected data logging device. The headphones sound driver remained autonomous and stayed functional regardless to the data logging circuit state. Several cloud data logging and monitoring services were considered such as google spreadsheets and librato.com eventually selecting ubidots.com as the logging service due to the ease of integration with the Particle Photon kit.

Step 2: Extracting Key Semantic Interactions from raw sensor data
In order to gain useful insights that will later allow identify clusters of users based on the way they interact with the product, five Semantic Features were defined:
1. Cycling
2. Walking
3. Working
4. Running
5. Resting

Those five features could be identified using the 10 raw data parameters (described in step 1) and machine learning algorithms. K-Nearest Neighbour (KNN) was selected (in the future I plan to use Deep Neural Networks).

Experiment 1 - Testing with simulated users

In order to prove the feasibility of the data logging and analysis theory two data sets were created:

1. Training data set aimed at extracting the Key Semantic Interactions
2. Testing dataset simulating 50 individual users.

Several data recording sessions were carried out. Each session was one hour long in total. Sensor readings were logged and uploaded every 10 seconds, resulting in 300-400 samples per session. Each sample included the 10 raw sensor data parameters from the 6 sensors described in step 1. During each session the same user was performing a different activity wearing the headphones: Working (sitting in front of a desk), Walking, Running, Cycling and Resting. Only one type of activity was recorded during each session.

Training data

The training data set was created from 30 samples of each activity. Those samples were tagged, each with a corresponding activity index and then used as the training data for the KNN machine learning algorithm aimed at translating the low level sensor recordings (temperature, accelerometer etc) into high level Semantic Interactions (Cycling, Working etc.).

Testing Data

500 samples were split into 5 groups of 100 samples each, to simulate 50 users with 10 samples per user. This means that each simulated user was represented by 10 samples of the same activity — 10 users per activity. The simulated user samples were untagged. This data was fed into a KNN function in matlab which successfully identified the untagged activities for each user (Fig 8).

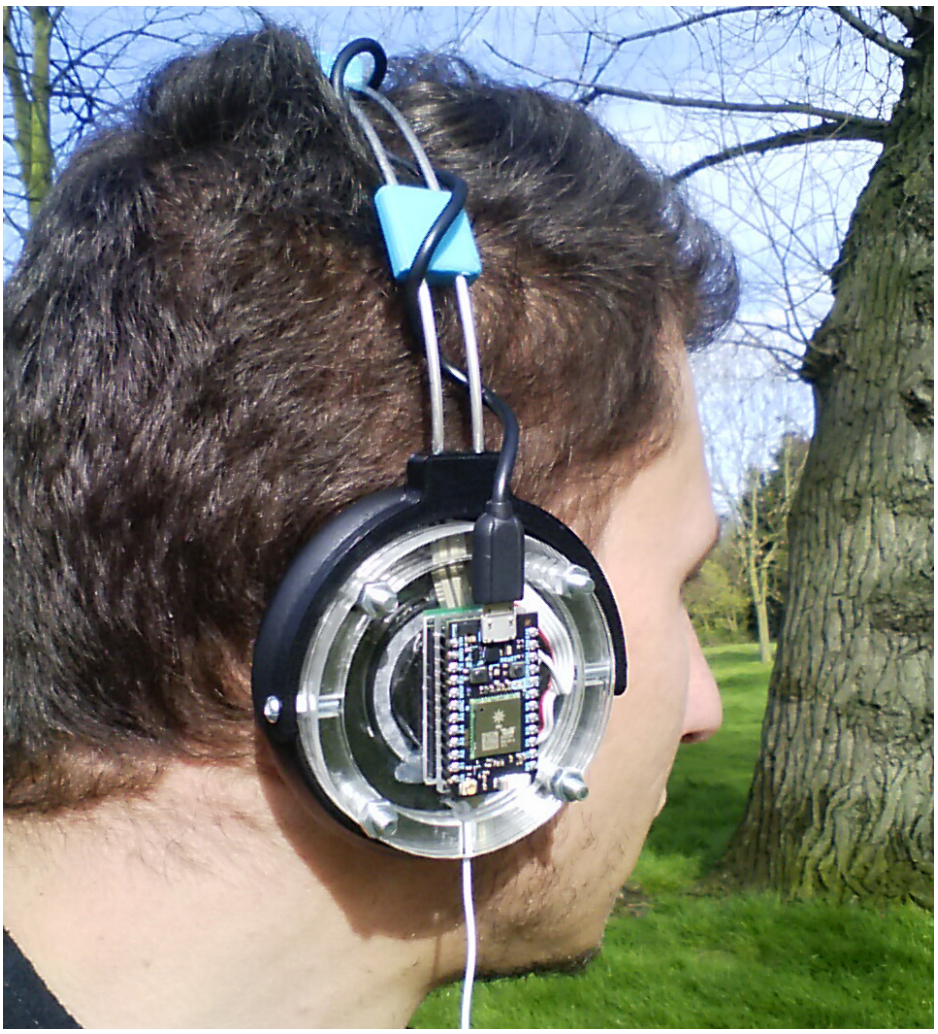

Fig 7: Logging sensors data while running

The next step was feeding the Semantic Interaction profile of all the 50 users (obtained by the KNN) into a K-means clustering function. The algorithm was able to automatically identify that 5 clusters of users exit in the data, thus successfully uncovering the groups of users in the Cycling, Walking, Working, Running and Resting user groups. To be able to plot this 5-dimensional data in a 2-dimensional chart, Principle Component Analysis (PCA) was applied as a dimensionality reduction technique (fig x1). A similar approach was used to render the data in a 3D chart as well (fig 9,10).

Run	Wal	Wor	Cyc	Res
9	0	0	1	0
10	0	0	0	0
9	0	0	1	0
10	0	0	0	0
10	0	0	0	0
10	0	0	0	0
9	0	0	1	0
9	0	0	1	0
10	0	0	0	0
9	0	0	1	0
0	10	0	0	0
0	10	0	0	0
0	10	0	0	0
0	10	0	0	0
0	10	0	0	0
1	9	0	0	0
0	10	0	0	0
0	10	0	0	0
0	10	0	0	0
1	9	0	0	0
0	1	9	0	0
0	0	10	0	0
0	0	10	0	0
0	1	9	0	0
0	0	10	0	0
0	0	10	0	0
0	0	10	0	0
0	0	10	0	0
0	0	10	0	0
0	0	10	0	0
0	0	0	10	0
0	2	0	8	0
0	3	0	7	0
1	3	0	6	0
0	2	0	8	0
0	4	0	6	0
0	3	0	7	0
0	5	0	5	0
1	7	0	2	0
0	9	0	1	0
0	0	0	0	10
0	0	0	0	10
0	0	0	0	10
0	0	0	0	10
0	0	0	0	10
0	0	0	0	10
0	6	0	0	4
0	0	0	0	10
0	0	0	0	10
0	0	0	0	10

50 simulated users
10 samples per user

Fig 8: Matlab KNN result

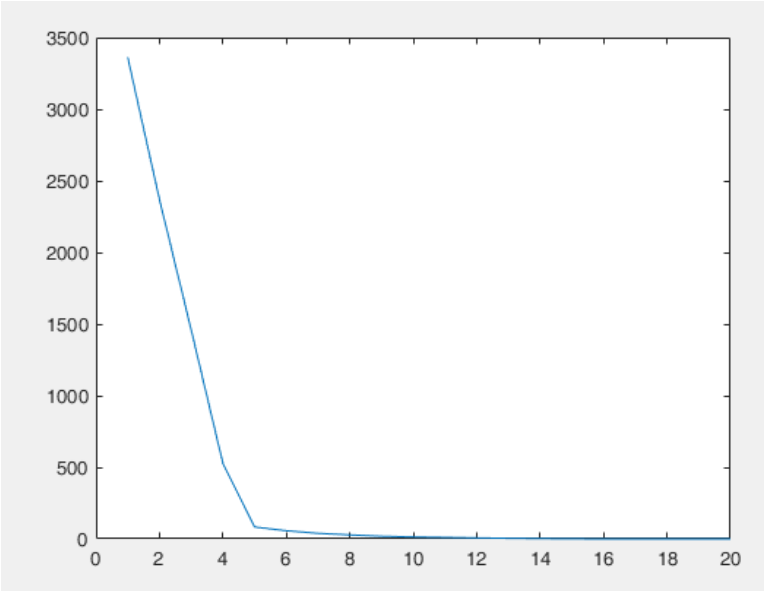

Fig 9: Mean distance of cluster members from the cluster center as a function of "K"

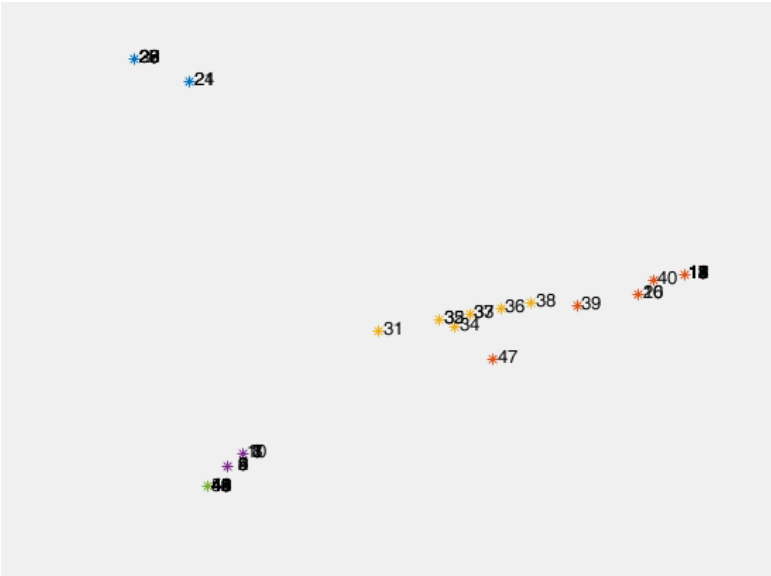

Fig 10: Matlab PCA 2D Plot

Experiment 2 - Simulating a more realistic user behaviour:

The next experiment was to create a new group of 40 simulated users, with 20 sensor samples per user of two mixed activities (10 samples per activity). The 40 users were split into 4 groups of 10 users in each group:
Group 1: Working + resting,
Group 2: Running + Walking,
Group 3: Working + Cycling,
Group 4: Only Resting.

The training data set remained the same as in the previous experiment. This time the KNN function identified the 1st, 2nd and the 4th group of user activities quite well. In the 3rd group the algorithm identified some of the activities as walking, instead of cycling or working. The best K this time was also bit off: 5-6 instead of the anticipated 4. I believe that a larger learning dataset could resolve such confusions. Once again PCA was applied to display the user clusters in a 2D and 3D charts.

Run	Wal	Wor	Cyc	Res
0	2	8	0	10
0	0	9	0	11
0	0	10	0	10
0	0	10	0	10
0	0	10	0	10
0	0	9	0	11
0	7	9	0	4
0	0	10	0	10
0	0	10	0	10
0	0	10	0	10
10	10	0	0	0
10	10	0	0	0
10	10	0	0	0
10	10	0	0	0
10	10	0	0	0
11	9	0	0	0
10	10	0	0	0
9	9	0	1	1
10	10	0	0	0
10	9	0	1	0
0	1	9	10	0
0	1	10	9	0
1	3	9	7	0
1	1	10	8	0
0	2	9	9	0
0	5	8	7	0
0	3	8	9	0
0	8	5	7	0
1	8	7	4	0
0	7	6	5	2
0	0	0	11	9
0	0	0	19	1
0	0	0	6	14
0	0	1	0	19
0	0	0	0	20
0	0	0	0	20
0	0	0	0	20
0	0	0	0	20
0	0	0	0	20
4	2	0	0	14

Fig 11: Matlab KNN result

40 simulated users
20 samples per user

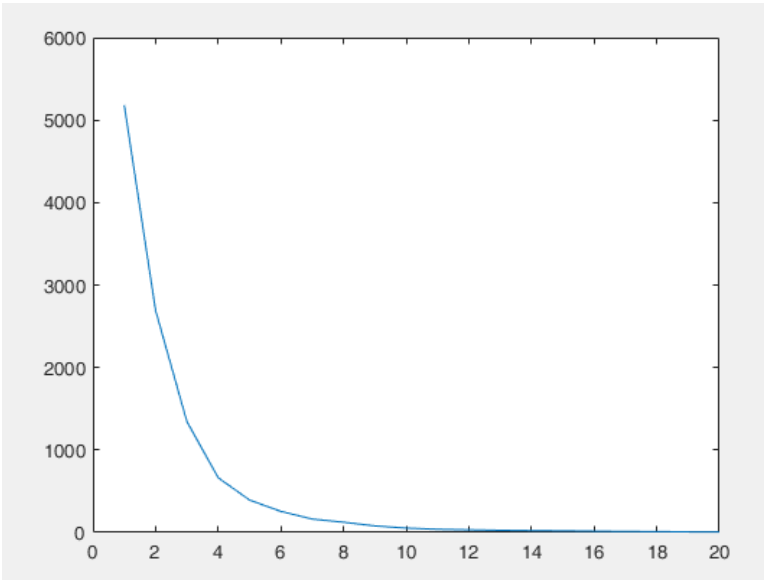

Fig 12: Mean distance of cluster members from the cluster center as a function of "K"

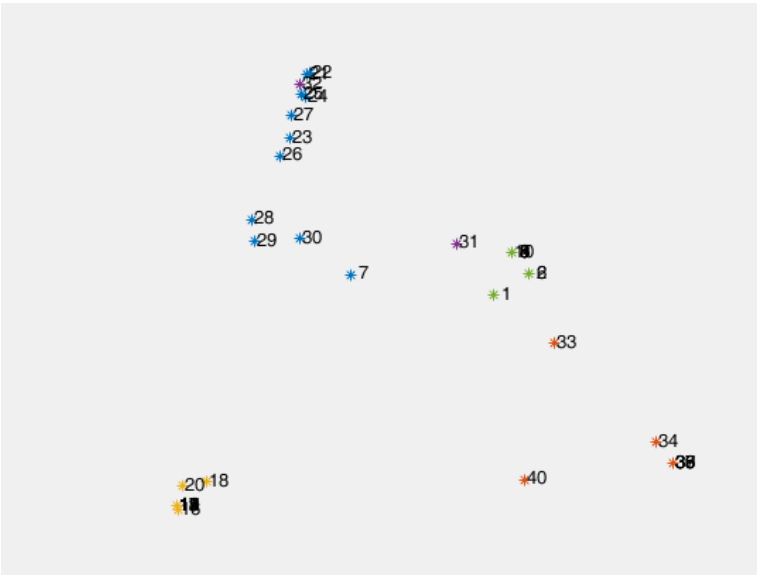

Fig 13: Matlab PCA 2D Plot

Experiment 3 - Testing with Real users (still ongoing):

After validating our algorithmic approach on simulated data, the next step was giving the headphones to actual users. Three users were tested so far, wearing the headphones during their daily routine.
I then asked the users to report what activities they were doing in order to quantify the success of our Semantic Interactions extraction process:

User 1 :
- working - 200 data samples
- identified by KNN with 90% accuracy

User 2:
- working - 190 data samples
- identified by KNN with 98.9% accuracy
- walking - 210 data samples
- identified by KNN with 96.2% accuracy

User 3:
- walking - 270 samples
- identified by KNN with 99.6% accuracy

KNN and PCA will be applied in a later stage once larger amount of users will be logged.

```
>> data_loader
user 1:
    Run   Wal   Wor   Cyc   Res
     0    17   180     3     0

>> data_loader
user 2:
    Run   Wal   Wor   Cyc   Res
     1   202   188     9     0

>> data_loader
user 3:
    Run   Wal   Wor   Cyc   Res
     0   269     1     0     0
```

Fig 14: Matlab KNN Results

Those experiments proved the feasibility of the main assumptions of my thesis:

- **Perform automatic Semantic Feature Analysis and translate raw sensor data to activities (using basic machine learning algorithms such as KNN)**
- **The ability to identify user personas based on their behaviour patterns**
- **Groups the user personas who share similar behaviour patterns and make sure they are split among those groups in the most efficient way (using K-Means and by identifying the best 'K').**
- **Generate a report that presents the user clusters in a 2 or 3 dimensional chart using PCA .**

Simulating Big Data

Although the results of the above experiments are exiting, to make the insights from such system valuable for product manufacturers and designers, this system must be able to generate more interesting and surprising insights that go beyond the basic analysis of the basic interaction and use case scenarios such as how many users use the product while running and how many other users are mainly use the product while working and resting. To affect design decision making in a meaningful way the system should be able to demonstrate new and unexpected correlations between the insights from the smart product itself and other aspects of the user lifestyle. These insights could be presented in the form of automatically generated user profiles and persona cards that display habits and user features that could only be discovered through a Big Data analysis and could not be achieved via the traditional methods like surveys and user interviews. To achieve such results the system should take in account and analyze information from many smart devices that the user will own or interact with during his daily routine. I predict such scenario will be possible in several years time. In order to simulate this future scenario at present day and on a smaller scale, a personality survey was carried out in order to try and gain new and unexpected insights to affect design decision making when designing the next generation of headphones.

The survey consisted of 32 questions split into 6 categories:

1. Headphones using habits
2. Daily habits
3. Weekly habits
4. Monthly and Yearly habits
5. Personal preferences
6. Basic info

260 responses were gathered. The survey results are currently being processed using the K-Means algorithm and a Decision Tree algorithm. I believe this analysis will lead to some interesting unexpected insights regarding users habits. Having said that, this survey and its results is only a tiny simulation attempting to get a small taste of potential insights that in the future will be gained from Big Data collected from billions of devices and millions of users. Due to the limitations of such a manual data collection method I predict that some insights will have to be slightly emphasized and adjusted to make the vision of the project more interesting, surprising and intriguing.

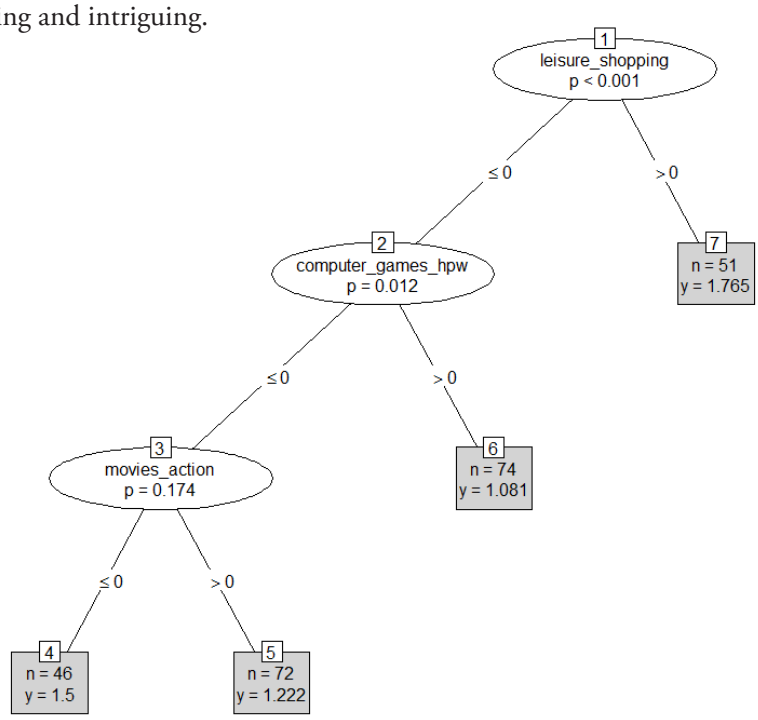

Fig 15: Processing survey results data via decision tree

Next steps

During the next few weeks I intend to use those insights to produce several iterations of the headphones prototype to demonstrate how the product design might evolve by taking those insights into consideration, given the limited amount of time, and the main goals of the project those iterations will remain on the "working prototypes" level and I will not attempt to reach a finalized production ready product.

To make the system output and the insights more legible I suggest to translate the the charts and matrices generated by the algorithm to a more user friendly interface in the manner of the currently widely popular analytics with a few novel adjustments. As explained in Chapter-2, alongside the familiar charts that display the basic usability statistics, I suggest that the system procedurally generates accurate objective user persona cards which will translate the data insights into meaningful representations of user personalities and their lifestyle. The user's personality and lifestyle features could then be interpreted by the designers to corresponding design decisions in the next generation of the product.

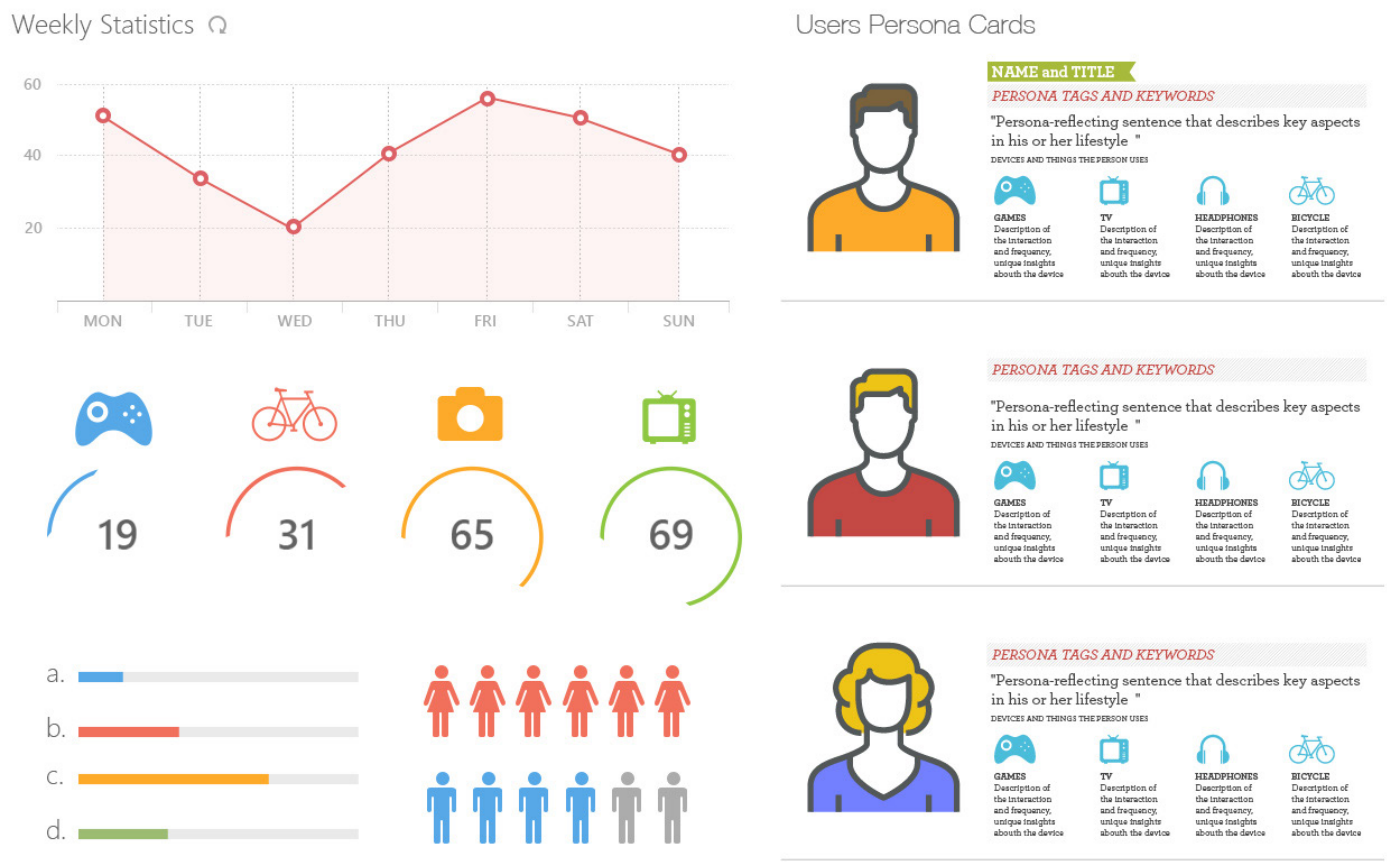

Fig 16: Vision of an analytics interface featuring persona cards

By relying on Big Data coming from millions of smart devices across the IoT, I believe that the new unexpected insights about users behaviour, personas and lifestyle will enhance the designer's creativity by allowing them to brainstorm and come up with different solutions for those new insights that will lead to the development of novel interesting features and products.

Another potentially interesting feature the system could include are:
1. physical product heat maps
2. remote A:B testing for different versions of products
3. discover predict and report products faults and their life cycle patterns.

In order to demonstrate the potential applications of the methods described above to a wider range of products (beyond the showcased headphones), A chart of other potential scenarios will be produced during the next few weeks. This chart will feature 3-4 other products, low and high tech to better illustrate and inspire potential application of the concepts explored in this project.

Real World Application

"To build momentum for the IoT, AT&T, Cisco, GE, IBM, and Intel formed the Industrial Internet Consortium (IIC) in March 2014. Their stated goal is to "identify requirements for open interoperability standards and define common architectures to connect smart devices, machines, people, processes, and data" throughout industry. The IIC will push for better access to what information technology experts often refer to as Big Data while improving the integration of the physical and digital worlds. The IIC is managed by the Boston-based Object Management Group, an Internet trade association." — Stanley Przybylinski [4]

In my vision the best way to make such system a reality is to have it as an open platform for all the IoT product companies. Such platform will allow a certain company to opt-in and share the data from its products in exchange for data from other companies and products. This scenario will allow the most efficient way of Big Data sharing and gaining insight from the widest range of smart devices possible, thus leading to better profiling and smarter insights. In such scenario companies that manufacture smart refrigerators will be able to gain insights from companies that manufacture smartwatches and companies that make smart garments thus getting better understanding of their users. This scenario is challenging and will require creating standards and cooperation between different product manufacturing companies that will have to comply with the system standards.

"In order for these scenarios to play out, companies need to cooperate and agree on certain APIs and communication protocols to get things to play nice."
— Scott Jenson [6]

Another faster way to realize this scenario would be developing such system for a specific company that will have a wide portfolio of IoT devices that could easily share the information between each other within that company smart product eco system. The major pitfall of such an approach would be that the vast majority of users own different products from different manufacturers.

Stakeholders, users, targets:

I believe such a system can be of benefit to several groups of professionals who work within the IoT / Smart Products Industry. The system could affect the decision making of a company on several levels. When looking at a classic company structure the departments that would benefit from the system are:

1. Design
2. Engineering
3. Sales and Marketing
4. The General Manager and other strategic decision makers.

The end consumers of the IoT products designed with the help of such system will also benefit from an increasing number of more personalized products that will continuously evolve and adapt to their specific needs.

Sustainability and Privacy

"The IoT can eliminate nearly all the uncertainty about what users encounter in the field, in the later stages of product life cycles. The ways in which products wear out, and when and how they are replaced, can provide vital insights about what will be needed in next-generation products." "The products that emerge from tomorrow's manufacturing enterprises will be more functional, more robust, longer-lived, more adaptable, more scalable, and more sustainable."
- Stanley Przybylinski [4]

Another trend that is coming along with the IoT revolution is "Servitization" (A term popularized by the Parametric Technology Corp.). This trend means that more users move from owning devices to leasing services. I don't need to to buy and fill my home with CDs and and Cassettes to have a collection of all the movies I like, I pay Spotify and Netflix to watch them on demand. Many people don't own smartphones or cars anymore they lease them from service providers, which handle the upgrades and the recycling of the physical products. I believe this Servitization will move to more aspects of our daily life. We will pay to have different kitchen services like bread warming and food cooling. We won't have to own fridges and toasters but lease them instead. IoT smart devices will enable the service providers to better control their inventory and provide higher quality services based on the insight from those devices.

The main benefit from a service based approach is that disposal and recycling are done in a centralized manner. This will increase the value of recycling because:

1. It is done at mass
2. The manufacturer knows best which parts and materials can be reused and how
3. The future production line can be designed in the first place to optimize the existing materials and parts

Privacy is an important aspect of any system that deals with human behaviour data collection. I believe that any product designed to be part of a system such as described in this project or the IoT in the general should include an option for the user to opt out at any given time. As well as making the users aware of them becoming participants once they start using any of the smart devices that are part of the network. Users should also be provided with full transparency on which data is being collected and how it is being used. This will enable users to make informed decisions on where they feel comfortable on privacy-vs-functionality continuum. I believe that the benefits for the users of such system will be greater than the privacy concerns. The best example for this is the continuously growing smartphone industry, which despite the endless privacy issues keeps thriving. More people become smartphone owners which shows that the benefits they gain from them are far greater than the concerns of privacy loss. I believe that will be the case for the vast majority of all the other IoT devices. Having said that, I still believe the privacy issue is to remain top priority for any IoT product designer and manufacturer.

Research Background

My research in the field started about a year ago when I was was working on my dissertation. I began by reading articles and books by AI researchers and visionaries such as Ray Kurzweil, Nick Bostrom and Eliezer S. Yudkowsky. Talking about the history, today's trends and the future of AI. I became fascinated with concepts such General and Super Intelligence and the debates surrounding them.

Wishing to get a better understanding of how AI works, I started looking for a way to get my hands dirty. I found the gaming industry as a great entry point into the field. I started by reading several articles (and still following the blog) by Michael Cook who was at a time a PhD student in Imperial College and now a Senior Research Fellow at the University of Falmouth and the Computational creativity group in Goldsmith university. Michael's research got me fascinated with the topic of Creative Computing. I started digging deeper into the field reading more publications by other researchers. One article led to another and a great book named "The Nature of Code" by Daniel Shiffman proved to be a great hands on introduction to Genetic Algorithms and neural networks.

I managed to arrange meetings with several researchers based in Imperial, Goldsmith and other parts of the world such as: Dr Petar Kormushev, PhD students Zafeirios Fountas, Pedro Mediano, and Christian Guckelsberger, Jeremy Gow and Dr. Antonios Liapis. Big Data and The internet of Things were also impossible to avoid, with articles on the topic published on daily basis. The more I read and the more people I spoke to I came to realize that many of the principles and tools used in the AI research world can be applied and enhance Design.

Within the vast realm of AI, I identified two areas of interest that in my opinion have the greatest potential becoming truly helpful tools for designers:
One is Procedural Content Generation (PCG) and Genetic Algorithms, a popular topic in the gaming industry that can help designers explore large design variations and enhance creativity using Mixed Initiative design tools. The other is Big Data. For a while I had a hard time finding a way for designers to benefit from it, but later on having a brainstorming session with Dr Michael Fink (Head of the Computer Science and Design Program in Bezalel Design Academy and the Hebrew University), we pointed out the great potential of Big Data coming out from IoT devices and how it might affect the future of design. As mentioned in the acknowledgments Dr M. Fink was of great help and contributed a major portion of his time, knowledge and experience to bring the project to its current level of insights and functionality.

Given the short time I had I've decided to focus on the Big Data approach as the main topic of the project with having notions of PCG and possible combinations between the two as a future vision and potential exploration area after my graduation.

Personal learning objectives and inspiration

I was exposed to the topic of Artificial Intelligence and its recent raising popularity about a year ago when I was looking for a topic for my dissertation. Since then I got fascinated with the topic and how quick the results of the latest AI research are being implemented in the daily life of millions of people. I found the topic of creativity within the AI realm specifically interesting. I believe that machines and designers can enhance each other's creativity in many interesting ways, many of which yet to be explored.

By doing this project I aspired to learn more about the different approaches to AI and the current research trends. In the future I wish to gain even deeper understanding on the building blocks of other machine learning techniques, genetic algorithms and neural networks. In my future endeavours I hope to gain further interesting insights about how designers could use the tools used in the AI realm to enhance their work and creativity. I also hope my project will inspire other designers to start thinking, making and demanding new design oriented tools to be built upon big data and Machine Learning.

Conclusion

In this project I explored the process of migrating and adapting current analytics systems used in the software industry to the physical product industry. A key insight (which would be relevant for the software industry as well), is considering adding new features to those systems, that focus on analysing the persona and the lifestyle of the user instead of the product performance. I believe such insights could be gained by analysing Big Data from an environment of devices and not only one specific device - multiple data sources such as different smart products and objects the user will interact with. Analysis of such data will enable to automatically generate an objective user profile with new, previously hard to extract insights. Thus disrupting the current costly and time consuming methods of manual surveys and interviews and improve the designer-user feedback loop.

Analyzing vast amounts of user interactions across numerous products will allow the generation of key insights regarding usability trends and will radically affect the way we plan, design, evolve,maintain and recycle products. The analytics systems could be trained to go beyond analysing trends but to suggest solutions to fit those those trends, such as removing or emphasizing a redundant feature or splitting a product line into several new lines.

The process and the methods described in the project share the common belief that IoT products have great potential to lead to better sustainability. As product designers will be understanding their users better, so will the products they design serve those user more efficiently and for longer periods of time. Product manufacturers will better understand the product lifecycle and be able to monitor and predict faults. The response time to such faults will become significantly shorter and will allow better preventive care which will once again will make the products more reliable and last longer. Servitization will push this further as users will be consuming services and leave the hardware management part to the service providers and the product companies which in their turn will gain better control of their product lifecycle.

Another interesting insight is that machine learning methods could be easily applied to smart products. This could lead to the ability to teach the products to recognize new interactions and behaviours without changing the hardware, and by only updating the firmware. In some cases even a firmware update won't be needed as most of the computation and analysis will be happening in the cloud. Users will also be able to teach their products themselves to better recognize and understand them. This in turn will lead to many new insights about the way the products being used.

To make the visions in this project become a reality it is essential to make more designers and decision makers in the physical product industry become aware of the benefits described in this paper, to the increase the demand for such tools to be developed. Above that in order for such tools to work as predicted and be able to collect and process Big Data from a large range of devices, a standardization of the IoT will be needed. This is a major challenge that I believe will be solved within several years time as it is currently being tackled by the largest players in the industry such as AT&T, Cisco, GE, IBM, and Intel.

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Appendecies

Notes

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1236,-0.9966,-0.9627,-1.8036,1.0015,-0.1336,-1.4264,0.6292,-0.6074,0.2839,-1.3879,-1.323,-2.0747,0.7118,1.094,-0.2813,-2.1072,-1.4929,-0.0009,
.1427,0.1171,-1.2029,-1.8287,0.9786,0.2024,-2.242,1.0126,-3.4331,0.3515,-0.2052,-1.0828,-2.1148,0.6578,1.0643,-0.1193,2.498,2.3138,-2.0757,0.7
.8509,-2.3471,-0.0017,-1.8713,0.9372,-0.219,2.5515,-0.3618,-1.6934,-0.6899,-2.1729,-0.8425,-2.16,0.5931,1.0359,-0.1428,2.5515,-2.0512,0.421,-1
0.3095,0.0438,-0.0017,-1.919,0.889,-0.4654,-0.1182,-0.5283,0.8746,0.2918,-0.954,-0.7224,-2.2404,0.4769,1.011,0.4846,-1.9875,0.7526,-1.4489,2.3
.6719,-1.4691,-0.362,-1.9517,0.8506,0.1799,0.7547,0.1331,-2.5413,0.5512,-1.8025,-1.5633,-2.3056,0.3629,0.9805,-0.1177,2.5515,-3.4244,0.5511,0.
526,-1.103,-0.4822,-1.9893,0.8126,-0.1065,-1.0568,-1.4282,0.0627,-2.4533,-0.4098,-2.0437,-2.3784,0.1964,0.9401,1.2393,2.4954,0.6363,-0.8987,-2
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4642,-0.2226,-1.323,-2.0747,0.7118,-0.7988,-1.8386,1.033,-0.9695,-0.7128,-2.2395,-2.4041,-1.5726,1.1769,0.8459,0.2576,-0.5904,0.2314,-0.6989,-
0.9199,-9.2728,-1.0828,-2.1148,0.6578,0.2683,-2.2478,1.2175,-1.2084,-0.0602,0.5904,-1.2029,-1.5977,1.1498,0.7936,0.3169,-0.1047,-1.0004,-1.362
0.3504,1.0176,-0.8425,-2.16,0.5931,0.3583,2.5515,-0.3294,-4.233,-2.4111,-1.3351,-0.8425,-1.6178,1.1287,0.7475,-0.222,-1.7683,-1.4689,2.2909,-0
,1.1362,0.0223,2.0856,-2.284,-1.3341,1.264,-0.1453,-2.1062,1.5949,0.0107,0.7869,-1.6334,-0.8425,-1.914,0.6904,0.4984,1.1727,0.5177,-2.2449,-0.
2879,0.782,1.3187,-1.4431,-1.3592,1.2496,-0.1878,-1.1484,0.3679,2.7115,-0.6776,0.328,-1.2029,-1.9868,0.6029,0.2714,1.0764,1.7639,-1.5692,-0.57
-0.8299,2.4871,-0.9406,-2.1639,-1.3743,1.2358,-0.7543,-1.2202,1.3924,-1.601,-2.5541,-1.2334,-0.7224,-2.0471,0.5072,0.4529,2.5515,-2.1902,1.959
0.0099,0.603,-0.3581,-1.6834,-1.3969,1.2227,0.2867,-1.6783,1.0437,-2.016,-0.7392,-0.4728,-2.284,-2.1148,0.3851,1.0337,-0.6586,1.3145,-2.4601,-
,0.8497,0.718,-0.5879,-1.323,-1.4195,1.2044,0.8727,2.5515,3.1178,-2.1126,0.0057,1.2884,-1.6834,-2.1902,0.195,2.2047,0.0416,0.1451,0.3978,-0.20
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2.9868,-0.8269,-3.0139,-1.2029,-1.4622,1.1691,0.8538,1.3143,0.5357,-0.8402,0.3891,0.6137,-1.0828,-1.535,1.2326,0.0116,0.1858,1.7986,3.1389,2.1
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-1.9429,-0.4398,0.8947,-1.2029,-1.7132,1.0833,1.7317,1.2039,-0.4528,0.1014,0.9199,-9.2728,-0.8425,-1.6354,1.1053,0.8625,2.5515,-1.034,-0.1448,