Designing for algorithmic awareness
Materializing machine learning

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Abstract

The following paper explores how to materialize machine learning in order to make it tangible and sensible thereby offering users the needed tools for engaging the technology in reflective use. The project draws inspiration from the Static! research program on designing for energy awareness. Their approach to energy as a design material is adapted to the field of machine learning in order to use their tactics to engage the problem of unpacking and materializing machine learning with the goal of enabling reflective use. The project is grounded in Spotify and their use of machine learning. In particular their Discover Weekly feature is argued for as an example of a service that relies heavily on machine learning algorithms. With inspiration from The Living Lamp the combination of algae and microcontroller is framed as a computational composite. The composite is analysed based on the material strategy. The analysis is directed towards exploring the composites suitability for materializing the qualities of machine learning. The composite was found suitable for the design problem. Subsequently the composite is engaged in a prototype centric design process aimed at using it to materialize machine learning. The end result of the process is a functional prototype named Growing Data. The design uses the algae/computer composite to grow algae in relation to the data a user's music listening activities produce, thereby becoming a local representation of the distant abstract data that feed into the service’s machine learning algorithms. It exemplifies one possible strategy for materializing machine learning.
Introduction

Machine learning is becoming a larger and larger part of today's technological landscape. The possibilities seem vast and almost endless from applications in driverless cars (Pomerleau, 1991) to fine tuning music and film recommendation (Lops, 2011). The technology has even been applied to enable automatic drug discovery in the medical sector (Agarwal et. al., 2010).

Machine learning has its root in hardcore science, where it was valued for its ability to sift through incredible amounts of data, in ways impossible or at least impractical to any human.

In recent years the technology has departed from its roots and is becoming a part of an increasing number of commercial products, and will undoubtedly find its way into even more in the future. At the moment machine learning is at work when Google photos classifies and categorizes your photos to make them searchable by the content of the photo. When a online retailer, like Amazon, suggests an item that might be of interest, that power comes from machine learning algorithms. While indulging in the vast amounts of media content available on services, like Netflix and Spotify, machine learning algorithms run underneath the surface, hidden out of sight. The algorithms analyze your activity and compare it to the millions of other users to suggest you what you might like to listen to or watch next. These services, and the activities and rituals that accompany our use of them, demonstrate that machine learning is becoming increasingly interwoven into personal and domestic life. It plays a role in what we purchase, consume, watch, and listen to.

Related work

Traditionally the field of machine learning is dominated by engineering centric approaches with a heavy focus on optimization of the algorithmic techniques in order to make these faster, more accurate and applicable to novel areas. Rebecca Fiebrink’s work on the subject of “Real-time Human Interaction with Supervised Learning Algorithms for Music Composition and Performance” (Fiebrink, 2011) stands in stark contrast to the prevailing utilitarian focus within the field. In her thesis she argues for machine learning as an interest for the field of HCI research and its focus on the broader human context of computing systems. One of the key outcomes of her thesis is “a general-purpose software system for applying standard supervised learning algorithms in music and other real-time problem domains. This system, called the Wekinator[...]is published as a freely-available, open source software project, and several composers have already employed it in the creation of new musical instruments and compositions” (p. 1).

Bjorn Karmann’s (2016) graduation project “Objectifier” can be seen as an extension to the more artistically oriented work of Fiebrink on Wekinator. Building on the open-source software developed by Fiebrink, Objectifier is a small device that allows users to train a simple artificial intelligence without the use of coding. The interaction is described akin to the training of a dog, where cycles of Pavlovian conditioning are used to pair action and reaction - input and output. The project envisions “a shift from a passive consumer to an active, playful director of domestic technology” (Karmann, 2016, p. 1).

However technology is a double-edged sword. The merits of machine learning are apparent to most. A future, where driverless cars reduce road fatalities, algorithms help doctors diagnose diseases more effectively, and even
your grandma can train artificial intelligence, looks promising in all its techno utopian glory. However, the very same technology can in turn empower destructive ideologies. For this reason we as designers and researchers must question the techno utopian hype surrounding machine learning.

One such enquiry into the less appealing aspects of machine learning and machine vision is Zach Blas’s facial weaponization suite (2013). The suite consists of a series of “collective masks” that cannot be detected as human faces by biometric facial recognition technologies: “One mask, the Fag Face Mask, generated from the biometric facial data of many queer men’s faces, is a response to scientific studies that link determining sexual orientation through rapid facial recognition techniques.” (Blas, 2013, p.1). The other masks investigate and debate issues of racism in facial recognition technologies, feminism’s relations to concealment and imperceptibility and security technology at the Mexico-US border.

Similarly, Adam Harvey’s (2017) project “CV dazzle - Camouflage from face detection” explores how makeup and style can be used to hide from machine vision. The project at the same time provides an insight into how machine vision works and point to how to intervene in the power relationship that already exists.

From the above it is clear that the same technology that can help your grandma train an artificial intelligence to turn on the radio when she walks into the room, can at the same time be racist and oppressive. However the work presented in this paper does not aim to idolize or demonize machine learning. Instead it takes the position that what is needed is to render the often invisible machine learning processes tangible to its users. Thereby allowing user to engage in reflective use. The modest hope is that this allows users to acknowledge their role in the human machine relationship surrounding machine learning. Passing judgement on machine learning as either good or bad is not the goal of this project.

The Static! research program (Mazé, 2010) serves as inspiration towards how to approach the problem as problem-finding rather than problem-solving with the aim of enabling reflection on the implications of technology. What I argue for in this paper is a departure from hiding the complexities towards making them tangible. The implications of how machine learning algorithms affects us is already complex and abstract before the expert concealment performed by designers.

The research presented in this paper is centered around the following research question:

*How can machine learning be unpacked in a fashion that allows for the opening of a space for reflection where the user can gain the recognition of themselves as subject of machine learning?*
Machine learning algorithms can be perceived as abstract constructions that live in the digital realm outside the perception of most people. Making them tangible and open for reflection are therefore an especially wicked design problem that is not easily tackled. For that reason the project draws on the work produced in the Static! project (Mazé, 2010). A project that dealt with the similarly abstract material - electricity.

Static! - Designing for energy awareness

The Static! research program was established in 2004 and in the following years the program produced a series of inspiring projects that each “investigated the power of product design to materialize energy” (Mazé, 2010, p. 11). This was a radically different approach to sustainable design. They did not look to technology and design as a way to design better more efficient electronics that could solve the problems at hand. In contrast they attempted to “render it more visible and experiential in everyday life - and thus increase reflection and choice in daily life and lifestyles” (Mazé, 2010, p. 22).

In their work they argue that the problem of energy (over)consumption is the abstract nature of energy and its consumption (Mazé, 2010).

Machine learning algorithms and sustainable design might not seem to have much in common. However the Static! research program and their approach provide valuable insight into how to tackle both the problem of how to engage users in reflection and how to approach machine learning algorithms as a formgiving exercise.
Abstract materials
The authors provide a compelling account of electricity as abstract and point to the design of everyday things as part of the course.

Similarly the algorithmic processes that make up machine learning is equally - if not more - abstract to the user. Machine learning algorithms are hidden underneath the surface and are often abstract, incomprehensible and complex. A testament to this point is the fact that even the engineers responsible does not fully comprehend how they achieve their magical feasts (Bishop, 2006). To the end user the algorithms are hidden away, a technicality of no concern to them. The underlying infrastructure that enable suggestions and recommendations are hidden away behind neat user interfaces that enable a smooth user experience.

Static! is also a critique of the industrial design as profession and its role in expanding the consumption of electrical appliances (Enevi, 2007, p. 1). While industrial designs was hard at work on expanding consumption of electronic home appliances, interaction design worked equally hard on expanding consumption of digital artifacts - and recently through these, machine learning algorithms. Just as the expert tactics developed in HCI, and interaction design, was used to render the algorithms invisible, they can be used to give them material form and make them tangible and open for reflection.

Awareness
The insight that the problems surrounding electricity was one of awareness resonates with the position held by the author, that the problems in machine learning are a lack of awareness. Their insight that “we might consider the designed object as an opportunity for unpacking otherwise invisible and hidden processes” (Mazé, 2010, p. 20) offer a transferable strategy to approach machine learning.

The Static! research program provides an alternative to problem-solving. Instead of trying to solve the problems of energy with design and technology, both design and technology can play an important role in problem-finding - to expose the complex issues that lie underneath the surface.

However, there is a key difference between energy and algorithms. Static! operates from a departure point in the well established field of sustainable design. The consequences of energy consumption are abstract and detached from our everyday life. It is however well documented, and climate change deniers aside, there seems to be a consensus about the potentially harmful consequences. The same can not be said about the consequences of machine learning.

Unpacking
The author (Mazé, 2010) call for, what is described as, unpacking in contrast to packaging processes. He describe unpackaging as:

“Just as products can be considered to hide aspects of a process in the form of an apparently discrete and self contained material object, this same object can also be seen as an opportunity to express and materialize underlying processes” (Maze, 2010, p. 26).

While done in an often humorous way, the unpacking perspective is in effect peeling away the layers of concealment put in place by other designers.

Instead of thinking of the algorithmic processes of machine learning as something to be served to the user through a sleek user experience, unpacking provides an alternative perspective using “the object as a site for the
expression of otherwise intangible distant processes” (Mazé, 2010, p. 26)

Response
Static!’s approach to sustainable design build on two primary ideas:

“first, that we can explore design based on engagement rather than problem-solving, and secondly, that we can think of design not as packaging, but as a matter of unpacking complex issues[…]” (Mazé, 2010, p. 27).

In the Static! research program the two ideas is unfolded through two primary themes ‘working with energy as material’ and ‘reflective forms of use’.

From energy as material to algorithms as material

The idea of energy as a material stems from previous work (Löwgren & Stolterman, 2004) where digital technologies are framed as a material without form. Here they argue that “The digital technology - can in many ways be seen as a material without qualities” (Löwgren & Stolterman, 2004, p. 3)

Viewing electricity is similar light enables a designer to engage in formgiving practice with electricity as a material. However their aim to apply design in order to give form to energy to make it more present and tangible, is about more than visualizing energy. They further call for “connecting use - and users - to the systems behind” (Mazé, 2010, p. 28).

Transferring this to machine learning, a subject even closer to the initial work on information technology, it is possible to argue for machine learning and its algorithms as a material without qualities. For this reason the following project attempt to explore the algorithms that make up machine learning as material that can be subjected to formgiving with the expressed aim of finding ways to make it “more present and pressing - and thereby also something that invites reflection and engagement”(Mazé, 2010, p. 28).

Reflective use

In the Static! research program it is made clear that they make no attempts at solving the problem related to electricity and energy consumption. In contrast “[...]the goal is not to provide a user with a solution to a given problem but to create an incitement and a space for reflection” (Mazé, 2010, p. 25). The authors depart from the roots in HCI as concerned with usability and ease of use. The departure from usability provides several design opening. In particular “Venturing beyond notions of utility and usability, this has brought new perspectives on what the use of technology is, and could be, about” (Mazé, 2010, p. 29) and “[...] the expanded range of values associated with technology has also opened up a space for more critical exploration of its role” (p.29).

The ideal is that “Exposing such values in design can allow subsequent engagement with not only practical functionality of a design object but with more complicated and less tangible aspects of use - thereby opening up for more reflective forms of use” (Mazé, 2010, p.30).

The concept of reflective use allows the project at hand to be approached as problem-finding rather than problem-solving. To encourage users to reflect on the implications rather than provide a solution to fix them.
Prototypes served as the pivotal point for the explorations surrounding machine learning. In regards to the development and use of prototypes the project relies on Stephanie Houde and Charles Hill (2010) and their seminal paper on the subject of “What do Prototypes Prototype?”.

Houde and Hills define a prototype “[...] as any representation of a design idea, regardless of medium”(Houde and Hill, 2010, p. 3). This includes everything from sketches on a napkin to advanced hardware prototypes. This paper aligns itself with Houde and Hills definition of prototypes and uses it interchangeably with sketches to mean any materialization of an idea, independent of medium.

In order to guide work with prototypes the authors offer the following model (Figure 1), with the goal of separating design issues into three classes of questions with each their individual approaches:

![Figure 1. Model based on Houde and Hill (2010)](image)

Before proceeding each aspect will be briefly described. However this paper only provides a brief description and refer to the original paper for a more detailed description and discussion of the properties.

**Role** prototypes that ask questions within the role dimension are concerned with what the design can and should do for the user. Not how
it should look or feel or how to achieve the function on a technical level.

**Look and feel** centric prototypes have an explicit focus on the sensory experience of a design. The look and feel prototypes are closely related to traditional form-giving. This class of prototypes does not focus on how to make the prototyped look and feel possible on a technical level and does not ask questions about what role it should play in a user's life.

**Implementation** is concerned with the technicalities of the design. The focus is on how to make the design achieve an intended function - not how it should look or feel, or the role it should play. This usually requires a working system to be built.

Finally the authors add a fourth possible classification, being **Integration**. Integration prototypes are properly what is most commonly associated with prototypes. The holistic prototype that encapsulates the entire user experience of a given design. This is the class of prototype that most closely resembles the final product without emphasising one aspect or the other. With the addition of integration the final model takes the following form:

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**Prototyping methods**

For the project various prototyping techniques was applied - ranging from paper sketches and storyboards to software and hardware prototypes. All of these are considered commonplace enough that they do not warrant further elaboration.

In addition to these general types of prototypes, experience prototypes was also utilized. Experience prototypes are described “as a form of prototyping that enables design team members, users and clients to gain first-hand appreciation of existing or future conditions through active engagement with prototypes” (Buchenau & Suri, 2000, p.1). The concept of experience prototypes are not tied to any specific class of prototypes, instead it is an attitude that “[...] emphasize the experiential aspect of whatever representations are needed to successfully (re)live or convey an experience with a product, space or system” (Buchenau & Suri, 2000, p.2).
The focus is on creating artifacts, of any kind, that enable the designer or participant to experience what it might be like to interact with the design. Experience prototypes can, in Houde and Hill (2010) terms, be used to experience any dimension of a design.

Experience prototypes inform the design process by emphasising experiencing different aspects of the design as opposed to being reduced to contemplating what it might be like to experience it.
The first exploration consists of the ideas that spun out of the initial engagement with the technology. The result is a series of sketches of concepts for how to materialize machine learning in a tangible artifact. These initial sketches, or prototypes in Houde and Hills (2010) terms, focus on the role the design could play in the user's life. Each design explore different functionalities and how the might serve to materialize machine learning in the eyes of the user. All of the sketches also explore what the artifact could look like. With a strong emphasis on could. The physical form is less of interest than the role it would play in a user's life. That places the exploration presented in the coming chapter in the role dimension of Houde and Hills (2010) model, with a slight movement toward the look of the look and feel dimension. The prototypes are placed entirely opposite the implementation dimension since no consideration to the technical feasibility of the designs.

Figure 3. The initial explorations mapped out in Houde and Hill’s (2010) model.
Gaydar

The gaydar was a concept that worked out the premise that provided with a dataset consisting of pictures and audio samples of homosexual individuals it would be possible to identify an individual’s sexuality with the use of machine vision and audio processing. Hence the artifact would give the user to obtain the absurd notion of a gaydar sixthsense.

The design artifact mimics that of a directional microphone to bring forth associations to the the stereotypical images of a 1970’s spy. The use of the gaydar is similar to the use of a directional microphone. The user directs the device towards a person of interest and the device will process information from its sensors through machine learning algorithms to determine the sexuality of the person of interest. The result is displayed on a small screen placed on the back of the device.

Effeuiller la marguerite

The concept was based on the game of “He loves me, he loves me not” - in French Effeuiller la marguerite.

In the concept the petals was replaced with data tokens consisting of messages or audio samples from the object of affection. Instead plucking the petals from the flower the electronic petals are plugged into a flower like hub. Upon the insertion of the last petal a algorithm will inform the user whether their affection is returned or not. The algorithm is trained on the exchanges of in love individuals.
A machine(d) body

The concept mimics the shape of a traditional mirror. The artifact has however been devoid of the reflective surface that most often characterize a mirror. In its place is a camera module. Traditional interaction with a mirror is often an act of assessing oneself, whether for the purpose of inspecting and evaluating a outfit or performing the same evaluation on the body itself. In the concept that activity has been augmented, or replaced, with a machine learning algorithm which the user teach their preferred body image. Instead of doing the evaluation yourself the mirror simply judge your look as in line with the ideal or not.

Summarization

While the concepts do indeed embody and give form to problems in machine learning I argue that they are too far removed from the everyday lifeworld of the user. The consequence is that I suspect that they would fail to engage the user in the wanted critical reflection. The objective is to arrive at an artifacts that is “strangely familiar” (Dunne & Raby, 2013). The artifact should be close enough to the existing life world of the user to promote reflection.

The concepts raise awareness about issues in machine learning but fail to unpack and materialise the underlying technology. They serve more as dystopian vision of the future rather than thoughtful unpacking of the technology. The ongoing process the design work should be centered around shedding light on the role of algorithms in contexts that more closely resembles those of the users.

In addition to the above mentioned critique of the initial explorations the key problem identified is that the exploration proved to wide. It was not grounded in any concrete issue, product or technology. The result was that by trying to tackle the entirety of machine learning in a project of such limited scope it became unfocused. Reflection on issues related to machine learning without a concrete grounding runs the risk of becoming to abstract and speculative. The question becomes issues for whom in what context? The aim to uncover universal issues is by far a too ambitious one.

In addition the explorations face the problem of being novel. All of them are entirely new artifacts that do not fit into any existing mental models belonging to the user. I argue that it would be beneficial to the project if it adopted the tactic of augmenting existing machine learning practices instead of trying to invent new ones. This tactic ensures that the design stays relatable to the user and thereby ideally it becomes suited to open up at space for reflection.
To remedy the shortcoming of the initial exploration, the following investigation aimed to uncover where machine learning is an essential material in determining the normal appearance or behavior of the artifact. This tactic was inspired by Ernevi, Palm and Redström (2007) in their work on Erratic appliances.

In the introduction to this paper several cases were mentioned where machine learning is at work. Compiling a list of products and services that utilized machine learning would easily fill this paper, given the rapid adoption of the technology. As such that is by no means the aim or within the scope. Instead the focus is on a few cases where machine learning is central to the perceived functionality of the product. Perceived functionality is used to describe the cases where machine learning is a central building block in the artefact that meets the user.

Recommender systems offer a suitable point of departure given their heavy reliance on machine learning algorithms.

**Recommender systems**

In this category we find the video streaming service Netflix, the online retailer Amazon, and the music streaming service Spotify. Recommender systems are at work in a myriad of other artifacts to numerous to mention and has been subject of intensive research within the field of machine learning (Lops, 2011).

Recommender systems have been a field of research since the 1990’s (Resnick & Varian, 1997) and research in integrating this field with machine learning was done as early as 1998 (Billsus & Pazzani). As the name suggests the field focused on providing appropriate recommendations. The field of recommender systems can be said to be one of
the earliest commercial applications of machine learning.

Finding a suitable service as the point of departure

Through extensive literature search it has not been possible to find any research on how, or even, if users perceive their role in this human-machine relationship. The hypothesis is that users give little thought to how machine learning might influence them. One could argue, that this in part could be due to the hard work to provide a smooth user journey and hide away any complexities. This raises the question of how it would impact the user experience if this concealment was peeled away and the underlying data collection and subsequent learning was exposed. This framing avoid any normative judgement of machine learning as either good or bad, but opens up a space for reflection by making process of being learning upon visible and experienceable. The hope is that this would force the user to acknowledge their role in the human-machine relationship.

Recommender systems play a significant role in determining what content users are presented. This is true for any act of curating content. What sets the current generation of recommender systems apart is that the recommendations are tailored based on the users own data. By a machine learning algorithm that carefully studies user behavior and acts accordingly. For this reason recommender systems provide an interesting case because of the power it holds to control and arrange a small subsection of our reality. A key disadvantage to recommender systems, as the setting for exposing machine learning, is that as of now they are almost exclusively at use in screen based environments. In order to enable reflection a tangible artifact would be more suited and open to reflection.

Selecting the appropriate instance of a recommender system is crucial, since certain qualities is needed for it to be appropriate as the vehicle for unpacking machine learning. While filled to the brim with machine learning algorithms the online retailer Amazon only engages the user in relatively short sessions. This leads to the concerns that a shopping session, which most likely would occur at most once a week, simply does not provide the design space necessary to open up a space for reflection. In addition the fact that Amazon is a retailer and thus deal in the exchange of goods for money means that the machine algorithms take on a somewhat more villainous role. The assumption is that exposing machine learning algorithms in this context would run the risk of villainizing the service as a manipulative one. Since the goal is not to pass judgement of machine learning this would not open up a space for reflection on the user's own view on the practice. Instead it would most likely amount to little more than finger pointing.

In contrast to shopping on Amazon, Spotify follows its user throughout the day for extended periods of time. Furthermore the practice of handing over your listening habits to a service to provide music recommendations is argued to be much less value laden than the money centric activities involved in Amazon's offerings.

For the reasons elaborated upon above I chose to proceed with Spotify and its Discover Weekly feature as the foundation for the design.

Spotify and Discover Weekly

The following section digs deeper into how Spotify and in particular its Discover Weekly
feature work and gives a more detailed overview of its features in order to enable the coming work on using the service and the foundation for materializing machine learning. It is important to state that the goal is not to redesign Spotify or critique the existing service. Due to the consideration described earlier it was deemed that in order to prompt reflection the design had to be grounding in existing products in order not to dismissed as pure science fiction. For this reason the fidelity of the following section is aimed, not at giving an in-depth account of the feature, instead the aim is to map out the component in a way that it can be manipulated and used as a vehicle for unpacking machine learning.

On the face of it Discover Weekly is by no means complex. It is a playlist like any other Spotify playlist, containing 30 songs. In this regard the playlist in appearance looks like the other curated Spotify playlist. What sets it apart is the fact that the playlist is updated once every monday, and that it is tailored to each individual user. This gives it the appearance of a custom curated mixtape that arrive each monday, custom tailored to each user. The interaction with the playlist is on the face of it no different than any other playlist. The unique thing about it is how it utilizes advanced machine learning algorithms to generate the content. Hidden away behind the interface out of sight for any standard user.

Spotify has not made much information about how the feature specifically works public. However two sources give an interesting look under the hood. Firstly a slide deck is published by the two Spotify engineers Chris Johnson and Edward Newertt (2015) for DataEngConf. Through the slides it is possible to understand some of the technical aspect of discover weekly. Secondly it is an in depth article written by Adam Pasnick (2015), featuring Mathew Orgel, who at the time oversaw the service. From the two sources it is possible to understand how Discover Weekly works, at least on a somewhat abstracted level. Since the purpose of this project is not concerned with advancing, changing or solving existing machine learning practices, an abstracted understanding of the underlying processes is adequate.

The data that feed Spotify's machine learning algorithms are aggregated from several different sources.

Firstly one of the main ingredients in the algorithms come from playlists. The playlists provide an enormous data set for use in the machine learning algorithms. The DataEngConf slides cites 1.5 billion user generated playlists (Johnson & Newett, 2015). The article, also from 2015, estimates around 2 billion playlists (Pasick, 2015). The following quote neatly summarizes how Spotify makes use of playlists to generate their Discover Weekly playlists:

“Spotify considers everything from professionally curated playlists like RapCaviar to your cousin Joe’s summer barbecue jams. It gives extra weight to the company’s own playlists and those with more followers. Then it attempts to fill in the blanks between your listening habits and those with similar tastes. In the simplest terms, if Spotify notices that two of your favorite songs tend to appear on playlists along with a third song you haven’t heard before, it will suggest the new song to you” (Pasick, 2015, p. 1).

Secondly the algorithm relies on what Spotify describes as each user’s unique taste profile (Pasick, 2015). The way that Spotify generates these taste profiles for each user is highly technical, and as such outside the scope of this paper. For an in depth technical explanation of how it is achieved see (Johnson & Newett, 2015). For the purpose of this paper only a
simplified overview will be given. At its core, taste profiles consists of Spotify creating a profile of each user’s individualized taste in music. These are never showed to the user and only serve to guide the underlying machinery. These are achieved by running Natural language processing machine learning algorithms on blogs and other relevant sources. In layman's terms this means that they make machine learning algorithms read music sites in order to analyse how different artists are described. This is combined with deep learning techniques applied to audio files to map out songs in a latent space representation. Each of these processes are highly complex and diving further into the technicalities are outside the scope of this paper, and would not likely further inform the design task at hand.

At this point it should be clear that Spotify's Discover Weekly, as it exists now, is only possible because of machine learning. The following quote from Edward Newett is a testament to this point: “We’ve been experimenting with different approaches with deep learning and neural nets, and it is one of the most important features for what generates Discover Weekly,”. Spotify is a real world embodiment of machine learning and an example of a service where machine learning is massively at work hidden behind the scenes. To the average user the algorithms are hidden away out of sight behind a neat user experience. This is not necessarily a bad thing, but it does however make it uniquely suitable as grounding for the wanted space for reflection.

The above section should provide the needed description of the feature to enable a design around it while also clearly outline how machine learning is integral to the service. This, combined with the ubiquitous nature of the service, makes it ideal as the grounding for the coming work to expose machine learning in a way that opens up a space for reflection. Furthermore, the, to some degree, value neutral nature of sharing music data - compared to for instance financial data, makes it possible to work towards a design that exposes without condemning machine learning.
Previously parallels were drawn from machine learning to the intangible nature of electricity and digital technologies as material without form. For this reason, in order to establish the wanted space for reflection, a physical form is needed. A material to give form to, and materialize the underlying machine learning processes. Digital material being materials without form means that unlike manipulating, or shaping an existing form, a new one has to be invented. The material form has to be one which can, if not duplicated then at least, mirror some of the qualities that lie in the underlying processes. In order to be able to qualify the selection of a material form it is of import to briefly map out the core qualities of the underlying process sought to be materialized. These processes being the machine learning activities that make Discover Weekly possible.

The pivotal point for the generation of the Discover Weekly playlist is the user's listening habits. Each time a user listens to a track, the algorithms learns. Each time a user saves a track to a playlist, the algorithms learns and each time the users chooses to skip a song, the algorithm learns. All of the action of the users is carefully interpreted by the algorithms to create the taste profile that serves as the departure point for benchmarking whether or not a certain user will enjoy a certain track. There is this symbiotic relationship between the algorithms and the user. The user feeds the algorithms with their listening data. In return the algorithms return a carefully curated personalized playlist. The information the user provides further informs the algorithms and allows them to make increasingly accurate recommendation for other users.

In this relationship there is a strong link to other users and one could imagine designs that would embody the invisible connection that each user have to other users. However given the scope of the project, and the fact that the design should function as an individual objects
the design will refrain from tackling the social and interconnected aspect of the service.

The material chosen should be able to embody the information that grows for each song the users hear, and every time they save a song that they found enjoyable to a playlist. The material should be able to make the distant, abstract, and growing body of data present and tangible. The material should be able to embody how machine learning algorithms are fed data in order to grow and become more efficient and advanced. In this aspect they have an almost biological quality to them. For this reason it was chosen to draw inspiration from the living lamp project.

The Living Lamp

Unrelated to the project detailed in this paper I functioned as co-facilitator for a DIYbio(do it yourself biology) and maker workshop titled “The Living Lamp”. The workshop was executed as a part of the 2017 edition of the Made in Space technology festival and was developed by Keenan Pinto.

![Image](image)

Figure 7. The living lamp. Left assembled and right in it constituent parts.

The workshop was centered around building one of Pinto’s inventions, the Living Lamp (Figure 7). The Living Lamp consists of an Erlenmeyer flask with an algae solution and a base that hosts the electronic components. There is a Wemos microcontroller in the base, it is delivering the computational power. The microcontroller is connected to a ring of neopixel LEDs and a air pump. Two switches is also connected for toggling the on/off of the air pump and the LEDs, respectively.

The living part of the lamp is the algae solution inside the Erlenmeyer flask. The solution is made out of a dose of living algae organisms, fertilizer and natron combined with water to dilute the mixture. This provides the basis for growing a colony of algae. Besides the need for the above mentioned starting mixture, the algae need light and movement in the water in order to aerate it. The air pump provides movement and the LED provides the source of light.

The Living Lamp provides a suitable starting point for the design at hand. It is a tangible object designed to be placed within a person's living space making it ideal for being the pivotal point for the wanted space for reflection. By being a tangible object placed within the user's living space, it is fitting as the vessel for embodying the distant and abstract machine learning processes. The inspiration drawn from The Living Lamp is the core functionality of a self contained object that can grow algae. As such algae become the primary design material of investigation. Its ability to rapidly multiply and grow in a closed system makes it useful for materializing the expression of the otherwise intangible distant, and the growing body of machine learning data.

Algae as a design material

The design problem at hand is focused on using algae as “[…]a site for the expression of otherwise intangible distant processes” (Mazé, 2010, p. 26) and shape it into an object that can “express and materialize underlying processes” (Maze, 2010, p. 26). In order to undertake the design problem one must first understand algae as a material. As a carpenter
must understand the qualities that lie in wood before he builds a chair.

In order to establish this understanding, I turn to Anna Vallgårda and Tomas Sokoler and their material strategy (2010). Through the lens of their material strategy it is possible to understand the combination of algae and microcontroller as a computational composite. This understanding provides valuable insight how to engage with the composite in a formgiving practice to create an expression that make machine learning tangible.

“The leitmotif for the strategy is “function resides in the expression of things,” articulated by Hallnäs and Redström (2006, p. 166). This means that the expression or the form is pivotal to the functionality and that one cannot be designed independently of the other. (Vallgårda & Sokoler, 2010) For the project at hand the function wanted is the materialization of the distant machine learning data. Accepting that “function resides in the expression of things” (Vallgårda & Sokoler, 2010) it is clear that knowledge is needed of the material in order to form it into an expression where that functionality can reside.

The material strategy align with the views held by Löwgren & Stolterman (2004) on digital technologies as a material without qualities in that “[...], the computer can be manipulated into innumerable forms. In and by themselves, however, they lack expressiveness and human perceivable form” (Vallgårda & Sokoler, 2010).

Computational composites

The pivotal point for the material strategy is the concept of computational composites, which has its roots in previous work (Vallgårda & Redström, 2007). A computational composite in its most basic sense is “a material composition of which the computer is one constituent” (Vallgårda & Sokoler, 2010). Vallgårda and Sokoler point to the exchange of energy between the constituents of any composite as the way that the materials can affect each other and the combined composite. For the computational component of a composite the energy is primarily electrical energy, while the other constituents energetic potential is located with the realm of thermal, mechanical or chemical energy (Vallgårda & Sokoler, 2010). The exchange between electrical and other types of energy is defined by (Vallgårda & Sokoler, 2010) as transduction, and is done through a transducer. The authors hold that for a computer to participate in this exchange of energy, and thereby be a functional part of a composite, it most include a transducer (Vallgårda & Sokoler, 2010). This makes transducer the element that binds the constituents of a composite together (Vallgårda & Sokoler, 2010).

Returning to The Living Lamp I argue that the combination of microcontroller and algae have the qualities that qualify it as a computational composite. The microcontroller and algae are connected through the addition of the transducers, being the DC-motor in the air pump that allows the transfer of electrical energy into mechanical movement that pushes air into the mixture, and the LED that allows the transfer from electrical energy to light. The energy added to the algae, by the transducer, is then lastly transferred to growth in the algae by meeting the requirements needed for photosynthesis. As such The Living Lamp can control the growth of the algae, and thereby the expression. It is, however, not the same fine grained control as seen in many other composites. Such an inclusion of a non traditional material into the realm of computational composites align well with the purpose of the material strategy being: “to explore how materials that are not traditionally associated with computational technology can help to form new expressions of computations” (Vallgårda & Sokoler, 2010).
(Vallgårda & Sokoler, 2010) argue that: “[...] most computational composites tend to be art pieces or one-off prototypes rather than fully developed materials ready for designers to use” (p. 5). This however, is not viewed as a shortcoming, rather the authors argues that “[...] the ideas invested in these are crucial for the ability for technologically and imaginable mature this new material branch” (p. 5). This is certainly true for an algae/computer composite, it is by no means a fully matured or realised composite.

The authors further provide a mapping of existing exemplary samples that make use of computational composites (Figure 8). The mapping is done along two dimension: material vs. product/building and the degree of open-endedness of the material properties.

![Figure 8. Original diagram of computational composites (Vallgårda & Sokoler, 2010)](image)

Embed in The Living Lamp the composite could be argued to be placed far out on the axis towards product/building with fairly predefined properties. However isolating the algae/computer composite makes it possible to view it more as a material, and less as a predefined product/building. The properties are at the current moment somewhat predetermined and limited to controlling the growth of algae through the embedded transducers. Given these consideration the following mapping is suggested (Figure 9):

![Figure 9. Diagram with the living lamp and algae/computer composite mapped out. Adapted from Vallgårda and Sokoler (2010)](image)

As such The Living Lamp is used as a prototyping tool in order to explore the properties and technical possibilities that lie in an algae/computer composite. The focus is on using the prototype to understand the material, and it is only concerned with the role it plays in the user's life in terms of how the material properties are suited to achieve the desired functionality, being to materialize machine learning. Since the technicalities of the material are so closely linked to the look and feel the mapping of this prototype is shifted towards the look and feel dimension. (Figure 10).
Accepting the the combination of algae and computer as a composite material, the logical next question becomes: what are these properties and how is it possible to develop a formgiving practice around them?

Vallgårda and Sokoler (2010) articulate some of the possible material properties of a computer and the potential material properties of computational composites. In the following section the properties and how they are embodied in the algae/computer composite, will be described. It will furthermore be discussed how the particular embodiment of the properties make it suitable for embodying the machine learning processes present in Spotify's Discover Weekly.

**Temporality**

The property of temporality relates to the power of computation to change the expression of a given material over time.

Looking at the algae/computer composite through the lens of temporality it is primarily the movement in the mixture, the light added, and the growth of algae that exhibit temporal change. The movement in the water and the light exhibit fairly straightforward temporal properties. In can be on or off and modulated in between the two states. The effect of the two on the growth of algae does however allow a more complex temporal form to emmerge. As the algae are aerated and exposed to light, the requirements for photosynthesis are met, which leads to growth of the algae. It multiplies. As new algae organism are created in the mixture its color is affected. Depending on the concentration of the starting mixture it can be almost transparent and almost inseparable in expression to water. As the algae grow the mixture changes in color from its starting point towards a deep green.

In addition to the change in color the organism also begin to fill the mixture with their physical presence. The effect of this is a change of transparent fluid towards a more opaque one. This has the effect that it begins to catch or block out light. This makes the composite able to go from transparent to opaque over time, albeit not a rapid change. This might provide several design possibilities with the material.

This ability to change the expression of the composite over time is what makes it possible to map the machine learning processes over time to changes in the material.

**Reversibility and accumulation**

The property of temporality expressed through change is closely linked to the property of reversibility and accumulation. The changes can both be reversible or accumulative and a combination of the two. thereof. The authors state that “In computational composites there are two sources of memory: one is the computer and the other is in the material components” (Vallgårda & Sokoler, 2010, p. 8).

The choice of whether to include both reversibility and accumulation or only one have a great impact on the expression of a object. Chronos Chromos Concrete (Vallgårda & Sokoler) are able to accumulate changes and
subsequently reverse these entirely, returning to its initial state. This makes it ideal for a building material that can serve multiple functionalities. In contrast the Burn-out Tablecloth (Landin, Persson, & Worbin, 2008) are only accumulating changes with no ability to reverse to its previous state due to the aggressive change of burning patterns in the table cloth in response to mobile phone signals. This gives the material the ability to embody consequence is a more pressing manner than it would if the imprint could simply be reversed. By choosing to only accumulate changes in the material it opens up a space for reflection on mobile use in an arguably much stronger fashion. Imagine a table made out of the Chronos Chromos Concrete that responds to nearby phone signals by displaying a pattern in its surface. Due to its reversible properties it would not embody nearly the same kind of consequence as the Burn-out Tablecloth. The table would be able to reset and return to its initial state reducing it to a simple visualization without consequence. Due to the computational constituent in the concrete composite it would of course be made to accumulate changes never reversing to any initial state. However the possibility of reversibility would always be there both from a technical view but most importantly from the view of the user. The non-computational constituent would never be permanently changed or scared. I argue that this makes for a less powerful expression of consequence.

Returning to the algae/computer composite, in its current form i only express the accumulative property. For every time the requirements for photosynthesis are meet the amount of algae are accumulated. For the project at hand the lack of reversibility fits neatly with the intention to map, albeit in an indirect manner, the growth of the algae to the distant machine learning processes. The moment data has left your local network it is no longer yours. There is no taking it back or controlling its usage. It merely accumulate on some distant server for Spotify to do with as they desire. This is apparent from the Spotify Terms and Conditions of Use (Spotify.com, 2017).

With the intention of mapping the distant data collected on the user to a local representation using the algae/computer composite it is only fitting that the composite mirror the accumulative properties of the data. Previously it was argued that the Burn-out Tablecloth was able to embody a strong sense of consequence by letting changes accumulate. Similarly it argued that by making the accumulative nature of the users data tangible it might open up the possibility for the user to reflect on this fact.

**Computed Causality**

The property of computed causality is properly one of the properties that most starkly differentiate the possible expressions of computational composites from any other form of composite material. The ability to establish any desired cause-and-effect is primarily limited by what transducer that bind the constituents together. This ability can be used to exaggerate or moderate existing casualties or even establish entirely new ones (Vallgårda & Sokoler, 2010).

In the algae/computer composite existing causality within the material is the cause-effect relationship between the conditions for photosynthesis and the subsequent growth of algae. By putting the computational constituent in control of the conditions it possible to control the growth of the algae. Not with the fine grained control it has over it LEDs or motors but does control it through the embedded transducers. Naturally there is no causal link between the data that reside in the domain of electrical energy and the growth of algae that reside in the domain of chemical energy. But by controlling the light need for
the chemical reactions it is possible to bridge this gap.

This opens up the possibility of establishing hitherto non-existent cause and effect. For the project at hand it allows the connection between the transfer of data and the growth of the algae. By establishing this causal relationship it in turn makes it possible to creating a local representation of the data transferred. Currently the data reside in the realm of electrical energy, not sensible to the human perception. A user cannot sense the data leaving their computer and have no idea of the temporal changes happening inside the realm of electricity or its accumulation on far away server. Through the algae/computer composite it is possible to make in sensible and tangible to human perception with the possible of enabling reflection on its existence.

Connectability

The property of connectability refers to the ability of computer to communicate with other computers (Vallgårda & Sokoler, 2010). The property of connectability is experienced in designs where the computer connects physically separated spaces. In relation to this they argue that it allow for “a material physically separated but behaving as if it were physically conjoined” (Vallgårda & Sokoler, 2010, p. 10).

This property is of paramount interest to the design problem at hand as the goal is explicitly to establish a link between the distant amount of data created by using Spotify and a tangible artifact. As stated earlier there is no natural link between the growth of algae and data but by combining the algae with a computer in a composite it becomes possible to create the expression of a connectability between the two. There is nothing in the core algae/computer composites that directly express connectability. It is a closed system with no communicative ability. However due to the fact that it is build around the Wemos microcontroller it have the potential to achieve a myriad of expression through connectability. The project at hand focuses on the connection between algae and distant data but it is certainly possible to imagine future research focused unearthing other connections.

In the above section The Living Lamp was described and an argument was made for framing the combination of algae with a microcontroller as a computational composite. This framing allowed the newly established composite to be analysed in terms of the four properties of computational composites presented in the material strategy (Vallgårda & Sokoler, 2010). Each property was also analysed with a focus on what kind of opportunities they afford in relation to the goal of making the intangible machine learning processes tangible in a design that utilize the algae/computer composite. The algae/computer composite is deemed suitable for tackling the design problem. The work forward focusses on how to engage the material in a formgiving process that shape its expression to achieve the functionality of making machine learning algorithms tangible.
Adapting The Living Lamp

The most straightforward design possibility would be to adapt the existing Living Lamp to the design problem at hand. For this reason the first design explorations focused on how to incorporate the wanted functionality and expression in the existing artifact. Doing this means connecting it together with Spotify and redesigning its expression to suit the goal of materializing machine learning processes.

Spotify has made an API (Application Programming Interface) available for their service. This makes it possible to create third party objects like bluetooth speakers that sends and receive commands to and from the Spotify application. By writing a small application that utilizes the API it would be possible to access whether or not a song was playing, and thereby sending data to Spotify, on the Spotify account running on a connected computer. This could in turn be used as input for the microcontroller in The Living Lamp triggering the light and air pump and thereby fulfilling the requirement for photosynthesis and the subsequent growth in the algae. The result would establishing a connection between playing a song, thereby feeding the machine learning algorithms, and feeding the algae.

Storyboard prototype

However before being derailed by the self perceived genius of using the existing Living Lamp in this new role, it was decided to do a series of simple prototypes to test out the idea before dedicating time and resources to developing a working prototype of the idea. The prototype made was a simple storyboard of how the existing Living Lamp would function as the materialization of the data collection that enables machine learning. The storyboard features a user by his desk as he presses play in the Spotify application the lamp is activated establishing the link between the act of listening to music and the activity of
the lamp. The storyboard thereafter details how the algae grow in relation to the user’s listening activities. In the last frame the user looks at the lamp and reflects on the distant data that it represents. The storyboard can be classified as a role prototype due to its questions about the role and functionality in the user's life. It asks “How would the lamp function as a materialization of the data collection that enable machine learning”. It explores the context it would be placed in, and how, and if, the user can achieve the intended functionality.

![Figure 11. Storyboard of possible use scenario.](image)

It became apparent from the storyboard that in order for events to play out as depicted, the user would have to be informed about the mapping between the algae and the distant data it represent. Otherwise the events depicted might well end with a frame depicting a user happy about how his listening habits had grown a flask of algae with no reflection on any sort of data or machine learning. This raises the problem of how to make it apparent to the user that it is not the music that feeds the algae, instead it is the data the listening activity produces. The insight is somewhat obvious in nature, but if not for the storyboard, it could have been overlooked as the link between data and algae was so solidified in the mind of the designer at this point.

Experience prototyping in context

To supplement the questions asked in the storyboard a simple experience prototype was deviced. Storyboards rely on scenarios that, to a certain degree, is spun out of pure imagination, experience prototypes served as a tool to balance this, and to get a first hand experience of the role and functionality of the design. The prototype was inspired by the often simple, quick and low cost prototypes described by Buchenau and Suri (2000), used to get a first hand feeling for the user experience.

To experience what role the design would play in a user life the prototype simply consisted of placing a living lamp of the desk of the designer. To simulated the intended functionality the designer turned the lamp on each time Spotify was turned on. This simulated the experience of linking the act of listening to music to the activity of the living lamp. The experience prototype was acted out throughout a week.

The experience prototype deepened the concern that in the current form the living lamp did not materialize machine learning or its data, it merely provided an unrelated visualization of listening to music. It did however indicate that the placement of the device within the proximity of the listening activity allowed it to achieve ambient attention throughout the day.

Experience prototyping with another designer

The previous prototypes mainly focus on the role and functionality of the design while paying little or no attention to how the device looks and feels and how it should actually be made to work. For this reason the following exploration focused on how to device a prototype that could begin to inform the look and feel of the design in addition to deepening
the understanding of its role. The problems of the mapping between data and algae were likewise problems that need to be explored through the look and feel of the design because of how closely linked their are to the physical form of the design.

In order not to dedicate too much time and resources towards, what could be a ultimately failed design, it was decided to use the existing Living Lamp in combination with Wizard of Oz and role playing techniques as an experience prototype to explore the look and feel. Up until this point the design had only ever been in the hands of one designer, the author. Accepting the fact that only so much can be ascribed to a designer's self-judgement, it was decided to recruit a fellow designer and Spotify user as a participant in a short session surrounding the prototype. The session consisted of a short role playing session with the prototype, where the other designer would be the user while the the functionality was simulated by simply turning it on or off according to whether or not music was playing. Following the session was a discussing focusing of the experience of interacting with the artifact and its look and feel.

![Image](image.png)

**Figure 12. Experience prototype with fellow designer**

The questions of interest in this prototype was firstly if it was clear that the algae was a materialization of the data the music listening activity produces. This question grew out of engagement with previous prototypes that indicated that the link between data and algae was too weak. And secondly to explore what values the participant associated with the current form. One of the main goals of the project was to enable reflection on machine learning not pass judgement on it. This must be reflected in the look and feel of the artifact.

The session yielded several insights into the designs role and look and feel. When asked to describe how she experiences the connection between the lamp and her listening activities, it was described as “a quirky on/off switch” and that the only link was that when music was turned on the lamp turned on too. It did not prompt any deeper reflection. The respondent argued that much could be improved by how the story of the lamp was framed. Hinting that maybe the design does not necessarily have to be intuitive and self explanatory. The respondent furthermore pointed out that the current form could be a visualization for anything in its current form. No part of its look and feel made her think of data, music or how one produces the other.

Upon being informed of the intent of the lamp to give form to the data produced by the listening activity she argued that if the production of data was more closely linked to feedback it could strengthen the mapping, for example in the form of light turning on everytime a new song came on. Out of this grew a discussion on how the data is an invisible byproduct of listening to music, and the problem of separating the music and the data byproduct. However, as a Spotify user herself, she felt that the existence of Discover Weekly, and its spot on recommendation, left her with a feeling of a system that learned and grew, although with no link to how.

While merely a result of the low-fi prototype the respondent noted that it worked in the designs favor that control of the music was still situated on the laptop or smartphone, since
the interaction normally resided. The respondent furthermore raised concern that given the slowly evolving temporal form it was hard to experience the full design without being in possession of the design over a longer period.

When asked about what association the current form conjured she described it as reminding her of a chemistry class in primary school due to its resemblance to a chemistry experiment. She continued that her associations quickly continued towards illicit drug manufacturing, due to its resemblance to processes seen in the TV series Breaking Bad. When asked about what implication those associations had, she noted that it made it seem somewhat dangerous, like a unknown chemistry experiment. The design lead her to speculate about whether or not it might produce toxic gasses. None of her association were related to data or music once again stating that it could visualize anything.

To summarize, the respondent did not experience any link between the lamp and data, to her it was a lamp that used Spotify as an on/off switch. It failed to link the algae to the data in any notable way, instead the algae was linked to the music. In terms of the look of the artifact it gave the impression of being some kind of chemistry experiment with a possible dangerous subtext. The look was to not related to music or the data it produces in any notable way.

The findings from the session inspire the ongoing design process by stressing that the current mapping between data and algae is too weak and need further work in order to be experienceable. It brings to light the problem of how the data and the music can be separated. The findings furthermore highlights that using the look and feel of the existing living lamp does not work without modifications. It is not suitable as a unbiased materialization of the underlying machine learning processes. This is due to how it looks like a chemistry experiment unrelated to neither music nor data. It its argued that the design needs to be more firmly rooted in the activity of the listening activity to be experienced as anything else than a gimmicky addition with an unclear link to music or data.

Experience prototyping added functionality

Following the previously described session another one was executed focusing on a slightly modified prototype. It had become clear that the mapping between algae and data was too unclear. In order to remedy this shortcoming efforts, it was focused on how the two tightly connected phenomena of listening to music and feeding the machine learning algorithms data could be separated. Initially they appear inseparable, one and the same thing. However, after returning to the information about Discover Weekly provided by Johnson and Newertt (2015) it became clear that private session feature of Spotify might provide a way to separate the two. The feature, while toggled on, ensure that no activity is shared on Spotify social or social media. According to the two engineers, it does however also mean that no data is send to its machine learning algorithms. In effect this means that two different modes of listening to Spotify exists, one that send data and one that does not.

This realization gave birth to the idea that by including this feature explicitly in the Living Lamp it would be possible for the user to experience that only listening activity that transmit data feeds the algae.

In order to explore if this would strengthen the mapping between algae and data the roleplaying scenario was once again played out with the addition of a makeshift button that toggled privacy mode on and off. The simulated behavior was adapted to only turn
on when the privacy mode was off and the music was playing.

![Image](image.png)

Figure 13. Simple experience prototype to explore the idea of a privacy switch.

The main questions of this prototype was if the addition of a privacy button would enable a stronger mapping between algae and data and if the toggle button had the appropriate look and feel for this feature.

The initial response was that it did in fact remedy the weak mapping. After playing around with the button and experiencing the simulated behaviour of the lamp the respondent felt that the addition made it possible to differentiate between two types of listening activities, one that feed the lamp and one that did not. Due to it utilizing an already known feature it was clear that the difference was about the sharing of data. However concerns were voiced that the feature is normally used to ensure that data is not sent and displayed on social media to ensure that a user can keep their Justin Bieber and Nickelback marathons to themselves. This caused the respondent to experience that the privacy switch kept data from being shared with the lamp and social media, but it did not make her feel that it was kept from Spotify. It was argued that this was due to the functionality the privacy mode normally delivered.

The respondent once again critiqued the lack of feedback that directly indicated the transfer of data. She argued that with a stronger feedback was needed to establish that the lamp is fed data.

To summarize the respondent found that the addition of the switch helped remedy the weak mapping located in the previous prototype. It effectively gave her the tools to establish two types of feedback from her listening activity making it possible to differentiate between listening that transferred data and listening that did not. However a new problem was unearthed. Who is the data private from? Using an existing feature made it possible to separate the two but it also carried with it the existing rationality for using it - too keep data from social media. It was also argued that additional feedback was needed to emphasize the transference of data. This gave raise to multiple ideas of symbolic gestures and metaphor as tool for making the mapping between data and the physical reality more apparent.

The findings inspire the ongoing design process by confirming the use of the privacy mode as a way to make data and music separable. However it simultaneously brought several new design problems to light, as a consequence of using the privacy feature. Going forward a primary concern should be how to resolve these issues while maintaining the separation of data and music. This should be done by making it clear that the data is kept from Spotify and their machine learning algorithms and not only from social media and other prying eyes.

The Living Lamp served as a perfect prototype tool for exploring the possibilities of a algae/computer composite. However when it was attempted to adapt it to the wanted
functionality of materializing the data that fed the machine learning algorithms, it became apparent that it had several shortcomings making it unfit for the design problems at hand.
In the following chapter the main results of the projects are detailed and the final design is presented. Before proceeding to the final design the main findings are presented.

The first chapter approaches this question by looking to other projects with similar goals. In this regard Static! was identified as an inspiration. Through adapting their work on designing for energy awareness it was possible to frame the problem as designing for algorithmic awareness. To design for engagement rather than problem-solving. Inspired by their tactics the goal became to unpack machine learning in a way that made it present and tangible. Thereby raising awareness and allowing the user to engage in reflective use.

Following the newly establish scope for the project a series of design were developed. Each aimed to materialize machine learning in different ways with the hope of enabling reflective use. However through the analysis of the concepts it became clear that they, while materializing machine learning, were too far removed from reality. Each was an entirely new artifact removed from the existing life world of the user. They were dystopian science fiction and were discarded as such. It was argued that their failure came from lack of grounding in the existing reality.

To address the shortcomings of the initial explorations it was decided to take a step back from science fiction and towards reality. Inspired by Erratic Appliances (Ernevi, Palm & Redström, 2007) research was focused towards unearthing where machine learning is an essential material in determining the normal appearance or behavior of the artifact. The field, recommender systems, where machine learning is heavily applied, was surveyed. It was found that in this field several existing products or services relied on machine learning as an essential material. The field was analysed for the potential as a grounding for
the project. As a result of the analysis Spotify it was chosen based on the argument that if the goal was to unpack machine learning without passing judgement, then music related machine learning was less value laden than other more sensitive application, such as the financial applications of Amazon. Furthermore the pattern of use seen in Spotify fitted better with the intention of engaging the user in ongoing reflective use. The subsequent research established a deeper understanding of how Spotify applies machine learning. The research found the Discover Weekly feature to be the most promising due to how directly users were in contact with the machine learning while it still being hidden.

Settled on a grounding the next step was to explore how to materialize machine learning in the given context. The first step in this direction was to map out the qualities of this particular application of machine learning. It was chosen to focus on the data that feeds the machine learning algorithms. Without it there would be no machine learning. As such a material was needed that could materialize this growing, abstract and distant body of data. For this purpose The Living Lamp was identified as a source of inspiration. In particular the idea of a self contained systems with the ability to grow algae hinted several design opening in relation to materializing the growing amount of data.

In the following section the combination of computer and microcontroller was framed as a computational composite. This framing allowed the material, its qualities, and its suitability to be analysed. Firstly its growing temporal form was found suiting for materializing machine learning. Secondly an argument was made that the composites accumulative properties fitted the accumulative nature of the data collection while its lack of reversibility embodied a strong sense of consequence. Thirdly the property of computed causality was found to be central in making the machine learning tangible through the new composite. Lastly the property of connectivity used to understand how the composite could be shaped to establish a link between distant and abstract data and local representation in the shape of algae.

Based on the findings from the material exploration, The Living Lamp seemed like the perfect fit. However it was decided to test out its suitability through a series of prototypes. Firstly the concept was prototyped in a storyboard. The storyboard raised the concern that music and data was one and the same thing in that concept. It was found that there was no way of understanding that the algae grew in response to the data the music produced and not as a byproduct from the music itself.

In order to further explore the concept a simple experience prototype was devised. In all its simplicity the prototype consisted of placing the design on the desk and the roleplaying the functionality over a week. The prototype informed the ongoing design work by confirming the placement as appropriate and further deepened the concern that the lamp did not materialize machine learning in an appropriate way.

Acknowledging that fact that only so much can be ascribed to a designer's self-judgement, a fellow designer was recruited as participants in two experience prototypes. The first using an unmodified lamp and simulated functionality found that the responded did not experience any link between the design and any data, it was just a weird looking lamp that used spotify as on/off switch. Furthermore the look and feel of the design produced associations to chemistry experiment with a possible dangerous subtext. The look and feel of the artifact was furthermore criticised for being completely unrelated to music listening. I was stated that the artifact could be a
visualization for anything, and needed to be more integrated into the aesthetic that surrounds music in order not to be a strange addition.

The second experience prototype tested out the idea of using Spotify’s privacy mode to separate data and music. The result of the prototype was that the inclusion of the privacy mode made it possible to separate music and data as two different entities. It however also highlighted the problem of how to make it clear who the data was private from. Furthermore it was argued that a more prominent form of feedback from the data transfer was needed. Lastly it was found that keeping the control of the music in the application, as opposed to moving it to the artifact, allowed the device to be connected to existing patterns of use.

Below the different activities are mapped out in Houde and Hill’s (2010) model in order to understand how the different designerly activities and their result each inform different parts of the design.

![Diagram showing different designerly activities mapped onto Houde and Hill's (2010) model.](image)

**Figure 14. Chapters mapped on Houde and Hill (2010) model.**

From the model it can be seen how each activity informed the design in their respective dimension. From the early exploration of the role through Static! and early sketches, towards the questions of implementation from the material research, onto the look and feel centric experience prototypes.

The final design aims to take the most salient finding from each dimension and combine them into an integration prototype that aims to represent the complete user experience in a functional prototype that aims to address the research question, and the design problem uncovered in previous activities.
Growing data

Figure 15. Use scenario for final design

Sitting by your desk you decide to listen to some music. You open then familiar Spotify application, browses through the vast amount of music and decide what you want to jam to.

But something is different. Resting on the desk is an unfamiliar device. The square shaped device brings forward associations of record players. But it is clearly not one. It has a moveable rod similar to the tone arm on a record player, but in the place of the stylus, a toroid shaped piece of wood concludes the rod. In the spot where one would expect a record to be placed a perforated container filled with a transparent greenish liquid catches you eye. Right beneath the container there is a small switch with an inscription that reads “Privacy mode”.

As you press the play icon in the Spotify application the arm on the device swings in over the container in a movement similar to the one of an automatic record player. As the arm concludes its movement the underside of wooden toroid light up, illuminating the liquid. As the light turns on the liquid starts to stir. After half a minute the light turns off, the liquid settles down and rod returns to its initial placement.

The song ends. As the next song in the queue starts, the arm swing back over the liquid and once again illuminates the spinning liquid. Before the song ends you slide the privacy switch to on and Spotify stops transmitting data. As the next song comes on the device remains still. You slide the switch off, and the arm begins its journey towards to the liquid.

Over the next weeks the liquid has turn from its initial transparent greenish tint to an opaque deep moss green color.

Figure 16. The final design named Growing Data

That device is named Growing Data (Figure 15). The green liquid is algae and its change in color and is a consequence of the light and the stirring fulfilling its requirements for photosynthesis, resulting in the algae multiplying. Whether or not those requirements are met, relies on your stance towards sharing your data. The algae is only aerate and subjected to light as a result of you sharing your data with Spotify's machine learning algorithms. The algae grows when Spotify's storage of data grows.

Physical form

The final design is a departure from The Living Lamp. The lamp served as sufficient prototyping tool for exploring the idea of a algae/computer composite that materialized machine learning but was ultimately found unfit for tackling the design problem due to its non-existent links to music and a unintentional aesthetic.

For this reason the final design attempts to move, look, and feel in a direction that is more closely related to jamming to Bon Jovi than primary school chemistry class.

Since one of the primary design constraints are to make the data tangible and open for
reflection, especially older designs sparked the imagination. The reason for this is simple. They hail from a time before music made the leap from tangible objects like cd’s and vinyls towards the ephemeral digital world of mp3 files and streaming services. They involve movement and manipulating physical artifacts - The spinning of a CD or vinyl record and the movement of the pick-up as it engages the vinyl to conjure music.

Growing Data is designed to imitate the look and feel of a minimalist 1960’s record player. The reason for this design choice is twofold. Firstly it gives the algae/computer composite an aesthetic that ties it together with music. Looking at the design with its shape and tonearm, like contraption the aim is for the first associations to be towards music. Secondly the goal of minimalistic clean shape and color is to focus on the new behavior instead of a radically novel form factor. This tactic was inspired by Para Functionality (Dunne, 2005) and the idea of an artifact that is strangely familiar (Dunne & Raby, 2013).

It is strangely familiar because its design positions are closely towards a record player. But several cues inform the onlooker that it is not one. The primary functionality of a record player is centered around the spinning record, the tone arm and the interaction between the two. The pick up that normally connects to the tone arm has been replaced with a toroid shaped piece of wood that emits light and the spinning record is replaced by a container filled with algae. And where the on/off switch could be placed a label now informs the user that it control the privacy mode.

It no longer plays music. It grows algae in response to the data the music feeds the machine learning algorithms.

The functionality of the prototype is achieved through an Arduino microcontroller connected to a laptop running a VB.NET application that broadcasts the current playing song on Spotify via the COM port to the Arduino. This is used to control the servo motor that moves the rod. The aeration is done by a small motor that spins a magnetic pellet. The choice of a magnetic spinner over the previous air pump was made due firstly to achieve as less experimental look and secondly to reduce noise in operation. The light on the underside of the toroid I likewise connected and controlled by the Arduino. The above transducers give the microcontroller to power to control the growth requirement for the algae. Due to access limitations in the Spotify application, it has not been possible to toggle privacy mode in Spotify for this prototype. It should however be possible given the appropriate developer credentials. It remains unimplemented in the current prototype, but is deemed technically feasible.

**Interaction**

While the physical form was radically altered from the experience prototypes the interaction remains largely the same.

The user plays music in the Spotify application with no alteration. The primary change is the result it produces. In addition to the music coming out of their speaker, the data is deposited in the algae in the form of growth. The only direct interaction with the artifact is performed by using the switch to control the privacy mode. This was added in response to the findings from chapter 6.

The final design sparked many ideas for adding new interactions to the design. The most straightforward would be to use the tonearm to turn on the music aligning it with the mental models the user have of a record player. However it was chosen to respect the findings from the experience prototypes and keep the existing application as the primary point of interaction. Firstly this avoids the temptation to design a tangible interface for
Temporal form

The temporal form, in large parts, remains similar to earlier prototypes. It has however been tweaked and modified in response to the findings.

The design display both long term and short term temporal changes. The long term temporal form is that of the growing algae as described in chapter 5. This allows the algae to turn from a transparent greenish liquid to a opaque deep moss green. As the Spotify's store of data grow, the algae grow. A mapping is thereby established between the growth of data and the growth of the algae. It is important to note that it is by no means a representative mapping. There is no link between for instance ten grams of algae and ten megabytes of data. Only the growth is embodied.

The short term temporal changes are where most change have been made from experience prototypes to final design. The way the algae is illuminated provided a series of design openings for accommodating the previous findings and remedy the shortcomings of the previous design.

In order to more clearly provide feedback on the transference of data as suggested in response to earlier prototypes the light was connected to the moving rod. This allowed movement to be added. As the user presses play, the rod swing over the container in a similar movement to that of record player. It is argued that this provides clearer feedback that you action triggered the event. When the rod arrives over the container the lights begin to turn on in a circular pattern similar to that of a loading icon using the metaphor that the data is transferred to the algae in a sort of pouring motion. The toroid rest over the container feeding it light for half a minute. That is the time it takes for Spotify's machine learning algorithms to judge your fondness for a given track (Johnson & Newett, 2015). As the illumination sequence is completed the arm swings back to it initial position. The sequence is repeated for any subsequent track played without privacy mode enabled. The effect of concluding the sequence before a track ends is what creates an expression of each track as separate data point. Without this change the device would simply stay on for an entire listening session. The stirring of the algae is simply mapped to the light. When the light is on the solution is stirred.

With the final design presented I return to the research question. The final design uses the algae/computer composite to embody the creation and transference of data that feed into the machine learning processes. A process that is normally hidden and invisible to the user. This follows the ideal of “the object as a site for the expression of otherwise intangible distant processes” (Mazé, 2010, p. 26). As such the design is used to unpack one of the central processes in machine learning - the collection of data to train the algorithms. This connects the user to the underlying processes by making them sensible. The result is a design that makes the processes tangible, present and invite reflection.

The design does not solve any of the problems of machine learning, neither does it aim to. The aim was to open up a space for reflection, where the user can gain the recognition of themselves as a part of the human-machine relationship of machine learning. Echoing the position of the Static! project (Mazé, 2010) the goal is not usability or utility but to expose the underlying processes. The design aims to
allow engagement with more than the functionality of the design. It aims for engaging the users in reflective forms of use.
In the following chapter the final outcome of the project is discussed. Due to the scope of the paper only the most salient point of the processes and the design will be discussed.

**Users**

Throughout the paper use and user has been mentioned a multitude of time. On the topic of users and use this project aligns itself with the views held by Static! designers Enevi, Palm, and Redström (2008).

“When we talk about ‘use’ and ‘users’ above, it is clearly a matter of certain ideas about ‘use’ that guide the design process and not some group of real people (which one might expect should this have been a more typical user-centered design project)” (p. 7).

While the design process did involve outside participants it was limited, and not in a way that would satisfy any participatory designers criteria.

This raises questions of how would the design work deployed for an extended period of time and subject to real use? Would it in fact open up a space for reflection? And what kind of reflection would be made inside this space? It could also be that the design invited alternate use. Would people use it as a tool for shaping their Discover Weekly playlist? And could this help them gain the recognition of themselves as subjects of machine learning? This kind of questions about how it would work in the field, its use, and implications remain speculative at this stage.

The concept is experimental and explorative and is not intended as a commercial product, it does not solve problems, but aims to create a space for reflection in line with the ideals held by Static! (Mazé, 2010). For this reason the question is not if users would like to own one,
but if and what reflections the design could facilitate.

The amount of unanswered question could on the face of it indicate a unfinished project. However Enevi et.al (2008) point to the importance of understanding the difference between the experimental design research presented in this paper and more use- and user-centered research.

Future work on answering the question raised through user-centered design is by no means dismissed. However the design process described in this paper should not be seen as a mere preparation for a user-center design project. Enevi et. al. (2008) point to this kind of experimental design work as central to furthering the possibilities in design through extending knowledge of material, etc. This is also the reason for the in depth exploration of the algae/computer composite.

There is a key difference in the question of “What reflections on machine learning arise out of the interaction with growing data?” and the question of “How can an artifact express the underlying machine learning processes?”. While the project can only speculate towards the first question it provides a compelling account of one possible strategy for expression the invisible data that feed the machine learning algorithms. As such it became a question of expression in use and aesthetics of use.

**Prototyping**

For this purpose the design project made use of prototyping techniques inspired by Houde and Hill (2010). Their creation, evaluation and the findings they produced has already been cover at length throughout the previous chapters. The prototypes allowed the design problem of materializing machine learning to be explored in different dimensions. The question on what reflections that rise out of the design is at this point speculative. However, the designerly exploration provided answers to how an artifact could be made to materialize machine learning in a way that allowed the user to effectively understand the intended mapping between algae and data.

While it remains unverified that the design enables a space for reflection I feel confident in asserting that it does provide the tools for such an reflection based on the findings produced in chapter 6.

**Private from who?**

While almost all of the failings of earlier design proposals was addressed in the final design, one point of critique remains unresolved. The experience prototypes found that the initial design had trouble communicating who the data was private from. Whether this shortcoming has been rectified in the final design is doubtful. There is reason to believe that users would maintain their conceptual model of privacy mode as a feature to hide their listening habit from social media and not as the intended function of stopping the transmission of data to Spotify. However demanding that a design is entirely self explanatory might be too harsh a judgement to pass. A design never exist in a vacuum and the problem could easily be rectified by framing the design appropriately.
Chapter 9 - Conclusion

The work presented in this paper has been focused on materializing machine learning in a design that made the invisible, hidden and abstract processes sensible in order to enable reflection. The approach to the problem was greatly inspired by the Static! research program (Mazé, 2010). Their approach to designing for energy awareness was adapted to the context of machine learning. This allowed the design problem to be approached as one of awareness and reflective use.

To delimit these investigations for the purposes of this short study, the project was grounded in the specific case of Spotify’s Discover Weekly.

The design project aimed to materialize the data collection that serve as the basis for machine learning algorithms at work in Spotify. With inspiration from The Living Lamp project the combination of algae and microcontroller was framed as a computational composite. Subsequently the properties of this composite was analysed through the material strategy (Vallgårda & Sokoler, 2010). The analysis found the properties suitable for the design due to its ability to mirror the most important qualities of the processes sought to be materialized.

The following design process explored the possibility of using the composite in a design that could materialize machine learning in the context of Spotify. The design space were explored through a series of prototypes. Each prototype informed the ongoing design process and served to refine the concept by identifying and resolving design problems.

The project resulted in a final design in the form of a functional prototype named ‘Growing Data’. The final design utilize the concepts of unpackaging and reflective use offered by Static! (Mazé, 2010) in combination with the algae/computer composite to embody one possible strategy
towards materializing machine learning with the goal of enabling reflective use. The design is a result of extensive prototyping and analysis. As such it is possible to conclude that the prototype offer the tools for effectively creating a local representation of the distant and growing data. However, extended field studies are needed in order to explore the reflective space and which concrete reflections there might arise out of it.

While the design brings about a slew of new questions and design possibilities, it offers one possible answer to the most salient one - how to unpack and materialize machine learning with the goal of enabling reflective use. The particulars of this reflection remain speculative at this point.
References


