SCALES OF RECOGNITION

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Thank you to my friends, teachers, family and loved ones for their support and advice.

TABLE OF CONTENTS

PART I

Within the built environment, systems of power and control are increasingly replacing human agents with Artificial Intelligence (AI) in judgement and decision making processes relating to ethical, societal and moral issues. AI is now making judgements and decisions that encompass employment access, policing, and real estate development, consistently remaking and arranging space, subjecting our most vulnerable populations to its logic as they move throughout their daily lives.

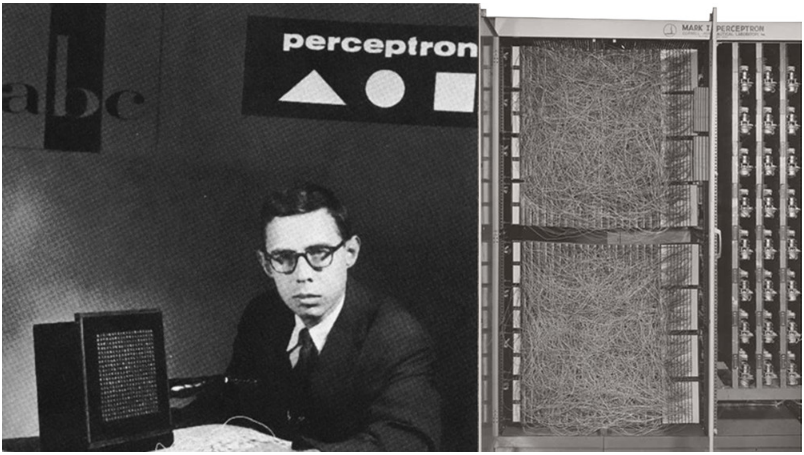
This paper will highlight how and where AI is being applied within the built environment and revisit the historical, societal and philosophical conditions that have paved the way to our present state of *A New Dark Age*, as artist and author James Bridle believes (Bridle, 2018). What are the overt and covert biases, behaviours, and operations built into AI that result in specific outcomes that demonstrate the visible, physical consequences of an invisible, digital technology?

I argue that the makeup of both the design and how we think and speak about AI contributes to its unfettered application. This replacement of empathy with automation creates a self-fulfilling prophecy in which human and machine decisions are mixed together in an entanglement of ethics and consequence. For example, adding a machinic actor as city planner/policy maker may speed up development but removes crucial human empathy for issues like social housing and can greatly accelerate gentrification, further isolating our most vulnerable populations. The pervasive presence of AI integrated into the built environment means that we have to shift our mode of thinking on who is viewing and experiencing the world in which we live. Humans and the natural world are no longer the sole dwellers of the built environment; it is now an environment in which AI and the digital world are viewing, experiencing and evaluating based on its data collection qualities.

As humans currently existing within this cohabitative built environment we are consistently subjected to various forms of oppressive surveillance via AI systems. Our behaviours, attitudes and desires are surveilled, reduced and extracted as data and used as currency for the aims of those in power. As an artist/ designer an acceptance of this shift in worldview is essential in order to resist this oppressive reduction. We first need to understand what AI is, how it works, and design ways of researching AI in order to resist its extreme algorithmic reduction of human life. My ongoing design research is an attempt to understand the basic principles of AI's operation using a "hacked" AI drawing machine to see the strengths and weaknesses of both AI and humans in a co-authorization scenario. Design principles stemming from the strength/ weakness analysis are crucial for designing in a world where both humans and AI cohabitate, and can be applied to designing objects that attempt to take back some of our compromised human agency.

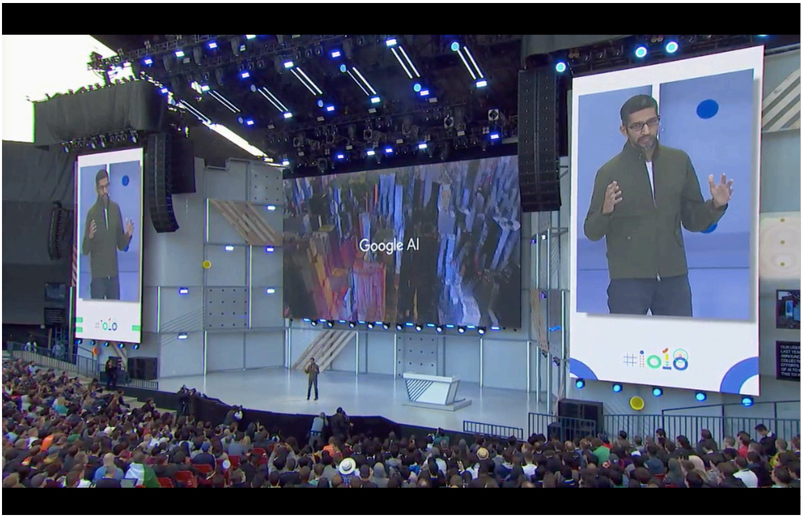
CHAOS MEETS ORDER

Currently, it can be argued that we are living in a time of instability. Impending climate change, a globalized hyper-capitalist society, political drama and mass surveillance vis-à-vis social media are just a few of many ingredients that are allowing AI to flourish within our self-surveillance, capitalist system (Zuboff, 2015). Today we desire efficiency, order, and control to unburden us from the chaotic present. The antidote to this chaos is AI; the simulation of human intelligence processes by machinic systems such as learning, reasoning and self-correction (Kumar, 2018). We can trace back its conceptual origin to to the 17th century philosopher Gottfried Leibniz, who believed that formal reasoning could be as precise as machinic calculation (McCorduck, 1979, p.41). This was the beginning of framing how to make human thinking more machine-like and vice versa; a question that has driven the development of AI forward ever since. In the 20th and 21st centuries, development of AI was, and still is (like most technologies) linked to government funded military endeavours. Today, due to sufficient computing power, mass quantities of information, and the powerful influence of *Big Tech*, AI is flourishing both in popular discourse and in the billions of dollars invested.



The Perceptron was an early hardware based algorithm designed for image recognition for the US Navy, 1958, Cornell University.

The majority of AI development stems from the American Silicon Valley elite. Many of these technophiles believe that everything can and should be reduced and categorized into data (Dormehl, 2014). The media is full of tech gurus like rock-star Google CEO Sundar Pinchai who proclaim AI to be the next messiah. While viewing a YouTube video of the unveiling of Google Duplex, the AI-assisted voice-calling service, it is clear that Pinchai is a celebrity in the eyes of thousands of cheering fans. Pinchai does not state how AI works but what AI can do for us, and we in turn “leave it to the experts” to relieve us from chaos and the complexity of its solution. Many hold false beliefs that our most complex, ingrained problems can be fixed with an apolitical technology (AI in our present case) and that technology is capable of freeing us from our flawed human biases of racism, sexism and nationalism. This deterministic belief leads us on a questionable path for dealing with complex societal problems we feel we cannot solve on our own (Morozov, 291).



Sundar Pinchai speaks at Google I/O Conference, 2018, Grubb, J, Youtube.

UBIQUITY AND THE 3 SCALES OF CONTROL

Currently AI is ubiquitous existing in our phones, ATM machines, travel apps, security cameras, websites, and airport security lineups. In both the public and private sphere, AI is enthusiastically implemented into multiple aspects of contemporary life with little to no regulation. Its networked, expandable nature allows AI to be used at multiple scales of control and conditioning.

For the purpose of this thesis I will illustrate three:

- Scale 1. The Body: AI is being used to define what constitutes as both acceptable body language and acceptable body physicality. Using these acceptable definitions it serves to regulate, reject and control the deviant body as it moves through space.

- Scale 2. The Neighbourhood: operating at the neighbourhood scale and using archival datasets, AI is being used as a self-fulfilling prophecy oracle, predicting the future actions of marginalized "at risk" residents.

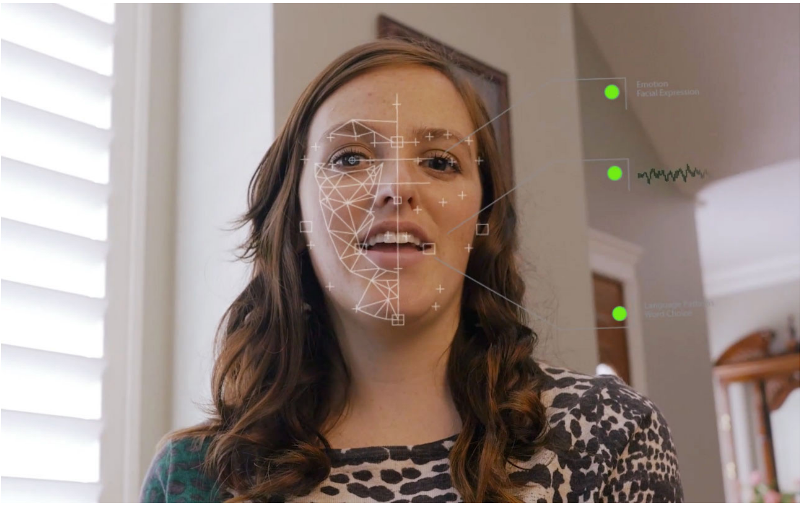
- Scale 3. The State: AI is being used to monitor every aspect of life through its integration into the design of both private and public, social and political interfaces, directly influencing who is provided with, or denied access to, essential services including healthcare, travel and basic human rights.

SCALE 1: THE BODY

THE PRESENT

When there was once face-to-face contact during a job interview, there is now HireVue: a facial recognition software that assesses your facial expressions and determines your acceptability for a human interview. HireVue claims to streamline the interview process, saving thousands in expenses and hiring personnel (HireVue, 2018). Corporations such as Dutch Royal Shell and Unilever use HireVue as the last step before meeting with a human interviewer. Upon completion of an online form, you are instructed to download the app and speak into the phone, as you would video-chat a friend, only this time you are speaking to yourself. Answering twelve pre-determined questions about your attitude, past experience and difficult workplace challenges, an AI analyzes your facial expressions and characteristics and assigns a score and rank based on the previous users of HireVue. If you receive a high score, you are granted a second human-led interview. A low score equals the denial of a second interview and the frustration of not knowing what type of facial characteristics the AI was looking for.

Here, the AI functions as a glorified invisible gatekeeper determining very physical outcomes, such as who gets access to employment and capital, in turn impacting job security and access to housing.

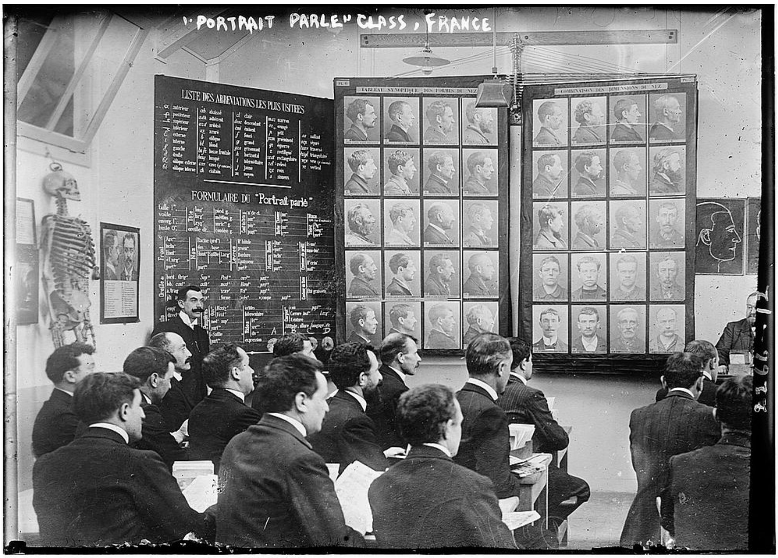


Woman speaks into HireVue App as facial features are analyzed, 2017, HireVue.

THE PAST

This is not the first time facial expressions were thought to be a judge of character. In 19th century Paris, corresponding with the rise of phrenology, French police chief Alphonse Bertillon assembled a catalogue of frontal and side photographs of the heads of individual criminal suspects, forming the early typology of the criminal head shot. Bertillon claimed he could tell a criminal by their facial features and characteristics, an extremely problematic association stemming from the false belief that non-caucasian physical characteristics were correlated to a lack of intelligence. In an attempt to reduce instances of recidivism, the medium of photography was used as an oppressive tool, stripping down the offenders to their facial characteristics, effectively dehumanizing them to a number within the filing cabinet archive. Bertillon created a typological archive by sorting and categorizing the offenders by their race and gender (Sekula, 1986). For Bertillon, the promise of certainty (preventing crime) through the analysis (categorizing mug shots) of the dehumanized subjects character is the repeated destiny we live through today with AI-assisted HireVue. The software promises certainty (the promise of a good employee) through the analysis (HireVue questionnaire procedure) of the dehumanized subjects (hopeful applicants).

The early record of Bertillon's photographic archive eerily forms the basis of how we understand data sets today. Bertillon's filing cabinet was filled with attempts at description (e.g. white, male, Christian) as a way to control and categorize the deviant individual in society. Within the HireVue app there exists thousands of taxonomized hopeful applicants, labeled and filtered down into categories such as "high amounts of eye contact". The 19th century relationship between photography and the filing cabinet is incredibly similar to today's relationship between AI and the data set. The relationship between the medium of photography, the index, the index file and the cabinet mirrors; the relationship between data gathering via surveillance, training the machine learning software for an AI that functions as a future version of Bertillon. Just like the filing cabinet, the applicant is nothing without the larger data set in which they exist. Hirevue's applicants are less than a reductive description filed away within Bertillon's archive; the applicants are now reduced down to nothing but a twitch in their lower jaw.



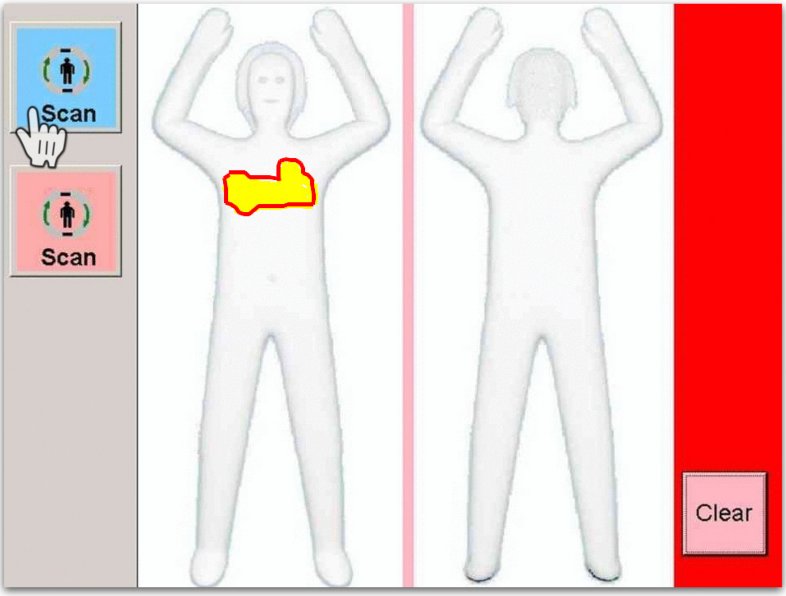
Portrait Parle Class taught by Alphonse Bertillon, 1911, Bain News Service.

Assigning characteristics to facial expressions relies on the false belief that your outer expressions and physiognomy dictate your future performance. If an individual possesses a facial disfigurement or impairment from a previous injury they would score lower, becoming the outlier regardless of their qualifications. This poses the question: is such an individual outlier even capable of existing within the data set? This issue of the outlier is a result of what MIT researcher Sascha Contanza-Chock calls "embodied knowledge" existing within AI systems (Contanza-Chock, 2017, p.5). HireVue's AI is pre-trained to recognize what the human creator tells the software are favorable facial characteristics, i.e. a symmetrical smile excluding the possibility of twitches or nervous facial tics. The software is a manifestation of the creator's fundamental attitudes towards the world that stem from the creator's backgrounds and lived experiences. While there is great progress made to diversify who creates AI, the majority remain white, upper-middle class males of Silicon Valley. Similarly, AI continues to reflect American national interests, as the majority of stakeholders, investors and computing technology are located in the U.S. Inherent biases of privilege, patriarchal worldviews and neoliberalism are just some of the driving forces behind AI's development.

MOVING THROUGH SPACE

In her award-winning essay *AI, Design Justice and the Escape from the Matrix of Domination*, Costanza-Chock describes an airport security screening process that she routinely experiences. The airport security scanners that use AI have a binary cisgendered bias built into them. When Costanza-Chock, a trans-femme steps into the x-ray booth there is confusion: is Costanza-Chock a man or a woman? The labeling and taxonomization of the AI system simply does not allow for other bodily narratives to come through. “Embodied knowledge” is designed into AI, reflecting the worldview of the creators proving that AI is inherently linked to the actions, intentions and outcomes that we as human beings wish and implement for it (M Bruinsma, 2019, personal communication, 8 March). Technology is therefore strictly not capable of being apolitical. Our human unconscious and conscious biases and interpretations, (i.e. there can only be two genders) are projected through an AI system onto our desired outcomes (regulation of who gets access to certain spaces), which in this case severely alters the way a non-normative body navigates or is impeded through space.

Capable of moving through and around bodies, AI is used to register, regulate and measure bodies against normative behaviour, implementing “grammars of action”; a concept developed by designer Phillip Agre wherein objects are capable of normalizing actions of behaviour, similar to how language is subjected to normalization through the application of grammar (Agre, 2003). The government-enforced views that render trans bodies as non-normal are multi-scalar. Filtering down from law courts, to the corporations manufacturing the technology, to the airport security staff, into the lines of code instructing a threshold of normativity, AI is capable of enforcing institutionalized executive power once again (F Türetken 2019, personal communication 20 May).



Airport security interface demonstrating the bodily areas of scrutiny, 2016, TSA.

AI systems impact not only the body and how it moves through space but also the very space into which the body moves through. Similar to Bertillon's criminal photographic archive, AI is used as a tool to label entire neighbourhoods, effectively taxonomizing the citizens that reside within them. The very neighbourhood itself is re-constituted as an indicator of the character of the residents and their actions when moving through said neighbourhood. Not only is there speculation of a bad neighbourhood; the taxonomization is raised to the level of empirical fact as it is based on the false belief that data is a source of undisputable evidence.

SCALE 2:
THE NEIGHBOURHOOD

THE PRESENT

In nearly half of all states in the U.S., AI-assisted predictive policing is being championed by the California startup PredPol (Bridle, 2018, p.144). PredPol uses pre-existing police databases and AI machine learning to actively predict the likelihood of crime, creating red flag zones in certain neighbourhoods where crimes have occurred in the past. PredPol predicts what time crimes are most likely to occur and where, sending out a patrol car to the scene regardless if there has been a crime committed. By relying on the combination of data and AI over humans as decision makers, PredPol believes the problem of racial bias is removed from the police force, as the biased individual officer is no longer the deciding agent. The deciding agent is now the AI, which operates on the belief that past behaviour dictates future actions using archival police data as its worldview (Wang, 2017).

As researcher Jackie Wang writes in her essay *This is a Story About Nerds and Cops*, "…the archival police data is undoubtedly racially charged, as history has shown, where and who is being targeted as criminal has always been racialized" (Wang, 2017, p.6). The worldview of PredPol's AI is solely based on the data it is trained on, and that data allows the AI to create new predictions based on past scenarios. The archival data sets in question are categorized and labeled based on the programmer's choice of how and what to label. The AI then interprets this data based on the way the programmer tells it to interpret or learn. Usually, interpretation means linking labeled data (i.e. race) to equal pre-assigned patterns of the programmer's creation (increased likelihood of crime) via an algorithmic equation. In all instances you have the process of categorization and classification of worlds in order for the AI to interpret said worlds. In this case this classification of worlds equals labeling a neighbourhood "a red-flag zone" and classifying those individuals existing within those zones as suspect.

PredPol's creation of invisible red-flag zones can pose many risks for a human being as there is no way of knowing if you have entered such an area. Reduced to a data input, or what philosopher Giles Deleuze refers to as a *dividual*, (Deleuze, 1990) the actions you undertake in that area could mean something completely different and dangerous in this context. A police officer knowingly entering a neighbourhood corner where crime is most likely to happen could have an increased tendency to be more aggressive. As patrol cars and arrests increase, a state of heightened paranoia can occur. Fresh crime data reinforces existing narratives and can lead to a reduction in government funding from the social sector and an increase of militarization of the police force to combat the ever-increasing crime data. In this sense AI is capable of both psychologically and physically remaking and rearranging the space in which we move (Wang, 2017, p.5). However we must not forget that humans are behind the decision to send a patrol car to the neighbourhood, crime notwithstanding. In an interview conducted April 15th, 2019 AI expert and researcher Emma van Zoelen believes that the problem lies in the fact that instead of asking why such a high crime rate is occurring in such neighbourhoods, there is an immediate lead up of actions that accelerate the arrest of the individual.

Computer generated "predictive policing" zones at the Los Angeles Police Department Unified Command Post (UCP) in Los Angeles, 2017, AP Photo/Damian Dovarganes.

This idea of labeling the past and projecting it onto the future comes from the field of Behaviourism, a 1960's American ideology led by Frederich Skinner who believed that crime was a function of freedom, and that society had to be regulated and fully controlled (Teixeira-Pinto, 2015, p.27). Behaviourists believed that if you designed the system you could control the behaviour. As researcher Ana Teixeira-Pinto writes in her essay *The Pigeon and the Machine: The Concept of Control in Behaviourism and Cybernetics*, "…this violence through prediction re-inscribes the past of a neighbourhood onto its future, therefore defining its history" (Teixeira-Pinto, 2015, p.32). While Bertillon used photography as his medium, PredPol uses mapping to subject an entire neighborhood to further demonstrate oppressive control over its residents. Within PredPol the emphasis lies not in prevention of what is considered "bad" behaviour, but the belief that the bad behaviour will occur inevitably because of past evidence. This emphasis reinforces biased social narratives, justifying the excuse to arrest individuals to prove that the red-flag zones are indeed dangerous.

THE PAST

In 1978 researchers at the MIT Media Lab faced a similar question of how best to combat urban crime. The previous decade's race riots and white flight to the suburbs shifted the view of American urban centers as impending war zones, making urban defence a growing profitable sector

(Halpern, 2015 p.58). Their solution was the Aspen Movie Map, a fully immersive photo-collage video experience. The Aspen Movie Map was initially to be used by the US Military as a way to familiarize soldiers with the location of the next offensive by visually implanting geographic knowledge into the soldier's minds in an immersive simulated warzone. Instead, this became the method with which the local police force analyzed downtown urban centers. Its military origins enabled the Aspen Movie Map to pave the way for computational representation, surveillance and tracking.

A user experiences the Aspen Movie Map via three screens, 1980, MIT Architecture Machine Group.

Like today's PredPol, the focus of the Aspen Movie Map was not on how to *prevent* crime, but how to *simulate* and *prepare* urban defence strategies against the surveilled subject. The human beings existing within these virtual neighbourhood landscapes (today's red-flag zones) were viewed like subjects (data or dots on a map); a population no longer viwered as individuals but units of attention and nervous actions (Halpern, 2015, p.57). The Aspen Movie Map marked a shift in how populations are viewed today by Big Tech. Population, like everything else, could now be seen as data and therefore subject to control and regulation.

CYBERNETIC SYSTEMS AND THE FEEDBACK LOOP

In order to control the population there needs to be a system in place to control the behaviour. The field of Cybernetics, pioneered by philosopher and mathematician Norbert Wiener, believed that both humans and machines would exhibit similar reactions when placed into a designed system (Weiner, 1961). A human, equaling units of attention and nervous actions, will behave similarly to a machine, equaling input stimulus and response. Control and conditioning of the behaviour is achieved using the Cybernetic concept of the feedback loop (Teixeria-Pinto, 2015, 29). The loop describes the infrastructure of the system: stimulation, action and reaction. The reaction alters the input, which is fed back into stimulation to be repeated again and again, forming a machinic system's process of learning (M Bruinsma 2019, personal communication, 20 May). As author Steve Rushton states “feedback loops are their own reality creators” (Rushton, 2013).

The very extreme physical consequence of a feedback loop can be found in the recent rise of young women getting plastic surgery to look more like their Snapchat filters, 2018, Broadly, Vice Identity.

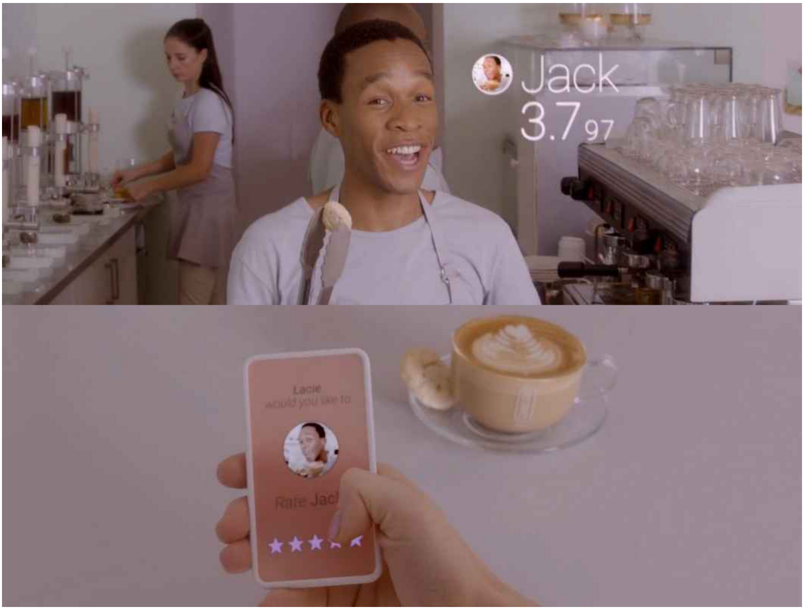
This idea that an AI used in a behavioural conditioning system is capable of creating reality is present in my final example. Echoing a Behaviourist desire, China’s Social Credit System promises to prevent rising social tensions from taking on a political form by conditioning the citizens in an ever-expanding feedback loop where they must constantly monitor and adapt their behaviours in order to go about their daily life. As writer and editor Max Bruinsma states, the system draws parallels to communist East Germany (1949-1990) during which the Stasi created an all-encompassing system of (self) surveillance, which utilized the pervasive presence of unknown 'citizen informants' to condition citizens to act out what the state considered acceptable behaviour. Using both citizens and AI in China's Social Credit System allows surveillance to be taken to an unprecedented level. Our final scale exists as Scale 3: The State.

SCALE 3: THE STATE

China's trial of the AI-assisted Social Credit System or the (cuter, less dystopian name) Sesame Credit System will be mandatory for all Chinese citizens by 2020 (CGTN, 2019). The system draws ties to an environment evoking George Orwell's *1984* combining high amounts of multiple surveillance types, including both AI-assisted (CCTV cameras), and human neighbourhood intelligence officers to track the behaviour of all Chinese citizens extending into every aspect of life including driving habits, grocery shopping and paying your mortgage. Awarding or removing points for certain behaviours, the Chinese government has promoted the system around the idea of trust; if you are trustworthy you win and your score will increase; become untrustworthy and a low score makes it impossible to hide. Do something good, like help your elderly neighbor cross the street, and your score increases (CGTN, 2019). A high score results in benefits. Tax deductions, lower rent and fast tracking for a housing mortgage are just a few of the benefits available. However, to name one example, if you can't pay your mortgage on time you lose points. A low ranking/score can ban you from high-speed train travel, bar you from application for housing, and prohibit the purchase of plane tickets. Already over 10 million people have been barred access to high-speed travel during the trial period of this system (ABC News, 2018). The Social Credit System functions as a fully cybernetic system where every move, decision and behaviour of the citizen has consequence as they are tracked and ranked as points.

Community message board of the Social Credit System where low score offenders behaviour is displayed, 2017, Vice News.

Although the use of AI is present, what is crucial to remember is that the state is behind the creation of such a system, linking a citizen's points to access of essential services. The Chinese government predefines what is bad behaviour according to its own rules. How they determine those rules is unknown. This is a system designed to justify punishment of government critique that has the potential to develop into a gamification universe, (Pelling, 2011) where citizens are constantly changing and modifying their behaviour in order to keep their point score high, removing the natural motivation to do good deeds.



Still from the TV series Black Mirror S3 Ep1 NoseDive. The episode is set in a world where people can rate eachother, affecting their socio-economic status similar to the Social Credit System. 2016, Brooker.

Therein lies a true a manifestation of the ultimate socially distributed panopticon (Deleuze, 1980); Jeremy Bentham's infamous prison design where just the notion of the security guard watching the prisoners is enough to give the feeling and the full effects of surveillance. Embodied surveillance within the citizen changes not only their outer behaviour but also their inner psychological condition as well. In his 2013 lecture titled *Interior Decorating in War Time*, author Matthew Stadler reflects on how digital technology threatens our current state of the interior. “People are neither solitary nor social but fully human in their agency to partake in both, or not. Denying a person the right to solitude and society, access to both and the ability to choose undermines their human rights” (Stadler, 2013. p.5).

The Social Credit System enables the collapse of the domestic interior, as it is no longer a refuge, but an extension of the exterior surveilled society. The interior becomes the home of internal surveillance with what you buy, what you eat, and what you wear all contributing to your score. The system extends to every aspect of life both public and private sphere, making the private sphere less definable, accelerating its disintegration.

We must not assume that this is only going to exist in the contained sphere of China. It is obvious to state that after the implementation of the system is established, there will be other countries looking towards adopting some of these principles. Currently in the West it could be argued that we already exist within a cybernetic environment of human- machine interaction and exchange.

FRAGMENTED SYSTEMS OF CONTROL

Perhaps we exist in an all-encompassing feedback loop system already, but one that is more fragmented, that collapses and reassembles depending on our position as we move through space throughout the day. It exists at different scales, expanding and collapsing as we perform different actions, enabling the most mundane functions of our lives to produce valuable data. The simple act of having a conversation with another human being, shown in the interview process of HireVue, or walking to the corner store allowing you to unknowingly enter a red-flag zone, can be calculated, tracked and analyzed to determine what risk or potential you possess. AI is capable of classifying and taxonomizing our most basic daily routines, and based on the intention behind the system we stand to lose.

AI mirrors its inherently biased human creators in its outcomes because of its systematic operational design. Human authors create and label the outlier-less data set, then instruct the AI based on their decisions, creating an amplified, networked echo chamber. The main goal of eliminating human bias is not eliminated; in fact it is amplified with its consequences playing out in real time. We must remember that humans reside behind the decisions to send a patrol car to a red-flag zone or to trust an app to provide good employees for hire. By prioritizing data as undisputable evidence and assigning actions based on that evidence, humans are enabling a false belief that AI can provide the clarity needed to make tough judgement decisions. However we currently have no choice but to navigate and move within these pervasive multi-scalar systems within the built environment.

HOW AN AI SEES: RECOGNITION

Throughout all scales the act of recognition was at play. In Scale 1: The Body, recognition was needed in order to read facial expressions. In Scale 2: The Neighbourhood, The body was recognized and tracked via CCTV camera, and the neighbourhood was recognized and labeled accordingly. In Scale 3: The State, recognition plays a vital role in the constant tracking systems at play in China's Social Credit System. I decided to explore ways to combat being recognized and therefore being surveilled, interpreted and predicted.

As Matthew Stadler states, "As an aesthetic system war has one fundamental weakness, it cannot proceed without an absolute distinction between ally and enemy. Confused by the noise of human judgement, ambiguity and indecision, war's gears jam up. Digital interactions - where all knowledge is reconfigured as information; where algorithms can swiftly assign a one or a zero for enemy or ally (right or wrong) - frees the gears and war swells into dominance. So: Fill the net of surveillance with every human failing - imprecision, paradox, multiple identities…incompleteness, doubt - all the human capacities that prevent us from…seeing enemy or ally." (Stadler, 2013, p.20)

It is in this spirit where we begin to resist. When an object is not recognized AI is unable to track the object or gain valuable data, failing to recognize the activity that the human user is undertaking. Unpredictability is desirable for a similar reason. If the ability to accurately predict and categorize is AI's sole mission, then make it difficult. Not knowing is a strength.

PART II

FIGHTING BACK

As an artist/designer, I am consistently involved with the intentional restructuring of matter and space in order to achieve certain outcomes. Arguably, as illustrated above, AI is indeed capable of the very same actions. As AI-assisted systems exist at every scale, I have to be aware that what I design/create will eventually be viewed by an AI, and therefore be subjected to its surveillance, interpretation and the connection of patterns of behaviour, inscribing and subjecting my design to an intended outcome. We need to design not only with the knowledge that a human will be viewing and experiencing our work but a machine as well. How can we protect human agency while still existing in a fragmented, expanding-collapsing system as described above? If we want to challenge these power structures of oppression as demonstrated in Scales 1 through 3 we have to come up with ways to resist. In order to do that I realized I had to look at the strengths and the weaknesses of AI as design principles.

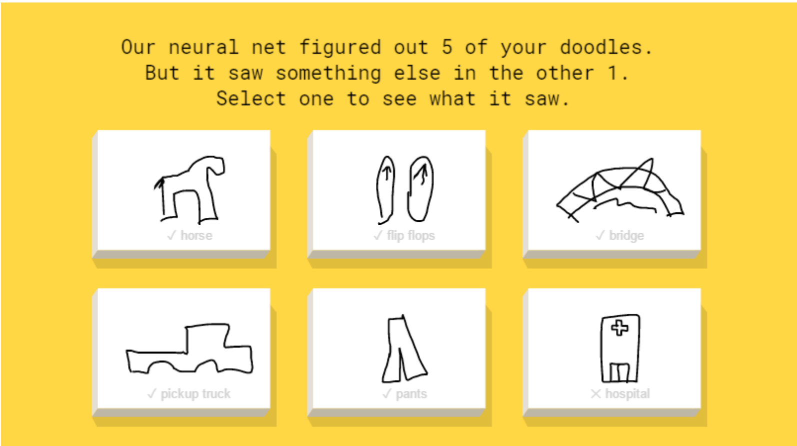
In order to better study an AI's attributes and failings I set up an abstracted framework to represent various stages of the AI process. The processes that I selected were:

- Surveillance (Recognition)
- Analysis
- Interpretation
- Prediction
- Modification of Behaviour

My tool of abstraction was the act of drawing. Using the Google QuickDraw Dataset, an AI trained on millions of doodle-like drawings by multiple human authors, I worked with programmer and AI expert Emma Van Zoelen to modify the code, enabling the AI and myself to draw together in an exchange of interpretation and prediction on the same screen. Using the concept of two players, (myself and the AI) with each stroke I made the AI responded with a stroke of its own: its interpretation of my initial stroke. This interaction illustrates a negotiation and exchange as I deliberately modified my strokes to the AI's strokes in an attempt to "make the drawing work" for my own standards, while simultaneously the AI undertakes a similar process, learning from my responses, attempting to predict what it believes my intended drawing is to be, forming a classic example of a feedback loop.

The intention behind creating a drawing machine was not to draw or design something specific but to use it as a way to represent the differences between AI and humans when faced with the same collective task. Emphasis was on how to simulate a human-machine feedback loop relationship in a way I could understand as a designer;

the act of drawing was a natural choice. Functioning as an abstraction of the various stages of the AI process, the Drawing Machine gave me the ability to analyze and understand both an AI's strengths and its weaknesses. That knowledge can be used to our advantage when designing principles in a world for both humans and AI.



Interface of Google Quick Draw's AI correctly guessing 5 out of 6 doodles. 2016, Google.

The Drawing Machine process can be described as follows:

- Step 1: Surveillance - I take the first turn making a stroke on the screen while my drawing partner (the AI) surveils my actions.

- Step 2: Analysis - The AI reads my stroke as data and compares it to each of the 50, 000,000 drawings in its training library.

• Step 3: Interpretation - The AI attempts to interpret the stroke. It may, for example, decide the stroke is similar to a drawing of a bicycle in its training library, and begin its prediction.

• Step 4: Prediction - The AI thinks I am drawing a bicycle and therefore attempts to draw a highly reductivist squiggle of a bicycle, altering the drawing.

• Step 5: Modification of Behaviour - I surveil what my drawing partner has done, and using my own judgement modify the drawing to suit my needs.

Repeat the process: every step of the process is designed so that the AI and myself have equal authorship over the work. I concluded with three design principles that resist AI's recognition.

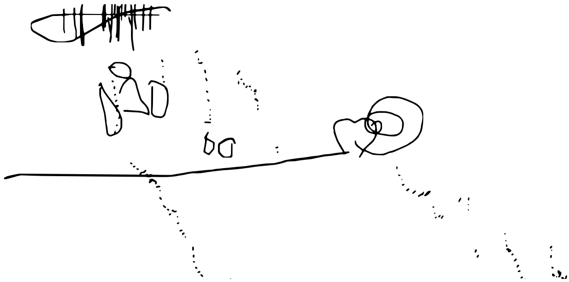
PRINCIPLE 1: COMPLEXITY

When the selected subject of the Drawing AI is undefined, the possibilities for what it could draw are endless. But when its task is to predict what I am drawing it fails to draw anything recognizable to the human eye. When I switch my drawing subject every turn, (one turn I am drawing a frog, in the next a bicycle) the AI tries to make its prediction on the frog/bicycle hybrid. The lines become more erratic, and nonsensical; the AI seems to be getting more and more confused. When the AI has all options open to interpretation, it fails because the answer is not clear. The answer is to look at how an AI defines a category and then design with the principle of multiple categorizations. The AI cannot categorize the subject because one exists within several conflicting categories.

Drawing of everything co-authored by and AI and myself, 2019.

PRINCIPLE 2: ULTRA MINIMALISM

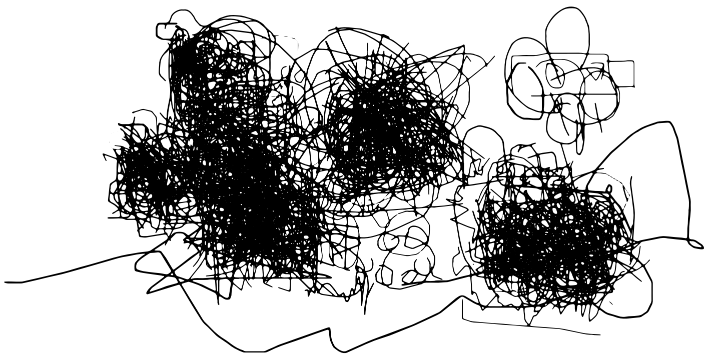
Conversely, when I began a new drawing with a simple, straight line, the AI couldn’t make a prediction at all. There was simply not enough useful information. A lack of stimulant meant that it didn’t know if anything was there at all for it to respond to.



Drawing of a straight line co-authored by an AI and myself. The scattered fragments occurs when we made an “error” in the code, in this case projecting human meaning onto the error, makes the AI appear like it has some sort of erratic creative autonomy 2019.

PRINCIPLE 3: EXPLOIT EXPECTATIONS

In one of my drawing experiments I modified the code so that the AI repetitively made predictions even when I was absent. The AI was executing its function but the exercise failed to succeed as co-authorship as I excluded myself as a drawing partner. The AI thought that I was still drawing and so it executed its function of predicting.



Drawing co-authored by an AI and myself, with the human author mostly absent.2019.

In the 1990 holiday hit *Home Alone*, 7 year-old Kevin McCallister is defending his home against the bumbling Wet Bandits. Believing the parents have gone out of town, the bandits, played by actors Joe Pesci and Daniel Stern, drive by the McCallister home late at night with the intent of pulling off a robbery. Instead Kevin has rigged a system of deception. A combination of moving mannequins and cardboard cutouts paired with loud music give the impression that the McCallister's are indeed home. The burglars are temporarily stumped and flee the scene. Kevin used the principles of vision and sound as tools to defend his territory, knowing when and how the burglars would surveil his parent's home. Kevin knew this because he overheard the Wet Bandits plan to return to the McCallister home that evening. He foresaw how the threat would unfold and then exploited their expectations to thwart a robbery.

I propose a similar tactic. Understand what the AI is looking for and how the AI is looking for it and then give the AI what it is looking for. Because what it is looking for is not necessarily you, it will still execute its function, and you may be able to satisfy its desire for input in other ways. Artist Adam Harvey proposes a similar concept in his project HyperFace, a textile prototype designed to distract facial recognition algorithms. As the project description states, " … HyperFace does not seek computer vision anonymity through minimizing the confidence score of an actual face but offers a higher confidence score for a nearby false pixelated face by exploiting a common algorithmic preference for highest confidence facial region” (Harvey, 2017).

Rendering of HyperFace Textile Prototype, 2017, Harvey.

THE ADVERSARIAL OBJECT

As the design principle of ultra-minimalism has already largely been played out via 20th and 21st century modernism, I chose to go forward with the remaining two principles of Complexity and Exploit Expectations to guide my design proposal. As Scale 3 has demonstrated, the collapse of the interior is imminent via internal surveillance that enable our surrounding existing spaces and objects to be recognizable to an AI. I propose thinking forward into a future where this is by default the case and design speculative interior objects that contain the ability to bypass this data collection. These objects specifically work against the theory of camouflage as a means to avoid detection, paradoxically allowing them to be recognized. As Matthew Stadler states "…in the digital age hiding is not possible nor is it desirable, so the focus is on agency not privacy (Stadler, 2013, p.17).

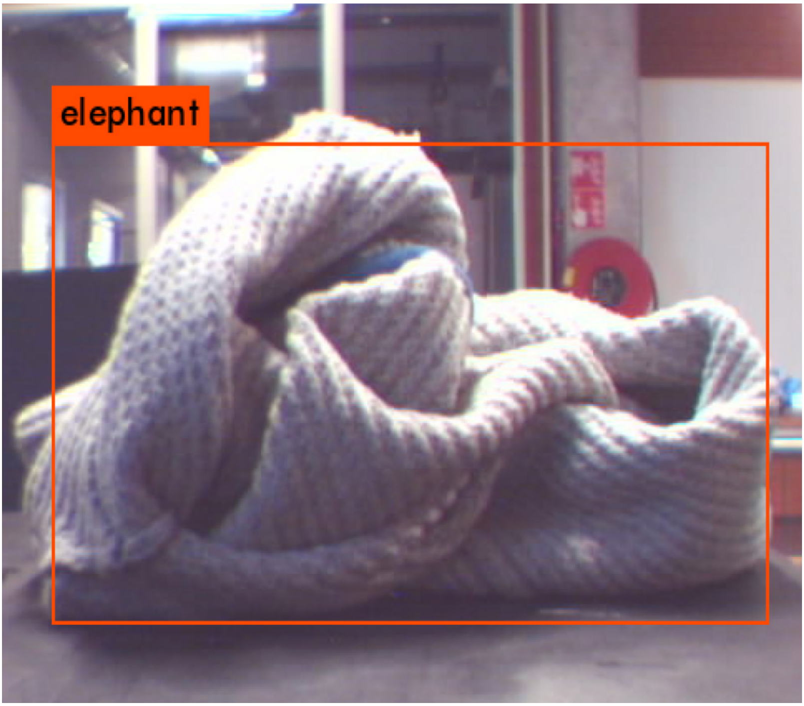
These objects enable the agency of the user to have the ability to choose when or whether they allow the objects activities of the user to be recognized. In an interview uploaded on YouTube, American artist Trevor Paglen describes his piece *Atlas of Invisible Images* as "… invisible images because they are images that are not for us, they are images for computers." (ViceNews, 2017)

These interior objects have a dual function as they are both for us and for our surveilling AI.

Photograph from Paglens Invisible Images series made with a Generative Adversarial Network (GAN), 2017, Paglen.

USING YOLO

To test my design principles in a real world application I chose to work with object recognition software. The software I am using is an open-source software called YOLO v3 (You Only Look Once) created by Joseph Redmon, Santosh Divvala, Ross Girshick and Ali Farhadi. Using the well-known training set ImageNet, a 1000-class competition dataset, YOLO uses Convolutional Neural Networks (CNN's), an advanced form of machine learning, to simultaneously detect an objects category and its location in space. The software scans an image, video, or live stream and identifies what objects are present and where they are, assigning a confidence rating between 0-100 percent related to the likelihood of correct detection and correct location indicated via a bounding box (Redmon et al., 2015, p.3).



In an initial trial of the software, my grey sweater is detected to be 67% likely an elephant, 2019, Baldwin.

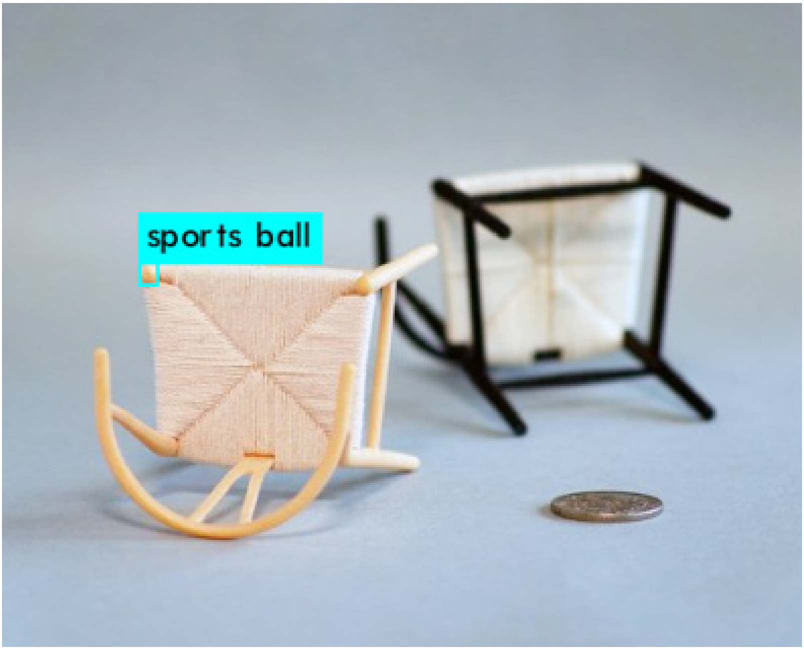
As Redmon et al, write in their paper *Introducing YOLO Real-Time Object Detection Software*, the software has several limitations. YOLO can only assign one category or class to each bounding box, eliminating identification of objects that have multiple classes. Additionally, the software also struggles with objects in new or unusual aspect ratios or configurations (Redmon et al., 2016, p.4). However, as YOLO is constantly being developed at a rapid pace it is able to identify more unusual examples. A way of improving YOLO is by training the software on multiple challenging or adversarial examples, similar to a bouncer scanning a photo album of all prohibited club goers before the night begins. Eventually, through adversarial training YOLO will become an expert at identifying unusual objects.

To test out the software's capabilities of what it can and cannot recognize, I undertook a series of experiments. Below are the results of my research findings, a list of multiple factors present that enable or inhibit detection. YOLO can be applied to detecting an object in both pre-recorded and live capture/streaming images and film.

IMAGE TESTING

- Unusual placement angles.

When a chair is placed upside down, it is either not detected or it is detected as another object such as sports ball. However as discussed earlier, this can easily be resolved by training the software on examples of chairs tilted upside down.



Unusual placement of chairs, 2019, Baldwin.

- Contrast from background

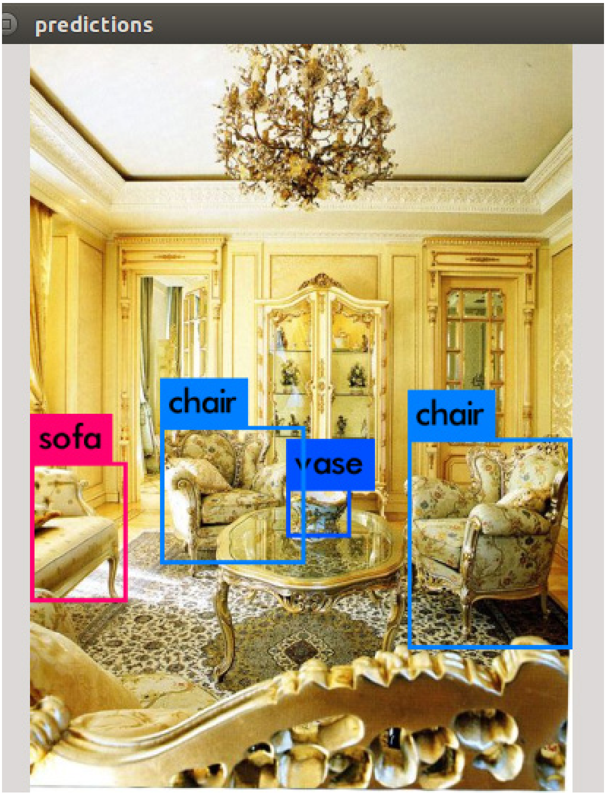
Phillip Starke's ghost chair in black is detected as 99% certain that it is a chair. The grey smoke finish is detected with 73% confidence but the clear translucent finish is undetectable paired with the white background.

Phillip Starke's ghost chair in black, 2019, Baldwin.

Chair with grey smoke finish, 2019, Baldwin.

Chair with a clear translucent finish, 2019, Baldwin.

My next test was of an image of a Rococo interior since the decadent wall murals, upholstery and drapery blend together. Here, ornament works almost as an attempt to camouflage, however YOLO was successful at identifying almost all the furniture in the image. Therefore, the background to the object plays a role in how likely the object resides within that classification. However, one cannot guarantee that the background of the objects with the interior will always work its favour.

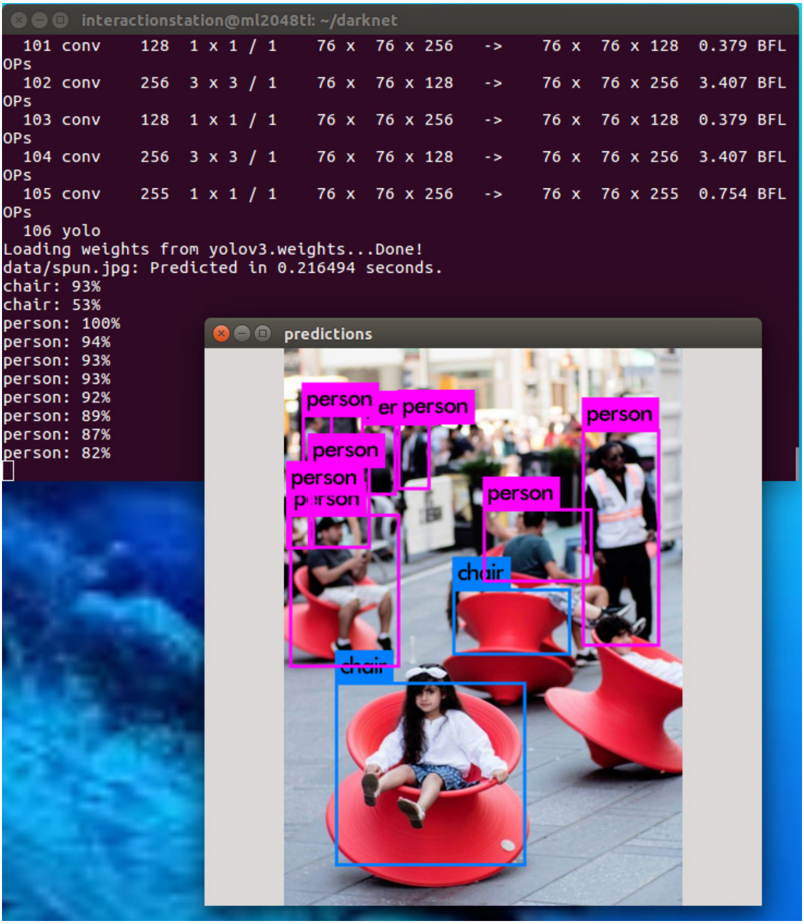


Rococo interior, 2019, Baldwin.

- Form of the object in question

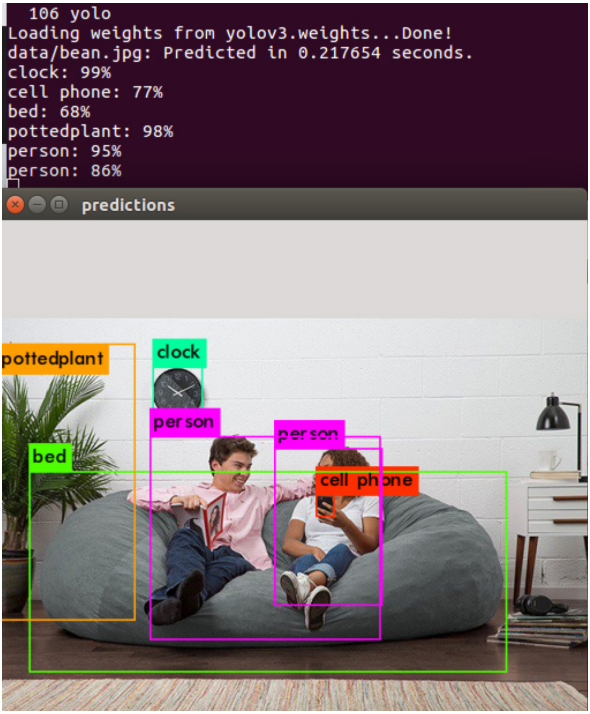
The obvious question arises: can’t one just design a chair that looks nothing like what we think a chair looks like? I tested both images and video recordings of Thomas Heatherwick’s Spun chair (a rubber chair that looks most like a giant spinning top).

YOLO was 93% certain that this was indeed a chair. The objects classification is largely due to the familiar body positions that are associated with that object.



Thomas Heatherwick's Spun Chair, 2019, Baldwin.

Additionally, in an image of a low beanbag chair YOLO wrongly detects that the object is a bed. We can deduce that it is due to the fact that in the image the human users are reclining almost at a full horizontal position associated with sleeping.



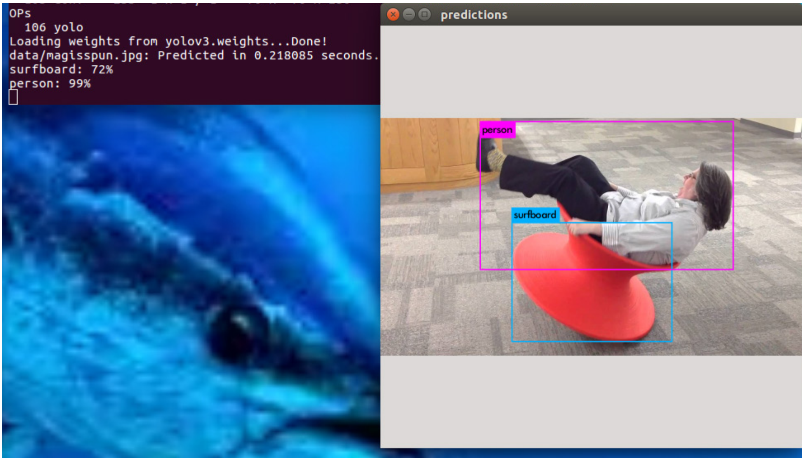
Incorrect detection using YOLO, 2019, Baldwin.

The classification through form is also largely to do with a question of the strongest most recognizable features coming through. For instance, the image of the spork shows an enlarged spoon cavity that seems to overpower the small fork tongs at the top of the object. Therefore YOLO is 85% certain that the object is a spoon.

Image of a spork, 2019, Baldwin.

- Activity of the person present

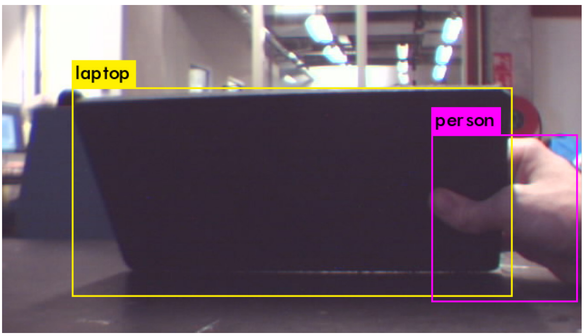
When there is an image of a chair, there usually will be a person sitting in a typical seated position. When the person is in an atypical seated position, for instance titled 45 degrees backwards, YOLO believes that the chair is not a chair; it is 72% certain that the chair is a surfboard.



Identification of chair as surfboard, 2019, Baldwin.

•Physical placement and association

Chairs are usually placed near tables and vases are most likely placed ontop of tables. The likelihood of association due to prior training has a large influence as well. If I have an image of a desk, it is most likely that the object on that desk will be a computer mouse or laptop.



Laptop and person identification, 2019, Baldwin.

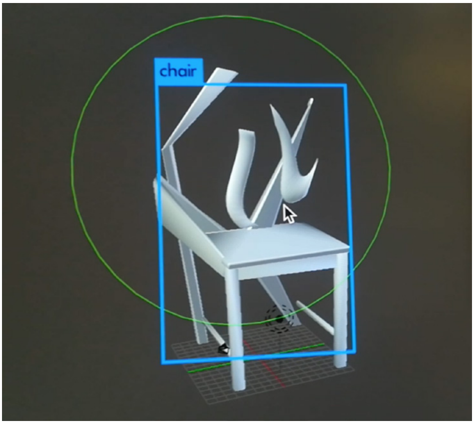
FILM TESTING

Researchers from Auburn University in Alabama used a technique of iterative optimization within the parameter space of a 3D renderer, (Tiernan, 2018). They used 3D space to estimate changes in object geometry, lighting, background and camera settings as tools to study the recognition software. I used a similar approach in my next round of tests where I combined multiple 3D interior objects together using the 3D modeling software Blender.

I conducted a series of experiments where I simultaneously manipulated the object's geometry and camera angles, taking screenshots and recording videos of the process to be fed back into YOLO, to see what exactly could it recognize and what manipulations made it difficult. The following three tests lead me to the next phase of my design.

- Morphing Form

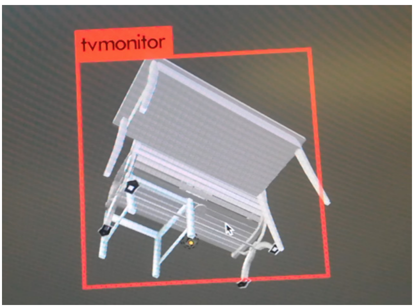
Using a distort tool I push a 3D model of a chair to its limits, making note of the exact threshold when, according to YOLO, the chair is no longer a chair.



Limit of chair recognition, 2019, Baldwin.

- Camera vantage point

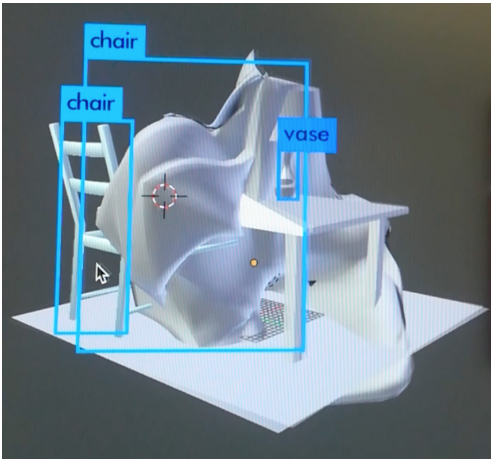
If we are to view the furniture compilation from below, the software is unable to successfully detect anything. However, as discussed above, the orientation of the object is not enough to thwart recognition, if the user still comfortably sits on an upside-down chair as they normally would, it would still be recognized as a chair.



New orientation to thwart recognition, 2019, Baldwin.

• Partial obscurity

Taking a large unusual form and wedging entire objects within it, the objects are still recognized but now part of a larger composition.



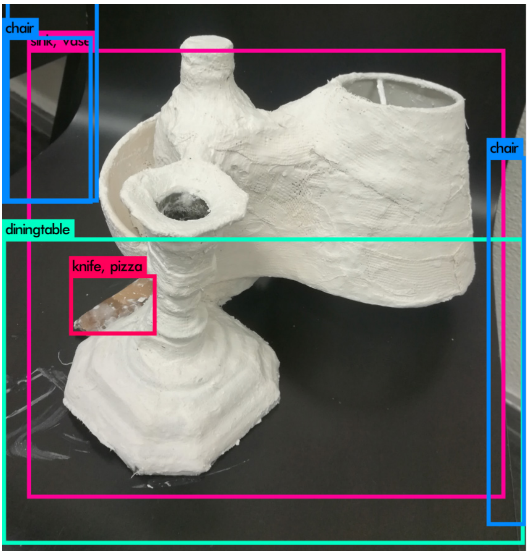
Chairs and vases blended into a composite, 2019, Baldwin.

YOLO and other object recognition software are constantly being improved and trained through adversarial examples. Therefore, the factors of recognition as outlined above are factors to be wary of. Priority is given to keep some human familiarity of the object's former life pre-machinic surveillance. The aim is not create objects that are distorted or configured beyond recognition but to give a sort of comfort for the human user while enabling agency. With this knowledge in mind, can we then allow the software to recognize to its machinic heart's content?

Similar to the principle behind Adam Harvey's Hyperface prototype, if we cannot prevent recognition then can over-recognition be a way to become unrecognizable?

PROCESS

Everyday objects from my apartment are 3D scanned and reassembled via the 3D modeling software Blender. The hybrid forms are then returned to the physical world via 3d printing. Finally, the object is draped with a unifying material layer to both conceal and enable recognition. Here, form is used as a mode of rebellion by merging multiple iconographies to achieve a purposeful irregularity.

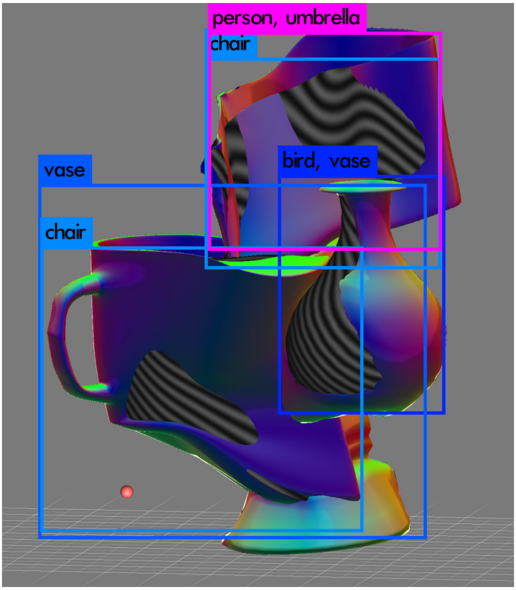


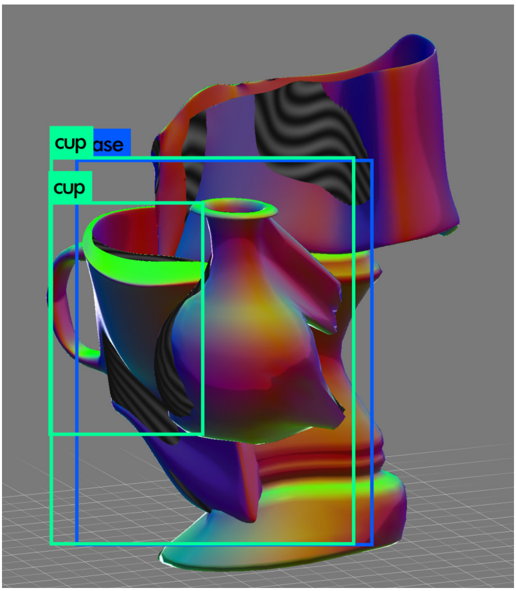
Early prototype assembling physical objects with plaster bandages, triggering identification of a sink, vase, knife and pizza.

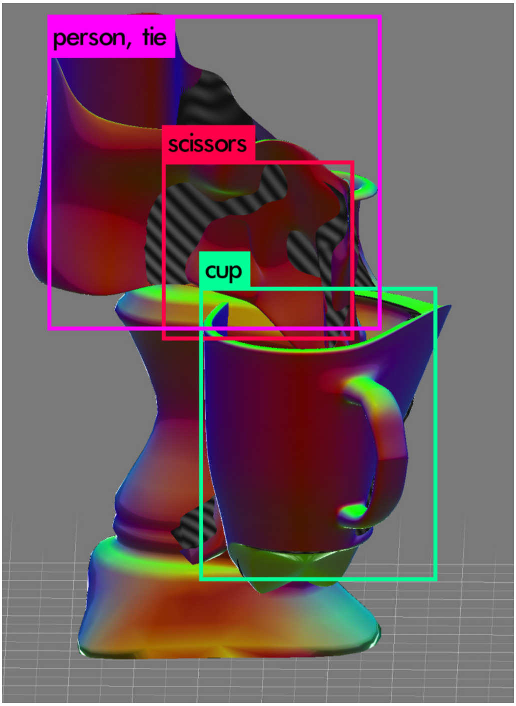
In a similar vein the 20th century Japanese ceramicist Takiguchi Kazuo deployed a method of deforming his pots purposefully to oppose the folk art aesthetics of the time known as Mingei, (Faulkner, 1993). Kazuo assembled several archetypical forms then draped a thin layer of clay over the shapes to create new hybrids. Rebellion was achieved through abstract and non-functional form making, similar to my own work.

Untitled, glazed stoneware, 2001, Kazuo.

These objects utilize the design principle of Complexity to reside within multiple categorizations. Normal everyday items such as a lamp, table, or chair, are formed, reconfigured and morphed into completely new objects while still containing traces of their archetypes. The design principle of Exploit Expectations is found as the archetypes of these objects remain present, triggering identification that the object is in fact a chair, a table, or book etc.


person, umbrella
chair
vase
bird, vase
chair


cup
ase
cup

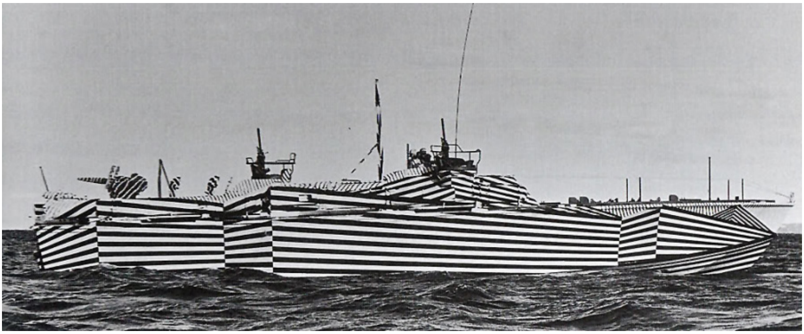


Rendering of early digital prototype using Blender and Meshmixer then fed into YOLO for recognition testing, 2019, Baldwin.

The unusual morphed forms of the object encourage a variety of uses, as the user is free to use the object in other ways. The human agent can choose to drink from the cup or read from the book - archetypes that are defined and obvious to the software - or they can use the object alternatively as a lamp, or as a table. The concept of affordances or suggestions of how an object might be used is utilized as a strength to thwart detection.

When surveilling the object YOLO will still identify the human user, as the human is not hidden or camouflaged. However, since the software does not know whether the person is drinking from a cup, or resting on a sofa, it cannot gather the accurate data it needs. The data gathered is irrelevant and inaccurate functioning as what is known as *dirty data* (Steyerl, 2018). Data is not just about collection it is about collecting *useful data* and extracting information from it. In this case, these interior assemblages serve as a physical adversarial example, a technique employed in machine learning that attempts to fool AI models through malicious input (Geng, Veerapanenwi, 2018). The objects present a design shift on *who* and *how* is viewing whom and what within the interior, still allowing surveillance to take place but gaining back the human agency to choose.

During WWI battle ships were painted in a graphic pattern, transforming them into what we know today as *dazzle ships*. This pattern prevented the enemy from knowing the direction the targeted ship would take, making it difficult to estimate the ships range and speed needed for missile coordinates. Today, our machine learning equivalent is the adversarial example, a layer of carefully constructed noise over an image functioning like an optical illusion for a human brain. For an AI recognition system, adversarial noise is capable of transforming an image of a panda into a pickup truck. Here, instead of pixels, form is used as an adversary, allowing the object to become so recognizable that its actual purpose and function is obscured.



Dazzle ship, 1918, Wikipedia.

UNDOING CERTAINTY

Within every scale the cohabitation of human and AI create zones of temporary surveillance flux that we enter unknowingly. Political and corporate power structures are behind this application, subjecting vulnerable populations to this heavy surveillance. We have to design ways of living within. As shown in the multiple present scales, we cannot opt out, nor is opting out the point. As artists/designers we design the space in which we move, space that is being surveilled by AI. We must shift to designing with the knowledge that AI will be viewing and subjecting whatever we design to data collection and analysis. Knowledge on how AI works and what it is looking for can have a role in subverting those surveilled spaces and gaining back human agency. Designing not only for human vision but also for machinic vision, we should be able to make the choice of whether or not we, the spaces we live in, and the objects we surround ourselves with, have the ability to be recognizable by AI.

We desire privacy but is privacy the point? In digital relationships visibility and sharing are strengths (Stadler, 2013, p.13). Therefore the goal is not to hide but to simply be unrecognizable - two very different concepts - subverting the concept of the data outlier as strength rather than as weakness. In her essay *A Sea of Data, Pattern Recognition and Corporate Animism*, Hito Steyerl reflects on the how recognition played a role in the 1998 arrest of George Michael, with Michael turning what could have been a career-ending PR scandal into his hit single and music video titled Outside. Steyerl ponders the invitation from Michael to all of us existing within a cohabitative AI-human environment to go outside, celebrating our multiple categorizations, becoming so recognizable you are unrecognizable (Steyerl, 2018). These ongoing design explorations are not fixed principles. They are subject to change and evolution; a starting point for shifting toward a design that can undo a future filled with what Steyerl calls, “false algorithmic certainties”.

REFERENCES

ABC News Australia, (2018) Exposing China's Digital Dystopian Dictatorship, video recording, YouTube, viewed 6th March 2019, <https://www.youtube.com/watch?v=eViswN602_k >.

AI Now Institute. (2017) Top Ten Recommendations for the AI field in 2017 in Medium (online) Available at < https://medium.com/@AINowInstitute/the-10-top-recommendations-for-the-ai-field-in-2017-b3253624a7 > Accessed, February 14th, 2019

Bridle, J. (2018) New Dark Age, Technology and the End of the Future, London, Verso

Bridle, J. (2011) New Aesthetic Tumblr, viewed Nov 6th 2018 < http://www.newaesthetic.tumblr.com>.

Business Insider. (2017) 'HireVue Uses AI for job interview', in Business Insider (online) Available at <https://www.businessinsider.nl/hirevue-uses-ai-for-job-interview-applicants-goldman-sachs-unilever-2017-8/?international=true&r=US > Accessed January 20th, 2019

CGTN, (2019) My vlog: CGTN Reporter Tries out China's Social Credit System, video recording, YouTube, viewed 21st March 2019, <https://www.youtube.com/watch?v=TXOJSUpJz1w>.

Constanza-Chock, S. (2018) 'Design Justice, AI and Escape from the Matrix of Domination' in Journal of Science and Design, (online) Available at <https://jods.mitpress.mit.edu/pub/costanza-chock >Accessed March 6th, 2019

Deleuze, G, Guattari, F. (1980) A Thousand Plateaus, Minneapolis, University of Minnesota Press

Dormehl, L. (2014) The Formula: How Algorithms Solve All Our Problems and Create More, London, WH Allen

Faulkner, R. (1993) “Modern Japanese StudioCeramics in Great Britain and Their Representation in the Victoria and Albert Museum,” in Frederick Baekland and Robert Moes, Modern Japanese Ceramics in American Collections, Japan Society, New York, , p. 58.

Geng, D. Veerapenani, R. (2018) Tricking Neural Networks, Create Your Own Adversarial Examples, viewed May 15th, 2019. <https://medium.com/@ml.at.berkeley/tricking-neural-networks-create-your-own-adversarial-examples-a61eb7620fd8>.

Google (2019) Quick! Draw: The Data, viewed April 16th, 2019. < https://quickdraw.withgoogle.com/data>.

Grubb, J. (2018) Google Duplex: A.I. Assistant Calls Local Businesses To Make Appointments, video recording, YouTube, viewed 21st January 2019, <https://www.youtube.com/watch?v=D5VN56jQMWM>.

Halpern, O. (2015) “The Trauma Machine, Demo’s immersive Technologies and the Politics of Simulation” in Pasquinelli, M. (ed.) Augmented Intelligence Traumas. Luneburg, Menso Press

Harvey, A. (2017) HyperFace, viewed May 9th, 2019. < https://ahprojects.com/hyperface/>.

Het Nieuwe Institute, (2015) 9th Benno Premsela Lecture by Matthew Stadler: Interior Decorating in Wartime, video recording, Vimeo, viewed Feb 24th 2019, < https://vimeo.com/80487823>

HireVue, (2018) Why HireVue, viewed Jan 20th, 2019. <https://www.hirevue.com/why-hirevue>.

Kumar, C. (2018) Artificial Intelligence, Definitions, Types, Examples, Technologies, viewed May 21st, 2019. <https://medium.com/@chethankumargn/artificial-intelligence-definition-types-examples-technologies-962ea75c7b9b>.

Morozov, E. (2011) The Net Delusion: The Dark Side of Internet Freedom, New York, Public Affairs

Pelling, N. (2011) The (Short) Pre-History of “Gamification” viewed May 11th 2019. <https://nanodome.wordpress.com/2011/08/09/the-short-prehistory-of-gamification/>.

Redmon, J. Divvala, S. Girschick, R. Farhadi, A. (2016) You Only Look Once: Unified, Real-Time Object Detection.viewed May 15th, 2019. <https://pjreddie.com/darknet/yolo/>.

Rushton, S. (2011) ‘Feedback as Self-performance’ in Turner, R, (ed.) Sniff Scrape Crawl… on privacy, surveillance and our shadowy data-double. London, Mute Press.

Sekula, A. (1986) ”The Body and the Archive”. In October, vol. 39, 1986, pp. 3–64. , JSTOR, Available at: www.jstor.org/stable/778312

Steyerl, H. (2018) – “A Sea of Data: Pattern Recognition and Corporate Animism.” In Apprich, C. (ed.) Pattern Discrimination. Luneburg, Menso Press

Stewart, Matthew. (2019) ‘The Real-Estate Sector is using AI to Gentrify’ in Failed Architecture (online) Available at <https://failedarchitecture.com/the-extractive-growth-of-artificially-intelligent-real-estate/ > Accessed February 27th, 2019

Teixeira Pinto, A. (2015) “The Pigeon and the Machine: The Concept of Control in Behaviourism and Cybernetics” in Pasquinelli, M. (ed.) Augmented Intelligence Traumas. Luneburg, Menso Press

Tiernan, R. (2018) “Googles Image Recognition AI Fooled by New Tricks” (online) Available at <https://www.zdnet.com/article/googles-best-image-recognition-system-flummoxed-by-fakes/>. Accessed May 20th 2019

Van der Meulen, S. Bruinsma, M. (2018) “Man as aggregate of data: What computers shouldn’t do” in AI and Society, London, Springer.

Van Zoelen, E. (2019) Interview with Emma van Zoelan, Gill Baldwin, 16th April 2019.

Vice News. (2017) Trevor Paglen Show Us How Machines See the World, video recording, YouTube, viewed 28th, May 2019, < https://www.youtube.com/watch?v=HEI8cuGKiNk>.

Wang, J. (2017) '"This Is a Story About Nerds and Cops": PredPol and Algorithmic Policing - Journal #87 December 2017 - e-flux', E-Flux. Available at <http://www.e-flux.com/journal/87/169043/this-is-a-story-about-nerds-and-cops-predpol-and-algorithmic-policing/.

Wiener, N. (1961) Cybernetics: or Control and Communication in the Animal and the Machine, Cambridge, MA, MIT Press

Zuboff, S. (2015) 'Big other: Surveillance capitalism and the prospects of an information civilization', Journal of Information Technology. Nature Publishing Group, 30(1), pp. 75–89. doi: 10.1057/jit.2015.

BIBLIOGRAPHY

Bratton, B. (2015) ‘Outing Artificial Intelligence: Reckoning with Turing Tests’ in Pasquinelli, M. (ed.) Augmented Intelligence Traumas. Luneburg, Menso Press

Cheng, I. Emissionary Forks At Perfection, (2018), video installation, Louis Vuitton Foundation, Venice.

Disruption Network Lab, (2018), DNL #13 HATE NEWS, Panel with David Carrol, Bernd Fix, Maloes de Valk and Theresa Züger, video recording, viewed November 6th 2018. <https://www.youtube.com/watch?v=RIrutnCv4Qo >.

Elahi, H. (2005) Tracking Transcience, viewed November 1st 2018. < http://elahi.umd.edu/track/ >.

Giedion, S. (1948) Mechanization Takes Command: a Contribution to Anonymous History, New York, Oxford University Press

Hogan, M, Sheppard, T. (2015) Information Access and Materiality in An Age of Big Data Surveillance, Journal of Information Policy, (online)vol 5, p 6-3, Available at https://www.jstor.org/stable/10.5325/jinfopoli.5.2015.0006, Accessed:13th, November 2018.

Klingemann, M. (2018) Mario Klingemann, Artist working with Code, AI and Data, in Quasimondo (online) Available at<http://quasimondo.com/ >Accessed, January 28th 2019.

Kogan, G. (2018) ITP/NYU, The Entire Class in 60 minutes: Learning Generative Neural Networks for Creatives, video recording, viewed January 14th, 2019. <https://ml4a.github.io/classes/itp-F18/01/>

Lovink, T. N. (2018) ‘Social Media Critique Interview’, pp. 1–7.

Lucas, R. (2014) Xanadu as Phalastery, in New Left Review, (online) Available at https://newleftreview.org/II/86/rob-lucas-xanadu-as-phalanstery, Accessed 13, November, 2018.

Mansoux, A. (2008) ‘The Art of Surviving in Sim Cities’, in Dekker, A, Wolfsberger, A (ed.) Walled Garden. Amsterdam, Virtueel Platform.

McCorduck, P (2004), Machines Who Think (2nd ed.), Natick, MA: A. K. Peters, Ltd.,

Metahaven, Kruk, V. van de Velden, D. (2015) ‘Captives of the Cloud Part 1-3’, in Black Transparency The Right to Know in the Age of Mass Surveilance, Berlin, Sternberg Press

Morozov, E. (2015) “Socialize the Data Centres”, New Left Review, (online) Available at https://newleftreview.org/II/91/evgeny-morozov-socialize-the-data-centres, Accessed 13, November, 2018.

Lahoud, A, (2015) ‘Error Correction, Chilean Cybernetics and Chicago’s Economists’ in Pasquinelli, M. (ed.) Augmented Intelligence Traumas. Luneburg, Menso Press.

Rushkoff, D. (2010) Program or Be Programmed, Ten Commands For A Digital Age, Berkeley, Soft Skull Press.

Smithsonian American Art Museum, (2018), Artist Lecture with Trevor Paglen, video recording, YouTube, viewed November 6th 2018. <https://www.youtube.com/watch?v=EP-Vb-S9KFs>.

Wijnsma, L. (2017) Smell of Data Part 1 – Digital Jungle. video recording. Vimeo, viewed November 13th, 2018. <https://vimeo.com/215522451>.

Wijnsma, L. (2017) Smell of Data Part 2 – Making Leaks Sensible. video recording. Vimeo, viewed November 13th, 2018. < https://vimeo.com/215786891 >.

Wijnsma, L. (2017) Smell of Data Part 3 –Smell As A Warning Mechanism. video recording. Vimeo, viewed November 13th, 2018. < https://vimeo.com/215784958>.

Wijnsma, L. (2017) Smell of Data Part 4 –Training the Instinct. video recording. Vimeo, viewed November 13th, 2018. < https://vimeo.com/215800325>.

Wijnsma, L. (2017) Smell of Data Part 5 –Introduction Of A New Smell. video recording. Vimeo, viewed November 13th, 2018. < https://vimeo.com/222510854>.

IMAGE LIST

Fig. 01: Cornell University Library. (2018). Chronology of Artificial Intelligence. [image] Available at: https://ici.radiocanada.ca/nouvelles/special/2017/02/intelligence-artificielle/ligne-temps-chronologie-developpement.html (Accessed: 21 March 2019).

Fig. 02: Grubb, J. (2018). Google Duplex: A.I. Assistant Calls Local Businesses To Make Appointments. [screenshot] Available at: https://www.youtube.com/watch?v=D5VN56jQMWM (Accessed: 25 March 2019).

Fig. 03: McLaren. S. (2018). 9 Ways AI Will Reshape Recruiting (and How You Can Prepare). [image] Available at: https://business.linkedin.com/talent-solutions/blog/future-of-recruiting/2018/9-ways-ai-will-reshape-recruiting-and-how-you-can-prepare (Accessed: 22 March 2019).

Fig. 04: Bain News Service. (1911). "Portrait Parle" Class, France [image] Available at:https://commons.wikimedia.org/wiki/File:Parle_class_2162889173_72eaace2e1_o.jpg (Accessed: 18 February 2019).

Fig. 05: TSA. (2016). Traveling While Trans, the Promise of Better Treatment. [image] Available at: https://trans-fusion.blogspot.com/2016/01/traveling-while-trans-false-promise-of.html (Accessed: 18 February 2019).

Fig. 06: Dovarganes, D. (2018). Police Are Considering the Ethics of AI Too. [image] Available at: https://www.cbc.ca/radio/spark/406-tech-in-policing-1.4833189/police-are-considering-the-ethics-of-ai-too-1.4833194 (Accessed: 22 March 2019).

Fig. 07: MIT Architecture Machine Group. (1980). Using the Aspen Movie Map from an Experimental Rig [image] Available at: https://www.computerhistory.org/atchm/going-places-a-history-of-google-maps-with-street-view/ (Accessed: 20 February 2019).

Fig. 08: Broadly Vice Identity. (2018). I Got Surgery to Look Like My Selfie Filters. [image] Available at: https://www.vice.com/en_us/article/mby5by/cosmetic-plastic-surgery-social-media-seflies (Accessed: 20 February 2019).

Fig. 09: VICE News. (2018). China's "Social Credit System" Has Caused More Than Just Public Shaming. [screenshot] Available at: https://www.youtube.com/watch?v=Dkw15LkZ_Kw (Accessed: 18 February 2019).

Fig. 10: Brooker, C. (2018). Still from NoseDive: Black Mirror S3 E1. [image] Available at: https://medium.com/@elisavainteract/dystopian-experience-design-a8d0644893b7 (Accessed: 10 May 2019).

Fig. 11: Jongejan, J et al, Google AI Experiments. (2016). Quick Draw! [image] Available at: https://quickdraw.withgoogle.com/ (Accessed: 15 April 2019).

Fig. 12: Baldwin, G. (2019). Drawing of Everything. [screenshot] (Accessed: 16 April 2019).

Fig. 13: Baldwin, G. (2019). Minimal Drawing. [screenshot] (Accessed: 16 April 2019).

Fig. 14: Baldwin, G. (2019). Drawing of Exploitation. [screenshot] (Accessed: 16 April 2019).

Fig. 15: Harvey, A. (2019). HyperFace Type-01 Prototype. [rendering] Available at: https://ahprojects.com/hyperface/(Accessed: 28 April 2019).

Fig. 16: Paglen, T. (2018) Invisible Images (image) Available at: http://www.warscapes.com/reviews/what-machines-see-trevor-paglen-invisible-images (Accessed: 05 June 2019).

Fig. 17: Baldwin, G. (2019). My Sweater Elephant. [screenshot] (Accessed: 16 May 2019).

Fig. 18: Baldwin, G. (2019). Upside down Chair [screenshot](Accessed: 16 May 2019).

Fig. 19abc: Baldwin, G. (2019). Ghost Chair. [screenshot] (Accessed: 16 May 2019).

Fig. 20: Baldwin, G. (2019). Rococo . [screenshot] (Accessed: 16 May 2019).

Fig. 21: Baldwin, G. (2019). Spun Chair . [screenshot] (Accessed: 16 May 2019).

Fig. 22: Baldwin, G. (2019). Beanbag. [screenshot] (Accessed: 16 May 2019).

Fig. 23: Baldwin, G. (2019).Spork. [screenshot] (Accessed: 16 May 2019).

Fig. 24: Baldwin, G. (2019). Surfboard. [screenshot] (Accessed: 16 May 2019).

Fig. 25: Baldwin, G. (2019). Laptop. [screenshot] (Accessed: 16 May 2019).

Fig. 26: Baldwin, G. (2019). Distort. [screenshot] (Accessed: 16 May 2019).

Fig. 27: Baldwin, G. (2019). UpsideDown. [screenshot] (Accessed: 16 May 2019).

Fig. 28: Baldwin, G. (2019). Morphed. [screenshot] (Accessed: 16 May 2019).

Fig. 29: Baldwin, G. (2019). Plastercast. [photo] (Accessed: 16 May 2019).

Fig. 30: Kazuo, T. (2001). Untilted glazed Stoneware. [image] Available at: http://www.pierremariegiraud.com/en/artistes/oeuvres/1141/kazuo-takiguchi (Accessed: 20 May 2019).

Fig. 31abc: Baldwin, G. (2019). Blender Prototype. [screenshot] (Accessed: 16 May 2019).

Fig. 32: US National Archives. (1918). Dazzleship. [image] Available at: http://www.graphicine.com/razzle-dazzle-art-on-ships-the-art-of-war/ (Accessed: 20 May 2019).