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"Instrumentalization Theory: An Analytical Heuristic For A Heightened Social Awareness Of Machine Learning Algorithms In Social Media"

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Abstract

New innovations in information management and communication technologies have produced technological assemblages which have radically altered the way people socialize and interact with the world. The most significant and ubiquitous of these technologies is what is colloquially referred to as 'machine learning.' Like most, if not all, technologies, machine learning models are neither wholly good nor bad. Their functional ethics are largely determined by the context in which they are employed. However, their ubiquity demands that we develop a heightened social consciousness of the way machine learning simultaneous constrains, manipulates and democratizes social processes. In order to develop better social understanding of technologies that incorporate machine learning, we must clarify how and why corporate engineers and executives scale and implement machine learning into their respective applications and services. Unfortunately, high-level calculus and computer science obscure this situation and make formulating a critical space for humanist theorists and Science and Technology policymakers an exhaustive discursive endeavor. The absence of a well understood discourse on the manner in which machine-learning algorithms are implemented represents a kind of socio- technical opacity, which obscures technological processes for contextualized corporate, design and user-motivated ethics. In order to address this problem, I propose to analyze the primary machine-learning algorithm models which organize and rank the information presented on social media newsfeed. An analysis that clarifies the function of machine learning algorithms can promote academic research and provide the impetus for Science and Technology policy incentives. Finally, this sort of analysis suggests the need for a regulatory agency for machine learning algorithms prior to their implementation in to public production site environments(i.e. social media)

Introduction

In the last decade and a half social networking technology has risen to global prominence. Applications and websites that enable users to create and share content as a means of social networking have created a new means of communication, but most importantly a new digital space in which communication and ethics can be generated and managed. Already there are calls for Facebook Inc. to develop machine learning models to distinguish between political fact and lie in digital journalism. Done without adequate ethical consideration, this could result in unforeseen ethical and social implications. This is but one of many emerging discursive issues surrounding machine-learning in social media. One of the profoundly wonderful characteristics of the modern era is its ability to quickly build new technologies to grapple with modern issues of information management overload and sustainability. But a key disadvantage of such an exponential rate of technological innovation is that the humanist theories which should be associated with their ethical implementation and use lag behind developmentally. This limits public and academic discourse and prevents rhetoric and Science and Technology scholars from properly evaluating the communicative ethics of new digital technologies. A key meta-physical characteristic of present technological usage is reductionism, described by philosophers as the manner in which objects are stripped of their natural connections so that new, implicit, social andtechnical connections emerge in their place. Instrumentalization theory, first postulated by Andrew Feenberg in 'A Critical Theory of Technology' (1991), provides a dual-level(primary and secondary) analytical heuristic to probe the implications of social processes that are socio- technically reduced in a digital space which is algorithmically designed, determined and managed. Feenberg's instrumentalization theory stresses the notion that, like any tool, technology embodies the ethics and ontological nature of the individuals who design and create them. As such, his theory exposes a deep exigency for a synthesized rationality towards the democratic and ethical implementation and critique of new technological systems. The emergence of ubiquitous social media which reduce social interactions provides a tangible space to use Feenberg's dual level (primary, secondary) instrumentalization theory to develop a humanist approach to technological critique and design.

Section 1: Instrumentalization Theory as an Analytical Heuristic

Andrew Feenberg is deeply engrained within Critical Theory's critique on the philosophy of technology. In *Critical Theory of Technology*, Feenberg lays out the various figures from the Frankfurt School who influenced his outlook on the state of technological critique today (namely Martin Heidegger's *Question Concerning Technology*, Adorno & Horkheimer's *Dialectic of Enlightenment*, Marcuse's *1-Dimensional Man*, and Habermas's *Towards a Rational Society*). The critique of technology is a key feature of Critical Theory dating back to its founders Adorno and Horkheimer's disparaging notion that any form of technical development was "a substrate of domination" (6). Over time many rhetorical and philosophical luminaries have added their perspectives to the lexicon, but none more prolific or integral to present understandings of technology as Herbert Marcuse and Jurgen Habermas. Constructivism and Marcuse's reductionist theory of technology posited that technology embodied a specific cultural incentive for the alteration and domination of nature. For Marcuse technology was not a single device, or technic as he would say, but "was a social process in which technics proper (that is, the technical apparatus of industry, transportation, communication) is but a partial factor…[humans] are themselves an integral part and factor of technology, not only as the men who invent or attend to machinery but also as the social groups which direct its application and utilization" (Marcuse 65). As such, it operates as a broad ranging criticism of technology's allegiance to capitalist industry and culture as the main generator of its' authoritarian and reductive characteristics.

The Dual Ethics of Technology

As Feenberg writes, "the debate between Marcuse and Habermas over technology marked a significant turning point in the history of the Frankfurt School. After the 1960's Habermas's influence grew as Marcuse's declined and Critical Theory adopted a far less utopian stance" (Feenberg 45). It is here that Habermas, a late-coming philosophical member of Marcuse's same Frankfurt School, provides Critical Theory with a counterpoint to constructivist thought, the view that technology holds an inherently reductionist or enframing characteristic. In Habermas's view, the technical control of nature is a genuine species-wide interest for humans, an interest with no ties to any singular cultural or economic feature. When Feenberg views the state of the debate he observes that "while much of Habermas's argument remains persuasive, his defense of modernity now seems to concede far too much to claims of autonomous technology" (Feenberg 45). In Habermasian communicative rationality theory, technology operates not as an artificial technic subject to the perpetuation of ideological control, as Marcuse would attest, but rather an ideology. According to Habermas, through a reduction of questions of what a good, well-lived life is to technical concerns for experts, contemporary elites eliminate the need for a public democratic discourse of values, thereby depoliticizing them. In this view, technology only operates as a veil to mask the value-laden nature of government decision making (Habermas 83).

Marcuse, Heidegger, Habermas and Marx all contributed to Feenberg's understanding and valuing of positivistic and socially constraining features of technology. Feenberg defines a good society as one which "enlarges the personal freedom of its members while enabling them to participate effectively in a widening range of public activities. At the highest level, public life involves choices about what it means to be human. Today these choices are increasingly mediated by technical decisions" ("Transforming Technology: A Critical Theory Revisited" 3). As such, the design of technology is an ontological decision fraught with political consequences. Traditional accounts of technology, determinist and instrumentalist, highlight efficiency as the principle of selection which determines a successful or failed technology. In the formation of his instrumentalization theory, Feenberg argues that the intervention of interests and subjective ideologies into technological design does not reduce efficiency but rather biases its' achievement according to a broader social program, which he refers to as a 'technical code'. According to Feenberg, the technical code is the rule in which technologies are realized in a social context with biases reflecting the unequal distribution of social power. Feenberg postulated instrumentalization theory as a means of uniting the insights of substantivist understandings of technology in which technology reduces and enframes natural processes and elements into raw materials for extraction, and the constructivism of contemporary historians and sociologists who argued that technology is nothing more than extension of natural human processes. Feenberg unites the pessimistic distrust of technology's potential from the philosophy of technology, courtesy of Heidegger and Marcuse, and Habermas's accommodating and forgiving interpretation of technological usage in his theory. Instrumentalization theory states that technology must be analyzed at two levels, the level of our original functional relation to reality (Primary) and the level of implementation and design (Secondary). Both the primary and secondary levels of instrumentalization theory contain contingent elements and ontological operations which help distinguish between both analytical spaces. Most importantly, instrumentalization theory makes explicit the dual nature of technological processes in its' deconstruction of the manner in which technology simultaneously constrains material social processes, while also providing access to expedited and efficient digital applications leveragedby new technologies.

Primary Instrumentalization

In primary instrumentalization technological functions are **decontextualized** and **reduced** from everyday life. Later the user is positioned to relate to them. The decontextualization and reduction processes of the primary level all occur under a **distancing effect**, where the function and the subject are reduced for maximum manipulation and control bythose who design the technology. When examined through the lens of primary instrumentalization theory, humans are continuously decontextualized through computer usage. This process is more easily grasped when viewed and understood as a version of Heidegger's revealing. "The computer simplifies a full-blown person into a 'user' in order to incorporate himor her into the network. Users are decontextualized in the sense that they are stripped of body and community in front of the terminal and positioned as detached terminal subjects" (Feenberg, 59). It is in the repositioning of people into users in a technical space that in turn reveals new opportunity or affordances for new technical actions. This process can be applied to multiple other technological arrangements as well, to follow the earlier example, such as digital social networks.

Secondary Instrumentalization

In secondary instrumentalization the focus lies on the social, political and cultural forces which influence design choices. This analytical level addresses primary instrumentalization by **systematizing**, technically incorporating, the reduced functions, whereby decontextualized technical objects are combined with each other and re-embedded in the natural environment. Technical objects can then be **mediated** by Actors (designers) for aesthetic and ethical considerations ("A Critical Theory of Technology" 50). Feenberg utilizes the example of the cutting of a tree to create lumber to further highlight the manner in which primary and secondary instrumentalization inform each other's socio-technical ethical constraints. "Cutting down a tree to make lumber and building a house with it are not the primary and secondary instrumentalizations respectively. Cutting down a tree 'decontextualizes' it but in line with various technical, legal and aesthetic considerations determining what trees can become lumber of what size and shape and are salable as such" (Feenberg, 50). Let's expand on this, prior to a tree being cut down or **decontextualized** the loggers must address numerous social and technical requirements imposed on them by their corporate employers and political leaders. Laws such as the U.S. Lacey Act imposes or **mediates** strict limitations on what types of trees can be logged. This mediation has been in turn informed by subsequent decontextualization processes. Illegal logging (primary instrumentalization) informs the prohibition of logging certain species of trees (secondary instrumentalization), which in turn informs the new decontextualization practices of the loggers who are now performing an adjusted primary instrumentalization.

Section 2: Machine Learning: Ubiquity and Socio-Technical Opacity

Machine learning relies on an automated process that extracts patterns from data and then models that pattern to generate predictive decisions from data present in any available information set. Supervised machine learning techniques automatically learn a model of the relationship between a set of descriptive features and a target feature based on a set of historical examples, or instances. This 'model' can then be used to make further predictions for new instances (Kelleher et. al. 3). Facebook uses machine learning algorithms for classification, ranking, and content understanding devices. According to Hazelwood, et al. in 'Applied Machine Learning at Facebook: A Datacenter Infrastructure Perspective', the applications leveraged by machine learning include but are not limited to the Facebook Newsfeed, Serving Advertisements, Search Functions, Classifying Objects, Facial Recognition, and Language Translation. The machine learning algorithms used by Facebook to enable these applications to function properly include Multi-Layer Perceptrons (MLP), Support Vector Machines (SVM), Gradient Boosted Decision Trees (GBDT), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN) (Hazelwood et al. 3).Facebook's machine-learning artificial intelligence 'ecosystem', as Hazelwood describes it, can be categorized into 3 primary sections: frameworks, platforms, and infrastructure (Hazelwood et al. 1). Hazelwood, et al., expand on Robinson's earlier explanation of the Facebook machine learning infrastructure in their explanation of the Facebook 'ecosystem'. Frameworks are needed to create, migrate and train machine learning models, while platforms are used for model deployment and management. Infrastructure, asRobinson demonstrated earlier, is needed to compute workloads and store data.

The Functional Ethic of Machine Learning Algorithms

Arlindo Oliveira in *the Digital Mind* provides a simplified description of Machine Learning as it relates to artificial intelligence which is helpful in contextualizing ML models as inherently neutral technology in regard to their function. According to Oliveira, the quintessential problem of machine learning consists, in its most simplified form, of inferring general rules or behaviors from a number of specific concrete experiences. This general processis referred to as inductive learning. Inductive learning is performed by learning a general rule from a set of labeled instances. Oliveira provides multiple practical examples and analogies to describe different ML models, such as GBDT and K-Nearest Neighbor, methodologically referred to as similarity-based learning. Oliveira cites David Hume, and his critique of induction- based learning in order to critique the inference methods of machine learning models that are currently being deployed in various industries, including social media. Hume points out that induction from past experience cannot provide guaranteed results, as our ability to learn from experience exists only because there is some regularity in the data that we are able to explore.

Oliveira refers to this inductive bias as the generator of the variety of different algorithmic machine learning models we see today. Oliveira goes on to demonstrate that all learning algorithms have the same inherent outcomes when their respective performances are averaged across all possible problems in a given domain. Commonly referred to as the *No Free Lunch Theorem*, it describes the fact that all learning algorithms are equally good if a preference for a specific learning bias can't be established. When incorporating the *No Free Lunch Theorem* intoa rhetorical analysis of the functional ethics of machine learning algorithms one comes to understand that no one model is more ethical or unethical in its implementation than another. As such, the inherent functional ethic of machine learning algorithms when employed in public production environments is one of general neutrality. This perceived neutral functional ethic in turn lends itself to obfuscating secondary ad hoc and corporate technical ethics which motivate their purposes, and also highlights the fact that any and all algorithms are susceptible to a dominating technical code which holds the potential to perpetuate obfuscation indefinitely. As we established in the previous sections, the technical code that comes to dominate the neutral function of machine learning comes in the form of the digital infrastructure which models are deployed into.

The Socio-Technical Opacity of Machine Learning in Social Media and the Obfuscation ofAlgorithmic Bias

The last few sections have examined the manner in which algorithmic processes and the infrastructure that enable their deployment to constitute a socio-technical opacity, but the question obviously arises, so what? Surely, human beings have successfully engaged with black- boxed technology in the past without severe social repercussions. This is true to an extent, but it would be a grave mistake to compare present digital technologies to other technological innovations of the 20th century, like the telephone or radio. With those technologies, the technical code is more or less easily discerned in the immediacy of the technical product, in the case of thephone and radio it is the successful audio transmission of a voice from one location to another.

However, the opacity present in machine learning masks its' dual technical codes, one informedby the users it interacts with and assists, and the other by its creators and the infrastructure it exists in. Opacity creates the illusion of technological neutrality and fogs human understanding of the influence technology has on the development of how they interact with the world. In a world that is becoming increasingly constituted by automated technologies, to lack an appropriate understanding of their functions is akin to lacking basic awareness of your own human rights. The persistence of socio-technical opacity in relation to automated technologies, machine learning algorithms in particular, erodes and effaces the democratic potential and promise of new digital technologies.

Section 3: An Instrumentalized Analysis of Machine Learning & the Need for a Heightened Socio-Technical Awareness in Science and Technology Policy

We would like to believe that social media is a perfectly neutral networking tool to maintain communication with our friends, loved ones and the world at large, however, scholars from the Frankfurt School and theorists inspired by them, like Feenberg, would disagree as to the existence of a truly neutral technological arrangement. "Neutrality generally refers to the indifference of a specific means to the range of possible ends it can serve … There is no such thing as technology as such. Today we employ this specific technology with limitations that are due not only to the state of our knowledge but also to the power structures that bias this knowledge and its applications. This really existing contemporary technology favors specific ends and obstructs others" (Feenberg, 182). According to Lars Backstrom, the Engineering Manager for NewsFeed Ranking at Facebook, there are "as many as 100,000 individual weights that produce NewsFeed. The three original EdgeRank elements- Affinity, Weight, Time Decay- are still factors in NewsFeed ranking, but other things are equally important" (McGee, 2014).

Outside of the standard Affinity, Weight and Time Decay weight factors, the new algorithm alsoconsiders a user's relationship settings, post types, spam reporting, network exploration, device considerations, and story bumping.

Facebook Inc.'s Technical Code

Facebook has experienced multiple iterations of its page ranking algorithm but for the purposes of this analysis shall be limited to EdgeRank and its current machine learning based algorithm. The earlier iteration, EdgeRank, collected, organized, and ranked undiscovered content based on three elements: affinity (the proximity of content to the technical user), weight(the action a user took when interacting with content) and time decay (which values newer content over pre-existing content). "Every item that shows up on the NewsFeed is considered an object. If you have an object in the NewsFeed (say a status update), whenever another user interacts with that object, they are creating an edge, which includes actions like tags and comments" (Kincaid, 2010). When each edge factor was multiplied by the other, the resulting value represented the contents' relevancy score represented algorithmically as $\sum \mu w d$. Affinity, weight, and decay were all presented to the user via their content interface. It is in this way that the EdgeRank algorithm incorporates Feenberg's primary and secondary instrumentalizations simultaneously, much like the tree being cut for wood the algorithmically generated content on the NewsFeed has already been mediated for worth. When a user creates an edge factor througha de-worlding interaction (primary) the content is at the same time undergoing a new disclosing when the EdgeRank algorithm recalculates the content's relevancy score (secondary).

What Ethical Concerns Surrounding Machine Learning Implementation Should American Science and Technology Policy Consider

Because of its' capacity to highlight both the problematic and positive ethics of technology, I believe Feenberg's theory of instrumentalization can serve as the theoretical foundation for future considerations for Science and Technology policy related to machine learning and other ubiquitous socialization technologies with socio-reductive characteristics. More than 3 years after H.R. 5051, the OPEN Government Data Act, attempted to create a means to publish all non-federally restricted data in an open source format in order to produce a standardized use of big data for both federal and public use, we have now entered an age where private companies are able to dictate the rules of information management and metadata commodification through machine learning. Since the 2016 American Presidential election, which saw one of the most blatant violations of consumer privacy in internet history when the personally identifiable information of 87 million Facebook users was made available to Cambridge Analytica, not to mention the use of Facebook's vulnerable infrastructure by Russian hackers to disseminate political and social falsehoods, questions about the integrity of America's digital society remain unanswered. While Cambridge Analytica was dissolved in 2018 for allegations of bribery and sexual "honey-potting" on the behalf of their clients, looking at Facebook today, it is not clear if attempts made by Mark Zuckerberg or his Director of Artificial Intelligence have solved the issue of information privacy. After all, Facebook does not sell personal information but rather makes our personal information available to outside vendors. If Facebook's automated digital infrastructure provides machine learning with its opaque technical code, then the rules of ethical machine learning use falls to the vendors who are on the receiving end of Facebook's ML driven meta-data acquisitions. This reliance on the supposed ethics of third-party vendors is deeply troubling.

References:

- Adorno,TheodorW.,andMaxHorkheimer.*DialecticofEnlightenment*.London:Verso,2016. Burrell, Jenna. “How the Machine Thinks: Understanding Opacity in Machine Learning
- Algorithms.”*SSRN Electronic Journal*,2015.https://doi.org/10.2139/ssrn.2660674.
- Coppins,McKay.“TheBillion- ollarDisinformationCampaigntoReelectthePresident.”*The Atlantic*, Atlantic Media Company, 7 Feb. 2020, www.theatlantic.com/magazine/archive/2020/03/the-2020-disinformation-war/605530/.
- Feenberg, Andrew. *Critical Theory of Technology*. New York: Oxford University Press, 1991. Feenberg,Andrew.*AlternativeModernity: the Technical Turn in Philosophy and Socia lTheory*.
- Berkeley:UniversityofCaliforniaPress,2008.
- Feenberg,Andrew."MarcuseorHabermas:TwoCritiquesofTechnology."*Inquiry*39.Accessed July 1, 2019.