JUDGMENT DAY: BIG DATA AS THE BIG DECIDER

BY

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Abstract

This Digital Age has borne witness to not only an influx of information but also the need to make use of this information. The rapid growth of information results in the pervasion of Big Data in “all areas of human endeavor” (Mayer-Schönberger & Cukier, 2013). Including Big Data evaluations, or algorithmic outputs, in our decision-making process has significant material consequences and the changes how we discuss the role of Big Data in our decision-making process. To understand who we are, Arendt argues that judgment occurs through speech and action (Arendt, 1958). Humans are accustomed to undergoing deliberative processes to make decisions. Algorithms produce automatic outputs which changes, and in some cases removes the deliberative space. When we rely on black boxed algorithms or technology that could produce or reinforce disparate impact on individuals, how we engage in those deliberations modifies human judgment in some way. This thesis analyzes discourses around the implementation of Big Data our justice and finance systems. Through a risk assessment algorithm called COMPAS and credit scores, discourses are predominantly framed around perceived notions of objectivity in the data. Ultimately, the role of human judgment shifts but is still necessary if we are to continue relying on technological advancements for the betterment of society.

Chapter 1 – Introduction to Big Data and Human Judgment

Albert Einstein once noted “[i]t has become appallingly obvious that our technology has exceeded our humanity” (Szczerba, 2015). The prevalence of technology in human lives is undeniable, and in the Digital Age, Big Data becomes very influential in how individuals and institutions make decisions. Big Data is a new wrinkle in technological advancements that influences societal operations including changes in business enterprise, movements in the financial sector, innovations of the transportation industry, evolution of the entertainment industry, and all other arenas impacted by our growing reliance on information. This Digital Age has borne witness to not only an influx of information but also the need to make use of this information. The rapid growth of information results in the pervasion of Big Data in “all areas of human endeavor” (Mayer-Schönberger & Cukier, 2013). Einstein’s quote captures the essence of the relationship between technology and humanity, acknowledging that Big Data has seeped into all aspects of human interaction. This thesis investigates how discourses of Big Data characterizes human judgment in light of the mass amounts of information produced in the Digital Age.

The ubiquity of technology enables the collection of mass amounts of data, which can be used to evaluate trends, identify patterns, and ultimately affect how individuals engage in the decision-making process. The idea that more information, and the ability to assess that information, renders better judgment lies at the heart of this analysis. Big Data is found in the most mundane places, where individuals turn to various technologies to ease the decision-making process, from medical decisions to transportation choices (Feibus, 2017). As anyone who owns a FitBit knows, fitness trackers gather massive amounts of information about an individual's vital signs (and whatever other readings are gathered from the tracker) to predict heart attacks. Likewise, drivers rely on an app's ability to collate vast amounts of information, from accidents, construction, and speed of traffic, to determine driving conditions for even the most prosaic task of driving home after work – an act we carry out 5 days a week for the greater part of our lives. We check a common GPS, perhaps Google Maps, to ensure that we are taking the best route home. These technologies tell us how long the drive will be, notifies us of any accidents, construction, and other potential delays on our route. They essentially render an easily digestible decision: what is the fastest way home.

Big Data is used in the most mundane way, but the results can have huge impacts on how one makes decisions. If a fitness tracker informs a patient and her physician that she will have a heart attack in two years or even that there is an accident on a usual route home, it is likely that the patient will try to undergo some lifestyle changes to prevent or prolong a heart attack or an employee will likely take a different route home. These examples highlight how Big Data might influence the decision-making process of how individuals respond given that information. However, this information is often used to narrow, as opposed to expand, choices.

This potential prediction of heart attacks through fitness trackers elucidates some of the questions surrounding our reliance on Big Data. First, the fitness tracker invites previously non-existent fears in the patient about the likelihood of a heart attack. While family history and nutritional habits could generate some concerns about disruptions with the heart, the specificity of the prediction based on the sweeping data collection uncovers both positive and negative implications for the technology. This technology could spark change in the patient's life or just the interpretation of this value could be erroneous. On one hand, this technology could present the patient with an opportunity to change their behavior to avoid the heart attack or it could have the adverse effect on the patient producing a sense of hopelessness surrounding her heart health. On the other hand, we should consider if the tracker was correct in its prediction and how primary care physicians use that information in conjunction with the myriad of other factors (e.g. family history, diet, exercise, etc.) used to assess patients' risk to heart attacks. The doctor's delivery of the information to the patient also matters – is it that the patient will have a heart attack in two years or if the patient fails to potentially adapt her lifestyle, she is projected to have a heart attack around that time.

As we seek to understand the role of Big Data and its impact on human judgment, there a number of things to consider: how Big Data arrives at output, the perceived accuracy of that evaluation, the value of this evaluation in relation to other factors that carry weight in making a decision, how Big Data evaluations are communicated, and ultimately what we decide to do with these evaluations. These nuances are important things to consider to understand how the discourses of Big Data characterize human judgment. We all want certainty and facts when rendering judgment, and we hope technological advancements help in that cause, but our trust in technology affects how much power we ascribe to it in making decisions. This exploration of how discourses around Big Data characterize human judgment seeks to understand that dynamic of decision making.

Big Data and the Algorithm

We live in a digital era, which changes the way information is stored and used. The proliferation of data acquisition and storage gives rise to ways of processing and analyzing data that far exceeds human ability. Big Data flourishes as we attempt to make use of all this data. The term “Big Data” has become commonplace, usually meaning different things to different people. For the purposes of this thesis, the McKinsey Global Institute states that datasets greater in size than the typical database software tools used to capture, store, manage, manipulate, and analyze are referred to as Big Data (Manyika et al., 2011).

One of the most commonly accepted definitions of Big Data is Doug Laney’s 3 V’s of Big Data: Volume, Variety, and Velocity. Other definitions have included two additional V’s: Veracity and Value (Davenport, 2014; Wrench, Thomas-Maddox, Richmond, & McCroskey, 2015). These definitions are all strong foundations for understanding Big Data, but for the purposes of this thesis, I chose the first cited definition provided by the McKinsey Report because of the terminology: “manipulate” and “analyze.” A ‘typical’ database is intentionally left subjective for different sectors as the sizes of datasets continue to increase, this definition gives flexibility for that continued growth (Manyika et al., 2011). Since Big Data has 5 prominent characteristics, the analysis requires computational power beyond human capability to keep up with speed, size, and all other factors accounted for in these evaluations. Terms “manipulate” and “analyze” allude to the processes behind Big Data that reveal aspects of analysis that are of interest to rhetorical scholars. These rhetorics of Big Data, the discourses that suggest using Big Data to drive decision-making, highlight numerous questions as to how we think of human judgment. Rhetorical scholars are interested in how discourses affect public judgment. Hence, the appeal to Big Data as a better form of decision-making rests on certain appeals that help us understand the role of human judgment in the digital age.

Big Data is so large of a data set that algorithms are used to process these data and aid in identifying trends, patterns, and anomalies. Big Data is just data – random information points without assigned value until they are put through some meaning-making process, the algorithm. An algorithm is a set of formulaic rules and processes initially programmed by humans to sift through data sets to create a particular output: a pattern, trend, suggestion, etc. Algorithms are a series of if-then statements used to identify those trends (Mayer-Schönberger & Cukier, 2013; Whipple, 2013). Algorithms are our way of grappling with immense datasets – so large that we design it to be self-learning so it can understand how to compute the large data set. Algorithms can make predictions after collecting and accounting for billions of data points – predictions which are used to aid in the decision-making process. Furthermore, algorithms are types of programming that process this voluminous information. In other words, the algorithms "judge" the Big Data. Like Big Data, the rhetorical framing of algorithms as modes of assessments further complicates the way we think of judgment in the Digital Age.

The information revolution has been around since the 1960s, but only as recently as the year 2000 has information storage reflected this shift. In 2000, seventy-five percent of information stored was non-digital; in contrast to the year 2013, only 2 percent of stored information was non-digital (Mayer-Schönberger & Cukier, 2013). Our reliance on evidence and data for decision-making is embedded in scientific processes, which helps explain the attractiveness of Big Data in making insights that would elude human ability to assess information. However, the shift into the Digital Age changes how we process the data, and more importantly how we talk about it. For instance, the phenomenon of Big Data has enabled us to do many things that we either could not do in the past or accomplish things more efficiently such as: find business trends, combat crime, prevent disease, and more (McNeely, 2015). Increased digitization and access to data have further solidified human reliance on and enchantment with Big Data.

We consume Big Data by regularly consulting it for guiding decision-making. For instance, Google Maps, Rotten Tomatoes, Siri, and even Yelp represent a few of the applications commonly used to influence choices, both large and small, in our day-to-day lives. Google Maps suggests what routes to take, Rotten Tomatoes suggests what movies to watch, Siri can offer simple suggestions for attire based on weather outside, and Yelp influences what restaurants to visit. These programs offer such recommendations through an amalgam of data that suggests a particular output or preference, based on what data it is programmed to privilege. Our utilization of the data is changing the process of decision-making.

Before Big Data, people were more likely to consult family or friends for simpler decisions such as what new movies to see. Judgments and action were the result of deliberation, even as it included a variety of evidence. Even if our family or friends recommend a particular movie, we are likely to check Google reviews, Rotten Tomatoes, or apps like Fandango to verify other movie reviews before seeing a movie just to ensure that the data concur. We still consult what the “numbers” say or what the data suggest to seek validation for our decision-making. These few examples frame the active, yet often overlooked, role of Big Data in even the most monotonous decision-making process.

Our mass consumption of data aligns with the rapid production and storage of new, abundant amounts of information. “The amount of stored information grows four times faster than the world economy, while the processing power of computers grows nine times faster” (Mayer-Schönberger & Cukier, 2013). This influx of information happens quickly as do the technological advancements required to process the data. This leads to two types of data: structured and unstructured. Both have utility, but one is much easier to process. Structured data is quantifiable values such as biological sex, income, education level or age that function as identifying elements usually calculated and easily measurable values. Unstructured data include things more difficult to standardize or quantify such as messages or types of status updates on social media (Mitra, 2014). The unstructured data is more difficult to capture and requires more sophisticated algorithms to process but is also factored into Big Data evaluations. This type of data is the more ineffable type that complicates identifications of patterns, trends, and predictions. And yet, this data is still used in identifying trends, patterns, assessments that remains very persuasive in the decision making process.

With so much data, it is inevitable that the data include noise – irrelevant, unnecessary information in a data set (Waldherr, Maier, Miltner, & Günther, 2017). Even as noise and unstructured data produce results that programmers question or attempt to fix, the rhetorical force of Big Data as conduit for objective assessments remains an influential element in the deliberative process. In other words, the algorithmic results stand in for the right judgment or decision, regardless of whether there are flaws in the data or the processing. This thesis engages how discourses around Big Data, and the algorithmic processes that assess the data, function in deliberations to alter human judgment and frame effective decision-making. This project does not explore the technical aspects of Big Data or the nuances of algorithms, as that requires a technical expertise beyond the scope of this thesis. Rather, Big Data is being explored as a rhetorical phenomenon that shifts assumptions about deliberation and the proper role of human judgment in the decision-making process. To be sure, Big Data and their attending algorithms have enabled precision and improved decision-making in countless human endeavors. Google Maps is almost always correct and is certainly helpful. Evidence-based medicine has improved the quality of care for numerous patients. Assessments of climate change are becoming increasingly precise, and notably more persuasive. However, the question of exactitude based on technical aspects of algorithms is not the focus of this project. Rather, the moment a decision is rendered based on the result of Big Data (such as tenure decision based on the results of an Academic Analytics assessment), there is a shift in the deliberative process and the role of human judgment in weighing arguments and evidence (Hartelius & Mitchell, 2014). The public discourse around Big Data as the legitimizing feature of a given decision invites rhetorical investigation.

Algorithms are all around us from coupon pop-ups on handheld devices based on location and buying habits, survey displays on screens when we leave restaurants, and more. Even insurance companies use data points mined from cell phones to determine individual insurance rates, as driving practices are tracked through phones, GPS, or other technological devices (Olson, 2014). Moreover, algorithms process data points to directly suggest how we spend our money. Shopping on Amazon reveals a list of suggestions nestled under "Customers who bought this item also bought…" Customers produce a few data points which would be actual purchases. Then aspects of more data are incorporated into other different data points: search history, cookies on the computer, what other who bought the same product also bought, to develop a list of suggestions. This process is engaging because algorithms determine what other data are important. These suggestions increase visibility of other products and pique your interest in potential other products based on Big Data information, thus influencing your decision to purchase them.

Recommendations proposed by algorithms are not unique to Amazon, but include social media ads, clothing lines, preferred sites, and all other places we leave our digital data footprints for algorithms to process. Buying a good, liking a post, or even traveling to a certain area are all new data points used to predict future behavior or reveal trends and patterns. So, if you follow the "advice" of algorithms and make that choice, who is expressing agency – you or the algorithm? Especially if algorithms are a reflection of your past decisions…or is it? Big Data offers suggestions which we can choose to accept and follow or reject and dismiss. Therefore, algorithms interface with us, offer us recommendations, and greatly influence our decisions.

The Black Box

When individuals render a decision, they typically have the ability to justify or identify the reasons they came to such a conclusion. Even if they justify a decision based upon how they feel, such a reasoning would serve as an understandable, if not unsatisfying, explanation. Algorithms also render a result that presumably could be explained by its programming. However, sophisticated, and proprietary, algorithms often become "black boxed," in which the programming does not necessarily explain the result. The dual meaning of the term "black box" highlights essential features of Big Data and reveals how algorithms can also occupy that black boxed space. Black box "…[c]an refer to a recording device, like the data-monitoring systems in planes, trains, and cars. Or it can mean a system whose workings are mysterious; we can observe its inputs and outputs, but we cannot tell how one becomes the other. We face these two meanings daily: tracked ever more closely by firms and government, we have no clear idea of just how far much of this information can travel, how it is used or its consequences" (Pasquale, 2015).

The black box of Big Data came into being through technological advances which have enabled search engines, credit raters, major banks, and even the TSA to gather massive amounts of data on each of us. Data points are collected and produce rankings, scores, and risk calculations which all have vital consequences (Pasquale, 2015). In other words, the algorithmic processes inform decisions with significant implications, but they can elude deliberative scrutiny and the burden to justify the result. There has been a gradual acceptance and normalizing of datafication –"transformation of social action into online quantified data, thus allowing for real-time tracking and predictive analysis" (Mayer-Schönberger & Cukier, 2013; van Dijck, 2014). There is a general acceptance and trust in the objective quantification and tracking of human behaviors (van Dijck, 2014). This acceptance and trust highlights the appeal to Big Data and why we generally accept algorithmic outputs as more reliable than human judgments.

An additional element to the black boxing of algorithms is the fact that algorithms have to be dynamic. These formulaic processes are necessary to process vast amounts of data, but in order to function properly, algorithms often learn as they encounter new data points. It would be pointless to assume Big Data is good when algorithms are incapable of reacting to new data points. It has to learn to identify new patterns and make predications based on those identified trends as new data become available. Algorithms are programmed to be self-learning and consistently making evaluations based on data collection. Thus, we assume that they are "objective" mechanisms of data processing, but how it is programmed effects how it learns.

Big Data, Rhetoric, and Judgment

Rhetoric is the art of persuasion, creating certainty within uncertainty. It emerged in a moment in which a rule by the people relied on persuasion. The deliberative body had to render decisions on various motions, and the best possible decisions relied on good arguments and sound judgment. Relying solely, or primarily, on Big Data evaluations to render judgment presents a drastic shift in how deliberations are done between individuals. Thus, analyzing how discourses about the trust in Big Data output as a form of rendering judgment presents a unique moment when the aspect of judgment shifts from a more visible deliberative process.

I discuss how perceptions of Big Data frame the discourses of judgment. Moreover, the proliferation of our increased reliance on Big Data invites questions about the role of judgment, how we understand the locus of responsibility in decision-making, what we think about human agency in the era of Big Data, how we assign meaning to algorithms, how that affects our understandings of expertise, and how discourses around uncertainty change due to a disproportionate trust in technology over the human. This thesis does not make staunch normative claims about the role of Big Data in decision-making; rather, how the discourses of Big Data change questions of agency apropos to human judgment. Data is a requirement for strong decision-making just as evidence is a requirement for producing strong arguments. This thesis does not make any claims about the value of data nor wish to imply that data should be devalued. Rather, suggest that the discourses of Big Data position it as an autonomous form of judgment that shifts questions of agency, responsibility, and…in human judgment.

Judgment is a uniquely human act through speech and action. Hannah Arendt (1958) notes that "…[d]isclosure of who somebody is, is implicit in both his words and his deeds…Without the accompaniment of speech, at any rate, action would lose its revelatory character, but, at the same token, it would lose its subject, as it were; not acting men but performing robots would achieve what, humanly speaking, would remain incomprehensible," (Arendt, 1958, p. 178) Without speech and action working cohesively as one, the human experience is tainted or hindered in some way. Speech functions as a deliberative performance unique to human beings.

According to Arendt, performing robots achieve something that is incomprehensible to the human – without speech and deliberation, we are unable to comprehend what is being produced. Our reliance on Big Data produces evaluations which often eludes a deliberative process that is visible to most, but is ascribed value or something comprehensible to humans. Black boxed algorithms serve as objective methods of rendering judgment although we are unable to engage in open deliberations about how that decision was reached. There is an embodied nature of speech and trust in Arendt's discussion of judgment. But, when black boxed algorithms are introduced, Big Data evaluations are protected from the scrutiny. The lack of embodiment adds a wrinkle to the discussion of trust. Removal of the human body and the focus on quantifiable data points in the decision-making process functions as an impetus for the appeal of Big Data as more objective (van Dijck, 2014).

The discourses of algorithmic data as final, objective pronouncements challenge the nuances of deliberations. Of course there is more complexity that goes into decision-making, but discourses that reference Big Data as shorthand for justifying a particular decision frames human judgment as problematic and inferior, undermining the virtues of democratic deliberation. That choice has rhetorical consequences. Without the visibility of deliberation, there are some aspects of decision-making that are not being considered or openly discussed, resulting in ethical concerns overshadowed by the willful acceptance of Big Data evaluations. A rhetorical interruption occurs when speech and action are no longer necessary for comprehension and judgment, but trust is given to technology without that element of visibility in the decision-making process due to black boxing.

Speech – logos, and action – ethos, are both necessary in the visibility of who someone is and necessary in all human affairs, namely persuasion and the deliberative process (Arendt, 1958). According to Aristotle (2007), there are three significant elements of persuasion: ethos (the trustworthiness, good character, and goodwill of the speaker), logos (the logical appeal of the discourse), and pathos (the emotional dispositions of audiences that affect their judgment). Artistic and Inartistic proofs—persuasive appeals generated internal and external to the speaker—have long been combined to help render judgment for persuadable audiences. However, Big Data is a set of information – empirical data points which provide the ethos of credibility grounded in perceived objectivity, independent of the individual or perceived fallible speaker. For Big

Data, the appeals of ethos and logos collapse into one, skirting the more ethical dimensions associated with ethos.

Decisions and judgment may not always be the same. When someone makes a decision, we can ask why they arrived at that particular conclusion. We can evaluate the factors that were weighed in that decision, and they can justify such a conclusion, even if it is an unsatisfying judgment. These may not always be good justifications or explanations, but they are justifications nonetheless. When we evaluate those justifications, we can explore one's ability to make all types of judgments – good, bad, moral, evil, weak, strong, etc. On the contrary, when it comes to Big Data we have reached a point where the algorithms are so complex and the data so large that even computer programs cannot always reverse engineer or understand how algorithms rendered a decision (Pasquale, 2015). If the algorithmic result eludes explanation, but the result remains accepted, the rhetorical justification for algorithms in rendering a decision becomes tautological: no need to explain how algorithms achieved the results, algorithms are correct.

Individuals have had to justify their arguments, burdened with the task of limiting uncertainty for his/her choice to other party. This is especially true in deliberative settings in which one's argument provides a justification for one's judgment. If Big Data has complicated relationships with justifying judgment, then how would that affect the development of an argument? The human-technology relationship implies that humans place a significant amount of trust in technology thus resulting in a shift in trust from individuals to numbers. Humans grasp on to data as more trustworthy than the assumed fallibility of human judgment. When Big Data becomes the locus of certainty when rendering decisions, human judgment is presumed as uncertain and less valuable.

A rhetorical assessment of Big Data is appropriate because this central question is focused on deliberation and how individuals make persuasive arguments to render a decision. For centuries, humans have shouldered the enjoyment and burden of constructing arguments to persuade audiences. The visibility of human deliberation is removed from the decision-making process when Big Data is ascribed objectivity above human deliberation of arguments. The connection between science and rhetoric used to be a difficult assessment because descriptions of science usually revolve around objectivism, foundationalism, and logical empiricism. Science employs a type of anti-rhetoric to gin up its persuasive appeal (Gaonkar, 1993). The rhetorical investigation of Big Data is valuable because it addresses the agency of decision-making, the movement of source credibility between humans and technology, as well as how these perceptions impact judgment. The appeal to Big Data, however, lies in its anti-rhetorical nature, suppressing the idea that it is 'persuasive' and thrusting its claim to objectivity to the forefront.

Handing over decision-making to Big Data evaluations rest upon a discursive structure that legitimizes certain types of decisions, and on what constitutes acceptable grounds for such a decision. If we cede judgment to algorithms under the presumptions of objectivity and efficiency, new questions of morality and ethics of relinquishing that agency to algorithms arise (Mayer-Schönberger & Cukier, 2013). Relying on Big Data as a consulting entity adds a fairly new form of evidence to the decision-making process. I neither wish to overstate nor diminish the role of Big Data in the decision-making process. One of this goals of this work is not to claim that humans solely rely on Big Data for decisions. Rather, to discern what it means when humans do entrust decisions to Big Data, and how the language of Big Data shapes the value of human and computer judgment.

When we allow algorithms to make decisions for us, we give the technology a type of authority. As Pasquale (2015) notes, “[a]uthority is increasingly expressed algorithmically – decisions that used to be based on human reflection are now made automatically” (Pasquale, 2015, p. 8). When we act as agents that give authority to Big Data to decide over human deliberation, we engage in discourses that legitimize algorithms as having an authorizing function. Implications surrounding the human-technology relationship need to be explored when algorithmic output is trusted independent of human deliberations. Under what conditions do algorithmic reasoning assume such authority? How do we give it such authority, and what does that mean? My case studies examine how discourses legitimize the use of Big Data in the decision-making process without human deliberations.

More Data Yields Better Decisions

The scientific revolution put a premium on empirical data as the cornerstone to knowledge and validity (Kuhn, 1996). This highlights how the appeal to Big Data and algorithms fits within certain structures of judgment and highlights some presumptions in how we make decisions. The appeal of Big Data rests on a premise of fallibility in human judgment, or at least the limits of humans’ ability to render judgment given immense data sets. An underlying feature of such judgments privilege notions of objectivity. As beings rotten with perfection, objectivity has been ascribed to the move towards perfection (Burke, 1985). From scientific research to the administration of justice, we highlight objectivity as the foundation to "perfect" decision-making. In other words, being objective or seemingly unbiased is a way to pierce the fog that clouds human judgment.

In the language of Burke, "objectivity" becomes a god-term that we strive towards. In our strides toward perfection, we seek the epistemological objective truth. Science is one of the most commonly accepted methods for seeking that truth. Science is also valued as objective because of the Scientific Method, the process that has to occur for something to be considered "science." It is objective because it evaluates numerous variables, or data points, and understands them through a controlled process that looks for relationships between such variables. The scientific process celebrates the analysis of larger sample sizes, more tests, more variables – which is indicative of our enchantment with more data as a greater measure of objectivity. We perceive objective as good and more as getting us closer to objectivity.

There are numerous contexts in which people employ the discourse of objectivity as a process of legitimizing a decision. Objectivity is one of the foundations of decision-making that is perceived as good or sound. For example, journalism aspires to be "objective" – meaning that one accounts for all sides of the story, and many valorize and attack journalism for its adherence to objectivity. The way journalism operationalizes objectivity is to eliminate bias. Presenting "all sides of the story" is a common way to achieve that balance. This illustrates the point that we see objectivity as related to more data being better and its ability to lead to the objective truth. This requires fathering more perspectives, or data, to create these narratives.

Other examples of human activities that privilege notions of objectivity include the law and science. Objectivity is a pervasive phenomenon in many spaces and forms. Since this is our perception of objectivity, it affirms that we want to make decisions most aligned with what is true. There is a plethora of avenues in which we assume objectivity yields the best decisions: science, law (justice), sporting competitions, academic debate tournaments, and much more. This highlights the ubiquity of objectivity, in many spaces and forms as well as some similarities as to how objectivity serves as a rhetorically legitimizing function for decision-making. This is where the rhetorical cachet unfolds with Big Data generated decisions. As we privilege objectivity, Big Data is reflective of our longing to move towards perfection, while we seek the truth through the use of more data.

The efficacy of Big Data rests on several assumptions ranging from "objectivity" as better for judgments, more data results in better decision-making, the idea that faster decisions are stronger decisions, and a few others. Two major assumptions stem from the argument that more data can yield better decisions because it accounts for more variables. The first presumption is that more data present objective decision-making. Understanding that humans are merely consuming a perception of objectivity leads to a fundamental rhetorical question: how do the discourses of objectivity impact the power of arguments made by humans versus the output of Big Data? In other words, if we privilege the recommendations of Big Data over the recommendations of humans, how does that affect or shape our understanding of human judgment? How do we think about human expertise and experience in light of Big Data? Source credibility is a significant element in rendering judgment which could lead to follow-up question: how do discourses shift if Big Data is perceived as the ultimate credible source for making said judgment?

Since we have a bias towards more evidence or more data as producing more objective judgment, we are constantly seeking greater quantities of data. There is an increasing request for "moar" data – a combination of "more" and "roar," which illustrates the insatiable human desire to consistently make Big Data a greater ubiquitous force in everyday life through decision-making (Oremus & Glaser, 2017). Although, "moar" data present nothing more than a veneer of objectivity (Oremus & Glaser, 2017). Good judgment often resides in how we view judgment based on "objectivity" and the assumption that more evidence is preferable. Humans have ascribed both of those features to Big Data – perceived objectivity and more data are better.

The "roar" metaphor is suggestive of the loudness and breadth of data. This alludes to both the production of data through increasing speeds and technologies along with our consumption of said data. As we consume more, we inadvertently relinquish more of our digital footprints, whereabouts, likes, privacy, etc. making assess to that data "more" consequential. The roar elicits the signal of power, furthering this notion of the ascribed objective power of more data.

The second assumption of more data yielding better decisions perhaps further deduces why more is considered better; there is the expectation that more data will result in more nuanced decisions, thus resulting in better decisions (Oremus & Glaser, 2017). For example, there are differences in the calculation of credit scores from person to person. Credit card companies have access to a wide range of data about the people they serve, and most people have no idea how a credit algorithm dictates a credit score. A couple who sought marriage counseling was given a lower credit score. The particular couple is unaware that this caused their credit score to drop, but marriage counseling might not lower credit scores for everyone (Pasquale, 2015). Credit card companies also differ in what factors are most important when impacting scores. The question of who decides what is important in the factoring of a credit score and how algorithmic outputs include a presumed and unknown nuance is addressed in the following chapter.

The fact that algorithms process values differently for different customers seems to represent a paradox – algorithms are perceived as objective, although it subjectively assigns different meaning to values for different people while also presenting nuanced assessments. Big Data enables humans to operate under the assumption that objective numbers diminish the need for “personal trust” (Hill, Kennedy, & Gerrard, 2016). Because algorithms can be self-learning, and process information at such a high rate with such vast amounts of information, there is an uncertainty around how algorithms reach particular conclusions. Meanwhile, the rhetoric that algorithms are self-learning speaks to how they offer better conclusions.

We seem to accept Big Data as certain, despite the fact that there is a great deal of uncertainty surrounding how algorithms process these massive quantities of data (Pasquale, 2015). To revisit the credit card example, agents of these companies are unable to fully explain each factor that impacts the credit score of a client; however, the agent trusts that the credit score is correct. Decisions about credit limits, mortgage loans, interest rates, etc. are made based on the evaluation from algorithms that the company, even the programmers, do not always fully understand. This example highlights how people use credit scores without knowing how they work, although their outputs have very important and material consequences. We perceive Big Data as certain, and there are discourses around algorithms that seek to cultivate certainty by taking human subjectivity out of the equation.

Humans are so enamored with algorithms that even very subjective activities are sometimes reduced to quantifiable amounts. The reduction of subjectivity, human expression, and to a quantifiable measure makes it easier for commerce. Hence, algorithms enable the perception that everything is quantifiable through a numeric value. For instance, art was intended to capture aspects of human individuality, not intended for quantification through Big Data but function as an individual form of expression. However, there are algorithms that try to quantify the economic value of art (Whipple, 2013). Those appeals to quantifiability are often used to create short cuts when making decisions. Algorithms can take something very subjective, such as art, which affects us in all kinds of emotive ways and reduce its qualities to something quantifiable – numbers, patterns, and trends (Fuller, 2017).

Big Data and algorithms, as pervasive technological advancements, are designed make decisions easier, faster, and more efficient. There are lots of public discourse around the value of Big Data in rendering decision and judgment. Algorithms are programmed with the intent of making decisions easier and more tailored to the individual. Algorithms introduce another step in the deliberative process as the individual renders a judgment because it produces an output without a clearly delineating how and why it reached that output.

All told, this thesis does not contest the notion of objectivity or even suggest that Big Data is bad or should not be part of the process of judgment. Rather, this thesis explores how the rhetorics of Big Data, with its assumptions that objectivity and more data render better decisions, shape our understandings of human judgment.

Professional Implementation of Big Data

The advent of Big Data has infiltrated the economic sector and some businesses have rapidly adjusted to ensure their competitiveness in the market. With the advances in technology, there is an expectation that organizations will collect mass quantities of data and follow-through with Big Data evaluations. Companies today insist on gathering as much data as possible as a method of increasing their assets (Kraska, 2013). Businesses on the forefront of Big Data are often implementing data-driven decision-making (DDD) as a method of incorporating the benefits of Big Data and human experience in the decision-making process (Elish & boyd, 2017; Provost & Fawcett, 2013). When it comes to business, trades, or other financial exchanges, efficiency is crucial. But that does not quality as the same criteria for sound arguments.

Organizations are capable of using Big Data as part of the deliberation process to achieve what is considered as the best outcome. For example, a marketing team could choose advertisements based on experience and eye for the campaign. The team could also conduct an analysis on how consumers will react to certain advertisements. DDD uses both approaches as valuable insights for making the best decision (Provost & Fawcett, 2013). This example asks if Big Data evaluations are actually a part of the deliberative process, if these evaluations can be used as "evidence" that serve other arguments, or if the "results" of algorithm usage overwhelms other counterarguments.

The reliance of Big Data in making decisions highlights a fissure between experience and the amalgam of data points. This exhibits questions of quality, quantity, and what type of evidence is necessary when rendering a decision. In other words, the consideration between following through with a Big Data evaluation opposed to a personal judgment suggests that certain types of evidence are more germane to certain types of decisions.

It is reasonable to consult data to make sound decisions; however, this could lead to a situation where people say that Big Data is just one part of the decision-making process when in reality, people still cede judgment to the algorithm. The reliance on algorithmic output could alleviate humans from the decision-making risk and responsibility. This potential raises ethical concerns for carrying out Big Data evaluations without consulting the cause of that evaluation and potential lasting impact. What happens to our understanding and discussion of ethics if we blame Big Data for our actions? The implementation of Big Data as a mode of decision-making that could exonerate humans of responsibility and consequences associated with their judgments.

When we only have to follow-through with the suggestions of the data and results are favorable, we only reap the benefits without considering other potential consequences of the self-learning algorithm. Placing the decision-making onus on Big Data further relieves humans from shouldering the responsibility of consequences. The yielding of authority to programmed algorithms similarly requires the yielding of privacy and could result in lasting changes around how we justify our decision-making practices.

Public and Technical Spheres

The proliferation of Big Data has changed how deliberations occur because algorithms function as technical mechanisms which hope to address social matters. According to Goodnight (2012), there are multiple spheres of argument in which certain types of evidence and appeals to reason are most salient. Goodnight highlights three main argument spheres: the public sphere, the private or personal sphere, and the technical sphere. The public sphere deals with arguments of general importance, typically issues and arguments that are relevant to the body politic. The private or personal sphere arguments address matters that involve individual decisions or issues that are relevant to domestic life.

The technical sphere is reserved for deliberations amongst the few, experts who specialize in specific content area. For example, a technical sphere could include science, law, medicine, or any other field that has a specialized vocabulary and modes of argument. Goodnight argues that the technical sphere is colonizing the public and private spheres by making personal or public decisions based on technical arguments (Goodnight, 2012). Personal or public decisions that are driven by the recommendations of experts or the quantifiable evidence generated from specialized fields highlight how the technical sphere arguments drive the judgment in these other two spheres. This presents one of the very reasons the use of algorithms and Big Data is the very definition of the technical sphere colonizing the public sphere. Big Data functions as a product of the technical sphere that drives decision making in the other two spheres. Examples of Big Data use in personal decisions include Google Maps, Rotten Tomatoes, Amazon, among others. The reliance on this Big Data outputs demonstrate how much these technical forms of decision-making infiltrate our lives.

In the technical sphere, expertise might have an element of distrust attached to it because the public is unable to engage in the arena or make sense of how the expert presents his or her arguments (Farrell & Goodnight, 1981). Scientific expertise problematizes democratic deliberations because it is such an exclusionary space. Ruptures in the technical discourses ensue when rhetorical crises unfold and experts are unable to effectively communicate their arguments. This becomes even more salient when we are unable to understand the algorithmic processes, inviting even more questions regarding the implications of technical discourses affecting public and private judgment.

Expertise functions as a mode of credibility, and the knowledge offered by an expert has been significant to the functioning human society. “The disclosure of who somebody is, is implicit in both his or her words and his or her deeds” (Arendt, 1958). Speakers perceived as good and experienced gain credibility in the eyes of the audience. For instance, visiting an Apple or Android store for a malfunctioning phone, calling an exterminator to terminate pests or even visiting mechanics to solve issues with cars are a few of examples of how expertise is sought after in day-to-day life (Hartelius, 2011). Expertise is a foundational part of a productive economy and a healthy democracy. Big Data presents an opportunity for a paradigm shift in how we understand the discourses of expertise. As people consult or rely on Big Data at higher rates, I discuss what happens to traditional notions of human expertise. And again, how that figures into notions of human judgment. The age of Big Data seems to change the way we think about expertise, and how the discourses of expertise function in making decisions.

Experts profess their expertise and the public is left to accept to reject their claims; while, Big Data reframes our understanding of asserting expertise because of its inherent perception as objective. Experts gain their titles through nature of time spent in their respective field, networking or institutional clout, utility, patterns of success, and performance (Hartelius, 2011; Majdik & Keith, 2011; Nichols, 2017). "…[I]t is also grounded in a fierce struggle over ownership and legitimacy. To be an expert is to lay claim to a piece of the world, to define yourself in relation to certain insights into human experience," (Hartelius, 2011). Expertise provided a form of unique evidence until the use of algorithms. As experts bolster their credibility for their audience, it is challenged by the perceived objectivity of algorithmic outputs. Human experts shoulder the burden of earning and demonstrating their status as an expert, and that credibility relies on objectivity.

On the contrary, Big Data is already ascribed to be objective, inadvertently placing algorithms on a higher tier than a human expert. The current public environment is awash with anti-expert (and anti-elite) discourses that suggest experts lack objectivity and embrace condescension. Being a scientist or a professor do not have the same credibility as before. Hence the many mechanisms experts use to defend their title and status are no longer salient, but Big Data is given the benefit of the doubt (Nichols, 2017). Since both forms of expertise, human expertise and Big Data, are grounded in appeals to objectivity, the Big Data algorithm seems to win based on such a standard. This raises questions as to how do we understand the role of human expertise in making judgments, and how do we justify the role of human expertise as relevant to particular types of decisions. There are conditions in which Big Data flourishes and I explore how they supplant other arguments or appeals of expertise.

We commonly operate under the assumption that more data creates expertise (Hartelius, 2011). It is an expectation that data is valuable and dependable; therefore, any malfunctions or shortcomings associated with data are due to human error. The acknowledgement of human error further addresses the notion of uncertainty – we accept our potential to be erroneous but seek to distance ourselves from the potential of technological error. When we question our judgments in the decision-making process because of the perceived objectivity of Big Data, we deviate from human experts and the status of expert, placing our trust in an algorithm. The transferring of expertise from the human brain to data points has further implications for how Big Data communicates across audiences.

Chapter Preview

The animating questions that guide this thesis are: how does the discourse of Big Data in helping us make decisions frame understandings of judgment? How is our understanding of responsibility shifted when we claim that a Big Data evaluation told us which decision to make? If we are responsible for our judgment and if we rely on Big Data for decision-making, how does that shape the discourses of judgment and responsibility? How does Big Data frame discourses around judgments of expertise? I cover these questions across to two case studies and use the literature to guide these questions. The case studies for the next two chapters demonstrate how Big Data in public policy questions discourses of fairness and justice, problematizing assumptions about how Big Data promotes objective and unbiased decisions.

The first case study, "Investigating Algorithmic Injustice," examines how Big Data algorithms are used in the courts to determine risk factors of defendants (Angwin, Larson, Mattu, & Kirchner, 2016). The calculation of these scores show that Black people, even with the same past offenses as a White counterpart, will automatically receive a higher risk score. This risk score is intended to present how likely an individual is to be a repeat offender and in some cases, a Black defendant had less criminal offenses that a White defendant, but the Black defendant still received a higher risk score. Numbers present the illusion of objectivity therefore, serving as a numeric foundation for racism (Oremus & Glaser, 2017; Porter, 1995).

This chapter studies discourses when the objectivity of Big Data is questioned on a basis of race. Who claims responsibility for biased Big Data evaluations? This case study addresses the ethical implications of giving over decision-making on policing to a computer and how individuals respond when there is an awareness that the perceived objectivity of Big Data is threatened. Putting the onus on the data to explain phenomenon or guide social practices can have detrimental consequences for some marginalized groups, arguably stemming from some of the aforementioned underlying assumptions of Big Data. It answers the question, if discourse exchanges occur surrounding projected risk factors which spheres will these discourses happen and asserts who will have access to those spaces.

The second case study explores public discourses around credit card scores. In an effort to promote discourse of fairness, banks rely on credit score algorithms to determine who qualifies for a loan and at what interest rate. These discourses focus on arguments about how people, and even programmers, are unsure of how algorithms achieved an end, but still acts on its decisions. We rely on Big Data to drive policy making and this study will highlight Big Data in helping drive decisions around commerce. I have alluded to some scenarios of mystery surrounding credit scores in this chapter as an introduction to potential problems of complete Big Data reliance in this chapter. *The Black Box Society* provides the foundation for this case study – to examine how a technical discourse is ruptured because we are unsure of how to reverse code the credit score algorithm.

In both of these case studies are underlying questions of discrimination and bias. They claim to be objective, and all the discourses embrace notions of unbiased results (usually within the framework of efficiency), but alas, there are elements of fundamental lack of objectivity. These case studies also involve questions of economics – which is steeped in a discourse of fairness (ala neoliberalism) and justice – which is supposed to remove bias for the appeal of court of law. The case studies explore how discourses are framed in two very important systems within our nation – justice and finance, in the name of objectivity along with evidence of discriminatory impact.

This thesis briefly examines some of the discourses surrounding Big Data and how we employ it as a new form of judgment – one that, in some cases, could potentially contradict the foundation of agency. One of the major goals of technology is to make life as efficient as possible. Big Data functions as one of those advancements that make life more manageable, but it is unique in how much influence on human judgment it exhausts.

Chapter 2 – Algorithmic Injustice

Justice is premised on objectivity and fairness before the law, but there is a long history of human bias in our American justice system from *Brown vs. Board of Education* in 1954, anti-miscegenation laws of the 1960s, miseducation about the AIDS crisis in the 1980s, currently the mass incarceration of Black men, commonly referred to as the New Jim Crow, and many more instances (Alexander, 2012). When we think of justice, we think of the removal of bias and an appeal to the rule of law, but concerns that the justice system is open to human bias, undermines the discourses of "fairness." The appeal of Big data in justice is to curtail human bias, presuming that judgments based on Big Data promote objectivity.

Part of the narrative of Big Data's appeal is the fact that individuals regardless of political affiliation have interest in a data-driven justice system. For Liberals, a data-driven justice system will be less punitive and will account for subconscious biases of police, judges, and probation officers. Conservatives appeal to the financial benefits of limiting the overcrowding of our prison system by only spending tax dollars on imprisoning criminals who truly present a danger to society (Barry-Jester, Casselman, & Goldstein, 2015). Prison privatization could shift these views, but the argument is not regarding the partisanship of the issue. Rather, to demonstrate that both political major parties advocate for the use of perceived objective decision-making tools in the justice system. The inclusion of algorithms in the justice system is generally desirable from both ends of the political spectrum – an acknowledgment of potential erroneous human judgments.

One of the most prominent uses of Big Data in the criminal justice system is the implementation of algorithms in quantifying associated risk for offenders. Risk assessment scores were designed to gauge a defendant's likelihood to reoffend after considering a number of known factors – past offenses, education levels, if parents were past offenders, personality traits such as intelligence or extroversion as well as a host of unknown factors (Angwin et al., 2016; Barry-Jester et al., 2015). With over sixty risk assessment tools in use already, the most commonly used and the tool primarily investigated in this study is the Correctional Offender Management Profiling for Alternative Sanctions (COMPAS).

Finalist for Pulitzer Prize in Explanatory Reporting and Gerald Loeb Award winning reporter at the *Wall Street Journal*, Julia Angwin, led a private investigation of the use of algorithms in risk assessment factors in court decisions. The study, *Machine Bias: Investigating Algorithmic Injustice* presents a thorough investigation of the present biases in algorithms currently being implemented in court room decisions to assess perceived risk of defendants, projecting bias against Black offenders. COMPAS is the algorithm studied in this particular case study. It also features short-detailed narratives about some of the offenders' cases which demonstrate some potential concerns associated with the utilization of algorithms in our judicial system.

Tim Brennan, Professor of Statistics at the University of Colorado, and Dave Wells, an associate who was leading a corrections program facility in Michigan, founded Northpointe together. Northpointe was established in 1989 as a "consulting and research firm that delivers evidence-based software products, training, and implementation services to more than two hundred federal, state, and local criminal justice systems and policy makers throughout the US," (Brennan & Wells, n.d.). They intended to create a strong classification system for the jail and named their product the COMPAS (Angwin et al., 2016). Brennan suggested that existing risk assessment tools did not address major theories about the causes of crime which are important in considering crime prevention. This tool was unique because it addressed almost twenty-five major theories of criminality including "criminal personality," "social isolation," "substance abuse," and "residence/stability," (Angwin et al., 2016).

The inclusion of crime theories in the calculations of the COMPAS algorithm strengthens the claim of nuance in the algorithm, therefore it is presumed to make better decisions. COMPAS it set apart from other risk assessment tools because the focus on criminality suggests that this algorithm is the most advanced in accurately assessing risk for offenders (Angwin et al., 2016). This challenges human judgment because this measurement tool claims to incorporate and account for measures of criminality, beyond the capacity of human brain. In spite of the many factors that law enforcement officials include in their decisions regarding defendants, causes of criminal offenses based on individual defendant profiles are beyond the capacity of the human brain to accurately deduce. Therefore, claiming that the COMPAS accounts for causes of crime is a rhetorical mechanism for demonstrating how algorithms function above human competency.

Discussions in Public and Technical Spheres of COMPAS

Machine Bias: Investigating Algorithmic Injustice has sparked conversations in both public and technical spheres which highlight how the different framing of these arguments are leveraged to address the nondisclosure of the algorithmic code. The creators of the COMPAS software from Northpointe claim that they are unable to release information about all elements included in the algorithm because it is proprietary information (Angwin et al., 2016; Barry-Jester et al., 2015; Corbett-Davies, Pierson, Feller, & Goel, 2016). Proprietary questions constrain and shape appeals about the algorithms applicability. These statements made by the creators of the Northpointe software function as a tactic to ensure they maintain ownership of their algorithm and continue to profit from the measurement instrument and simultaneously prevent a rupture in the technical sphere, as they, or at least their algorithm, assume the role of expert in rendering judgment.

A rhetorical crisis unfolds for investigators and scholars who study the evaluations of their algorithms find evidence of discrimination on the foundation of race. A rhetorical crisis exists when "limits of technical communicative discourse are severe, recurrent, and perhaps irreparable," (Farrell & Goodnight, 1981). The rhetorical crisis that befell creators of the COMPAS algorithm was ProPublica's *Machine Bias* and the heated debates that broke out in courts across the country because of these bias reports (Angwin et al., 2016; Corbett-Davies et al., 2016). Northpointe Inc. Research Department initially was unable to adequately retort the arguments supported by *Machine Bias.* To respond, Northpoint produced a thirty-seven-page response questioning ProPublica's analysis which subsequently led researchers to weigh in on the validity of the measure (Angwin & Larson, 2016; Dieterich, Mendoza, & Brennan, 2016). Three dominant opinions are presented through these analyses and rebuttals – COMPAS is bias against

Blacks, COMPAS is accurately not bias against Blacks, and both arguments are simultaneously correct.

"There's software used across the country to predict future criminals. And it's biased against Blacks" (Angwin et al., 2016). This was the major claim of the ProPublica case findings – the report that is unearthing some of the potential concerns with algorithms in the judiciary. Rhetorically, this argument seeks to involve the public directly in the conversation and demystify the embedded racism in the algorithm. There are at least three major articles on the ProPublica website about this one case and garnered so much attention that it was nominated for a Pulitzer Prize. The actual investigation of over 10,000 criminal defendants in Broward County, Florida compared with their recidivism rates over a two-year period sought to give some transparency to the accuracy, or lack thereof, for the algorithm (Angwin & Larson, 2016; Angwin et al., 2016; Corbett-Davies et al., 2016; Larson, Mattu, Kirchner, & Angwin, 2016). The approach of these investigators was to decolonize the public sphere by elucidating the results of the algorithm's performance and using the ProPublica as a platform for moving the conversation out of the technical sphere.

"ProPublica focused on classification statistics that did not take into account the different base rates of recidivism for Blacks and Whites. Their use of these statistics resulted in false assertions in their article that were repeated subsequently in interviews and in articles in the national media. When the correct classification statistics are used, the data do not substantiate the ProPublica claim of racial bias towards Blacks" (Dieterich et al., 2016). COMPAS came under fire for bias, evidenced in the arguments produced in the Algorithmic Injustice Machine Bias case. Northpointe responded with a technical report that places value in numbers to corroborate the validity of their measurement tool. This document is still reserved for those in the technical sphere because it is not easily accessible, except through a link on ProPublica's site, and the jargon is not easily digestible for public. Northpointe's tactic for rebuttal is to respond with the numbers – maintaining a claim of objectivity for the tool and how it is discussed. This is tautological defense – the base of the criticism lies in the unquantifiable aspects of bias, but Northpointe levies a defense related to quantitative assessments.

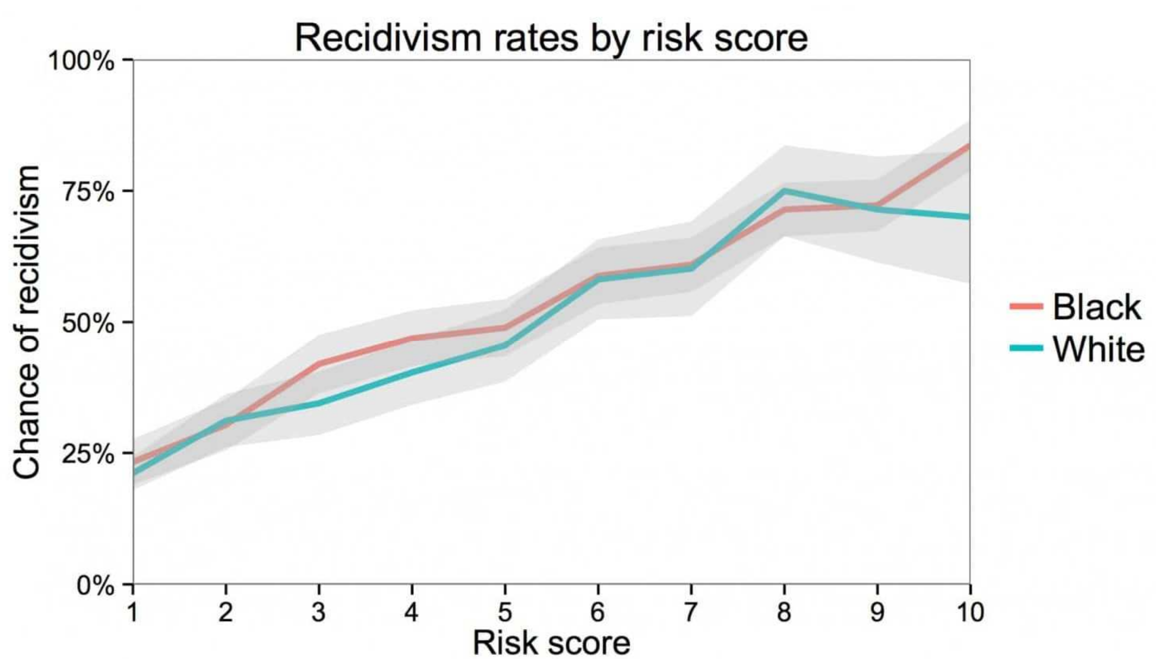
Northpointe chose to attack elements of Angwin's investigation and classification techniques instead of disclosing more parts of the algorithm. The designers behind this code are unrelenting in their dedication to protecting the treasury of information that is the code behind COMPAS. It was a necessary move for both their public image to ensure that companies still wanted to use their product and for their profit margins with potential future consumers. Protecting the intricacies of the algorithm ensures that companies continue to have to purchase the tool as opposed to redesigning their own or using it for free. Keeping information in the technical sphere might not be the strongest move for public opinion but since COMPAS is still being used throughout parts of the nation, maintaining limited visibility of the technical sphere profits Northpointe. This further problematizes the divide of the public and technical spheres. The proprietary dimension complicates this dynamic, because the appeal to technical arguments obscures the economic dimension. In other words, the employment of algorithms is more than just a problem because technical sphere arguments insulate it from critique, but further obscures the issue because of economic motivations.

Academic researchers argued that both parties are simultaneously correct published through a *Washington Post* article. Researchers stated while referencing the COMPAS algorithm, “Surprisingly, there is a mathematical limit to how fair any algorithm – or human decision-maker – can ever be” (Corbett-Davies et al., 2016). Fairness, as presented in this article, is a difference of how the algorithm is measured between the two parties. Using Northpointe’s measurements, “within each risk category, the proportion of defendants who reoffended is approximately the same regardless of race.” White defendants are less likely to be classified as medium or high risk opposed to Black defendants (33 percent vs. 58 percent), but Black defendants are more likely to have prior arrests which is presentative of reoffending so the values mirror the reality. Refer to Figure 1. It is noteworthy that the Northpointe algorithm does not include race as a factor but there are other factors directly correlated with race which have a major impact on the accuracy of the risk prediction (Angwin et al., 2016; Corbett-Davies et al., 2016).

At the same time, of those who did not reoffend, Blacks are twice as more likely than Whites to be classified as medium or high risk (42 percent vs. 22 percent). This substantiates ProPublica’s point and demonstrates how Black defendants have harsher experiences with the justice system when the COMPAS algorithm is factored in the court decision-making process. Refer to Figure 2. “Black defendants who don’t reoffend are predicted to be riskier than White defendants who do not reoffend,” (Corbett-Davies et al., 2016). Framing both of these arguments as a ‘mathematical guarantee’ removes the issue from the algorithm or statistics. “If Northpointe’s definition of fairness holds, and if the recidivism rate for Black defendants is higher than for Whites, the imbalance

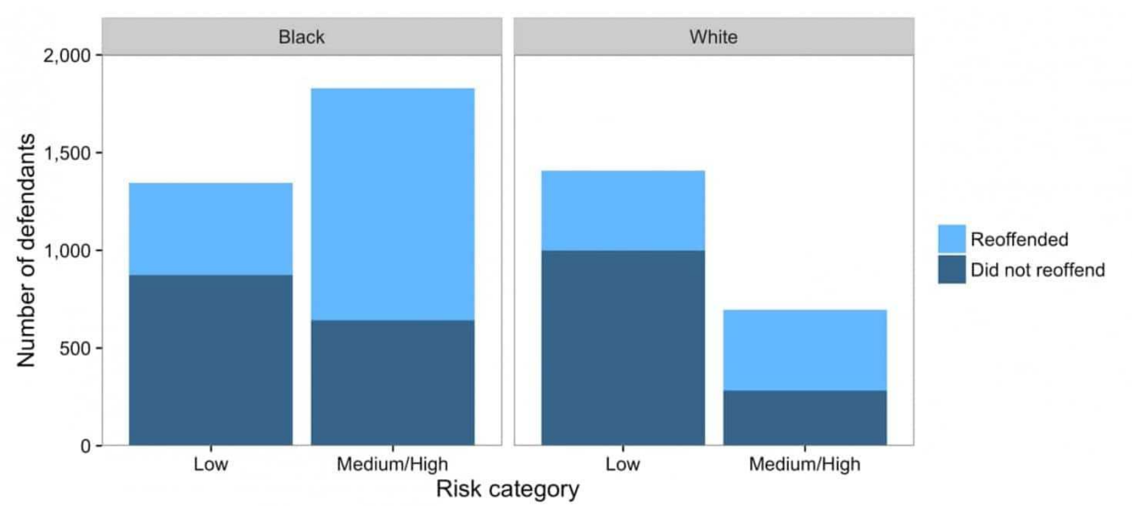
ProPublica highlighted will always occur" (Corbett-Davies et al., 2016). Ultimately, the article did exactly what it set out to do – prove both that the COMPAS algorithm is fair and discriminatory by showing that it reflects the current reality of the criminal justice system. In an effort to define, quantify, and program fairness, we created problems as the algorithm functions to make "fair" decisions.

Figure 1



Recidivism rate by risk score and race. White and black defendants with the same risk score are roughly equally likely to reoffend. The gray bands show 95 percent confidence intervals (Angwin et al., 2016).

Figure 2



Distribution of defendants across risk categories by race. Black defendants reoffended at a higher rate than whites, and accordingly, a higher proportion of black defendants are deemed medium or high risk. As a result, blacks who do not reoffend are also more likely to be classified higher risk than whites who do not reoffend (Angwin et al., 2016).

ProPublica presents a case for social justice and raising awareness regarding the implementation of risk assessment tools on the foundation of racial discrimination. Northpointe seeks to maintain profit margins and keep the tool in use, perhaps even widen its market. The initial purpose of the creation of COMPAS as a means of classification and limiting recidivism could be plausible but since the information behind the algorithm has been repeatedly referred to as “proprietary,” financial gain is just as much a factor – if not the primary focus for this organization. Researchers who support both points simultaneously want to encourage further use of statistical risk assessments, but also invite debates about the role of algorithms and limitation of human decision-making in the criminal justice system. There is a Minority Report, pre-crime element to this. This algorithm is used to identify possible recidivism and suggest some actions to curtail possible future crime. However, this disproportionally affects African-Americans and that their defense appeals to tropes of fairness, incorporating technical arguments that obscure the proprietary dimensions to the algorithm. The upshot is that there is limited opportunities for dialectical scrutiny over the appropriateness/efficacy of the algorithm in matters of justice.

There are implications for the value placed on human judgment based on the different platforms and discursive spheres. To some extent, both new cycle discourses – ProPublica and *The Washington Post* are requesting a moment of reevaluation in how Big Data is used in the criminal justice system – *The Washington Post* is requesting that moment to a lesser degree than ProPublica but a request just the same. Part of the debate and appeal for human consideration should be the question of whether algorithms are actually changing the justice system to make it more objective or if they are merely a new way of reinforcing bias practices in an already discriminatory system.

Northpointe is a for-profit organization who reserved their discussion of COMPAS to the technical sphere by only focusing on the numerical findings to undermine the claims made by ProPublica. Northpointe refrained from the heightened visibility of their findings which suggests that human judgment is not as significant as the numeric values of the algorithm. This organization chose an anti-rhetorical approach as a mode of persuasion by focusing on objective numbers (Gaonkar, 1993). The discourse in the technical sphere is limited in its purview because the test of fairness merely reflects the bias that is already too prominent in the justice system. Goodnight states that the technical, expert-based arguments are "colonizing" public deliberations, hence judgment would turn over to experts who possess the technical knowledge (Goodnight, 2012). That technical knowledge is couched in technical discourses, quantified information, etc. the implementation of algorithms in the decision-making process is a logical extension of the concerns of the technical sphere, as the algorithm even crowds out the expert – on the grounds that the algorithm could be even MORE objective. Human judgment is further diminished when bias systems exist and are reinforced by statistical computations that claim to produce more nuanced assessments. Risk assessment tools lower the reliance and trust of human judgment because technology is automatically ascribed as objective and knowingly maintains higher computing power than the human brain.

The use of the COMPAS algorithm rests on the assumption that these evaluations produce an objectivity beyond human judgment. This focus on objectivity presents our rottenness with perfection, something that we perceive will clear the smog of human judgment (Burke, 1985). *The Washington Post* article asserts that "human decision-makers are biased in ways that machines are not" (Corbett-Davies et al., 2016). The notion that more data yields better decision-making is presented in the inclusion of causes of criminality and several other factors used in the computation of the COMPAS tool as a step closer to a more objective decisions regarding offenders. However, ProPublica substantiates that an objective reflection of a discriminatory system still fails to accomplish true objectivity. Just as fairness on the foundation of an unfair system still does not equate to fairness.

Judging the Use and Misuse of the Algorithm

Judges must have knowledge of the law and then render judgment based on the evidence presented and the circumstances of the case in how it conforms to the law. The rule of law provides the grounds, but the law cannot cover every instance. Hence the judge must make evaluations within uncertainty, based on facts, laws, procedures, and precedents. Judges use their experience in order to render judgment on a particular case.

Judges, those entrusted to make final decisions in the courts, have responded to some statements about their use of risk assessments in their individual processes of rendering judgment. Although the Northpointe software was not intended to be used in sentencing, the risk assessments are being used however judges see fit.

For instance, defendant Paul Zilly from Barron County, Wisconsin was convicted of stealing a lawnmower and some tools after a long battle with meth but was working towards recovery with help from a Christian pastor. Zilly was initially offered a year in county jail followed by supervision to help Zilly with "staying on the right path" (Angwin et al., 2016). However, Judge James Babler saw Zilly's score provided by Northpointe's software which ranked him as medium risk for recidivism and high risk for future violent crime. Although the plea deal was already agreed on by the prosecution and defense, Babler overturned the deal imposing two years in state prison and three years of supervision (Angwin et al., 2016).

Babler stated in court, "When I look at the risk assessment, it is about as bad as it could be" (Angwin et al., 2016). This case demonstrates how we give authority to technology when we allow algorithms to make decisions for us. This The decision for Zilly's punishment for his crime was initially made with human reflection and deliberations outside of the courtroom, but Judge Babler allowed the numbers to supersede human judgment in sentencing. In fact, his entire justification for his change in judgment is the value produced by algorithms – which presents a shift in trust from the individual to technology.

In Babler's decision to trust the algorithm, he accomplishes three things: asserts the authority of the algorithm, demonstrates genuine trust in the validity of the evaluation, and alleviates himself from guilt regarding his decision. He used his agency to thrust a Big Data evaluation as the greatest form of evidence in the proceedings against Paul Zilly. The initial punishment seemed to reflect the "human" aspect of judgment which accounted for the crime committed while also offering a valid chance at rehabilitation. Unfortunately, since COMPAS presented a high-risk score, this defendant was given a harsher punishment further hindering Zilly's potential for success after release. The programmer used a discourse that distances himself from the perceived flaws in the algorithm, insulating it as just an instrument, but still suggests that it is the best instrument to provide the assessments it promises to deliver. There are rhetorical maneuvers that absolves both the human programmer and the instrument from "blame"; it's results just are.

Zilly's case was later appealed by a public defender and Brennan, one of the creators of COMPAS, was called as a witness on Zilly's behalf. Brennan said he did not design his software for use in sentencing. "I wanted to stay away from the courts. But as time went on I started realizing that many decisions are made, you know, in the courts. So I gradually softened on whether this could be used in the courts or not," said Brennan (qtd in Angwin et al., 2016). The fact that we misapply instruments in decision-making is a designers' first defense, which reinforces the discourse of human failure. It thwarts the narrative that it is not the instrument's fault but how flawed humans use it – and the enthymematic conclusion affirms the need for ceding judgment. If we think of this in the framework of economics, certainly COMPAS might be constrained in the types of appeals it makes – we do not want to blame the technology. This raises ethical concerns, if everyone keeps misusing the tool to ill effects then what responsibility the creators have?

Brennan's response shows how this tool was designed to help with more alternative treatments to limit recidivism but has actively been consulted in court cases – sometimes even given full agency in the decision-making process. This argument suggests that the algorithm is trusted enough to be used at any point in the decision-making process; although, Judge Babler openly admitted to distrusting his own judgment over the Big Data evaluation. This represents just one case where the judge was honest about removing personal judgment from the process when confronted with a risk assessment tool. This presents the insidious nature of algorithms in trusting our own judgment – even an expert, like a judge, is not immune to ceding judgment to algorithms in questions of justice.

Just as Judge Babler chooses to heavily rely on the algorithm for his decision-making, there are judges who choose to rely on personal judgment – namely Broward County Judge John Hurley. Judge Hurley stated that the risk assessment measurement was helpful in the beginning of his career but now he chooses to rely on his personal judgment. He predominantly considers factors including offender's prior criminal record, type of crime committed, ties to the community, and history of failing to appear in court (Angwin et al., 2016). However, there is a case where the recommended bond was $0 for petty theft of a kid's bike that was immediately returned and Judge Hurley placed bond at $1,000. He cannot say if the a risk score influenced his decision (Angwin et al., 2016).

These judges claim to represent two opposite sides of the spectrum when it comes to their reliance on the risk assessment score when rendering judgment. A common theme in both of these discourses is the fact that both judges feel comfortable in their capacity to render judgment. There is no moment of apology or doubt. Even when Judge Hurley could not remember what led him to his decision in the case of the $1,000 bond, he was comfortable saying that he could not remember what caused his decision. Babler seems to use the risk assessment as his deliberative explanation for this judgment while Hurley named a few factors but if he was unsure, he was comfortable in saying that. Babler focused on the perceived objectivity of COMPAS while Hurley relied on his expertise. Perhaps these represent some of the concerns that are aroused when we consider the current state of human-decision making in the justice process. These two comments also demonstrate that even with the risk assessment, there will always be varying methods in how the tool is implemented – still on a case-by-case basis.

The programming of the algorithm limits public access to the information and even disables defendants from challenging rulings based on risk assessments. The manner in which scores have value assigned to them and experts – in this case, judges or those with decision-making power in the judiciary, trust these algorithmic outputs without full transparency of data points included in the algorithm represents a colonization of the public sphere. The use of the COMPAS algorithm has sparked the appealed case heard by the Supreme Court of *Wisconsin vs. Eric L. Loomis*. Wisconsin was also the first state to purchase Northpointe technology, the COMPAS algorithm, and hastily incorporated it in their judicial system. Loomis was sentenced to six years in prison because of his risk assessment score. The case was appealed on the basis that because Loomis did not know what was behind the algorithm that produced the score, it is withholding of information and unconstitutional violation of due process (Liptak, 2017). Loomis was denied access to the proprietary information of COMPAS and courts found in favor of Wisconsin (Angwin & Larson, 2016; Angwin et al., 2016; Corbett-Davies et al., 2016; Larson et al., 2016). Sentencing algorithms alter judgment standards and affect questions of due process by obscuring evidence assessments. The implications of algorithmic decision making are much-needed reassessment of information as a public good (Noble, 2018).

The Supreme Court validated their decision by stating that Loomis would have been granted the same sentence because he is a risk to the community because of his crime and fleeing the police (Liptak, 2017). It is a lot simpler to see an answer on a test than explain how the answer was arrived, especially if no details of deliberation have to be included. The courts responded by saying – ‘oh this high-risk assessment matches what would have been decided without the score.’ That is an unsettling argument because it alleviates individuals of shouldering the burden of explaining how they reached a conclusion. This addresses how the employment of the algorithm stops dialectical scrutiny due to black boxing. Therefore, even if the same decision is reached, it does not prove that viability or even the fairness of the tool. Perhaps the risk assessment also creates a moment when it is easier to rely on a perceived objective value opposed to explaining an actual human judgment should those evaluations differ.

In April 2017, Chief Justice John G. Roberts Jr. visited Rensselaer Polytechnic Institute where he responded to a student by saying that the day is here when smart machines and artificial intelligence is already in judicial decision-making; but, it is also putting a strain on how the judiciary does things (Liptak, 2017). The highest judge of the US Supreme Court, openly acknowledges the discomfort in this transitionary phase of properly incorporating algorithms in the justice system. Big Data has been used in the justice system for years – fingerprint scans, documenting offenders' information, face recognition software and more - and is not new to how data is managed. However, the implementation of algorithms to render judgment presents challenges that seem to be blindly accepted before the validity and consequences of these algorithms have been adequately tested.

Scholars Say COMPAS Lacks a Human Compass

The ubiquity of Big Data has seeped into our criminal justice system, a system that dictates major parts of our lives – freedom. One common theme throughout most of the discourses surrounding the implementation of these algorithms in the justice system is the emphasis on recidivism. An obvious disconnect between the algorithm and its goal of limiting recidivism is how criminal activity is lowered. Although COMPAS was created to classify and better assess alternative forms of rehabilitation, the function and presence of the algorithm has shifted (Angwin et al., 2016). The "humane" aspect of punishment in the judicial system seems to be reserved for Whites and not offered to Blacks, which further solidifies racial disparities in the court systems in the United States.

Scholars who study the social implications of algorithms acknowledge that racism is embedded into source codes in most technical platforms, namely Google (Noble, 2018). These scholars are requesting a moment of reevaluation for how algorithms are implemented and the value judgments behind programmers who actually write the algorithmic codes. Problems with Big Data are larger than misrepresentation but include decision-making protocols that favor corporate elites and the powerful. They are implicated in global economic & social inequality which is exactly why COMPAS is concurrently fair and discriminatory (Noble, 2018). The algorithmic language is inherently discriminatory, factors used to assess risk assessment are correlated with race, and the algorithm accurately reflects the current status of the criminal justice system.

Human judgment is limited by bias, but it is not systematically coded in a bias measurement. Furthermore, the acknowledgment of bias in human judgment results in deliberations of decisions which can be adjusted, modified, or even questioned as necessary. The justice system itself employs juries, attorneys, judges, and even different levels of courts: district, appellate, and supreme which acknowledge variations in human judgment. Although, human bias is not ideal, it is a known factor that can be changed or shifted. Risk assessments are unchanging regardless of the judiciary. “There is a missing social and human context in some types of algorithmically driven decision making, and this matters for everyone engaging with these types of technologies in everyday life” (Noble, 2018). Ultimately, the discourses surrounding COMPAS acknowledge that this technology lacks the inclusion of the social and human compass – a compass that we cannot afford to abandon in the name of objectivity.

Chapter 3 – No Sympathy for the Score

"Karyn Morton applied for a Capital One credit card online, the company's website offered her two cards based on information gathered from a data mining company after Karyn clicked once on the company's website. Capital One accurately identified Karyn as a Black, Detroit homeowner who reads major metropolitan newspapers and watches the NAACP Image Awards. But Capital One assumed that Karyn was over sixty-five years old, retired, without children, and some high school education. Although, Karyn was thirty-three years old, had a five-year old child, a law degree, and earned a salary three times higher than Capital One's prediction. Capital One classified her as a "City Roots" segment and offered her two cards with a zero interest, six-month "teaser" rate. Six months later the interest rate shot up to either 24.9% or 13.9%.

In contrast, analyzing Thomas Burney after he clicked once, Capital One correctly labeled him as a White college graduate who skis but predicted a higher salary than his actual one. The company's data software classified Thomas in its "God Country" segment and offered him a card with a relatively low 11.9% interest rate," (Freeman, 2017).

Money lending is as old as currency and rife with all kinds of problems. Before the advent of the credit card, the process for lending between lenders and potential consumers was a character-based judgment. Often, representatives would ask relatives or local merchants for opinions of the potential customers before agreeing to a loan transaction (Konsko, 2014). The challenge for this process was lender-bias. It presented challenges to immigrants, women, the elderly, low-income, LGBTQ community, people of color, and various other minority groups who were subject to lending discrimination (Henderson, Herring, Horton, & Thomas, 2015). For instance, from 1921-1950 the Federal Home Loan Bank Board "defined undesirable residents as racial or ethnic minorities, or low-income inhabitants." The board also referred to these filters as "scientific appraisal" standards (L. L. Woods, 2012). While the federal government was expanding home ownership to millions of Americans, racial minorities and low-income individuals were denied that same access through redlining (L. L. Woods, 2012). The prejudiced allocation of resources and reinforcement of those practices expose the regularity of human bias. Yet, there was no recourse for those disadvantaged. Character-based lending practices presented a faulty system for borrowing money, and the referral of the standard as a "scientific appraisal," alludes to the narrative appeal of science as objective. Hence, we needed something more objective to account for the bias in human judgment which led us to the implementation of the credit score.

In an attempt to create a more universal currency after the excitement of the first Diner's Club card in 1950, the finance industry shifted primary reliance on character-based judgments to reliance on a numeric value with the introduction of the credit card (Editors of Encyclopedia Britannica, n.d.). The first credit card scoring system was designed by Bill Fair and Earl Isaac in 1958. The system, currently known as the FICO score, was used to predict consumer behavior which spread into various areas of lending – mortgage, small business, consumer, etc. (Komorad, 2002). The use of credit cascaded across the US economy, but the public was so gravely misinformed about the use of credit that it warranted government intervention. In 1968, the Truth in Lending Act was passed by the Supreme Court requiring lenders to provide disclosures to consumers and information promoting credit card education (Miller, 1978). These policies were have been regulated by the Consumer Financial Protection Bureau ("Truth in Lending (Regulation Z)," 2016).

Even as recent as May of 2017, the Supreme Court ruled that cities are capable of suing big banks for the effects of discriminatory practices under the Fair Housing Act (Chappell, 2017). "Critics have questioned the accuracy and fairness of credit-score models. They charge that in some cases, credit-scoring is inherently biased against minority groups such as Blacks and Hispanics," (Henderson et al., 2015). Discriminatory practices still exist and produce impactful decisions for our social operations. The US government has consistently passed legislation to regulate and equalize lending practices in our nation.

Using data points to justify and produce decisions as the basis of fairness presents an attractive appeal for the introduction of algorithms into the lending process. Before credit scores, lenders could choose to lend money to anyone who they deemed able and willing to pay off their debts, although there was no regard for individual lender bias in assessing who has the opportunity to borrow money. Even if lenders or organizations tried to be aware of personal biases, there was no adequate measurement to ensure that bias was not systematically used against specific groups or types of people. Algorithms were intended to rationalize financial decisions by replacing bias and gut instincts with sound decision frameworks (Pasquale, 2015). Since credit scores, algorithms use various data points to produce a value that determines the likelihood someone will deliver the lenders' return on investment.

With the advent of and increased reliance on credit scores, Big Data has drastically shifted how this financial exchange occurs and the discursive elements we employ to discuss the role of credit cards in awarding credit lines to borrowers. The study of credit scores and the impact they have in our society demonstrates how the façade of objectivity functions to secure our trust in Big Data supposedly delivering us of human bias. Although we benefit from Big Data, how it operates and how algorithms are programmed to make decisions are mostly unknown to us.

Salience of the Credit Score

One of the most elusive and critical algorithmic decisions that affect us throughout our lifetime is the credit score. Credit scores enable individuals to get better loans, save money in various ways (i.e. landlords, employers, utility companies, etc.), housing and employment opportunities, detection of credit fraud, qualification of types of credit cards, and even the attraction of romantic partners (Investopedia Staff, 2003; L. Woods, 2016). A strong score provides purchasing power and lower interest rates which equates to nearly hundreds of thousands dollars saved over a lifetime (Pasquale, 2015). On the other hand, a weak credit score results in higher interest rates, potential missed employment opportunities, denials in purchasing, and traps some individuals in the vicious cycle of trying to recover from the number while faced with the aforementioned challenges. The inability to manage limited financial capital to its highest potential will severely limit someone's ability to economically grow in their lifetime – even preventing someone from getting a job.

Organizations try to incorporate more data into benefit from greater precision, hence the attraction to Big Data. The hiring process presents one of those spaces where we surrender some decision-making authority to algorithmic outputs. Companies today insist on gathering as much data as possible as a method of increasing their assets (Kraska, 2013). One of the greatest assets to an organization is the employee and credit scores are now being included in hiring decisions. Bad credit scores can result in employment discrimination (Ludwig, 2015).

We cede authority to algorithms when human judgment of a candidate is not sufficient reasoning to hire someone. The use of the credit score in hiring demonstrates how the credit score is applied in spaces that differ from its initial purpose. "Credit scores have escaped from their native financial context and established themselves as arbiters of general reliability in other areas," (Pasquale, 2015, p. 23). The hiring dilemma further perpetuates the cyclic tension of a bad credit score – individuals are denied access to good employment opportunities because of a bad score but without the job, are also unable to improve the score. Human judgment in the hiring process accounts for data points that are not quantifiable in the credit score such as personality, timeliness, presentation, etc. When we empower algorithms to decide who qualifies for an employment opportunity, we give numeric values more agency on unknown data points opposed to human judgment.

The credit score is one of the most critical scores ascribed to us, with some arguing that it is more significant than our individual social security numbers (L. Woods, 2016). The social security number used to be considered the single most important identifier of any American citizens – which inevitably has all types of implications for rights as a citizen and protections under the federal government (Rashid, 2017). The social security number is an identifier while the credit score is an enabler. I make this comparison to emphasize why the black boxing of the credit score is relevant to our understanding of decisions and how Big Data is used to leverage those decisions. The credit score is almost as important as social security numbers for American citizens and an essential consideration in major aspects of our lives, yet most citizens do not fully understand how it computes.

Algorithms are designed to digest and produce values based on the data points and host information which is considered proprietary thus inaccessible to the public (Liptak, 2017; Noble, 2018; Pasquale, 2015). The capacity of human judgment is limited when the inner workings of algorithms are kept hidden. Reliance on Big Data evaluations as a primary form of decision-making creates the opportunity for increased opacity behind processes. For instance, in 2011 banks' direct-deposit advances caused a lending debate which garnered the attention of the Office of Comptroller of the Currency (OCC), an organization which regulates national banks. Direct banking loans were riskier than payday loans because unlike payday lenders who were subject to state regulation, banks were only subject to federal regulations therefore operating under different policies (Randall & Zibel, 2011). The OCC claimed that these cash advances "raise operational and credit risks and supervisory concerns." Banks argued that they offered loans appropriately to "enable customers to live within their means." Various representatives from banks offered a statement claiming how they actually keep consumers informed of the risk (Randall & Zibel, 2011). For instance, “We are very up-front with our customers and let them know that it is an expensive form of credit,” said spokeswoman Richele Messick from Wells Fargo (Randall & Zibel, 2011). Since information behind algorithms is proprietary, we have to assess whether we should rely on such things when making decisions. The competency for human judgment is challenged when access to the data is denied.

The 2008 housing crisis almost collapsed the US banking system which required direct intervention from the Federal Reserve (Pasquale, 2015). This crisis almost toppled a system central to the US economy and much of the cause of it was the secrecy of the financial market – resulting in major losses for some and major gains for others. The claim here is not that Big Data caused the housing crisis. Rather, the lack of visibility surrounding the financial markets and how they function left the public ignorant and exposed while facing the crisis. Big Data helped create predictive values and run analyses on individuals which essentially was used as a classification process predominantly harming those classified as “high cost” or “unreliable” (Pasquale, 2015). This predictive score mirrors how we discuss consequences associated with our financial decisions. The lack of transparency about these values and how these values were produced disabled a large amount of people from making wiser decisions regarding their futures. Human judgment is diminished when we are not equipped with all of the facts to make well-informed decisions. Algorithms are given the agency to render the final decision if unknown predictive values dictate major aspects of our lives.

Heightened secrecy of processes and increased access to information through Big Data present two major building blocks of the Big Data black box (Pasquale, 2015). I take caution in stating how much each sphere contributes to the existence of this box because limited visibility is integral to its role in society. It would be incorrect to claim that the technical sphere has complete control and knowledge over the processes behind Big Data, especially when some coders have difficulty reverse engineering self-learning algorithms to understand how it achieved its values. However, members of the technical sphere are, at least, aware that Big Data plays a key part in decision-making for various sectors of US society – financial, health, education, justice, etc.

This knowledge gives agents within the technical sphere an advantage in rendering personal judgments. Members of the technical sphere have greater access to resources to educate themselves – either through further inquiry about some features included in algorithms, seeking ways to resist some collection of personal information, and any other tactics to ensure that Big Data functions as a resource as opposed to an obstacle in their personal lives. A breach between agents of the technical and public spheres consistently expands as visibility of processes decreases and information access increases. Even if members of the technical sphere do not have a full understanding of how algorithms produce values, those members have a baseline awareness that the Big Data black box exists and maintains a level of secrecy or influence beyond the access of the public sphere.

Discourses Surrounding Credit Scores

To analyze the discourses surrounding credit, I focused in on media searches that discuss credit scores and discrimination. "[I] am troubled when I read allegations in the press that FICO Scores discriminate against people of color. That's because a credit score is nothing more than the output of a mathematical formula built to rank-order the likelihood that a person will repay the debts," (Huynh, 2012). News sources and blogs primarily discussed how scores could be improved and genuinely seemed to try educating the public (DiGangi, 2016; Investopedia Staff, 2003; Leamy, 2009). The most recent occurrence regarding credit scores is that tax liens could be taken out of the calculation of the score, which could result in a score bump for many (Dickler, 2018a, 2018b; Sweet, 2017). These discourses present a moment when agents of the technical sphere aim to make some information regarding the credit score digestible to the public.

Scholars focused predominantly on the inequity of the credit score. Most of these studies focused on disparities within the housing or lending markets (Henderson et al., 2015; Levinger, Benton, & Meier, 2011; Meier & Sprenger, 2010; Mian & Sufi, 2011; Riley, Nguyen, & Manturuk, 2015). These articles suggest that there is still a lack of education surrounding the credit score and discrepancies within the housing market, zoning, or redlining persists. One study "found that lenders set credit limits on revolving accounts based in part on the racial composition of the neighborhood in which the borrower resides. It concluded that "it appears likely that a race variable appears somewhere in the determination of credit availability," (Henderson et al., 2015).

Self-awareness of credit rating and surface level education about the credit score is proven to have bearing on how well consumers can use credit scores to their advantage. "[C]ontrolling for credit score and sociodemographic variables, consumers who underestimated their creditworthiness reported having credit cards with higher interest rates…Here we demonstrate that imperfect consumer knowledge is systematic and frequently carries serious consequences, (Levinger et al., 2011). This study used financial literacy as a foundation for understanding potential disparate impact among credit scores and uncovered that even imperfect knowledge of the score is systematic. Some scholars have even tried to study and understand which type of consumers are more or less likely to have higher credit scores based on if consumers are more present or forward thinking individuals (Meier & Sprenger, 2010). This study in particular tries to quantify some elements of human behavior associated with decision-making behind the credit score.

The inequity behind credit scores has been well-documented while legislation has been passed to place some regulations on credit since the late 90s. The dot com bubble and the aftermath of 9/11 were two major events that occurred heightening our interest in exploding credit. In the early 2000s, "while lowered interest rates achieved the goal of stimulating the economy, the government failed to keep borrowing in check and millions of Americans eventually found themselves with more debt than they could realistically afford to repay," (Bond, 2013). One of the government responses to this credit bubble burst was The Fair and Accurate Credit Transactions (FACT) Act. It was passed in 2003 granting Americans access to an annual credit report (Levinger et al., 2011; Pasquale, 2015). An annual credit report merely offers the public a veneer of transparency about the credit score, although algorithms behind the score are still black boxed (Pasquale, 2015). The government offers each citizen an individual report that places onus on the individual to ensure his or her credit is strong. Discourses seem to acknowledge the role of human decision-making as a method of improving individual credit scores.

Some of the discrepancies resulting from the leveraging of the credit score have been documented and addressed through changes in legislation, agencies, and tips on best practices for score improvement. For instance, the Federal Reserve produced a 2007 report showing that White and Asians had higher credit scores than Blacks and Hispanics. Although, "the Equal Credit Opportunity Act doesn't allow creditors in the United States to discriminate based on race, color, religion, national origin, sex, marital status, age – but taking into account a person's network could allow creditors to end-run those requirements" (Waddell, 2016). In 2014, according to the New America's Open Technology Institute, "…[a]s individuals increasingly face technologically mediated discrimination based on their positions within networks, it may be incomplete. In the most visible examples of networked discrimination, it is easy to see inequities along the lines of race and class because these are often proxies for networked position" (boyd, Levy, & Marwick, 2014). The credit score has been leveraged in many different ways for use beyond its initial purpose that has coded bias into various systems.

Current discussions about the credit score seem to divert attention from the bias of the score and just presents the best ways to work around that bias. The reliance on credit scores as a primary decision-making tool in lieu of human judgment presents a moment when we calcify bias and discrimination under the guise of a discernible number. Informing the public of how to improve their score puts the onus on the individual to ensure that their individual credit score works for them despite some of the discrepancies in credit score calculation.

The use of credit scores highlights one of the greatest concerns with algorithms – the secrecy and black boxing of a value that has lasting implications for our futures. Individuals have always shouldered the enjoyment and burden of making a decision as well as explicating how they arrived at those decisions. Algorithms remove human capacity to logically explain how they arrived at a decision. There is a cycle that begins –

a decision was made because the algorithms said so but we cannot understand why the algorithms produced the value it produced because the information is black boxed. Therefore, being unable to discern how algorithms reached a decision significantly limits human agency when it comes to rendering judgment. Without the deliberative process to understand how we achieve certain outcomes, we create experiences where algorithms decide critical aspects of our futures without understanding the why behind said decision.

Chapter 4 – Conclusion

> "The study of Big Data could lead to a more comprehensive understanding of social reality. But achieving that understanding will require developing a sense of the complex materiality of our Big-Data producing information systems, and empathy for the people who fund, design, build, use, and exploit them. Without that sense and empathy, when we are asking what we have learned from Big Data, we may be left pointing mutely at our data centers," (OPREA, 2016; Shaw, 2015).

In this thesis, I examine discourses surrounding the implementation of algorithms in two major sectors of American society: law and finance. The first is the use of the COMPAS algorithm, a risk assessment tool used to classify offenders' likelihood to reoffend, in the judicial sector. The second is the credit score, algorithms designed to assign a numeric value regarding consumers' likelihood to pay debts. Introducing the use of Big Data into these spaces had an attractive appeal because it seeks to remove human bias from the decision-making process, thus shifting some social processes from fallible human judgments to perceived objective Big Data evaluations. The arguments of attractiveness advocating the use of Big Data, arguments surrounding the application of the algorithm, and arguments regarding limited visibility of the data included in algorithmic processing are three major themes highlighted in these case studies which undermine the role of human judgment in the decision-making process.

Attractive Appeal

The attractive appeal arguments for both of these cases has an emphasis placed on fairness by removing human error from these processes which ultimately have lifelong consequences for the masses. Credit scores were intended to ensure that consumers were not subjected to unfair lending practices based on lender bias (Pasquale, 2015). The intended use for COMPAS was to properly classify offenders for their occupancy jails or prisons and actively consider alternative rehabilitation opportunities for defenders (Angwin et al., 2016). These arguments for the utilization of Big Data in these spaces are robust because they directly align with shifting the agency of judgment towards objectivity and away from imminent human error. The arguments garner support for the algorithm's role as a credible source for producing evaluations because it processes vastly greater data points than the human mind without the fear of inaccuracy. Discourses demonstrated that most people agreed that the infiltration of Big Data in our systems was the best response to the inevitable issue of human fallibility.

To correct our errors, we designed algorithms to address and correct our lapses in judgment, but the misapplication of these algorithmic tools was apparent in both case studies. The credit score has a much farther reach than just a numeric value to mitigate human bias in a lending or borrowing financial exchange (Pasquale, 2015). The COMPAS algorithm was not designed to be used in sentencing of offenders (Angwin et al., 2016). The argument is not that algorithms are inherently flawed. Any potential human error in the design of algorithms is not the focus of this thesis. Rather, we are flawed in how we employ these tools which are designed to serve one purpose. When we actively engage in the multi-purposing of algorithms we cede even more decision-making agency away from ourselves than was initially designated. Because the discourse around algorithms frames human judgment as flawed and algorithms as objective, interlocutors are left with few rhetorical resources to challenge shortcomings in the use of Big Data within these public policy deliberations.

Misapplication

The misapplication of Big Data evaluations reinforces the appeal that humans are erroneous and should cede judgment to some greater form of objective decision-making. The support for the use of Big Data in our social systems clouds our ability to acknowledge when algorithms are misused or ascribed meaning beyond its initial purpose. When the intention of algorithms was addressed in discourses, creators or supporters of algorithms minimized the fact that it was being misused and continued to blame human error. The rhetoric around Big Data insulates it from criticism by increasing the burden of proof for individuals to say 'the data is wrong.' This harkens back to the argument of perceived objectivity of Big Data – utilizing it can only make current systems better in whatever space it is used, because it is presumably better than human judgment.

Even with the aid of the perceived objective algorithm, the reliance we place on algorithms dulls our ability to understand when algorithms are misapplied. The *Algorithmic Injustice* case study reveals that people fall somewhere on the 'personal reliance on algorithmic output' spectrum. Some people do not factor the data into their judgments like Judge John Hurley or completely rely on it like Judge James Babler. These present two extremes of how Big Data evaluations are factored when humans render final judgment in the judiciary. It is unclear where others fall on this spectrum, if they explain where they fall on the spectrum, and how their reliance on Big Data shifts for different decisions. Meanwhile, these conversations suggest that it is acceptable for those who already have the agency to make final decisions to merely consult more objective measures as they see fit. The subjectivity in how the decisions of algorithms are employed on an individual basis illustrates that there is bias in the personal application of these evaluations. These discourses illustrate that when judges explained their decisions, subjective implementation of the COMPAS algorithm was acceptable without contestation.

Visibility

The limited visibility of the data points and decision-making process behind the algorithm directly challenges the deliberative process that humans have used in the past to justify their decisions. The deliberative process – one of enjoyment and a shouldered burden of proof for us is crippled by algorithms which we cannot explain. The appeal of relying on objective measures stifles some of the discourses surrounding potential unfairness of how algorithms are wielded and our critical judgment skills. For instance, in a study in which two groups of students were given math problems to solve – one group was given a calculator which was programmed to be incorrect and the other was not allowed a calculator. The group with the calculator did not bother to check their work, even in the most mundane calculations. If we solely rely on calculators, or any technology presumed as objective, without thinking about our responses or understandings then what we get will be incorrect. Our thinking and actual understanding of the tool matters (Russell, 2017; Vilson, 2013). Furthermore, some judicial cases cannot be overturned when cases rest on risk assessment scores just as credit scores are values that the consumers are personally responsible for improving through a set of guidelines, while the data points used in these algorithms are held in secrecy. It is extremely difficult, if not impossible to 'overturn' or challenge the credit score. Information is black boxed and deliberations are discouraged which simultaneously constrain the opportunities to exercise strong human judgment.

This analysis manifests how the claim of objectivity from Big Data functions to reinforce the heightened secrecy of information – namely what data points are included in the processing of algorithms whose evaluations have lifelong consequences for our lives. Algorithms have added a layer of proprietary to technical sophistication which creates further distance from the public sphere. For instance, just enough information is divulged to the public about potential ways to improve a credit score which is a pretense of transparency (Clements, 2018; Investopedia Staff, 2003; Leamy, 2009; L. Woods, 2016). In the case of the judiciary, some parts of the COMPAS algorithm were explicit – race was not included as a data point although a few data points correlating with race were included, prior arrest history was included, and a few other points were available to the public but the rest of the information was considered proprietary (Corbett-Davies et al., 2016; Dieterich et al., 2016; Noble, 2018). This presents a fissure between the technical and public spheres – the technical sphere further colonizes the public sphere by widening the gap by ensuring that visibility and access to information are limited in the name of objectivity. These arguments prevent us from engaging the technical sphere at all under the basis that human judgment is fallible.

Call to Action

Currently, the use of Big Data and the future of artificial intelligence are hot topics of discussion. Silicon Valley, Google, and other technology giants are in the limelight for some of their practices and products that do not seem to reflect some of the expectations of the public (Noble, 2018; Sydell, 2018). Facebook founder and CEO Mark Zuckerberg recently testified on Capitol Hill regarding a security breach with Cambridge Analytica of 87 million users of data (Rizzo & Kelly, 2018; Snell & Selyukh, 2018; Swaine, 2018). Privacy violations are paramount, as such breaches literally affected democratic decision-making. These occurrences suggest that there are efforts from the the public to gain more visibility and have a more active role in ensuring that technology is beneficial to society. Agents within the technical sphere seem receptive to those requests through public acknowledgment of remorse regarding bias practices (Sydell, 2018). These dialogues assert that the role of technology and its implementation in our society is a major social concern – one that is alive and well.

One of the greatest challenges of this thesis was that even after researching the discourses surrounding credit scores, I still experienced difficulty finding revealing discourses about the topic. Few sources called for the heightened visibility of credit score calculation opposed to discourses surrounding risk assessment scores. Since these two systems function differently – the justice system operates through open deliberations while the finance system operates through more private communications, and it seems that the discourses reflect that difference. Racial injustice is a known issue in our society – one heavily studied and perhaps the cause for the extensive research done within

Algorithmic Injustice. Likewise, there are some discussions surrounding discrimination regarding credit scores, and yet most discourses are primarily focused on score improvement. Limited visibility of the credit score overall seemed accepted by the public sphere despite its critical consequences for the livelihood of American citizens. The public sphere seemed to have different goals for different systems, thus giving different algorithms different agencies in the decision-making process.

Big Data is a global phenomenon which has a present role and will continue to have lasting impact for nations all around the world. Both of the cases mentioned have the undertones of racism which perhaps could be an occurrence unique to the US because of the role of slavery in the development of our nation. However, the lesson is translatable. "Algorithms are not immune from the fundamental problem of discrimination, in which negative and baseless assumptions congeal into prejudice" (Noble, 2018). We are grateful to the data scientists, programmers, and engineers who write these codes in the hopes of enlivening informed deliberations and improving decision-making. And yet, any biases in algorithms or misapplication of the tool can exacerbate the problems when the discourses valorizing Big Data function to undermine deliberations that identify shortcomings in algorithmic assessments and systematic bias is ascribed the meaning of objective.

Although Big Data is beneficial to the betterment of society and makes our lives easier, we must pause to incorporate the deliberative element behind our actions. Speech and action are necessary for us to comprehend who we are (Arendt, 1958). Reliance on the unknowns of Big Data and algorithms as a solid foundation for explaining our actions is not sufficient for maintaining the value of human judgment. We must ask ourselves who will be hurt by these changes? Does objective mean that we appropriately reflect the current system or do we seek to change a flawed system? How can we make this truly objective? How will we measure it? Is our chosen tool valid and reliable? Who says? What data have we included to reach these decisions? These considerations could ensure that we are not reduced to performing robots and limit our incomprehensible behaviors – critical acts and decisions based on opaque Big Data evaluations (Arendt, 1958). We cannot sacrifice the human for the dollar or the machine in the name of objectivity, science, algorithm, or Big Data. Numeric values cannot be devoid of speech and action to ensure that it is in fact the human rendering the final say on Judgment Day.

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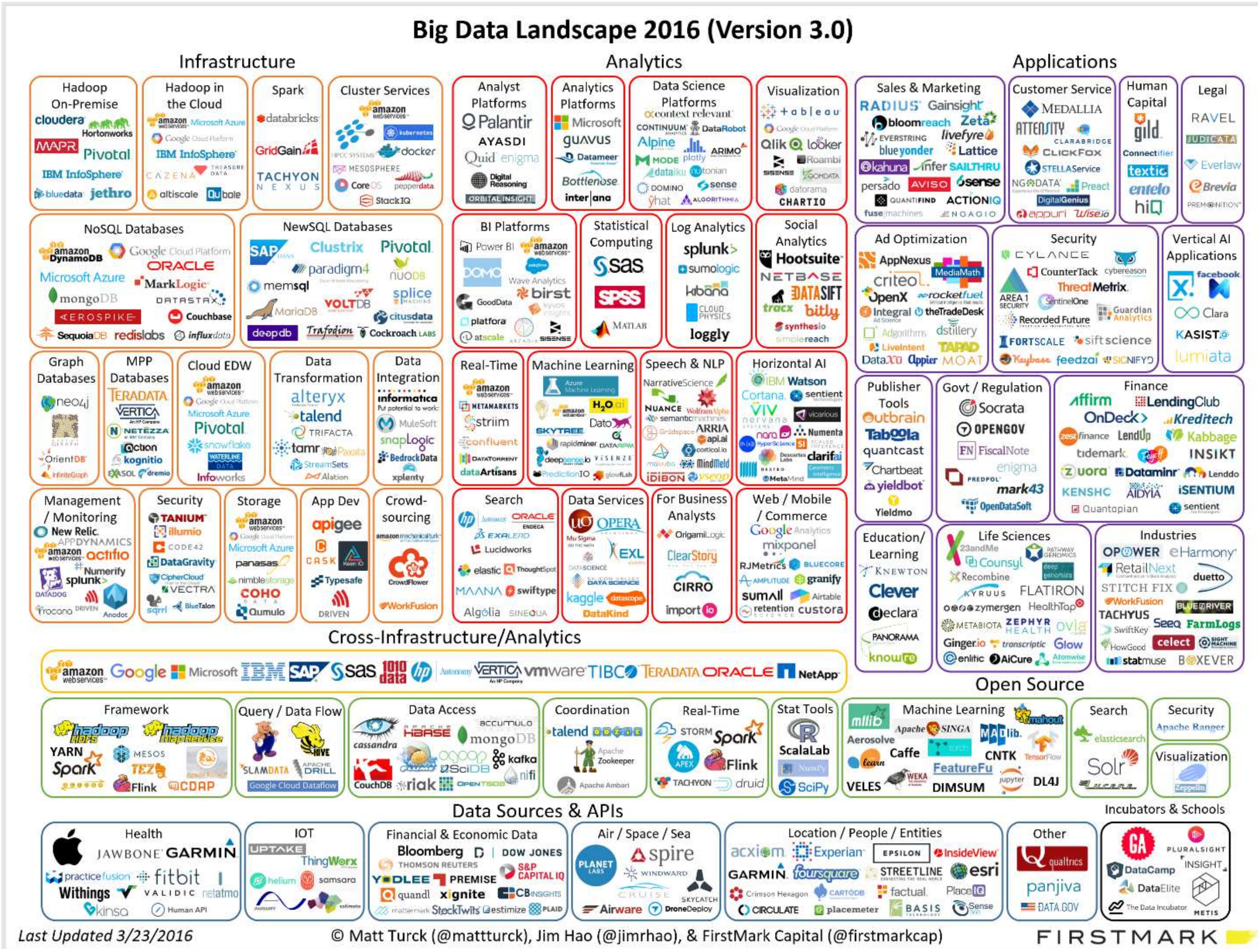
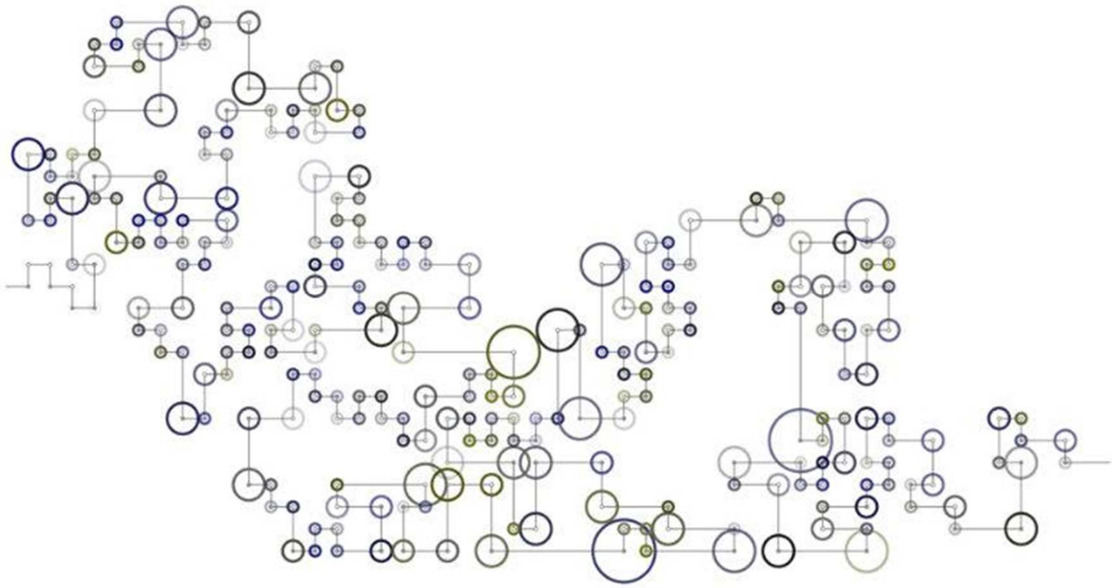
Appendix

Figure 1



This image shows how different technologies and algorithms are employed for different topics. Different types of algorithms are used for Big Data mining and there are sophisticated theories that go into developing such algorithms. Algorithms apply to a range of sophisticated methods such as Signal and Image Processing, Probability Theory, Mathematical Numerical Optimization, Neural Network Theory, Numerical Linear and Tensor Algebra (Khan, Shakil, & Alam, 2018).

Figure 2



This image offers a visual representation of an algorithm and how various data points are included in the series of if-them process statements that go into an algorithmic output (Mathisen, 2017).

Curriculm Vitae: Tyiste Taylor

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EDUCATION

Master's in Communication **Anticipated May 2018**

Current GPA: 3.9

Wake Forest University- Winston-Salem, NC

Bachelor of Arts in Communication with a Minor in Sociology **May 2015**

GPA: Major 3.74, Cumulative 3.57 – Dean's List

Wake Forest University-Winston-Salem, NC

Study Abroad – Worrell House Program (Wake Forest University) **Fall 2012**

London, England

- Exposed to curriculum of London History, Government and Politics, and Drama through London Theatre

Summer Management Program (WFU School of Business) **Summer 2013**

Winston-Salem, NC

- Completed five-week intensive training in business disciplines including: Accounting, Finance, Marketing, Information Systems, Business Law, Operations, Entrepreneurship, and Strategic Management

DIGITAL EXPERIENCE

Communications and External Relations **November 2016 – April 2017**

Wake Forest University-Winston-Salem, NC

- Provided assistance in launch of new Wake Forest websites.
- Assumed responsibility for updating older websites by scanning for misspellings and broken links.
- Recently exposed to Google Analytics and basic HTML code.

Jr. Search/Taxonomy Coordinator **October 2015 – January 2016**

Lowe's Corporate-Charlotte, NC

- Updates Lowe's product descriptions through Excel

- Gained a basic understanding of how search impacts sales and improves consumer usability of website
- Learned basic coding in Excel Developer
- Maintained and updated large macro builders for Lowe's product descriptions

Buyer/Planner **July 2015 – September 2015**

Specialty Manufacturing Inc.-Charlotte, NC

- Updated reports for analyzing part usage and purchased parts for manufacturing plant from globally diverse suppliers.
- Managed various transactions within Syteline database on everyday basis which were highlighted through reports in Excel.

Digital Marketing Intern **June 2011 – August 2014**

Electrolux-Charlotte, NC

- Spearheaded the completion of approximately 150 Electrolux product videos through Easy2 demo software.
- Investigated the feasibility of incorporating new iBeacon technology into Electrolux products.
- Tested various Electrolux websites for malfunctions or misplaced data.
- Updated the work timeline in Microsoft Excel for individual products, product lines, and other brands.
- Reviewed raw statistics and analyzed the effectiveness of promotional tactics.

Administrative Assistant Intern **June 2010-August 2010**

Mayor's Youth Employment Program- City of Charlotte, NC

- Assisted city officials in day-to-day logistical activities and designed publications to advertise communal events

ADDITIONAL EXPERIENCE

Graduate Hall Director **July 2017 – Present**

Wake Forest University-Winston-Salem, NC

- Supervise, train and evaluate a staff of seven undergraduate Resident Advisers (RAs) in a residential community.
- Manage the day-to-day operations of a 270 person suite-style upperclassmen residence hall.
    - Handle administrative tasks including facilities walk-throughs, room inspections and maintain community budgetary oversight.
- Serve as a role model and mentor to undergraduate students.

Teaching Assistant **August 2016 – Present**

Wake Forest University- Winston-Salem, NC

- Designed weekly lesson plans to aid in the development of students in public speaking.
- Offered direct students on a one-on-one basis, graded assignments, and engaged in timely email correspondences.
- Demonstrated protection for technology through assumed responsibility for a department-owned digital camera.

Mentor for Benjamin Franklin Transatlantic Fellowship **June 2017 – July 2017**

US Department of State-Winston-Salem, NC

- Organized and taught topic-focused workshops on civic engagement.
- Helped escort 55 international high-school fellows around the United States.

Resident Adviser **August 2013 – May 2015**

Wake Forest University –Winston-Salem, NC

- Fostered a more inclusive community for my assigned residents by physically visiting their rooms, contacting them via email or text, and engaging in one-on-one conversations with them.
- Managed an organizational budget of over $50,000 and formulated proposed budgets for the year.
- Provided educationally engaging programming initiatives for residential students within my community and beyond.

AWARDS AND ACHIEVEMENTS

Graduate Hall Director of the Year *April 2018*

National Residence Hall Honorary GA of the Month *March 2018*

Champion of Change Award Recipient *March 2018*

Treasurer of Lambda Pi Eta (National Communication Honor Society) *2014 – May 2015*

Financial Administrator of Resident Student Association *August – December 2014*

Keynote Speaker for the National Association of Negro Business & Professional Women's Youth Club Inc. *March 2014*

Magnolia Scholar (First-Generation College Student) *2011 – May 2015*

Zachary T. Smith Merit Scholar *2011 – May 2015*

West Charlotte High School Scholar and Hall of Fame *2011 – May 2015*

Foundation for the Carolinas Scholar *2011 – May 2015*

Rotary Scholar *2011 – May 2015*