Ravie Lakshmanan

Online Reputations and Beyond: Rise of Intelligent Recruiting in the Workplace

Class of 2018

Advisor: Susan McGregor
Assistant Director of the Tow Center for Digital Journalism

Jager Hartman, 24, graduated from Columbia University with a Master's degree in Data Science just last December. Since then he has established something of a set routine: actively scour for jobs that he thinks he is a good fit for, then spend hours researching about companies before submitting his resume and cover letter. "It's the usual boring stuff that you do to stand apart from the rest," says Jager, in hopes of landing a full-time job.

The process of job-hunting has also introduced Jager to the realities of what it means to "stand apart" in a competitive job market, such as restructuring his resume so that his job applications would get the attention of recruiters and HR departments. "It makes you tweak your resume in a way that's not very appealing," says Jager. "Shrink the text, fit in as many buzzwords as you can, and leave out all the content so that you get pushed to the top of the pile, but I don't know. I don't know how I feel about doing that."

It is no surprise that the jobs market has become increasingly competitive. Cut-throat even. According to U.S. Hiring Trends Report[1] published last year by talent acquisitions provider iCIMS for the year 2016, it was found that white-collar positions received substantially more applicants per posting, on average, than the blue-collar and pink-collar positions. Software engineering and web developer positions, for example, had a cumulative average of 66 applicants per posting, making such high-paying jobs more popular among job seekers, and therefore that much more competitive.

Artificial intelligence and machine learning, the same technologies that enable us to book the cheapest flight for our next vacation or find the most efficient route to our destination, are quietly transforming both job-seeking and the workplace. Even in non-technology fields, these tools are revamping the very means companies look for job candidates, get the most out of employees and retain top talent.

But just as algorithms steadily infiltrate different aspects of our day-to-day lives and make decisions on our behalf, they have also come increasingly under scrutiny for being as biased as the humans they sometimes replace. The question is: are these technologies improving the efficiency of hiring and retaining employees, or simply hard-coding existing stereotypes? But what is even bias? How do we define fairness? These are hard questions that come with no easy answers.

Artificial Intelligence as a Means for Recruiting

Be they students fresh out of grad school, or professionals switching jobs, most job-seekers go through an experience similar to Jager's. But landing a job is the culmination of a long process, made more complex today in an environment where many AI technologies are influencing a

[1] "U.S. Hiring Trends Report: 2016 - iCIMS." 15 Mar. 2017, https://www.icims.com/hiring-insights/us-hiring-trends/ebook-us-hiring-trends-report-2016. Accessed 13 Apr. 2018.

range of decisions ranging from hiring best candidates to tracking how employees are spending their day at work.

But increasingly, companies are using algorithms to analyze a vast amounts of data about applicants, even searching social media footprint and analyzing video interviews of job candidates in order to "compare" an applicant's facial movements, vocabulary and body language with the expressions of their best employees.

Even more, companies are also heavily counting on AI services to determine employee happiness by scanning their emails, measuring the time they have spent in their current job and the number of managers they have had to determine when an employee is most likely to quit his job.

Can an AI do a better job than humans?

Historically, company job matches were done manually by either an internal or an external recruiting team. By letting a computer program make hiring decisions for a company, the prevailing notion is that the process can be made more efficient - both by selecting the most qualified people from a deluge of applications and side-stepping human bias to identify top talent from a diverse pool of candidates.

A wealth of tech startups and “intelligent recruiting” tools have sprung up in recent years claiming to be able to help companies build a more inclusive workforce. The Gapjumpers[2] platform, for example, promises “blind audition” technology where “gender, education and background don’t matter” in the quest to find top talent. Entelo[3] markets its recruitment software as the best method for “hiring the right people”, while Doxa[4] helps employees “find tech companies where female employees thrive.” From HireVue[5] to Textio[6] to Korn Ferry[7], there is no shortage of companies looking to the “magic” of algorithms to make hiring an effective and efficient process.

German-based SAP has its own variant too. Called SAP Resume Matching[8], the software tool aims to mitigate “recruiter bias in candidate screening” by making use of machine learning to sift through thousands of applications much faster. By taking into account the historical applicant data and their skill sets, the tool scores each applicant against specific open positions. Hiring managers, armed with this information, can just use these shortlisted resumes to hire top talent.

---

2 "GapJumpers." https://www.gapjumpers.me/. Accessed 13 Apr. 2018.
3 "Entelo." https://www.entelo.com/. Accessed 13 Apr. 2018.
4 "Doxa." http://www.doxascore.com/. Accessed 13 Apr. 2018.
5 "HireVue." https://www.hirevue.com/. Accessed 13 Apr. 2018.
6 "Textio." https://textio.com/. Accessed 13 Apr. 2018.
7 "Futurestep - Korn Ferry." https://www.kornferry.com/futurestep/. Accessed 13 Apr. 2018.
8 "Find the Best Talent Faster with SAP Resume Matching - SAP.com." https://www.sap.com/documents/2017/08/fea3fccf-cd7c-0010-82c7-eda71af511fa.html. Accessed 13 Apr. 2018.

Apart from rapid identification of candidates with the best skills, increased productivity of recruiting staff is a key metric as well. Think about this: why should a HR manager spend his time reading thousands of resumes when a software can present him with a list of top 10 candidates?

Entelo, an intelligent hiring startup based out of San Francisco Bay Area, offers similar services to SAP, but includes information beyond resumes. Boasting of over 700 clients spanning across different industries, the company searches the web for public information of people and uses it to target recruiters for potential matches that fit their job description.

"Entelo Envoy[9] automatically scours the web and delivers qualified candidates directly to a recruiter's inbox," says Lisa Cohen, Senior Manager for Public Relations & Communications at Entelo, adding "it helps them focus on things like forging better relations with candidates and closing mission-critical hires."

The results of this pivot are encouraging thus far, with Entelo's clients reporting reduced cost per hire, increased recruiter productivity and dramatic savings in time spent in sourcing candidates for just one role by as much as 96 percent[10]. "Unlike traditional platforms, Entelo Envoy saves about 10-15 hours per week, allowing me to push volume while maintaining a personalized candidate experience for each prospective hire," says Chris Hartzell, Talent Lead at Tubi, a video on demand startup based out of San Francisco. "Automating the tedious work in the recruiting process is a big win for our team."

The unintended side-effect of this "social recruiting" is that candidates may be negatively or positively assessed by the personal data available on them through a simple Google search. According to a 2009 survey by Microsoft of HR professionals, recruiters, and consumers[11], 70% of HR professionals reported that they rejected candidates after mining their data.

Entelo, which maintains a database of over 500 million candidates, uses AI not just for shortlisting new-hire candidates, but also to predict when someone is likely to change their job. By analyzing the behavior of hundreds of millions of job seekers Entelo helps companies determine the best time to send recruiting emails to potential applicants.

But Entelo's software is not strictly machine-driven: recruiters can tell the software if the candidates it suggests are way off track and why in order to fine-tune its search more precisely.

---

[9] "AI Recruiting Software: Envoy | Entelo." https://www.entelo.com/products/envoy/. Accessed 13 Apr. 2018.

[10] "Anaplan Fuels Aggressive Growth With Automated ... - Entelo Blog." 22 Jan. 2018, https://blog.entelo.com/anaplan-fuels-aggressive-growth-with-automated-recruiting. Accessed 13 Apr. 2018.

[11] "Online Reputation in a Connected World - Microsoft Download Center." http://download.microsoft.com/download/c/d/2/cd233e13-a600-482f-9c97-545bb4ae93b1/dpd_online%20reputation%20research_overview.doc. Accessed 13 Apr. 2018.

With Entelo's algorithms thus performing a wide range of tasks, Cohen says there are safeguards in place to ensure that there is no bias. "Humans miss things all the time, but we believe that our software does a good job of ranking candidates. We have found that nearly 80% of candidates delivered by Envoy are 'accepted' by recruiters and sent email communication."

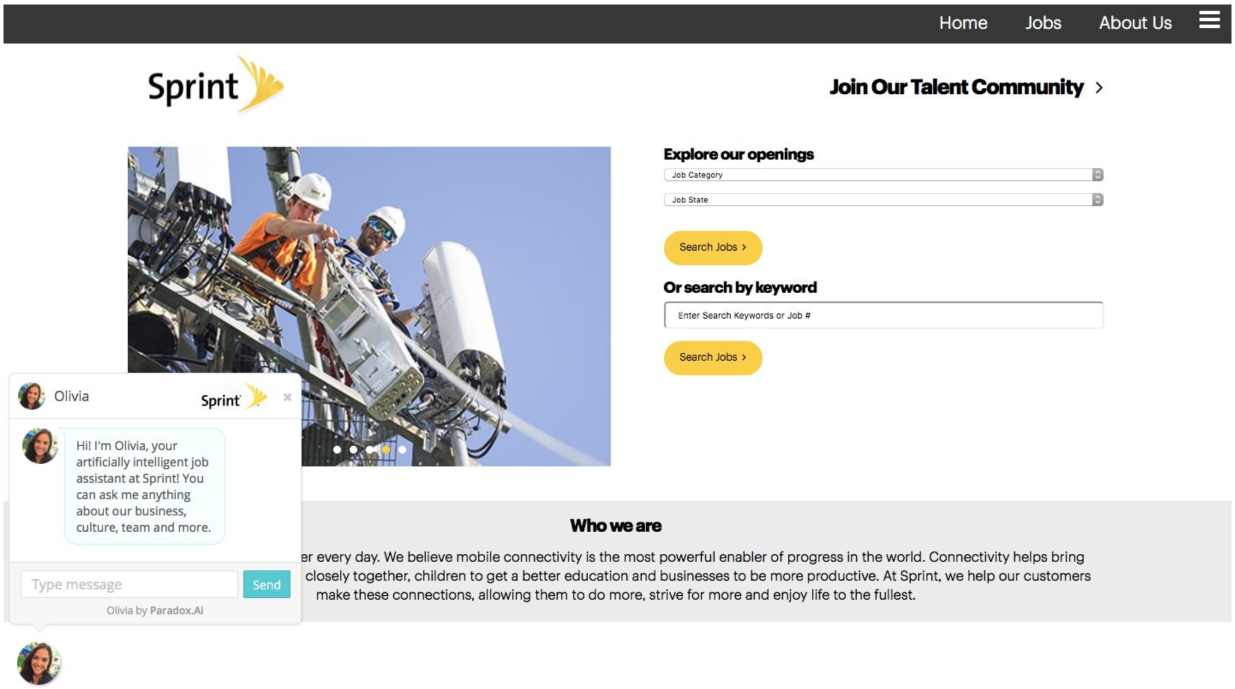
Similarly, Knockri[12], a Canadian startup, helps companies automate their candidate-screening process by shortlisting applicants, based on their skills to identify the best fit for an in-person interview. Profillic[13], a new startup founded by Gaurav Ragtah, also aims to streamline recruitment process by making it possible for companies to identify top technical talent through role-specific quizzes.

Similar to Profillic is a Bengaluru-based startup called Belong, a recruitment platform that aims to use data-driven approaches to pull information on candidates from all over the Web, including sites like GitHub and Twitter. It then generates a ranking of the best candidates based on the requirements for a given position.

Also joining the growing number of startups seeking to make the job hunting process a bit easier is Paradox, whose AI-based software tool Olivia is a one stop solution for shortlisting candidates, scheduling interviews and letting prospective applicants get getting to know the companies who are hiring new talent. An extension of the tool is its virtual chat assistant that companies can incorporate into their websites.

"Paradox was formed with an intention to make this process of recruiting more easier through technology at a large scale," says Rob McIntosh, Chief AI evangelist and advisor at Paradox. "We work with our clients to directly integrate Olivia into their websites so that interested candidates can converse with the assistant and provide relevant details about the job they are interested in."

[12] "Knockri I AI Video Recruiting." https://www.knockri.com/. Accessed 13 Apr. 2018.
[13] "Profillic: follow what's hot in data science with friends & experts." https://www.profillic.com/. Accessed 13 Apr. 2018.



Sprint's career section integrates with Olivia

While Rob acknowledges the value add Olivia can bring for its clients, he also admits that algorithmic hiring practices are subject to the same potential for bias as traditional recruiters. "It's no different from human bias," says Rob. Because the Paradox software depends on the hiring company to provide clear job descriptions, he says, "If the companies have flawed inputs, then it does not matter if the algorithm is correct."

To help avoid such biased results, Paradox instructs companies in detail on how to set up and use the software as part of their onboarding process. "Crafting a good job description also matters a lot," says Rob.

Woo, another Bay Area startup, not only lets corporations make hiring decisions, but also uses AI to allow candidates to find jobs that fit them the best. The software, called Helena, and launched late last year[14], gives job seekers a way to anonymously get connected with companies.

"Our platform appeals to discreet job seekers," says Arlene Zeitouni, a PR associate at Woo. "According to Zeitouni, "First a match is made by our AI technology, then the candidate gets sent the opportunity. Only if they decide they are interested will we introduce them to the company." Zeitouni suggests that the platform is particularly appealing to job-seekers, "with 83% of candidates still engaged 2 years after signing up."

[14] "Woo lands $7 million and launches an AI headhunter | VentureBeat." 27 Nov. 2017, https://venturebeat.com/2017/11/27/woo-lands-7-million-and-launches-an-ai-headhunter/. Accessed 13 Apr. 2018.

Helena’s automated matching technology today results in 40% conversion from candidate screening to interview, but clearly as with any other algorithm driven by AI, the effectiveness of the software largely depends on the data against which it’s trained. Adds Arlene, “All of our data is produced internally by our recruiting team, and we ensure that our software is tested against a broad set of data, including the candidate’s background and experience, in order to minimize bias.”

Dangers of Algorithmic Decision Making

Algorithmic decision making systems may undoubtedly be efficient for the organizations that use them, but their opacity and potential for discrimination has also come under fire in recent years. In a 2016 story that garnered widespread attention, the non-profit news site ProPublica, a Pulitzer Prize–winning nonprofit news organization, in 2016, analyzed a risk assessment software called COMPAS[15] (Correctional Offender Management Profiling for Alternative Sanctions) that’s used by judges and parole officers to predict recidivism rates among prisoners.

The ProPublica analysis found that the COMPAS algorithm “correctly predicted recidivism for black and white defendants at roughly the same rate.” But when it was was wrong, it was wrong in different ways for different races. Specifically, ProPublica found that, “blacks are almost twice as likely as whites to be labeled a higher risk but not actually re-offend,” and that white people “are much more likely than blacks to be labeled lower risk but go on to commit other crimes."

Author Cathy O’Neil, in her 2016 book Weapons of Math Destruction[16], shared a wide-range of stories where people have been deemed unfit for their jobs in one way or the other by an algorithm. Sample a few: a highly-regarded teacher who was fired due to a low score on a teacher assessment tool, a college student who couldn’t get a minimum wage job at a grocery store because of his answers on a personality test, and people who had their credit card spending limits lowered because they shopped at certain stores.

Frank Pasquale also documented the dangers of big data and black box algorithms in his book The Black Box Society. Technology giants like Facebook and Google, of course, have had their share of trouble as well.who have become the biggest platforms for news distribution today. Zeynep Tufekci, an associate professor at the School of Information and Library Science at the University of North Carolina at Chapel Hill, talked about how Facebook’s business model, which

[15] "Machine Bias — ProPublica." 23 May. 2016, https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing. Accessed 13 Apr. 2018.
[16] "Weapons of Math Destruction." https://weaponsofmathdestructionbook.com/. Accessed 13 Apr. 2018.

prioritizes that values engagement over everything, can become a conduit for biases to creep into its algorithms[17].

Matthias Spielkamp, executive director of AlgorithmWatch[18], a non-profit organisation to evaluate and shed light on algorithmic processes that have a social relevance, has also written about the need to determine the extent to which “lawmakers, judges, and the public should have a say in which measures of fairness get prioritized by algorithms.[19]”

Virginia Eubanks, an Associate Professor of Political Science at the University at Albany, SUNY, talked about the nature of discriminatory nature of these algorithms in areas such as law enforcement, welfare, and child protection and how they “act less like data sifters and more like gatekeepers, mediating access to public resources, assessing risks, and sorting groups of people into ‘deserving’ and ‘undeserving’ and ‘suspicious’ and ‘unsuspicious’ categories.[20]”

In the workplace, companies like Uber have been held to task[21] for psychologically pushing drivers by enticing them with rewards and virtual female personas to make them undertake more trips.

These examples serve not only to highlight the different ways algorithms have made inroads into our lives, but to make matters worse, the opacity and black box nature of these systems makes it all the more difficult to seek recourse when an algorithm makes a mistake. Even more frustratingly, can we ever know if an algorithm is making a mistake?

“AI has this veneer of objectivity,” says Arvind Narayanan, a computer science professor at Princeton who leads the university’s Web Transparency & Accountability Project[22]. “As these technologies continue to get commercialized, it is very important that we design algorithms that account for various biases. But technologists alone cannot solve these problems. It calls for a collaboration between engineers, domain experts and social scientists to understand the trade-offs between different notions of fairness and define which biases are desirable or unacceptable.”

---

[17] "Opinion | The Real Bias Built In at Facebook - The New York Times." 18 May. 2016, https://www.nytimes.com/2016/05/19/opinion/the-real-bias-built-in-at-facebook.html. Accessed 13 Apr. 2018.
[18] "AlgorithmWatch." https://algorithmwatch.org/en/. Accessed 13 Apr. 2018.
[19] "Inspecting Algorithms for Bias - MIT Technology Review." 12 Jun. 2017, https://www.technologyreview.com/s/607955/inspecting-algorithms-for-bias/. Accessed 13 Apr. 2018.
[20] "The dangers of letting algorithms enforce policy.." 30 Apr. 2015, http://www.slate.com/articles/technology/future_tense/2015/04/the_dangers_of_letting_algorithms_enforce_policy.html. Accessed 13 Apr. 2018.
[21] "How Uber Uses Psychological Tricks to Push Its Drivers' Buttons - The ...." 2 Apr. 2017, https://www.nytimes.com/interactive/2017/04/02/technology/uber-drivers-psychological-tricks.html. Accessed 13 Apr. 2018.
[22] "Princeton WebTAP – Web Transparency & Accountability Project ...." https://webtap.princeton.edu/. Accessed 13 Apr. 2018.

What Happens When a Candidate is Unfairly Rejected?

Jager's job hunting has seen its highs and lows. "I can tell if a software was screening my job application," says Jager with a laugh. "It's actually when you get a reply in less than 24 hours that states you are not the right fit for this job and you look at what they want and what you have and what's on your resume, and it's like I am above and beyond the qualifications, this was a lowball job and it doesn't make any sense."

Since then he has religiously reworked his resume such that it hits all the key points. "I have at least getting a lot more phone interviews using the new resume," Jager says. "It has been quite a learning experience."
For some candidates, however, a resume tweak isn't enough, however. In 2017, Kyle Behm[23], a high achieving university student, found himself ineligible for even minimum wage jobs because the personality tests on his job applications rejected him out of hand.

Behm believes the rejections were due to his honestly answering questions about his Although he did suffer from bipolar disorder, for which he has been treated. The fact that the recruitment software, developed by a company called Kronos, was flagging him ineligible based on his mental health led his father Roland Behm to file a class-action suit alleging that the use of the exam during the job application process was unlawful. The lawsuit, as it stands, is still pending.

Can Algorithms Be Improved?

Bias in artificial intelligence systems has recently become the focus of academic research. One of the more recent studies[24] come from Aylin Caliskan, Joanna J. Bryson and Arvind Narayanan, who found that a machine learning tool called word embedding, used extensively in machine translation to interpret natural language, exhibited gender and racial biases. The words "female" and "woman", for example, were more closely associated with professions like arts and humanities and with the home, while "male" and "man" were associated with maths and engineering professions.

The findings suggest that algorithms have acquired the same biases that lead people to match pleasant words and white faces in implicit association tests[25].

Highlighting the biased nature of data that's used to train algorithms, Narayanan stresses that "These are hard problems. There is no right definition of fairness. Different metrics matter to different stakeholders." He also emphasized the need for bias assessment of training data sets.

---

[23] "How algorithms rule our working lives | Cathy O'Neil | Science | The ...." https://www.theguardian.com/science/2016/sep/01/how-algorithms-rule-our-working-lives. Accessed 13 Apr. 2018.
[24] "Semantics derived automatically from language corpora contain ...." 14 Apr. 2017, http://science.sciencemag.org/content/sci/356/6334/183.full.pdf. Accessed 13 Apr. 2018.
[25] "Project Implicit." https://implicit.harvard.edu/. Accessed 13 Apr. 2018.

Similarly a Stanford study[26] found that an internet-trained AI associated stereotypically white names with positive words like “love,” and black names with negative words like “failure” and “cancer,” reflecting the biases that could into designing artificial intelligence systems.

Even more recently, facial recognition technology has been used to identify[27] if a person was rich or poor, while another study[28], undertaken at Stanford, used it to identify gay people with surprising precision, raising concerns about how such a tool could be used in countries where homosexuality is considered as a crime.

A research undertaken by Anja Lambrecht and Catherine Tucker uncovered biases in STEM career ads[29], which showed how an algorithm that delivered ads promoting job opportunities in STEM fields were biased against women.

Likewise, experiments conducted by Carnegie Mellon University, published in a July 2015 titled “Questioning the Fairness of Targeting Ads Online[30],” showed how fewer women were the target of Google ads that promised jobs that paid them over $200,000 a year. The study emphasized the need for better transparency and clarity on who is ultimately responsible - advertisers themselves or a consequence of machine learning algorithms that inevitably power such recommendation engines.

A study of bias in algorithmic recruitment[31], undertaken by Chelsea Barabas in 2009, also examined the various tools available at companies’ disposal to run machine learning algorithms that are used for recruitment.

Advances in Auditing Algorithms

Researcher Andrew Tutt, in a paper in 2016, stressed the need for an “FDA for Algorithms,”[32] adding, “The rise of increasingly complex algorithms calls for critical thought about how to best

---

[26] "Even artificial intelligence can acquire biases against race and gender ...." 13 Apr. 2017, http://www.sciencemag.org/news/2017/04/even-artificial-intelligence-can-acquire-biases-against-race-and-gender. Accessed 13 Apr. 2018.
[27] "Our faces reveal whether we're rich or poor -- ScienceDaily." 5 Jul. 2017, https://www.sciencedaily.com/releases/2017/07/170705133020.htm. Accessed 13 Apr. 2018.
[28] "OSF | Deep neural networks are more ...." 15 Feb. 2017, https://osf.io/zn79k/. Accessed 13 Apr. 2018.
[29] "Algorithmic Bias? An Empirical Study into Apparent ... - SSRN papers." 9 Mar. 2018, https://papers.ssrn.com/abstract=2852260. Accessed 13 Apr. 2018.
[30] "Questioning the Fairness of Targeting Ads Online - Carnegie Mellon ...." https://www.cmu.edu/news/stories/archives/2015/july/online-ads-research.html. Accessed 13 Apr. 2018.
[31] "Engineering the American Dream: A Study of Bias and Perceptions of ...." https://d2i0qtqt78gzuz.cloudfront.net/wp/wp-content/uploads/2016/06/270086393-Chelsea-Barabas-Engineering-the-American-Dream-A-Study-of-Bias-and-Perceptions-of-Merit-in-the-High-Tech-Labor-Market.pdf?x67991. Accessed 13 Apr. 2018.
[32] "An FDA for Algorithms by Andrew Tutt - SSRN papers." 15 Mar. 2016, https://papers.ssrn.com/abstract=2747994. Accessed 13 Apr. 2018.

prevent, deter and compensate for the harms that they cause. Algorithmic regulation will require federal uniformity, expert judgment, political independence and pre-market review to prevent – without stifling innovation – the introduction of unacceptably dangerous algorithms into the market."

One promising candidate for fairness testing is called Themis[33], software developed at the University of Massachusetts as a means to test discriminatory behavior in algorithmic systems. Given a set of inputs that goes into designing an AI-based algorithm, the software is tested for bias through a series of causal experiments to determine causation between inputs and outputs.

For example, an AI-based job recruiting software that takes into account the applicant's age and race is considered fair with respect to those characteristics if for all pairs of individuals with identical name, education history, past work experience and skill set but different age or race, it either shortlists all of them for interviews or rejects all of them.

"There is a lot of bias that has crept into software systems today," says Yuriy Brun, associate professor of Computer Science at the University of Massachusetts, and one of the lead authors of the study. "But developers have no way of knowing if they have knowingly or unknowingly coded any biases into them. This method is meant to support them during software development. It's no different from finding bugs in the software during testing."

What's more interesting is that Themis can also uncover "apparent discrimination", a new term coined by the authors, in software. Suppose a job recruiting tool only places higher preference to candidates who have worked in a top company like XYZ in making its decision and XYZ's employee diversity is skewed towards white males. By doing so, the software is more likely to favor a white male over other candidates even if race or gender is not explicitly factored into the decision making process.

"The testing highlights the need for fairness in design, from early on in the process," says Brun. "This is also why there needs to be more collaboration with stakeholders, policy experts and understand the problem domain and come up with fairness definitions."

Ask him about whether Themis has been deployed officially, Brun adds that "We have been in early talks with companies and law enforcement agencies about integrating our testing tool into existing software. It's still in preliminary stages."

Can there be any Regulation?

Given how important it is to not let preconceived biases decide how an algorithm should function, regulating the use of AI-based tools necessitates the need for bias testing and

---

[33] "Fairness Testing: Testing Software for Discrimination." 11 Sep. 2017, https://arxiv.org/abs/1709.03221. Accessed 13 Apr. 2018.

assessing them for risks associated with disparate impact. But the catch here is that we may never know. Because companies that design such tech is so often closely guarded as proprietary and a trade secret, it makes the task of independent regulation and audit that much more complicated.

The White House, in an October 2016 report titled “Preparing for the Future of Artificial Intelligence[34]”, said “the approach to regulation of AI-enabled products to protect public safety should be informed by assessment of the aspects of risk that the addition of AI may reduce, alongside the aspects of risk that it may increase.”

One solution is to create a special regulatory agency that would have powers to audit algorithms. One of the advocates of this idea is Ben Shneiderman[35], professor at the University of Maryland. He compares such a future agency to the Federal Trade Commission or National Transportation Safety Board – a US agency that is responsible for investigating civil transportation accidents. In his opinion such institutions should have power to license algorithms, monitor their use and conduct investigations when there are suspicions that the algorithm may have negative consequences.

On the contrary, Andrew Tutt argues that the rising complexity of machine learning algorithms raises a variety of challenges when those algorithms harm people, (1) difficulty in measuring algorithmic responsibility i.e. is the decision an unintended software “bug” or a “feature” (2) difficulty in tracing algorithmic responsibility i.e. does the algorithm behave according to the legal standard, and (3) difficulty in fixing human responsibility i.e. how much of the harm can be assigned to the software developer.

Tutt also proposes a federal agency[36] that “could act as a standards-setting body that coordinates and develops classifications, design standards, and best practices” that ensures transparency and prior approval before deployment.

Who is Overseeing?

There have been a number of organizations and government-run agencies that have sprung up in recent years to examine algorithmic decision making and its societal impact.

---

[34] "Preparing for the Future of Artificial Intelligence - Obama White House." 12 Oct. 2016, https://obamawhitehouse.archives.gov/sites/default/files/whitehouse_files/microsites/ostp/NSTC/preparing_for_the_future_of_ai.pdf. Accessed 13 Apr. 2018.
[35] "Ben Shneiderman - UMD CS - University of Maryland." https://www.cs.umd.edu/users/ben/. Accessed 13 Apr. 2018.
[36] "An FDA for Algorithms by Andrew Tutt - SSRN papers." 15 Mar. 2016, https://papers.ssrn.com/abstract=2747994. Accessed 13 Apr. 2018.

The U.S. Equal Employment Opportunity Commission[37][38], in 2016, discussed the potential implications of using big data for hiring and how it can impact equal employment opportunities. "Big Data has the potential to drive innovations that reduce bias in employment decisions and help employers make better decisions in hiring, performance evaluations, and promotions," said then-chair Jenny R. Yang. "At the same time, it is critical that these tools are designed to promote fairness and opportunity, so that reliance on these expanding sources of data does not create new barriers to opportunity."

On January 17, 2017, the Future of Life Institute published a list of 23 Principles for Beneficial Artificial Intelligence[39], created by a gathering of researchers that delved into the research and ethical issues surrounding artificial intelligence.

In addition, there are also a number of research research institutes, like New York University's newly launched AI Now[40], MIT's Algorithmic Justice League[41] and AlgorithmWatch, all of which are aiming for increased algorithmic transparency and accountability[42], while researching the socio-economic impact of artificial intelligence. Google's own subsidiary AI-focused DeepMind opened an Ethics & Society[43] research unit recently to explore the real-world impacts of AI.

While government agencies have spoken about big data and highlighted the multi-faceted concerns that it raises, there is still little formal guidance from regulatory sources. Complicating the narrative further is the lack of proper legal recourse, with current legal frameworks ill-equipped to remedy hiring tools that have a disparate impact on marginalized groups.

A report published by American Bar Association last year[44] found that "as of October 13, 2017, a WestlawNext Boolean search for "adv: 'big data' and 'disparate impact'" returned no employment-related cases," suggesting no case law has been documented or that existing cases have been brought to court using different terminology.

The Road Ahead

---

[37] "Meeting of October 13, 2016 - Big Data in the Workplace ... - EEOC." 13 Oct. 2016, https://www.eeoc.gov/eeoc/meetings/10-13-16/transcript.cfm. Accessed 13 Apr. 2018.
[38] "Use of Big Data Has Implications for Equal Employment ... - EEOC." 13 Oct. 2016, https://www.eeoc.gov/eeoc/newsroom/release/10-13-16.cfm. Accessed 13 Apr. 2018.
[39] "AI Principles - Future of Life Institute." https://futureoflife.org/ai-principles/. Accessed 13 Apr. 2018.
[40] "AI Now Institute." https://ainowinstitute.org/. Accessed 13 Apr. 2018.
[41] "Algorithmic Justice League." https://www.ajlunited.org/. Accessed 13 Apr. 2018.
[42] "AI Experts Want to End 'Black Box' Algorithms in Government | WIRED." 18 Oct. 2017, https://www.wired.com/story/ai-experts-want-to-end-black-box-algorithms-in-government/. Accessed 13 Apr. 2018.
[43] "DeepMind Ethics & Society | DeepMind." 3 Oct. 2017, https://deepmind.com/applied/deepmind-ethics-society/. Accessed 13 Apr. 2018.
[44] "Big Data in Employment Law: What Employers and Legal Counsel Need to Know." https://www.americanbar.org/content/dam/aba/events/labor_law/2017/11/conference/papers/Gay-Paper%20on%20Big%20Data%20%20for%20ABA%20LEL%20Conference.authcheckdam.PDF/. Accessed 13 Apr. 2018.

The implications are loud and clear. Big data is really future of hiring. But using automated, algorithmic, machine-based outputs to understand and decide on behalf of humans is at a tricky crossroads. Data-driven employment opportunities are changing the ways that candidates are assessed for employment, thereby posing a greater entry barrier for some applicants more so than others.

With non-work related data is often used in hiring algorithms, lack of clarity about what data is included or how much control users have over how they are being interpreted makes it the task of algorithmic decision difficult to regulate. Online reputations can also be flagged in ways that are misleading, denying job seekers of potential opportunities.

“The biggest concern I have about these tools is the lack of transparency and awareness,” says Jager. “As a data science student who has studied artificial intelligence and machine learning, I know how these systems generally work. But it’s a bigger issue for people who don’t come from computer science background. Because they are completely in the dark.”

Source List:

1. Lisa Cohen, Senior Manager for Public Relations & Communications, Entelo
2. Rob McIntosh, Chief AI evangelist and advisor, Paradox
3. Arlene Zeitouni, a PR associate at Woo
4. Jager Hartman, MS Student in Data Science, Columbia University, jwh2163@columbia.edu
5. Prof. Augustin Chaintreau, Assistant Professor in Computer Science, Columbia University, www.cs.columbia.edu/~augustin/
6. Prof. Arvind Narayanan, assistant professor of computer science Princeton University http://randomwalker.info
7. Yuriy Brun, Associate professor of Computer Science at the University of Massachusetts http://people.cs.umass.edu/~brun/
8. Shon Burton, CEO, HiringSolved shon@hiringsolved.com