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Big Data, Bigger Risk: Recognizing and Managing the Perils of Using Algorithms in Recruiting and Hiring

Mark J. Girouard*

Machine learning algorithms have the potential to significantly streamline the recruiting and hiring process, from identifying qualified passive candidates to efficiently winnowing down the increasingly large volume of applications that employers now regularly receive. The author of this article discusses the use of algorithms in sourcing, recruiting, and selecting talent and offers recommendation for employers.

Increasingly, employers are turning to machine learning algorithms or other "big data" solutions to source, recruit, screen, select, and manage talent. These tools have the potential to significantly streamline the recruiting and hiring process, from identifying qualified passive candidates to efficiently winnowing down the increasingly large volume of applications that employers now regularly receive. While these tools can reduce the time and costs associated with finding and selecting talent, they also have the potential to create legal risk for employers.

Background

These developments have not gone unnoticed by regulators or private litigants. For example, in 2016 the federal Equal Employment Opportunity Commission ("EEOC") convened a public meeting to explore the legal implications of resume-scraping tools, machine learning algorithms, and other big data solutions for federal anti-discrimination law.[1] Since that meeting, however, the EEOC has yet to articulate clear guidelines to direct the use of these developing technologies in practice. In addition, challenges to the use of algorithms in sourcing, recruiting, and selecting talent have begun to work their way through the courts. But there have not yet been any landmark legal decisions establishing precedent to

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guide employers as they begin to operate in this space. In light of this uncertainty, employers should proceed cautiously, including by considering the recommendations outlined below.

Broadly speaking, machine learning refers to any set of analytical procedures that identify patterns in data to provide insight and understanding. In the employment context, this broad concept encompasses everything from basic resume-scraping tools, to complex systems that analyze audio, facial images, and verbal and non-verbal responses to video interviews. As these approaches have grown more sophisticated, they have also become more difficult for end users to understand. Indeed, the term "black box" has often been used to refer to the complex and seemingly opaque processes used by a trained algorithm to make recommendations about employment decisions. Such ambiguity makes these approaches susceptible to a perception of a lack of transparency, and even unfairness, increasing the risk of legal challenge. It also means that, if challenged, employers may struggle to defend their tools if they are unable to identify the features used to select from among applicants.

Litigation

In the context of sourcing talent, a little over a year ago, three employers—T-Mobile, Amazon, and Cox Communications—were sued for allegedly discriminating on the basis of age in the way they source potential applicants via Facebook.[2] The complaint targets not only those three employers but also an alleged defendant class comprising hundreds of major American employers who have used age restrictions when advertising employment opportunities on Facebook.[3] Primarily, the allegations focus on employers who intentionally chose to direct ads to Facebook users within a specific age range (e.g., users aged 18 to 45). But the complaint also sweeps in Facebook's algorithms that may restrict which users see an employer's recruitment ads based on characteristics that are correlated with age. For example, the complaint notes that Facebook's "look-a-like" tool allows employers to upload information about their current workforce, which the tool then uses to identify a target audience of users with similar characteristics.[4] The plaintiffs allege that this tool can result in a pool of potential applicants that replicates age-based or other demographic disparities that already exist in the employer's workforce.[5] Moreover, the plaintiffs assert that Facebook is acting as the employers' agent when it applies this and other algorithmic tools, making the employers responsible for any disparities in users' access to information about employment opportunities that may flow from these tools.[6]

The parties to the lawsuit have spent the last year in a pitched battle over whether the complaint sufficiently states viable claims, and the court heard arguments on pending motions to dismiss in April of this year. Until the viability of the plaintiffs' claims—including their claims about algorithmic tools—is more settled, employers are well advised to take a close look at their social media recruiting practices. Even if they are not actively limiting recruitment ads on the basis of age or other protected characteristics, they should consider whether existing disparities in representation of protected groups in their workforce are significant enough such that use of look-a-like functions and similar tools might replicate those differences. Likewise, they should consider if other characteristics built into their profile of an ideal candidate could be viewed a proxy for age (e.g., graduation year, or maximum years of work experience) or membership in another demographic group, making an algorithm that capitalizes on those characteristics a source of heightened legal risk.

Uniform Guidelines on Employee Selection Procedures

A cautious approach is also warranted on the selection front. As noted above, the EEOC has studied the implications of machine learning to anti-discrimination law, but it has yet to articulate any guidance in this area. As such, questions of whether and how employers should lawfully use these cutting-edge technologies continue to be informed by standards that were developed over 40 years ago. In 1978, the EEOC and other federal agencies jointly issued the Uniform Guidelines on Employee Selection Procedures ("UGESP") to establish a single set of principles for determining the proper use of pre-employment tests and other selection procedures under Title VII of the Civil Rights Act of 1964. Although the UGESP are not legally binding, courts have recognized that they are entitled to "great deference."[7] The UGESP apply to tests or other selection procedures used as the basis for an "employment decision." Covered employment decisions include, but are not limited to, "hiring, promotion, demotion, membership (for example, in a labor organization), referral, [and] retention[.]"[8] The phrase "test and other selection procedure" is also defined broadly, and includes as any "measure, combination of measures, or procedure used as a basis for any employment decision."[9] This definition extends to "the full range of assessment techniques from traditional paper and pencil tests, performance tests, training programs, or probationary periods and physical, educational, and work experience requirements through informal or casual interviews and unscored application forms."[10] While this definition does not expressly reference machine learning algorithms, it is clearly broad enough to encompass them.

The UGESP require employers with 100 or more employees to maintain and have available, for each job, information on whether the "overall selection process" for that job results in adverse impact based on a protected characteristic.[11] The overall selection process is the combined effect of all selection procedures leading to a final employment decision.[12] Adverse-impact records must show whether the overall selection process for a job disproportionately excludes protected class groups. If an overall selection process has adverse impact against any protected class group, the employer must then assess the adverse impact of each of the individual selection procedures that make up the overall process.[13]

A finding of adverse impact also triggers the UGESP "validation" obligations. That is, if a selection process has adverse impact, the employer must have available, for each component of the process that was determined to have adverse impact, documentation regarding the validity of the component.[14] Validity is the demonstration of the job relatedness of the selection procedure. Although the requirement to perform a validity study is not triggered until a selection procedure is shown to have adverse impact, the UGESP nonetheless strongly encourage employers to "consider the potential benefit from having a validation study completed or well underway before [selection] procedures are administered for use in employment decisions."[15] Further, they caution employers who choose to continue using a selection process or procedure that has adverse impact and has not been validated, and who wait until that procedure is challenged to attempt to document the tool's validity, that they face a significantly increased risk that they will be found to have engaged in willful discriminatory practices and will be held liable for back pay and attorneys' fees.[16]

Algorithmic Selection Solutions and the UGESP

While the UGESP detail several approaches an employer can use to establish the validity of selection tools, the technique best suited to the assessment of machine learning algorithms and similar tools is criterion-related validity, which is demonstrated by identifying criteria that indicate successful job performance and then statistically correlating test scores with the criteria so identified.[17] An employment test has criterion-related validity when the data demonstrate a significant positive correlation between an applicant's degree of success on the test and his or her degree of success in some measure of job performance.[18] The UGESP also provide that for any type of validity study, there must first be a review of information about the job(s) for which a selection procedure is to be used.[19] Generally, this review must include a formal analysis of the areas of knowledge, skill, ability, and other characteristics that are important to success in the job.

But many algorithmic selection solutions skip the job-analysis step. For example, such a tool may review a set of data about high-performing employees and learn that certain characteristics are highly correlated with performance. Based on those correlations, they determine that those are the characteristics an employer should look for when making hiring decisions. But machine learning analyses are only as good as the data used to build them. For example, a machine learning model built on data about a group of high-performing incumbents could identify traits that—while shared by those employees—are not the reason for their success in the job. That is, the identified traits are simply a reflection of dust bowl empiricism rather than being grounded in a theory—based on job analysis—of what is actually important to succeed in the job. In some cases, the trait or combination of traits identified by the algorithm may also be highly correlated with gender, race, or other protected characteristics. Put differently, by capitalizing on chance, an algorithm may learn and perpetuate bias present in the data used to train it.

Nonetheless, the UGESP does allow employers to build selection tools around factors such as production rate, error rate, tardiness, absenteeism, or length of service without the need for a full-blown job analysis.[20] Employers venturing into the algorithmic selection space may want to consider tools that account for these kinds of factors rather than correlations that, due to their complexity, may defy simple explanation. Similarly, under the UGESP, an overall measure of performance may be used in a validity study without a formal job analysis, but only if the employer can demonstrate that the measure of performance was carefully developed, including that controls were put in place to ensure standardization.[21] This requirement points to another way that employers moving into this space can attempt to bolster the defensibility of their algorithmic selection tools. By documenting—in the validation study for such a tool—that the measure of performance was standardized and unbiased, employers can blunt arguments that they should have conducted a more formal job analysis study, while at the same time attempting to ensure that their algorithm is not learning from—and then replicating—existing disparities in the their workforce. As noted, machine learning approaches to selection can be criticized for being driven primarily by empirical evidence as opposed to theory. Indeed, their goal is to maximize prediction rather than explanation. However, theory and job relevance are critical for supporting elements used to select job candidates. Thus, legal risk decreases as the algorithms are more strongly tied to theory. Put differently, machine learning approaches are complemented by deep content knowledge where they are being applied.

Additional Challenges

The ability of machine learning tools to grow over time presents additional challenges, both in terms of establishing validity and meeting another requirement of the UGESP; namely, that validity studies must investigate whether there are other alternative selection procedures that have equal or greater validity while showing less potential for adverse impact against members of protected groups. Although some machine learning models are static or frozen once an organization begins using them to make decisions, it is possible—and increasingly common—to build models that are dynamic and automatically update over time as they attempt to improve prediction. This creates the risk that evidence supporting validity, as well as evidence that the employer considered less-discriminatory alternatives, might be wiped away when the algorithm updates itself. Additionally, when the weights associated with different factors self-adjust, or the factors themselves change, applicants are not all held to the same standard. That is, applicants are selected based on different criteria as the model evolves. In this way, the selection process lacks standardization, and if challenged, the algorithm an employer is attempting to defend may differ from that used at the time of hire. Again, it is advisable to proceed with caution and, until legal standards coalesce, consider approaches that are more static, and therefore easier to explain and defend.

Conclusion

Despite the notes of caution struck in this article, machine learning algorithms and other big data solutions offer many benefits over traditional sourcing and selection techniques. They have the potential to increase the efficiency of the hiring process by reducing recruiter and hiring manager time spent identifying and screening applicants. They can automate processes that previously required significant manual human evaluation and analyst time. And they have the potential to improve consistency and objectivity in the hiring process, thereby reducing subjectivity inherent in hiring procedures that incorporate human judgment and the attendant risk of disparate treatment. At the same time, until clear legal guidance develops, employers may choose to move cautiously, focusing on processes with greater clarity, such as where the tools' findings are aligned with the results of a job-analysis study or have some other theoretical basis that lends itself to explanation, rather than existing in a black box where the employer has less immediate insight into how the algorithm selects one applicant (or potential plaintiff) over another.

Notes

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1. *See* Equal Employment Opportunity Commission, *Meeting of October 13, 2016—Big Data in the Workplace: Examining Implications for Equal Employment Opportunity Law* (*available at* https://www.eeoc.gov/eeoc/meetings/10-13-16/index.cfm).

2. *See Communications Workers of America, et al. v. T-Mobile US, Inc., et al.*, No. 17-cv-07232-BLF (N.D. Cal.), Third Amended Class and Collective Action Complaint, at Dkt. No. 72.

3. *See id.*, ¶ 134 (defining a defendant class that includes all employers who annually employee at least 2,500 employees and use age restrictions in sourcing and recruiting potential applicants on Facebook).

4. *See id.*, ¶ 82-84, 86, 96.

5. *See id.*

6. *See id.*

7. *See Allen v. Entergy Corp.*, 181 F.3d 902, 905 (8th Cir. 1999); *Clady v. Los Angeles County*, 770 F.2d 1421, 1428 (9th Cir. 1985).

8. 29 C.F.R. § 1607.2B.

9. *Id.*, § 1607.16G; Uniform Employee Selection Guidelines Interpretations and Clarification (Questions and Answers) ("Q&A"); Q&As 5, 6, 16.

10. 29 C.F.R. § 1607.16G; *see also* Q&A No. 5 (explaining that covered selection procedures include "interviews, review of experience or education from application forms, work samples, physical requirements, and evaluations of performance").

11. 29 C.F.R. § 1607.4A.

12. Where there is more than one route to a particular employment decision, the total selection process includes the combined results of all routes. Q&A 14. For example, if internal and external candidates follow different paths to a particular job, the "total selection process" would look at the combined results of both sets of candidates.

13. 29 C.F.R. §§ 1607.4C; 1607.15A(2)(a); Q&A 13.

14. *See id.*, § 1607.15A(3).

15. Q&A 41.

16. *Id.*

17. *See id.* § 1607.5(B) (providing that evidence of the validity of a selection procedure by a criterion-related study should consist of "empirical data demonstrating that the selection procedure is predictive of or significantly correlated with important elements of job performance").

18. This relationship is expressed as a "correlation coefficient." A correlation coefficient of −1.0 indicates a completely negative relationship: the better one does on the test, the worse one performs on the job. A correlation coefficient of +1.0 indicates a complete identity between relative test scores and relative job performance. *See Clady v. County of Los Angeles*, 770 F.2d 1421, 1426 n. 5 (9th Cir. 1985); *see also Hamer v. Atlanta*, 872 F.2d 1521, 1524-26 (11th Cir. 1989).

19. 29 C.F.R. § 1607.14A.

20. *Id.*; §§ 1607.14A, 1607.14B(3).

21. *Id.*