Machine Learning at the Patent Office: Lessons for Patents and Administrative Law

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ABSTRACT: The empirical data indicate that a relatively small increment of additional U.S. Patent and Trademark Office ("Patent Office" or "USPTO") investment in prior art search at the initial examination stage could be a cost-effective mechanism for improving accuracy in the patent system. This contribution argues that machine learning provides a promising arena for such investment. Notably, the use of machine learning in patent examination does not raise the same potent concerns about individual rights and discrimination that it raises in other areas of administrative and judicial process. To be sure, even an apparently easy case like prior art search at the USPTO poses challenges. The most important generalizable challenge relates to explainability. The USPTO has stressed transparency to the general public as necessary for achieving adequate explainability. However, at least in contexts like prior art search, adequate explainability does not require full transparency. Moreover, full transparency would chill provision of private sector expertise and would be susceptible to gaming.

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I. INTRODUCTION

A voluminous body of scholarly and popular commentary discusses the use of predictive algorithms by government actors. The decision rule in question can be explicitly specified by humans. Conventional linear regression, for example, is a specific, human-generated data model that transforms inputs into outputs.[1] Alternatively, the decision rule can emerge from algorithmic or machine learning. Although machine learning encompasses many algorithms of varying complexity, a distinctive feature of the genre is that the learning algorithm does not represent the decision rule; instead, the algorithm "learns" the decision rules from data known as training data.[2]

In both cases, the commentary has often been highly critical, particularly in addressing deployment of algorithms in areas like predictive policing and criminal risk assessment.[3] Commentators have expressed concern about classification based on legally protected characteristics and inaccurate adjudication of individual rights.[4]

Understandably, legal commentators have paid less attention to decision-making contexts where bias and rights are not first-order concerns.[5] Yet those contexts, which can involve decisions that are quite important for social welfare, are also worthy of study.

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1. RICHARD A. BERK, STATISTICAL LEARNING FROM A REGRESSION PERSPECTIVE 327 (2d ed. 2016).

2. *See generally* David Lehr & Paul Ohm, *Playing with the Data: What Legal Scholars Should Learn About Machine Learning*, 51 U.C. DAVIS L. REV. 653 (2017) (providing a review of machine learning and drawing attention to ways in which legal scholars have mischaracterized machine learning).

3. *See, e.g.*, Elizabeth E. Joh, *The New Surveillance Discretion: Automated Suspicion, Big Data, and Policing*, 10 HARV. L. & POL'Y REV. 15, 15–19, 30–32 (2016); Dawinder S. Sidhu, *Moneyball Sentencing*, 56 B.C. L. REV. 671, 673–76 (2015); Sonja B. Starr, *Evidence-Based Sentencing and the Scientific Rationalization of Discrimination*, 66 STAN. L. REV. 803, 805–08 (2014). In the area of criminal justice, a somewhat related literature addresses the issue of forensic evidence generated by software. *See generally* Andrea Roth, *Machine Testimony*, 126 YALE L.J. 1972 (2017) (arguing that such testimony presents challenges).

4. *See* sources cited *supra* note 3.

5. For a notable exception, see generally Cary Coglianese & David Lehr, *Regulating by Robot: Administrative Decision Making in the Machine-Learning Era*, 105 GEO. L.J. 1147 (2017) (discussing a broad range of administrative decision making).

Within the spectrum of agency action, the patent examination practices of the U.S. Patent and Trademark Office ("Patent Office" or "USPTO")[6] represent one such case.[7] The Patent Office receives hundreds of thousands of patent applications every year, and the examiners who process the applications operate under severe time pressure. Scholars differ over whether *granted* patents should be viewed strictly through a consequentialist lens.[8] But most analysts would agree that examination of patent *applications* has a strong consequentialist flavor. Relatedly, because patent applicants do not have property rights in applications,[9] constitutional due process limitations on examination may be less constraining, both doctrinally and normatively, than limitations on the cancellation of granted patents.

Perhaps not surprisingly, then, a number of commentators who have discussed the strenuous workload burden that patent examiners face have noted in passing the applicability of machine learning.[10] As they have mentioned, machine learning could be particularly useful for the time-intensive but critical task of searching the prior learning ("prior art") to determine whether, at the time of patent filing, the invention claimed was novel and nonobvious. Indeed, even though patent law does not require patent applicants to do a prior art search, the patent services marketplace now includes firms that purport to perform such searches using machine learning.[11]

6. In the case of this Essay, which discusses only patents, "Patent Office" is an appropriate shorthand term.

7. This contribution focuses on the use of machine learning in searching for prior art. Other legal scholars have addressed the question of whether algorithms could be considered inventors for purposes of patent law. *See, e.g.*, Ryan Abbott, *I Think, Therefore I Invent: Creative Computers and the Future of Patent Law*, 57 B.C. L. REV. 1079, 1098–113 (2016). Although this Essay touches on the use of machine learning to facilitate invention, and the related question of what such use means for the patent law construct of "the person having ordinary skill in the art," it does not directly address questions of inventorship. *Id.* at 1083. More generally, it does not address the many knotty legal, social, and ethical questions that would be raised by the development of a truly "general" artificial intelligence.

8. As Jonathan Masur's contribution to this Symposium points out, a consequentialist lens does not require viewing patents as a form of regulation. *See* Jonathan S. Masur, *Institutional Design and the Nature of Patents*, 104 IOWA L. REV. 2535, 2542–46 (2019). Nonetheless, consequentialist views and a regulatory perspective on patents do tend to be correlated.

9. *See infra* text accompanying notes 62–65.

10. *See, e.g.*, Harry Surden, *Technological Cost as Law in Intellectual Property*, 27 HARV. J.L. & TECH. 135, 201 (2013) ("Numerous machine learning and data mining techniques have developed out of the computer science domain in the last ten years that can be usefully deployed on [the prior art] problem."); Ryan Whalen, *Complex Innovation and the Patent Office*, 17 CHI.-KENT J. INTELL. PROP. 226, 265–66 (2018) ("Another potential reform . . . would be to use algorithmic methods to more clearly identify analogous prior art.").

11. *See infra* text accompanying note 125.

As it happens, the Patent Office has begun efforts to use machine learning in the area of prior art search.[12] Thus far, these efforts have largely gone unexamined in the legal literature, particularly from the perspective of administrative law and policy. The Patent Office's foray into machine learning not only provides a window into potential improvement of the patent system, but it also offers lessons that may generalize to other agencies whose processing of large volumes of information does not implicate bias or individual rights.

The most important generalizable challenge involves the complex normative goal of explainability.[13] Thus far, the Patent Office has appeared to stress transparency to the general public as necessary for achieving explainability.[14] The relationship between explainability and transparency must, however, be parsed carefully, in a manner that is attentive to context. In contexts like prior art search, such parsing reveals that full transparency is not necessary for achieving an adequate level of explainability.

That said, it is important to recognize that the Patent Office is in a difficult position. Stakeholders that seek to secure patents as well as the Patent Office's reviewing court, the Court of Appeals for the Federal Circuit, heavily scrutinize the Patent Office's decisions. Additionally, the Federal Circuit has sometimes rejected conventional principles of administrative law.[15] So the Patent Office's cautious attitude is understandable. Moreover, administrative law doctrine is hardly stable. Indeed, some prominent commentators have recently argued that the Supreme Court is preparing to exert significantly more scrutiny over agencies, putting the administrative state "under siege."[16] And in recent years, the Supreme Court has appeared eager to use review of the Patent Office's administrative apparatus to craft its evolving views of administrative law.[17] Therefore, a machine-learning-use case that should, at

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12. The Patent Office has also begun to use machine learning for purposes of classification. I will not directly address classification issues except to note that using machine learning to update classification on a regular basis might make classification correspond better to the realities of increasingly collaborative and interdisciplinary research. *See infra* Part IV.

13. The term "explainability" has different meanings to different audiences. I parse the term and the related issue of "interpretability" below. *See infra* Section III.A.

14. *See, e.g.*, U.S. PATENT & TRADEMARK OFFICE, DEP'T OF COMMERCE, USPTO'S CHALLENGE TO IMPROVE PATENT SEARCH WITH ARTIFICIAL INTELLIGENCE: REQUEST FOR INFORMATION 2 (2018) ("As a federal agency, it is important for the USPTO to be able to explain all prosecution decisions made. Because of this, solution capabilities must be transparent to the USPTO and as well to the general public. Black box solutions will not be accepted.").

15. *See, e.g.*, Stuart Minor Benjamin & Arti K. Rai, *Who's Afraid of the APA? What the Patent System Can Learn from Administrative Law*, 95 GEO. L.J. 269, 279–313 (2007).

16. Gillian E. Metzger, *Foreword: 1930s Redux: The Administrative State Under Siege*, 131 HARV. L. REV. 1, 17–31 (2017) (discussing Supreme Court skepticism of agency action).

17. In the 2017 term, for example, the Court heard two challenges to decisionmaking by a *single institution* (the Patent Trial and Appeals Board) within the Patent Office. *See, e.g.*, Oil States Energy Servs., LLC v. Greene's Energy Grp., LLC, 138 S. Ct. 1365, 1370–72 (2018); SAS Inst. Inc. v. Iancu, 138 S. Ct. 1348, 1352–54 (2018). For another example of the Court hearing a case

least in theory, be relatively straightforward may not end up being so straightforward in practice.

Ultimately, however, despite the political challenges associated with machine learning, its use by the Patent Office should both increase efficiency and provide for a model for other agencies burdened by large volumes of scientific and technical information. Machine learning is well worth a try. Part II of this Essay reviews the case for stricter patent examination *ex ante*, assesses the intersection between strictness and time expenditure, and introduces the possibility of reducing time expenditure on prior art search through the use of machine learning. Part III introduces the central normative challenge of explainability. After enunciating general doctrinal and normative principles regarding explainability, this Essay uses these principles to argue that using machine learning to improve prior art search should, at least in theory, be an easy case. Part IV discusses what the Patent Office has done thus far, and the disjunction between theory and reality. Throughout Part IV, the Essay alludes to lessons the Patent Office use case can teach for agency use of machine learning more generally. Part V concludes.

II. THE CASE FOR MORE INTENSIVE *EX ANTE* EXAMINATION

After the Federal Circuit repeatedly rejected Patent Office attempts to use the doctrine of patent-eligible subject matter to curb "abstract" patent applications, particularly in the area of software, the Office was overwhelmed with applications that used nonstandard vocabulary and ambitious claiming techniques. This flood of questionable applications, coupled with fiscal pressures that favored issuance over rejection and certain legal standards that made rejections difficult, led the Office to issue many patents that were widely viewed as low quality.[18]

Moreover, despite early academic claims that greater administrative scrutiny by the Patent Office would not be cost-effective because either post-issuance maintenance fees[19] or Article III courts[20] would more efficiently address any problems bad patents created, the policy consensus moved towards advocating greater administrative involvement. The initial thrust, advocated by the Federal Trade Commission ("FTC") and the National Academy of Science ("NAS") in important reports issued in 2003 and 2004

in its 2018 term involving the PTAB, see Transcript of Oral Argument, *Return Mail, Inc. v. U.S. Postal Serv.* (2019) (No. 17-1594), 2019 WL 719101.

18. *See, e.g.*, JAMES BESSEN & MICHAEL J. MEURER, PATENT FAILURE: HOW JUDGES, BUREAUCRATS, AND LAWYERS PUT INNOVATORS AT RISK 18–19 (Princeton University Press 2008).

19. *See generally* Joshua S. Gans et al., *Patent Renewal Fees and Self-Funding Patent Offices*, 4 TOPICS IN THEORETICAL ECON. 1 (2004) (discussing economic theory that assumes policymakers cannot measure the social value of invention, and therefore the socially optimal approach is to encourage the maximal number of patent applications, grant such applications, and then cull *ex post* through renewal fees). This theory abstracts away the possibility that litigation seeking to enforce patents with little or no social value can nonetheless create substantial private value.

20. Mark A. Lemley, *Rational Ignorance at the Patent Office*, 95 NW. U. L. REV. 1495, 1528–31 (2001).

respectively, was towards fortification of administrative procedures through the creation of a robust, trial-type system of post-grant opposition.[21] When spikes in costly Article III patent litigation and nuisance value settlements over the next few years bolstered the views of the FTC and NAS, Congress ultimately adopted a version of their recommendations in the America Invents Act of 2011 ("AIA").[22]

Congress chose to implement administrative post-grant review through the creation of a Patent Trial and Appeals Board ("PTAB").[23] The PTAB has been widely used. However, it has also been quite controversial, particularly among those who view granted patents as "private rights" that should be revoked through judicial procedures only. A seven-member Supreme Court majority in the 2018 decision *Oil States Energy Services, LLC v. Greene's Energy Group, LLC*,[24] rejected this "private rights" claim. But two dissenters vigorously disagreed. Moreover, as discussed in Part IV, even if post-grant review as a whole may now be secure against constitutional challenge, the case law that treats granted patents as property rights places significant constraints on administrative revocation of patents.

Thus, even after the AIA, scholars, policy analysts, and the Patent Office have continued to pursue the goal of improving quality on the safer legal terrain of better initial examination. One group of arguments has focused on encouraging examiners to deploy relatively low-cost interventions, such as the doctrine of written description, as well as doctrinal protections against vagueness and functional claiming.[25] These interventions, which are relatively easy to deploy simply by reading the patent application, police excessive patent scope as well as the notice function that patents are supposed to serve.[26]

The more challenging question involves the cost-effectiveness of devoting significant resources to examine patents *ex ante*. More specifically, the scholarly discussion has focused on the cost-effectiveness, or lack thereof, of potential increases in time allocated to searching prior art to determine novelty and nonobviousness.[27] An application fails novelty if all elements of

21. *See* FED. TRADE COMM'N, TO PROMOTE INNOVATION: THE PROPER BALANCE OF COMPETITION AND PATENT LAW AND POLICY 17–18 (2003); NAT'L RESEARCH COUNCIL, A PATENT SYSTEM FOR THE 21ST CENTURY 96–97 (Stephen A. Merrill et al. eds., 2004).

22. Leahy–Smith America Invents Act, Pub. L. No. 112-29, 125 Stat. 284 (2011) (codified as amended at 35 U.S.C. § 1 (2012)).

23. *See generally* Saurabh Vishnubhakat et al., *Strategic Decision Making in Dual PTAB and District Court Proceedings*, 31 BERKELEY TECH. L.J. 45 (2016) (explaining the relationship between PTAB and Article III litigation).

24. Oil States Energy Servs., LLC v. Greene's Energy Grp., LLC, 138 S. Ct. 1365, 1378–79 (2018).

25. *See* Arti K. Rai, *Improving (Software) Patent Quality Through the Administrative Process*, 51 HOUS. L. REV. 503, 519–33 (2013).

26. For a thorough discussion of why notice is a critical feature of the patent system, see Peter S. Menell & Michael J. Meurer, *Notice Failure and Notice Externalities*, 5 J. LEGAL ANALYSIS 1, 2 (2013).

27. *See, e.g.*, *infra* note 30 and accompanying text.

the claimed invention can be found in a single prior art reference.[28] A patent fails nonobviousness if, given the prior art, making the claimed invention would have been obvious "to a person having ordinary skill in the art."[29] Finding the prior art necessary to make proper novelty and nonobviousness evaluations can be time consuming. Indeed, in a survey conducted by the Government Accountability Office ("GAO") in 2015, 67% of examiners reported that "they [had] somewhat or much less time than [they] needed to complete . . . prior art searches."[30]

In a recent paper,[31] Michael Frakes and Melissa Wasserman supplement their extensive prior empirical work on patent examination with new examination and litigation data to argue for the cost-effectiveness of giving examiners more time to complete prior art searches.[32] According to Frakes and Wasserman, a doubling of examiner hours might cost as much as $660 million annually.[33] However, this investment would more than pay for itself through reduced prosecution cost (due to a decrease in number of rounds of review), as well as reduced patent litigation (including reduced PTAB litigation) over granted patents.[34] *A fortiori*, if AI-based prior art search assistance to examiners could achieve this reduction in prosecution and litigation cost for an investment of less than $660 million annually, it would be cost-effective.[35]

For purposes of enhancing prior art search, different types of machine learning algorithms could be deployed. I engage the technical specifics of what the Patent Office has done in Part IV. The legal analysis of Part III, however, requires a general understanding of what types of machine learning are likely to prove useful for prior art search. Accordingly, I provide here a high-level overview.

For purposes of searching scientific and technical literature, machine learning that involves the creation of a high-dimensional vector space of concepts could be particularly useful. Many different machine learning

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28. 35 U.S.C. § 102 (2012).

29. *Id.* at § 103.

30. U.S. GOV'T ACCOUNTABILITY OFFICE, GAO-16-479, INTELLECTUAL PROPERTY: PATENT OFFICE SHOULD STRENGTHEN SEARCH CAPABILITIES AND BETTER MONITOR EXAMINERS' WORK 21 (2016), https://www.gao.gov/assets/680/678149.pdf.

31. Michael D. Frakes & Melissa F. Wasserman, *Irrational Ignorance at the Patent Office*, 72 VAND. L. REV. 975, 982–87 (2019).

32. *See, e.g.*, Michael D. Frakes & Melissa F. Wasserman, *Is the Time Allocated to Review Patent Applications Inducing Examiners to Grant Invalid Patents?: Evidence from Micro-Level Application Data*, 99 REV. ECON. & STAT. 550, 550–51 (2017).

33. Frakes & Wasserman, *supra* note 31, at 1019–20.

34. *Id.* at 1021.

35. *Id.* Of course, it's possible that the use of AI in litigation would also reduce costs associated with litigation. But there is no reason to believe that, as a percentage matter, cost reduction in litigation would substantially exceed cost reduction in prosecution. Such disproportionate reduction would be necessary to overcome the force of the basic point made by Frakes and Wasserman.

approaches with varying levels of sophistication can produce such vector spaces. For illustrative purposes, I mention here one well-established, relatively "low-tech" technique known as latent semantic analysis ("LSA").[36]

In contrast with Boolean search, which requires use of precisely the same word for purposes of finding similarity between documents, LSA methods view the frequent *co-occurrence* of words in documents as indicative of conceptual similarity between the words.[37] If, for example, the words "gene" and "encode" frequently co-occur together in documents, those terms might be linked into a single concept. The LSA would then associate documents that used that concept. LSA can also be used to link words in *documents* that have been deemed to be similar.[38] For example, in the context of patents, LSA might link words in documents that formed the basis for an examiner's prior art rejection of a patent application with words in the patent application.

Application of concept-semantic machine learning methods to a body of patent or non-patent scientific literature allows the creation of a high-dimensional vector space model of concepts. For purposes of prior art search, documents that represented the basis for prior art-based rejections might be particularly useful. More specifically, a conceptual model based on documents that had destroyed novelty or created obviousness for prior patent applications could be used to find the prior art most likely to be related to a given patent application.[39]

I address in Part III the legal architecture surrounding use of machine learning in the administrative state, both generally and in the specific case of patents. I conclude that, both doctrinally and normatively, deploying machine learning to perform prior art search in patent examination should represent a relatively easy case.

III. AN EASY CASE?

In the area of prior art examination, the central constitutional and non-constitutional administrative law challenge raised by machine learning involves the concept of explainability. This Part begins with an account of explainability that draws upon both the computer science literature and the role of explanation in administrative law. I then apply the general discussion to the specific case of prior art search in patent examination.

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36. Other approaches to vector space models include (for example) Word2Vec and Doc2Vec.

37. Ryan Whalen, *Boundary Spanning Innovation and the Patent System: Interdisciplinary Challenges for a Specialized Examination System*, 47 RES. POL'Y 1334, 1337–38 (2018).

38. *See id.* at 1337.

39. *See generally* Walid Shalaby & Wlodek Zadrozny, *Patent Retrieval: A Literature Review*, KNOWLEDGE & INFO. SYS., Jan. 2019, https://arxiv.org/pdf/1701.00324.pdf (discussing usefulness of datasets containing novelty-breaking documents found in examiners' search reports).

A. EXPLAINABILITY: GENERAL CONSIDERATIONS

In what follows, I introduce the problem of explainability in machine learning. I then outline principles of constitutional and non-constitutional administrative law that require some level of explainability.

In conventional computer science, a human designs the decision-making algorithm and the computer then applies this algorithm to data. With machine learning, the human programs a computer to learn from training data for purposes of developing its own decision-making model. Although applying human intuitions about explanation to decision-making models developed by machines is far from easy, a fast-growing body of literature on explainability in machine learning now proposes a variety of different definitions.[40] For present purposes, I view explainability on a spectrum, with "complete" explainability meaning that the algorithm's complete decisionmaking can be made fully understandable to the relevant human audience. On the other end of the spectrum, the relevant human audience would be completely incapable of parsing the decision-making process by which the computer generated its output.

For several reasons, more than one of which may apply in any given case, complete explanation of decisions made based on machine learning may be difficult to achieve. These include *non-transparency*—the relevant details concerning source code, training data, and resulting model are considered trade secrets—and *complexity*—a complete and accurate explanation can be generated (e.g., by revealing source code, training data, and all the mathematical operations and parameters in the resulting model), but it would not be comprehensible, even to a human domain expert.[41]

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40. This literature also uses the term "interpretability." For some, the two terms appear interchangeable—a system is interpretable if it can explain its reasoning. Finale Doshi-Velez & Been Kim, *Towards a Rigorous Science of Interpretable Machine Learning*, ARXIV 1 (Mar. 2, 2017), https://arxiv.org/pdf/1702.08608.pdf ("[A] popular fallback is the criterion of *interpretability*: if the system can *explain* its reasoning, we then can verify whether that reasoning is sound with respect to these auxiliary criteria."). For others, explainability is more demanding than interpretability—it requires not simply a summary of what the model was likely to have done as a statistical matter but completeness—a description of "the operation of a system in an accurate way." *See* Leilani H. Gilpin et al., *Explaining Explanations: An Overview of Interpretability of Machine Learning*, ARXIV 2 (Feb. 3, 2019), https://arxiv.org/pdf/1806.00069.pdf.

41. A challenge related to complexity is that of *non-intuitiveness*: The correlations upon which the model relies might seem inexplicable to the human. Computer scientist Ed Felten has recently focused on these challenges. *See generally* Ed Felten, PowerPoint Presentation at Duke Law Conference on AI in the Administrative State: Applications, Innovations, Transparency, Adaptivity, *AI 101: An Opinionated Computer Scientist's View* (May 4, 2018), *available at* https://law.duke.edu/sites/default/files/centers/cip/ai-in-admin-state_felten_slides.pdf (detailing a brief history of AI and some of the problems with explainability). Felten also notes lack of justification—the explanation does not appear fair—as an axis on which explanation might fall short. *Id.* at slide 21. Because I focus in this Essay on information processing that does not involve bias against legally protected characteristics or infringement on individual rights, I do not explore justification.

If complete explanation falls short on any of these axes, the relevant question is whether such failure should preclude use of the algorithm by the agency. In what follows, I analyze the question from doctrinal and normative perspectives.

I begin with a brief introduction to constitutional and non-constitutional administrative doctrines that encourage explanation. The most important constitutional doctrine is procedural due process, and it has already been raised by parties challenging claims of trade secrecy over ordinary algorithms. Criminal justice occupies center stage in both the litigation activity and scholarly conversation addressing the intersection of procedural due process and trade secrecy. For example, in *State v. Loomis*,[42] the defendant argued that the proprietary nature of the COMPAS[43] risk assessment algorithm violated procedural due process because it prevented challenges to scientific validity.[44] In rejecting the due process challenge, the Wisconsin Supreme Court emphasized aspects of the information available to the defendant that, in its view, created a sufficient level of explainability: (1) the defendant's own risk scores in different categories were available to the defendant; (2) a publicly available guide to COMPAS explained the sorts of static and dynamic information (e.g., criminal history, criminal associates, substance abuse) on which risk scores were based; and (3) a list of 21 questions on criminal history that was used in Loomis's case.[45] The Court also limited the use of COMPAS to questions such as "diverting low-risk prison-bound offenders to a non-prison alternative" and required that the use of COMPAS be accompanied by a written advisory of its limitations.[46]

To be sure, commentators have been quite critical of cases like *Loomis* in the criminal justice arena in which courts have accepted assertions of trade secrecy.[47] Even so, the Wisconsin Supreme Court's creation of a doctrinal apparatus for balancing, even in the high-stakes context of criminal justice, is noteworthy.

In the more traditional civil context of administrative agency action, the fact-intensive and context specific *Mathews v. Eldridge* balancing test provides the doctrinal infrastructure.[48] Under this test, the level of process due is determined by the private interest affected by the action; the probable value, given the baseline risk of erroneous deprivation, "of additional or substitute

42. State v. Loomis, 881 N.W.2d 749, 753 (Wis. 2016). Although the litigation does not address the issue, COMPAS does not appear to be a machine-learning algorithm.

43. COMPAS is an acronym for "Correctional Offender Management Profiling for Alternative Sanctions." *Id.* at 753 n.10.

44. *Id.* at 760.

45. *Id.* at 761–62.

46. *Id.* at 767–70.

47. *See, e.g.*, Rebecca Wexler, *Life, Liberty, and Trade Secrets: Intellectual Property in the Criminal Justice System*, 70 STAN. L. REV. 1343, 1346–49 (2018).

48. Mathews v. Eldridge, 424 U.S. 319, 334–36 (1976).

procedural safeguards" in reducing risk; and the government's interest, including "the fiscal and administrative burdens" of any additional or substitute procedures.[49] Although this balancing test is not necessarily especially demanding, a recent district court case denied a defendant school district's motion for summary judgment on the plaintiff teachers' claim that the district's use of a trade secret-protected algorithm for calculating teacher effectiveness scores violated procedural due process.[50] According to the court, teachers faced with the possibility of termination based on an algorithmically derived score had a right to challenge the algorithms and data on which the scores were based.[51]

Non-constitutional administrative law also requires some level of explanation. In general, all agency adjudication and rulemaking that is not "committed to agency discretion"[52] must satisfy the demands of "arbitrary[] [and] capricious" review.[53] As the Supreme Court explained in its canonical *State Farm* decision, in order to satisfy arbitrary and capricious review, agencies must engage in reasoned decisionmaking—they must articulate "a 'rational connection between the facts found and the choice made.'"[54] Moreover, the underlying agency fact-finding must itself either be supported by "substantial evidence" (in the case of a formal adjudication) or must satisfy the arbitrary and capricious standard (in the case of informal adjudication).[55]

Although adequate explanation is clearly important, it does not—and should not—require either that complex models be considered categorically out of bounds or that algorithmic decisionmaking always be fully transparent. To the contrary, as the *Mathews* balancing test suggests, levels of explainability should be tailored to the stakes involved. In high-stakes contexts, particularly contexts where gaming of the algorithmic model is not an issue,[56] policy makers may simply want to avoid algorithms that cannot be explained to the relevant human audience, whether for reasons for trade secrecy or complexity.[57] In those cases, transparent, simple models developed through public incentive mechanisms such as prizes or government funding might be preferable. But where the individual interests at stake are less acute, improvements in efficiency (and, at least potentially, accuracy) achieved by

49. *Id.* at 335.

50. 5 U.S.C. § 706(2)(A)–(E) (2012); Hous. Fed'n of Teachers, Local 2415 v. Hous. Indep. Sch. Dist., 251 F. Supp. 3d 1168, 1180 (S.D. Tex. 2017).

51. *Hous. Fed'n of Teachers, Local 2415*, 251 F. Supp. 3d at 1176–77.

52. 5 U.S.C. § 701(a)(2).

53. *Id.* § 706(2)(A).

54. Motor Vehicle Mfrs. Ass'n v. State Farm Mut. Auto. Ins. Co., 463 U.S. 29, 43 (1983) (quoting Burlington Truck Lines, Inc. v. United States, 371 U.S. 156, 168 (1962)).

55. 5 U.S.C. § 706(2)(A), (E).

56. On gaming of administrative algorithms by sophisticated regulated entities, see *infra* Section IV.D.

57. Cynthia Rudin, *Please Stop Explaining Black Box Models for High-Stakes Decisions*, ARXIV 1–3 (Dec. 5, 2018), https://arxiv.org/pdf/1811.10154.pdf.

highly complex algorithms (e.g., deep learning neural nets) may outweigh explainability.

To the extent that the decision-making model in question is provided by the private sector, protecting trade secrecy may be a key concern. Trade secrecy may have become particularly important in the wake of certain U.S. Supreme Court decisions that make the conventional alternative of software patents difficult to secure.[58] Requirements that machine learning be at least partly explainable are not, however, necessarily in tension with some protection against immediate reproduction. For example, clear explanations of the model's goal, and which inputs most likely influenced a given prediction can provide adequate explanation without yielding immediate reproduction.[59]

Conversely, certain types of disclosure may unduly facilitate reproduction without being either necessary or sufficient for achieving an acceptable level of explainability. For example, full source code transparency with respect to the learning algorithm may "teach[] a reviewer very little, since the code only exposes the machine learning method used and not the data-driven decision rule."[60] At the same time, such source code transparency could make reproduction substantially easier. Indeed, if source code transparency were combined with transparency of training data, reproduction would presumably be straightforward.

Importantly, none of the limitations on transparency that emerge from trade secrecy vis-à-vis the general public need apply, or should apply, either to an agency or to reviewing courts. For an agency, the Freedom of Information Act ("FOIA") explicitly contemplates protection of commercially confidential information by exempting such information from public disclosure.[61] Thus agencies can and should fully examine all aspects of any private sector algorithms and training data upon which they rely. For their part, reviewing courts can and should be able to review commercially confidential information *in camera*.[62] The latter option may be particularly useful in cases where litigants have raised questions regarding what Joshua Kroll and his colleagues have called "procedural regularity"—that is, concerns that the agency is applying its machine learning apparatus consistently across cases.[63]

58. Kate Gaudry & Samuel Hayim, *Artificial Intelligence Technologies Facing Heavy Scrutiny at the USPTO*, IPWATCHDOG (Nov. 28, 2018), https://www.ipwatchdog.com/2018/11/28/artificial-intelligence-technologies-facing-heavy-scrutiny-uspto/id=103762 (discussing the impact of the Supreme Court's decision in Alice Corp. Pty. Ltd. v. CLS Bank Int'l, 573 U.S. 208 (2014)).

59. While not directly relevant to explanation, information about performance metrics and confidence levels with respect to a given prediction is, of course, also helpful.

60. Joshua A. Kroll et al., *Accountable Algorithms*, 165 U. PA. L. REV. 633, 638 (2017).

61. 5 U.S.C. § 552(b)(4) (2012) (exempting commercially confidential information from FOIA).

62. *See* Kroll et al., *supra* note 60, at 703.

63. *See generally id.* at 637, 703 (discussing various technical pre-commitment mechanisms by which agencies and courts can ensure procedural regularity).

Additionally, agencies should demand, and make transparent to the public, data on performance.

B. EXPLAINABILITY IN PRIOR ART SEARCH

With this general background in mind, we can now turn to explainability in the specific context of prior art search at the USPTO. In what follows, I focus on doctrinal and normative questions raised when machine learning is used for prior art search. I address first constitutional questions and then questions of non-constitutional administrative law.

On the constitutional front, the threshold doctrinal distinction between grants and applications bears mention: Although the Supreme Court has indicated that granted patents are property for purposes of due process protection,[64] patent *applications* do not represent such property.[65] More broadly, the question of what, if any, due process protections attach to applications for government benefits remains unsettled. As a normative matter, commentators have argued persuasively that grossly irregular government action should be avoided, whether in the context of a benefit that is removed or the context of failure to grant a benefit.[66]

The gross irregularity standard advocated by commentators as a normative matter is probably less strict than the various doctrinal requirements for agency action mandated by the Administrative Procedure Act ("APA"). It is almost certainly less strict than the Federal Circuit's actual application of APA standards. Therefore, in what follows, I focus on judicial review under the APA.[67]

64. *See, e.g.*, Fla. Prepaid Postsecondary Educ. Expense Bd. v. Coll. Sav. Bank, 527 U.S. 627, 642 (1999) (noting that patents are "surely included within the 'property' of which no person may be deprived by a State without due process of law").

65. *Id.* at 643.

66. *See, e.g.*, William Van Alstyne, *Cracks in "The New Property": Adjudicative Due Process in the Administrative State*, 62 CORNELL L. REV. 445, 449–51 (1977).

67. The question of judicial review under the APA is complicated slightly by case law holding that the APA governs only patent denials and that the Patent Act, rather than the APA, dictates how courts should review the Patent Office's decision to *grant* a patent. Specifically, the Federal Circuit's 2012 decision in *Pregis Corp. v. Kappos*, 700 F.3d 1348 (Fed. Cir. 2012), states that the patent statute "provides an intricate scheme for administrative and judicial review of PTO patentability determinations that evinces a clear Congressional intent to preclude actions under the APA seeking review of the PTO's reasons for deciding to issue a patent." *Id.* at 1358. Additionally, although the Supreme Court has not addressed the preclusion issue squarely, its unanimous 2011 decision in *Microsoft Corp. v. i4i Ltd. P'ship*, 564 U.S. 91 (2011), relies on language found in the 1952 patent rather than the APA. *Id.* at 96–97. According to the Court, the 1952 patent statute, which simply "[states] that '[a] [granted] patent shall be presumed valid[,]'" in fact codifies the Court's own prior statement in the 1934 case *Radio Corp. of Am. v. Radio Eng'g Labs., Inc.* that clear and convincing evidence is needed to overturn an issued patent. *Id.* at 106 (second alteration in original) (quoting 35 U.S.C. § 282(a) (1952)); Radio Corp. of Am. v. Radio Eng'g Labs., Inc., 293 U.S. 1, 7 (1934). Elsewhere, I have written about the reasons why these doctrinal departures from standard APA principles are problematic as a normative matter. *See* Stuart Minor Benjamin & Arti K. Rai, *Administrative Power in the Era of Patent Stare Decisis*,

Within patent law, agency determination of what constitutes prior art is relevant to the novelty and non-obviousness requirements and is considered a question of fact. Furthermore, in the context of informal proceedings like patent examination, boilerplate administrative law requires that agency fact-finding on questions like the relevant prior art pass "arbitrary[] [and] capricious" review.[68]

The Federal Circuit, directed by the Supreme Court to apply administrative law to these proceedings, has deviated from the standard approach and instead applies "substantial evidence" review.[69] Although the difference between the two standards is not necessarily dramatic in theory, in practice the Federal Circuit has sometimes used the substantial evidence standard quite aggressively, to require very exacting scrutiny of patent examiner decisions. For example, in the era before the Supreme Court's 2007 decision in *KSR International Co. v. Teleflex Inc.*,[70] the Court routinely imposed a rigid requirement that the examiner show explicit documentary evidence of a motivation to combine prior art references.[71] Even after the Supreme Court decision in *KSR*, influential commentators have expressed concern that the Federal Circuit may be drifting back towards a rigid requirement.[72]

Equally important, the Federal Circuit often characterizes "ultimate" determinations of patent validity as questions of law.[73] Moreover, it has held that even in the context of administrative appeals, the appropriate standard

65 DUKE L.J. 1563, 1594 (2016). John Duffy's contribution to this Symposium also discusses this doctrinal departure. *See* John F. Duffy, *Reasoned Decisionmaking vs. Rational Ignorance at the Patent Office*, 104 IOWA L. REV. 2351, 2352–53 (2019). APA principles *should* apply to PTO decisions generally, whether these constitute denials appealed directly to the Federal Circuit or judicial review of a granted patent. As a practical matter, however, given the current case law, AI-enabled decisionmaking in patent examination is likely to be challenged only in cases where the application is denied. The discussion in the text therefore assumes a patent denial context.

68. 5 U.S.C. § 706(2)(A) (2012).

69. *In re* Gartside, 203 F.3d 1305, 1312–13 (Fed. Cir. 2000).

70. KSR Int'l Co. v. Teleflex Inc., 550 U.S. 398 (2007).

71. *See, e.g.*, Benjamin & Rai, *supra* note 15, at 290–92 (discussing cases that the Court included prior art references).

72. For example, in the Federal Circuit's first *en banc* decision on obviousness since *KSR*, *Apple Inc. v. Samsung Elecs. Co.*, Judge Dyk accused "the majority [of] lower[ing] the bar for nonobviousness" in a way that "is contrary to *KSR*." *See* Apple Inc. v. Samsung Elecs. Co., 839 F.3d 1034, 1076 (Fed. Cir. 2016) (en banc) (Dyk, J., dissenting). In response to a petition for certiorari, the Supreme Court called for the views of the Solicitor General ("CVSG") concerning whether certiorari should be granted. The Solicitor General also expressed concern that the Federal Circuit might be drifting back to "rigid and mandatory formulas." Brief for the United States as Amicus Curiae at 16, *Apple Inc.*, 839 F.3d 1034 (No. 16-1102), 2017 WL 4457613, at *16. One of the cases it highlighted in this regard was an appeal from a PTO patent denial, *In re Stepan Co.*, 868 F.3d 1342 (Fed. Cir. 2017). *Id.* at *16–17.

73. *See, e.g.*, *In re* Karpf, No. 2018-2090, 2019 WL 384543, at *3 (Fed. Cir. Jan. 30, 2019) (stating that the PTAB's "ultimate judgment of obviousness is a legal conclusion" that is reviewed *de novo*). In the context of judicial review of legal determinations by administrative agencies, boilerplate administrative law holds that courts should choose between one of a number of different administrative deference regimes.

of review is *de novo*.[74] This means that Federal Circuit judges skeptical of the use of machine learning to identify prior art could focus on the *de novo* aspect of their reviewing authority to overturn a Patent Office determination that a given invention lacked novelty or was nonobvious.[75]

How might substantial evidence review of fact-finding, combined with *de novo* review of the ultimate validity decision, play out in the case of an examiner whose rejection of an application on obviousness grounds relied heavily on prior art identified through machine learning?[76] In many cases, the Patent Office could argue persuasively that the explainability of the algorithm used to find the art was largely irrelevant. What was instead important was the examiner's reasoning regarding why, given the prior art, a rejection was appropriate.

A more challenging scenario might involve a situation where the examiner's rejection relied on art that the applicant argued was far afield from the area of invention and therefore not appropriately included in the knowledge base of a fictional person having ordinary skill in the art. In that case, the Federal Circuit would be called upon to determine how the longstanding patent law doctrine of "analogous art" applied to references identified through machine learning. The analogous art doctrine requires that the cited art come "from the same field of endeavor" as the invention on which a patent is being sought or that it be "reasonably pertinent to the particular problem that the inventor is" trying to solve.[77]

In the case of purportedly non-analogous art, the agency could point to overlap in the references cited by the patent application and the prior art. But if the agency had to demonstrate the more abstract principle of conceptual similarity, some level of algorithmic explainability could be important. For example, if relatively simple vector space models had been used by the agency/examiner, their relative understandability to humans would presumably enhance the agency's case. With a vector space model that was

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74. *Id.*

75. As Rebecca Eisenberg's contribution to this Symposium emphasizes, the Federal Circuit has often reviewed mixed questions of law and fact aggressively. *See* Rebecca S. Eisenberg, *A Functional Approach to Judicial Review of PTAB Rulings on Mixed Questions of Law and Fact*, 104 IOWA L. REV. 2387, 2396–98 (2019).

76. As noted in the prior Section, another evidentiary requirement to which agency decisionmaking is subject is the *State Farm* requirement of "reasoned decisionmaking." *See* Motor Vehicle Mfrs. Ass'n v. State Farm Mut. Auto. Ins. Co., 463 U.S. 29, 51–54 (1983). Interestingly, the Federal Circuit has applied this requirement relatively infrequently to Patent Office decisionmaking in the initial examination phase. A search of Westlaw's "Federal Circuit" database for the term "reasoned decisionmaking" revealed only one case, *In re Sang-Su Lee*, 277 F.3d 1338, 1346 (Fed. Cir. 2002). The *In re Sang-Su Lee* decision essentially used the doctrine to bolster its claim regarding the lack of foundation for the examiner's decision to combine prior art references. *See id.* at 1342–44. Thus, at least as a doctrinal matter, reasoned decisionmaking does not appear to require much more than the substantial evidence standard.

77. *See, e.g.*, *In re* Klein, 647 F.3d 1343, 1348 (Fed. Cir. 2011) (quoting *In re* Bigio, 381 F.3d 1320, 1325 (Fed. Cir. 2004)) (applying the analogous art doctrine).

relatively explainable in terms of how it was created (e.g., basics of learning algorithm and training data), and in terms of the actual decision rules used, the agency could make a credible case that the apparently non-analogous art was in fact not particularly distant, conceptually, from the invention. The agency would probably be able to make its case without revealing more specific information (e.g., source code and training data) critical to reproducibility.

Thus far, the discussion has suggested that Patent Office use of machine learning to find prior art should not require complete explainability. So, the Patent Office's apparent desire for robust transparency, discussed in the next Section, is perhaps puzzling. More generally, while theory might suggest that AI at the Patent Office should be an easy case, practice suggests that it is not. The next Part turns to the disjunction between theory and practice.

IV. THE PTO AND MACHINE LEARNING: COMPARING THEORY AND PRACTICE

In this Part, I introduce the mechanics of prior art search and discuss the significant challenges that the Patent Office has faced in its effort to use machine learning to improve search. I then reflect on larger implications of the divergence between theory and practice.

A. *THE BASICS OF SEARCH*

Upon receiving a filing, the Patent Office classifies it into one or more technology classes and then assigns it to a group of examiners (called an Art Unit) who have domain-specific knowledge in the primary class.[78] Until recently, the Patent Office used a U.S.-specific technology classification system known as the USPC.[79] It has now adopted the internationally recognized Cooperative Patent Classification ("CPC") system, which is generally considered more accurate.[80]

Prior art searches conducted by examiners use technology classes and keywords to search Patent Office databases and other online repositories.[81] The most commonly used search tools are the Examiner Automated Search Tool ("EAST") and the Web-based Examiner Search Tool ("WEST") software.[82] Examiners can also use an automated tool known as the Patent Linguistic Utility Service ("PLUS") that is available through the Patent

78. Andrew Chin, *Search for Tomorrow: Some Side Effects of Patent Office Automation*, 87 N.C. L. REV. 1617, 1625–34 (2009).

79. *Id.* at 1629–30.

80. *Manual of Patent Examination and Procedure*, USPTO, Ch. 0900, https://www.uspto.gov/web/offices/pac/mpep/s905.html (last visited May 1, 2019).

81. *See* Chin, *supra* note 78, at 1619–20, 1629.

82. *See id.* at 1622.

Office's Scientific and Technical Information Center ("STIC").[83] This tool relies primarily on keyword search, namely identifying "frequently-used terms"[84] in the "patent application and retrieving published patent documents that exhibit a high level of textual similarity to these keywords."[85]

A 2009 study by Professor Andrew Chin analyzed examiner prior art search patterns from all 3,266,297 patents in the Patent Office's PatFT database as of May 1, 2007.[86] It found that, in the period between 1990 and 2007, the use of keyword searches by examiners rose continuously.[87] Chin also noted, however, that keyword search can have significant limitations in terms of achieving either precision or recall—that is, for purposes of minimizing either false positives or false negatives.[88]

Other commentators have noted that keyword search is particularly unhelpful for software-related applications, which often use inconsistent terminology to describe the same concept.[89] Indeed, in a 2009 study I conducted with John Allison and Bhaven Sampat, we determined that patents identified as "software" through keyword search had little overlap with those Allison had identified as software through close study of individual patents.[90]

Notably, although they rely on keyword search, examiners are aware of its limitations. A web-based survey of a stratified random sample of 3,336 patent examiners conducted by the Government Accountability Office ("GAO") in 2015 found that 76% of the surveyed examiners thought that search engines that "automatically search[ed] for *concepts* and synonyms related to the search terms entered by the examiner" would make prior art searches somewhat or much easier.[91]

Computer scientists at the Patent Office have also been critical of keyword search, emphasizing that "simple keyword searches have limited utility in the patent prosecution context because of the high prevalence of

83. Request for Comments on Enhancing Patent Quality, 80 Fed. Reg. 6475, 6479 (Feb. 5, 2015) (to be codified at 37 C.F.R. pt. 1).

84. *Id.*

85. Arthi M. Krishna et al., *User Interface for Customizing Patents Search: An Exploratory Study, in* 617 HCI INTERNATIONAL 2016—POSTERS' EXTENDED ABSTRACTS 264, 265 (Constantine Stephanidis ed., 2016).

86. Chin, *supra* note 78, at 1636–37.

87. *Id.* at 1642.

88. *Id.* at 1628.

89. U.S. GOV'T ACCOUNTABILITY OFFICE, *supra* note 30, at 19.

90. Arti K. Rai et al., *University Software Ownership and Litigation: A First Examination,* 87 N.C. L. REV. 1519, 1530–31 (2009).

91. U.S. GOV'T ACCOUNTABILITY OFFICE, *supra* note 30, at 25 (emphasis added). The GAO survey covered all of the utility patent centers that conduct initial examinations and had an 80% response rate. *Id.* at 65.

uncommon language patterns and intentional creation by patent applications of 'abstract vocabulary' specific to their claimed invention."[92]

Fast searches with high precision and recall are critical because, as discussed in Part II, the data indicate not only that examiners operate under time pressures that lead to patent grants,[93] but also that time pressure is particularly acute with respect to prior art search.[94]

B. Steps Toward Machine Learning

In a 2015 request for comments on techniques for improving patent quality, the Patent Office asked for input on new automated pre-examination search tools beyond PLUS.[95] Specifically, it sought comments on "concept-semantic" tools that move beyond keyword search.[96] Notably, at the time the Patent Office was seeking comments from outside contractors on enhancing patent search, Patent Office computer scientists were working in-house on developing a search system called Sigma.[97]

A 2016 paper from these scientists describes the Sigma product.[98] As Figure 1 (below) from the paper shows, the product allows the examiner to attach a weight to whatever part of the patent they find most relevant (e.g., title, claims, specification, abstract). The MoreLikeThis parser used by Sigma identified "the top unique terms in the input document, and uses these terms to retrieve related documents."[99] The Sigma product also has validation indicators that allow for fine-tuning.[100] These validation indicators show whether the "similar" patents are from the same family as the application or share a CPC or USPC with the application, whether there is overlap in the patents cited by the result and the patents cited by the application, and whether the application and the result are from a shared art unit.[101]

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92. Krishna et al., *supra* note 85, at 265 (endnote omitted). Although the Patent Office diplomatically attributes intentionality to "patent applications" rather than patent *applicants*, the inference is clear. *Id.* A recent publication by computer scientists working in the area of patent search states the problem more bluntly, noting that inventors attempt to establish novelty by "us[ing] jargon and complex vocabulary to refer to the same concepts. They also use vague and abstract terms in order to broaden the scope of their patent protection[,] making the problem of patent analysis linguistically challenging." Shalaby & Zadrozny, *supra* note 39, at 2.

93. *See supra* Part II.

94. *See supra* Part II.

95. Request for Comments on Enhancing Patent Quality, *supra* note 83.

96. *Id.*

97. Krishna et al., *supra* note 85, at 266–69.

98. *Id.*

99. *Id.* at 266.

100. *See id.* at 268.

101. *Id.*

Figure 1: Interface Showing Patents Similar to US11061715[102]

Important as the Sigma effort was, however, some of the foundations upon which it first began do not represent machine learning. Figure 2 shows a flowchart of how the algorithm preprocesses input. The Wordnet software, for example, involves synonym lookup in a general dictionary.[103] In a move towards machine learning, the Patent Office did begin to enhance Wordnet by adding "synonyms" based on the co-occurrence of words in historical examiner search queries.[104]

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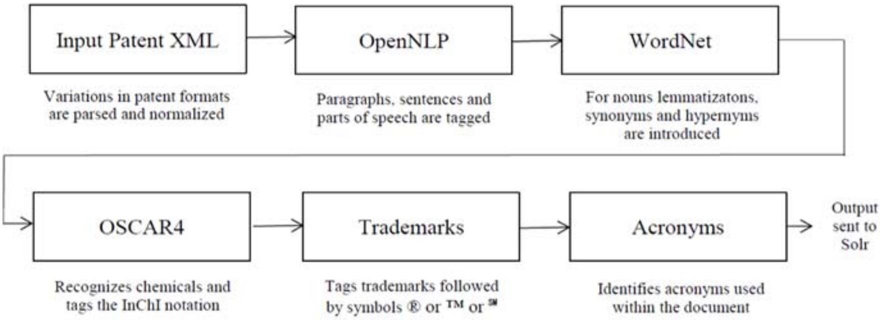
102. *Id.* at 265 fig.1.
103. *Id.* at 267.
104. *Id.*

Figure 2: Algorithm[105]



C. *Challenges of Human Capital and Data*

It is unclear whether Sigma was ever deployed, even as an experiment, within the Patent Office itself. According to a November 2018 speech by Patent Office Director Andrei Iancu, the Patent Office is now testing a new product, Unity, that will allow "federated search across patents, publications, nonpatent literature and images."[106]

Some insight into Sigma's apparent lack of appeal, and the accompanying human capital challenge, might be gleaned from an experiment using Sigma that was run on business school students in cooperation with the Patent Office.[107] The experiment randomly assigned business school students with and without computer science backgrounds to traditional Boolean search and to the Sigma tool.[108] It found that students with computer science backgrounds were able to use the Sigma tool to improve their efficiency in finding prior art.[109] By contrast, those without a computer science background did better with traditional Boolean search, even though the Boolean search retrieved more irrelevant documents.[110] The authors suggest that these results show that students without computer science backgrounds were comparatively skilled at sifting through the irrelevant documents quickly.[111] Although the experiment has obvious

105. *Id.* at 266–68.

106. Jimmy Hoover, *USPTO Testing AI Software to Help Examiners ID Prior Art*, LAW 360 (Nov. 15, 2018, 7:18 PM), https://www.law360.com/articles/1095703/uspto-testing-ai-software-to-help-examiners-id-prior-art.

107. Prithwiraj Choudhury et al., *Machine Learning and Human Capital: Experimental Evidence on Productivity Complementarities* 2–3, 13 (Harvard Bus. Sch., Working Paper No. 18-605, 2018), https://www.hbs.edu/faculty/Publication%20Files/18-065_c065462c-0791-4356-8e09-46e1b251c1c8.pdf.

108. *Id.* at 13–17.

109. *Id.* at 26.

110. *Id.*

111. *Id.*

limitations with respect to external validity, it does provide some insight into the "absorptive capacity"[112] necessary for adoption of machine learning techniques.

In the case of the Patent Office, the reality of a relatively powerful labor union complicates the human capital issue. The labor union should not, in principle, necessarily oppose a tool that would allow more effective search within the same number of hours. Indeed, to the extent that machine learning allows examiners to shift their efforts towards higher-skill activities like developing a clear record of their legal reasoning, it has the potential to improve job satisfaction. But fears regarding reduction in hours available to examine patents, or perhaps even a reduction in workforce, may motivate opposition.

Another significant challenge will involve finding good training data to "teach" machine-learning algorithms. Both as a historical matter and in current practice, the time pressures discussed in Part II yield prior art searches and office actions that are less than optimal.[113] Models of inventive "distance" based on these data are thus likely to be flawed. Additionally, we have now a significant amount of empirical evidence indicating that invention occurs through "recombination" of areas of prior art that were once distinct.[114] If and when recombination of this once-conceptually distinct art becomes standard, training data consisting of prior art searches and office actions that predated the now-standardized recombination will be stale. These recombined technologies will require new training data. Additionally, training data should include not simply examiner search, but data from cases—either at the PTAB or in federal court—where additional, invalidating prior art was found. More generally, the Patent Office's methods should take full advantage of the learning and updating possibilities offered by machine learning.

The search problem may be exacerbated by aggressive private sector use of AI assistance in the context of its own invention. For example, areas like drug discovery increasingly rely on the pattern recognition at which AI excels.[115] In general, the average scientist assisted by machine learning is likely

112. *See generally* Wesley M. Cohen & Daniel A. Levinthal, *Absorptive Capacity: A New Perspective on Learning and Innovation*, 35 ADMIN. SCI. Q. 128 (1990) (discussing absorptive capacity and its necessary role in innovation).

113. *See supra* Part II.

114. Hyejin Youn et al., *Invention as a Combinatorial Process: Evidence from U.S. Patents*, 12 J. ROYAL SOC'Y. INTERFACE at 1–2 (2015), https://royalsocietypublishing.org/doi/pdf/10.1098/rsif.2015.0272. Whether these tendencies towards recombination, often produced by teams of inventors working together, should lead to assessments of nonobviousness based not on an individual level of skill in the art, but on a team level of skill is an interesting and important question, but one that is beyond the scope of this Essay.

115. *See, e.g.*, Mariya Popova et al., *Deep Reinforcement Learning for De Novo Drug Design*, 4 SCI. ADVANCE, at 9–11 (2018), http://advances.sciencemag.org/content/advances/4/7/eaap7885.full.pdf; Nic Fleming, *How Artificial Intelligence Is Changing Drug Discovery*, NATURE (May 30, 2018), https://www.nature.com/articles/d41586-018-05267-x.

to prove significantly more "skilled in the art" than an unaided scientist.[116] To the extent that the AI-assisted search used by the Patent Office does not account for potentially rapid change in the average skill of practitioners itself spurred by AI, it will fall short.

At the same time the Patent Office was working on developing machine learning capabilities in-house, it was also examining the possibility of procuring machine learning capabilities from vendors that have emerged in the patent space. According to then-Director Michelle Lee, the Patent Office awarded a contract in July 2016 to a private firm known as "AI Patents to begin developing a new automated search system."[117] According to its website, AI Patents uses a version of concept-based search, with initial training of the model done in part on examination reports from the United States and Europe.[118] Ultimately, AI Patents did not secure a follow-up contract with the Patent Office. According to AI Patents, tensions over full transparency were a sticking point.[119]

The next Section discusses in greater detail interactions between transparency and agency "make or buy" decisions.

D. Explainability and Transparency Challenges

AI Patents and other commercial vendors generally emphasize their unique proprietary algorithms and unique data sources.[120] In contrast, the Patent Office's computer scientists have emphasized transparency. For

116. 35 U.S.C. § 112 (2012). *See generally* Ryan Abbott, *Everything Is Obvious*, 66 UCLA L. REV. 2 (2019) (arguing that in certain areas machine learning has already led to substantial improvement in the aptitude of the person having ordinary skill in the art and forecasting a future in which even more dramatic increases are likely).

117. Michelle K. Lee, Director, USPTO, Remarks by Director Michelle K. Lee at the Patent Quality Conference Keynote (Dec. 13, 2016), https://www.uspto.gov/about-us/news-updates/remarks-director-michelle-k-lee-patent-quality-conference-keynote.

118. *See Executive Summary*, AI PATENTS, https://www.aipatents.com/summary.html (last visited May 1, 2019) ("AI Patents uses thousands of patent examination reports from the American and European patent offices to learn about textual relationship[s] that describe the same scientific concepts and applies this learning to compare inventions.").

119. Felten, *supra* note 41, at slides 21–22.

120. Consider, for example, the following excerpts from an e-book advertisement produced by InnovationQ, another "semantic search" firm:

> InnovationQ Plus is powered by *proprietary, patent-protected semantic search technology* that enables the use of natural language to discover and visualize relevant content buried deep within complex patent and other technical documents. . . . While InnovationQ Plus uses some of the latest neural network machine learning technology, other vendors may still be using the much older search methodology of Latent Semantic Indexing as the basis of a semantic search.

IP.COM, INCREASE INTELLIGENCE AROUND IP WITH SEMANTIC SEARCH 5, 12, https://ip.com/wp-content/uploads/2017/11/IQ_SemanticSearch_Ebook.pdf (last visited May 1, 2019) (ebook) (emphasis added). The e-book advertisement also stresses InnovationQ's unique data, specifically its unique collection of non-patent literature.

example, in the case of Sigma, the Patent Office's explanatory paper notes that

> [c]ontrary to the approach of treating the search algorithm as a black box, all components of the search algorithm are explained, and these components expose controls that can be adjusted by the user. This level of transparency and interactivity of the algorithm not only enables the experts to get the best use of the tool, but also is crucial in gains the trust of the users.[121]

Similarly, the Patent Office's recent request for information on how to improve patent search with artificial intelligence states prominently that disclosure is the standard: "As a federal agency, it is important for the USPTO to be able to explain all prosecution decisions made. Because of this, solution capabilities must be transparent to the USPTO and as well to the general public. Black box solutions will not be accepted."[122]

American administrative law traditions rightly value transparency as a mechanism for ensuring accountability. Moreover, as Colleen Chien's contribution to this Symposium emphasizes, the Patent Office has an admirable recent history of using open data to promote experimentation and learning.[123] As discussed in Part III, however, explainability and transparency are not identical concepts.[124] Moreover, neither full explainability nor full transparency is always necessary.

In eschewing trade secrecy, the Patent Office goes beyond current doctrine and places a heavy burden on its own internal resources. The Office creates the risk that it will exacerbate an already significant deficit in computational resources relative to the private sector.

Relatedly, to the extent it is fully transparent, the Patent Office is also vulnerable to gaming by those who want to manipulate its processes. Already, private sector firms advertise products, purportedly based on AI, that use publicly available examination data to predict the likelihood of examination outcomes in different art units, with the intention of assisting applicants in efforts to avoid art units that are perceived as too strict.[125]

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121. Arthi Krishna et al., U.S. PATENT & TRADEMARK OFFICE, TECHNICAL REPORT FS-16-02, EXAMINER ASSISTED AUTOMATED PATENTS SEARCH 1 (2016), https://www.aaai.org/ocs/index.php/FSS/FSS16/paper/view/14096/13682.

122. U.S. PATENT & TRADEMARK OFFICE, *supra* note 14.

123. *See generally* Colleen V. Chien, *Rigorous Policy Pilots: Experimentation in the Administration of the Law*, 104 IOWA L. REV. 2313 (2019) (arguing that framing new policy ideas as pilot policies will make it more likely for the policies to be adopted).

124. *See supra* Part III.

125. *See, e.g.*, *Top Five Ways Artificial Intelligence Can Improve Patent Prosecution*, LEXISNEXIS IP (Feb. 2, 2017), https://www.lexisnexisip.com/knowledge-center/top-five-ways-artificial-intelligence-can-improve-patent-prosecution; *TurboPatent Launches AI-Powered RoboReview to Improve Patent Drafting*, TURBOPATENT, https://turbopatent.com/turbopatent-launches-ai-powered-roboreview-to-improve-patent-drafting (last visited May 1, 2019). Analysts have also trained algorithmic classifiers to predict likelihood of rejection of claims as drawn to subject matter that is not eligible

In enforcement contexts, a well-established body of FOIA case law recognizes the possibility of gaming produced by transparency and explicitly allows agencies to withhold information likely to induce gaming. For example, the IRS has long used discrimination function ("DIF") scores to evaluate tax returns and determine which files to audit.[126] Courts have determined that release of this information would compromise the integrity of the IRS regulatory function by allowing individuals to manipulate their DIF scores and is, therefore, exempt under a number of different FOIA provisions that protect enforcement-related information.[127]

Because the Patent Office is not an enforcement agency, it cannot rely on FOIA's enforcement exception.[128] But the principles that animate FOIA's law enforcement exemption might, as a normative matter, tilt the scales in favor of some level of opacity. To put the point more sharply, if the Patent Office were to use private sector machine learning services, trade secrecy could provide a doctrinal basis for opacity that was normatively justified not only on conventional incentive grounds, but also because of concerns about gaming. But the Patent Office has, at least thus far, apparently not chosen to take a route that leaves it the option of relying on outside contractors' trade secrecy.[129]

As noted, the Patent Office's caution is quite understandable. Neither past Federal Circuit nor future Supreme Court decisions are necessarily going to be friendly to exercise of administrative power on its part. As various scholars have noted, however, the Patent Office has in the past been willing to take chances on potential hostile courts, particularly by allying itself with the Solicitor General.[130] Machine learning represents another case in which the Patent Office should take a chance.

V. CONCLUSION

The Patent Office's foray into machine learning for patent examination offers a window into how such use, even by agencies that don't address "hot button" questions of rights, bias, and privacy might nonetheless face constitutional and non-constitutional administrative law challenges. For these

for patenting under Section 101. *See, e.g.*, Ben Dugan, *Mechanizing* Alice*: Automating the Subject Matter Eligibility Test of* Alice v. CLS Bank, 2018 U. ILL. J.L. TECH. & POL'Y 33, 44–47.

126. *How Tax Returns Are Selected for Audit: Explaining DIF Scores and UI DIF Scores*, BROTMAN L., http://info.sambrotman.com/blog/how-tax-returns-are-selected-for-audit (last visited May 1, 2019).

127. *See, e.g.*, Gillin v. IRS, 980 F.2d 819, 822 (1st Cir. 1992); Lamb v. IRS, 871 F. Supp. 301, 304 (E.D. Mich. 1994) (finding that the IRS properly withheld DIF scores).

128. 5 U.S.C. § 552(b)(7) (2012).

129. Of course, to the extent that challengers to particular granted patents use private sector machine learning services to ferret out prior art, the PTAB's decisionmaking will be able to take advantage of private sector resources.

130. *See generally* John F. Duffy, *The Federal Circuit in the Shadow of the Solicitor General*, 78 GEO. WASH. L. REV. 518 (2010) (discussing the role of the executive branch in convincing the Supreme Court to overturn the Federal Circuit).

agencies, the most significant challenge will likely involve parsing the relationship between explainability and transparency.

As a positive matter, the Patent Office's relative weakness as an agency, and the uncertain future of administrative law, complicates what might otherwise seem an easy case. But from a normative standpoint, use of machine learning to search prior art is often self-validating (or self-invalidating). Because human examiners make the ultimate decision on novelty and nonobviousness, parties can (and do) simply argue over whether the art found is analogous or non-analogous. Only in cases where the art seems quite far afield will explainability of the process become particularly important. In that case, prior art search offers a lower-stakes adjudicatory context in which full explainability and transparency are not essential.

Widening the lens a bit, the Patent Office use case shows that machine learning may have significant benefits for the administrative state. Regrettably, challenges by powerful stakeholders to agencies' use of machine learning may create problematic intelligence asymmetries between the public and private sectors.