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Stanford Computational Antitrust

ARTICLE

Can Computational Antitrust Succeed?

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Abstract. Computational antitrust comes to us at a time when courts and agencies are underfunded and overwhelmed, all while having to apply indeterminate rules to massive amounts of information in fast-moving markets. In the same way that Amazon disrupted e-commerce through its inventory and sales algorithms and TikTok's progressive recommendation system keeps users hooked, computational antitrust holds the promise to revolutionize antitrust law. Implemented well, computational antitrust can help courts curate and refine precedential antitrust cases, identify anticompetitive effects, and model innovation effects and counterfactuals in killer acquisition cases. The beauty of AI is that it can reach outcomes humans alone cannot define as "good" or "better" as the untrained neural network interrogates itself via the process of trial and error. The maximization process is dynamic, with the AI being capable of scouring options to optimize the best rewards under the given circumstances,[1] mirroring how courts operationalize antitrust policy–computing the expected reward from executing a policy in a given environment. At the same time, any system is only as good as its weakest link, and computational antitrust is no exception. The synergistic possibilities that humans and algorithms offer depend on their interplay. Humans may lean on ideology as a heuristic when they must interpret the rule of reason according to economic theory and evidence. For this reason, it becomes imperative to understand, mitigate, and, where appropriate, harness those biases.

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[1] Brian S. Haney, *AI Patents: A Data Driven Approach* 19 Chi -Kent J. Intell. Prop. 407, 432 (2020).

I. Introduction

Launched in January 2021, Stanford University Codex Center's "Computational Antitrust" project studies the use of legal informatics to navigate complex and dynamic markets by automating antitrust procedures and improving antitrust analysis.[2] An undertow of ideological currents has always swept antitrust law.[3] In these waters, judges have extraordinary discretion in using economic theory and data to shape jurisprudence in erratic ways.[4] For the first time in antitrust's turbulent history, things could get much easier.

In the same way that Amazon disrupted e-commerce through its inventory and sales algorithms and TikTok's progressive recommendation system keeps users hooked, computational antitrust holds the promise to revolutionize antitrust law.[5] The team at Stanford is not alone with such bold plans. For instance, Giovanna Massarotto & Ashwin Ittoo built and tested an unsupervised antitrust machine learning (AML) application.[6] The algorithm autonomously datamined cases to discover underlying patterns and correlated them.[7] Progeny of algorithms like those Massarotto and Ittoo used could one day curate enormous data across decades and diverse industries, forensically detecting anomalies in market behavior and simulating to the nth degree the consequences of structural and behavioral remedies before a case ever gets to trial.

The promise of computational antitrust has attracted scores of admirers. The U.S. Justice Department announced its participation in the Stanford project shortly after its launch, and its website boasts no less than fifty other agencies spanning the economic powerhouses of Asia, North America, and Europe, as well as a diverse array of agencies from Latin America, the Middle East, and Africa.[8] Guiding the team's advisory board is a who's who of academics from antitrust law and computer science.[9]

With such lofty goals, the interest of a dazzling array of agencies, and the support of leading thinkers, it was a matter of time before the buzz would carry over into popular press, including the *New York Times* and *Le Monde*.[10] Doubtless,

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[2] *Project*, CODEX: STAN. CENTER FOR LEGAL INFORMATICS, https://law.stanford.edu/codex-the-stanford-center-for-legal-informatics/computational-antitrust-project (last visited Mar. 17, 2021); *see also* Thibault Schrepel, *Computational Antitrust: An Introduction and Research Agenda*, 1 STAN. COMPUTATIONAL ANTITRUST 1 (2021).

[3] *See generally* Marina Lao, *Ideology Matters in the Antitrust Debate*, 79 ANTITRUST L.J. 649 (2014).

[4] *See generally* Daryl Lim, *Retooling the Patent-Antitrust Intersection: Insights from Behavioral Economics*, 69 BAYLOR L. REV. 124, 144 (2017).

[5] *C.f.* Riccardo Guidotti, *Artificial Intelligence and Explainability*, in ARTIFICIAL INTELLIGENCE IN THE AUDIOVISUAL SECTOR 2, 8-10 (European Audiovisual Observatory, 2020), https://rm.coe.int/iris-special-2-2020en-artificial-intelligence-in-the-audiovisual-secto/1680a11e0b.

[6] *See* Giovanna Massarotto & Ashwin Ittoo, *Gleaning Insight from Antitrust Cases Using Machine Learning*, 1 STAN. COMPUTATIONAL ANTIRUST 16 (2021).

[7] *See id*. at 29-31.

[8] *Agencies*, CODEX: STAN. CENTER FOR LEGAL INFORMATICS https://law.stanford.edu/codex-the-stanford-center-for-legal-informatics/computational-antitrust-agencies (last visited Mar. 17, 2021).

[9] *Id.*; *see also DOJ Teams Up with Stanford Law for Antitrust Project*, COMPETITION POLICY INT'L (Jan. 19, 2021), https://www.competitionpolicyinternational.com/doj-teams-up-with-stanford-law-for-antitrust-project.

[10] *The intriguing idea of 'computational antitrust,'* N.Y. TIMES (Feb. 11, 2021), https://perma.cc/DS29-2LGY; *L'intelligence artificielle, précieuse alliée de la lutte contre les pratiques anticoncurrentielles*, LE MONDE (Feb. 15,

computation antitrust is an exciting proposition, but can it succeed? Humans have always muddled through when theory and empirical information are inadequate—we may do so poorly. Where can computational antitrust make the greatest difference? What are its perils? And what should its next steps be?

II. Three Tasks for Computational Antitrust

The Chicago School believes that antitrust law should be grounded in the belief that unrestrained competitive forces best allocate economic resources, offering the lowest prices and highest quality.[11] Chicago School antitrust, which dominated U.S. antitrust law for decades, believes *laissez faire* competition best delivers those results.[12] Judge Easterbrook summed it up by warning that judicial "[w]isdom lags far behind the market,"[13] and "[o]nly someone with a very detailed knowledge of the market process, as well as the time and data needed for evaluation, would be able to answer that question. Sometimes no one can answer it."[14] Until "doubts" about "the ability of courts to make things better even with the best data . . . have been overcome," there should not be antitrust enforcement.[15]

For the first time, computational antitrust holds the promise to soothe Chicagoan skepticism of false positives and judicial inaptitude. To do so, it should focus on three key tasks. First, computational antitrust should help judges and parties curate the law and facts. Second, computational antitrust should help with simulations in killer acquisition cases, where incumbents to maintain market share by buying and burying, rather than beating, rival technologies. It could do so by adding a new dimension of rigor to merger retrospectives. Third, it should help private plaintiffs and agencies persuade courts, particularly those sympathetic to Chicago School antitrust, that intervention will bring about a net positive result. In doing so, computational antitrust can empower plaintiffs to play the role antitrust policy envisions as guardians of a competitively robust marketplace.

2021), https://www.lemonde.fr/idees/article/2021/02/15/l-intelligence-artificielle-precieuse-alliee-de-la-lutte-contre-les-pratiques-anticoncurrentielles_6069968_3232.html.

[11] *See, e.g.*, Oliver E. Williamson, *The Economics of Antitrust: Transaction Cost Considerations*, 122 U. PA. L. REV. 1439, 1494-96 (1974).

[12] William E. Kovacic, *The Chicago Obsession in the Interpretation of US Antitrust History*, 87 U. CHI. L. REV. 459, 459, 462 (2020).

[13] *See* Frank H. Easterbrook, *The Limits of Antitrust*, 63 TEX. L. REV. 1, 5 (1984).

[14] *Id.*

[15] Frank H. Easterbrook, *Workable Antitrust Policy*, 84 MICH. L. REV. 1696, 1701 (1986).

A – Curating Law and Facts

Precedent can be unhelpful when the allegedly anticompetitive practice is new or where precedents are inconsistent with each other. Idiosyncratic rules make litigation highly costly and protracted when disputes arise, requiring extensive discovery and costly expert analysis.[16] As judges struggle to apply the rule of reason, they may end up confusing the doctrine even further.

Computational antitrust can scour reported cases to assess how past courts weighed competitive effects and identify influential factors. Some factors may be conventional. Others may be previously unobserved. For instance, algorithms could scour cases and match them against depositions and other preprocessed evidence to provide quicker and more consistent analyses. Big data, deep learning, and data mining can help identify relevant market variables even in the absence of an established theory and, more broadly, detect connections without (current) legal significance that parties do not know or have no capacity to examine.[17] Algorithms could also account for interactions among indicators that escape even expert witnesses, contextualize and associate information with the familiar, and provide predictions based on untrained parameters.[18]

Consider how unsupervised data mining algorithms might zero in on data clusters and probe those clusters to find other abstractions.[19] Or how principal component analysis identifies factors carrying the greatest weight in functions and zeroes in on the most important dimensions of datasets to show the stampeding factors.[20] Or how convolutional neural networks can abstract local features from examples by recognizing specific facts in opinions.[21]

Cases presenting the same set of facts would reach the same outcome as precedential cases presenting the same set of markers. For instance, an algorithm might be trained to identify circumstances when a defendant's denial of essential technological inputs is incidental to activity that does not improve the incumbent's product, but serves only to degrade the quality or quantity of rivals' products. Once algorithms produce their recommendation, judges may choose to accept or reject the AI's recommendation. More imminently, judges could simply use AI to suggest factors in the case for particularly close attention.

Case law provides only a starting point because precedent may or may not be based on sound economic analyses and ideology. Training AI using case precedents

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[16] *See e.g.*, Rohit Chopra & Lina M. Khan, *The Case for "Unfair Methods of Competition" Rulemaking*, 87 U. CHI. L. REV. 357, 359 (2020).

[17] *See* Theodore W. Ruger et al., *The Supreme Court Forecasting Project: Legal and Political Science Approaches to Predicting Supreme Court Decisionmaking*, 104 COLUM. L. REV. 1150, 1150 (2004).

[18] Similarly, AI-based support vector machines (SVMs) can find relationships between sets of antitrust cases while handling outlier or mislabeled cases, allowing SVM to crunch abrogated case law. *See, e.g.*, AURÉLIEN GÉRON, HANDS-ON MACHINE LEARNING WITH SCIKIT-LEARN & TENSORFLOW 145-67 (Nicole Tache et al. eds., 1st ed. 2017).

[19] PEDRO DOMINGOS, THE MASTER ALGORITHM 210 (2015).

[20] *Id.* at 217.

[21] *See, e.g.*, SEAN GERRISH, HOW SMART MACHINES THINK 135 (2018).

alone risks distorting economic realities further. For this reason, AI needs to be able to stress test outcomes of precedent against current market data of the case at hand.

Second, computational antitrust can help establish a new set of per se rules to simplify judging based on algorithmically derived presumptions. Courts have devised per se rules by, for example, using the damning presence of an agreement to fix prices as a sign of market inefficiency without engaging in a counterfactual exercise, giving defendants no opportunity to prove the value of those restraints.[22] A judge's unfamiliarity with the industry at issue would be less of an impediment as they would be able to apply precedent across industries, or as the Supreme Court wrote, "establish[] one uniform rule applicable to all industries alike."[23] Indeed, courts have noted that far from being a reason not to apply the per se rule, a judge's lack of experience in an industry is precisely the reason why they should do so.[24]

However, like the tide receding from the shoreline, the receding cover of per se rules left lower courts the unenviable task of weighing counterfactuals based on shifting social and economic theories, leaving more and more adjudication taking place under conditions of ignorance and uncertainty due to imperfect information and our limited capacity for cognition[25] By 1977, the Supreme Court declared, "[p]er se rules of illegality are appropriate only when they relate to conduct that is manifestly anticompetitive."[26]

Computational antitrust could allow judges to gradually broaden the instances when it might be appropriate to apply per se rules of illegality *and legality*. They can rely on computing muscle and a trove of data analytics to confidently assume that a confluence of certain facts would likely result in anticompetitive harm or not. AI can help keep the weighting of the probability of events consistent while adjusting weights in the data sets based on new economic evidence to reward producers who best serve consumer wants without requiring courts to act as central planners.

In sum, computational antitrust can significantly reduce the time and effort needed to analyze a case. More importantly, courts and agencies stand a much better chance at applying legal principles consistently, even when facts are idiosyncratic.[27] This reason alone would be enough to rally support for computational antitrust, but there are two further tasks that it should help address.

B – Forecast Killer Acquisitions

Merger analysis attempts to compare a hypothetical market outcome with the merger or acquisition with a hypothetical market outcome without it.[28] When the case involves acquisitions targeting companies in the early stages of product

[22] *Id.*

[23] Arizona v. Maricopa Cnty. Med. Soc'y, 457 U.S. 332, 349-51 (1982).

[24] *Id.*

[25] Jonathan Jacobson & Christopher Mufarrige, *Acquisitions of "Nascent" Competitors*, ANTITRUST SOURCE, Aug. 2020, at 11.

[26] Continental T.V., Inc. v. GTE Sylvania, Inc., 433 U.S. 36, 49-50 (1977).

[27] *See e.g.*, Colin S. Diver, *The Optimal Precision of Administrative Rules*, 93 YALE L.J. 65 (1983).

[28] *See, e.g.*, Brown Shoe Co. v. United States, 370 U.S. 294, 323 (1962).

development—"killer acquisitions"—the analysis must not only forecast a world where something has not yet happened; it must do so without the data points that a history of actual marketplace competition provides.[29] There are usually no direct competitors to the acquired companies to challenge these acquisitions, and harm to the acquirers' competitors may be too speculative at that point to support or a lawsuit or even to provide sufficient incentive to sue.

Nonetheless, the law requires judges to combine muddled precedent and guesswork to reach legally enforceable conclusions that affect not just the parties before them but also, through the precedential force of their own opinions, those across other industries for years to come. Given how difficult these counterfactual inquiries seem, one option is to give up on antitrust enforcement. This is exactly what supporters of killer acquisitions argue: whether users would be even better off without the acquisition is speculative.[30] They have argued that "the ability of the enforcer to predict technological changes and synergies in assessing the future pro- and anticompetitive effect of a transaction" is a key challenge.[31] Instead, they praise these acquisitions for allowing acquirers to improve product offerings, provide greater access to research and development capabilities, supply the acquired firm's users with greater support, and reward venture capitalists.[32]

However, it is also possible that competitive pressures from nascent rivalry increase the incumbent's competitive pressure to innovate in anticipation, suggesting that antitrust law should move toward prohibiting killer acquisitions. Empirical work by Carolina Destailleur et al. modeled killer acquisitions and illustrate how an incumbent firm buys the early-stage one before it can undermine the established firm's dominance and disrupt the industry.[33] They argue that "even though it is unforeseeable which projects could have been further developed and useful for society if the target had not been acquired at an early stage, and which ones could not, considering that the market and consumers might be significantly affected by these transactions, antitrust authorities should be worried or at least vigilant on this situation."[34] In essence, nascent rivals compete for the market, not merely within the market, and a bias toward intervention would aid dynamic efficiency since innovation may be the only way to dislodge the incumbent.[35]

Agencies currently employ merger retrospectives to improve review procedures and avoid generalizations.[36] They typically use a "differences-in-differences" (DiD) method to compare the merged entity to a control group unaffected by the merger

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[29] C. Scott Hemphill & Tim Wu, *Nascent Competitors*, 168 U. PA. L. REV. 1879, 1888 (2020).

[30] *Id*.

[31] EUROPEAN COMMISSION, DIGITALISATION AND ITS IMPACT ON INNOVATION 71 (2020) https://op.europa.eu/en/publication-detail/-/publication/203fa0ec-e742-11ea-ad25-01aa75ed71a1/language-en.

[32] Jacobson & Mufarrige, *supra* note 25, at 1.

[33] Carolina Destailleur et al., *Killer Acquisitions: Is Antitrust Prepared to Deal with Innovative Young Rivals*?, *in* MULHERES NO ANTITRUSTE. VOLUME II. SÃO PAULO: SINGULAR 26, 30 (Isabela Maiolino, ed., 2020), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3644593

[34] *Id*., at 36.

[35] *See* Hemphill & Wu, *supra* note 29, at 1888.

[36] *See* Rebecca Kelly Slaughter, Commissioner, Fed. Trade Comm'n, Merger Retrospective Lessons from Mr. Rogers, Remarks at the Hearings on Competition and Consumer Protection in the 21st Century: Merger Retrospectives (Apr. 12, 2019).

and study differences in product price, quality, output, and innovation over time.[37] Unfortunately, retrospectives are primitive and not very useful for killer acquisition cases.

First, merger retrospectives require precise data on market products, both pre- and post-merger, as well as data on the agency's predictions.[38] However, a merger might affect several marketsor be difficult to quantify.[39] Second, methodology for a merger retrospective may scrutinize data sources, price measures, control groups, and statistical methods. These may affect the measured effect or counterfactual.[40] Third, for them to be useful, merger retrospectives need to go beyond price effects. Too many retrospective merger studies rely heavily on pricing data because that is what is most readily available. However, that limits its usefulness in capturing the many nonprice dimensions of competition that truly inform the antitrust analysis.[41]

Enter computational antitrust, which works prospectively. This feature allows the algorithm to navigate dynamic market environments and not to stop the environment before computing.[42] To the extent variables in its dataset need modification, AI training techniques use autoencoders to update word embeddings, machine translation, document clustering, sentiment analysis, and paraphrase detection.[43] Stacking autoencoders on top of each other allows the first autoencoder to focus on encoding features at one level of abstraction. The next autoencoder uses the earlier output to recognize fact patterns and focus on encoding more abstract features.[44] Defining features broadly helps avoid overfitting, which happens when the learner fits the function to the data.[45] Overfitting also happens in legal reasoning when one ties a rule to the facts. The solution is to include more examples in training and testing the function against other test examples.[46]

With algorithmic assistance, stakeholders can control the variables and use reinforcement learning to employ an iterative process of updating those policies to converge on an optimal policy and optimal value function through a finite number of iterations.[47] In this way, computational antitrust can help generalize market

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[37] *See* Joseph J. Simons, Chairman, Fed. Trade Comm'n, Opening Remarks at the Hearings on Competition and Consumer Protection in the 21st Century: Merger Retrospectives (Apr. 12, 2019).

[38] *See* Dennis W. Carlton, *Why We Need to Measure the Effect of Merger Policy and How to Do It*, 5 COMP. POL'Y INT'L 77 (2009).

[39] *See* Karen Hoffman Lent & Kenneth B. Schwartz, *A Caution for Retrospective Merger Reviews*, MONDAQ (May 29, 2019), https://www.mondaq.com/unitedstates/maprivate-equity/809820/a-caution-for-retrospective-merger-reviews.

[40] *See id*.

[41] *See* Carlton, *supra* note 38.

[42] *Id*.

[43] See Venkata Krishna Jonnalagadda, *Sparse, Stacked and Variational Autoencoder*, MEDIUM (Dec. 6, 2018), https://medium.com/@venkatakrishna.jonnalagadda/sparse-stacked-and-variational-autoencoder-efe5bfe73b64.

[44] Gideon Lewis-Kraus, *The Great A.I. Awakening*, N.Y. TIMES (Dec. 14, 2016), https://www.nytimes.com/2016/12/14/magazine/the-great-ai-awakening.html.

[45] GÉRON, *supra* note 18, at 26-28.

[46] *Id*. at 29.

[47] *See id*.

information to help judges better assess predictions about intervention and achieve policy goals by formulating better antitrust rules.[48]

Repeated simulations will help courts and agencies determine optimal contestability conditions and better map synergies that affect innovation pathways by tracing user adoption of the technology. In doing so, computational antitrust could narrow the range of estimates and have designated numerical values. For instance, "probable" could mean a 60-80 percent chance of happening—this would reduce the risk of confusion. Moreover, by requiring computational antitrust to translate terms like "fair chance" to numbers, it encourages those involved in the process to think more carefully about how they arrived at the numerical range, reducing cognitive bias by metacognition.[49] Over time and with practice, the AI-human teams will get better at distinguishing finer shades of uncertainty.

C – Save the Antitrust Plaintiff

Antitrust plaintiffs face systemic biases that computational antitrust may help address. For instance, in an antitrust suit, plaintiffs must cumulatively show market power and an antitrust injury.[50] By comparison, defendants can rebut each element in multiple ways. The procedural asymmetry between plaintiffs and defendants translates into plaintiffs expending resources to establish each element of their cause of action, while defendants focus on a single ground to defend. Plaintiffs face rigorous scrutiny in their attempt to vindicate their rights.

Work by Gideon Parchomovsky and Alex Stein shows that the best way to realize the goals of compensation and deterrence generally is to enable victims to pursue individual justice against those who wronged them.[51] Compensation funds also recompense victims but do little to prevent future wrongs.[52] Against this backdrop, Andrew Gavil and Steven Salop observed that Chicago's "[t]he goal of preventing false positives provided a focus for the comparative evaluation of alternative legal rules, and became a barometer for evaluating the scope of antitrust prohibitions. This translated into a call for a higher evidentiary burden on plaintiffs in cases alleging exclusionary conduct, which included a requirement of more economic evidence to support competitive harm allegations.".″[53]

Under Chicago's rule, plaintiffs lose an overwhelming majority of cases in the face of heightened procedural, evidential, and substantive barriers,[54] even while judges relax scrutiny of vertical agreements, dominant firm behavior, and mergers

[48] MAX TEGMARK, LIFE 3.0: BEING HUMAN IN THE AGE OF ARTIFICIAL INTELLIGENCE 85-86 (2017).
[49] Daryl Lim, *Predictive Analytics*, 51 LOY. U. CHI. L.J. 161, 232 (2019).
[50] Brunswick Corp. v. Pueblo Bowl-O-Mat, Inc. 429 U.S. 477 (1977).
[51] Gideon Parchomovsky & Alex Stein, *Empowering Individual Plaintiffs*, 102 CORNELL L. REV. 1319, 1325 (2017).
[52] *Id.*
[53] Andrew I. Gavil & Steven C. Salop, Probability, Presumptions and Evidentiary Burdens in Antitrust Analysis: Revitalizing the Rule of Reason for Exclusionary Conduct, 168 U. PA. L. REV. 2107, 2111–12 (2020).
[54] Lina M. Khan, *The End of Antitrust History Revisited*, 133 HARV. L. REV. 1655, 1676 (2020). *See also, e.g.*, Michael A. Carrier, *The Rule of Reason: An Empirical Update for the 21st Century*, 16 GEO. MASON L. REV. 827, 828-30 (2009).

to benefit defendants.[55] Judge Posner summed it up by observing the rule of reason was simply a "euphemism for non-liability."[56] Empowering judges to focus on adjudication will be crucial for courts to administer justice more efficiently and effectively in antitrust cases.

Adherents to the Chicago School believe anticompetitive exclusion is ineffective and enjoy several ready justifications, including preventing free-riding, minimizing transaction costs, and permitting straightforward profit maximization.[57] Unfortunately, Chicago School antitrust has not developed a reliable way to weigh false positive and false negative risks or estimate their relative costs.[58] Yet this has not stopped judges, worried about chilling procompetitive conduct and the high costs of litigation on the one hand, while dismissive of the costs of failing to deter harmful conduct on the other, from relying on unsupported claims about competitive effects.[59]

Uncertainty may skew actors towards corporate opportunism. Businesses have much to gain, and the likelihood of being successfully sued for treble damages is low when rules are uncertain.[60] Judicial permissiveness exacerbates this state of affairs.[61] Judges, overwhelmed by complex rules and markets and wary of private litigation, embraced Chicago's statements of faith in the market's ability to renew itself, in turn systematically diminishing antitrust plaintiffs' ability to prevail.[62]

Over the last several decades, courts have indeed taken on this article of faith in blessing widening price-cost margins, regarding them as nothing more than free-market efficiencies at work.[63] Consider how Chief Justice Roberts, writing for the dissent in *Actavis*, a case involving pharmaceutical patents, used consumer welfare precisely as the basis for approving reverse payment settlements that resulted in substantially higher prices to consumers.[64] Similarly, the majority in *American Express*, a case dealing with Amex's anti-steering rules, paid lip service to consumer welfare while endorsing higher consumer prices.[65]

Plaintiffs are indispensable to our legal system. They play a pivotal role in exposing misconduct and help the system achieve its policy goals. Erase any meaningful chance of success, and the checks against behavior that stifles market competition will stumble and collapse. Computational antitrust may give plaintiffs

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[55] *See e.g.,* Brunswick Corp v. Pueblo Bowl-O-Mat, Inc., 429 U.S. 477 (1977).

[56] Richard A. Posner, *The Rule of Reason and the Economic Approach: Reflections on the Sylvania Decision*, 45 U. CHI. L. REV. 1, 14 (1977).

[57] *See* Richard A. Posner, *Exclusionary Practices and the Antitrust Laws*, 41 U. CHI. L. REV. 506, 508 (1974).

[58] Lao, *supra* note 3, at 663.

[59] Andrew I. Gavil & Steven C. Salop, *Probability, Presumptions and Evidentiary Burdens in Antitrust Analysis: Revitalizing the Rule of Reason for Exclusionary Conduct*, 168 U. PA. L. REV. 2107, 2124 (2020).

[60] *Id.*

[61] *Id.*

[62] *See* William E. Kovacic, *The Chicago Obsession in the Interpretation of US Antitrust History*, 87 U. CHI. L. REV. 459 (2020) ("Discussions about the evolution of the US antitrust system since the early 1970s often dwell upon the influence of the Chicago School in shaping substantive rules and enforcement policy.").

[63] Herbert J. Hovenkamp, *Antitrust: What Counts as Consumer Welfare?*, FACULTY SCHOLARSHIP AT PENN LAW (2020), https://scholarship.law.upenn.edu/faculty_scholarship/2194.

[64] *See* FTC v. Actavis, Inc., 570 U.S. 136, 161 (2013) (Roberts, C.J., dissenting).

[65] Ohio v. Am. Express Co., 138 S. Ct. 2274 (2018).

a better basis to overcome Chicago School misgivings to prove improper, actionable antitrust violations. It may assist others further afield as well. Restoring a reasonable chance of succeeding in litigation to plaintiffs helps preserve public trust in the law, and it is the right thing to do.

III. The Perils of Computational Antitrust

Reflecting on computational antitrust, Eleanor Fox noted that "[w]hen you talk about data, you also have to talk about values . . . And assumptions."[66] Fox touches on a fundamental obstacle to the success of computational antitrust. Humans are not designed to process vast amounts of quantitative data, a problem the economic literature calls "bounded rationality."[67] They rely on heuristics such as ideology to navigate the world, shaped by personal experiences, beliefs, and biology.[68] When humans code, their coding is not value-neutral, and biases may seep into the algorithmic code, filtering into training data and the weights judges may assign to the algorithm.[69] Algorithms will likely be path-dependent, as Tom Nachbar observed, "based on decisions made in previous iterations of the program—prompting a cascading search for purpose."[70]

Of course, training datasets themselves may contain biases and lead to unfair and legally erroneous decisions. For example, a case from the 1970s would likely have been decided on Chicago School's terms, weighing potential losses to dynamic efficiency more than the intervention's potential gains.[71] Earlier cases may be more Neo-Brandeisian by comparison, favoring small businesses because of a political preference for atomism over economic efficiency.[72] Moreover, the training data may identify the criteria for evaluation and replicate the problems as we advance if based on bad theories. This problem is all the more systemic in reinforcement learning, where the reward may be a biased identification, generating even more bias over time, raising the risk of what Nachbar labeled "snowballing unfairness."[73]

Andrew Selbst expressed concern that using AI in adjudication exchanges one problem-bounded rationality for another: the inability to oversee or understand how AI decides completely.[74] Sophisticated algorithms are too complicated to be read and evaluated even by data scientists and software engineers.[75] Moreover, the

[66] N.Y. TIMES, *supra* note 9.

[67] *See* Shyamkrishna Balganesh, *Foreseeability and Copyright Incentives*, 122 HARV. L. REV. 1569, 1574 (2009).

[68] Daniel R. Cahoy, *Patently Uncertain*, 17 NW. J. TECH. & INTELL. PROP. 1, 13 (2019).

[69] *See* Dan L. Burk, *Algorithmic Fair Use*, 86 U. CHI. L. REV. 283, 283 (2019).

[70] Thomas Nachbar, *Algorithmic Fairness, Algorithmic Discrimination*, 48 FLA. ST. U. L. REV. (forthcoming 2021).

[71] *See, e.g.*, Roger G. Noll & James E. Krier, *Some Implications of Cognitive Psychology for Risk Regulation*, 19 J. LEGAL STUD. 747, 758 (1990).

[72] *See, e.g.*, United States v. Aluminum Co. of Am., 148 F.2d 416 (1945).

[73] Thomas Nachbar, *Algorithmic Fairness, Algorithmic Discrimination*, 48 FLA. ST. U. L. REV. (forthcoming 2021).

[74] Andrew D. Selbst, *Negligence and AI's Human Users*, 100 B.U. L. REV. 1315, 1362 (2020).

[75] *See, e.g.*, Yavar Bathaee, *The Artificial Intelligence Black Box and the Failure of Intent and Causation*, 31 HARV. J.L. & TECH. 889, 907 (2018).

massive scale of datasets makes it hard to scrutinize their contents and perpetuate algorithmic bias thoroughly.[76]

Before rejecting computational antitrust on the grounds of transparency, however, it is helpful to recall that human decision-making is not significantly more accountable than AI. Consider, for example, how antitrust's rule of reason itself is a black box. Simply put, it is a sequence of rules operationalizing policy judgments about how antitrust law should weigh economic costs, benefits, and possibilities. To say a restraint on competition is legal is to say it was, on balance, benign. Chief Justice Roberts complained about the "amorphous rule of reason."[77] Justice Breyer observed that implementing procompetitive benefits in the rule of reason analysis is an "absolute mystery."[78]

Courts operating on ideology may write for justification and not for explanation. This conclusion discounts the precedents' value as accurately revealing the facts that the legal principles within those precedents are supposed to operate on. In contrast, computational antitrust may provide a better forum for stakeholders to improve the process once it is known that the algorithm produces systematically problematic outcomes.[79]

The temptation to dumb down computational antitrust to further explainability should similarly be avoided. The lack of explainability is a feature of AI's ability to recognize connections not obvious to humans, and indeed the purpose of using them in the first place.[80] Dumbing down AI to improve its explainability comes with further problems: the algorithm may become less effective or more vulnerable to gaming and adversarial learning by regulated parties.[81]

For these reasons, those seeking transparency may find accountability both a more realistic and helpful goal.[82] Accountability attempts to explain what both the algorithms and their users seek to achieve.[83] We can use an interpretable model, substituting components in the system with more interpretable facets with computational antitrust. Decision trees used in AI analyses reliably track how courts apply legal standards to facts.[84] Decision trees are composed of internal nodes representing tests on features or attributes, with each branch representing a

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[76] Khari Johnson, *AI Research Survey Finds Machine Learning Needs a Culture Change*, VENTUREBEAT (Dec. 26, 2020, 8:45 AM), https://venturebeat.com/2020/12/26/ai-research-survey-finds-machine-learning-needs-a-culture-change/.

[77] FTC v. Actavis, Inc., 570 U.S. 136, 160 (2013) (Roberts, C.J., dissenting).

[78] Transcript of Oral Argument at 24, Ohio v. Am. Express Co., 138 S. Ct. 2274 (2018) (No. 16-1454). *See also* PHILLIP E. AREEDA & HERBERT HOVENKAMP, ANTITRUST LAW: AN ANALYSIS OF ANTITRUST PRINCIPLES AND THEIR APPLICATION ¶ 1504, at 414 (4th ed. 2017).

[79] *See* Maurice E. Stucke, *Does the Rule of Reason Violate the Rule of Law?*, 42 U.C. DAVIS L. REV. 1375, 1461–66 (2009).

[80] *Id.*

[81] *See* David Freeman Engstrom et al., *Government by Algorithm: Artificial Intelligence in Federal Administrative Agencies*, REPORT SUBMITTED TO THE ADMINISTRATIVE CONFERENCE OF THE UNITED STATES 86 (Feb. 2020), https://www.acus.gov/report/government-algorithm-artificial-intelligence-federal-administrative-agencies.

[82] Nachbar, *supra* note 69, at s61.

[83] *Id.* at 62.

[84] *See* Stephen McJohn & Ian McJohn, *Fair Use and Machine Learning*, 12 NE. U.L. REV. 99, 148 (2020).

possible outcome. The path from roots to leaves represents the classification rules.[85] The algorithm typically uses "if-then rules," where the "if" clause combines conditions on the input variables.[86]

The rule of reason is particularly suited to this technique since it also follows a logical sequence, allowing each step to be coded, disaggregated, and individually assessed by courts and data scientists. As the algorithm sorts through the data, decision trees can analyze and predict whether the facts lean toward a case being anticompetitive, qualifying predictions with a probability relative to other cases sharing similar attributes.[87]

Done well, computational antitrust will help minimize biases from human decision-making without compounding those biases with its own.[88] In the years ahead, ethics teams will likely become an essential department in antitrust agencies and economic consultancies such as finance, legal, marketing, and human resource departments already are. These teams can help decision-makers weigh benefits and harms of algorithmic processes and recommendations, flag their implications, develop guidelines, and clarify ethical conflicts.[89]

IV. Next Steps for Computational Antitrust

David Ricardo espoused a theory of labor allocation based on comparative advantage.[90] With computational antitrust, algorithms can reduce the cognitive bias in human judgment. In contrast, humans can mitigate the systemic weakness in an algorithm's ability to produce robust outcomes when there is little data or when it requires goal-setting and weighted values.[91]

Judges and enforcers can be resistant to evidence that undercuts our own beliefs, which can be a serious issue in the malleable environment where a legal policy or case law is decided, such as with antitrust law.[92] With computational antitrust, the algorithm can provide an initial prediction that stakeholders can use as a factor in their assessments. As computational antitrust becomes more commonly used, stakeholders' value judgments will be more valuable, not less, since the likelihood of getting it "right" in a given case will be all the greater.

Parties will need to do their part, presenting data to support the narratives they wish to advance. The usual rules of evidence will govern the data. Where they are lacking, such as is the "value of technology," parties will need to persuade the judge what that value should encompass. Defining payoffs will be hard, particularly

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[85] *See* Riccardo, *supra* note 4, at 13-14.
[86] *See id*.
[87] *See id.* at 21.
[88] *See* Meghan J. Ryan, *Secret Conviction Programs*, 77 WASH. & LEE L. REV. 269, 281–87 (2020).
[89] *See* Lim Sun Sun & Jeffrey Chan Kok Hui, *Moving AI Ethics Beyond Guidelines*, STRAITS TIMES, (Dec. 16, 2020), https://www.straitstimes.com/opinion/moving-ai-ethics-beyond-guidelines-0.
[90] *See generally* DAVID RICARDO, ON THE PRINCIPLES OF POLITICAL ECONOMY AND TAXATION (1817).
[91] AJAY AGRAWAL ET AL., PREDICTION MACHINES: THE SIMPLE ECONOMICS OF ARTIFICIAL INTELLIGENCE 2 (2018).
[92] *See generally* ZIVA KUNDA, SOCIAL COGNITION: MAKING SENSE OF PEOPLE (1999).

without markets to provide valuations (e.g., assessments of "good" outcomes, like what access to patented technology is worth), but as predictive algorithms gain additional knowledge about the probabilities of occurrence, ambiguity disappears, and the choices become clearer.[93] AI scoring tools can then help to standardize concepts against technical and commercial criteria, curating data on the value of technology, anticipated short and long-term implications, and the likelihood of commercial success.[94] In such instances, judges need to articulate what kinds of corrections to precedent are warranted, so AI does not increase biases rather than reduce them.

Computational antitrust could make antitrust suits faster and cheaper. Current rules make bringing an antitrust suit highly costly and protracted. The Supreme Court described antitrust litigation as "interminable"[95] with an "inevitably costly and protracted discovery phase,"[96] yielding an antitrust system that Maurice Stucke judged as "hopelessly beyond effective judicial supervision."[97] Once the antitrust matter gets to trial, its plod may fail to keep pace with the market.[98] It can take a decade or more to bring a case to judgment.[99] Lengthy, costly litigation may paralyze government-enforcement efforts in policing anticompetitive conduct. In this sense, computational antitrust could supercharge the velocity of litigation and make swift justice work for the benefit of all.

V. Conclusion

Computational antitrust comes to us at a time when courts and agencies are underfunded and overwhelmed, all while having to apply indeterminate rules to massive amounts of information in fast-moving markets. Thibault Schrepel, leader of the Stanford project, argues that automation is a way to "fight fire with fire."[100]

Implemented well, computational antitrust can help courts curate and refine precedential antitrust cases, identify anticompetitive effects, and model innovation effects and counterfactuals in killer acquisition cases. The beauty of AI is that it can reach outcomes humans alone cannot define as "good" or "better" as the untrained neural network interrogates itself via the process of trial and error. The maximization process is dynamic, with the AI being capable of scouring options to optimize the best rewards under the given circumstances,[101] mirroring how courts operationalize antitrust policy - computing the expected reward from executing a policy in a given environment.

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[93] *See* Gary Charness & Dan Levin, *When Optimal Choices Feel Wrong: A Laboratory Study of Bayesian Updating, Complexity, and Affect*, 95 AM. ECON. REV. 1300, 1300 (2005).

[94] Carlo Cotrone, *Overcoming Cognitive Bias in Patent Filing and Maintenance Decisions,* IPWATCHDOG (Dec. 4, 2019), https://www.ipwatchdog.com/2019/12/04/overcoming-cognitive-bias-patent-filing-maintenance-decisions/id=116566.

[95] Verizon Comms., Inc. v. Trinko, 540 U.S. 398, 414 (2004).

[96] Bell Atlantic Corp. v. Twombly, 550 U.S. 544, 558 (2007).

[97] Maurice E. Stucke, *Does the Rule of Reason Violate the Rule of Law?*, 42 U.C. DAVIS L. REV. 1375, 1378 (2009).

[98] *See, e.g.*, Kevin Caves & Hal Singer, *When the Econometrician Shrugged: Identifying and Plugging Gaps in the Consumer Welfare Standard*, 26 GEO. MASON L. REV. 395, 424 (2019).

[99] *See, e.g.*, Jonathan M. Jacobson, *Tackling the Time and Cost of Antitrust Litigation*, 32 ANTITRUST 3 (2017).

[100] N.Y. TIMES, *supra* note 9.

[101] Brian S. Haney, *AI Patents: A Data Driven Approach* 19 CHICAGO -KENT J. INTELL. PROP. 407, 432 (2020).

At the same time, any system is only as good as its weakest link, and computational antitrust is no exception. The synergistic possibilities that humans and algorithms offer depend on their interplay. The algorithm and training sets must be constantly refined and debiased. And each slice of human ingenuity from a judge or enforcer comes spiked with a dose of cognitive bias. Humans may lean on ideology as a heuristic when they must interpret the rule of reason according to economic theory and evidence. For this reason, it becomes imperative to understand, mitigate, and, where appropriate, harness those biases.

The cumulative sum of the Stanford project's efforts will draw responses from others whose vantage points are informed by their own experiences and insights. Similarly, new behavioral insights and technological advances may be adapted to refine computational antitrust analysis and develop creative responses to anticompetitive behavior in yet undiscovered commercial frontiers.[102] The enterprise of developing a coherent understanding of computational antitrust's implications on the status quo has only begun. In this, in all our endeavors, we can be grateful to the Stanford project team for providing a focal point for our collective efforts.

[102] *See e.g.* Lim, *supra* note 4 at 144.