

Can We Teach Antitrust to an Algorithm?

By Giovanna Massarotto & Ashwin Ittoo



Can We Teach Antitrust to an Algorithm?

By Giovanna Massarotto* & Ashwin Ittoo**

The answer is “Yes.” Prof. Ashwin Ittoo and I have built a machine learning (“ML”) algorithm — an AI application — to assist antitrust agencies in enforcing antitrust (“AML”).¹

1. Why an ML algorithm?

ML is the main AI application² and it is commonly referred as weak AI, because the algorithm is not *intelligent* by itself but rather learns from a large amount of data — *big data*. Thanks to an increasingly high-speed internet connectivity and devices, such as smartphones, we are always online and data has become today’s most valuable resource.³ Today, most companies are jumping into the data industry to exploit data in the field of AI and create new applications. Data and AI techniques can be used to create a variety of different AI applications in any sectors, including Siri speech recognition or AI techniques to suggest movies that we might like on Netflix. There are a number of AI techniques, which are mainly distinguished into two macro categories: supervised (“SL”) and unsupervised learning (“UL”). The main difference is that a supervised algorithm is fed by a large amount of data and learns a specific

task you ask for. In other words, you provide data classified into variables and you ask the algorithm to identify the value related to a specific variable. In unsupervised learning such as clustering, which we adopted in our ML, you do not ask the algorithm to find something in particular (namely learn a specific task) but allow the algorithm to learn completely on its own. Unlike SL, in UL the algorithm looks for identifying rules or associations from data—there is no prior training or exploration phases.⁴

2. AML

In the development of our AML we started analyzing data from my book “Antitrust Settlements — How a Simple Agreement Can Drive the Economy” which analyzed a large amount of antitrust cases in the two main antitrust jurisdictions — the U.S. and EU. But we soon realized that there were too many differences in these two jurisdictions and our algorithm was unable to identify any useful patterns from recent cases. Thus, we selected the U.S. jurisdiction by focusing on the FTC’s enforcement actions under Section 5 of the FTC Act. The DOJ and the FTC have different

* Adjunct Professor University of Iowa, Research Associate UCL CBT.

** Associate Professor, University of Liege.

¹ Giovanna Massarotto & Ashwin Ittoo, *Can AI Replace the FTC?* (Nov. 18, 2020) available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3732766.

² THOMAS HARDJONO, DAVID L. SHRIER & ALEX PENTHLAND, *TRUSTED DATA, A NEW FRAMEWORK FOR IDENTITY AND DATA SHARING* (MIT Press, 2019).

³ Giovanna Massarotto, *From Standard Oil to Google: How the Role of Antitrust Law Has Changed*, 41 *WORLD COMPETITION* 395 (2018); GIOVANNA MASSAROTTO, *ANTITRUST SETTLEMENTS: HOW A SIMPLE AGREEMENT CAN DRIVE THE ECONOMY* 145 (Wolters Kluwer, 2019).

⁴ Massarotto & Ittoo, *supra* note 1.

powers and tasks, although some might overlap.⁵ We did not include mergers, but rather focused on Section 5 of the FTC Act cases, which are settled through consent decrees over 90 percent of the time.⁶ We selected about seventy cases of these Section 5 proceedings settled by means of consent decrees and classified them into variables, such as industry, types of conduct, and remedies. Initially there were thirteen variables, including the industry; three different types of investigated conduct, and four remedies, distinguishing between structural and behavioral remedies.

Having collected and classified our data in a dataset we applied different AI techniques. We used UL methods as we thought it would be more interesting to see what the algorithm would learn on its own rather than asking the algorithm to perform a specific task (find a specific variable). More specifically, we used clustering methods to attempt to automatically identify similar cases in our dataset. We investigated three different clustering algorithms, namely K-Means, Bisecting K-Means and K-Modes, to determine which one was most suitable for our task. In addition, we also determined which features (characteristics/variables) of the cases were the most pertinent. To this aim, we relied on two SL methods, viz. Random Forests and Support Vector Machines. The results (in terms of feature importance) of these two methods corroborated each other.

Overall, we were interested in understanding whether a similar algorithm could be built to suggest possible anticompetitive practices to the FTC, as well as what remedies to enforce.

3. AML Results

Having adopted different ML techniques, the best performing algorithm detected four clusters. We tested these four clusters and their variables to identify those that were more informative. In particular, some insightful results have been revealed from cluster 4, which mainly clustered price-fixing cases in the healthcare/pharmaceutical industry by suggesting “limitation in the exchange of information” and “compliance obligations” as remedies. Cluster 3 seems to suggest that, in cases where the FTC investigated merely one anticompetitive practice or two, the agency imposes no remedies or a selection of remedies, including “compliance obligation,” “the implementation of a compliance program,” or “limitation in the exchange of information.” Cluster 2 concerns cases where the FTC investigated more than two anticompetitive practices by adopting “compliance obligations” as remedy by default. The second remedy suggested in this cluster is “limitation in the exchange of information,” which makes antitrust sense, as seventy percent of cases detected in this cluster are concerned with “conspiracy” conduct. Finally, cluster 1 is interesting as it clustered cases from the

⁵ Federal Trade Commission, The Enforcers, <https://www.ftc.gov/tips-advice/competition-guidance/guide-antitrust-laws/enforcers> (last visited Sep. 30, 2020).

⁶ Joshua D. Wright & Douglas H. Ginsburg, *The Economic Analysis of Antitrust Consents*, 3 EUR. J. OF L. AND ECONOMICS, Forthcoming (Mar. 14, 2018). Available at <https://ssrn.com/abstract=3140736>.

healthcare industry with those from the computer industry by detecting similar conduct.

We also tested and analyzed the variables from both an antitrust and technical perspective. From a technical point of view, the different techniques revealed four different types of conduct and one remedy as the most informative variables. In short, the distinction between structural and behavioral remedies, the year, the name of cases, and other remedies that we used as variables to classify antitrust cases were excluded. From an antitrust perspective the exclusion of these variables make sense. Section 5 of the FTC Act has not changed over time, antitrust conducts are prosecuted in all industries in the same way, although in some industries some anticompetitive practices are, as we have seen, more common. The distinction between structural and behavioral remedies looks meaningless, as we identified the type of conduct in more detail (e.g. price fixing, exchange of information, and refusal to deal).

4. Conclusions

In conclusion, we found that teaching antitrust to an algorithm is actually feasible, as both the clusters and variables that our ML detected seem to make antitrust sense. We admit that AI cannot replace the FTC. However, AI methods can be useful in making antitrust enforcement actions faster and more efficient. Moreover, we noted that these tools can make antitrust enforcement more predictable for companies. Thus, this would help market players to better understand what can and cannot be considered anticompetitive, in addition to suggesting procompetitive remedies to adopt if a specific anticompetitive practice is detected.

In summary, we do not actually think that AI techniques can replace antitrust enforcers. But we do believe that antitrust enforcers can exploit AI methods to make their work more efficient in today's fast-moving technological markets