

Price-Bots, Are R2-D2 and C-3PO Tacitly Colluding?

By Michelle A. Cleary



Michelle A. Cleary is a Senior Consultant at The Brattle Group

Artificial intelligence (“AI”) raises concerns for antitrust enforcers. Indeed, the FTC has been gathering expertise on AI, which it covered during its recent hearings.¹ Through AI, companies are better able to analyze large amounts of data and engage with customers. AI can also allow firms to track and communicate with competitors, beyond the capability of human counterparts. For example, AI has become increasingly sophisticated in that it allows firms to react to changes in the marketplace and set prices within milliseconds. These AI-based technologies present unique challenges with respect to antitrust regulation. It is not clear whether antitrust enforcers’ toolset can measure the impact of these new technologies and, if so, assess liability in a way that can protect consumers. Do antitrust authorities need to adapt?

At the 2018 ABA Antitrust Section Spring Meeting, the Civil Practice and Procedure Committee devoted the program, “Price-Bots, Are R2D2 and C3PO Tacitly Colluding?,” to addressing these questions. The program was chaired by Paul Saint-Antoine with Lesli Esposito, Co-Chair of DLA Piper’s Antitrust and Trade Regulation Practice, as moderator (and contributor). Other panelists included Professor Joshua Gans, Professor of Strategic Management, Jeffrey S. Kroll Chair of Technical Innovation at the Rotman School of Management, University of Toronto, and Academic Advisor to The Brattle Group; Professor Maurice E. Stucke, Professor at University of Tennessee College of Law, and Dr. Ai Deng, Principal at Bates White Economic Consulting and lecturer at Johns Hopkins University’s Advance Academic Program.

Dr. Deng kicked off the discussion explaining that while the terms “artificial intelligence” and “machine learning” are used interchangeably in the antitrust community, machine learning is not “intelligence” but rather a way to achieve intelligence.² Machines “learn” in three major ways: (1) examples; (2) differences; and (3) trial and error. Data such as prices and price drivers—often supply and demand factors—are examples from which machines learn. Machines also learn through grouping or separating data points based on how similar or different they are; this form of learning is essentially pattern recognition or, once a norm is established, anomaly detection (such as fraud

¹ Fed. Trade Comm’n, HEARING #7: COMPETITION AND CONSUMER PROTECTION IN THE 21ST CENTURY (Nov. 13-14, 2018), <https://www.ftc.gov/news-events/events-calendar/ftc-hearing-7-competition-consumer-protection-21st-century>.

² Ai Deng, *An Antitrust Lawyer’s Guide to Machine Learning* (Jan. 9, 2018), <https://ssrn.com/abstract=3082514>.

detection).³ The third mode of machine learning, through trial and error, is feedback-oriented (or “reinforced learning”) where rewards are granted for good outcomes or performance.⁴ For example, AlphaGo is a reinforced learning (RL) algorithm that learned the ancient game of Go by studying thousands of games played by humans and by playing itself millions of times; it prevailed over human world champions in 2016 and 2017.⁵

Dr. Deng explained that machines learn through algorithms. Algorithms are merely detailed, step-by-step procedures designed by humans to solve problems. For example, a pricing algorithm can be designed to set prices based on competitors’ prices and customer demographics. Pricing algorithms can also be “dynamic,” whereby they allow for prices to respond quickly to changes in the market.⁶

The antitrust concern is that, as these pricing algorithms become more prevalent and complicated, they could lead to anticompetitive outcomes. Dr. Deng explained that some in the antitrust community are especially concerned with deep learning, or deep neural networks, because they involve extremely complex algorithms based on non-linear transformations of data and their intricacy makes it hard to unravel the decision making process.⁷ The process of deep learning potentially inhibits enforcers from explicitly identifying an anticompetitive objective or coordinated behavior.⁸ Dr. Deng then discussed why some of the concerns are mitigated by realizing that the algorithm-prescribed behavior is observable and can often be interpreted by antitrust enforcers.⁹

The panel discussed four potential anticompetitive scenarios in which algorithms can play a role: (1) the messenger; (2) hub-and-spoke; (3) the predictable agent; and (4) the digital eye.¹⁰

³ *Id.*

⁴ *Id.*

⁵ *Id.*; Joshua Gans and Avi Goldfarb, *How AI Will Change the Way We Make Decisions*, HARV. BUS. REV., July 26, 2017, <https://hbr.org/2017/07/how-ai-will-change-the-way-we-make-decisions>.

⁶ Ai Deng, *When Machines Learn to Collude: Lessons from a Recent Research Study on Artificial Intelligence* (Aug. 30, 2017), <https://ssrn.com/abstract=3029662>; Antonio Capobianco, Pedro Gonzaga, and Anita Nyesö, ALGORITHMS AND COLLUSION – BACKGROUND NOTE BY THE SECRETARIAT (June 9, 2017), [https://one.oecd.org/document/DAF/COMP\(2017\)4/en/pdf](https://one.oecd.org/document/DAF/COMP(2017)4/en/pdf).

⁷ Indeed, then FTC Commissioner, Terrell McSweeney, in a speech to the University of Oxford Center for Competition Law and Policy in May 2017, remarked, “Pricing algorithms raise three issues from a competition perspective. First, they may increase the effectiveness of overt collusion. Second, they may facilitate coordinated interaction in the absence of a traditional ‘agreement’ between competitors. And third, they may enable price discrimination strategies that lead to higher prices for certain groups of customers.” Terrell McSweeney, Fed. Trade Comm’n, *Algorithms and Coordinated Effects* (May 22, 2017), https://www.ftc.gov/system/files/documents/public_statements/1220673/mcsweeney_-_oxford_cclp_remarks_-_algorithms_and_coordinated_effects_5-22-17.pdf.

⁸ Ariel Ezrachi and Maurice E. Stucke, ALGORITHMIC COLLUSION: PROBLEMS AND COUNTER-MEASURES (May 31, 2017), <https://www.oecd.org/officialdocuments/publicdisplaydocumentpdf/?cote=DAF/COMP/WD%282017%2925&docLanguage=En>.

⁹ Ai Deng, *Four Reasons We May Not See Colluding Robots Anytime Soon*, LAW 360 (Oct. 3, 2017), <https://www.law360.com/articles/970553/4-reasons-we-may-not-see-colluding-robots-anytime-soon>.

¹⁰ Ariel Ezrachi and Maurice E. Stucke, *Artificial Intelligence & Collusion: When Computers Inhibit Competition*, 2017 U. ILL. L. REV. (2017), <https://ssrn.com/abstract=2591874>.

The messenger scenario is a scheme in which manufacturers agree to use certain algorithms to coordinate prices and keep prices artificially high (the *US v. Topkins* poster case is an example).¹¹ Professor Stucke explained that this scenario is the digital equivalent of the proverbial smoke-filled room agreement—i.e., competitors make a conscious price-fixing agreement, which is executed via algorithms that follow human instructions to effectuate and monitor the cartel and punish defectors. Hence, the computers are merely acting as “messengers” among the various human co-conspirators in the antitrust scheme.¹²

The second scenario, hub-and-spoke, can manifest itself in algorithmic pricing. Professor Stucke explained that one could envision a scenario in which competitors either outsource algorithmic pricing to the same third-party vendor or use the same platform to price their competing products (in the classic sense, the manufacturers would be the spokes and the third party, or platform, would be the hub).¹³ In this scenario, while none of the manufacturers communicates with one another directly, Sherman Act Section 1 would require evidence that the parties understood they would be using the same pricing algorithm.¹⁴ The primary issue, then, is whether to view these agreements as a series of parallel, unilateral vertical agreements (and evaluate each of them separately under the “rule of reason” standard) or as horizontal agreements (which may then pose a *per se* risk).

Next, Dr. Deng discussed the third potentially anticompetitive application of algorithms: the predictable agent (tacit collusion).¹⁵ Simply put, tacit collusion is a situation where competitors engage in collusive behaviour without explicit agreement to do so. Dr. Deng first emphasized that there were no known cases of tacitly colluding robots so far. He then discussed the technical challenges of designing such an algorithm, drawing insights from the latest AI research. He stated that because designing collusive robots is nontrivial, there may very well be paper trails, such as R&D documentation and even marketing materials, of such an attempt. This is important because antitrust enforcers in an investigation and private parties in litigation could look for such documents and interpreting them may not require much

¹¹ In *US v. Topkins*, David Topkins and co-conspirators agreed to fix the prices of certain posters sold through Amazon. According to the Department of Justice’s April 6, 2015 press release, “[t]hey adopted specific pricing algorithms for the sale of certain posters with the goal of coordinating changes to their respective prices and wrote computer code that instructed algorithm-based software to set prices in conformity with this agreement.” Press Release, Dep’t. of Justice (15-421), Former E-Commerce Executive Charged with Price Fixing in the Antitrust Division’s First Online Marketplace Prosecution (April 6, 2015), <https://www.justice.gov/opa/pr/former-e-commerce-executive-charged-price-fixing-antitrust-divisions-first-online-marketplace>. This is hardly machine learning and just a tool used by human cartel members. Deng, *supra* note 2.

¹² Ezrachi and Stucke, *supra* note 10.

¹³ *Interstate Circuit v. United States*, 306 U.S. 208, 227 (1939); *see also id.*

¹⁴ This is in contrast to tacit collusion which was discussed later in the program.

¹⁵ As described by the DOJ and FTC in a joint paper to the OECD, “Absent concerted action, independent adoption of the same or similar pricing algorithms is unlikely to lead to antitrust liability even if it makes interdependent pricing more likely... [E]nforcement agencies normally police the risk for interdependence through merger control (due, in part, to the difficulties in crafting an adequate remedy to interdependence) while prosecuting collusion directly. This distinction remains appropriate when evaluating the use of algorithms.” Capobianco, *supra* note 6. Panellists agree this would be difficult to prosecute under current laws. Ezrachi and Stucke, *supra* note 10.

technical expertise. Turning to the economics literature, Dr. Deng pointed out that certain structural characteristics of the market, such as the number of competitors, market shares, stability of demand, homogeneity of the product, and barriers to entry, along with transparency of prices affect a market's conduciveness to tacit collusion. He recommended that antitrust agencies keep a close eye on homogenous product markets where algorithms could significantly enhance the transparency.

Professor Stucke discussed the scenario of a concentrated market with a homogenous good, such as petrol oil. In a non-digital market, gasoline prices are transparent, but changes in prices are not easily visible across the board in real-time. In this scenario, petrol stations that discount prices may increase their traffic and profits by developing a reputation for having lower prices. The limited transparency and delayed action of competitors are likely to benefit both the station that discounts prices as well as the consumers. Here, conscious parallelism (tacit collusion) is harder to maintain. However, in the same market, where pricing data are digital and available in real-time, the pricing dynamics could change. In other words, in a market where information is digital, transparency is increased, which allows cartel members to more easily detect cheaters (maintaining the cartel).

Indeed, there are real world examples of the impact of transparency via digital, real-time pricing information. Professor Stucke illustrated this point with an example of petrol stations in Germany.¹⁶ The German government required the gas stations to report prices for gasoline or diesel fuel in real-time and then transmitted the price data to consumers, hoping to increase competition so that consumers would find the cheapest gas. However, this had the opposite effect: instead of lowering prices to consumers, the enhanced market transparency allowed for increased prices. Given the government-imposed digital pricing system, the data were reported so quickly that stations could respond to each other in seconds, and when one gas station withdrew a discount, the others could follow. In contrast, in a less transparent market without real-time price transparency, other gas stations might not have immediately detected a competitor's withdrawal of a discount and may instead have maintained lower prices for a longer period to the benefit of consumers.¹⁷

The fourth scenario, the digital eye is the most speculative, and therefore the most heavily debated. In this situation, computers have the enhanced ability to process large amounts of data at real-time speeds and can achieve a "divine" view of markets. Additionally, machines engage in autonomous decision-making based on advanced neural networks which are designed to maximize profits.¹⁸ As Professor Gans explained, in this scenario, there is no

¹⁶ Ezrachi and Stucke, *supra* note 8.

¹⁷ *Id.*

¹⁸ Here the algorithms are designed to prohibit illegal activity, such as price-fixing, but the machines are allowed to experiment through self-learning to achieve goals. Ezrachi and Stucke, *supra* note 10; Ariel Ezrachi and Maurice E. Stucke, *How Pricing Bots Could Form Cartels and Make Things More Expensive*, HARV. BUS. REV., Oct. 27, 2016, <https://hbr.org/2016/10/how-pricing-bots->

evidence of an anticompetitive agreement or intent, yet the AI is sufficiently sophisticated that it can produce an anticompetitive outcome, akin to tacit collusion.

Professor Gans believes the current technology is not sufficiently developed enough for the AI to “collude” without human intervention. He explains that while we already have evidence where AIs have learned to play complex games against themselves and humans (*e.g.*, Google Deep Minds learned to play certain Atari games at a “super human” performance level),¹⁹ the AIs did not acquire a fundamental understanding of the games but rather learned through examples and repetitive playing. AIs have the ability to observe data, uncover rules, and unpack information, but they cannot exercise judgment.²⁰

In an attempt to demystify myths about AI, Professor Gans explained that essentially what AI does well is the prediction or forecasting of information we did not know using information we do know. As explained in his latest book, *Prediction Machines*, prediction is the process of filling in missing information; it takes information you have (or data) and uses it to generate information you don’t have. Prediction techniques include data classification, clustering, regression, decision trees, Bayesian estimation, neural networks, topological data analysis, deep learning, reinforcement learning, and capsule networking. Prediction is used for traditional tasks, such as inventory management and demand forecasting, but, because the cost of prediction is becoming cheaper, it is being used for tasks and problems that were not traditionally addressed by prediction models.²¹

By way of example, Professor Gans explained that prediction models are increasingly being applied to transportation problems. Self-driving cars vehicles use AI to predict how a human driver would react using a set of inputs such as camera images, distances as measured through LIDAR, and mapping data.²² Autonomous vehicles existed for a couple of decades in controlled environments based on “if-then” logic until it was recently determined that prediction models could address navigational tasks. Instead of telling the car what to do in each scenario, engineers recognized they could instead focus on a prediction model: What would a human do? AI learns to direct an autonomous vehicle based on millions of observations of

could-form-cartels-and-make-things-more-expensive; Ariel Ezrachi and Maurice E. Stucke, VIRTUAL COMPETITION: THE PROMISE AND PERILS OF THE ALGORITHM-DRIVEN ECONOMY 39 (HARVARD UNIV. PRESS 2016).

¹⁹ Ajay Agrawal, Joshua Gans, and Avi Goldfarb, *How AI Will Change Strategy: A Thought Experiment*, HARV. BUS. REV., Oct. 3, 2017, <https://hbr.org/2017/10/how-ai-will-change-strategy-a-thought-experiment>.

²⁰ Ajay Agrawal, Joshua Gans, and Avi Goldfarb, PREDICTION MACHINES: THE SIMPLE ECONOMICS OF ARTIFICIAL INTELLIGENCE, (HARV. BUS. REV. PRESS 2018).

²¹ *Id.*

²² Ajay Agrawal and Avi Goldfarb, *What to Expect from Artificial Intelligence*, MIT SLOAN MGMT REV. (Feb. 7, 2017), <https://sloanreview.mit.edu/article/what-to-expect-from-artificial-intelligence/>.

human drivers and thereby predicts what a human driver would do given specific road conditions.²³

Recent advancements in machine learning have lowered the costs of prediction thereby expanding the applications of AI substantially (including applications such as translation, fraud detection, credit worthiness, and medical diagnostics).²⁴ When an input drops in price, the value of its complements increases. For example, when the cost of coffee drops, the value of milk, cream, and sugar also increases. Similarly with autonomous vehicles, a drop in the cost of prediction increases the value of sensors to capture data on the vehicle's surroundings. Generally speaking, as explained in *Prediction Machines*, "[p]rediction facilitates decisions by reducing uncertainty, while judgment assigns value . . . judgment is the skill used to determine a payoff, utility reward, or profit. The most significant implication of prediction machines is that they increase the value of judgment."²⁵ While cheap prediction has increased the usage of price-bots, collusion still requires judgment (and thus human intervention). AIs cannot therefore autonomously collude unless it is explicitly written in their code.

In contrast, Professor Stucke warns that there can be anticompetitive intent and effort without an "agreement." As described by the Organisation for Economic Co-operation and Development Secretariat, one could conclude that the fast adjustment of prices in reaction to competitors until convergence is reached is tantamount to an agreement.²⁶ Moreover, Professor Stucke explains that companies are using data and AI to get ahead, and one should look beyond algorithmic price "collusion" for potential harm to consumers. For example, when the *Wall Street Journal* employed algorithms to help with price optimization, this led to price increases on average of about 5%; the AI learned to price higher to consumers who were not as price-sensitive (although this would appear to be more like simple price discrimination than collusion).²⁷

Professor Stucke discussed the Facebook-Cambridge Analytica scandal, whereby Facebook improperly shared user data that purportedly influenced the 2016 U.S. presidential election as an example of AI performing discriminatory tactics. Facebook users did not know data was being collected on them, and Professor Stucke explains that this can be thought as an excess "price." Professor Stucke highlighted that there is a loss of trust with how companies are using data. Moreover, there is a new wave of AI coming and the current enforcement toolset is not up to the task from an antitrust perspective.

In contrast, Professor Gans explains that the law should not run ahead of the industry. Technology changes all the time: before there was Facebook, there

²³ Agrawal, Gans, and Goldfarb, *supra* note 20.

²⁴ This is basic economics, as the price of a product falls, the more people use it. *Id.*

²⁵ *Id.*

²⁶ OECD, *supra* note 6.

²⁷ Ezrachi and Stucke, *supra* note 18, at 39.

was MySpace; now there is Twitter. High-tech firms are particularly vulnerable to market disruptions.²⁸ AIs are prediction-based and are not capable of making judgments, or “colluding.” Therefore, there is no need to change laws to address what could happen in the future; enforcers’ tool set is currently adequate for evaluating potential antitrust violations as long as the statute requires collusion.

Professor Gans also postulates that consumers do not place as great of a value on privacy as one may think. And, consumer protection laws raise slightly different issues than antitrust laws, and even there, behavioural discrimination need not always be concerning. For example, casinos discriminate amongst customers by issuing inducements to high-rollers and this is not necessarily a bad thing. Generally speaking, competition law encourages companies to lower prices and increase consumer purchases; consumer protection laws may encourage consumers to buy less.

There was a brief discussion of AI in the merger context, especially in concentrated industries, where data is important to the competitive process. Issues may arise where two firms compete as sellers of AI (much like big data) or, in some jurisdictions, issues may arise where the combined firm has unique capabilities vis-à-vis new entrants or smaller rivals.

Professor Stucke closed the program with a list of the following Do’s and Don’ts for practitioners in advising their clients:

Don’t

- Agree with competitors to fix prices, allocate markets, or rig bids.
- Adopt specific algorithms to implement an illegal agreement.
- Agree with competitors to use similar pricing algorithms.
- Agree to use a third-party pricing algorithm based on the assurance that your rivals will use the same algorithm.
- Communicate or meet with competitors about their pricing algorithms (at least without first consulting with antitrust counsel).
- Discuss with, or complain to, a third-party vendor of pricing algorithms about its pricing for competitors.
- Agree to share data with rivals’ algorithms before making data publicly available.

Do

- Discuss with clients why they are switching to pricing algorithms and any expected plausible, legitimate business rationale.
- Consider antitrust risks when outsourcing pricing to third-party vendor that is also pricing for rivals.

²⁸ For more discussion on disruption, see Joshua Gans, *THE DISRUPTION DILEMMA* (MIT PRESS 2016).

- Consider what data is being publicly shared and the extent to which the data benefits customers versus rivals (“cheap talk”).
- Consider whether company conduct can be construed as “plus factor” evidence that the firm acted contrary to its economic interests if done unilaterally (*e.g.*, a subset of firms restricts production when prices and profits are increasing).

* * * * *