

ETHICAL IMPLICATIONS OF ARTIFICIAL INTELLIGENCE, MACHINE LEARNING, AND BIG DATA

Jasvinder Mann, Gregory Zaric, and Kyle Maclean wrote this note solely to provide material for class discussion. The authors do not intend to illustrate either effective or ineffective handling of a managerial situation. The authors may have disguised certain names and other identifying information to protect confidentiality.

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Technology is advancing at a rapid rate, changing various aspects of our everyday lives. Businesses and governments are trying to adapt to this change by embracing positive aspects and remaining attentive to the negative. This note will focus on technologies such as artificial intelligence (AI), machine learning (ML), and big data. It is important to discuss not only the ethical issues that these technologies create within our society but also how these ethical issues are being addressed.

DEFINITIONS

AI is the simulation of human intelligence by machines. ML is typically seen as a subset of AI. ML uses algorithms that parse data and learn from it. Big data consists of large volumes of data that can be analyzed to obtain key insights such as patterns or trends. ML algorithms can use big data to learn and to create a more dynamic AI system.

Thinking about Ethics

Today we see AI as a form of technology that is becoming a part of our everyday lives and is able to perform human-like functions to various degrees. The personal interactions that individuals have with voice assistants such as Alexa or Siri on their smartphones are prime examples of how AI is being integrated into our lives. In 2019, approximately 111.8 million people in the United States used a voice assistant at least once a month.¹

In 2018, Google LLC (Google) released an AI voice assistant called Google Duplex. At the product unveiling, Google demonstrated how the system was able to have a casual conversation with a person. Google Duplex could speak as an average person would; the AI voice assistant was able to call a local hair salon and book an appointment for a client. Google Duplex was able to respond accurately, giving the recipient the impression that they were communicating with a human. This seemingly fun, light-hearted presentation raised ethical concerns:² Was it ethical to use AI that made a real person think they were talking to another real person (as opposed to an AI system)? Should laws make it mandatory for the person on the other end of the line to be informed that they were talking to an AI system? Could Google Duplex, or a product that functioned in the same manner, be abused? What were the potential ramifications if an AI system like this was abused?

All of these questions are valid. Thinking about the ethical aspects of AI is a form of safety engineering, where precautionary steps in AI's advancement can prevent major issues from arising. AI will further integrate into the daily operations of companies, and customers will increasingly purchase products that involve customer–AI interactions. This should encourage business leaders to possess, at the very least, a surface-level understanding of AI's mechanics and the implications that the technology can present.

EXAMPLES OF ETHICAL ISSUES

Several ethical concerns arise from the use of current technologies. Below, we provide a list of examples highlighting how AI, ML, and big data can be troublesome. These examples provide a meaningful understanding of how these emerging technologies affect the world around us.

Resume Screening Bias

Many businesses use AI to screen resumes and provide a list of the top candidates; doing so makes the hiring process more efficient. However, notable concerns have arisen in these systems, with one prominent example from Amazon.com Inc. (Amazon). Amazon noticed that its internally developed recruiting system was biased against women.³ Its models had been trained using the historical data of successful applicants, but most of those applicants were men. The system seemed to display a negative bias against words such as “women’s,” and had downgraded graduates from two women’s colleges.⁴ Amazon tried to edit the program to make it as unbiased as possible; however, the company decided to scrap the project because there was no guarantee that the sorting of candidates would not be discriminatory.

Mortgage Interest Rate Bias

There has been evidence that both face-to-face and algorithmic lenders have charged higher mortgage interest rates to Black and Latino borrowers than to white borrowers with comparable credit scores.⁵ Even when an attempt is made to create a fair system, there may be other factors that can create an indirect form of racial discrimination. For instance, Adair Morse, a finance professor at the Haas School of Business at the University of California, Berkeley, mentions the idea of “algorithmic strategic planning.”⁶ Morse states that this is where an AI may use geography to consider an area where people may not shop around much for different rates and may be more inclined to accept higher prices.⁷ The concern with this approach is that minorities may shop around less and not examine other options.⁸ This could be due to various factors, such as someone living in a financial desert where they have less access to a range of products or someone who encounters monopoly pricing. Although algorithms may not be overtly trying to target minorities in this manner, they inadvertently can. This approach could lead to higher prices in areas where there are more minorities, creating discrepancies in borrowing rates.⁹

Data Collection Concerns

In an article published in the *Financial Post*, James McLeod described what he interpreted as an excessive amount of personal-data collection by the Tim Hortons phone application (app), owned by parent company Restaurant Brands International Inc. (RBI). McLeod stated that he was able to obtain the data the app stored about him by filing a request through Canada’s *Personal Information Protection and Electronics Documents Act* (PIPEDA). He noted that Tim Hortons had recorded his geographical area using longitude and latitude more than 2,700 times in less than five months, which was an average of 18 times per day.¹⁰

Tim Hortons also recorded whether a customer was home or not. The app even collected location data any time it suspected that the app holder was going to a competitor's location; for example, recording that the app holder may have entered a Starbucks. Erinn Atwater, director of research and funding at Open Privacy Research Society, a non-profit organization that advocates better privacy practices, concluded that the information obtained was far more invasive than what she would consider acceptable for such an app.¹¹ This situation raises questions about the ethical implications of the amount of data that apps are collecting about us and whether we really know what we are consenting to.

Duncan Fulton, the chief corporate officer of RBI, said in a statement that RBI was not even on the forefront of this technology in terms of tracking data. Fulton claimed that RBI collected this data to stay competitive in the industry.¹² As competition sought to grow, RBI used its app to stay vigilant, tracking what its customers wanted.

Data Breaches

Even if a company does not have negative intentions, bad actors can illegally obtain the data that organizations have collected. A prime example of this occurred in 2017 when Equifax Inc., a credit reporting agency, had a data breach that affected up to 143 million people.¹³ The information taken included names, dates of birth, social security numbers, driver's licence numbers, addresses, and, in some cases, credit card numbers. This sensitive information could lead to identity theft. The ramifications of a breach like this are yet to be seen; this particular data has not yet been released on the dark web,¹⁴ where large data dumps of private information commonly occur. This breach may have occurred for reasons related to espionage instead of identity theft.¹⁵ Nonetheless, millions of people's lives could be severely affected—at any time—if whoever caused the breach leaked the information.

Surveillance Concerns

The use of AI in surveillance is also causing concerns. The tracking software used in the previously mentioned Tim Hortons app, for example, raises ethical concerns: what if other aspects of our lives are being recorded? Facial recognition, voice recognition, personal contacts, and a plethora of other aspects of our lives and identities can be stored on a typical smartphone.

There are terms and conditions set between a user and a smartphone company, as well as between a user and all of the apps that they use. But will a user read through all of these terms and conditions? Can all of this information about the user be breached or shared as part of a partnership agreement? Do we want anyone to know when we typically leave for work or come home? Do we want anyone to have several months' worth of data on where we are throughout the day?

Further, there is suspicion that AI and other software in devices is used in espionage to spy on citizens. This is why some countries, such as the United States, Australia, and New Zealand, have banned products from companies such as Huawei Technologies Co. Ltd. (Huawei). These governments have concluded that Huawei presents a threat to national security because the company can access vast amounts of information about citizens and it is closely tied to the Chinese government.¹⁶

Apps on cell phones raise similar concerns. For instance, concerns about TikTok, an app owned by Beijing-based company ByteDance Ltd., have been raised globally due to TikTok's ties to the Chinese government.¹⁷ India has recently banned the app, and countries such as the United States are investigating what they should do as a public policy issue.¹⁸

Two articles published by the *New York Times* provide valuable insight into the ethics of facial recognition software. In 2019, Sahil Chinoy and his team used three cameras and Amazon's commercial facial recognition software, called Rekognition, to see if they were able to identify any of the individuals walking by in a New York neighbourhood around Bryant Park.¹⁹ The images that they input to identify faces were available from public websites. The system was able to detect close to 2,750 faces in a nine-hour period. The team was able to identify several people, including a professor on his way to meet with a job candidate. The entire operation cost less than US\$100, demonstrating that not much financial capital was needed to run the operation.

There are already websites that continuously live stream public camera footage, and there is potential for someone to use such footage in unethical ways. The American Civil Liberties Union addresses issues with public video surveillance, providing examples of voyeurism, blackmail, and stalking.²⁰ Facial recognition technology combined with public video surveillance can augment these issues. Jennifer Lynch, surveillance litigation director at the Electronic Frontier Foundation, said that the technology has progressed at a much faster rate than she had once thought and that she would support a ban by the government on any facial recognition technology.²¹

In a *New York Times* article, Kashmir Hill reported on a situation where facial recognition was used in wrongly identifying someone who allegedly committed a crime.²² Robert Julian-Borchak Williams was arrested under the belief that he had committed larceny. A facial recognition system supplied to the Detroit Police Department by DataWorks Plus LLC misidentified Williams as the suspect caught on a camera.²³ While Williams was detained, the police asked him if he was the man in the image, and Williams placed the picture of the suspect next to himself and said, "No." He then asked the police if they thought that all Black men looked alike.²⁴ The police quickly realized that they had apprehended the wrong person. The facial recognition system seemed to have displayed racial bias in identifying the two men as the same person.

Reports have shown that facial recognition systems can more accurately identify a white person than a Black person.²⁵ Due to racial tensions with law enforcement, in June 2020, Amazon, IBM, and Google all stated that they would stop or pause offering their facial recognition systems to law enforcement agencies.²⁶ However, this is a small step since most of the companies that produce facial recognition software are small and not well known.

Automation and Jobs

Automation has already had a large impact on low-skill jobs, and AI may enhance automation's effects in industries like truck driving. Self-driving trucks are already being road-tested. Tesla Inc. (Tesla), a leader in self-driving cars, is trying to create a self-driving vehicle that drives just as well as, if not better than, human-driven vehicles.²⁷ Soon Tesla will be releasing semi-trucks with Tesla's own self-driving software.²⁸ The potential loss of trucking jobs could create massive disruptions in society because truck driving is one of the largest occupations in the United States; in 2016, the country had over 3.5 million truck drivers.²⁹

In the United States, close to 5 million jobs in the manufacturing sector were lost between 2000 and 2016—some due to trade deals, where factories were moved, and some due to automation, where companies were able to use robots to do human jobs more efficiently.³⁰ The loss of these jobs could lead to the loss of other jobs. For durable manufacturing (i.e., the manufacturing of durable goods such as automobiles, electronics, and appliances), it was estimated that for every 100 jobs lost in that industry, 744.1 jobs would be indirectly lost.³¹

If the trucking industry were to make a major shift toward automated vehicles, the loss of truck driving jobs could indirectly affect other jobs. For every 100 jobs lost in the transportation and warehousing sector, 276

jobs could be indirectly lost.³² Although one might expect to find another job or be retrained after losing a job, job retraining programs are usually not successful.³³ Further, job losses in some parts of the United States have been associated with an increase in opioid use.³⁴

Several industries will be affected by the expansion of automation through AI. White-collar jobs will also face AI-related disruption. Jobs with analytical and technical roles may face the most exposure to disruption, and jobs with more interpersonal roles, such as those in education and health care, may not be as affected.³⁵

What we can safely assume is that as AI becomes a more integrated part of society, jobs will become increasingly different from what they are today. This is not to say that AI will only have a negative effect on job outcomes; AI can create more jobs and can help companies to expand faster or allow a firm to operate more efficiently. Jobs may change, and new jobs will be required to fill roles that we do not yet know even exist. We need to plan for when some jobs do become obsolete and try to mitigate the negative aspects of job loss.

REGULATION AND POLICY

AI is being used more in everyday tasks such as firms' hiring procedures or when financial institutions decide to advance loans. There have already been instances of these algorithms being biased in discriminating against people of a certain race or gender, as previously discussed. This highlights the human rights risks intertwined with AI and why regulations may need to be enacted.

It is uncertain what government policies can be implemented regarding the loss of jobs as a result of automation. Many people, such as Steven Mnuchin, the US Secretary of the Treasury under President Trump, do not believe that jobs will even be lost to automation. In March 2017, Mnuchin had no fears about AI displacing jobs for at least another 50 to 100 years, claiming that such an occurrence was so far into the future that he was not even thinking about the potential of job loss due to AI.³⁶ At the same time, Andrew Yang, entrepreneur and former 2020 presidential candidate, made the potential for job loss due to automation the central pillar of his campaign. His solution to combat the increased threat of job loss was to implement a universal basic income (UBI), an idea that allowed him to reach the national debate stage, where he announced that he would give US\$1,000 to 10 families to demonstrate the benefits of UBI.³⁷

Consent

The principle of requiring consent is vital to maintaining a sense of autonomy and control over the decisions we make. Apps are able to collect our personal data because we agree to let them do so. The laws of most developed nations require a company to obtain consent before it begins to collect user data.

There are four main components to informed consent:³⁸

- *Information*: Individuals must be provided with all pertinent information.
- *Understanding*: Individuals should understand the information.
- *Volunteering*: Individuals should genuinely volunteer to participate; there should be no coercion or manipulation.
- *Decision-making capacity*: Individuals should have the capacity to weigh the risk and benefits of the decision they make when agreeing to consent.

Questions can arise as to whether all of these aspects of consent are adequately addressed when we agree to something. Can the terms in an agreement be too complex for the general public to understand? Can the technology being used to process data be too complex to understand? These factors will have to be considered when creating policies.

The Institute of Electrical and Electronics Engineers (IEEE)

There are professional bodies looking at the creation of ethical standards and solutions to combat rising concerns. The IEEE is the world's largest technical professional organization dedicated to the advancement of technology.³⁹ The IEEE Global Initiative on Ethics of Autonomous and Intelligent Systems aims to deeply reflect on human well-being—something that may not be normally considered—in the designing of automated and intelligent systems. The initiative's mission is to ensure that every stakeholder involved in the development of the technology is educated, trained, and empowered. Each stakeholder should prioritize the ethical implications of new technologies so that such technologies can benefit humanity. The initiative has a list of standards that focus on the use of ethical metrics, design, data governance, and processing for autonomous and intelligent systems. The standards try to maximize transparency and data privacy while limiting any algorithmic bias.⁴⁰

General Data Protection Regulation (GDPR)

Policies that create positive change to mitigate issues surrounding our data are being developed around the world. A notable example of this is the European Union (EU) GDPR. The GDPR covers several topics, including “rights of data subjects,” “transfers of personal data to third countries or international organizations,” and “remedies, liabilities and penalties.”⁴¹

The GDPR attempts to create a consolidated approach to handling data and providing the highest degree of data protection to individuals within the EU. It does this by focusing on giving citizens control over the use of their own personal data, and it regulates the transfer of data on EU citizens to areas outside of the EU's control.⁴²

Each of the 11 chapters of the GDPR contains articles that lay out all the legal requirements related to that chapter's topic. In chapter 3, key principles regarding the rights of the data subject are outlined. For instance, section 3, article 17 discusses the right to erasure (right to be forgotten), which requires an organization to erase an individual's personal data upon request without undue delay. Guidelines presented in article 17 create a finer scope of how this right can be used, but the general idea is that, going forward, each person will have the power to control some aspect of their data.⁴³

PIPEDA

McLeod's use of PIPEDA allowed him to discover what data the Tim Hortons app was collecting about him.⁴⁴ PIPEDA shares many of the same principles as the GDPR, allowing the citizens and residents of Canada to have a degree of autonomy over their data. PIPEDA gives individuals the authority to obtain information with regard to why a corporation is collecting a person's data and how the corporation is disclosing the collection of such information.

PIPEDA became law in 2000; in 2015, the *Digital Privacy Act* became law and amended PIPEDA.⁴⁵ These updates and additional regulations demonstrate both the fluidity of data law and how the law changes with the times.

Some of the provisions of PIPEDA deal exclusively with the data and how data is used. Policies will also need to deal with the problem of not knowing how decisions are being formulated in AI systems. Calculations done by neural networks and other advanced algorithms exist in a “black box,” making them difficult to understand (see Exhibits 1 to 3). This, again, raises the issue of informed consent. Can we understand what we are consenting to if we do not know how our data is being processed?

EXPLAINABLE AND INTERPRETABLE MODELS

Processing data in AI is complex and challenging to understand. A potential solution to understanding how our data is being processed is to use explainable models. In AI, explainable models are techniques that humans can use to explain the results of the black box by trying to show how the results in a system like a neural network (NN) have been computed. This creates explainable AI (XAI).⁴⁶ Decision trees, such as classification and regression trees (CART), can be used to explain a machine-learning neural network (see Exhibits 4 and 5). However, classification and regression trees when used as an explainable model are used after the results from the NN have been obtained to explain how a NN arrived at its conclusion.

Cynthia Rudin, a computer science professor from Duke University, argues that explainable models just describe what is assumed to have happened in a black box, and instead industries for the most part should be using interpretable models exclusively.⁴⁷ Interpretable models display each step of the process so that decisions can be easily understood. Decision Trees like CART can be both explainable and interpretable, but instead of using decision trees alongside a NN to explain the NN, the decision tree should be used in isolation, to be interpreted. To simplify the difference between the two, explainable models are used to explain results from a black box and interpretable models are used by themselves to derive results, not explaining the results of a black box.

Rudin questions Article 22 of the previously mentioned GDPR, where EU citizens are given the right to receive an explanation for algorithmic decisions.⁴⁸ She mentions if only an explanation is needed for an automated response, it is not certain whether the explanation needs to be accurate or complete; as such, less than adequate explanations may undercut the intended goals of the GDPR. Rudin proposes a possible mandate, where no black box algorithm should be used when there exists an interpretable model with the same level of performance. She states that this will not solve all the issues but may decrease the use of black box algorithms.⁴⁹

It is expected that data users to be accountable for what they have done with the data they obtained. That accountability involves explaining how a result or decision is derived, and ensuring accountability is an integral part of any government regulation. Explainable and interpretable models are being investigated because an organization—regardless of whether it is a business or a government—should be able to present the underlying reason for any decision that it has made. Doing so enables the organization to avoid any bias. Reasons will be needed to address some of the previously mentioned issues, such as providing transparent hiring and lending practices that do not discriminate against people.

CONCLUSION

Countries can enact laws and regulations and use them to govern activities within their borders, protecting their citizens. However, if countries allow AI systems to go unchecked, issues may arise that may negatively affect other countries. As viewed through a business lens, it may be easier for companies and organizations to operate globally if a certain set of international practices were established.

There are attempts to address AI in the same way that climate change and biotechnology have been addressed. Organizations such as the International Bioethics Committee, which is a branch of the United Nations Educational, Scientific and Cultural Organization, have paved a path toward ensuring that biotechnological research respects human dignity and freedom around the world.⁵⁰ Recently, the Paris Agreement, which builds upon the United Nations Framework Convention on Climate Change, took a global approach to tackling climate change. Although countries will enact policy in their own ways, the world is nevertheless taking steps toward a collaborative approach to a crisis.⁵¹ The United Nations Interregional Crime and Justice Research Institute has already taken steps with the creation of the Centre for Artificial Intelligence and Robotics. The goal is to have the centre serve as an international resource in all matters related to AI and robotics.⁵²

Unpredictable events may happen through the continuous progression of AI; technology usually does not advance in a linear fashion, so disruptions will occur with little to no foresight. Industry leaders will have to take up the mantle and navigate the future of AI, trying to maximize the benefits offered by AI while minimizing any of its potential costs. It does not take someone with a technical expertise to understand the ethical implications that AI could have. To obtain further knowledge on the regulations around automation and intelligent systems, individuals can look at what their federal or state government is doing. New stories are continuously published addressing the concerns these technologies present; staying informed will be important in navigating the future.

EXHIBIT 1: NEURAL NETWORKS

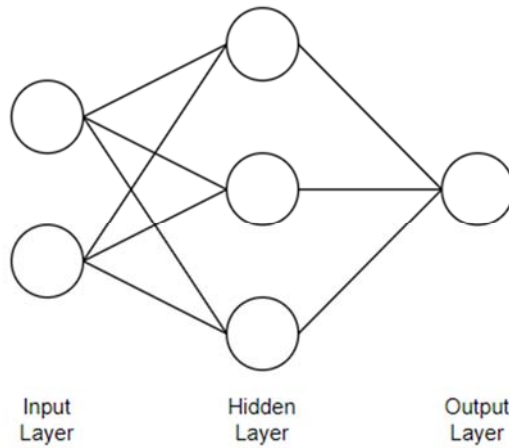
A neural network (NN) is a type of machine learning model whereby a computer learns to perform a task by analyzing datasets. NNs are modelled broadly on the human brain, where potentially millions of simple processing nodes are connected to one another and are designed to recognize patterns. A parallel is drawn to the brain because any time a neuron—computer or human—reaches a threshold as a result of a strong enough stimulus, the neuron fires an action potential.

NNs can also be used for numerical classification, forecasting and prediction, as a substitute to standard statistical techniques such as logistic regression and linear regression. However, much of the enthusiasm for NNs is due to their ability to work with complex patterns that arise from a broad set of real-life data, such as sounds, text, and images, which are translated into numerical information for the NN to interpret. Organized in layers, NNs are trained by inputting data to the input or first layer; the data then passes through the subsequent layers, arriving at the output layer (see Exhibits 2 and 3). The weights on the arcs between the layers are estimated during the training phase. Once the weights have been estimated, then the NN can be used.

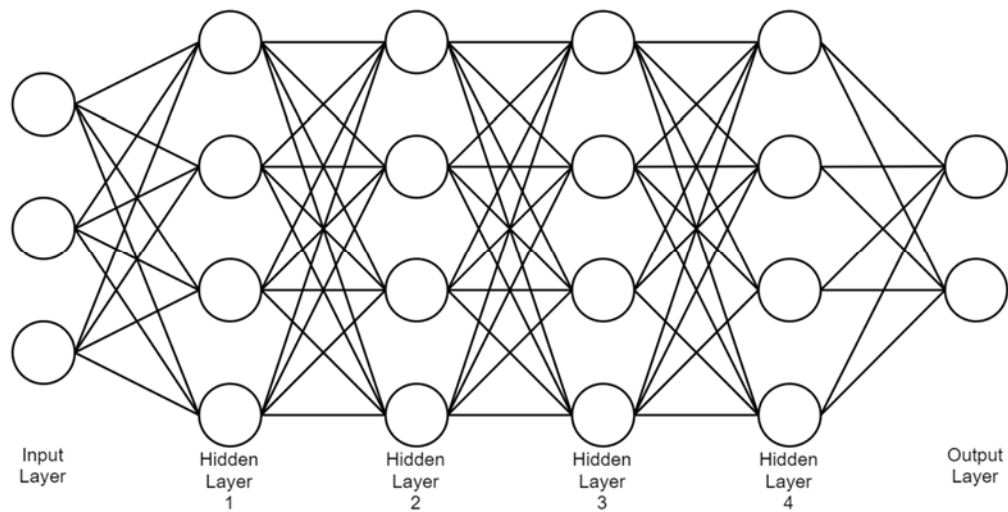
It is common for the weights to be initially assigned randomly, then optimized through a training algorithm. Common algorithms for training NNs (i.e., assigning appropriate values to the weights between the nodes) include forward propagation and backpropagation. Both types of algorithms work iteratively by trying to reduce prediction errors, either forwards (from the input layer to the output layer of the NN) or backwards (from the output layer to the input layer of the NN). In a forward propagation algorithm, activated nodes transfer information to nodes of the next layer. Once the information reaches the output layer, the output is compared to the actual result. If there was an error in the output, the magnitude of the error is obtained, assessing how much higher or lower the output was in comparison to the expected answer. Backpropagation is where this information obtained through forward propagation is sent backward through the layers, and weights are adjusted accordingly. The processes of forward propagation and backpropagation are iteratively performed and typically continue until the training data continuously yields similar enough results.

A major concern with NNs is that the final, trained network, may appear to process information in a “black box.” We know what information was input and we know the output, but we do not know the processes taken to get there. For a large NN, it is difficult, if not impossible, to explain why a particular set of inputs led to a particular output. This is in contrast to statistical models (e.g., linear regression or logistic regression) in which the calculation linking inputs and outputs is clearly specified in the model. This is also in contrast to CART models (see Exhibit 4), where there is a visual representation linking inputs and outputs. Much of the time, nodes are set at random weights to start, and the iterative cycle of forward propagation and backpropagation that changes the weights is complex. We currently have no way of understanding the actual process, which raises concerns.

Source: Created by the authors based on Larry Hardesty, “Explained: Neural Networks,” MIT News, April 24, 2017, accessed July 10, 2020, <http://news.mit.edu/2017/explained-neural-networks-deep-learning-0414>; Imad Dabbura, “Coding Neural Network—Forward Propagation and Backpropagation [sic],” Towards Data Science, March 31, 2018, accessed August 24, 2020, <https://towardsdatascience.com/coding-neural-network-forward-propagation-and-backpropagation-ccf8cf369f76>.

EXHIBIT 2: NEURAL NETWORK WITH A SINGLE HIDDEN LAYER

Source: Created by the case authors.

EXHIBIT 3: NEURAL NETWORK WITH MULTIPLE HIDDEN LAYERS

Source: Created by the case authors.

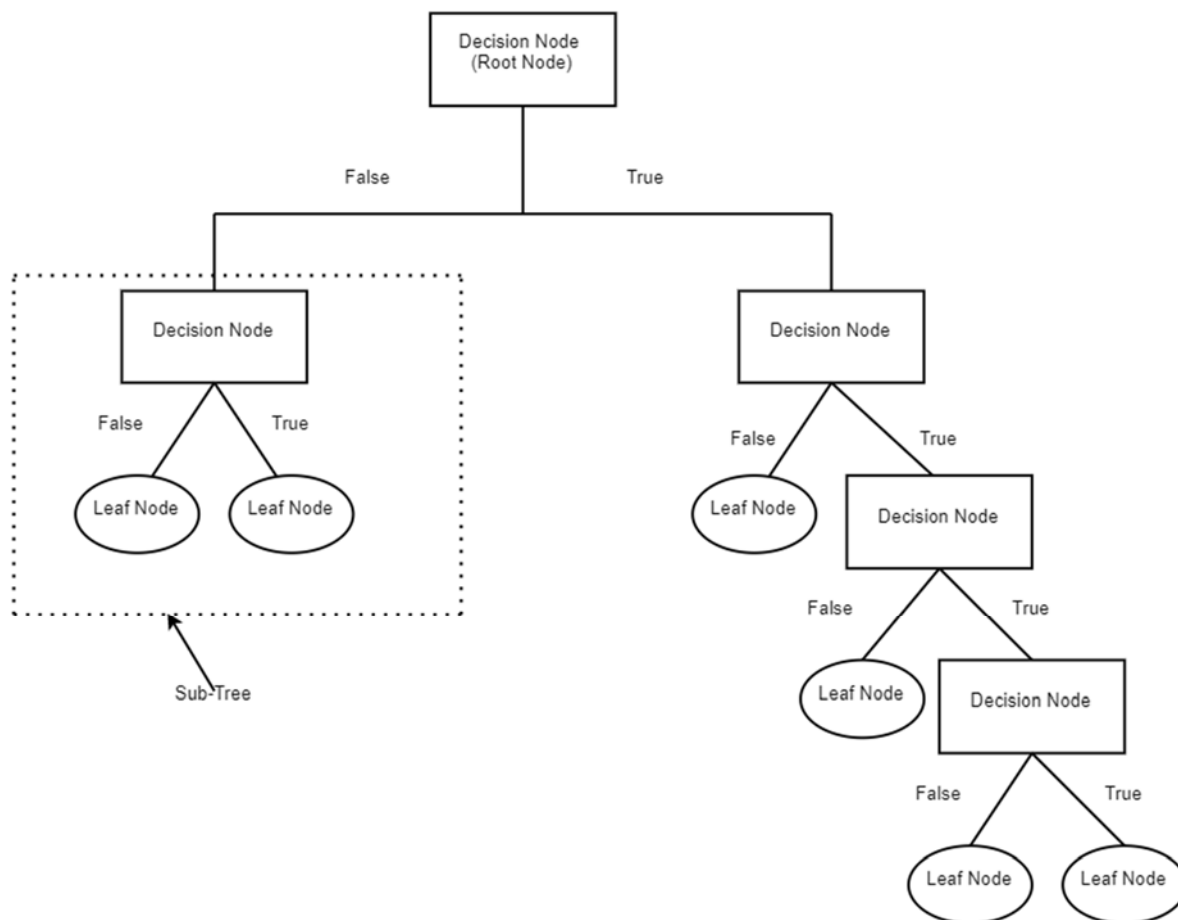
EXHIBIT 4: CLASSIFICATION AND REGRESSION TREES

Classification and regression trees (CART) are decision trees that can be seen as upside down trees with the roots at the top and the branches expanding below. Decision trees are used to explain an output by simply following the path that the sample makes through the tree; the output is given once the sample makes it to a leaf node (see Exhibit 5). This process enables us to provide a logical explanation for how a decision was reached.

The decision-making process can be viewed as a series of simple “if” statements: IF X_1 AND X_2 AND X_3 AND X_4 , then Y . In deciding whether a sign is a stop sign, the logic can be deduced as follows: IF the sign is an octagon AND the sign is red AND the sign has the word *stop* written on it AND the word *stop* is written in white, then it is a stop sign. Easily interpretable, these decision-making steps show how decision trees are a key piece of explainable AI.

Source: Özgür Genç, “Notes on Artificial Intelligence, Machine Learning and Deep Learning for Curious People,” Towards Data Science, January 25, 2019, accessed July 10, 2020, <https://towardsdatascience.com/notes-on-artificial-intelligence-ai-machine-learning-ml-and-deep-learning-dl-for-56e51a2071c2>; Jason Brownlee, “Classification and Regression Trees for Machine Learning,” Machine Learning Mastery, April 12, 2016, accessed July 10, 2020, <https://machinelearningmastery.com/classification-and-regression-trees-for-machine-learning/>; Jaime Zornoza, “Explainable Artificial Intelligence,” Towards Data Science, April 15, 2020, accessed July 10, 2020, <https://towardsdatascience.com/explainable-artificial-intelligence-14944563cc79>.

EXHIBIT 5: DECISION TREE



Source: Created by the case authors.

ENDNOTES

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- ¹⁰ James McLeod, "Double-Double Tracking: How Tim Hortons Knows Where You Sleep, Work and Vacation," *Financial Post*, June 12, 2020, accessed July 30, 2020, <https://financialpost.com/technology/tim-hortons-app-tracking-customers-intimate-data>.
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- ¹² Ibid.
- ¹³ Josh Fruhlinger, "Equifax Data Breach FAQ: What Happened, Who Was Affected, What Was the Impact?," CSO Online, February 12, 2020, accessed July 10, 2020, <https://www.csoonline.com/article/3444488/equifax-data-breach-faq-what-happened-who-was-affected-what-was-the-impact.html>.
- ¹⁴ The *dark web* is Internet space that is not indexed by search engines. A specific Internet browser is required to access the content on the dark web, a great portion of which is related to illegal activity. The *deep web* also consists of content not indexed by search engines; however, the lack of indexing is because the content is behind a paywall or requires credentials for access. Regular browsers can be used to access the content in the deep web provided the user has the necessary credentials to access the website. Darren Guccione, "What Is the Dark Web? How to Access It and What You'll Find," CSO, November 18, 2020, accessed December 9, 2020, <https://www.csoonline.com/article/3249765/what-is-the-dark-web-how-to-access-it-and-what-youll-find.html>.
- ¹⁵ Fruhlinger, "Equifax Data Breach FAQ," op. cit. One theory was that the Equifax data was collected as part of a larger operation to mine big data from several sources to learn about U.S. government officials and intelligence operatives.
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