ARTIFICIAL INTELLIGENCE
What it is and Legal Considerations for the Advertising Industry

By Lyric Kaplan
Associate in the Privacy & Data Security Group
Frankfurt, Kurnit, Klein & Selz

I. Introduction

Artificial intelligence ("AI") is a twenty-first-century buzzword. It is as revolutionary and as disruptive as the internet in the 90s.[1] It will enter every facet of our lives and livelihoods and dwarf any prior technologies impact on the modern world. AI has been part of the popular lexicon for over half a century and in people's imaginations for far longer.

AI began with Alan Turing, a man well before his time, known for developing a predecessor to the modern computer and helping Allied forces break German military codes during World War II.[2] In 1950, his paper *Computing Machinery and Intelligence* questioned whether machines could think and whether machines could learn from experiences much like a child.[3] To develop empirical evidence for this hypothesis, he developed the Turing Test which is similar to the imitation game. A Victorian-style competition where a human judge via computer chats with unknown interlocutors and determines which is the real person and which is the chatbot created to trick the judge.[4] It was not until 2014 that a virtual 13-year-old boy named Eugene allegedly beat the Turing test.[5]

In 1956, John McCarthy at the Dartmouth Summer Research Project on Artificial Intelligence coined the phrase "artificial intelligence." The historic conference brought top researchers together to discuss AI openly. Even though the conference failed to agree on standard methods for pursuing AI research, it was the catalyst that made many agree that AI was achievable. Application of AI to various domains was slow at first, with the expected fits and starts of any new technology but has become an indispensable element of every sector, including advertising, marketing, entertainment, manufacturing, financial services, health care, law, social media, national defense, electoral politics, and more.

In its infancy, AI has already permanently altered the digital advertising landscape. In 2019, 80% of the digital media market is using AI in advertising, and 40% of sales and marketing teams agree the technology is essential to their department's success. [6][7] The predominant form of AI-powered digital advertising today is programmatic advertising or "companies using algorithms to buy and place ads in those little boxes all over the internet."[8] Behind the majority of ads placed in front of a user, are AI technologies that power the real-time delivery systems. In 2017, Google and Facebook captured 90% of the new advertising business with AI advertising products.[9] AI allows brands to advertise at scale, but scale alone is insufficient to compete with giant data companies. Brands are feeling the pressure to deliver more relevant, contextual, and personalized ads based on individual consumer preferences. Tools powered by AI offer advertisers the opportunity to make ads "more intelligent and more human at scale."[10] To understand how AI can make better ads, we will explore what artificial intelligence is, how it works, and the legal considerations.

II. What is Artificial Intelligence?

AI is a human-made or synthetic intelligence, enabling computer systems to complete tasks that would typically necessitate human intelligence.[11] The technology includes many different technical methods, various academic disciplines, spans industries and decades of research. This section cannot possibly cover all AI has to offer so it will dive into machine learning, Recommender Systems and the importance of data.

There are three generations of AI: narrow, general, and superintelligence.[12] Currently, artificial 'narrow' intelligence ("ANI") can perform a specific task as well as or better than humans and is the only generation to see mainstream success. For example, modern cell phone users have become accustomed to well-known features ANI products provide customers, such as predictive texting, data management, and voice recognition. Every AI product available today is ANI. The next generation, artificial 'general' intelligence ("AGI"), goes beyond solving a particular problem to autonomously developing solutions to any problem.[13] In the future, artificial 'super' intelligence ("ASI") will have the ability to surpass the most gifted and brightest human minds. While AGI is not yet possible, the possibility of ASI remains uncertain.

Due to AI's limitless potential benefits, there has been an exponential expansion of AI development, and it has become a mainstream concept including as the subject of blockbuster motion pictures (e.g., The Terminator, Ex Machina, and The Matrix). Development of useful ANI applications will continue until 2030 and could solve a constellation of societal problems and alter our daily lives. [14] For example, smart vehicles could save thousands of lives by preventing drunk driving accidents and exponentially increase mobility for the elderly and disabled. Smart buildings could reduce carbon emissions and save energy. Precision medicine may improve quality of life and potentially even extend one's lifespan.[15] While impressive, these technologies are tailored to complete specific tasks. Each application requires years of research and development and unique construction. In the future, AI will continue to be implemented in targeted treatments (e.g., more self-driving cars, and healthcare diagnostics) and proliferate in international industries struggling to attract youth (e.g., food processing, agriculture, fulfillment centers and factories).[16]

III. How Does it Work?

A. Machine Learning

The most common form of ANI is machine learning ("ML"). Due to numerous publications about AI and ML, the public is bewildered by these concepts and unable to distinguish or define them. In 1959, Arthur Samuel coined machine learning as "the ability to learn without being explicitly programmed."[17] ML involves a statistical process that begins with an extensive data set and attempts to derive rules or procedures that explain the data or predict outcomes.[18] This technical process is a subdivision of ANI but focuses on algorithms that can learn a given task by looking at examples. So, in place of hard-coding software routines that have explicit instructions to accomplish a specific task, ML trains an algorithm to learn how to complete the work. Training algorithms require feeding it massive amounts of data and enabling the algorithm to adjust to improve itself. Algorithms are detailed step-by-step instructions that solve a problem or complete a task.

There are many different flavors of ML, depending on the objective and algorithm. Generally, ML algorithms fall into three main groups: supervised, unsupervised, and reinforcement learning.[19] Supervised learning is similar to how people learn from a teacher. The teacher provides examples to memorize, and the student then derives general rules from those examples. Technically, supervised learning occurs when an algorithm learns from labeled example data and the related desired responses. The algorithm later predicts correct responses when fed new examples.

Another kind of ML is unsupervised learning. An algorithm learns from unlabeled examples and no associated response. Unsupervised learning leaves the algorithm to define the underlying structure of the data by finding patterns invisible to the human eye. These algorithms tend to restructure data into new features that can "represent a class or a new series of uncorrelated values."[20] Unsupervised learning has helped provide insight into the meaning of data. This type of learning is similar to humans observing the degrees of similarity between objects to determine when certain objects are part of the same class. Many web-based marketing Recommender Systems use unsupervised learning. For example, marketing automation algorithms derive customer product suggestions based on past purchases. Some of these algorithms evaluate what group a customer most resembles and then infers likely product preferences based on the group that customer matches. Other algorithms based on collaborative filtering for example, generate product suggestions based on similarities between customers.

Reinforcement learning resembles unsupervised learning because the algorithm uses unlabeled examples. However, the examples are accompanied by a reward element, a positive or negative feedback based on the desired outcome. It is compared to humans learning by trial and error. By connecting the application, the algorithm must make a decision that has consequences. Therefore, reinforcement learning is prescriptive and not descriptive. An example of reinforcement learning is when a computer learns to play video games by itself. How this happens is an application gives the algorithm examples of specific situations (e.g., the gamer trying to avoid the enemy and is stuck in the maze), then the application tells the algorithm the outcome of decisions it has made. The algorithm learns from the errors and determines dangerous decisions and necessary courses of action to ensure survival or in other words, maximize the reward.

ML has dramatically improved many areas of interest like targeted advertising and product pricing. Targeting audiences with ML enable a level of specificity that optimizes ad campaigns and reduces waste.[21] Facebook Business Manager makes advertisers lives easier by targeting audiences based on their interests gleaned from Facebook profiles and activities. ML algorithms generate interest insights. Furthermore, determining price for a product takes a significant amount of market research and analysis. With ML, brands and advertisers can take advantage of dynamic pricing which correlates sales trends and price with other variables like available inventory.

B. Deep Learning and Neural Networks

The current 'state of the art' subdivision of machine learning is deep learning which has fueled substantial improvements, particularly in speech recognition and computer vision.[22] Deep learning entails feeding massive amounts of data through non-linear neural networks. These brain-inspired networks are interconnected layers of artificial neurons. They feed data into each other and learn specific tasks by modifying the importance given to input data as it goes through layers. [23] During neural network training, the weights connected to different inputs will continue to change until the neural network's output is 'close enough' to the desired result. The model is ready when accuracy is quantitatively measured using validation data (i.e., data not used to train the model). At that point, the network has learned how to carry out the specific task.

Neural networks mimic natural world evolution, but this happens at an exponentially faster pace. Algorithms quickly adapt to patterns and discovered results, thereby becoming increasingly accurate and valid. It would be too time-consuming or complicated for human researchers to identify the data patterns and trends that neural networks can. Consequently, this creates outputs that are too complex to code manually with traditional programming techniques. The complexity of processing vast data sets through such massive networks creates the "black box effect."[24] To simplify, it means we know what data goes in and what results come out but have little to no understanding of what happens in the middle. This type of ML is transparent in the way that it simulates trial and error of human behavior, but the speed and scale make it impossible for the human brain to keep track of the expanding processes and millions of micro-decisions powering outputs.

An approach to deep learning known as "transfer learning" highlights and exacerbates the black box effect. Transfer learning is a technique where one model has learned to complete one task, and that knowledge is transferred to complete a related task. For example, Business B has access to vast data sets to train a deep neural network for a specific task, such as classifying images among a thousand general categories. On the other hand, Entity E does not have the resources or access to such an extensive data set to train a model of their own. Instead, the entity can use the business's pre-trained network as a baseline for creating a new model that performs a related but different task, such as, recognizing brands in images. Entity E uses new data specific to the task of interest, to retrain the last few layers of the original model, thereby repurposing the model to complete a new task. Usually, the entity does not gain access to or ownership of the data used to train the initial model. The issue is technology companies create models they cannot fully understand, and then license these models to other entities with less transparency. Therefore, models are trained to make life-changing decisions, and the developers do not understand the decision-making process.

C. Recommender Systems

For our purposes, a "Recommender System" is a software engine optimized to present relevant content to users, with the goal of maximizing conversion. In this context, conversion can be a user purchasing a new laptop, reading an article, or watching a new TV show. Relevance is achieved by the use of algorithms, which, in most cases, are powered by some implementation of a supervised or unsupervised ML model. Typically, Recommender Systems use both products' and users' information and behavior as input and include one of the following approaches:

- **Collaborative filtering** predicts a person's interests based on other people's likes. It boils down to a simple idea, "you are likely to like what someone similar to you likes." For example, if Amy likes Product X and we find out that Chelsea is similar to Amy, perhaps Chelsea likes Product X too.
- **Content-based filtering** predicts products that are like other products. It relies heavily on product characteristics and does not focus on the user's interaction with the product.
- **Knowledge-based system** predicts user needs and preferences by drawing connections between a person's needs and a related product.
- **Hybrid system** is a combination of the above types of Recommender Systems or others not listed. [25]

Use cases include brands like Amazon that use collaborative filtering to personalize each customer's online store based on their interests. Using Recommender Systems vastly improves email and web-based advertising effectiveness.[26] Click-through and conversion rates vastly exceed untargeted content such as top-seller lists and banner advertisements.[27] Not only ecommerce platforms use Recommender Systems. Other brands like YouTube and Spotify also rely heavily on Recommender Systems to increase subscribership and customer retention.[28] According to Mckinsey and Company, "35 percent of purchases on Amazon and 75 percent of content watched on Netflix comes from recommendation algorithms.[29]

Specifically, Netflix uses a combination of algorithms to predict what a subscriber wants to watch based on past movies and television shows they have viewed, as well as what other similar subscribers have watched or liked. However, less well known is precisely how sophisticated these algorithms are and what they will look like in the future. As of December 2017, Netflix rolled out its new image algorithm that displays a unique set of images to each of its 100 million-plus subscribers that are designed to make them click on specific title images and keep them watching longer.[30] This type of algorithm seems harmless. It displays unique cover art that is the "most enticing image for the biggest number of users," reducing the time users spend searching for their next entertainment delight.[31] How does it work and what data does it collect from the users?

If Netflix were a country, its subscribers would be the 12th largest in the world. This giant is continually conducting a wide range of behavioral experiments on its vast subscriber base to customize offerings. "What you watch next, what you give thumbs up and thumbs down to, when you quit watching a not-so-bingeable show: All of this information can help engineers create a recommendation algorithm."[32] The new image algorithm is working in real-time to provide a unique image that it believes the particular user will respond positively to and is continuously collecting data from and learning from each of the 100 million-plus subscribers' actions and inaction on the site. That is a ton of data!

D. Data is the New Oil!

Machine learning is the most common type of AI because every industry has the same problem: they want to classify or predict something. For supervised ML to happen, large quantities of accurately labeled data to train algorithms is necessary. Usually, the more data, the higher the quality of the ML model. The more variables or features, the more complex and potentially accurate the model will be. Therefore, accurately labeled data is essential. This scarce resource constitutes the most significant pain point and barrier to entry to developing ML applications.

In this new wave of AI, there is a resurgence of ML techniques such as deep learning, enabled by the convergence of large quantities of data generated every day and the breakthroughs in computing power brought by graphical processing units. The ones who win the race are not the ones who can develop the best algorithm, but the ones who have access to the best data. In this context, the best data means behemoth amounts of rich data (e.g., granular, specific and accurately labeled data). In the best-case scenario, data wholly owned and only accessible to the company collecting it. For instance, Facebook owns the proprietary data generated on its social networking platform and subsidiary ventures such as Instagram and WhatsApp.

Something evident to privacy aficionados but invisible to users is Facebook and Google are in the data business. They collect an invaluable commodity, tons of rich data which is foundational to their business models and revenue streams.[33] Data companies begin by offering a free product, target a mass market, and start collecting user data. Once the product reaches critical mass, the data collected has a large enough scale to reveal more patterns with data analysis. The outliers' impact becomes de minimis, so the data set more accurately reflects the population at large. Ultimately, the exercise that these companies need to embark on to exist is to find insights and predictions regarding user profiles, preferences, and behavior. These companies then sell or share the data for various purposes, such as targeted advertising and direct marketing.

Due to the value of data, some companies will stretch ethical and legal limits to acquire as much as possible. Understanding the foundational notion that without data, a majority of modern AI ceases to exist, puts data privacy at the epicenter of concern. Recently coined, "data is the new oil" captures the idea that data is an internationally monetizable commodity. The one with the most quality data can create disruptive businesses and potential goldmines. It is a double-edged sword. By providing more data, customers get better recommendations and products (e.g., Google search, Amazon's one-day delivery) but data can be misused in creepy ways that are fundamentally incompatible with privacy laws.

IV. Old Law, New Technology

Technology always outpaces the slow-moving machinery that makes law. Currently, there is no law of AI inhibiting the private sector's research and development.[34] Instead, the United States tangentially regulates AI with a hodgepodge of privacy, consumer protection, intellectual property, due process, health and safety laws.[35] The regulatory gap in AI-specific requirements and standards leaves the industry to develop guidelines and best practices based on public response, risk tolerance, and anticipated return on investment. Legal considerations posed by artificial intelligence are particular to the industry and application. This section examines (1) algorithmic bias, (2) misleading and deceptive recommendations, and (3) conflicts with privacy laws, specifically the General Data Protection Regulation ("GDPR") and the California Consumer Privacy Act ("CCPA").

A. Algorithmic Bias and Discrimination

Algorithmic bias is a phenomenon that occurs when results produced by algorithms are systematically discriminatory. Using AI can lead to biased decision making. Biases come from unintended prejudices such as unconscious preconceived notions or imperfections in the underlying data. First, developers can have conscious or unconscious biases that affect framing of the algorithmic problem, data labeling or what data is collected. For example, confirmation bias or a tendency to lean toward data aligned with opinions, views, or belief, can skew data.[36]

Second, the underlying training data may have embedded biases. Algorithms risk replicating and amplifying human biases, especially those affected protected classifications of people. In many states, justice departments are using AI tools like COMPAS software that uses an algorithm to classify defendants as high-risk of re-offenders. In *State v. Loomis*, COMPAS gave the defendant a high-risk recidivism score.[37] He challenged his sentence due to denial of the opportunity to assess the algorithmic decision-making. The Wisconsin Supreme Court refused his request reasoning the output was sufficiently transparent.[38]

Moreover, there is historically less input data for minorities, women, or other underrepresented segments of society. By using only this one-sided historical data, outcomes discriminate against disadvantaged groups. For example, Amazon's hiring algorithm was dismissing female candidates because it had been trained with historical data that favored men.[39]

When ads are chosen based on algorithms, research has demonstrated historically discriminated-against groups are more likely to see undesirable ads and less likely to view desirable ads.[40] Researchers conducted a study on algorithmic serving of ads to women for science, technology, engineering and mathematics ("STEM") jobs across 190 countries.[41] Even though the ad was to promote job opportunities in STEM, the field test was framed to be gender-neutral. The empirical study found that the STEM ad was shown to 20% more men than women, especially for people 25 to 54 years old. In the advertising ecosystem, women's eyeballs are more valuable than men's eyeballs. Women make most of the household purchases and advertising to them is more likely to result in an inevitable sale. This actor valuation spills over into how ads are distributed throughout the ecosystem and are the cause for the disparity in ad serving based on gender. For society, this is a problem when the desirable ad highlights financial and housing opportunities, beneficial employment, or who gets the undesirable ads for things like predatory lending.

Today many people are aware of AI's ability to recommend television shows on Netflix and music on Spotify. However, less well known is AI's responsibility for determining approval for a home loan, bail amounts, sentencing, or recommended medical treatments. These decisions are monumental decisions drastically affecting people's daily lives and lifelong wellbeing. They are trusting AI to make the right choices. As the technology evolves and becomes more autonomous, users and engineers have a diminishing understanding of how AI is making decisions. The lack of transparency has caused growing concerns about accountability, transparency, and hidden biases that drive life-changing decisions.[42] These concerns multiply when considering transfer learning, evolutionary algorithms, and AI building AI that can resemble a tangled messes of connections nearly impossible to disassemble and fully understand.[43]

B. Misleading and Deceptive Recommendations

Intentional manipulation of algorithms or the underlying data can sabotage accuracy and misrepresent outputs. Tweaking weights associated with particular features to increase the likelihood that certain outcomes occur is one way to manipulate results. For example, if a customer is looking for running shoes on an ecommerce platform and a company paid for their shoes to be advertised first for the "running shoes" search result, the platform will present the company's shoes at the top of the customer's search results. The example is an oversimplification of the platform intentionally injecting bias into a Recommender System.

However, Recommender Systems are not simple. They generally include an ensemble of algorithms using different ML techniques with various features and weights associated with features or outcomes. Many companies add biases by applying weights associated with specific features. The reason is to make certain output products or content results more likely. Common reasons brands want to influence recommendation results is for paid ads, or to showcase their products or valuable partnerships. For example, Netflix Originals appear first because Netflix wants to prioritize its content. Spotify may have a partnership with an artist which means subscribers search results for indie artists returns the partner at the top of the list.

When a business is highlighting its products, the connection is apparent to consumers. Everyone knows Netflix wants viewers to be addicted to *Stranger Things* and *House of Cards* (i.e., Netflix Originals). Due to the opacity of most ML algorithms, adjusting weights associated with desired outcomes is invisible to consumers and extremely difficult to prove. How can data scientists evaluate if a recommendation is based on past behavior or partially influenced by a paid sponsorship that boosts results favoring partner products? Is it misleading or deceptive to lead customers to believe a product recommendation is based on their past behavior or profile by labeling it "More of What You Like" when in reality it is at the top of the list because it is a partner's content? It is near impossible to reverse engineer how complex Recommender Systems make decisions. Recall Recommender Systems are not one, but an ensemble of algorithms with tons of underlying data, different features and variables, developers with different conscious and unconscious prejudices that sneak into development, algorithmic biases, and much more. In the era of AI, the inherent opacity of ML favors companies willing not to disclose material connections. As "recommended content" labeling may lead to more impressions, awareness and inevitable purchases.

Section 5 of the Federal Trade Commission ("FTC") Act is at the core of the FTC's consumer protection powers prohibiting unfair and deceptive acts in or affecting commerce.[44] The broad enforcement authority includes policing misleading and deceptive advertising. The FTC's *Guide on Endorsements and Testimonials in Advertising* requires full disclosure of a connection when it is "between an endorser and the seller of an advertised product that might materially affect the weight and credibility of the endorsement (i.e., the connection is not reasonably expected by the audience)."[45] The guide does not provide examples of the Recommender System use case.

In 2015, the FTC released its *Enforcement Policy Statement on Deceptively Formatted Advertisements* and its *Native Advertising: A Guide for Business* (collectively the "FTC's Guidance").[46] The ability to skip and block digital advertisements has incentivized advertisers to offer native ads. Native ads are paid ads in a format matching both the function and form of the user experience in which the ad is placed. For example, think of a Google search. At the top are "Ads." If these ads did not have that label, the user would have a difficult time identifying the native ad as an advertisement. It is a sliding scale. The more the native ad is like other site content, the more likely clear, conspicuous, prominent, and unambiguous disclosures are necessary to prevent deceiving consumers. According to the FTC's Guidance, the format is deceptive if it "materially misleads consumers about the ads commercial nature through ***express or implied representation*** that it comes from a party other than the sponsoring advertiser."[47] The native ads should be transparent with clear identification; it is an advertisement.

The FTC's Guidance makes clear the same disclosure and transparency requirements apply to recommendation widgets. These are content-based recommendation tools displaying sponsored stories or paid ads close to site content via a widget. Some use contextual algorithms that recommend content that is like the content on the current page. Others can be "trending content" popular on the brand's page or behavioral recommendations that are trained on off-site data. ML techniques and Recommender Systems may power these tools. Brands using Recommender Systems or using third party vendors to display content on their websites and applications should disclose the material connection to any sponsored content or paid ads.

C. Privacy Law Challenges

The FTC and state attorney generals have been regulating privacy in the digital space for over 20 years. According to the FTC's Fair Information Practice Principles ("FIPPs"), companies online should follow fair information practices by giving consumers notice, choice, access to their information, security, minimize data collection and enforce these principles. FIPPs are guidelines, not binding legal authority. However, international and domestic privacy laws reinforce the principles, which some scholars argue are fundamentally incompatible with artificial intelligence.

1. Notice and Choice

California Online Privacy Protection Act ("CalOPPA") also requires notice to individuals. Privacy policies must inform individuals visiting a website or using an online service (e.g., mobile application) what personal information is collected about them, how it is used and whom it will be shared with.[48] Even though this is a state-specific law, California's economic importance as a state inadvertently forced all operators of websites and online services to post privacy policies. Moreover, CCPA requires disclosing:

- categories of personal information collected;
- business and commercial purposes the personal information is used;
- categories of third parties the personal information is disclosed to for business purposes;
- categories of third parties the personal information is sold to; and
- the mechanism consumers can exercise their rights (e.g., to opt-out, delete or access personal information).

It is challenging for companies to articulate all the ways data will be used, which makes providing full and fair disclosures to consumers problematic and raises ethical quandaries regarding the legal sufficiency of disclosures. At the time of collection, data scientists are usually not aware of all the ways that data will be used. Data is collected for one purpose, such as to provide a product or service and then repurposed for other reasons, like sending newsletters and training algorithms to make better predictions. We are in an era of over-collection and hoarding data because it is the new oil. Even though companies must provide sufficiently clear disclosures, some chose to bury blanket statements like "we use your information for marketing and advertising purposes" in lengthy legalese laden policies that only the lawyers drafting them read.

In the United States, the issue is not repurposing data but that consumers find some of the secondary purposes 'creepy' and a threat to their privacy.[49] For instance, a consumer buys baby clothes for their niece and then starts receiving Carter's ads on another platform. According to an InMoment 2018 CX Trends Report, 75 % of consumers find personalized brand experiences somewhat creepy, 22% look for less-creepy brands, and 9% of consumers would leave negative brand reviews for creepiness.[50] To avoid crossing the 'creepiness line,' brands should consider:

- following data minimization principles and not collecting more data than necessary to provide the service;
- not exploiting consumers' trust by failing to tell them how their data is used; and
- giving consumers value (i.e., 72% of consumers will tolerate 'invasive' AI that helps them solve a problem or provides desirable information in ads).

2. GDPR – Purpose Limitation and Data Subject Rights

In Europe, the GDPR's purpose limitation, secondary purpose restrictions, and automated-decision making rights hinder free-flowing innovation of AI. On May 25, 2018, the GDPR became effective and was a sweeping regulation that forever altered the international data protection landscape.[51] The fines under GDPR are up to 20 million euros or 4% of global turnover. Even for a company like Google, hefty GDPR fines can incentivize shifts in data practices and strategies.

Under the GDPR, there are strict purpose limitations that require the controller (or owner of the data) to only collect and process personal data for the "specific, explicit and legitimate purposes and not further process in a manner that is incompatible with those purposes."[52] If a consumer is willing to provide information for one purpose, the consent given for that purpose does not automatically extend to other unrelated purposes. Most users are unaware that every single action they take online from receiving an email, shopping for a phone on Amazon or asking Alexa to play the new Beyoncé single, leaves a piece of personal data behind that will be collected, analyzed, and repurposed for various unknown purposes. However, the GDPR throttles this behavior because if a brand wants to process the personal data or share it for secondary purposes (such as creating an AI application), that secondary purpose is only lawful when it is "compatible" with the original purpose for which the data was collected.

When personal data is further processed for (1) archiving purposes in the public interest, (2) scientific or historical research purposes, or (3) statistical purposes, then it is compatible with the initial purposes. If the original lawful basis for processing the personal data is compatible with the secondary purpose based on the compatibility factor test, then the data controller does not need a separate lawful basis for the secondary processing.[53]

However, if the processing is incompatible with the original specific purpose the controller must: (a) inform the data subjects and (b) obtain a separate lawful basis (e.g., consent). Many companies make the internal argument that the secondary purposes are compatible. However, brands should be careful when sharing large data sets for vendors or partners to create algorithms for secondary and likely incompatible purposes. Brands should conduct repermissioning campaigns when legally required to inform and ask data subjects to consent to further processing activities.

The purpose of the GDPR was to create a uniform regulation for data subjects to have more control over their information. Data subjects or people in the European Economic Area have various rights under GDPR. For example, data subjects have the right to be informed, erasure (or deletion explained below), object to processing, access, data portability, not discriminated against for exercising their rights and not be subject to automated decision-making.

Under GDPR Article 22, data subjects have the right not to be subject to decisions based only on automated processing, such as profiling, which produces legal or significant effects. Subject to regulatory guidance, AI used for sentencing, parole, and bail may be examples of decisions with legal effects. Data subjects may have the right to request human intervention in the decision-making, contest the decision, or receive an explanation of the decision-making process. With the opacity of AI, explanations may be an unrealistic request.

3. CCPA – Deletion and Data Sales

The CCPA goes into effect on January 1, 2020. It regulates the collection, use, and disclosure of personal information of California consumers (i.e., residents). Like GDPR, the CCPA gives consumers rights to be informed, access their information, and delete personal information about them. AI may be incompatible with the deletion rights under both laws. People can submit requests asking the business to erase their personal information. With AI applications, people's personal information is used to train algorithms. Even if the business deletes the data from data lakes in different departments, that person's data cannot be removed from the 'memory' of the algorithm. It is part of how the algorithm works and embedded permanently. For example, unintentional memorization can enable extraction of elements from the underlying data set. Therefore, brands that have algorithms will (1) delete the data from the data lakes and tell consumers it was deleted from their systems, (2) rely on exceptions to the deletion request, or (3) develop meaningful technical ways to comply by perhaps using synthetic data or creating training data.[54]

Another CCPA consumer right is opt-outs of data sales.[55] Under the CCPA, the definition of a 'sale' is broader than common conception. It is "selling, renting, releasing, disclosing, disseminating, making available, transferring, or otherwise communicating orally, in writing, or by electronic or other means, a consumer's personal information by the business to another business or a third party for monetary or other valuable consideration."[56] The broad definition has caused an uproar in the digital advertising community because exchanging information with a third party in the ecosystem for placing ads could be considered a sale.

V. Conclusion

In summary, AI is a synthetic intelligence that enables computer systems to complete tasks that would normally necessitate human intelligence. ML is a subdivision of AI but focuses on algorithms that can learn a given task by looking at example data. Within ML, deep learning is one technique that feeds massive amounts of data through non-linear neural networks, brain-inspired interconnected layers of algorithms. Recommender Systems can include various ML techniques and many companies use them for advantages like boosting click-through and conversion rates. Data is a necessary input to undergo most modern AI applications. Therefore, some companies will pursue collecting more and more data by pushing legal and ethical boundaries.

Law in the AI landscape is a hodgepodge of antiquated existing law that has not caught up with the new technology creating novel legal considerations. First, algorithmic bias can have a prejudicial impact on historically discriminated against segments of society. Second, scholars argue that AI may be fundamentally incompatible with privacy laws, such as the GDPR's purpose limitation, secondary purpose restrictions, and a data subject's right not to be subject to automated decision making. Moreover, the CCPA allows consumers to delete their information or opt-out of data sales, causing apprehension for companies with AI applications.

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[53] GDPR Recital 50 provides factors to determine compatibility such as links between the two purposes, nature of the personal data, context of collection, consequences of further processing, etc.

[54] Cal. Civ. Code §1798.105(d) Exceptions to deletion requests.

[55] Cal. Civ. Code §1798.120.

[56] Cal. Civ. Code §1798.140(t)(1).