# DECEPTIVELY SIMILAR: HUMAN AND MACHINE

What differentiates the human mind and computer intelligence? In the 2008 Turing Test competition, three out of twelve human judges could not discern a person from the winning artificial intelligence (AI) system (Christian, 2011, p. 2). Their failure is understandable. Like humans, artificial intelligences can learn and reason in a variety of contexts. Companies use algorithms to execute trades or evaluate applicants. Governments employ AI to reach verdicts and individuals will eventually hire them as drivers and assistants.

Replacing a human with a machine offers many potential benefits. As traders, algorithms cannot accept bribes or act fraudulently. Artificial intelligence may reduce partiality in the government. Journalist Charline Zeitoun (2018) observed how one U.S. parole committee implemented AI to overcome their “empty stomach syndrome,” referencing the board’s pre-lunch hunger that had contributed to a decreased likelihood of prisoner release (An aid to decision-making section, para. 2). Self-driving cars may eliminate human errors and reduce mortality rates on roads. Responses from 1,634 experts predict that AI-based translators, salespersons, novelists, and surgeons will outperform their human counterparts within four decades (Marshall, 2018, p. 579). AI is already transforming society, and may offer practical solutions to complex problems of the future.

Despite its usefulness, artificial intelligence is not a panacea. Evidence indicates that using AI to aid human decision-making can impact entire social classes in consistently unfavorable ways. This problem, known as algorithmic bias, emerges anytime machines involve humans. Crime prediction tools overly penalize black defendants. Automated resume screenings may disproportionately hire males. Rather than perpetuate unfairness, is it possible for algorithms to promote fairness? The STS research first traces bias and investigates the social consequences. Applying the the Social Construction of Technology framework, this study illuminates potential solutions to mitigate bias and encourages an ethical discussion.

Tightly coupled, the technical project and STS research both focus on language technologies. The technical team of systems engineering students is developing algorithms to improve a leading customer experience management service. To recommend business actions and improve customer outcomes, the research infers customer states based on their language. Acting upon assumptions about an individual's beliefs prompts a discussion regarding the societal implications.

## LEARNING AND AMPLYFYING HUMAN BIAS

The implementation of AI is prone to errors. As algorithms learn from human-centric data, they inadvertently gain human biases. For example, women have historically been unable to assume the same positions as men. Consequently, one 2016 study revealed that some automated resume screenings will excessively favor males for programming roles (Bolukabasi, Chang, Zou, Saligrama, and Kalai). Automating these biased systems could amplify existing demographic differences. Consider one of the 200 million users on Google Translate each day (as cited in Prates, Avelar, and Lamb, 2018, p. 4). Learning a new language, the user may encounter translations from gender-neutral Hungarian to English, seen in Figure 1 below. The translation

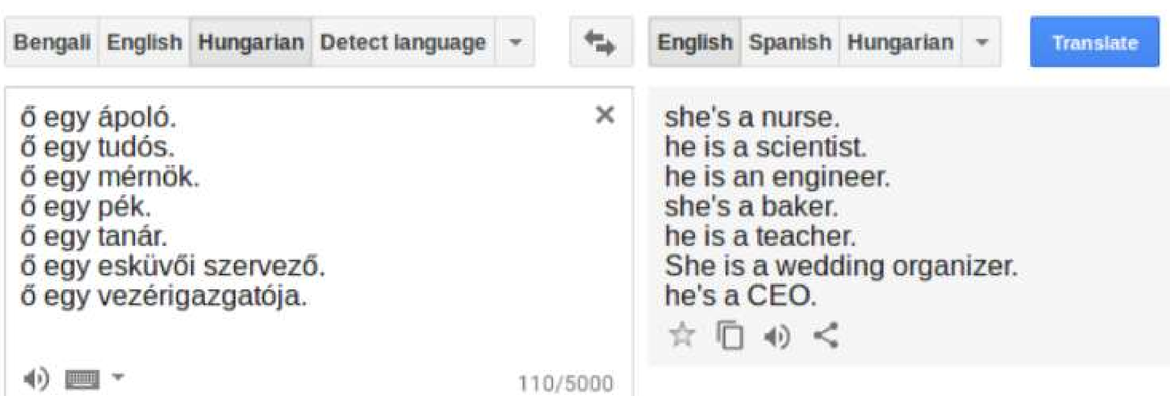


Figure 1: Gender Bias in Translation: Translating gender neutral pronouns and occupations makes biased assumptions about the intended gender. (Prates, Avelar, and Lamb, 2018)

engine, perhaps unbeknownst to its creators, reinforces controversial biases about the intended gender of the sentence. In the 2018 study, researchers Prates et al. determined Google Translate mirrored gender stereotypes, reverting to male pronouns as often as 72% of the time when translating science, technology, engineering, and mathematics professions (p. 12). Many other AI applications risk perpetuating discrimination. In 2018, the Microsoft chat bot Tay unleashed racist and sexist tweets only hours after its release (Zeitoun). The algorithm learned from hate speech and immoral comments infiltrating social media. Given the process by which AI learns, human bias and machine bias are intrinsically linked. To understand and limit bias, this study will first define the term and explain how it occurs in greater detail.

**HOW BIAS HAPPENS**

Batya Friedman, a pioneer of value sensitive design, and Helen Nissenbuam, a researcher of human values, formally denote a computer system biased if it "denies an opportunity or assigns an undesirable outcome to an individual or group of individuals on grounds that are unreasonable or inappropriate" (1997, p. 332). Perhaps surprisingly, bias can emerge well before researchers develop an algorithm. When framing the problem, creators must define modeling objectives, many of which are predisposed to bias. Crime risk assessment tools, for example, aim to predict a defendant's likelihood to reoffend (Hao, 2019a). Yet, historical crime data represents prior convictions without the veracity that the individual has committed the crime. Analyzing the crime prediction tool COMPAS used in Wisconsin and Florida, investigative journalists Angwin, Larson, Mattu, and Kirchner (2016) determined the system inaccurately predicted black defendants to be almost two times more likely to commit a future crime than white defendants (para. 15). While the assessment intends to remove human bias, the algorithm learns from years of "key decisions in the legal process, [which] have been in the hands of human beings guided by their instincts and personal biases" (Angwin et al., 2016, para. 20). This research design problem is especially relevant when considering language technologies. Natural language processing extracts meaning from words; however, it is the person speaking those words and *their* intended meaning that language processing tools actually want to capture. Consider the emerging problem of fake news in which websites or channels spread false information or propaganda as authentic news. From the course Carnegie Mellon course *Computational Ethics for NLP*, instructor Yulia Tsvetkov (2018) argues that users are more likely to open controversial or fake news stories, falsely signaling to a news feed algorithm like Facebook that the content is more relevant. This problem is difficult to solve because the relationship between the true objective and the available data is not clear.

The major form of algorithmic bias portrayed in the media manifests during the data collection process. In their 2016 peer-reviewed conference paper, researchers Dirk Hovy and Shannon Spruit (2016) describe algorithms that ingest imbalanced data to create *exclusion*. Hovy, a faculty member at the Center for Language Technology at the University of Copenhagen, has dedicated his career to studying the influence of language and engineering decisions (Hovy, 2018). Spruit is an active researcher of Ethics and Philosophy of Technology at Delft University of Technology in the Netherlands. The researchers indicate exclusion leads to demographic bias and misrepresentation. An October 2018 public interview between Alisa Chang and researcher Alice O'Toole illuminate the tendency for facial recognition software to be less accurate when making decisions regarding minorities. Since models learn from examples, the lack of data from these demographics contributes to exclusion. Hovy and Spruit (2016) encourage technical professionals to eliminate overfitting, which refers to models that too closely follows the training data, and to balance training data by oversampling under-represented demographics in order to overcome exclusion.

Consequences from a mistake in the model itself are known as overgeneralizations. Overgeneralization stems from insufficient data or overly-simplistic models that do not completely capture real-world complexities. Cathy O'Neil (2016) denotes these imperfect models "weapons of math destruction" since they harm society, especially poor and underprivileged groups. O'Neil explains how automated decision tools appear more frequently in poor areas because they are cheaper than human review (p. 5). The harmful side effect is unsuitable conclusions that further hinder these underprivileged communities.

## SOCIAL RAMIFICATIONS

Bias is a growing concern for politicians, data professionals, and public citizens. Democratic Representative Alexandria Ocasio-Cortez is using social media to draw attention to unfairness in AI technologies like facial recognition and crime prediction (Zakrewski, 2019). Responding to Cortez, *MIT Technology Review* and several top data scientists defended the need for a dialogue about bias. As individuals relinquish information to companies and government, they need to recognize the consequences of the use or misuse of personal data. Understanding the relevant social groups responsible for the creation and diffusion of technology is thus critical.

Establishing socially beneficial technology needs an answer to several key research questions. Can society limit biases from algorithms? Who is at fault for AI errors? This study invokes an ethical discussion regarding AI systems to identify opportunities that promote inclusion, equity, and fairness. Applying the Social Construction of Technology (SCOT) framework, the STS research identifies several approaches to address the challenges facing language-based AI technologies.

**DEBIASING: A COLLABORATIVE NEGOTIATION**

Developed by Pinch and Bijker (1984), SCOT identifies relevant social groups with whom engineers interact and inform. Pinch and Bijker claim the development of technology depends on a complex set of social, cultural, economic, and political factors. The best way to illustrate these relationships is through a diagram. The SCOT model, in Figure 2 below, places AI systems and its creators as the technological artifact in the center. Surrounding the artifact are key participants in AI development: academics, businesses, regulators, public citizens, and individuals facing discrimination. Contrasting technological determinism, this representation rejects that AI technology develops independently from society. While artificial intelligence undoubtedly influences society, its future development depends on the collective interests and perceptions of these social groups.

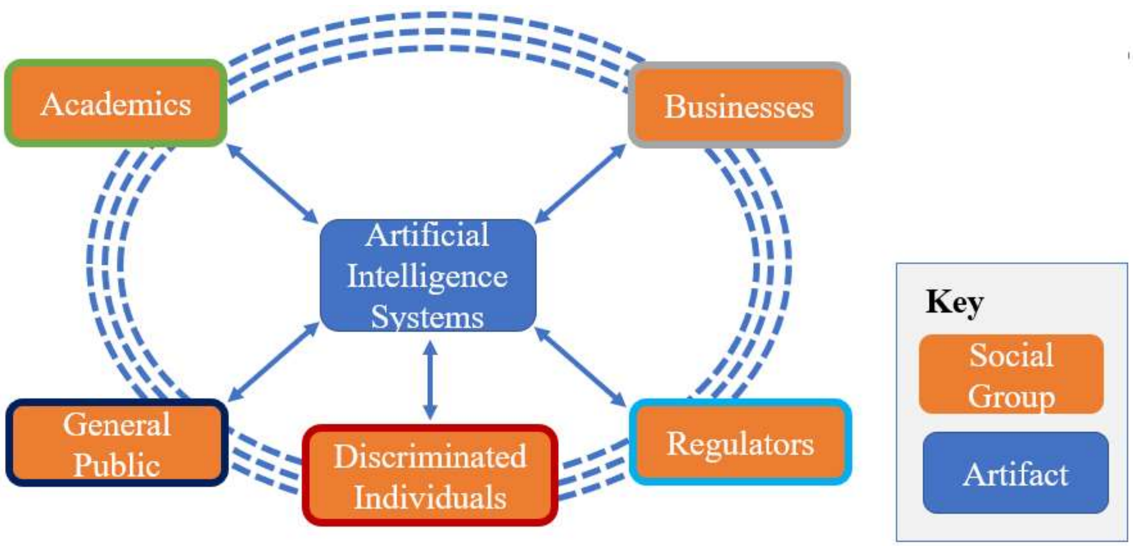


Figure 2: Social Construction of Artificial Intelligence: The social groups and artificial intelligence systems mutually shape one another. (Adapted by Wilson, 2018 from W.B. Carlson, 2008).

**SILOED SOCIAL GROUPS**

The prevailing thinking about bias as it currently stands rarely spreads across all stakeholders. The SCOT model in Figure 2 above encapsulates the relevant social groups to indicate their relationship; however, there remains a lack of shared understanding due to each group's underlying perceptions about AI and bias.

Data experts and engineers, often the group most aware about bias, experiment with technical approaches to mitigate bias in natural language processing. Attempts at simply omitting sensitive information have failed to adequately debias AI systems. While unintended, Tsvetsky (2018) points out that other variables, such as zip code and browsing history, can encode demographic information, thereby enabling models to prolong discrimination. Karen Hao, an artificial intelligence reporter, references several new technical approaches, fairness metrics and bias mitigation algorithms, in her February 2019 feature from *MIT Technology Review*. Despite these advancements, engineers cannot eradicate bias alone.

From security and hiring to customer service and marketing, businesses and governments implement artificial intelligence across many facets of their operation. Their perception of AI differs from that of the engineer. Instead, a company's primary focus is often profitability. Consider a credit card company that uses an algorithm to determine the creditworthiness of a loan applicant. To model this question, Hao (2019b) contends that the company must choose between maximizing profit margins or maximizing the number of repaid loans. "Those decisions," explains Solon Barocas, an assistant professor at Cornell University studying machine learning bias, "are made for business reasons other than fairness or discrimination" (as cited in Hao, 2019b, para. 4). In prioritizing other interests, businesses may overlook biased solutions. Moreover, these algorithms are typically proprietary, so academic researchers are unable to independently test for fairness and equity.

Public citizens, as users of AI technology, generally have the option to accept or reject technological artifacts. One crucial limitation of this interpretation is the lack of informed consent. Many users are taking involuntary risks when they are unaware how companies and governments use their data. Again, given the proprietary nature of these algorithms, individuals rarely have an idea or proof any unfairness occurs.

The specific individuals facing discrimination are a subset of users; however, their interpretations of the service may vary greatly. Even when bias is known, can these individuals afford to give up some of the opportunities AI offers? Consider a low-income, minority student that has accumulated debt. The student applies to several top paying jobs, but ultimately every company rejects the candidate based on automated resume screenings and pre-recorded videos. In this scenario, the student turns to a lower paying job that further handicaps them. Thus, the companies and organizations applying AI models gain power over individuals.

## CHANGING THE POWER DYNAMIC

Technology companies have the opportunity to shift authority. One encouraging example comes from Google. The company and many others like it collect data from individuals to offer services and capabilities. A heightened awareness of bias enables organizations to revisit products and prioritize engineering features to debias systems. Gender bias in translation, highlighted by researchers Prates, Avelar, and Lamb in Figure 1 on page 2, led to subsequent changes in Google's translation system. As researchers tested the public-facing algorithm for fairness, the silo mentality preventing fairness began to deteriorate. Public research brings the issue to the forefront of businesses, computer scientists, public citizens, and politicians.

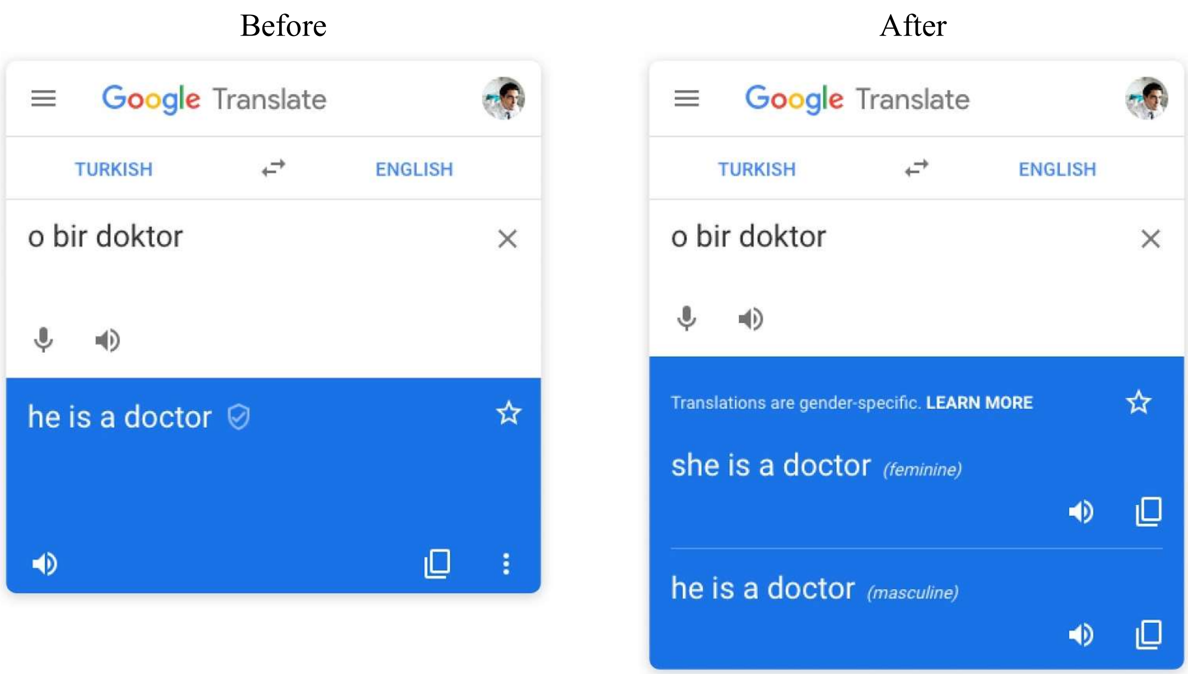


Figure 3: Debiased Translation: Improving translation quality and reducing gender bias required a design change and a robust model update (Johnson, 2018).

In Figure 3 above, Google successfully removed gender stereotypes that occurred when translating gender-neutral languages. Senior software engineer at Google Translate Melvin Johnson (2018) explains how the solution required significant improvements to the backend algorithm and updates to the user interface itself. To support multiple gender queries, the translation framework mandated significant upgrades for detecting gender-neutral inputs, generating gender-specific translations, and verifying accuracy (Johnson, 2018). Clearly, the investment to remove bias is large. Companies like Google may openly address bias issues in algorithms; however, the urgency level depends greatly on the company and its values given the dollars spent.

**Involving Stakeholders**

To address fairness issues, the SCOT model in Figure 2 on page 6 correctly emphasizes the negotiation across social groups. Researchers, regulators, and government entities assume an important role in prioritizing investments to prevent bias. Innovative, data-driven schools like the School of Data Science planned at the University of Virginia are already recognizing the need for responsible, ethical data practices (Hester, 2019). Researchers are essential for ideating and sharing new evaluation tools to verify algorithmic fairness. Without researchers' study of gender bias in word-embeddings, it is unclear whether Google would have made any changes to its translation system.

Similarly, Zakrewski (2019) believes politicians could have a role in limiting machine bias. Politicians can establish transparent testing, demand more information from technology companies, or instigate safeguards. As of early April 2019, congress introduced the Algorithmic Accountability Act, which would require companies to regularly test automated decision tools for fairness and enforce actions to remediate any issues (Electronic Privacy Information Center, 2019, para. 1). Other governmental organizations are internally prioritizing fairness. The Department of Defense (2019) recently released a strategy that emphasized the research and development of safe, explainable, and resilient AI systems. The department envisions public-private partnerships and international collaboration "to advance AI ethics and safety in the military context" (Department of Defense, 2019, p.8). This increased dialogue regarding AI ethics in academic, political, and public groups is promising. Nevertheless, without transparent and continuous testing, algorithms remain a risk to minorities.

**The Role of Individuals**

Crowdsourcing, the process of calling upon many users for input (Certom and Pimbert, 2015), may offer a solution. In their 2015 action research guidebook, researchers Certom and Pimbert recognize how democratizing research through crowdsourcing improves accuracy, transparency, and inclusion. Encouraging people to actively provide feedback on AI systems could help recognize and limit residual biases. For example, the June 2016 web query, in Figure 4 on the left, exposes a racist Google image algorithm. Users searching for “three black teenagers” discovered images of arrested individuals, which starkly contrasts the young models depicted in the search for “three white teenagers” (Tsvetkov, 2018, slide 8). The algorithm works by accumulating popular images, but the system inherently reflects societal asymmetries, thereby creating biased results. An intuitive reporting button for users would aid the system and the engineers in detecting biases and limiting their amplification. This process enables AI experts and users to share common ground, a fundamental goal of this STS research.

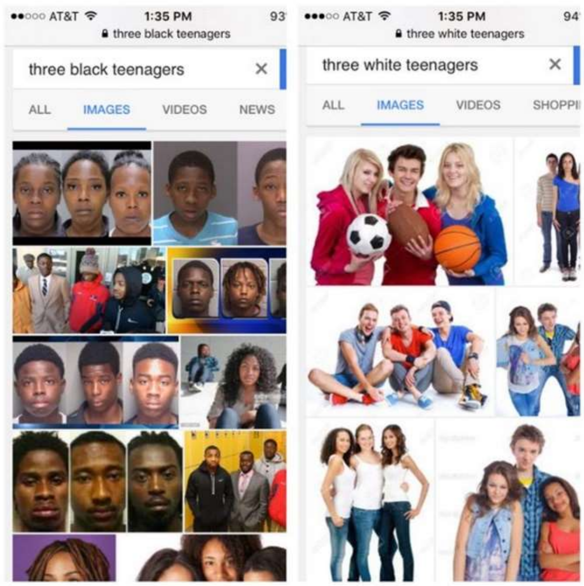


Figure 4: Racist Web Search: Two similar June 2016 Google searches show fun images for white people yet mugshots for black people (Tsvetkov, 2018, slide 8).

**SHARED RESPONSIBILITY**

All stakeholders need to work together to evaluate bias and generate awareness. The SCOT framework has limitations since the extent that each social group shapes technology is not necessarily equal. Hovy and Spruit (2016) claim that “language is a political instrument [and] an instrument of power” (p. 592) and thus language technologies are inherently political, too. Society should be concerned about autocratic algorithms overtaking decision-making processes. Investigating trust within socio-technical systems, Andras et al. (2018) contend that artificial intelligence has surpassed the level at which non-experts can understand the machine’s decision-making processes. As AI replaces human decision-makers, experts and businesses exert power over individuals. Thus, it is difficult for individuals to evaluate an algorithm's trustworthiness and fairness themselves.

**ETHICAL DISCUSSION**

If an algorithm is less biased than a human, but biased overall, should society still use it? The resolution depends on the social context. Ethics professors Hovy and Spruit (2016) ask creators, "would a false answer be worse than no answer?" (p. 593). Perhaps machines should not make decisions when the consequences are grave, for example, when sentencing someone to prison. A pragmatic approach is best to resolve conflicting principles during AI development. Each relevant social group has their own inherent biases and intrinsic beliefs. The resolution relies on the harmony of these inter-related perspectives.

Returning to the original research question, engineers cannot eliminate bias by themselves. Natural langue processing research outcomes suffer from alternative and unintended consequences. People can design solutions to detect fake news yet simultaneously manipulate algorithms to generate fake news (Hovy, 2016). Shared responsibility and moral obligation, on every social group relevant to the development of AI, ensures the best possible solution. Invoking duty ethics, there is an obligation on researchers and engineers to spread awareness. Equally important is the duty on organizations to promote a morally responsible environment and prioritize debiasing as well as the duty on users and the public to understand their rights or lack of rights when choosing a service. Other ethical theories, such as virtue ethics support similar ideals. Honesty, a virtue, suggests the need to disclose improper use or false information. Society cannot blame the algorithm itself. While many models are black boxes, meaning humans cannot clearly explain their decision-making process, stakeholders must continuously monitor them for bias.

## MOVING FORWARD

The ethical discussion regarding algorithmic bias and ethical AI in academic, political, and public groups is a promising start, but problems remain. Further decomposing technological artifacts into relevant social groups and their relationships may help illuminate morally imaginative solutions to exclusion and overgeneralization. Engineers have a responsibility to evaluate their models for bias, but technical solutions will never be completely impartial. Promoting feedback from the public enables artificial intelligence and engineers to know when and where bias occurs. Furthermore, companies can take a stance and invest heavily in debiasing algorithms. When algorithms are not as visible to the public, regulators should raise awareness and enforce research from government entities and academic institutions to assess algorithmic performance and increase transparency. Ultimately, employing AI to make decisions without understanding and limiting its bias is a threat to basic human rights and a violation of our duty to each other. Humans, not machines, are responsible for decisions that influence society.

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