Pitch Controlled Pong

The Zuckerberg Caricature: The Stereotypical Genius Computer Scientist And Its Negative Effect on Corporate Behavior

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On my honor as a University student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments.

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General Research Problem: Responsibility and Accountability in the Tech Industry

How can we aid technology companies to develop in accordance with social good?

Modern tech companies undeniably have a powerful influence over both social structures and the world economy. The five largest tech corporations in America—the five "FAANG" tech giants (Facebook, Amazon, Apple, Netflix, and Google)—have a market cap of over 2.4 trillion dollars, approximately equal to the GDP of France (Fernando, 2022, p. 1). With this vast influence, concerns over how it is to be wielded are inevitable. Through issues of misinformation and dangerous and radicalizing content on social media platforms, many have called for increased regulation and accountability of tech corporations (Biden et al. v. Knight et al., 2021). Most Americans believe that social media and tech companies have too much influence on both society and politics (Anderson, 2020). In addition, almost three-quarters of Americans are not confident that tech and social media companies would be able to prevent misuse of their platforms to compromise the integrity of our presidential elections (Green, 2020). With such widespread influence and so little public confidence in their scruple, how have tech corporations become such autonomous entities? While there are likely a variety of contributing factors, one topic worthy of exploration is the people composing the tech industry workforce. Since the tech sector workforce is composed of computer science and programming professionals, exploring the composition of the tech industry as a possible cause for its autonomy requires understanding: *How do the stereotypes associated with programming professionals influence the relationship with accountability in the tech industry?*

In addition, when the scale of influence is as vast as it has become for the tech giants, identifying and minimizing possible abuses of power comes to the forefront of public attention. Of the concerns, harmful content presented to individual users on social media and tech platforms is often prevalent in negative public opinion, and cited as a major concern surrounding the products these vastly influential corporations produce (Scheuerman et. al., 2021). Harmful content is a broad term, but refers generally to depictions of violence, sexually explicit content, spam, impersonations, false/misleading information, and phishing ploys. Phishing ploys specifically reference attempts to gain ungranted access to a system by exploiting a human limitation, such as soliciting passwords or banking information. (Khonji et. al., 2013). As the limitation of this harmful content is a major public concern towards social media technology, the processes for identification and removal of this content must be improved.

Identification of Harmful Social Media Content By AI Moderators

How can image recognition software be leveraged to identify harmful content on social media platforms?

Major social media platforms disallow harmful content from their platforms in their terms and conditions of use (*Twitter Terms of Service*, 2021). However, these rules are only an effective deterrent if there is adequate enforcement. Through the use of moderators, content that violates the platform's guidelines can be identified, but there are far more users than moderators. Spam and other harmful content reach millions of unwary users primarily through social media (Wang et. al., 2011, p. 46-54). Tools and approaches to limit the harmful content that is spread and made accessible on social media platforms will be necessary to help develop the future of social media more in line with social good.

AI software can be leveraged to identify content when moderators are overwhelmed. Artificial intelligence and machine learning techniques have already been implemented and explored in attempts to identify harmful content. Artificial intelligence has been trained using language identification to detect "fake news" and factual inaccuracies (Ozbay et. al., 2020).

Many other social media moderation artificial intelligence implementations utilize image recognition and analysis (Gillespie, 2020). However, there are few examples of artificial intelligence trained using video input.

To aid in the mission to reduce harmful content, dedicated video recognition software will be designed to classify violence in videos posted to social media so that they can be marked and taken off the platform. A deep learning model will be applied, and trained on video content acquired from alternate social media platforms such as Reddit, that have already been marked as violent. These platforms allow such content, with the acknowledgement that they are marked, so there is adequate training data available. The software will assign a violence score to a given input video, and if the score passes a predetermined threshold, the video would be marked for removal. The software would then be tested against a test set of video content acquired using the same method as the training data, but ensuring that the training and testing data are separate to ensure rigorous testing.

This implementation brings with it the concerns applied to all automated content detection, especially issues of training data selection. Any bias in labeled training data will be reflected in the classifying algorithm they are used to to train. In addition, AI is best utilized for extreme cases of harmful content, and struggles with more moderate offenses (Gillespie, 2020). We hope to address this issue using a continuous violence score, so that egregious content is removed, but less obvious content can be marked for human moderation.

Ideally, this pursuit will result in an effective classifier of violent video based content that could be effectively implemented on social media platforms to minimize this form of harmful content. This attempt at video recognition could serve as a starting point or trial for video training data in AI implemented content moderation. We hope to improve video content moderation, as well as video classification technology.

The Stereotypical Genius Computer Scientist And Its Effect On Tech Accountability

How do the stereotypes associated with programming professionals influence the relationship with accountability in the tech industry?

Many disciplines have commonalities or social expectations for the professionals within it, e.g., health care professions such as nursing are often associated with female gender stereotypes (*Effects of stereotypes on career choices,* 2022), but computer science, given its many depictions in media, has a most pronounced stereotype associated with it (Dou et al., 2020, p. 5). The image of a savant, locked away in a darkened room, face lit only by the pale blue glow of a computer monitor as they solve an unsolvable problem is littered throughout film and tv shows. Prominent examples include the depiction of Mark Zuckerberg in David Fincher's *The Social Network*, Elliot in Sam Esmail's *Mr. Robot,* and Q in *Skyfall* from the same director. Surveys of students and academic professionals find that in developing academics, people assume that computer scientists must be "very smart" (Wang et al., 2017, p. 51). Broader surveys also find computer scientists and students of the subject routinely described and stereotyped as "singularly focused" or obsessive, "asocial," "competitive," and "male" (Lewis et al., 2017, 23). Stereotypes are not necessarily reflective of the average computer scientist, but these stereotypes do have an impact on who pursues and continues with a career in computer science. Studies relating students' self-identification with common computer science stereotypes to their later pursuit of the field find that a stronger "fit" indicates a higher likelihood of a future pursuit of the subject (Lewis et al., 2017, 29). Given that students who exhibit or self-identify with CS stereotypes such as the five mentioned by Lewis et al. will have a stronger sense of "fit," then these traits are more likely to be represented in the CS demographic than the general population. The commonality of strong asocial, competitive, and obsessive traits among those designing socially and fiscally influential technology will likely have an effect on cooperation and transparency as design concerns. Reflected in Facebook's "move fast and break things" motto, tech companies composed of those exemplifying obsessive, asocial, and competitive behavior may have a different relationship with accountability than any technology dominated by a population with a lesser display of these traits.

Confounding Factors in Tech Accountability

Career-centric stereotypes are not the sole determinant of antisocial behavior, or the behavior exhibited in the other traits described above. For example, one researcher posits that aggression and aggressive behavior in a professional setting stem from corporate culture and competitive factors inherent in a capitalist workplace (Diamond, 1997). Even if aggression and competition are instilled upon computer science professionals by stereotypes, and potential computer scientists are filtered out by their alignment with these traits, one cannot discount these effects in exacerbating possible aggression, competition, and isolation. This investigation will seek to evaluate the extent to which these stereotypes relate to tech accountability, with the knowledge that exposure to stereotypes is not the sole cause of their appearance in tech culture.

Contemporary Work in Stereotypes and Computer Science

Much of the current literature discussing the stereotypes of computer science approach the stereotypes to evaluate their effect on the demographic makeup of the collegiate and professional computer science community. Current investigations cover the effect of perceived stereotypes on the gender makeup of computer science demographics, specifically how computer science stereotypes perceived as culturally masculine can serve as a barrier to entry for female programmers (Cheryan et. al., 2015). Similar investigations relate these same perceptions to the low percentages of racial minorities in the field of computer science (Dou et. al., 2020). There is also substantial literature identifying public perceptions of programming and professionals, as well as investigations into corporate culture and its effects on performance (Lewis et. al., 2016; Kitchell, 1995). However, the association between cultural stereotypes of programming and tech company accountability is absent. The effect of these stereotypes on the demographic makeup has been investigated, but their association with accountability remains to be seen.

Data Collection and Methods

To investigate the effect of these stereotypes on accountability, I will conduct a literature review from existing resources. First, I will well define the specific stereotypes of interest which are most relevant to accountability and cooperation. To effectively define and solidify the prevalence of these stereotypes, I will need to gather the results of previously conducted surveys on this topic of populations that can be reasonably generalized. Surveys conducted of only teachers and students, for example, may not be generalizable as those in academia may hold different opinions of computer science than the general population. I will then collect documentation and discussion of the culture behind various prominent tech companies, and relate this culture to the stereotypes investigated briefly above. These will ideally take the form of first person testimonials and descriptions from a selected group of companies, and possibly interviews about corporate culture. I will analyze these descriptions for indicators of the stereotypes I have defined in the previous step to assess the severity with which these stereotypes are represented at the selected companies.

The literature review will then turn to documentation of instances where the selected technology companies have violated community trust or operated in a way that demonstrates a disregard for accountability. I will realize this through a collection of reports on corporate action, specifically of instances where public outcry is notable. It is worth noting that this method will neglect instances of corporate negligence or lack of accountability that were not brought to public attention. This is simply a limitation of collecting information from what is publicly available. I will subsequently relate these instances to the available literature on the culture of these companies. Through the use of resources on the culture of these companies, I will gain insight on their relationship with and demonstration of the stereotypes previously mentioned, and review these relationships to see if there is legitimate connection between the specific stereotypes of CS students and the relationship with accountability of various tech companies.

By the end of this literature review, I should be able to effectively evaluate the extent to which the stereotypes of programming professionals are reflected in the culture of a select group of technology companies, and to what extent that in turn is related to each company's relationship with accountability. A better understanding of this relationship may allow legislators to more effectively regulate tech giants; with these traits in mind, legislators could work to foster a more collaborative relationship between the private tech industry and the government and public. Teachers and professors may be able to use this information so that they may be more conscientious about the way they present computer science. This literature review should provide a more comprehensive understanding of one possible factor in the pursuit of tech accountability.

Conclusion

Molding the technological progress of tech corporations to agree with social good will be essential to optimize future harm reduction. We must foster a more beneficial relationship between the producers of technological advancement and the will of society. Aiding in the identification of harmful content on the social media technology which has already become ubiquitous will help to set this precedent. In addition, understanding possible causes of the separation between technology companies and social good is an important step towards correcting it. This relationship holds more complexity than simply the stereotypes of the professionals involved, and future work identifying and investigating other factors in the accountability of technology companies would help to build on this knowledge. Both the development of content moderation technology and understanding of the effect of stereotypes on tech accountability will help guide technological progress into alignment with social good.

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