Abstract

Racial and gender discrimination have long plagued employment at every stage: in hiring, maintaining a job, and gaining promotion. LinkedIn, as a professional networking site that is used by hundreds of millions of people, a source of analysis for modern discrimination in the employment world. One of the key features of LinkedIn is that it connects individuals with other people in similar industries and professions through mutual connections and attributes. This can be done through the "People Also Viewed" on the right side of any user's profile. By programmatically gathering all of the profiles in the "People Also Viewed" tab for graduates of four American law schools and by analyzing these profiles for race and gender, the study cast light on the biases implicit in LinkedIn use.

The results show that racial and gender bias are prevalent on LinkedIn but not ubiquitous. Where racial bias occurred, members of racial minorities were more likely to appear in the "People Also Viewed" tab of the profile of a user who was of the same racial minority. For Blacks, the number was most extreme, as a Black profile is over six times as likely to show up in relation to another Black profile as it is to the average profile. Gender bias was more prevalent in the data, but not to the same degree. For all but one breakdown of the data, males were 9-18 percent more likely to appear in the profiles of other males and females were 19-31 percent likely to show up in the profiles of other females. The notable exception in the study was Hawaii, which did not show significant racial or gender bias. Save for Hawaii, these outcomes are concerning and show that bias does still exist in the modern professional networking world of LinkedIn. It is theorized that these biases are having a negative effect on the employability of marginalized groups.

Introduction

LinkedIn was founded in 2003 by Reid Hoffman as a business-oriented social networking platform [1]. The platform allows users to post professional profiles that highlight their work experience and skills, usually in a similar style to a resume or curriculum vitae. As with other social networking platforms, LinkedIn provides users with the option of uploading a photo to their profiles. LinkedIn also allows users to make connections with other users that they have worked with or know. Additionally, users have the ability able to examine the LinkedIn profiles of other people that they do not know. Since its inception, LinkedIn has grown to a base of 433 million users [1]. The platform is used by 25 percent of adult internet users, and by 46 percent of online adults who are college graduates, giving it importance in the online professional world [2]. As a service, LinkedIn allows users to propagate not only their resume, but to present a comprehensive professional representation of themselves [3]. A profile viewer can gauge how another professional looks and dresses, what their work history is like, and who they are connected to.

As it continues to grow in the 21st century, LinkedIn is changing the space of professional recruitment and networking. This professional space comes with a long history that has been central to the ability, or lack thereof, of marginalized groups to gain and maintain status and power in the United States. Through gaining employment and higher quality employment, groups like blacks and women have been able to make some gains in economic status over the past decades, though large economic disparities still exist [4,5]. At the same time, the hiring process and the workplace have long been plagued by problems of discrimination along a multitude of demographics lines, particularly in regards to race and gender. The literature shows that both race and gender impact a person's chances of chances of being hired for a job [6,7]. Additionally, knowing an applicant's demographic information at the time of hiring can change the perceptions of why they were hired, especially when an affirmative action policy is in place [8]. Once in a workplace, racial minorities and women continue to face disadvantage in winning promotion and in receiving equal pay for the same work as their white, male co-workers [8,9].

As an online platform for professional networking, LinkedIn offers a window for analysis of the state of racial and gender discrimination in the modern, digital world. By associating photographs with profiles, LinkedIn allows for the race and gender of many of its users to be easily identified. Additionally, through its network features, viewers can see who a user is connected with and what other users are deemed by LinkedIn to be similar to the user. On a user's public profile, this is most prominent through the "People Also Viewed" tab on the right side of a profile page. This tab provides the names and profile pictures of 10 other users that viewers of the profile have also looked at [10]. These combined elements of LinkedIn allow for research into how people are using LinkedIn. By searching for patterns in the occurrences of racial minorities and women, research can offer insight into the impacts of race and gender in the online professional world.

Background

Research shows that networks play an important role in finding employment. Granovetter, in 1973, showed that weak ties--acquaintances but not close friends of an individual--were significant elements in a network for helping an individual find a job [11]. Through a weak tie, an individual is connected with another group of people that the individual would not have otherwise known, and these connections provide access to resources like job opportunities. Further research built on Granovetter's work and showed that network structure is important in helping an individual maximize the weak ties in their network [12].

Studies have analyzed online social networks as well. Centola investigated the spread of health information through an online social network and found results that contradicted those of Granovetter. Health information spread more quickly through networks that were closely clustered than through networks that were inundated with weak ties, though this could be because of the sensitivity and importance of health information [13]. The relationship between employment and online social networks has also been analyzed to some extent. It has been shown that employers use social networks like Facebook and LinkedIn to evaluate candidates, and that factors like attractiveness and religion have an impact on the evaluation of candidates [14,15].

After a search of the literature, no research could be found that specifically analyzes the impact of race and gender on professional networking on LinkedIn. Research in this space could address questions of how racialized and gendered networks affect the ability of marginalized groups to find employment opportunities, and how profile-viewers perceive users based on their demographics and the demographics of the people they are connected to. Towards these ends, this study investigates how race and gender impact LinkedIn users. Through the analysis of a key feature of a user's LinkedIn page, the "People Also Viewed" tab, this research examines patterns in how users are associated with other users.

Methods

The first step in this research was to assemble a data set of LinkedIn profiles that could be analyzed. It was reasoned that users in the data set should have a high degree of similarity in their qualifications in order to control for skill level when analyzing race and gender. While an imperfect solution, it was decided to use a data set of LinkedIn profiles of graduates of clustered class years at the same university. By choosing similar graduates, it can be inferred that education level amongst graduates is almost the same and that number of years of work experience is roughly equivalent.

To accomplish this, classes of graduates were selected from four law schools: Louisiana State University, George Mason University, the University of Hawaii, and the University of Minnesota. The clusters of classes all graduated in the late 2000's or early 2010's, as can be seen in Table 1.

Table 1

School	Class Years	Number of Profiles
George Mason	2009-2011	422
Hawaii	2009-2010	167
Louisiana	2009-2010	345
Minnesota	2009	524

Table 2

School	Number with LinkedIn	Percentage with Linkedin
George Mason	239	57%
Hawaii	52	31%
Louisiana	164	48%
Minnesota	522*	%100

*Not all Minnesota profiles were used in the study

The LinkedIn profiles of graduates of these law schools were culled using a search by school and class year on LinkedIn. The results of these searches were then compared to the class rosters to determine the percentage of graduates from each school who use LinkedIn (Figure 2). Once all LinkedIn profiles had been catalogued, race and gender were inferred from each graduate's LinkedIn profile and documented.

The next step involved mining out the profiles of users in each graduate's "People Also Viewed" tab. This was done programmatically for each school, as follows:

1.) The list of graduate names and the list of corresponding LinkedIn profiles were zipped together into a list of tuples.
2.) Using Selenium Webdriver, the graduate's LinkedIn profile was opened in a Mozilla Firefox browser.
3.) Using Beautiful Soup, the html of the LinkedIn profile was read and parsed.
4.) A new directory was created for the graduate.
5.) The outgoing links to the 10 profiles in the "People Also Viewed tab" were accessed using their html class.
6.) For each outgoing link, a new browser was opened. A screenshot of the newly accessed profile was taken and saved to the directory of the original graduate.

After the LinkedIn profiles from the "People Also Viewed" tab had been fully mined out, each profile was examined manually to assign race and gender attributes. This was only done for profiles that had a photograph. Profiles without a photograph were counted but not assigned race and gender attributes given the difficulty in assigning race based on name alone.

Assignment of race and gender was performed by a subjective viewing of the profile's photograph and a categorization of the individual based on the researcher's understanding of prevailing societal notions of race and gender. In cases where the researcher had difficulty discerning race from the image, the name of the individual was also examined. Profiles were assigned to one of four categories for race (White, Black, Hispanic, or Asian) and one of two categories for gender (Male or Female). These attributes were then tabulated in reference to the original graduate profile. For each law school graduate, it was counted and recorded how many of each racial group and how many of each gender showed up in the "People Also Viewed" tab. Given that profiles without pictures were not assigned race or gender, the sum of each race category and the sum of both gender categories usually did not equal 10.

Following the tabulation of profiles in "People Also Viewed" for each graduate in the data set, the data was analyzed for pattern and correlation. This analysis was primarily done in Microsoft Excel. The data was both examined as a whole (all four law schools were examined together) and as broken down by law school. In each case, the data was again divided into subgroups by the race and gender of the graduate. Occurrences of race compared to the mean were calculated for each racial subgroup and occurrences of gender compared to the mean were calculated for each gender subgroup. When this process was done on all four law schools combined, race was broken down by the categories previously delineated: White, Black, Hispanic, and Asian. However, when this process was done at the individual law school level, race was broken down into two categories: White and Nonwhite. This modification had to be made because for many of the racial groups in individual law schools, the n-values were too low to calculate a significant value.

The final step in this study was statistical analysis of the calculated values. This analysis was carried out using StatPlus software. For each breakdown of the data into two categories (i.e. White-Nonwhite or Male-Female), a t-test was used to calculate significance. The two-tailed distribution was analyzed because there was no condition that would force one mean to be greater than the other, and a significance level of 0.05 was set. For each breakdown of the data into more than two categories (i.e. White-Black-Hispanic-Asian), an ANOVA test was used without any post-hoc testing. The absence of post-hoc testing was due to a limitation of the researcher's software, however its absence was deemed acceptable because in each case where the ANOVA returned statistical significance, the mean of interest (the mean of the same racial group as the subgroup being examined) was different enough from the other means that it was obvious that it was the mean causing the statistically significant result. Again, a significance level of 0.05 was set.

Results

Analysis of the data showed that racial and gender bias is prevalent, but not ubiquitous on LinkedIn. Results varied, both by demographic subgroup being examined and by law school being examined. In the aggregate data set of all law schools, racial and gender bias appeared across all but one subgroup. Overall, racial bias appeared to be stronger in cases where it existed, but gender bias appeared to be more consistent across the different breakdowns of the data.

Aggregate Law Schools

Figure 1

	White	Black	Hispanic	Asian
White, n=437	104%	82%	101%	73%
Black, n=14	82%	613%	89%	95%
Hispanic, n=20	100%	86%	155%	93%
Asian, n=44	69%	117%	71%	374%
Significance Tests	p=0.00029	p=2.84182E-9	p=0.65731	p=0.00000

Figure 1 shows the breakdown by race for the aggregate data set. The subgroup breakdowns appear on the left, along with the n-values. The percentages represent the occurrence of each racial group for that subgroup compared to the average occurrence of that racial group. Whites appeared most frequently in the profiles of other Whites, but not by a large difference. Whites appeared in the profiles of Blacks roughly 18 percent less than average, but they appeared in the profiles of Asians 31 percent less than average. The large difference for Asians, however, could be due to the fact that over half (24 out of 44) of the Asians in the aggregate sample came from Hawaii, which is a highly diverse state.

Blacks appeared more than six times as frequently as average in the profiles of other Blacks. They appeared 18 percent less in the profiles of Whites and 14 percent less in the profiles of Hispanics. Hispanics appeared more often in the profiles of other Hispanics, but this finding lacks statistical significance. Asians were more than 3.7 times as likely to appear in the profiles of other Asians, and 27 percent less likely to appear in the profiles of whites.

Figure 2

	White	Nonwhite
White, n=437	104%	82%
Nonwhite, n=78	79%	203%
	p=0.00017	p=0.00005

Figure 2 shows the aggregate data broken down into the less precise categories of White and Nonwhite. Whites showed up 21 percent less frequently in the profiles of Nonwhites and Nonwhites showed up 18 percent less frequently in the profiles of Whites. Nonwhites appeared over two times more in the profiles of other Nonwhites, though this was probably a reflection of the overrepresentation of people from the same racial group displayed in Figure 1.

Figure 3

	Male	Female
Male, n=316	109%	86%
Female, n=199	85%	123%
	p = 0.00001	p=0.00000108703

Figure 3 displays values for gender in the aggregate data set. Males showed up 9 percent more often in the profiles of other males, and females showed up 23 percent more often in the profiles of other females. Both genders appeared roughly 15 percent less in the profiles of the opposite gender.

By Law School

George Mason University

Figure 4

	White	Nonwhite
White, n=212	101%	85%
Nonwhite, n=27	92%	217%
	p=0.33815	p=0.03664

Figure 4 displays the White-Nonwhite breakdown for George Mason University. Whites showed up roughly equivalently in the profiles of Whites and Nonwhites, generating a statistically insignificant difference. Nonwhites showed up over twice as often in the profiles of Nonwhites, which is roughly equivalent to the corresponding Nonwhite-Nonwhite value for the aggregate data set.

Figure 5

	Male	Female
Male, n=154	109%	90%
Female, n=84	83%	119%
	p=0.00061	p=0.00587

Figure 5 shows subgrouping by gender for George Mason University. The results were very similar to the aggregate data set, with each gender showing up more often in profiles of the same gender.

University of Hawaii

Figure 6

	White	Nonwhite
White, n=26	103%	96%
Nonwhite, n=26	97%	104%
	p=0.73873	p=0.72012

Figure 6 shows the White-Nonwhite breakdown for the University of Hawaii. Whites and Nonwhites showed up roughly equivalently for both groups.

Figure 7

	Male	Female
Male, n=37	98%	102%
Female, n=15	106%	96%
	p=0.57636	p=0.88166

Figure 7 displays the gender breakdown for the University of Hawaii. Males and females showed up at almost the same rate for both groups.

Louisiana State University

Figure 8

	White	Nonwhite
White, n=154	100%	103%
Nonwhite, n=12	104%	64%
	p=0.80870	p=0.14667

Figure 8 displays the White-Nonwhite breakdown for Louisiana State University. There is no statistical difference between the values for either Whites or Nonwhites for either subgroup.

Figure 9

	Male	Female
Male, n=94	110%	86%
Female, n=72	87%	119%
	p=0.04618	p=0.00442

Figure 9 displays the gender breakdown for Louisiana State University. As with George Mason University, the results were very similar to the gender results for the aggregate data set.

University of Minnesota

Figure 10

	White	Nonwhite
White, n=46	109%	69%
Nonwhite, n=13	66%	211%
	p=0.00238	p=0.04140

Figure 10 shows the White-Nonwhite breakdown for the University of Minnesota. The results were slightly more accentuated than the aggregate data results, with Whites showing up more frequently in the profiles of other Whites and Nonwhites showing up more frequently in the profiles of other Nonwhites.

Figure 11

	Male	Female
Male, n=31	118%	72%
Female, n=28	80%	131%
	p=0.01050	p=0.0018

Figure 11 shows the gender breakdown for the University of Minnesota. Similarly to the racial breakdown in Figure 10, the results mirrored the aggregate data results for gender, but to a more extreme degree. Males appeared more frequently in the profiles of other males and females appeared more frequently in the profiles of other females.

Figure 12

	No Picture			No Picture
White, n=46	4.152		Male, n=31	4.742
Nonwhite, n=13	5.231		Female, n=28	4.000
	p=0.13131			p=0.16354

Figure 12 displays the breakdown for the University of Minnesota by both race and gender for average number of missing photograph profiles per graduate. Examining absence-of-photograph profiles produced no statistically significant results. None of the absence-of-photos graphs for all of the data produce statistical significant

Discussion

Through most but not all of the data, the race and gender of LinkedIn users were correlated to the race and gender of the people that appeared in the users' "People Also Viewed" tabs. Given that the list of individuals who appear in this tab in heavily driven by user viewing patterns, this data implies that both racial and gender biases exist in the way people are using LinkedIn. The notable exception to this trend was the University of Hawaii, where there was no correlation between the race and gender of a user and the race and gender of the individuals that the user was associated with through "People Also Viewed."

Racial bias presented itself in different ways across the data. Whites were heavily represented both in the data set and in the profiles that were associated with the users in the data set. However, the only breakdown that showed a significant correlation between the White status of a user and the number of White associations was the University of Minnesota. It is difficult to discern if the lack of correlation is accurate or if the data for Whites is not revealing because of the high prevalence of Whites both in the data set and in the networks of users in the data set. Stronger statistical testing may be needed to further analyze these results, or a more diverse data set may need to be tested.

For the individual law schools, race was not analyzed on an individual group level, but rather through a duality of White-Nonwhite. This framework presents its own problems, as aggregating all people who are not white overgeneralizes the minority experience in the United States. However, this decision was made to account for the fact that the n-values for some of the racial minority groups within individual law schools were quite small. Analysis showed that Nonwhites showed up more often in the profiles of other Nonwhites in the aggregate data set, for George Mason University, and for the University of Minnesota. In each case, the result was relatively consistent with Nonwhites appearing slightly more than twice as frequently as average in the profiles of other Nonwhites. Again, without deeper statistical analysis, it is difficult to know if the double rate of Nonwhites represents a trend in Nonwhite identity, consistent trends of the underlying minority groups that make up Nonwhites, or pure coincidence.

The breakdown by racial group in the aggregate data set can offer some insights towards what generated the Nonwhite results in the individual law school breakdowns. For two of the three minority racial groups, Blacks and Asians, members of the same racial group were more likely to appear in profiles. However there were not any discernable patterns of correlation between Nonwhites of different racial groups. This implies that the individual law school level data for Nonwhites is a product of individual racial groups and not a Nonwhite identity.

It should be noted that just because Blacks and Asians showed up more frequently in the profiles of individuals from the same racial group, it is not necessarily implied that people are using it in a biased or stereotypical way. It could just be that these results are reflective of communities, given that it is a well established fact that communities can be divided by race.

Hispanics showed up more often in the profiles of other Hispanics, but the finding was not statistically significant. Without more data, it is hard to tell if Hispanics truly are well integrated into LinkedIn or if the data is not representative.

A gender divide was evident across the data, with the notable exception of Hawaii. Males were consistently more likely to show up in other males profiles, and females were even more likely to show up in other females profiles. The values for this trend were startling consistent: in each of three law school data sets where it appeared, and in the aggregate data set, males were 9-18 percent more likely to appear in the profiles of other males and females were 19-31 percent likely to show up in the profiles of other females. Similarly to race, this trend does not necessarily indicate bias, but could be a reflection of people searching for their friends of belonging to single-gender organizations. However, given that males and females do not live in gender-divided communities in the same way that people live in racially-divided communities in the United States, these arguments for explaining the data are more tenuous than they are for race.

Examining the individual law school data, the University of Minnesota displayed the most pervasive bias along race and gender lines, while the University of Hawaii displayed no statistically significant bias for either metric. To dig deeper into these findings, the literature concerning integration in both states was explored. In a recent study, data from the U.S. Census and the National Center for Education Statistics compiled a list of the states in terms of their racial integration along employment, wealth, education, and civic engagement lines [16]. Hawaii was found to be number 25 on the list, while Minnesota was number 50. Additionally, the
U.S. Census data shows Hawaii to be the most diverse state in the nation, and research from the 1950's showed Hawaii's success in racially integrating schools [17,18]. The gender bias discrepancy is harder to explain, but it is possible that there are positive spillover effects from racial integration in Hawaii, and that the converse is true in Minnesota.

Excluding Hawaii, however, the race and gender correlations presented in this data are troubling. Given what is known about racial and gender discrimination through all levels of the professional process, it appears potentially harmful that marginalized groups are being clustered together. To develop this analysis more fully, two mechanisms of damage to marginalized groups have been theorized.

First, through the clustering of privileged groups and marginalized groups, industries or professions that are already dominated by the privileged group will maintain a network of individuals that are largely also part of the privileged group. If a company seeks to expand, and they look at the LinkedIn profiles of their employees who largely come from the privileged group, they will find disproportionately more of the same type of people in "People Also Viewed." A visceral example of this is the tech industry, which has a serious problem with gender disparity in the workforce [19]. A talent manager at a top tech company, searching for new employees by browsing the "People Also Viewed" tab of the company's current employees, would find a disproportionate number of men than were actually present in the pool of qualified candidates, because most of the company's employees are already men.

Second, the increased occurrence of marginalized groups in the profiles of individuals from the same marginalized group can amplify the stereotyping predispositions of a profile viewer. If the viewer looks at the profile of an individual from a marginalized group and associates that group with negative stereotypes about professional competency, the stereotyping process will become even more acute when the viewer sees other members of the same marginalized group in the "People Also Viewed" tab. Though it is no fault of the individuals whose profiles show up in the "People Also Viewed" tab, the presence of their profiles could magnify negative pressures on the user of the original profile.

These vexing problems on LinkedIn lead naturally to questions of what can be done to ensure that marginalized groups receive equal representation on the professional networking platform. Given that LinkedIn likely did not engineer these biases but rather simply reflects societal biases through its platform, it is unclear what LinkedIn's responsibility to address this issue is. Though LinkedIn will never be able to single-handedly solve racial and gender discrimination in the United States, it is in a unique position to regulate the biases that occur on its platform through the authority it has over its own networking algorithms. Perhaps it would useful for LinkedIn to implement a type of affirmative action in its algorithms to ensure that marginalized groups are represented fairly and equally.

Future research should replicate this type of study with different groups of graduates other than law students. It should also use a more diverse data set, which was certainly a limitation of this study. Future research could also do more analysis of the differences between Hawaii and Minnesota. What makes Hawaii so successful at integration while bias seems to haunt Minnesota? That study would focus more at the roots of racial and gender discrimination and would produce policy proposals with a much wider scope than just LinkedIn, however it would help determine why these biased trends occur on LinkedIn, and what can be done to mitigate them and to make the United States a more equitable place.

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