DSC 167 Paper 1

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1 Introduction

In today's mortgage lending system, there exists potentially undeserved biases against certain racial groups in the United States that stems from discriminatory attitudes and profit driven motives. The mortgage data being analyzed in this report is a compilation of public mortgage records that were filed in accordance with the Home Mortgage Disclosure Act (HMDA). This act was enacted in 1975 to "monitor minority access to the mortgage market" (Munnell et al., 25) with the intention of eliminating barriers for those of lower income to "escape or improve or improve poor neighborhoods" (Munnell et al., 25). However, a research study conducted on the HMDA datasets covering the years 1991-1993 that was published in "The American Economic Review" found that "minorities were two to three times as likely to be denied mortgage loans as whites" despite their income level. Although this disparity can be attributed to racial disparity, there are other factors that may explain this difference, such as debt history and credit score — both of which are not included in the dataset but are generally used in the judging process for loan applications. Due to this, there are limitations from being able to draw conclusions about racial discrimination throughout all the years of HMDA data. Despite this, an analysis of data from the Home Mortgage Disclosure Act reveals that there are inequities between different racial groups in the demographic parity of loans granted across the US. Additionally, this may contribute to evidence of taste based discrimination in lending which violates equal opportunity through allocative harms based on race.

2 Context

The current system of lending can be described as following a utilitarianism distribution scheme regarding the allocation of goods, which in this case would be loans. This entails providing loans based on the perceived utility, or the overall benefit, to the lender. More specifically, they judge if they will make money from the transaction. Lenders may draw conclusions about a racial group based on generalizations as an oversimplified and biased way to judge their utility. Justification may include "that minorities typically are less able to rely on friends or relatives to help them through tough economic times" (Ladd, 46) or that specific racial groups have lower income on average which will impact their ability to pay back the loans.

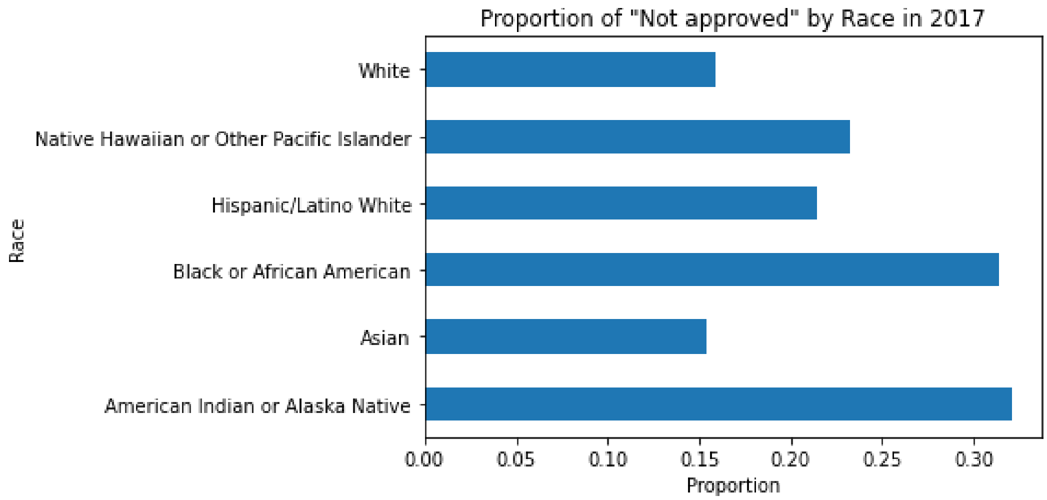
Such reasoning based on race, however, violates the Formal Equality of Opportunity which protects against unneeded use of traits, such as race, when judging people for an opportunity. While loans are advertised to be open to all, it has been discovered in many cases that race is being used to screen applicants since it is simple to judge whether an applicant will pay back a loan based on generalizations about the group that they are a part of. This use of race violates the Formal Equality of Opportunity since race is not a necessary trait to consider for loans.

These generalizations based on race can also be attributed to unfamiliarity. According to an investigation conducted by the Decatur Federal in Atlanta, they found that "lenders use rules of thumb to weight different components of a loan application differently by race" (Ladd, 48). This means that the primarily White dominated loan screening committees who are not as familiar with traits and values of other races turn to these generalizations as a metric to make judgements whether an applicant will pay back a loan or not. Additionally, those with less processed cases may be subject to statistical discrimination, which was explored in a study conducted by the Decatur Federal in Atlanta. They found that because loan officers provided more assistance to White applicants than minority applicants, there were significantly more White applicants on file, which leads to White applicants being more likely to be approved (Ladd, 48). All of these generalizations are based on race with the purpose to judge the overall utility of a loan. This leads to loans being distributed disproportionately in favor of the specific groups. This further reinforces socioeconomic differences in race in society. This difference in familiarity between racial groups exhibits an unequal power distribution. In this case the White applicants have more power due to having more familiarity and information about them, while the minorities have less power due to having less information about them. This difference in power results in the White applications being more likely to be accepted compared to applications from minority groups.

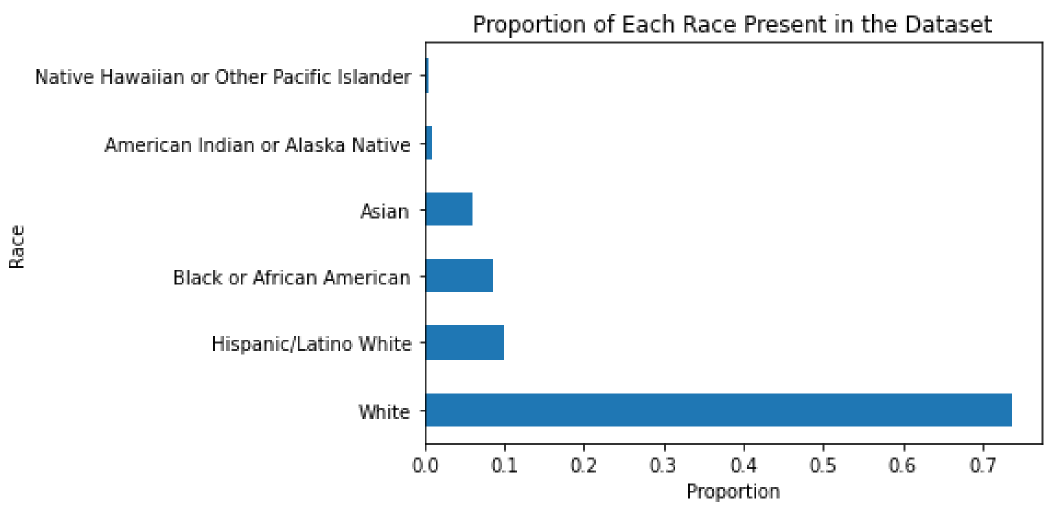
However, an opposing theory to the current distribution of loans is one by Rawls' which instead favors an egalitarian distribution of goods. Rawls' Difference Principle states that inequalities within society are permissible only when it "make[s] the least advantaged in society materially better off" (Stanford Encyclopedia of Philosophy). Rawls' principles are protected in American society by several laws including: the Equal Credit Opportunity Act which prohibits discrimination in credit transactions based on "race, color, religion, With these factors in mind, the HMDA data sets should not display any demographic disparity that can be directly attributed to discrimination based on race.

3 Data

The data used for this investigation includes 9221483 applicants after data cleaning, with several instances of demographic, loan, and financial information. Basic demographic information like race and ethnicity, basic loan information like loan amount and whether the loan was approved or denied, and basic financial information like income were used for this analysis. Most notably the data include several variables which are useful in providing some kind of explanation to evaluate inequities rooted in taste based discrimination between different racial groups for loans granted across the US. One such instance, useful in determining the demographic parity of loan granting is the proportion of loans denied by race.



Notably, we do not consider every ethnic and racial group as a result of very small group sizes. Instead, we consider the collected racial group data and create an additional group, "Hispanic/Latino White," in an attempt to capture differences as a result of ethnicity.



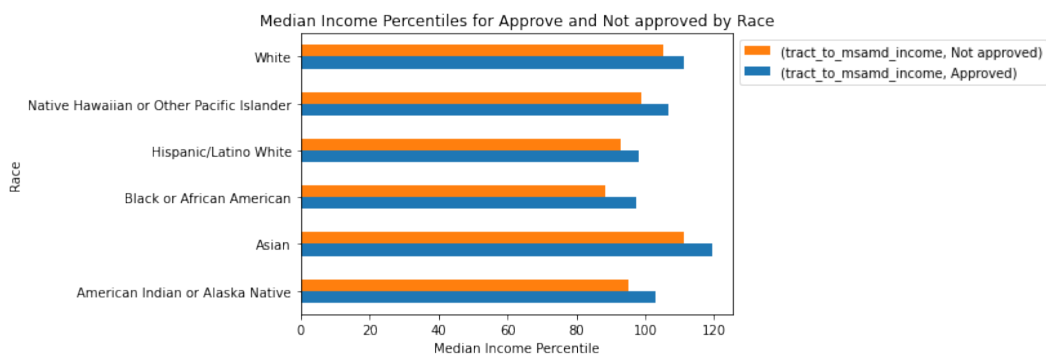
From this visualization, it is clear that information on non white racial groups is far more scarce. This is a pattern that can be connected back to the previous section's discussion of power. In this case, a lack of information on non white racial groups may systemically lead non white applicants to appear as more risky to lenders as a byproduct of less familiarity and less evidence of documented financial stability.

The absence of information on whether or not the applicant repaid a loan means that several metrics for an evaluation of fairness are not possible to calculate. While an alternative analysis is carried out with the use of income as a proxy for this metric, it will only be a rough approximation with no guarantee that the results hold in practice. Since the dataset did not include information about whether the loan was paid back or not, we decided to create our own Decision Tree Classification model to predict, based on the existing data, whether the loan will be rejected or not. With the prediction model, it can simulate the algorithm that loaning companies use to determine if a loan should be granted, and from this we can get the necessary values from a confusion matrix to calculate our fairness metric.

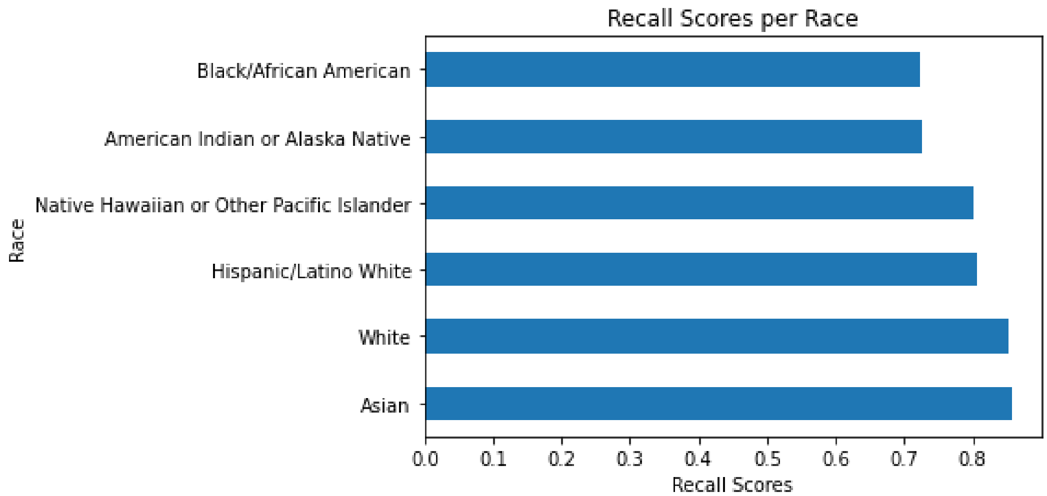
The absence of certain other data also limits the efficacy of this evaluation. In this case, there are applicants who selected "other," for their racial group. Additionally, the presence of mixed race applicants is unclear. Instances such as these limit available knowledge on the racial groups of certain applicants and may hide variations to the findings of this investigation.

4 Fairness Metric

The measure of true positive parity, or recall across racial groups, was examined when determining if there are demographic disparities between racial groups. The examination of demographic disparity was chosen to determine if the HMDA dataset would uphold the ideals put forth by Rawls' Difference Principle which are also reflected in the American laws passed, such as the Equal Credit Opportunity Act, with the purpose of allowing minorities access to equal opportunities of resources including mortgage loans. The metric of true positive parity was chosen because this investigation focuses on a primary harm of false negatives, those who are justified to be given a loan being denied. Given the data collected under the HDMA, the best, and only, proxy we have for an applicant's ability to repay a loan is income. To examine the role that income percentile with respect to an applicant's tract plays in the resulting loan decision, we look at the difference between the income percentile medians of approved and denied loan applications. The figure below demonstrates that, with some variation, the median income percentile for approved loans is higher than those who were denied.



Lastly, we evaluate fairness using a model trained to predict whether or not a loan will be approved or denied. This is a decision tree classifier which uses income percentile by tract, loan amount, and flat income in order to predict whether a loan was approved or denied. As per the fairness metric described earlier, recall, we evaluate our results from the model and find that White and Asian applicants are treated most generously, with the lowest false negative rate at .8518 and .8568 respectively. Native Hawaiian or Other Pacific Islander and Hispanic/Latino White are worse off than the previous group at .8004 and .8059 respectively. Lastly, Black/African American and American Indian or Alaska Native applicants are worst off at .7226 and .7264 respectively. It is notable that the Hispanic/Latino White group had a lower recall score than the White applicant group.



5 Results and Interpretation

From the results of the confusion matrix produced from the prediction model, it was found that White and Asian groups had much higher recall than the other minority groups as described above, meaning there were less people rejected for a loan that should have qualified to get one. The other groups that includes: Black/African American, Hispanic/Latino White, American Indian or Alaska Native, and Native Hawaiian or Other Pacific Islander had lower recall rates, meaning qualified individuals within those groups were rejected much more often. These differences in our chosen fairness metric demonstrates that there exists disparity between the demographic groups.

It is difficult to conclude with certainty that the difference in the approved and not approved rates between races can be completely attributed to racial discrimination due to the data set not having all the information that was considered in the loan application process, such as debt history or credit score. Additionally, due to the lack of information on if the loan was paid back, we have to depend on our prediction model to simulate the algorithm they utilized when screening applicants, which will not be as accurate as the actual decision making process used. The reasoning behind the demographic disparity can loosely be thought of as discrimination based off races due to loan companies making generalizations about each group due to lack of information. In the graph above titled: "Proportion of Each Race Present in the Data set", it is clear that approximately seventy-five percent of all application were submitted by a white applicant. Similar to what was discussed in the context, the larger number of White applicants can lead to loan officer being more familiar with them and therefore approving more of their applications. On the other hand, it also suggests that because the loan officers do not have as much exposure to the minority groups, they may rely on judgements based on race to infer certain traits related to whether the loan will be paid back or not. However, the Asian population held a similar recall as White applicants, despite their application count being lower than African American applicants who had one of the lowest recall. This suggests that there are more factors in play besides the familiarity theory. The only thing we are able to measure with certainty, given this data set, is demographic disparity through the differing recall scores based on our prediction model. We can conclude that there is significant demographic disparity between White applicants and minority groups.

References

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