Using Principal Component Analysis to Analyze Racial Impact on Housing Appraisals

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***Abstract*—The Greater Boston area has a history of housing discrimination, which disproportionately impacts people of color broadly, and Black people more specifically. Through this project, we aim to address the impact of race on housing appraisals using principal component analysis (PCA), k-nearest neighbor (kNN) classification, and linear regression to compare reconstructed appraisals using race-aware and race-blind data. Our preliminary results suggest that a neighborhood's racial makeup plays a significant factor in accurately appraising its property, but the relationship between the two parameters remains inconclusive.**

I. Introduction

From redlining to white flight, the Boston metropolitan area has a history of racial discrimination in its housing practices. Furthermore, the systemic racism in American society has permeated even the most objective of processes, including housing appraisals, which has led to the systemic devaluation of Black-owned property and barriers to accumulating assets and building generational wealth [1]. The Fair Housing Act (FHA) of 1968 was meant to address such issues by outlawing race-based housing discrimination; however, human bias often slips through traditional avenues of enforcement. The problem of racial housing discrimination has only grew more pervasive and pronounced throughout the decades, as "appraisals were affected to a larger extent by race in 2015 than in 1980" and "during that period, homes in white neighborhoods appreciated in value, on average, almost $200,000 more than comparable homes in neighborhoods of color" [1].

The data used is the Boston Housing Dataset, which first appeared in the 1978 paper by Harrison and Rubinfeld. It provides values for the following parameters, in increasing order of significance: CRIM, ZN, INDUS, CHAS, NOX, RM, AGE, DIS, RAD, TAX, PTRATIO, B, LSTAT, and MEDV. More detailed explanations can be found in the data description. The data concerns housing values in suburbs of Boston, and contains data for 506 neighborhoods.

Our work on this algorithm aims to preliminarily evaluate the efficacy of the FHA in successfully promoting equality, as our data set was sourced ten years after its passing. The consequences of our work are limited due to the small sample size and age of our data; however, the structure of our algorithms can serve as the basis for more advanced analysis in the future. In the presentation and use of this algorithm, it is imperative that we be sensitive to racial differences and emphasize that this is nowhere close to a solution, and thus should not be treated as such. This algorithm and accompanying report serve not to provide a solution, but rather to prove that such a problem exists and must be addressed.

II. Methods

Our method incorporates the eigenfaces method of recognition, using linear regression and principal component analysis to reconstruct the median property value based on a linear combination of the other parameters. The basic structure of the algorithm is very similar, with the exception that this algorithm analyzes pure numerical data instead of images; therefore, an eigenappraisal cannot be displayed.

Each set of data is mean centered; that is, the mean of the set is subtracted from each element. From the training data, a covariance matrix is constructed, which indicates the magnitude and direction of the linear relationship between each pair of parameters. In order to find the covariance matrix, the data from both the training and testing sets were mean-centered. In other words, for each set, the mean of that set was subtracted from each element. After mean-centering the data, the covariance is calculated by multiplying the transpose of the mean-centered training data by the mean-centered training data.

```
cov = trainMC' * trainMC;
```

The covariance matrix undergoes an eigendecomposition, producing matrix `V` with the eigenvectors and diagonal matrix `D` with corresponding eigenvalues.

```
[V, D] = eig(cov);
```

Using the eigenvectors of the data that we have, we are able to create "appraisalspace". This is done by multiplying the training and testing datasets by the eigenvectors of the housing data. For example, the projected training data is equal to the transpose of the eigenvectors matrix `V` and the transpose of the mean-centered training data, and this is the same for the testing data.

```
appraisalSpaceTrain = V' * trainingMC';
```

Now our data must be projected onto "appraisalspace" by multiplying our current variables for appraisalspace and our eigenvectors.

```
projAppraisalTrain =
          V * appraisalSpaceTrain;
```

With our training and testing data mean-centered and projected onto appraisalspace, we can do a `knnsearch` (nearest neighbor classification) on the two sets. The k-nearest neighbor algorithm takes a dataset and, for each element, finds its "nearest neighbor," or the element from another dataset with which the original element is correlated. For this algorithm, we want to take our testing data and see, from the training data, which neighborhood the testing data correlates with most strongly. Therefore, we perform `knnsearch` between the testing and training housing data. `knnsearch` returns the row number from the training data, or the of the neighborhood, and we assign the corresponding median value to the piece of testing data.

```
nearestNeighbor =
 knnsearch(projAppraisalTrain',
           projAppraisalTest');
```

Now that we know the nearest neighbor for every element of the testing data, we can extract the MEDV value from the nearest neighbor, or the value of the appraisal. Since the nearest neighbor of an element will have very similar characteristics to that element, the appraisal values of our testing data will be defined as the appraisal values of the nearest neighbors for each element. In other words, the generated values that will eventually be shown in our results are the appraisal values from the last column (the MEDV column) of the nearest neighbors.

Originally, we included the lower status population in our race-blind datasets, which did not take into account the number of black people in a neighborhood for making appraisals. However, the results were not accurate in neither the race-blind nor the race-aware were accurate. The differences between the generated values for housing appraisals and the actual values were rather large. After including the lower status population into the results, we ended up with similar inaccurate results. This is when we realized that the fourth column in the Boston Housing Dataset was a dummy variable that only consisted of values of 1 or 0. After taking the fourth column out of all training and testing datasets, the results were very accurate.

III. Results

Figure 1 shows the recreated appraised values against the actual median value drawn directly from the data. Overall, the race-aware algorithm is able to reconstruct to a fairly high degree of accuracy, and we find the accuracy to be 0.3814; that is, the average reconstructed appraisal is \$381.40 higher than the actual median value for that neighborhood. The accuracy was found by subtracting the actual median value from its corresponding reconstruction, then taking the mean of the resulting vector.

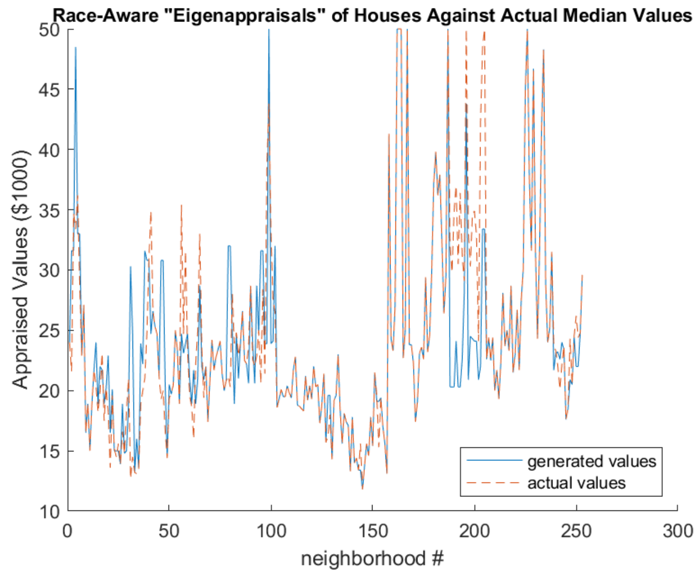

Figure 1. We find that an algorithm that is provided with LSTAT and B data can accurately recreate appraisals, with a mean error of $381.40.

Figure 2 compares the race-blind appraisal reconstructions against the actual median values. The algorithm produced race-blind appraisals using the same dataset as the race-aware results, except that the columns with the "B" value and "LSTAT," or "lower status," parameters were removed. We recognize that this approach fails to recognize the role that race may play in affecting other parameters, and regret that we are unable to produce a true race-blind dataset for use with this algorithm. We find that the accuracy of these appraisals is far lower than the ones produced when the B value is a parameter, with an accuracy of -3.1680, meaning that on average, the reconstructed race-blind appraisal was $3,168 lower than the actual median value of a house in that neighborhood. We notice a substantial drop in accuracy when the B value is removed as a parameter.

In Figure 3, the B value is directly compared to the accuracy of the race-blind appraisal, which is plotted in a way to reveal any relationships between the two, if they exist.

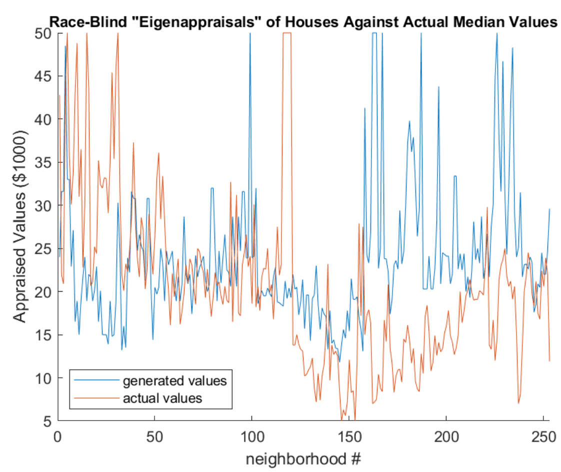

Figure 2. The accuracy drops significantly when the algorithm using data where LSTAT and B have been removed, with a mean error of $3,168.

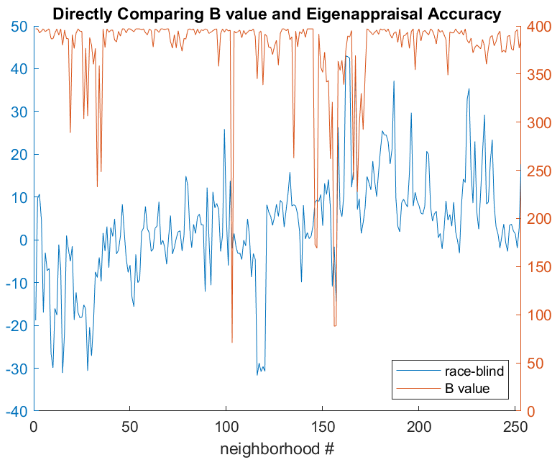

Figure 3. We fail to conclusively find any correlation between B value and race-blind eigenappraisal accuracy.

IV. Interpretation

When comparing Figure 1 and Figure 2, it is abundantly clear that the generated values in Figure 1 are much more accurate than those in Figure 2. When the algorithm attempts to appraise values without accounting for race and the population of the "lower status," the average difference between generated median values for a household by the algorithm and their actual median appraisals is approximately $3,168.00. Meanwhile, when the algorithm takes race into account, the error between the generated and actual appraisals decreases to approximately $381.40. These two figures show that the proportion of black people in the population and the percentage of lower status people in the population are two data that heavily impact the appraisals of these properties.

When examining the relationship between the number of black people in a neighborhood and the median appraisals of properties in that neighborhood, a preliminary look suggests little to no correlation between the two values. While the data for neighborhoods 1–50 seem to indicate a positive correlation between the B value and race-blind appraisal, suggesting that neighborhoods with a lower proportion of black residents tend to have lower housing appraisals, independent of the B value. However, the same trend does not fit the rest of the data, especially in neighborhoods 140–170, where the series of peaks in the housing values seems to correspond to a series of dips in the B value. Since a single type of correlation cannot be applied to the data at large, we tentatively conclude that the B value has no directional influence on the reconstructed appraisals, and that it only increases the accuracy of the reconstructions when included in the input data.

V. Connections

We conclude that the algorithm used is poorly suited for the sort of analysis, and that the data used was insufficient to draw any significant conclusions regarding the role of race in housing appraisals. We further realize that race has an impact on nearly every other parameter, and that we lack the means to create a truly race-neutral dataset for the algorithm. Thus, the question may be better addressed going forward through a human-centered perspective addressing bias rather than the statistical analysis discussed here, in order to shift the focus off the people living in a neighborhood and onto the individual appraisers and their racial biases.

The Boston Housing Dataset originally appeared in a 1978 paper by Harrison and Rubinfeld, as mentioned previously. Looking at the historical context of this data, it is shocking that this data was taken on neighborhoods around Boston approximately a decade after the passing of the Fair Housing Act on April 10, 1968. Despite this being another landmark piece of legislation for the civil rights movement and a great source of political capital for the Johnson Administration, there were many areas of the nation that still remained segregated, as the act was difficult to enforce [2]. Our results continue to reinforce the idea that the Fair Housing Act of 1968 was not as effective as it needed to be ten years after its passing, and gives us reason to believe that the current measures in place to promote racial equity and equality are similarly failing to facilitate meaningful change.

References

[1] Howell, Junia, and Elizabeth Korver-Glenn. "Race Determines Home Values More Today than It Did in 1980." *The Kinder Institute for Urban Research*, 24 Sept. 2020, kinder.rice.edu/urbanedge/2020/09/24/housing-racial-disparities-race-still-determines-home-values-America.

[2] "Fair Housing Act Overview and Challenges." *National Low Income Housing Coalition*, 23 Oct. 2018, nlihc.org/resource/fair-housing-act-overview-and-challenges.

APPENDIX

```matlab
function [NN] = eigenappraiser(test, train)
    % Mean ctr data
    testMC = test - mean(test);
    trainMC = train - mean(train);

    % covariance matrix
    covar = trainMC' * trainMC;

    % EVD
    [V, D] = eig(covar);    % V = eigenvectors, D = eigenvalues

    % creating appraisalspace
    appraisalSpaceTrain = V' * trainMC';
    appraisalSpaceTest = V' * testMC';

    % project onto appraisalspace
    projAppraisalTrain = V * appraisalSpaceTrain;
    projAppraisalTest = V * appraisalSpaceTest;

    % NN finding
    nearestNeighbor = knnsearch(projAppraisalTrain', projAppraisalTest');
    NN = nearestNeighbor;
end
```