Gentrification Prediction Map - Team 147

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Introduction

For most people, gentrification is an event that simply happens to them. Driven by economic forces (Redfern 2003), gentrifiers – primarily white and middle class – move into affordable neighborhoods, drive up prices, and eventually displace the culture and perhaps tenancy of long-term residents – who are primarily POC and lower income (Wyly and Hammel 2004).

This transformation has its pros and cons. On the one hand, gentrification can result in neighborhoods with greater racial diversity (Freeman 2009). But gentrification also results in higher income inequality (Freeman 2009), which has been linked to an "increase [in] both violent and property crime" (Atems 2020), as well as closures of long-standing businesses (Glaeser et al. 2023). Gentrification can also lead to negative health impacts, because of loss of services and common amenities (Anguelovski et al. 2021).

Aims and Objectives

Given the consequences of gentrification, our group aims to give more control to the people affected by giving them a map-based visual tool to predict a neighborhood's gentrification levels, similar to that seen in Mubarak et al.'s paper (Mubarak et al. 2022).

By having access to this information, those living in areas on the verge of gentrification can start taking measures to preserve their neighborhood, and figure out ways to turn a potential disaster into an opportunity (Thurber 2021). On the other hand, those looking to move can more easily find areas with rich histories and soon to appreciate property values (Wilhelmsson et al. 2021), which would allow buyers to maximize their investment, and allow renters to weigh short-term affordability vs the long-term risk of rising rents (Aljohani 2023). This would also enable urban planners and governments to implement public policy to minimize the negative and heighten the positive effects of gentrification (Lees and Ley 2008).

Literature Review

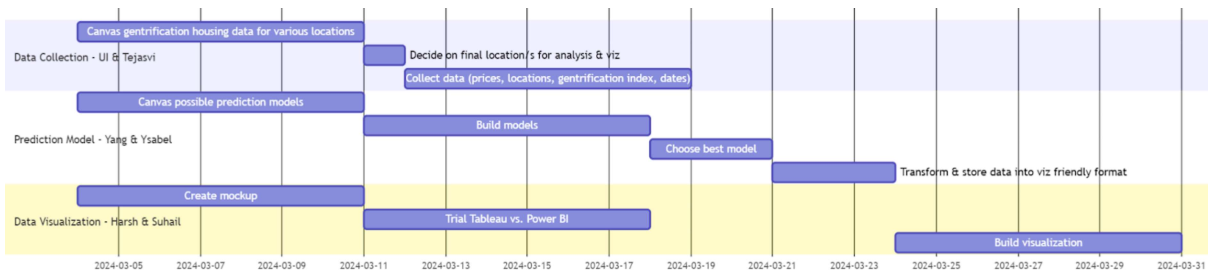
To predict gentrification, we first need to discuss how it is quantitatively measured. Classically, researchers have followed a two-step process: (1) identify if a neighborhood is eligible for gentrification, then (2) assess over time if the neighborhood gentrifies (Finio 2021). For example, using the Freeman methodology, a census tract is (1) marked eligible if (a) housing construction is below a metropolitan median, and (b) income is below the median, and (c) the tract is located in a central city. It is then (2) marked as gentrified if, after the measurement period, (a) there is a greater increase in educational attainment compared to the median and (b) an increase in real housing prices (Freeman 2005).

There is currently no standardized way to forecast gentrification. In a study comparing gentrification prediction models used by four US city governments, only 2 of 18 predictor variables were consistent for all models, and performance accuracies on a test city were highly varied, between 13.9% - 66% (Preis et al. 2021).

Models from academia are more promising. Stanford researchers trained a deep learning model on paired Google street view images to detect changes in infrastructure to predict gentrification with ~75% balanced accuracy (Huang et al. 2023). Deep learning methods are black boxes however and limit interpretability, which is important for public policy changes.

Researchers from Sydney (Thackway et al. 2023), Mexico City (Alejandro and Palafox 2019), and the UK (Gray et al. 2023) experimented with using tree based models to predict gentrification, achieving 74.7% balanced accuracy, 99.65% accuracy with 66% sensitivity, and 99.65% respectively. All three papers used census data, which is infrequent, to train the models whereas this group from Harvard used Yelp data and linear regression to show relevant correlation between certain businesses and indicators of gentrification (Glaeser 2018).

Research Design and Methods



All team members have contributed a similar amount of effort

Our scope will be limited to UK city neighborhoods, for three primary reasons: (1) quality census data, (2) extensive data on gentrification, being the birthplace of the term itself (Finio 2021), and (3) easily accessible house pricing data.

Because we need interpretability, we are planning to explore tree based models to build our predictor, though we are considering other methods as well, such as k-means. We will validate which model is most accurate using historical data.

Since we are planning to use government and public access data for our models, and we don't believe our datasets will be big enough to require hosting, we do not anticipate having costs.

Ethical Considerations

While our goal is to help those affected by gentrification gain more information and control over their neighborhoods, we know that giving the wrong people access to this information could also exacerbate the phenomenon. In particular, corporate landlords are infamous for purchasing property in bulk in gentrifying neighborhoods and evicting tenants at a higher rate than small landlords (Raymond et al. 2016). Given their resources however, it is certain that corporate landlords are already using ML techniques to predict gentrification. Our paper will not give them any new information, but will make it available to individuals who did not have prior access.

There is also the risk of building inaccurate models that could result in ineffective or harmful public policy. To mitigate this risk, we will try a variety of approaches to find the most accurate one, and make sure to report any shortcomings in the model.

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