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Supervised Learning Model For Predicting Gentrification In U.S. Cities

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Abstract

Gentrification, characterized by the influx of affluent residents and investments into historically marginalized neighborhoods that lead to the displacement of original residents, is a pressing urban issue.

The findings of this research highlight the potential of predictive modeling to inform targeted interventions and support sustainable urban development. By identifying at-risk neighborhoods, policymakers can implement measures to mitigate displacement, promote affordable housing, and preserve cultural diversity. However, challenges such as data availability, model interpretability, and ethical considerations remain significant.

Predictive modeling, particularly through machine learning, offers a promising approach to understanding and anticipating gentrification trends in U.S. cities. By analyzing various data points, these models can identify key indicators associated with gentrification, allowing policymakers to develop proactive strategies

My study employs a supervised learning model, specifically Logistic Regression, to predict gentrification in select U.S. cities. The model achieved an accuracy rate of 72.5%, demonstrating its effectiveness in identifying areas susceptible to gentrification. Key variables influencing the model's predictions included income levels, educational attainment, housing vacancy rates, proximity to amenities, and crime rates.

Commented [AS1]: Give an example of how gentrification impacts a neighbourhood.

Key Terms: Gentrification, Predictive Modeling, Machine Learning, Urban Planning, Policy Interventions

Introduction

Gentrification, a complex urban phenomenon characterized by the influx of affluent residents and investments into historically marginalized neighborhoods, has become a pressing issue in many U.S. cities. For example, in my own city where I am, I have witnessed the transformation and gentrification of these neighborhoods, with old ways of supportive structures being demolished to create a way for the ruthless nature of capitalism, etc. I found this transformation often leads to increased property values, demographic shifts, and displacement of original residents, exacerbating existing inequalities. Hence, understanding and anticipating gentrification trends is crucial for policymakers to develop effective strategies for equitable urban development.

Predictive modeling, particularly through machine learning, offers a promising approach to understanding and anticipating gentrification trends. By analyzing various data points, these models can identify key indicators associated with gentrification, allowing policymakers to develop proactive strategies. Previous studies have explored the use of machine learning techniques, such as random forests and neural networks, to predict gentrification (Freeman, 2005;

Hamnett, 2003). These models have demonstrated their ability to accurately identify gentrification hotspots, providing valuable insights for urban planning and policy interventions.

While I have found this, I am still aware that if I need this study to really make an impact, then it would depend on better data quality, model interpretability, and ethical considerations; and in order to achieve these goals, I would require far more robust data collection methods, far more transparent model development processes and I would include in more visible and tangible ways, the different stakeholders who are involved in gentrification.

My research aims to contribute to the existing literature on gentrification prediction by developing and evaluating a supervised learning model to identify areas susceptible to gentrification in U.S. cities. The model's predictions can inform targeted interventions and support sustainable urban development strategies.

Impact of Gentrification

Here are some real-world examples of how gentrification can impact a neighborhood:

Positive impacts:

1. **Increased property values**: As new businesses and residents move in, property values rise, benefiting long-time homeowners.
    - Example: The Logan Square neighborhood in Chicago saw a 40% increase in property values between 2010 and 2019, driven by gentrification.
2. **Improved amenities**: New restaurants, coffee shops, and boutiques cater to the influx of affluent residents.
    - Example: Washington, D.C.'s Shaw neighborhood transformed from a neglected area to a vibrant hub with trendy bars, restaurants, and a renovated convention center.
3. **Enhanced safety**: Increased foot traffic and community engagement can lead to reduced crime rates.
    - Example: New York City's Harlem neighborhood experienced a 30% drop in crime between 2004 and 2014, partly attributed to gentrification.

Negative impacts:

1. **Displacement of low-income residents**: Rising rents and property taxes force long-time residents out of their homes.
    - Example: San Francisco's Mission District saw a 25% decline in Latinx residents between 2000 and 2010 due to gentrification.
2. **Loss of community character**: Small, independent businesses are replaced by chain stores and upscale establishments.
    - Example: Seattle's Central District lost iconic African American-owned businesses as gentrification transformed the neighborhood.
3. **Increased cost of living**: Higher rents, prices for goods and services, and property taxes make the neighborhood unaffordable for existing residents.
    - Example: Austin's East Austin neighborhood experienced a 50% increase in median home prices between 2011 and 2019, pricing out long-time residents.

Mixed impacts:

1. **Cultural shifts**: New residents bring diverse perspectives but may also erase the neighborhood's cultural identity.
    - Example: Denver's RiNo (River North) arts district transformed from a predominantly Hispanic neighborhood to a trendy arts hub.
2. **Infrastructure upgrades**: New development brings improved infrastructure but may also increase traffic and congestion.
    - Example: Atlanta's BeltLine project brought new parks, trails, and transit options, but also drove up housing costs and displaced some long-time residents.

These examples illustrate the complex and multifaceted nature of gentrification, highlighting both benefits and drawbacks.

Literature Review

Forecasting gentrification in U.S. cities involves an approach that integrates various data sources and frameworks in order to create a predictive machine-learning model. The following literature review suggests that various machine-learning techniques can potentially analyze these dynamics and provide insights into future neighborhood changes.

The following studies have shown that some of the factors, like an increase in college-educated residents, rising property values, and demographic shifts, are solid indicators.

- Zuk et al. (2017) developed a predictive model using block-level census data, focusing on demographic shifts and housing market dynamics to forecast gentrification.
- Meyer (2018) emphasizes the connection between human capital growth and displacement, suggesting that neighborhoods with an influx of educated individuals are more susceptible to gentrification.
- Thackway et al. (2021) developed a tree-based model in Sydney that effectively captured urban dynamics while applying machine learning to predict neighborhood changes.
- In the U.S., Vergara (2023) developed an evaluation framework for predictive models of neighborhood change, emphasizing the need for accurate predictions and the use of various data sources.
- Moreover, according to Gray et al. (2023), geographically weighted regression models can help to capture the spatial variations in gentrification patterns, offering a more in-depth understanding of local dynamics.

Following studies have used spatial data about places to make the model's predictions more accurate.

- Glaeser et al.(2018) explored the integration of data sources like Yelp reviews and social media activity as a means to quantify neighborhood change and enhance predictive accuracy.
- Reades et al. (2018), supported the idea that machine learning can model complex socio-spatial processes, enabling predictions about future neighborhood changes based on historical data.
- Ilic et al. (2019) used deep learning to analyze Google Street View images and identify visual changes in neighborhoods, offering a way to detect signs of gentrification.

Methodology

Data Collection

To train the predictive model, we gathered a comprehensive dataset from the U.S. Census Bureau, focusing on relevant demographic, housing market, and neighborhood-level variables. These included:

- **Demographic data:** Population density, median household income, educational attainment, racial and ethnic composition
- **Housing market indicators:** Median property values, rental prices, housing vacancy rates
- **Neighborhood-level variables:** Proximity to amenities (parks, schools, public transportation), crime rates, quality of public infrastructure

We decided that we would collect data as a representative sample of U.S. cities to ensure that we are accommodating geographical diversity and capturing varying urban contexts in variables such as race, school rating, rent, and population density within a city, as they each have separate yet clear impacts on a city's long-term infrastructure. For example, a lower rent in an area with a good school zone could indicate impending gentrification, as wealthier people would be more likely to move into the area to take advantage of the superior schools, raising the rent prices in the process.

Data Preprocessing

Before training the model, we had to ensure that the data we had gathered was rigorously preprocessed to check on quality and consistency. Here, we went through the process of data cleaning, followed by feature engineering and then normalization, as explained below:

- **Data cleaning:** Handling missing values, outliers, and inconsistencies
- **Feature engineering:** Creating new features or transforming existing ones to improve model performance
- **Normalization:** Scaling numerical features to a common range to prevent bias

Model Selection and Training

After data preprocessing, we selected Logistic Regression as the most suitable algorithm for our binary classification task. Logistic Regression is a statistical model that estimates the probability of an event occurring based on a set of predictor variables.

The model was trained on a portion of the dataset, using a split between training and testing sets to evaluate its performance. Hyperparameter tuning was employed to optimize the model's parameters and improve its predictive accuracy.

Model Creation

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, random_state=0)
```

Evaluation

The model's performance was evaluated using various metrics, including:

- **Accuracy:** The proportion of correct predictions
- **Precision:** The proportion of positive predictions that were actually positive
- **Recall:** The proportion of actual positive cases that were correctly predicted as positive
- **F1-score:** The harmonic mean of precision and recall

These metrics provided a comprehensive assessment of the model's ability to accurately predict gentrification.

Results

The Logistic Regression model achieved an accuracy rate of 72.5% in predicting gentrification in the selected U.S. cities. Key variables influencing the model's predictions included income levels, educational attainment, housing vacancy rates, proximity to amenities, and crime rates.

Discussion

The findings of this study demonstrate the potential of predictive modeling to inform targeted interventions and support sustainable urban development. By identifying at-risk neighborhoods, policymakers can implement measures to mitigate displacement, promote affordable housing, and preserve cultural diversity.

However, challenges such as data availability, model interpretability, and ethical considerations remain significant. Future research should address these challenges and explore gentrification's long-term effects.

Conclusion

Predictive modeling offers a promising approach to understanding and anticipating gentrification trends in U.S. cities. By analyzing various data points, these models can identify key indicators associated with gentrification, allowing policymakers to develop proactive strategies.

This study has demonstrated the effectiveness of supervised learning models in predicting gentrification. The findings highlight the potential of these models to inform targeted interventions and support sustainable urban development. However, ongoing research and development are necessary to address the challenges and limitations associated with predictive modeling.

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