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Identifying localized amenities for gentrification using a machine learning-based framework

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ABSTRACT

The process of gentrification changes the composition and character of urban neighbourhoods in cities worldwide. Amenities such as art galleries, designer boutiques, fine dining, and specialty cafés interact with most gentrification processes and could act as indicators for measuring gentrification. Previous literature has explored the role of amenities in gentrification, and some have found distinctive amenity landscapes in different spatial contexts. However, there is a lack of a more generalized approach for identifying gentrification-related amenities across different regions. This study proposed a machine learning-based framework to identify localized gentrification amenities. Specifically, amenities were represented by Points of Interest (POIs) and matched to the North American Industry Classification System (NAICS), an industry classification system commonly used in amenity-related studies. Bridging POI categories and the NAICS hierarchy enables a dialog between big data and conventional statistical data. Then, given typical gentrification neighborhoods in an area, featured amenities can be identified via a supervised gradient boosting method. The framework was applied to Shenzhen, a major Chinese city. Results showed that Shenzhen has a distinct amenity landscape in its gentrified neighborhoods; for example, bubble tea beverage shops were recognized as a dominant amenity, as opposed to the cafés in many Western cities, as well as financial institutions, digital electronics, and car-related amenities. The proposed machine learning-based framework not only provides a generalized approach to identifying gentrification-related amenities in different regions, but also enables dynamic and fine-grained tracking of gentrification on the basis of big data.

1. Introduction

Gentrification is the process of changing the character of a neighbourhood through the influx of more affluent residents and businesses (Hamnett, 2003; Smith, 1996). This process has transformed the composition and residents of urban neighborhoods around the world (Kennedy & Leonard, 2001), especially in recent years. According to a study of gentrification in the 50 largest U.S. cities, approximately 20% or more of neighborhoods experienced gentrification between 2013 and 2017, compared with only 9% between 1990 and 2000 (Maciag, 2015; Richardson et al., 2020). These demographic changes bring the financial capacity and consumption taste of new residents into the neighbourhood, thus transforming physical landscapes for consumption, i.e., amenity landscapes.

Amenities refer to any feature that provides comfort, convenience, or pleasure, such as art galleries, designer boutiques, fine dining, upscale gyms, and nightclubs. As physical entities that reveal daily activities, consumption preferences, and cultures, amenity landscapes not only satisfy people's activities, desires, and demands, but also form some attributes of places that convey the meanings, memories, and feelings linked to spaces as places (Parker & Doak, 2012). Studies have agreed that during the gentrification process, 'hip' or 'classy' amenities appear to replace traditional and 'outdated' ones (Bridge & Dowling, 2001; Butler & Lees, 2006; Lees, 2003). Therefore, amenities can reflect gentrifiers' specific culture of consumption and reinforce their identity (Silver & Clark, 2016; Ley & Dobson, 2008).

Generally, amenities are locally embedded, which would create a distinguishing landscape when facing spatial and temporal variation of gentrification (Bridge & Dowling, 2001; Lees, 2000). Some studies have identified distinctive amenity landscapes, with which individual

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consumers discover and develop different senses of identity. For example, local gentrifiers in Mount Pleasant Street in Washington, D.C. seek to consume 'authentic' local culture and products (Riely, 2019), while in New York City, laundromats are uniquely and strongly tied to a gentrifying group (Glaeser et al., 2018). According to Sigler and Wachsmuth (2015), focusing on locality is beneficial for illuminating how the systems and practices of a city have been reshaped and transformed; thus, identifying localized amenities is important to the capture and study of gentrification. However, amenities proposed in the literature are usually somewhat subjective (Chapple et al., 2017), and some identifications of localized amenities remain an ad-hoc and site-specific endeavor (Berry et al., 2017; Bilal et al., 2018; Cole et al., 2021). In addition, the primary data sources for quantifying amenities, i.e., US Census Zip Code Business Patterns (BIZZIP) and Yellow Pages, are usually updated with relative low-frequency, and so pose difficulties when used for measuring gentrification (Glaeser et al., 2018; Meltzer & Capperis, 2016; Schuetz, 2014). Furthermore, the field is yet lacking in generalized approaches for identifying localized amenities of gentrification across different regions.

Rapid advances in machine learning have achieved some success in the urban social sciences, specifically benefiting from automatic feature learning and representation (Hwang & Sampson, 2014; Ilic et al., 2019; Reades et al., 2018). This study proposed a machine learning-based framework to identify localized amenities, taking points of interest (POIs), an emerging category of big data that features fine-grained business classification, as proxy for amenities. We further matched POIs to codes from the North American Industry Classification System (NAICS), a typical conventional statistical classification, by comparing the consistency of the entities described by the two taxonomies. This step bridges big data with conventional data. Given typical gentrification neighborhoods in an area, the supervised gradient boosting method can be applied to derive the feature importance of amenities, which in turn denote the amenities that comprise the features of gentrification in the area. Shenzhen, one of the most developed and dynamic cities in China, was used as a case study and its localized amenities were estimated and analyzed.

The contributions of this study are twofold. First, a generalized framework employing machine learning combined with POIs was provided to identify the localized amenities of gentrification. Second, the connection between POIs and widely available conventional data contributes to expanding the means of identifying gentrification. The proposed framework allows for dynamic and fine-grained tracking of gentrification using big data.

2. Related works

Gentrification explains major body transformations in a neighbourhood as low-income residents move out (Bereitschaft, 2020; Hamnett, 2003; Smith, 1996). To capture gentrification, one approach is to detect multi-year variation in neighbourhood socioeconomic characteristics such as composition, income, race, education, or housing costs (Corrigan et al., 2021; Ding et al., 2016; Preis et al., 2020). Those approaches face shortcomings in the form of lower spatial and temporal resolution due to primarily relying on aggregated public datasets, such as census or survey data, which frustrates the accurate estimation of gentrification (Easton et al., 2019; Yonto & Schuch, 2020). Given that gentrification displaces residents and further changes their amenity choices, variance in the amenity landscape offers another clue for estimating gentrification (Glaeser et al., 2018; Pegler et al., 2020).

Amenities reflect the location, functional convenience, and interrelation of different facilities, services, and land use (Clark et al., 2002; Ullman, 1954). Gentrification-related amenities can be categorized into three main types: restaurant, self-management, and creativity (Bridge & Dowling, 2001). Despite the variety of entities covered, Meltzer and Capperis (2016) assumed these amenities as being discretionary: services and facilities that are not basic but enhance quality of life. Hence, an increasing share of discretionary amenities in neighborhoods could demonstrate gentrification (Chapple et al., 2017). Table 1 lists some typical amenities representative of gentrification that have been defined in the literature.

The aggregation of amenities contributes to the overall sense of place and location. The (local) governments may make use of amenities as a means of increasing value because they make a neighbourhood attractive to prospective new residents (Clark et al., 2002). Often, gentrifiers are attracted to high amenity areas because they tend to express and structure their cultural tastes and identity labels through amenities (Ley, 1986; Silver & Clark, 2016). Correspondingly, the value of land or housing increases and induces gentrification. With the arrival of a new population, new cultural tastes and consumption patterns are embedded in the local environment; they are appropriated, commodified, and packaged by the market into new urban amenities. The original population and their symbolic attachments to places are slowly marginalized or even excluded, and gentrification is further intensified. Some literature refers to the changing commercial amenities of gentrifying neighborhoods as 'commercial gentrification', which has been understood as derivative of a more general conception of gentrification (Kosta, 2019; Grier & Perry, 2018; Lees, 2008). The concepts of entrepreneurial cities, cities as 'entertainment machines', 'consumer cities', and 'youthification' all underscore the importance of amenities in attracting talent (Gosnell & Abrams, 2011; Hjerpe et al., 2020; Li et al., 2019; Østbye et al., 2018). Meanwhile, amenities also reshape industry distribution by providing convenience and reducing production costs (Moeller, 2014). Consequently, amenities have emerged as a crucial determinant explaining urban development (Clark et al., 2002; Glaeser & Gottlieb, 2006; Peck, 2005).

The growing body of literature concerning the relationship between amenities and gentrification has identified distinctive amenity landscapes across different case studies. For example, the city of Madrid in Spain has dramatically transformed into an upper-middle and upper-class retail area characterized by clothing shops (Bilal et al., 2018). Meanwhile, the Detroit Shoreway neighbourhood of Cleveland, OH has as its most notable environmental improvement Edgewater Park (Berry et al., 2017). Within the Dallas metropolitan area, new hospitals and new types of health care facilities have been opened in wealthier parts (Cole et al., 2021). In the Harlem and Williamsburg neighborhoods of New York City, cafés and restaurants have replaced bodegas at street level (Zukin et al., 2009), while in the East Village, boutique clothing shops appeared on East 9th Street (Zukin & Kosta, 2004). These amenities may be embedded in their neighbourhood environments in different ways, including relying on a sense of neighbourhood to enhance their authenticity (Deener, 2007).

Yet, even as studies on particular gentrification proliferate, methodological treatment concerning how to define and measure the phenomenon remains inadequate. These studies have extracted distinctive amenities of a study area through qualitative methods such as observation and surveys, or accounting amenities composition over time (Glaeser et al., 2018; Kosta, 2019; Riely, 2019). As they mostly remain case-specific, it is difficult to effectively capture gentrification and expose a lingering methodological gap in measuring localized amenities of gentrification. One factor behind this problem might be the data utilized. Amenities-related indicators are usually measured in terms of business-type classification datasets, such as BIZZIP and Yellow Pages, because they record amenities' location and category information (Glaeser et al., 2018; Meltzer & Capperis, 2016; Schuetz, 2014). BIZZIP typically are categorized according to a scheme called the NAICS (Bajaj et al., 2011), which is general consistently applied across cases and, for the most part, available to public inspection. However, BIZZIP data often miss many small firms (Menger, 2020). Yellow pages are often collected and organized by a product called InfoUSA, which is an early source of POI data; however, these data are not as consistently categorized as BIZZIP data (Silver & Clark, 2016). Navigational POIs, as a type of business classification data, also have the potential to be a proxy for

Table 1
Amenities recognized as marking gentrification in the literature.

Category	Amenities	References
Restaurant	Coffee shops; Exotic restaurants; Gourmet food shops; Health food shops; Highest-quality greengrocers; 'Specialty' food stores; Slow food vendors; Desserts …	Bridge & Dowling, 2001; May, 1996; Rascoff, 2015; Glaeser et al., 2018
Self-management	Upscale gyms; Yoga studios; Medical facilities; Laundromats/dry cleaners; Beauty salons; Alternative therapies; Hairdressers …	Preis et al., 2020; Stehlin, 2015; Hoffman, 2013; Davis, 2011; Kern, 2007; Philp, 2009; McDowell, 1997
Creativity	Vintage stores; Art galleries; Boutiques; Craft shops; Knick-knack shops …	Zukin et al., 2009; Burger, 2006

amenities and are relatively comprehensive and consistent. Previously, POIs were used to identify urban land use because of their fine-grained classification (Gao et al., 2017; Yao et al., 2017). This study proposes a machine learning-based method combined with POI data to systematically identify localized amenities across locations, which, to our best knowledge, has not been studied before.

3. A machine learning-based approach to derive localized amenities using POI data

Due to their capabilities for automatic feature learning and representation, machine learning methods have recently emerged for identifying gentrification through tackling ample correlated variables across transport, housing, demographics, and other aspects (Hwang & Sampson, 2014; Ilic et al., 2019; Reades et al., 2018). Gentrification in a region can be represented by distinctive localized amenities, and we accordingly hypothesize that there is considerable association between gentrification and amenities in a given region. Therefore, machine learning-based approaches can automatically derive localized amenities for identifying gentrification. First, we employ a POI dataset from the whole city to represent amenities by proxy, generate different types of POI amenities based on based on POI classifications, and further match those POI amenities to NAICS codes. Finally, based on the matched amenities, supervised classification machine learning approaches are trained on gentrified neighborhoods to derive localized amenities.

3.1. Matching amenities POIs to NAICS codes

POIs denote specific physical locations that people may find useful or interesting, such as restaurants, retail stores, and grocery stores. It often records information about geographical coordinates and categories. The categories usually group businesses into a taxonomy hierarchy, including top-level, second-level, and third-level categories; major business sectors comprise the top level, while levels down the hierarchy gradually become more precise and concrete. At the third level, each category typically represents the functions or usage types of individual amenities, and even brand types. For example, the top-level category '*restaurants*' includes several second-level categories, such as *'café'*, *w*hich are further divided into third-level categories, such as *'Starbucks'* and '*COSTA*'. In summary, POI taxonomy classifications distinguish each type of classification object based on function, usage, or brand.

Here, amenities were first extracted from POIs. Inspired by the definition of amenities, these POI-based amenities were limited to businesses that serve neighborhoods and improve quality of life (as opposed to manufacturing enterprises, real estate and office buildings, government and administrative buildings, and public fundamentals). POI-based amenities mainly represent businesses having top-level categorizations of restaurant, shopping, finance and insurance, educational and cultural services, automotive services, daily life services, sports and leisure, health care services, and accommodation services. As specific examples, POI-based amenities include (generally as second-level or third-level categories) restaurants, beauty salons, banks, fitness facilities, barber/beauty shops, laundry, and pet care.

Then, the POI-based amenities were matched to NAICS codes. NAICS is a widely used classification system consisting of six-digit codes, and also features a gradually-specific hierarchical structure.[1] Matching of POIs to NAICS codes was done by comparing the consistency of the entities described by the two taxonomies. However, since NAICS offers more fine-grained detail than POI categories, it is infeasible to precisely match amenity categories across the two taxonomy systems at the same level. POI amenities can be converted into NAICS codes at the four-, five-, or six-digit level as long as heterogeneity is maximized between categories and homogeneity within categories. The full listing of included amenities is given in Appendix A, developed with reference to the study by Meltzer and Capperis (2016) and incorporating extensions and additions to account for cultural differences. By matching amenities to NAICS codes, we establish a bridge between POI categories and the NAICS hierarchy, which not only improves the generalizability and comparability of the framework and helps to summarize the main types of amenities related to gentrification, but also—and more importantly—enables dialogs between big data and conventional statistical data.

3.2. Identifying localized amenities using machine learning methods

According to empirical or other systematic criteria, neighborhoods in a specific location can be labeled manually as gentrified or not-gentrified. Based on those labeled samples, supervised classification models can then be applied to derive localized amenities. Generally, training of classification models can be used to generate the feature importance of amenities, which measures the respective individual contributions of amenities in identifying gentrification. This feature importance can be regarded as the localized amenities.

Regarding machine learning methods, although neural networks or support vector machines may produce good results, they are not ideal for this problem due to the high number of classes involved in the training process. This framework employs the gradient boosting decision trees (GBDT), which is the most frequently preferred supervised algorithm and has performed well in both industry and academia (Badillo et al., 2020). In GBDT, multiple decision trees are constructed, with each tree trained based on previous training. Each tree is trained to predict the pseudo-residuals of the previous tree, given a predetermined objective function. Inference on new instances is performed in an additive manner, with each tree adding its residuals to the aggregated results. GBDT can therefore improve overall prediction performance by compensating for errors in a single model with other models. It is considered to be the most appropriate approach when dealing with relational datasets, where each sample contains meaningful features of different nature (Zhang et al., 2017).

The target variable Y inputted into the model is a binary variable to indicate gentrification in a region. This variable can be defined based on the actual situation of localized gentrification, such as representing empirical or other reliable change criteria (Corrigan et al., 2021; Ding

[1] The first two digits of a code designate the sector, the third the subsector, the fourth the industry group, the fifth the NAICS industry, and the sixth the national industry (NAICS, 2012).

et al., 2016; Preis et al., 2020). Change in house prices is one of the most commonly used indictors. Following the definition of gentrification in NYU Furman Center (2020), the neighborhoods were considered "gentrified areas" and tagged with 1 when: 1) the average house prices were below the 40th percentile in 2016, and 2) the increased percentage was greater than the median value of all neighborhoods. The remaining areas were defined as non-gentrified areas and tagged with 0. The independent variables X are corresponding changes in the respective sums of each amenity category during the study period (from *t* to *t*-1). Datasets are usually divided into three subsets: train, validation and test sets. By fitting the train set and tuning model hyperparameters based on the validation set results, an improved trained model will be generated. Two specific results will be derived after inputting test datasets to the trained models: (1) the feature importance, i.e., localized amenities, and (2) gentrification classification, which denotes the probability of gentrification occurring in test datasets. The overall procedure is outlined in Fig. 1.

4. Case study

4.1. Study area and data

Located in the south of China and adjacent to Hong Kong, Shenzhen is one of the fastest growing cities in the world. Shenzhen gentrification comes with the government's efforts to tighten the land supply and achieve better land use efficiency through urban renewal. Projects related to urban renewal include the revitalization of the historical inner city, renovation of old factory buildings, upgrades of commerce, and rebuilding of offices and residences. As per the 13th Five-Year Plan (2016-2010), Shenzhen completed all forms of urban renewal over 30 km^2. Shenzhen's urban renewal was a government-guided market operation. The government tries to create cultural conditions by considering amenities as tangible objects that attract prospective people. For example, it turned empty workshops and warehouses into "cultural and creative industry clusters," replacing low-income neighborhoods with well-appointed apartments and trendy entertainment and business districts. These measures have successfully channeled a large volume of capital flow to urban renewal projects, with the active participation of private developers, who are the concrete implementers of renewal projects. In general, Shenzhen gentrification is related to the emerging neoliberal capital accumulation regime and towards a new market-society relationship that fosters consumer culture and gentrifiers' aestheticization (He, 2007). As a rising city, findings from Shenzhen may contribute to the gentrification literature.

This study takes neighborhoods as its spatial units; neighborhoods provide most public activity spaces, and amenities within them provide principal service functions required daily. Residents in a given neighbourhood are usually similar, having comparable socio-economic properties and values. Our collection in Shenzhen study area consists of 4,826 neighborhoods. The POI dataset was obtained from Baidu Map (a Chinese version of Google Map), which provides the geographic location and business information of all building entities in Shenzhen. Each POI includes the following attribute fields: "*Name*", "*Address*", "*Longitude*", "*Latitude*", and "*Categories*". The "*Categories*" consist of 16 top-level items, 77 s-level items, and about 800 third-level items.

Housing prices for each neighbourhood, used for defining the Y labels as described in section 3.2, were accessed from Anjuke (https://shenzhen.anjuke.com/), a website providing information about real estate transactions.

4.2. Experiment

This study identified localized amenities from 2016 to 2020 to probe the gentrification characteristics of Shenzhen. In our experiment, about half of the POIs were extracted and reclassified into 36 categories of amenities. The counts for each category were taken as the independent

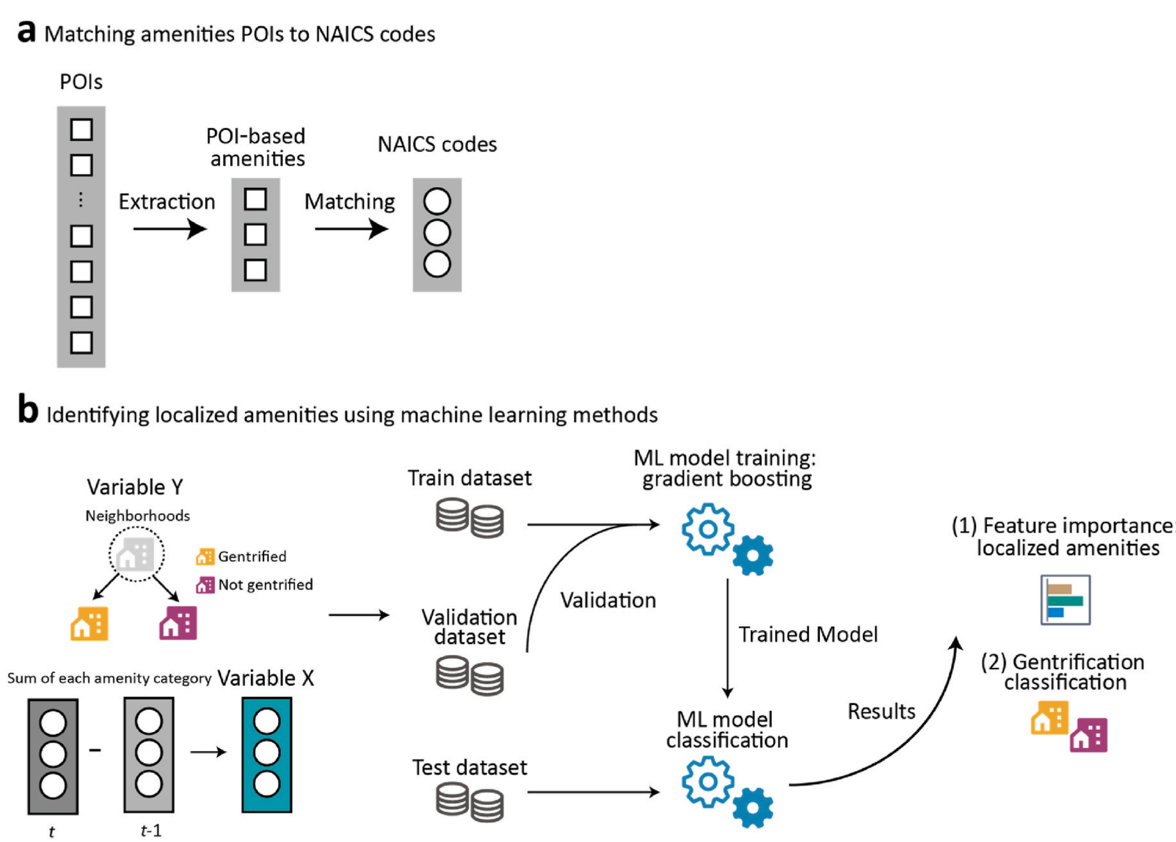

Fig. 1. Procedure for identifying localized amenities.

variables. Fig. 2 lists the top ten types of amenities among the POIs.

According to availability of the dependent variable Y, neighborhoods were divided into training, validation, and test datasets: (1) For the training and validation datasets (977 neighborhoods, 781 training [80%], 196 validation [20%]), we labeled Y based on change in house prices from 2016 to 2020. (2) Test datasets had no Y variables and included 3,849 neighborhoods (Fig. 3).

This experiment used three gradient boosting methods, XGBoost, CatBoost, and LightGBM. Five-fold cross-validation was applied while tuning model hyperparameters; that is, five procedures were run, each with a different one-fifth of the dataset reserved for validation, and the results of those runs were averaged to improve classification robustness and avoid overfitting (Flach, 2012). CatBoost demonstrated better performance in this classification task, with the best area under the curve (AUC) (Table 2). Consequently, feature importance was calculated from the CatBoost model. Since the amenities system of gentrification is a general and inclusive listing, all results from models with high accuracy could be considered.

4.2.1. *Localized amenities of gentrification in Shenzhen*

Fig. 4 illustrates the ranking of the primary amenities in gentrified Shenzhen neighborhoods from top to bottom by importance score, in which a higher score indicates more significant importance. Those amenities are categorized under restaurant, self-management, creative amenities as summarized by Bridge and Dowling (2001), and recreation, which contains several recreational amenities that do not fall into the first three categories.

(1) Restaurants

Full-service restaurants were important markers of gentrification in the study area. Nonalcoholic beverages followed restaurants in ranking, but cafés and bars were not among the top ten in the study area. The consumption of food has long been recognized as a pivotal mark for identifying gentrifiers, who have a higher propensity to eat out and consume particular cuisines, especially in a decorated restaurant setting (Bridge & Dowling, 2001). This may be because gentrifiers are usually money-rich, time-poor, and tend to distinguish themselves from other groups. However, gentrified neighborhoods in Shenzhen favored nonalcoholic beverages, namely bubble tea beverages, over cafés and bars, which typically constitute a close tie with food in Western cities. To our knowledge, this finding has not been reported in the literature previously. For example, Starbucks has become a famous bellwether of gentrification due to the franchise providing relaxed and conspicuous environments (Glaeser et al., 2018; Rascoff, 2015). Influenced by tea culture, Chinese urban consumers are more receptive to the taste of tea drinks. Bubble tea beverages, also known as pearl milk tea, bubble milk tea, recently have become highly adopted in China due to the delicious taste (specifically, it covers the bitterness of tea, which is less popular with younger generations of Chinese people), stress relief, advertisements, and celebrity. By the end of 2019, China was home to around 480,000 tea stores, and bubble tea had become the best seller in almost every one (Forward consulting, 2019). Now these beverages strive to become a lifestyle brand or cultural symbol, synonymous with concepts such as fashion, cool, and international. Some shops take Starbucks as a benchmark with respect to visuals, spaces, and prices (Daxue Consulting, 2020).

(2) Self-management

Self-management-related amenities, such as personal care services, sporting goods, hobby stores, and musical instrument stores, were in the top 20. To achieve upward social mobility and a sense of identity, gentrifiers generally concern themselves with maintaining body and brain health and a superior image (Bridge & Dowling, 2001; Dowling, 1999; McDowell, 1997). Our ranking also featured financial institutions for investment and profits. Growth in wealth for individuals is a vital element of social distinction and realizing upward social mobility (Ponzini, 2020). Shenzhen is one of China's financial centers, as it benefits from many preferential policies; in fact, the financial industry is the backbone of the city's economy, totaling 15 percent of its GDP (UNHSP, 2019). The China Merchants Bank, Ping An Insurance, the Shenzhen Stock Exchange, and the Shenzhen-Hong Kong Stock Connect all provide opportunities for investors. In addition to external conditions such as higher-degree marketization and the Hong Kong RMB Offshore Trading Center, the personal choices of gentrifiers regarding investment also explain the ranking of financial amenities.

(3) Creative amenities

Creativity-related amenities were mainly comprised of museums, art galleries, digital electronics stores, and similar entities. In Shenzhen, which is a global hub for hardware innovation, digital electronics, identified here as a typical creativity-related amenity, is also a marker of gentrification. A number of global high-tech enterprises were cultivated in Shenzhen, including Huawei, Tencent, and DJI, and Huaqiangbei, the "No.1 Electronic Street in China" has earned Shenzhen as the "Silicon Valley of Hardware". In addition, Shenzhen's "maker" population, who strive to realize their creative ideas, has grown continuously over recent years, with thousands of such businesses now active in the city.

(4) Recreation

Amenities for leisure and entertainment are also representative of gentrified neighborhoods in Shenzhen; these include hotels and the amusement and recreation industries. This is because leisure time has intrinsic value, carrying the potential of freedom, self-realization, fun, and relaxation (Junová, 2020). Moreover, higher wages and standard of living also promotes recreational activities. Importantly, motor vehicles and parts dealers ranked fifth. Unlike some Western cities, only a share of Shenzhen residents—about 20% in 2020 (SBS, 2020)—own private cars due to lack of parking and difficulty in accessing license plates. We have analyzed the amenities of Shenzhen at the whole-city scale. These distinctive amenities are a realistic representation of local gentrification in the city due to the closer relationship between amenities and gentrification in the Shenzhen context of thriving consumer culture.

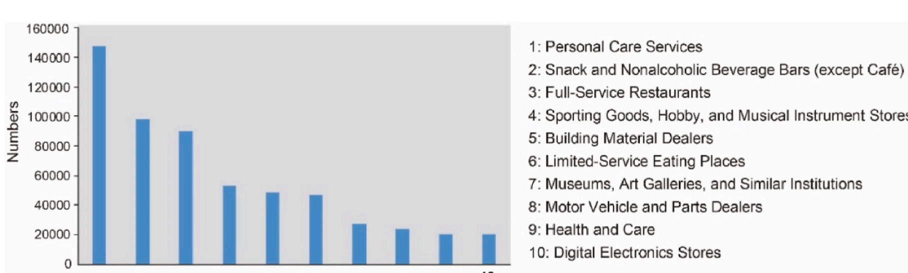

Fig. 2. Top ten types of amenities and corresponding entity counts, based on Baidu POIs.

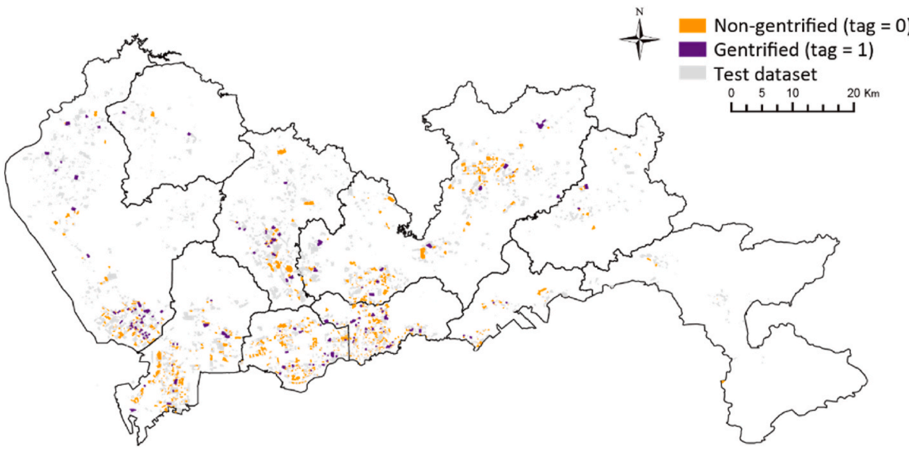

Fig. 3. Study area and gentrified neighborhoods.

Table 2
AUC using LightGBM, XGBoost, and CatBoost.

	LightGBM	XGBoost	CatBoost
Fold 0	0.938767	0.920499	*0.972155*
Fold 1	0.943844	0.925428	*0.97507*
Fold 2	0.940584	0.938109	*0.97219*
Fold 3	0.940312	0.929805	*0.976227*
Fold 4	0.955926	0.928517	*0.97466*
Average	0.943887	0.928472	***0.97406***

However, just as New York may have multiple amenities predominate in gentrified areas due to streets or districts having different characteristics, the same may apply for Shenzhen. Exploring characteristic gentrification at smaller scales also can be achieved using our proposed framework. Distinctive gentrification on the level of streets or districts was not our focus in this study, so no further analysis was conducted in that respect. Moreover, it remains uncertain if these model parameters and features can be directly applied to other cities or areas with no other data (than amenities) for gentrification prediction. We infer that for cities that share a similar socio-economic context or are at the same wave of gentrification, the models have a high potential for mutual transfer learning in identifying gentrification areas with the identified important features of amenities in areas. Ground control is required to calibrate results like remote sensing in relatively unknown regions. Therefore, the proposed model should serve as a first detection tool or starting point for further investigation of gentrification.

Fig. 4. Localized amenities recognized by CatBoost.

Using the local amenities proposed as indicative of gentrification in this study, we compared changes in neighborhoods from the year 2016–2020 and determined the corresponding gentrification probability using the above-trained CatBoost. The probability ranges from 0 to 1, with a higher value indicating higher probability of a neighbourhood undergoing gentrification. This study classified neighborhoods as being of lower, medium, or higher probability according to the Natural Breaks method. As shown in Fig. 5, neighborhoods with higher probabilities were mainly distributed along metro lines.

4.2.2. Validation

To validate the proposed framework and method, transit smart card data (including buses and metros) was used to measure displacement based on the assumption that the lower-income group uses public transit as a means of commuting (Gao et al., 2018). That is, transit smart card data can be used to validate the displacement of gentrification. Complete origin-destination information for every trip was extracted by cross-referencing terminal IDs and trading times. The method for tracking the residential relocation of lower-income residents has been detailed by Gao et al. (2018). This validation used transit smart card data from the first ten consecutive working days of May 2016 and December 2020. On each day, there were 2.7 million completed bus trips and 1.25 million subway trips.

This study took spatial displacement of the lower-income group to validate the results from machine learning approach. Average displacement was determined around neighborhoods having higher, medium, and lower gentrification probability, with circular buffers of 200 m for bus stops and 700 m for metro stations (Foda & Osman, 2010; García-Palomares et al., 2013). The results revealed that the higher the gentrification probability, the greater the average displacement of residents (Fig. 6). Although the calculated displacements have geographic offsets of 200–700 m (the walking distance to stations) relative to the actual displacements due to being extracted via public transit, which to some extent blunts the accuracy of this verification of our framework, this evidence from public transit data suggests that our machine learning-based framework can be used to identify localized amenities of gentrification.

5. Discussion

Since temporal change is also part of the geography of gentrification, a chronology of localized amenities was identified to explore changing consumer preference patterns over time among gentrifiers in Shenzhen. We additionally retrained the systems and compared their amenities based on data of 2016–2018 and 2018–2020. The CatBoost model performed well and outputted relatively accurate identification results; fully trained, its accuracy (AUC) was 0.972 and 0.967 for 2016–2018 and 2018–2020, respectively. ROC curves for the two period are depicted in Fig. 7; both curves closed upon the top-left corner.

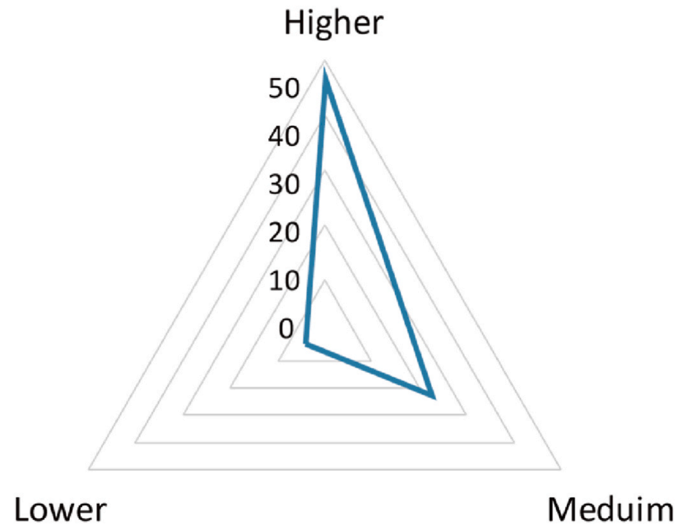

Fig. 6. Average displacements of neighborhoods according to gentrification probability.

We extracted the types of amenities that have ascended and descended in importance, signaling gentrification by more than five places from 2016 to 2018 and 2018 to 2020 (Table 3). As indicated in Table 3, wealth has been increasingly spent on improving houses and individual bodies and appearances, such as through jewelry and watches, sporting goods, hobbies, musical instrument stores, and boutiques, which allows the creation of a tasteful appearance catering to fashion. Fast food and auto mobile related places, the representatives of a fast paces and efficient life, have also risen in ranking. The prevalence of amenities related to banking and insurance carriers, health and care facilities (specifically including healthcare service premises and supplies), brand clothing, and books, among others.

The increase and decrease of specific amenities may be driven by the increase in value of the internet, which has influenced organizational processes and selling activities in numerous ways (Pantano & Timmermans, 2014). For daily activities in which the Internet can increase convenience and reduce costs, gentrifiers prefer online consumption, such as of medicines, clothing, and books; they also prefer saving and investing online. Meanwhile, for experiential consumption in which products are purchased for the way they make the buyer feel, or as a positive experience (Holbrook & Hirschman, 1982), gentrifiers would be more willing to patronize physical shops. That is, when shopping,

Fig. 5. Distribution of gentrification predictions.

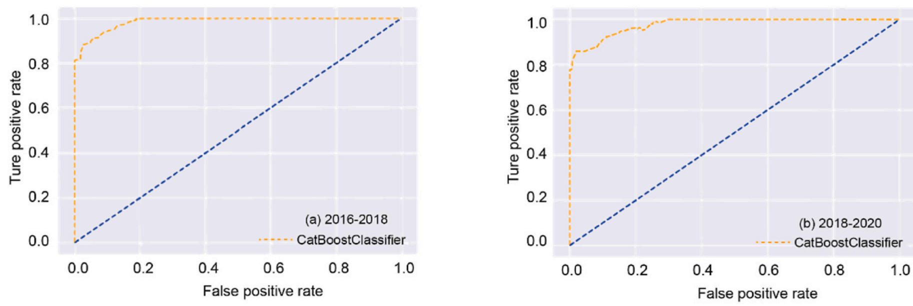

Fig. 7. ROC curves for (a) 2016–2018 and (b) 2018–2020 data.

Table 3
Specific amenities ascended and descended in importance rankings from 2016 to 2018 to 2018–2020.

Ascend	Descend
Motor Vehicle and Parts Dealers	Commercial Banking and Insurance Carriers
Sporting Goods, Hobby, and Musical Instrument Stores	Health and Care Facilities
Limited-Service Eateries	Branded Clothing, Shoes, Luggage & Leather Goods Stores
Jewelry and Watch Stores	Book, Periodical, and Music Stores
Professional, Scientific, and Technical Services	Niche Sports
Gift, Novelty, and Souvenir Stores	

eating, and entertainment not only provide a buyer with the utilitarian value of the service or product, but also appeal to individual emotional satisfaction. When consuming such amenities, the buyer feels excitement, pleasure, relaxation, and fond memories for some time. As the influence of the internet on consumption continues to increase, it is worth further studying how it will affect feature amenities in the gentrification process.

6. Conclusions

Distinctive amenity landscapes appear in the geographical variation of gentrification. Here, a machine learning-based framework combined with POI data was proposed to identify localized amenities of gentrification in a specific area. Our case study of Shenzhen showed distinctive amenity landscapes in its gentrified neighborhoods; for example, gentrified areas in Shenzhen are dominated by bubble tea beverages rather than cafés, which are a featured amenity in many Western cities. Other amenities such as financial institutions, digital electronics, and those relating to cars also exemplify Shenzhen's regional characteristics. Moreover, conceivably affected by online commerce, the patterns of consumption among gentrifiers in Shenzhen are transforming: amenities related to experiences have increasingly gained importance with gentrifiers who look for more than mere service or product delivery.

This study suggested a uniform framework for identifying localized amenities across different regions. This framework will make such information uniformly available for study at the neighbourhood, street, or maybe even finer-grained levels, which may then enable deploying this approach to answer site-specific gentrification questions. Furthermore, with regular updates of POIs or other classification codes, the framework can be used to continuously identify the localized amenities of gentrification, both past and present. In general, the proposed framework enables dynamic and fine-grained tracking of gentrification using a big data approach.

Author statement

Jin Zeng: Methodology, Data curation, Visualization, Writing-Original draft preparation. Yang Yue: Conceptualization, supervision and Writing- Reviewing and Editing. Qili Gao and Yanyan Gu: Writing-Reviewing and Editing; Chenglin Ma: Software, Validation.

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Appendix A

Table 1
POI amenity categories and corresponding NAICS codes.

Num.	Amenities system	NAICS code	POI categories
1	Limited-Service Eateries	Limited-Service Eating Places (7222)	Fast-Food Restaurants (Pizza Hut, KFC, McDonalds, etc.)
2	Full-Service Restaurants	Full-Service Restaurants (7221)	Foreign Restaurants (French, Korean, Japanese, Thai/ Vietnamese cuisine, etc.); Chinese Restaurants (Northeastern, Hunan, Cantonese, etc.); Casual Dining Restaurants
3	Florists	Florists (4531)	Flower Markets; Florists
4	Building Material Dealers	Building Material and Garden (444)	Lamps; Porcelain; Home Furniture; etc.
5	Sporting Goods, Hobby, and Musical Instrument Stores	Sporting Goods, Hobby, and Musical Instrument Stores (4511)	Sportswear and Accessories (Adidas, Nike, Puma, etc.); Outdoor Clothing and Gear (North Face, Columbia, etc.); Hobby and Musical Instrument Stores
6	Book, Periodical, and Music Stores	Book, Periodical, and Music Stores (4512)	Book, Periodical, and Music Stores
7	Gift, Novelty, and Souvenir Stores	Gift, Novelty, and Souvenir Stores (45322)	Gift, Novelty, and Souvenir Stores
8	Art Dealers	Art Dealers (45392)	Antique Painting and Calligraphy Shops; Art Shops
9		Cosmetics, Beauty Supplies, and Perfume Stores (44612)	

(continued on next page)

Table 1 (*continued*)

Num.	Amenities system	NAICS code	POI categories
	Cosmetics, Beauty Supplies, and Perfume Stores		Personal Products (Watsons, etc.); Cosmetics Shops (Channel, Lancôme, Estee Lauder, etc.)
10	Office Supplies and Stationery Stores	Office Supplies and Stationery Stores (45321)	Office Supplies and Stationery Stores
11	Motor Vehicle and Parts Dealers	Motor Vehicle and Parts Dealers (441)	Charging Stations; Petrol Stations; Car Clubs; Car Parts Sales; Car Care; Car Washes; Car Sales
12	Jewelry and Watch Stores	Jewelry, Luggage, and Leather Goods Stores (4483)	Jeweler and Crafts; Watch Shops
13	Cigarette and Liquor Stores	Beer, Wine, and Liquor Stores (4453)	Cigarette and Liquor Stores
14	Snack and Nonalcoholic Beverage Bars (except Cafés)	Snack and Nonalcoholic Beverage Bars (except Cafés) (722515)	Milk Tea Stores (Coco Tea, Hey Tea, etc.); Pastry Stores
15	Bars (Alcoholic Beverages) and Cafés	Drinking Places (Alcoholic Beverages) (7224)	Bars; Cafés (Pacific Coffee Company, COSTA, Starbucks, Luckin, etc.)
16	Chain Convenience Stores, Supermarkets, and Shopping Malls	Department Stores (452210)	Convenience Store Chains; Supermarkets (China Resources, Carrefour, Wal-Mart, etc.); Shopping Malls
17	Amusement and Recreation Industries	Amusement Arcades (713120)	Sports and Leisure Services; Entertainment Venues (Amusement Parks, KTV, Nightclubs, Game bars, etc.)
18	Pet, Pet Supplies Stores and Pet Hospitals	Pet and Pet Supplies Stores (453910); Veterinary Services (541940); Pet Care (except Veterinary) Services (812910)	Pet Stores; Pet Supplies Stores; Pet Hospitals
19	Digital Electronics Stores	Appliance, Television, and Other Electronics Stores (423620)	Digital Electronics Stores (Redmi, Huawei, Apple, etc.)
20	Noble Sports	Fitness and Recreational Sports Centers (713940)	Squash; Tennis; Ice Skating; Equestrian; Billiards; Golf
21	Other Recreational Sports Centers		Other Recreational Sports Centers
22	Fitness and Outdoor Gymnasiums		Fitness and Outdoor Gymnasiums
23	Plastic Surgery Hospitals	All Health and Personal Care	Plastic Surgery Hospitals
24	Hospitals	Stores (446199)	Hospitals
25	Branded Clothing, Shoes, Luggage & Leather Goods Stores	Clothing Stores (4481); Shoe Stores (448210)	Branded Clothing, Shoes, Luggage & Leather Goods Stores (Urban Revivo, Massimo Dutti, Suitsupply, etc.)
26	Securities & Commodity Exchanges	Investment Banking and Securities Dealing (523110); Securities Brokerage (523120)	Financial Service Institutions, Securities Companies, etc.
27	Commercial Banking and Insurance Carriers	Commercial Banking (522110); Insurance Agencies and Brokerages (524210)	Banks (ICBC, BOC, HSBC, Everbright, etc.); Insurance Companies (Taikang, Taiping Life, etc.)
28	Personal Care Services	Barber Shops (812111); Beauty Salons (812112); Dry cleaning and Laundry Services (812320); Nail Salons (812113); Pet Care (except Veterinary) Services (812910); Other Personal Care Services (812199)	Hairdressing; Dry Cleaning; Bath and Sauna; Pet Care; Baby Swimming; Nail Salons; etc.
29	Auction, Pawnshop and other Special Trading Facilities	All Other Professional, Scientific, and Technical Services (541990)	Accounting Firms; Law Firms; Appraisal Firms
30	Art Galleries and Similar Institutions	Libraries and Archives (519120); Museums (712110)	Museums Convention Centers; Science and Technology Museums; Art Museums; Libraries; Archives; Cultural Palaces; Exhibition Halls
31	Cinemas, Concert Halls and Theatres	Motion Picture Theaters (except Drive-Ins) (512131)	Cinemas; Concert Halls; Theatres
32	Hotels (except Motels)	Hotels (except Casino Hotels) and Motels (721110, part)	Starred Hotels; Chained Hotels
33	Health and Care	All Other Miscellaneous Ambulatory Health Care Services (621999); All Other Health and Personal Care Stores (446199)	Health Care Service Premises; Health Care Supplies
34	Information and Publishers	Media Representatives (541840); Newspaper Publishers (511110); Television Broadcasting (515120); Periodical Publishers (511120)	Newspapers; Media Agencies; TV Stations; Magazines
35	Auction, Pawnshop and Other Special Trading Sites	–	Auction, Pawnshop, and Other Special Trading Sites
36	Training Agencies and Schools	–	Training Agencies and Schools

Notes: The POIs categories are third-level categories, and appear in parentheses when second-level categories are available.

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