International Journal of
Geo-Information

MDPI

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Function2vec: A Geographic Knowledge Graph Model of Urban Function Evolution and Its Application

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Abstract: Urban function evolution (UFE) has become more and more complex in emerging cities. However, insufficient theoretical support exists for the visual expression of the spatial correlation between UFE patterns. In order to fill this gap, we use the 2013 and 2022 Point-of-Interest (POI) data of Shenzhen city to implement the funtion2vec model based on the node2vec model and urban tree theory. In this model, we first divide UFE patterns into three categories: Function Replace (FR), Function Newly Added (FNA), and Function Vanishing (FV). Then, we calculate the correlation between those UFE patterns using their functional vectors, resulting in a graph structure representing the urban function evolution network (UFEN). Based on our case study, we obtained the following conclusions: (1) From 2013 to 2022, the UFE in Shenzhen was primarily dominated by FR (89.44%). (2) FV and FNA exhibit a long-tailed distribution, adhering to the 20–80 law. (3) Through the UFEN based on FR, healthcare services are well suited to form mutual complementarities with other functions; science, education, and cultural services demand a higher complementarity with other functions; administrative offices exhibit a strong diversity in their evolutionary patterns; and the integration of transportation hubs with other functions results in a significantly deviating urban function evolution from its original pattern. The above conclusions suggest that function2vec can well express UFE in emerging cities by adding spatial correlation in UFE.

Keywords: urban function evolution; urban tree theory; function2vec; emerging cities

Citation: Li, T.; Zheng, M.; Wang, X.; Zheng, X. Function2vec: A Geographic Knowledge Graph Model of Urban Function Evolution and Its Application. *ISPRS Int. J. Geo-Inf.* **2023**, *12*, 458. https://doi.org/10.3390/ijgi12110458

Academic Editors: Guohui Xiao, Yu Feng, Linfang Ding, Younes Hamdani and Wolfgang Kainz

Received: 15 September 2023
Revised: 1 November 2023
Accepted: 7 November 2023
Published: 9 November 2023

1. Introduction

Urban function evolution (UFE) refers to the temporal and spatial changes in urban functions, including commercial, industrial, public services, and more functions. It represents the dynamic variation in urban functionalities over time, illustrating how cities adapt and transform to meet evolving needs and social demands [1,2]. In recent years, some emerging cities have experienced rapid development in terms of their urban functions due to factors such as policy requirements and market-driven economic forces [3,4]. The urban function evolution of these emerging cities may differ from that of cities with a long history [5,6]. Furthermore, some emerging cities are experiencing a rapid development of urban functions when various sustainable urban development concepts are gaining popularity worldwide. In their functional development, these cities often incorporate and adopt these sustainable development principles [7–10]. Understanding the UFE of these emerging cities holds valuable insight for guiding other developing countries toward sustainable urban development. However, previous research on these emerging cities has primarily focused on urban land expansion, and further investigation is needed to delve into the functional evolution [11–13].

According to item 11 of the United Nations Sustainable Development Goals, building inclusive, safe, risk-resilient, and sustainable cities and human communities depends on cities' commercial, cultural, scientific, medical, and other functions. According to government reports, various functions of cities are developing, but their supporting functions cannot be completed simultaneously. For example, the lack of sufficient commercial facilities around residential areas makes it inconvenient for residents.

In the process of urban function evolution, functions in a city are simultaneously replaced, added, and removed. The final result of this process is the state of functional matching. By studying the evolution of urban functions, we can trace all kinds of missing urban functions, such as misappropriating ecological protection functional areas for the construction of commercial and residential areas, and some public service functions have been converted to commercial ones. Therefore, UFE can provide a reference for the timely adjustment of urban planning.

Moreover, UFE heavily relied on scholars' comparative analysis of functional area [14–16] and sector delineation [15]. However, comparative analysis entails significant subjectivity, and the portioning of sectors can influence the representation of UFE. The emergence of big data and its related models has provided new methods for knowledge mining in UFE. For example, kernel density estimation, initially proposed by Rosenblatt (1955) and Parzen (1962), can showcase the spatial distribution characteristics of a specific function by simulating continuous changes in functional density. This method has been successfully applied in the big data-based analysis of UFE [17]. Li et al. [18] utilized kernel density analysis to describe the evolution of Live–Work–Play functions in some Chinese cities. Fu et al. [19] analyzed the UFE near subway stations using kernel density analysis. However, kernel density estimation may not effectively represent spatial adjacency relationships between different functions. Many researchers have introduced embedding techniques for mining knowledge in UFE to address this limitation. Yao et al. [20] introduced the word2vec model and incorporated spatial buffers into the computation of UFE. Then, Yan et al. [21] introduced the place2vec model by enabling the expression of K-nearest neighbor relationships between different functions. The block2vec model constructed multi-level spatial adjacency relationships (point-to-polygon) to demonstrate UFE [22].

Additionally, when expressing the UFE, previous studies often ignore the visual expression of the spatial correlation between UFE patterns. One of possible reasons why they ignore this issue is due to the lack of theoretical support for the visual expression of UFE, especially in cases where one function is replaced by another. This issue can make it difficult to accurately represent and analyze the relationships between UFE patterns. It is worth noting that urban network theory often classifies urban networks as specific structures, such as hexagonal, radial, and grid. Therefore, it is necessary to introduce a kind of urban network theory that can vividly express the spatial correlation between UFE patterns.

Urban networks can represent the interrelationships between cities during their development process [23–25]. Similarly, as the urban functional system serves as a subsystem of the city, there also exists a network for UFE, called the urban function evolution network (UFEN), which represents the interrelationships between different urban functions during the process of UFE. The UFEN can be interpreted as the spatial correlation between the UFE characteristics expressed by various urban function units (towns, clusters, and blocks). For instance, similar patterns exist for function transfer, reinforcement, and clearance; the functional centers may evolve in a single direction or from non-urban areas toward a specific functional center, and there might be frequent alternations of functional centers in a short period. However, based on the above discussions of UFE models, the consideration for the UFEN is lacking in current studies.

The term urban tree (UT), proposed by Fan et al. [26], expresses the presence of a tree-like structure in an urban network. Based on this theory, we can attempt to use the existing functions as the root of the tree-like structure while considering the newly added functions and replace functions as the tree branches. In addition, we need to find a possible technical method to apply this theory. Node2vec is a well-established graph embedding proposed by Grover et al. in 2016. It converts the connection features between network nodes into feature vectors using two sampling strategies: Depth-First Search (DFS) and Breadth-First Search (BFS) [27]. In 2022, Zhang et al. [28] modified Node2vec to create City2vec, which has been successfully applied in the field of urban geography to mine knowledge from the population mobility network.

Thus, in this study, in order to introduce one urban network theory to support the visual expression of the spatial correlation between different UFE patterns, we coupled the modified node2vec model with the UFE feature based on UT theory, creating the Function2vec model, and we then mined knowledge of a UFEN in a typical emerging city.

2. Study Area and Data

We used Shenzhen city as the study area (22°27′~22°52′ N, 113°46′~114°37′ E), which is an emerging city determined by the Chinese government. Its extent is shown in Figure 1. In the past ten years, the UFE in Shenzhen has been fast, and the urban spatial structure is complex. The industrial, residential, commercial, and public service functions are constantly changing in position and form, and the stage characteristics are apparent. In addition, there are still great differences in the development of different regions of Shenzhen. There are some problems in the functional configuration of some regions, and there is a significant imbalance in regional development. Therefore, it is necessary to understand the UFE pattern in Shenzhen to improve the current structure of urban functions.

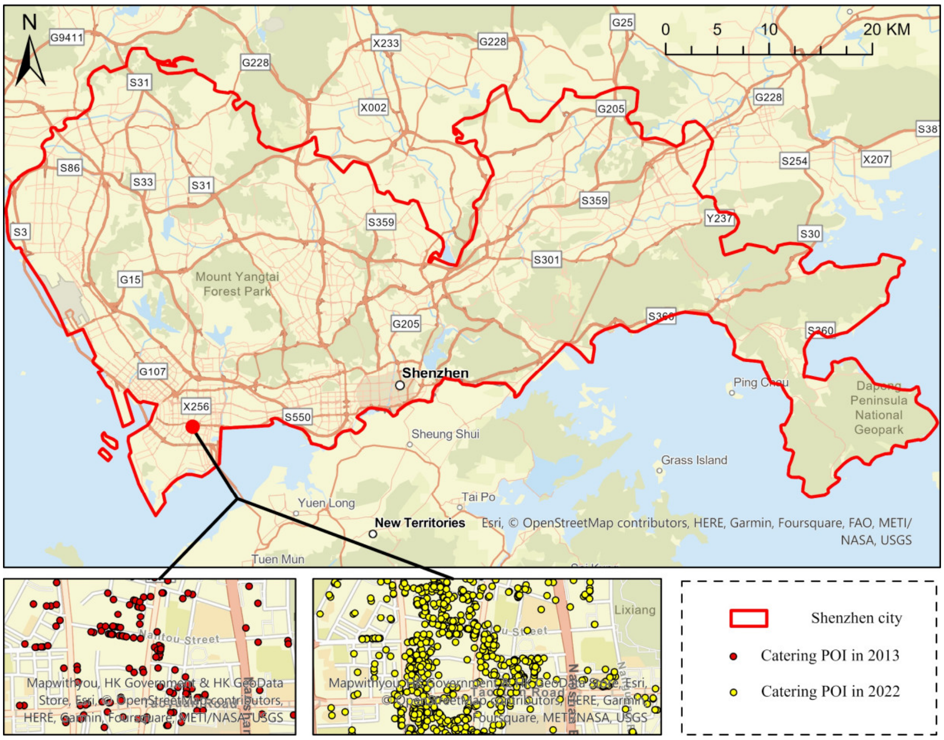

Figure 1. The extent of the study area (basemap source: https://www.openstreetmap.org, accessed on 20 January 2023).

Point-of-interest (POI) data are commonly used data samples in current urban studies. POI refers to the locations of objects (e.g., bus stations, schools, office buildings) on electronic maps. Considering the rapid development of Shenzhen city over the past decade, we obtained the 2013 and 2022 POI data from the Amap platform (https://www.amap.com/, accessed on 25 January 2023), and deleted duplicates and meaningless records. Referring to [29], we classified the urban functions based on POI categories, as shown in Table 1.

Table 1. Classification of urban functions.

Level 1 Type	Level 2 Type	POI Type
Industry	Industry	Companies
Business	Catering Shopping Sports and leisure Accommodation Finance Life service	Catering Shopping Sports and leisure Accommodation Finance Life service
Residential area	Residential area	Residence
Public service	Transportation hub Science, education, and culture Administrative office Healthcare service	Transport facilities services Scientific, educational, and cultural services Government and social organizations Healthcare service
Green space and square	Green space and square	Scenic spot

3. Method

3.1. The Construction of UFEN Based on Urban Tree Theory

Regarding urban tree theory, cities of different scales generally exhibit varying degrees of interconnections in terms of materials, energy, and information. These interconnections can form a hierarchical tree-like structure. Studies have concluded the following: (1) The clustering patterns of POI are the main factors in identifying urban functions [30]. (2) The boundaries of urban areas can be identified through the clustering patterns of POI [31]. (3) The system composed of function units represents a subsystem that expresses the internal structure of the urban system. These function units similarly exhibit interconnections and variations in terms of function scales [32,33]. Thus, by considering basic units that express urban functions (such as grids, blocks, and clusters) as the fundamental elements of a city, the hierarchical tree-like structure between cities can be mapped onto the UFE.

Figure 2 shows the UFEN used in this study. Firstly, we established the foundational structure of UFE, resembling a binary-tree-like structure. Considering the need to refine the relationship for UFE as much as possible, we decomposed all multifunctional combinations into pairwise function combinations. Subsequently, we further subdivided three patterns of UFE: (1) Function Replace (FR), which shows the replacement of the early phase function (root) by the later phase function (fruit). (2) Function Newly Added (FNA) indicates that the later phase function belongs to the newly added function. (3) Function Vanishing (FV) signifies that some functions present in the early phase have disappeared in the later phase. Our UFEN calculates the correlations between roots based on UFE (FR, FNA, FV). Then, we integrated the relationship of UFE with the correlation between UFE (calculated based on the correlation between roots) to obtain the UFEN structure.

In Figure 2, in the UFEN basic structure, the root is the early phase function and the fruit is the later phase function. Root strength is the quantity of the early phase function; branch strength is the strength of functional evolution; and transfer means that the same function is included in fruits linked with the branch. However, considering that urban functions always exist in all kinds of mixed patterns, we divided the function node (root and fruit) into "multi", "single", and "none". "multi" is the node that has mixed functions (F1F2, F1, F2. . . is one function); "single" is the node that has a single function (only F1, F2, F3. . .); and "none" is the node that does not include any function—it can be understood as a non-built-up area.

Furthermore, "single to multi" means that the root has a single function and the fruit has mixed functions; "multi to multi" means that the root has mixed functions and the fruit has mixed functions; "multi to single" means that the root has mixed functions and the fruit has a single function; "single to single" means that the root has a single function and the fruit has a single function; "none to multi" means that the root is a non-built-up area and the fruit has mixed functions; "none to single" means that the root is a non-built-up area and the fruit has a single function; "multi to none" means that the root has mixed functions and the fruit is a non-built-up area; "single to none" means that the root has a single function and the fruit is a non-built-up area.

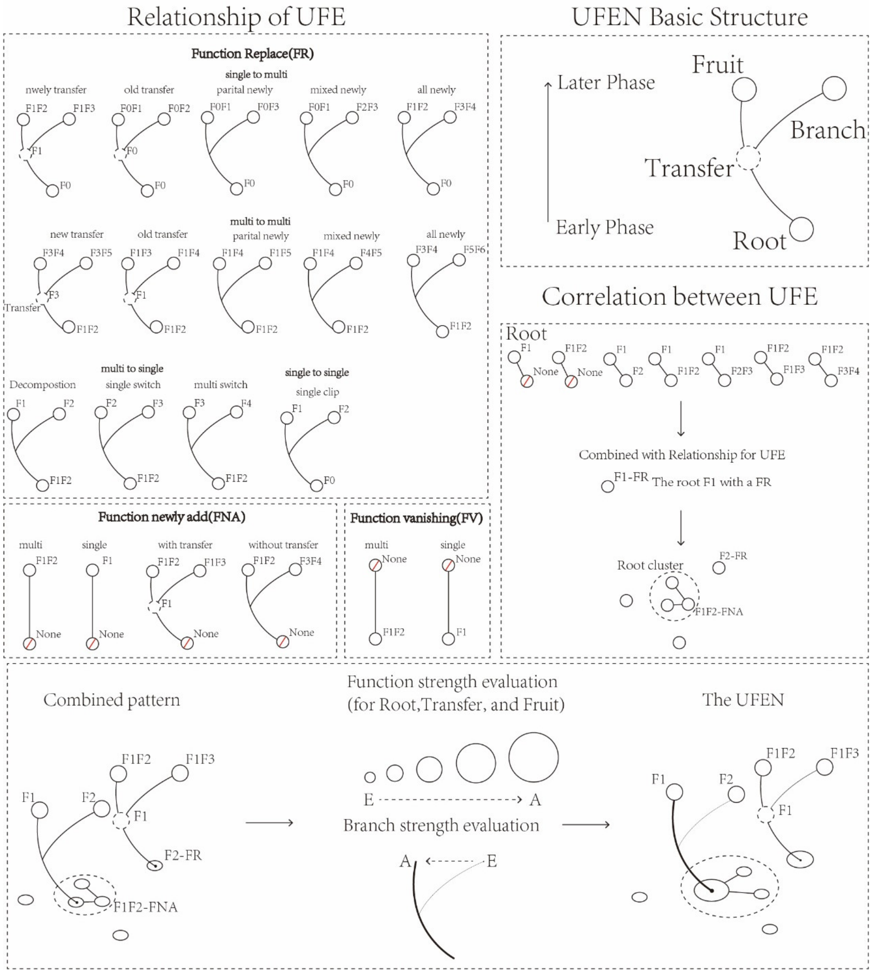

Figure 2. The construction of the urban function evolution network.

3.2. Expression of UFE Patterns Using FV, FNA, and FR

We refer to the calculation of the co-location pattern [34] and Liu et al.'s [35] service area to identify the function unit (FU). That is, according to the results of the co-location pattern, we select the service area that best reflects the characteristics of the co-location pattern as the FU. Based on Hu and Han's method, we identify the dominant functions (DFs) in the FU [36]. However, the distribution of DFs will change over time. In other words, the spatial extent of early function units (EFUs) may be redivided into other FUs following different DF distributions. Thus, we use the overlay analysis (overlay the Later Function unit (LFU) onto EFU) to determine the contribution of the area of the LFU to the area of the EFU, as shown in Equation (1).

$$link_{ij} = \left(i, j, areas_{ij}\right),\ areas_{ij} = \frac{area_{ij}}{area_i} \quad (1)$$

where i is the functional unit of the EFU; j is the functional unit of the LFU; $area_{ij}$ is the area where i and j intersect; $area_j$ is the area of functional unit j; $areas_{ij}$ is the contribution of i to j; and $link_{ij}$ is the temporal evolution from i to j.

Then, based on the DF distribution differences between the EFU and LFU, we obtain the UFEN basic structure (Figure 2). As shown in Figure 3, we combine the different distributions of DFs present in the two types of FU (in dashed boxes) to obtain all possible DF patterns (root-fruit) (each class of pattern is only displayed once). The number of occurrences for each pattern is obtained by calculating combinations of functions. According to these results, the links between the EFU and LFU are allocated to each category of DF (root-fruit). The connections between the FU are transformed into connections between the distribution of DFs, achieving the expression of UFE.

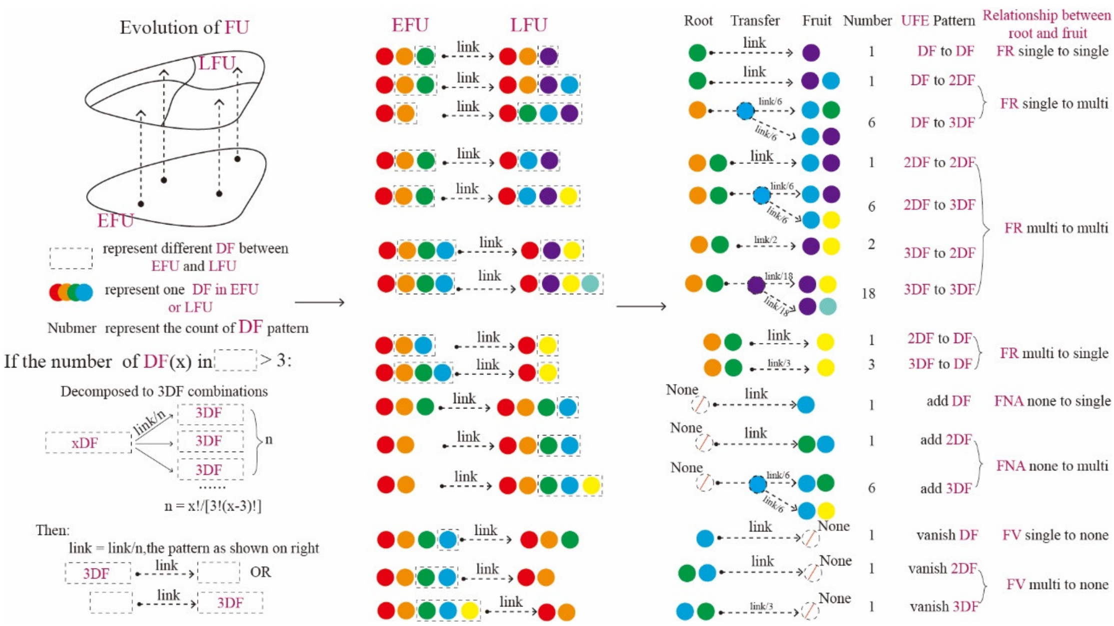

Figure 3. The process of using dominant functions expressing the urban function evolution (note: each color is only used to distinguish different functions in functional combinations).

In order to use DFs to present UFE in Figure 3, we classify the mixed functions existing in the functional units based on the binary tree structure and spatial overlay analysis to acquire the correct direction of UFE. That is, we use the spatial overlay analysis technique to express the corresponding spatial relationship between two phases of FUs. Then, we disassemble these corresponding relations according to the binary tree and finally obtain UFE patterns that cannot be further divided, with each combination containing no more than 2 functions.

3.3. Function2vec: Modifying the Node2vec for the Correlation between UFE Patterns

To calculate the correlation coefficient between UFE patterns, we use the functional types from the basic structure of the UFEN as nodes in the function2vecmodel, which is different from the original node2vec model. The preparing UFEN (PUFEN) is obtained from the overlapping function between each UFE in Figure 3. Then, we train the sampled sequences using the skip-gram model. And we obtain feature vectors for those functional nodes, which is the same as UFE. By calculating the Pearson correlation coefficient between these root vectors, we determine the degree of correlation between UFE patterns. In other words, the higher the correlation coefficient between two roots is, the more similar their UFE are.

(1) Function2vec considers the relationships between functions as a graph $G = (V, E)$ and then sets the number of functional nodes as V, where f is a $V \times N$ weight matrix. By inputting the sampled instances into an artificial neural network for training, we eventually obtain the matrix f, which records the feature vectors of each functional node. For each functional node $u \in V$, $N_S(u) \subset V$ serves as the network neighborhood feature of the functional node u in the preparing UFEN (PUFEN). Based on the skip-gram model, we seek

to optimize the following objective function, which maximizes the log-probability of observing a network neighborhood. $N_S(u)$ for a node u conditioned on its feature is given by f:

$$\max_{f} \sum_{u \in V} \log \Pr(N_S(u) | f(u)) \tag{2}$$

(2) Function2vec utilizes two sampling strategies, DFS (Depth-First Search) and BFS (Breath-First Search), shown in Figure 4. The BFS approach focuses on neighboring nodes. The DFS approach focuses more on further nodes. Parameter q allows the search to differentiate between "inward" and "outward" nodes. When q > 1, function2vec tends more to BFS; when q < 1, it tends more to DFS; and when q = 1, it performs a random search of functional nodes.

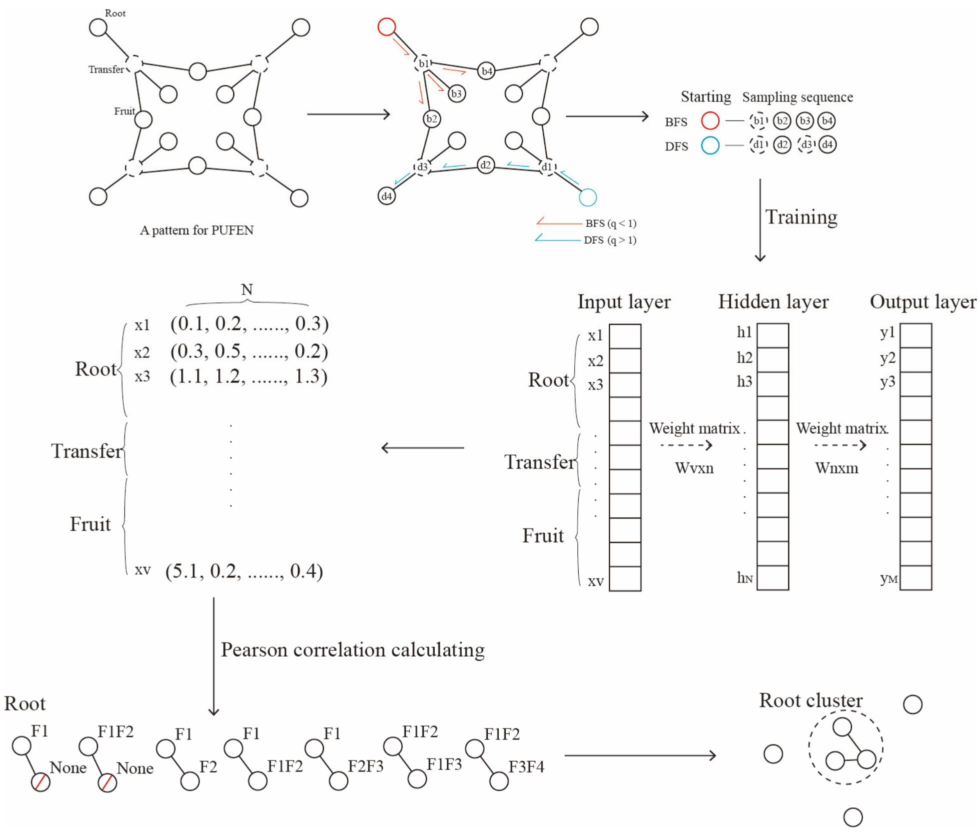

Figure 4. Obtaining root cluster using function2vec.

4. Results

4.1. Function Unit and Dominant Function

The function unit (FU) is the basis that influences the identification of the dominant function (DF) and UFE analysis. As shown in Figure 5, the number of Fus in 2022 has significantly increased compared to 2013, which is related to the increase in the number of POI records. This indicates that from 2013 to 2022, the main focus of UFE in Shenzhen has been concentrated in various built-up areas, with a relatively minimal impact on the natural background. The densification of functional units also suggests that functional zoning is gradually moving toward more refined development.

Based on the identification results of the FU, we conducted a statistical analysis of the number of various dominant functions within these units (Figure 6). In 2013, due to the relatively small number of Fus, the quantity of each DF did not exceed 1000. Healthcare service (741) is the most dominant function, while green space and square (395) is the least dominant function. However, in 2022, all categories of dominant functions significantly increased.

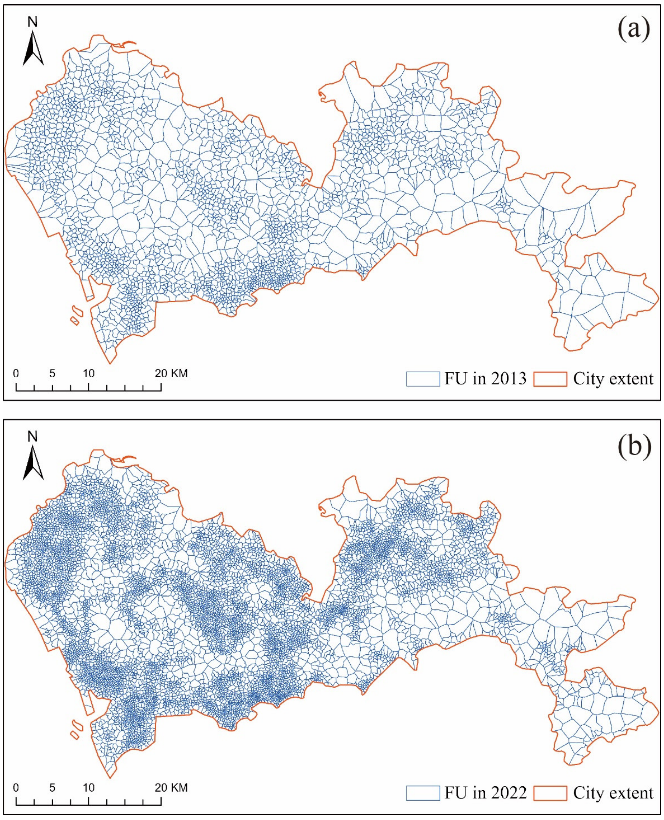

Figure 5. The distribution of function units in Shenzhen: (**a**) 2013; (**b**) 2022.

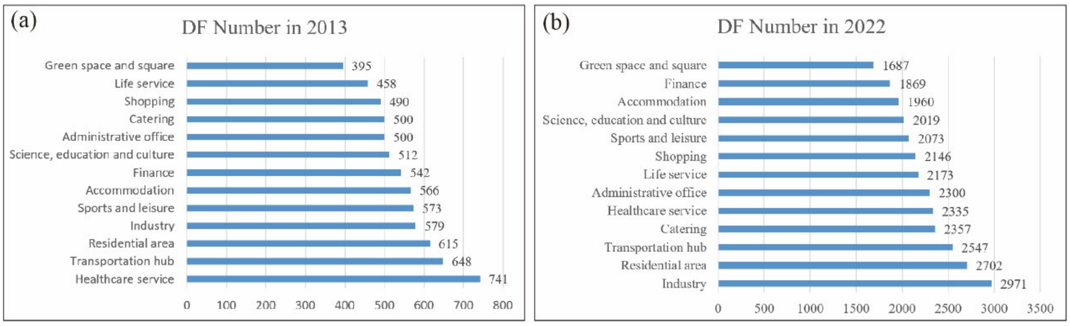

Figure 6. The number of dominant functions in 2013 and 2022: (**a**) 2013; (**b**) 2022.

4.2. The Proportion of UFE Patterns

In the Method section, we divided the UFE into three patterns: FNA, FR, and FV. FR was the main UFE pattern in Shenzhen from 2013 to 2022 (Figure 7). Among the sub-patterns within the FR, the "multi to multi" pattern had the highest frequency, with a total value of 1071.9. The other three sub-patterns of FR, namely "multi to single", "single to multi", and "single to single", had link values of 281.89, 266.45, and 140.19, respectively. These values significantly differ from the "multi to multi" pattern. This indicates that the UFE is primarily characterized by the mutual substitution between multiple diverse functions. "single to single" was the sub-pattern with the lowest link value of FR. During this period, "single to single" functional replacements were no longer in Shenzhen's dominant mode of UFE. However, regarding the FNA, the "none to single" link value was 49.13, slightly higher than the "none to multi" link value. Although the overall UFE in Shenzhen is currently characterized by "multi to multi", in areas where certain functions are relatively underdeveloped or weaker, the addition of new functions still primarily focuses on single functions.

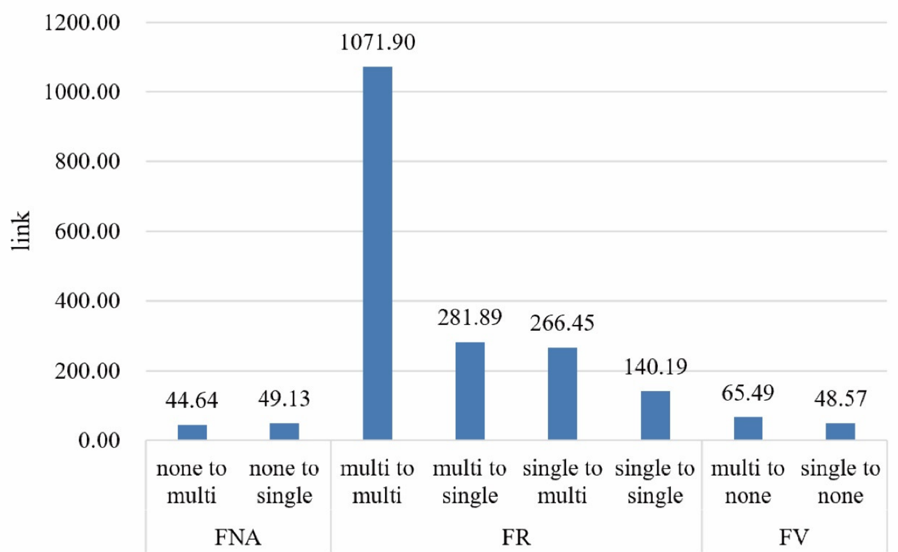

Figure 7. The proportion of different urban function evolution patterns.

FV and FNA are two relative concepts in UFE. As shown in Figure 8, these two curves exhibit a long-tail distribution (in descending order based on the size of their links), meaning that there is a significant difference between the link values of head functions and tail functions, with a large proportion of functions in the tail having relatively low link values. Approximately 80% of functions fall into the tail of the distribution, following a distribution pattern known as the 20–80 law. The FNA and FV are concentrated on a limited number of functions.

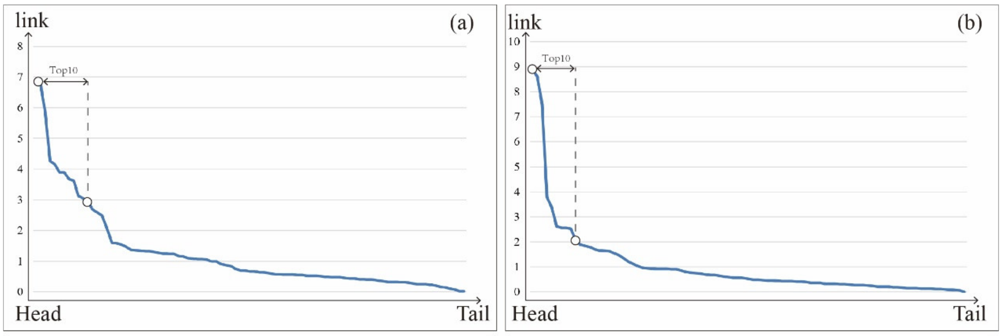

Figure 8. FV and FNA, a log-tailed distribution: (**a**) FV; (**b**) FNA.

4.3. Using UFEN to Express Function Replace

As the primary pattern of UFE in Shenzhen, FR encompasses diverse functions serving as roots. According to the United Nations Sustainable Development Goals (SDGs), public services such as the healthcare service, education, and transportation have always played a key role in the sustainable development process. So, we analyzed the UFEN focusing on the main correlations among the root functions of public services in Shenzhen. We assume that public service is the core of roots that only have public service. Other roots that include these public service functions as mixed functions are classified into three categories based on their degree of correlation with the core functions: (1) Direct correlation with the core, which refers to the direct correlation between the root and core functions; (2) indirect correlation with the core, which stands for the functions in direct correlation with the core; and (3) independent, which refers to core functions that coexist in a mixed manner but have no direct or indirect correlation with the core.

In this study, root strength only considers the sum of all correlation coefficients between the root and other roots to demonstrate the importance of that particular root in the UFEN.

In the UFEN structure, "Transfer" refers to the markings at the intersections of branches where the fruit nodes share the same function. These markings indicate that the function holds a significant position in the evolution from the root to the fruit nodes, highlighting its importance in the UFEN. Please find more details in Section 3.1.

4.3.1. UFEN Pattern with Healthcare Service Core

As shown in the red dashed box in Figure 9, when healthcare services serve as core functions, the related roots are primarily composed of mixed functions that include healthcare services. Its evolution primarily involves mixed functions composed of administrative offices, green space and squares, residential, catering, and shopping. This evolution indicates that improving healthcare services can lead to an increase in residential, public management, green space and squares, and commercial functions, which aligns with the importance people place on integrating healthcare services today.

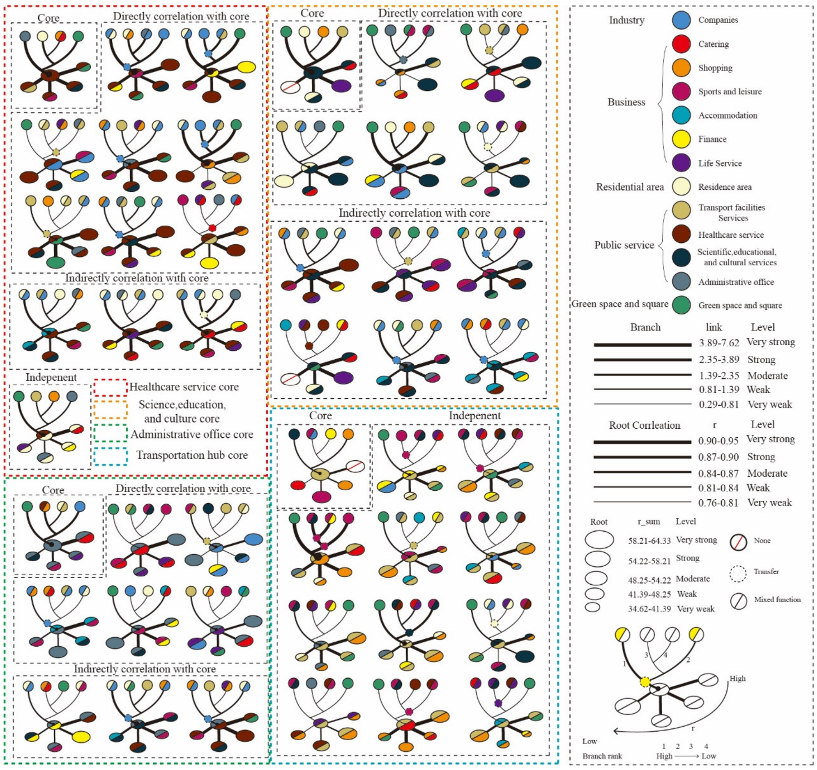

Figure 9. UFEN patterns based on Function Replace.

As for the "Directly correlation with core", we can observe that there is a strong direct correlation with the core root of healthcare services, primarily composed of mixed functions that include healthcare services. It indicates that healthcare services are suitable for forming complementary relationships with other functions, reinforcing the importance of integrating healthcare services with other functions. The other functions evolved from these roots mainly consist of industry, transportation, and green space and squares. There are notable occurrences of transfer between transportation hubs and industry. These findings suggest that industry and transportation hub growth follows as healthcare services develop to a specific scale.

The functions categorized as "Indirectly correlation with core" still primarily consist of mixed functions that include healthcare services. However, the evolution is mainly focused on residential areas. This result indicates that combining healthcare resources with commercial functions significantly attracts people to settle in the area.

Finally, the root consisting of a mix of healthcare services and residential functions does not show any correlation with the other roots. This means that this type of root independently evolved from 2013 to 2022. This can be understood as some regions initially focusing on establishing essential healthcare services and residential areas to attract population settlement. However, the residents will inevitably generate diverse demands, including commercial services, public services, and leisure, reflecting the need for a well-rounded and diverse environment to cater to their various needs. Therefore, this root exhibits evolution toward green space and squares, administrative offices, transportation hubs, and shopping, while residential and healthcare functions serve as the foundational functions attracting people to settle in the area.

4.3.2. UFEN Pattern with Science, Education, and Culture Core

As shown in the orange dashed box in Figure 9, when science, education, and cultural services serve as core functions, we can observe that their UFE is primarily focused on green space and squares, transportation hubs, and some other commercial functions. Notably, science, education, and cultural services strongly correlate with FNA, indicating that they are more closely related to FNA in the UFE. These results suggest that in some regions, a development path may emphasize education-driven urban development, highlighting the significance of incorporating science education and cultural services into the city's planning.

For the "Directly correlation with core" functions, we found that the functions mixed with science, education, and cultural services include industry, residential areas, as well as commercial and public services. The evolution of these functions also predominantly revolves around some single types, including green space and squares, administrative offices, transportation hubs, industry, residential areas, and commercial services. This is a reasonable result considering the high demands of student life in various aspects.

Furthermore, concerning the "Indirectly correlation with core" functions, industries are more frequently observed as transfer nodes, indicating that mixed functions with science, education, and cultural services often guide the development of industry–academia integration. For example, some technical schools are often located close to factories, while certain universities take on scientific research functions, attracting many companies to establish their presence in the surrounding areas.

4.3.3. UFEN Pattern with Administrative Office Core

As shown in the green dashed box in Figure 9, when administrative offices serve as the core root, the main UFE tends to include industry, green space and squares, transportation hubs, and residential areas. The roots that are similar to its UFE are mainly composed of mixed functions that include administrative offices, with commercial functions being predominant.

In terms of the "Directly correlation with core" functions, the evolution of administrative offices shows significant diversity, with relatively few instances of transfer. However, industry and transportation hubs are among the few transfer nodes, indicating that they remain crucial nodes in the evolution process. This correlation is related to the emphasis placed by government departments on investment attraction and transportation development. This diversity continues to exist regarding the "Indirectly correlation with core" functions.

4.3.4. UFEN Pattern with Transportation Hub Core

As shown in the blue dashed box in Figure 9, when transportation hubs serve as the core root, the main UFE tends to include various commercial functions and science, education, and cultural services. Similar to its UFE, the roots mainly consist of commercial services such as catering, sports and leisure, shopping, and FNA.

Unlike the three types of functions mentioned above, transportation hubs only exist in the "Independent" mode, meaning that the mixed functions formed by transportation hubs and other functions are not correlated with its core root. This result indicates that the combination of transportation hubs with other functions significantly influences their original evolution patterns. Transportation hubs serve as auxiliary functions in the development of commercial, science, education, and cultural services, as well as administrative office functions, providing essential support for their growth and integration within the urban environment. Among them, transportation hubs and shopping have high UFEN strength, meaning they exhibit a strong branch strength and root correlation. In summary, transportation hubs are an essential support function, and when mixed with other types of functions, they result in significantly different evolution patterns.

5. Discussion

5.1. The Applicability of Function2vec

The primary purpose of this study is to introduce urban tree theory to support the visual expression of the spatial correlation between UFE patterns. This spatial correlation mainly expresses whether two different functional evolution patterns simultaneously occur in the same area.

Function2vec is of reference value for modifying other models that study the spatial–temporal change of cities. Specifically, we think that it may also be applied to many subareas of urban function: the detection of the change in urban traffic flow, the allocation of urban medical resources, the evolution of urban crime in space, etc. Although the internal evolution of these urban functions still has its subsystems, the concept can be migrated from large to small and from coarse to fine, so there is still space for urban tree theory development in these areas.

The spatial correlation contained in the model has reference value for the urban function analysis of some cities with rapid functional development, such as Ghaziabad, Surat in India, Sana'a in Yemen, Kabul in Afghanistan, and Lagos in Nigeria. Due to the rapid development of these cities in a short period, the spatial organization of urban functions is relatively complex, and the rapid change of functional density leads to the fact that the originally planned grid units are not fully utilized. However, the basic functional units we constructed can show the actual extent of functional organization. In addition, the urban function evolution network can trace the evolutionary relationship between functions, which is more accurate and easier to analyze than the simple multi-phase urban functional density map comparison.

5.2. The Significance of Function2vec

Embedding was originally used in various cases of natural language processing [37]. Later, it could also be used to mine geospatial features. Yao et al. [20] used Word2vec to identify urban land-use types. Subsequently, more scholars began to explore urban functional characteristics based on this model. These modified models include Place2vec [38], Doc2vec [39], Block2vec [22], and so on. In addition, some scholars also used such models to elaborate the expression of urban facilities and urban geographical phenomena. For example, Liu et al. [40] combined Word2vec and t-SNE dimension reduction to investigate geographical semantic relationships of different types of POI; Crivellari et al. [41] used Word2vec to identify temporal and spatial characteristics of urban crime. However, these models ignore the complex network features of geographical phenomena. In other words, these models are still lacking in the feature mining of transportation networks and population migration networks. Therefore, Zhang et al. [28] modified the node2vec proposed by Grover et al. [27] into City2vec and applied it in the discovery of spatial characteristics of city population migration networks. However, the functional evolution network's temporal and spatial characteristics should be considered. As we mentioned earlier, Function2vec can express these features well. Function2vec based on node2vec expands the significance of embedding for geographical research. Scholars can apply these models to solve the problems related to spatiotemporal feature mining in the field of geographical research.

To sum up, our modified model has the following new features: (1) With the support of urban tree theory, the spatial correlation between UFE patterns can be visually expressed by tree-like structures. (2) It can distinguish the FNA, FR, and FV patterns of UFE. (3) The Pearson correlation coefficient can be introduced into the UFE model.

However, our research still has the following challenges and limitations: (1) The data expressing urban function are mainly POI data. Although these are the most commonly used data samples to identify urban function, the participation of multi-source data may be helpful to enrich the expression of UFE. (2) In this study, only Shenzhen is taken as the application area of the model, and this model can be used to compare and analyze several cities in the urban agglomeration in the future. (3) Urban tree theory is only one of many urban network theories, so we can try to introduce other urban network theories to express UFE.

6. Conclusions

This study constructed a UFEN to analyze the correlation between UFE patterns. The UFEN is based on UT theory and utilizes embedding to implement it. The main conclusions are as follows: (1) FU tends to become more concentrated and diversified as urban functions develop. In 2013 and 2022, the DFs, which have the largest number of FUs in Shenzhen, were healthcare services and industry. (2) From 2013 to 2022, FR mainly characterized the UFE in Shenzhen, and the "multi to multi" pattern had a link value of 1071.9, significantly higher than the link values of the other three sub-patterns. (3) Through the analysis of FV and FNA, we can observe that these two modes exhibit a long-tailed distribution, conforming to the 20–80 law. This result means that a large proportion of functions are concentrated in a relatively small number of categories. In contrast, the remaining functions are distributed among many categories, forming a long-tailed pattern. (4) Based on the UFEN constructed from FR, we can observe the following characteristics of urban functions that align with the United Nations Sustainable Development Goals (SDGs) in UFE: healthcare services are suitable for forming a mutual complementarity with other functions; science, education, and cultural services have higher requirements for complementarity with other functions; the evolution path of administrative offices exhibits a high diversity; and after mixing transportation hubs with other functions, it will result in a significant deviation from the original UFE pattern. Furthermore, industry plays a more frequent role as transfer nodes in the UFEN, indicating that this type of function is more likely to become a fruit node through interactions with other functions. In the later stages, it is necessary to consider integrating this model with other urban data samples and use the results obtained from this model to simulate the UFE.

Author Contributions: Writing—original draft preparation, Tianle Li; writing—review and editing, Minrui Zheng; data curation, Xiaoli Wang; supervision, Xinqi Zheng. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by National Natural Science Foundation of China, grant number No. 72033005 and No. 42201471.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

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