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Urban Regional Social Community Detection Using Location Based Social Network Big Data

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1 ABSTRACT

In this paper, we propose a methodology of applying location based social network (LBSN) Big Data to detect urban regional social communities (URSCs) and analyze their activation levels. For this, we first construct a social spatial network (SSN) based on the LBSN Big Data of a city. Then, by applying a modularity optimization algorithm to the SSN constructed, where modularity is a measure to check the strength of clustered networks, we detect the boundaries of the URSCs. The activation level of each detected URSC is further analyzed based on a diversity index, i.e., Shannon entropy. For experiments, we apply the proposed methodology to the city of Seoul where the LBSN Big Data is collected from Foursquare social networks. Through the experimental results, we observe that the detected URSCs match well with the URSCs known by the Seoul citizen from which we can confirm the effectiveness of our proposed methodology in detecting USRCs and analyzing their activation levels.

Keywords: location based social network big data, modularity analysis, shannon entropy, socio-spatial network, urban regional social community

2 INTRODUCTION

The world’s urban population [29] reached 55% in 2017 and this por- tion is expected to reach 68% in 2050 (UN, 2018). As a result of urban- ization, social and environmental problems in cities have attracted great attention [4, 22, 25, 26, 34]. In general, the urban environment is analyzed with three aspects: physical-, social-, and economic- environment [5]. In the research category of socio-economic en- vironment, through quantitatively assessing the activation level of urban areas, it is possible to check the environmental changes timely and establish policies for solving the urban problems such as urban decline. There have been several indexes for assessing the activation level of urban areas such as Indices of Multiple Depriva- tion (IMD) in UK and Socio-Economic Indexes for Area in Australia (SEIFA) in Australia [19].

Over the past few decades, cities have been faced severe social and economic problems, which have induced unbalance in the urban environment. For instance, the most deprived households are concentrated in the worst urban neighbourhoods [24]. The UK Governments have attempted to tackle the physical, social and economic consequences of these problems through a variety of mechanisms and policy initiatives [17]. The primary goal of the above trials is to reclaim the urban regional social communities (URSCs) in urban decline regions [17]. In particular, in order to reactivate the urban decline areas, it is important to identify the unique properties of the URSCs and establish customized policies for urban regeneration. Therefore, an accurate detection of URSCs should be conducted first to ensure the effective of the policies.

In general, URSCs are formed primarily from the interconnec- tions among people. In the past, such people’s interconnections were mostly happened within certain physical locations nearby. On the other hand, along with the popularity of Internet and advanced information technologies, the methods that people communicate have been introduced new paradigm. Social networking service (SNS) is a service that maintains the connections among people within a virtual space through Internet even the they are physi- cally separated far away from others. SNS connects people through multiple types of links representing friendship, common interest, knowledge sharing, and so on. In recent years, SNS data has been used as an efficient tool for analyzing urban land use, urban city center [10, 28, 35] and urban floating population [9, 32]. The cor- responding analytical results could further provide references for planning urban land use and determining the commercial facilities.

By incorporating actual location information into SNS, location based social network (LBSN) services not only allow people in the social network share location information itself, but also allow them to share location-tagged media contents such as photo, video and text which may further affect the interdependence of people [20]. In addition to the people-people links as in SNS, LBSN services could further enable people-place and place-place links. In modern society, people share various information such as impressions and evaluations about places they visited through LBSN services, and the shared information is delivered to

ISBN 978-3-9504173-8-8 (CD), 978-3-9504173-9-5 (print)
Editors: Manfred SCHRENK, Vasily V. POPOVICH, Peter ZEILE, Pietro ELISEI, Clemens BEYER, Judith RYSER, Christa REICHER, Canan ÇELIK

various people connected within LBSN. Based on the shared information, there even exists ap- plications recommending customized places for people which may further change human mobility patterns. Note that those change in human mobility patterns eventually affect the formation of URSCs. LBSN services have also induced a significant change in Internet search results. In these days, we can easily obtain the research results containing the information about the geographical proximity which is provided by the LBSN services [11]. Users of LBSN services can find each other in the physical space and interact with each other according to the relative distance [6]. Through introducing recommendation and estimation systems such as customized places, activities, friends, and routes, LBSN services show direct or indirect effects on human mobility patterns [3, 12, 15, 16, 21, 30, 33, 37–40].

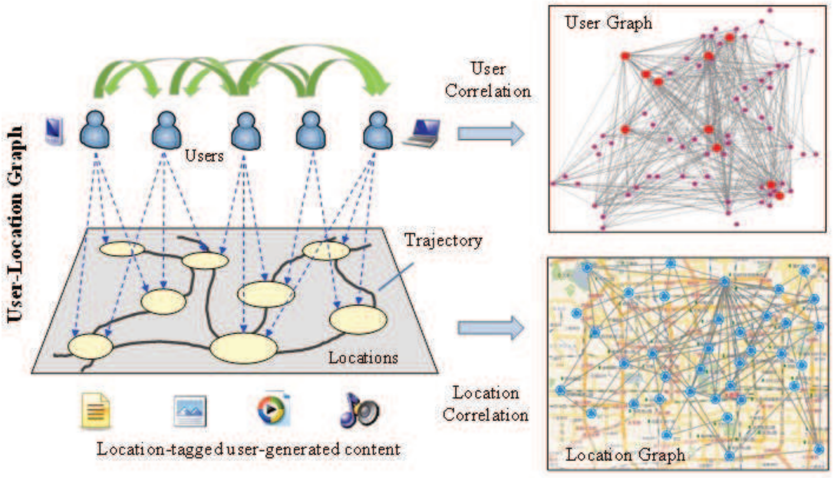

Fig. 1: Three major graphs extracted from LBSN.

In addition, because of the accumulated LBSN big data, which is easily accessible by people through internet, it enables research on social science based on spatial environment [20]. In particular, it is possible to analyze and predict the social ties and analyze the spatio-temporal human behavior. As case study, based on the spatial- temporal data of LBSN services, Cranshaw et al (2012) analyzed the human behavior, social dynamics, perception of urban region, and human mobility patterns.

The purpose of this study is to propose a methodology to detect URSCs using LBSN Big Data and analyze their activation levels. The structure of this paper is as follows. Section 2 introduces back- ground and related work. Section 3 describes the proposed method- ology. Section 4 presents the experiments and discusses the results. Finally, Section 5 summarizes the concluding remarks.

3 BACKGROUND AND RELATED WORK

3.1 Social Spatial Network

Wherever people live, there exists a social space which a place assigned with some value by people [36]. In general, those places defined in cities or architecture have the same context. Modern geography academically defines a physical space as the surface of the earth [8, 23] clarified the close relationship between the physical space and the social space by mentioning that a physical space becomes a social space when the physical space becomes to have cultural or local meanings. In other words, a social space (or place) is formed when socio-cultural meanings are attached to a physical space.

A social space is not an independent closed space and it can be interconnected with other social spaces through the social con- nections embedded in them. Note that those interconnections are possible even the social spaces are separated physically far apart. While the above mentioned long-distance interconnections were not possible in the past, nowadays they can be easily realized in the virtual space like Internet or social networks. Therefore, in addition to the interconnections among the social spaces physically close to each other, the virtual space provides more diverse communicating methods for the social spaces. At first, people share the discourse about some specific social spaces (or places) in a virtual space com- munity group. As the discourse sharing becomes more frequent, people turn out to visit the social spaces (or places) indeed. Through this example, we can observe the human movement between social spaces which can be defined as a new kind of interconnection. By considering those interconnections representing human movement, we can form a social spatial network (SSN) as will be defined in Section 3.1.

Fig. 2: The SSN constructeud for Seoul.

3.2 Detection of URSCs

In order to detect URSCs, Guo et al (2017) proposed a method of applying a modularity optimization algorithm to the (physical) street network of a city where the street network is analyzed from the topological aspect of urban spatial structures [31]. Hillier and Hanson (1984) suggested the theory of Space Syntax to analyze the topological aspect of urban spatial structures [2]. In general, Space Syntax assumes the interactive relationship between the spatial structure and the social structure. From the success of Space Syntax in the research area of urban spatial analytics, it is confirmed that the regional social properties such as floating population and activation levels can be analyzed from the spatial structure. In this respect, the approach of Guo et al (2017) detecting the URSCs based on the modularity analysis of the urban street network is reasonable[31]. Alternatively, Emanuele et al(2018) also applied the concept of modularity [18] to the street network and detected the regional social community of a country in order to protect disease diffusion, while the street network is analyzed from the geometrical aspect which is an alternation to the topological aspect [27].

This study aims to propose a methodology to detect the URSCs

in a city in terms of the topological aspect of spatial structure. In modern cities, the human movement pattern is not only affected by physical space, but also is influenced by the social media in the virtual space. Now it is very common to search the Internet before setting a specific destination place. When human movement patterns are concentrated at a specific urban area because of its common social properties, this urban area become a URSC.

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A URSC is ultimately formed based on the social interactions among people. Therefore, it is important to find the patterns of human interconnections in urban areas when detecting URSCs. In this context, this paper proposes a methodology of detecting URSCs by considering the human movement as the interconnection patterns. In particular, we detect URSCs from an SSN where social spaces are connected based on the human movement.

3.3 Activation Levels of URSCs

Once a URSC is detected, it is important to check its activation level based on which we can set policies for solving urban prob- lems associated with the URSC such as urban regeneration. There have been several ways to measure the activation level of URSCs. Indices of Multiple Deprivation (IMD) in UK and Socio-Economic Indexes for Area in Australia (SEIFA) were introduced to quantita- tively evaluate the activation levels of URSCs with respective to the physical-, social-, and economic-environment. Through analyzing the diversity of visitors, Desislava et al (2016) confirmed the close relationship between the visitors' diversity and IMD [13].

In this context, we propose to evaluate the activation level of each detected URSC based on the diversity property of the social spaces in each URSC.

4 THE PROPOSED METHODOLOGY

The proposed methodology of detecting URSCs from LBSN Big Data mainly consists of two steps: 1) construction of an SSN from LBSN Big Data of a city; 2) the URSC detection by applying modularity optimization algorithms to the SSN.

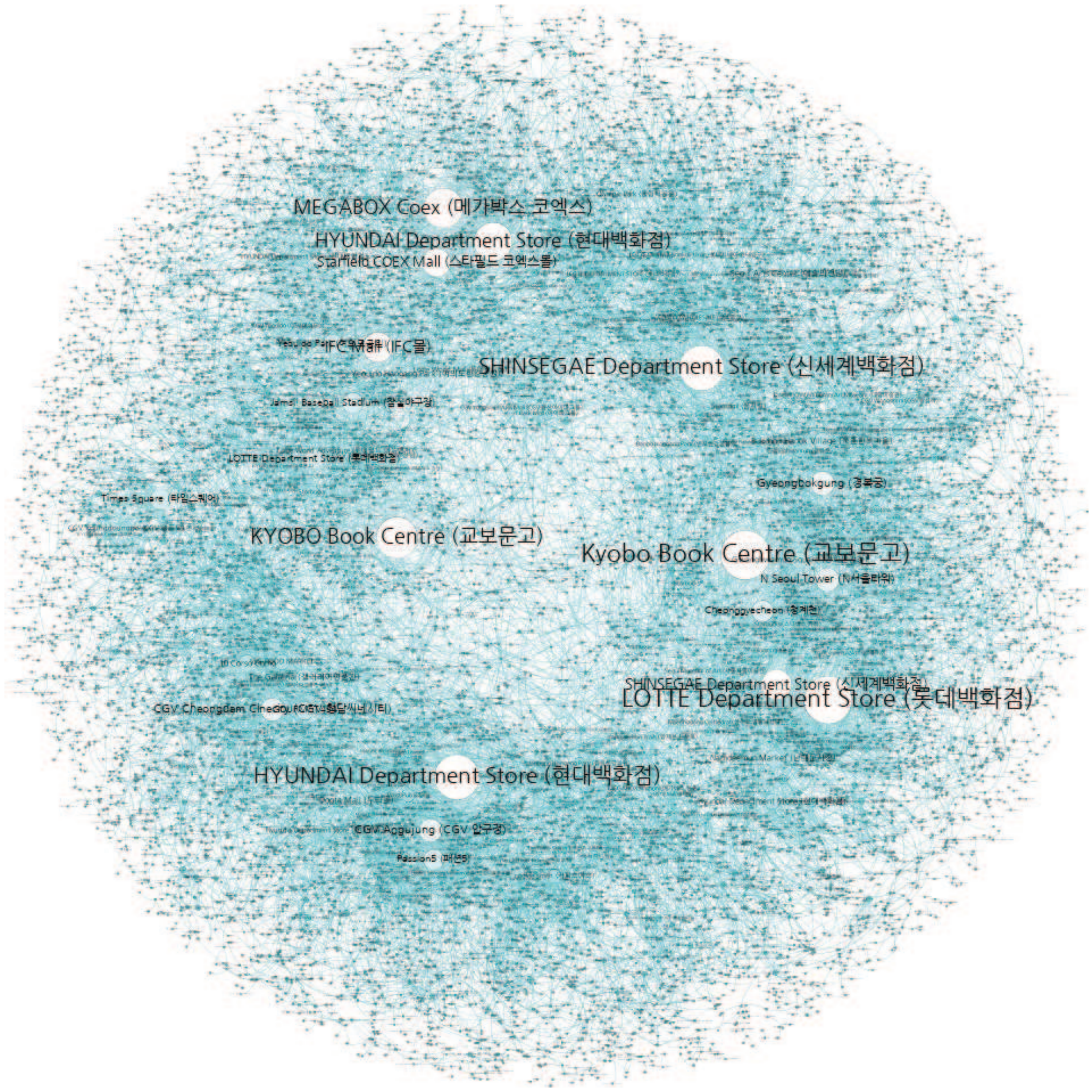

Fig. 3: Hubs in the SSN.

4.1 Construction fo the SSN

We construct an SSN by tracking human movements among the social spaces based on LBSN Big Data. We collect the LBSN Big Data from Foursquare, which is a representative LBSN service. Foursquare allows users to share geographical location information of a social space, number of visitors, tips, and so on. A venue in Foursquare represents a social space which has the categories of art & entertainment, college, events, food, entertainment, parks and recreation, professional, residence, shops & services, and transportation & travel. Within each category, there exists numerous types. Within each category, the social spaces are further distin- guished by a number of types. For example, there 56 types for the category art & entertainment. Through Foursquare Open API (Ap- plication Programming Interface) we have collected the LBSN Big Data accumulated from users. The following steps are introduced to build an SSN from the Foursquare LBSN Big Data:

- In the first step, we collect information about all the venues in the range of our interest and tag each venue as a node.
- In the second step, for each venue (or node), we assign di- rected edges up to 5 other venues (or nodes), each of which has the number of direct visits from the users, who are in the current venue, ranked top 5. The top 5 is chosen to ensure the reliable social connection between two venues. This in- formation could be extract by using the command of 'query NextVenue' in the Foursquare Open API.
- In the third stage, those nodes and edges collaboratively consist one SSN.

4.2 Activation Levels of URSCs

There are two main aspects of analyzing URSCs: 1) One is to investigate their spatial composition which can be analyzed by applying modularity to the SSN; 2) Another one is to assess the activation levels of the URSCs in a city which can be analyzed by applying the diversity index - Shannon entropy.

Fig. 4: The URSCs detected in Seoul.

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4.2.1 The Method of Modularity Optimization

Modularity optimization is frequently used for detecting community structure in general networks. In particular, modularity is one measure of the structure of community networks and is designed to measure the strength of division of a network into modules (or communities). Networks with high modularity have dense connections between the nodes within the modules but sparse connections between nodes in different modules. The modularity is a scalar value between âĹŠ1 and 1 that measures the density of links inside communities as compared to links between communities. In the case of the SSN where all the edges have the same weight as 1, the modularity of the SSN could be defined as

$$I_M = \frac{1}{2N}\sum_{i,j}\left[a_{i,j} - \frac{k_i k_j}{2N}\right]\delta(C_i, C_j) \quad (1)$$

Where ai, j is 1 if nodes I and j are connected, and 0 otherwise, $k_i = \sum_j a_i$, j , Ci is the community to which the node. i is assigned, δ(Ci ,Cj) is 1 if Ci = Cj and 0 otherwise, and $N = \frac{1}{2}\sum_{i,j} a_{i,j}$.

In this paper, we adopt the algorithm introduced by by Vincent et al (2008), which can heuristically realize the modularity optimiza- tion, and search for the URSCs from the SSN we have constructed where each social space is considered as a node while each edge between two nodes represents the connection between the two corresponding social spaces [3]. In particular, we used the open source called Gephi to implement the detection of URSCs [1].

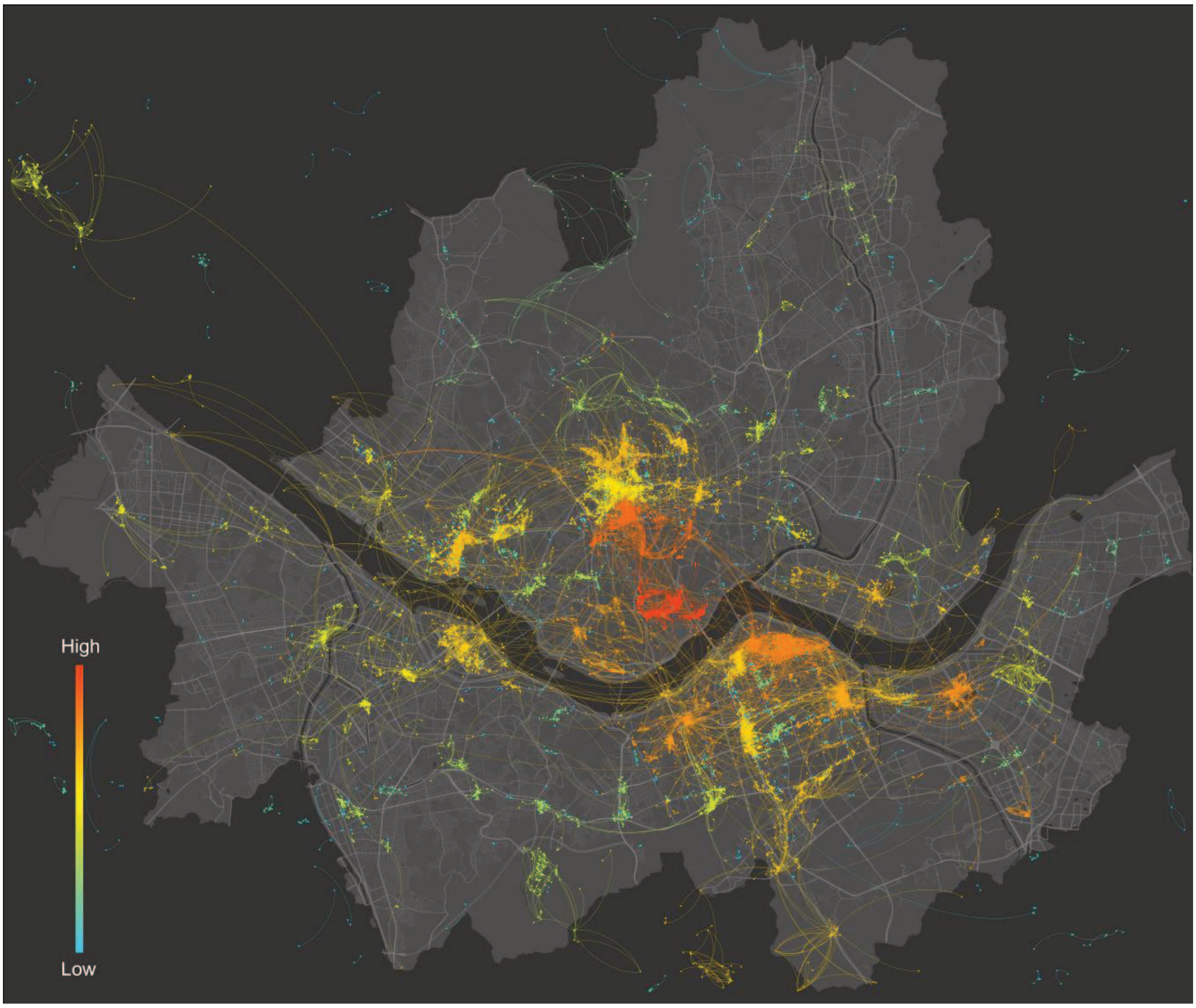

Fig. 5: The activation levels of the URSCs in Seoul.

4.2.2 Shannon Entropy for the Activation Level

While Shannon entropy [7] is well known as the measure for the information con- veyed by a dataset in Information Theory, it is also used frequently as a diversity index which quantitatively measure how many differ- ent types there are in a dataset (or a community) in Social Science. In this context, we use the Shannon entropy to represent the activa- tion level of a URSC. The Shannon entropy of each detected URSC can be calculated by

$$H = -\sum_{i=1}^{S}(p_i \ln p_i) \quad (2)$$

where

- S is the total number of types for the social spaces appeared in the URSC,
- i is the type index in the URSC,
- pi is the ratio of the number of social spaces tagged with type i over the total number of social spaces in the URSC.

5 EXPERIMENTS

5.1 Construction of the SSN for Seoul

We first collect the Foursquare Venues to construct the SSN for Seoul. The physical spatial range is taken as a square whose longi- tude and latitude coordinates of the southwest and northeast points are (126.7629, 37.4274) and (127.1829, 37.7074), respectively. We in- vestigate the temporal range from January 2010 to September 2017. As a result, there are total 11,076 nodes and 23,495 edges in the con- structed SSN which is shown in Figure 2. We can further observe that each node has the number of 2.121 edges on the average.

5.2 Experimental Results

Based on the constructed SSN for Seoul, we run Gephi and obtain the USRCs. The resulting network of USRCs has the modularity value of 0.921, which is quite close to 1, indicating a typical small- world network characteristic [14]. Through counting the number of edges between any two nodes, we find that the maximum length is 36 and the average length of the shortest path between any two nodes is 13.443.

Modularity Class ID URS Cs size	URSC's	URSC's Ranking	URSC's Activation level Ranking
368	Cheongdam-dong - Apgujeong Rodeo Street	1	3
442	Myeongdong - City Hall - Sungnyemun Area	2	2
283	COEX - Complex area	3	7
417	Gwanghwamun - Insadong - Cheonggyecheon area	4	17
382	Itaewon - Gyeongryeon Dangil - Haebangchon - Hannam-dong area	5	1
273	Gwanghwamun - Bukchon - Wolchon	6	8
147	Gangnam Station Area	7	15
338	Hongdae area	8	10
325	Express Bus Terminal - Seorae Village Cafe Street - Banpo Sports Complex	9	5
65	Yeouido	10	14
309	Gap-dong - Yangjae-dong	11	13
247	Jamsil Lotte World	12	4
333	Sinsa-dong road - Banpo Hangang Park area	13	12
260	Shinchon Ida street area	14	16
204	Namsan - Yongsan Station - National Museum of Korea	15	6
251	World Cup Stadium	16	19
349	Ttukseom Station - Seongseu Station - Gunsan Metropolitan Area	17	9
418	Dongdaemun Plaza - Plaza Mayor - Cheonggyecheon	18	11
476	Yeongdeungpo Times Square	19	18
473	North side of Bukhansan	20	32

Table 1: Ranking of teh URSC's size and the activation level.

We further analyze the degree distribution of the whole SSN where the degree is defined as the number of edges connected to each node (or social space). Figure 6 shows the degree distribution analyzed from our constructed SSN where x label shows the number of edges and y-label shows the number of nodes having the same number of edges. We can observe that the degree distribution has the power law scaling which

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indicates that there are some nodes (or social spaces) that act as hubs in the SSN. As seen from Figure 3, there are a few nodes having many edges connected. We use white circles to represent those typical hubs in the SSN while a larger circle area indicates a larger number of edges. Therefore, we

can conclude that this urban SSN is a typical scale-free network defined by Barabasi (2002). This characteristic indicates that there are some concentrated social spaces which are visited by people from many other social spaces. Barabasi (2002) explained that there exists a trend of 'the poor get poorer, the rich get richer' in the scale- free networks when evolving. In other words, when a new node is created in a scale-free network, it is highly likely connected to the nodes playing the role of hubs. The scale-free nature of this urban SSN suggests that it is necessary to consider the connection to surrounding hub social spaces when practicing urban regeneration.

Figure 2.1 shows the detected URSCs where different color rep- resent different URSC. While we observed a total of a total of 479 URSCs in Seoul based on the constructed SSN, the top 20 USRCs hav- ing largest number of nodes are presented in Table 2.1. The largest URSC is appeared in near in Gwanghwamun - Bukchon – Sogwon - Cheonggyecheon area. Those top 20 USRCs are enumerated in Table 1.

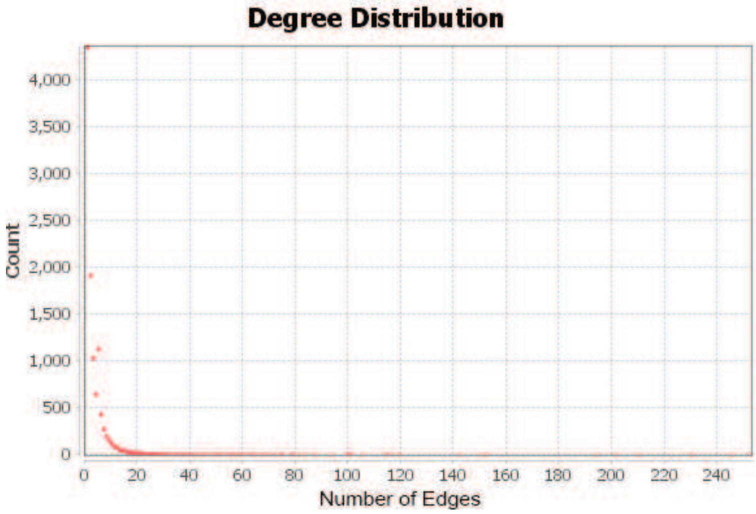

Fig 6: Degree distribution of the SSN.

Figure shows the activation levels of the USRCs detected in Seoul. In particular, top 20 USRCs showing highest activation levels are presented. We can observe that those USRCs almost overlap with the 20 USRCs presented in Figure 2.1. For comparison, we also show the activation levels in Table 1 where we can observe that among the top 20 USRCs having the largest number of social spaces, 19 are still ranked top 20 in terms of the activation levels. One expection is the region of 'North side of Bukhansan'. While North side of Bukhansan has a large number of social spaces (ranked top 20), as it is located far away from the center of Seoul, the corresponding activation level is relatively low.

5.3 Discussion

The methodology of detecting URSCs can be applied to urban re- generation which needs to simultaneously consider the problems related to the physical- and social-environment. Therefore, it is important to extract the boundaries of the URSCs in a city and evaluate the corresponding activation levels. The proposed method- ology is meaningful as we can investigate the social aspects which is confirmed from the experiment.

While we only applied Foursquare LBSN Big Data to check the proposed methodology, the accuracy would be improved if some other LBSN data like Twitter and Facebook is additionally consid- ered.

6 CONCLUSION AND FUTURE WORK

In this paper, we proposed a methodology of detecting URSCs by applying the LBSN Big Data. For this, we first constructed an SSN from the LBSN Big Data through representing social spaces and their connections by nodes and edges. Secondly, we adopted the method of modularity optimization, we detected the URSCs from the constructed SSN. Thirdly, we applied the diversity index, i.e., Shannon entropy to quantitatively evaluate the activation level of each URSC. As a case study, we apply the proposed methodology to the Seoul city and investigated the social aspects of Seoul in terms of URSCs and the activation levels.

7 ACKNOWLEDGEMENTS

This research was supported by Basic Science Research Program through the National Research Foundation of Korea(NRF) funded by the Ministry of Education(No. 2018R1D1A1A02085909)

This work is supported by the NRF Grant funded by the Korea government (MSIT) under Grant NRF-2018R1C1B6008126.

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