A Placeness Mining Scheme to Infer Land Use and Estimate Its Evolving Changes from Instagram Data

Abstract—**Placeness represents the social atmospheres embedded in a place and plays an important role in urban design and planning. Existing studies either correlate the general perception on a place with social media for understanding evolving placeness changes or infer land use from social media for identifying primary placeness. Delivering both approaches will benefit urban planners to facilitate the understanding of land use and its future directions. In this paper, we propose a novel placeness mining scheme, using social media data, that not only identifies the land use of a place but which also captures its physical changes over the time. For this, we utilize Instagram data accumulated along the Seoul Metro Line No.2. For placeness mining, we extract words for Instgram posts with the MS Cognitive API, apply word2vec and spectral clustering, and then build an inference model that can infer the role of a place and discover whether there have been any physical changes in the place any changes over time. The evaluation results assure that the proposed scheme can help urban planners to have a better understanding about what is actually going on in an urban space.**

Index Terms—**placeness, land use, social media, regression, spectral clustering, word2vec**

I. Introduction

Placeness, also known as "sense of place" [1], describes what social atmosphere a place has, and plays an important role in urban design and city planning [2]. It is based not only on the physical form of a place, but also on the projection of human perception. The former is composed of a space and its buildings, while the latter is built from the social and cultural perceptions of dwellers accumulated over a long period of time [3]. To understand the dynamic nature of a place, a number of attempts have been made to interpret the social and cultural semantics of a place by analyzing social media [4], [5]. Placeness discovery changes the ways in which we observe and conceptualize urban space, and more importantly helps urban designers better understand the use of places in cities [6], [7].

There have been studies that correlate general perceptions of places with social media, for understanding their evolving changes. Cranshaw et al. [8] apply spectral clustering to check-in data from Foursquare to extract the placeness of different areas, and verified their findings with general perception extracted from interviews. Jenkins et al. [9] apply topic modeling to Twitter to construct high-level categories, and show that those categories correspond to a general perspective given by Wikipedia. Frias-Martinez et al. [10] utilize geo-tagged Twitter data and train a neural network model to identify different types of land use, comparing with the official land use map. In summary, existing approaches either focus on modeling the aspect of how an area (physically) evolves over time by how it accumulates various social and cultural activities on it, or how the functional meaning of an area defined by the land use plan is represented by geo-tagged social media data. It is necessary to deliver both of them so that urban planners can have a better understanding about what is actually going on in an urban space they delineated with the land use boundaries. This will also complement current land use planning [11].

In this paper, we propose a novel placeness mining scheme based on social media data that can not only infer the urban planning category (land use tendency) of a given place but also tell whether there exist any physical setting (building use) changes over the time in that place. For this, We utilize images of Instagram posts for the corresponding places. We at first extract one descriptive sentence per picture with the Vision API of the Microsoft Cognitive Services [12]. Those sentences can describe the content of the image, which is related to the social meaning of the place. we then use Word2Vec and spectral clustering in words from the description sentences to find a certain type of a social activity in a target area, and create a cluster of words with similar contexts. We annotate each cluster as a social activity unit according to human perception, then we validate the annotated social activity using Amazon Mechanical Turk and select suitable social activities. In the extracted social activities, we pick out the social activities that are valid for regression and apply ML-based regression analysis. Through regression analysis, we build an inference model that correlates social media in urban area with its land use tendency in terms of residential/commercial ratio. We show that the resulting inference model has around half the error of baseline models used for comparison. For capturing physical changes in a target place, we first analyze what social activities are most visible in both residential tendency dominant areas and commercial tendency dominant areas. Then, we calculate how much those activities in a target place have increased or decreased. We leverage this value and build a mapping method that correlates such increase/decrease with the building use changes in a target place. For verifying the proposed scheme, we exploit Instagram data and land-use and building use data for areas along the metro line No.2 in Seoul, South Korea (Fig. 1). Line No.2 is the most popular metro line in Seoul, and each of its stations is an important public place we consider in our analysis. The evaluation results show that the proposed scheme can infer the land use tendency of a target place with an error which is two times less than the baseline, and estimate the presence of physical changes over the time.

The contributions of this paper are:

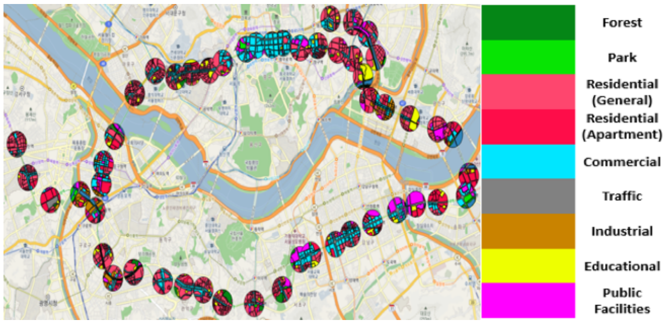


Fig. 1. LULC map on Seoul Metro Line No.2. We choose 24 stations which are used by many passengers.

- We present a methodology to both extract placeness related information from location based social media images, as well as to apply a grouping relevant to placeness on the result of the extraction.
- We represent locations in the dimensions found to be relevant to placeness, then apply predictive modeling to show the relation between land-use data and the extracted – placeness relevant – social media data.
- We can detect changes in the physical area over time using social activities.

The remaining parts of this paper are organized as follows. "Related Work" introduces placeness-based research and is divided by the domain and methodology used. "Dataset" introduces the source, format, and characteristic of the utilized data. "Methodology" presents the data mining in its individual steps. "Evaluation Results & Analysis" shows and explains results, and highlights and discusses findings and their meaning for our goal. "Conclusion & Remarks" wraps up the paper.

II. Related Work

Previous research has tried do derive the semantic meaning of places from social media. In addition, there have been studies to investigate the correlation between social media and physical space to the goal of increasing the efficiency of urban planning. In this section, we review relevant previous work on extracting semantic meaning of places from social media, as well as attempts to find correlation between physical spaces and different social media data sources.

A. Finding social and cultural semantics of a place

Research in this area focuses on which social an cultural activities are happening in given places. Extracting this information is challenging as places have certain dynamics, and because they depend on the people who are at those places – both aspects that change. Location based social media can help capture those dynamics, as it can express what people are doing when in those place. Hiruta et al. [13] categorized types of events in Twitter data, and identified which events occurred in a given region through keyword matching. Hochman et al. [4] observed temporal and spatial patterns in activities using visual signatures observed from a large collection of Instagram data, and discussed the diversity of cities by the differences in the observed patterns. Redi et al. [14] identified ambience of places by analyzing the facial expression in the foursquare profile picture of visitors. Santani et al. [15] utilized a convolutional neural network (CNN) to classify the ambience of places in foursquare images. They thereby outperformed traditional vision analysis such as Color(RGB), GIST, LBP, and HOG. Kalra et al. [5] identified objects in Instagram images using the Microsoft Vision API. They then inferred social activities and extracted placeness of different cities with time and demographic information.

B. Finding correlation between place and social media

Semantic meaning about places exists in social media information, but it is unknown how it relates to physical places. Finding an association between those would allow for a deeper insight into places for which social media information is available. To this end, some previous studies investigated the correlation between information available about places with social media data for those places. Cranshaw et al. [8] collected geospatial check-in data of urban areas from foursquare and applied spectral clustering to find locations with high activities. They further conducted a survey about the general perception of areas by their residents. Clustering and survey results agreed, indicating a direct relation between the two. Jenkins et al. [9] divided Twitter data into six high-level categories by topic modeling and observed which activities appeared in key locations in cities. They then investigated the correlation between the general perspective of each extracted location using Wikipedia data with activities found in social data of those locations. Zhan et al. [16] use a Laplacian Score for feature selection from Twitter check-in data and apply unsupervised clustering approach using K-means clustering and a supervised learning approach using random forest algorithm. They showed that model can inference the land use with high accuracy, and they also can achieve high inference accuracy (78.69%) when even only part(50%) of the ground truth information is provided. Frias-Martinez et al. [10] applied Self-Organizing Maps (SOM) to Twitter data. They identify areas of high activities and segment the map into corresponding land segments. They then analyzed the Tweeting activity signature of land segments and annotated the activities for each pattern. As a results they found correlation between the physical land use data of land segments and the activities extracted from Twitter.

III. Data Sources

A. Land Use/Land Cover (LULC) map

The Land Use / Land Cover (LULC) map is a type of thematic map that classifies feature types according to certain scientific criteria and color-indexes regions with homogeneous characteristics [17]. It visualizes the physical and functional status of the land and enables its quantitative analysis. Governments publish and periodically update the LULC map. The attributes used in the LULC map of South Korea are Forest, General Residential, Apartment Residential, Commercial, Park, Traffic, Industrial, Educational, and Public Facilities.

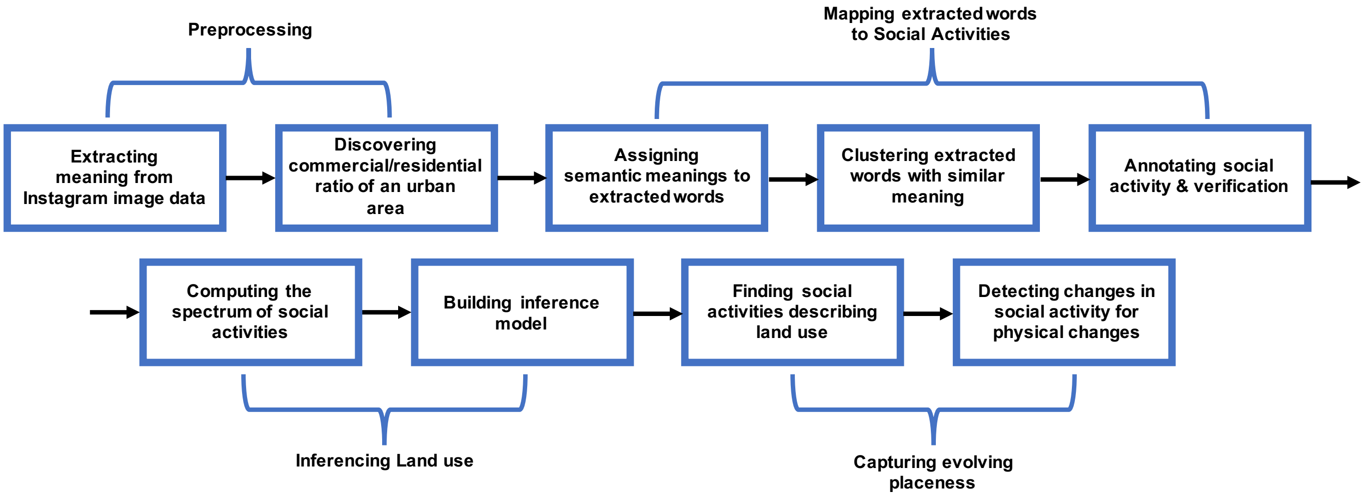


Fig. 2. An overall flow of the proposed scheme.

Especially in a urban area, General Residential, Apartment Residential, and Commercial are the dominating attributes. For our analysis, we use the 2018 LULC data for Seoul published by Ministry of Land, Infrastructure and Transport(MOLIT). For this we select the 24 most frequently used metro stations of line Nr.2, the most frequented metro line in Seoul. For the 24 selected stations of line Nr.2 we investigate the LULC data within a 500 m radius (Fig 1).

B. Social Media Data: Instagram

Instagram is one of the most popular social media platforms. Instagram posts mostly come with an image. Those images can provide information for deriving which activities were conducted when the picture was taken. Together with metadata of the Instagram post, like location from geo-tagging and time from the timestamp of the post, this allows for deriving which activities people performed where and when. We expect to capture the polymorphism of the places by diachronic analysis of the social activity of accumulated social media data. To collect Instagram data we rely on an adapted version of instagram-scraper[1], which was previously also utilized in [5]. We thereby collect public Instagram posts that occurred from beginning of 2015 to end of 2017, within a 500 m radius of the selected 24 stations of Seoul Metro Line No.2. This results in a total of 200K Instagram posts, where each of the 24 subway stations is covered by in between 10K to 20K posts.

IV. Methodology

A. Overview

Our methodology consists of three parts. First, we extract meaningful words for each Instagram image and map the extracted words to a set of social activities that express the social and cultural semantics of placeness. Second, we build a model that can infer the land use tendency of a place from social activities revealed in that place. Third, we estimate whether there have happened any physical changes in a place over the time by analyzing the flux of social activities. Fig. 2 gives an overview of processing in our methodology.

B. Preprocessing

1) Extracting meaning from Instagram image data: We extract one descriptive sentence for each image in our dataset with the Vision API provided by Microsoft Azure cognitive service [12]. This sentence is suitable for capturing placeness, as it captures the situation in the image, including both objects and actions. In addition, those sentences allow for creating a generic inference model of land use from, since they implicitly also capture a general description of the place. We extract nouns and verbs forms of the words in the sentences, and transform words into their singular form. We later on apply Word2Vec which is able to group words by the relations formed of their occurrences in the sentences. As a side effect, this also reduces noise (words that are not related to each other), thereby highlights the connectivity of nouns and verbs that are related.

2) Discovering commercial/residential ratio of an urban area: The attributes of an LULC map are typically divided into two types: commercial and residential (general residential & apartment residential). The ratio of commercial to residential area coverage appears to be under a Gaussian distribution in most urban areas. This also applies to Seoul. Other area types, such as park, industrial, educational, and public facilities have non-continuous values and are both observable as well as predictable from the presence of a particular facility. Furthermore, commercial and residential areas form the majority of areas. As a consequence, we define our target variable in the range $[0, 1]$ as the ratio of the total residential area res and the total commercial area $commer$ for each target location (Eq. 1).

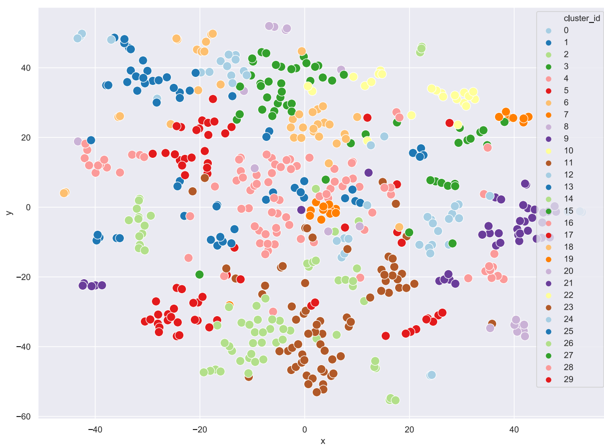
$$res\_ratio = \frac{res}{res + commer} \tag{1}$$

[1] instagram-scraper: https://github.com/rarcega/instagram-scraper.

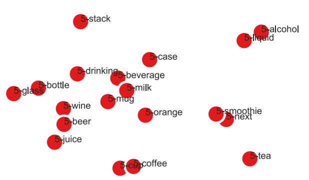
TABLE I

RESULTS OF LABELING APPROPRIATE SOCIAL ACTIVITY FOR EACH CLUSTER. EACH LABEL IS THE RESULT OF A SURVEY ABOUT HOW PEOPLE WHO LIVE IN TARGET AREA FEEL ABOUT EACH CLUSTER.

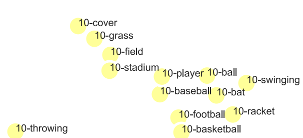
Social Activity	Words
Dining and Dessert	'food', 'filled', 'sandwich', 'piece', 'cake', 'top', 'meal', 'donut', 'icecream', 'fork', 'knife', 'bread', 'lobster', ...
Dining and cooking	'plate', 'pan', 'bowl', 'type', 'tray', 'meat', 'vegetable', 'soup', 'stove', 'cooking', 'dish', 'rice', ...
Working in office	'keyboard', 'computer', 'desktop', 'desk', 'monitor', 'mouse', 'using', 'piano', 'office', 'equipment'
Enjoying Concerts	'crowd', 'performing', 'stage', 'playing', 'instrument', 'band', 'court'
Drinking	'table', 'cup', 'coffee', 'glass', 'next', 'wine', 'bottle', 'item', 'beer', 'juice', 'drinking', 'beverage', 'alcohol', ...
Enjoying Sports	'field', 'football', 'grass', 'baseball', 'player', 'throwing', 'ball', 'racket', 'bat', 'basketball', 'swinging', 'stadium', ...
Shopping wearings	'photo', 'wearing', 'costume', 'shirt', 'hair', 'taking', 'selfie', 'hat', 'sunglass', 'smiling', 'jacket', 'dressed', ...
Watching Landscape	'view', 'city', 'sky', 'cloudy', 'refrigerator', 'sunset', 'park', 'hill', 'cloud', 'landscape', 'kite', 'ship', 'skyscraper', 'dark', ...
Taking a rest at home (with animal)	'dog', 'bed', 'mirror', 'baby', 'laptop', 'cat', 'floor', 'couch', 'sleeping', 'bedroom', 'sofa', 'pillow', ...



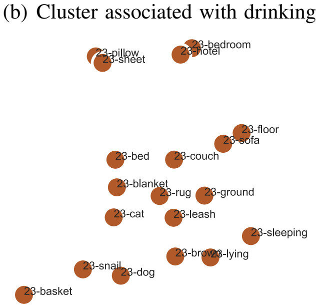
(a)



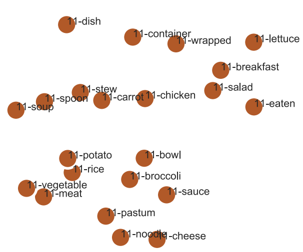
(b) Cluster associated with drinking



(c) Cluster associated with sports



(d) Cluster associated with house



(e) Cluster associated with eating

Fig. 3. (a) Spectral clustering result. After applying PCA and t-SNE on embedded word vectors, word clusters of words used in social media become visible to the human eye. (b-e) Clusters capture semantic meaning by grouping related words, as visible with four example clusters when zooming into (a).

C. *Mapping extracted words to Social Activities*

1) Assigning semantic meanings to extracted words: Identifying what people do at a place is very important for placeness mining. We define what people do in the place as social activities and we are looking for an approach to find them. However we don't know how many different social activities are emerging in the urban area, and defining social activity heuristically does not capture all the dynamics of the urban area. To capture bunch of social activities in the urban area, we think we have to divide the description sentence into more specific meanings. We expect to be able to discover various social activities from the position of each word in the sentence and the fragment of semantic meanings. To do this, we need an approach that can analyze what context each word has. Word2Vec [18] is a commonly used word embedding method that provides context-aware word embedding. We use Word2Vec to group similar words which emerge in an urban area. For example, after the verb "eat" there usually is the object to eat, and after "enjoy" there is the subject of enjoyment, like sports, performance, etc. Each words provide only fragmentary information about each social activity, but a group of words can increase their completeness. The sentences describing the Instagram image are refined into noun and verb sequences through preprocessing. We then use the gensim Word2Vec model [19] to transform those words into a 100-dimensional word2vec space. We embed words which appear five times or more through the gensim Word2Vec model parameter to reduce noise, and a total of 600 words are embedded. This results in a 600×100 word embedding matrix.

2) Clustering extracted words with similar meaning: The distribution of words in the 600×100 word embedding space can be represented by a subset of less than 100 dimensions. We therefore use PCA to reduce data dimensionality from 100 to 40. Together, those 40 components capture 90 percent of the variance, which is a commonly used way of determining the amount of components to be used with PCA [20]. We furthermore asses which words are bound within similar contexts. As visualizing high dimensional data is difficult, we employ t-SNE [21] to transfrom the 40 dimensional data into 2 dimensions. t-SNE stochastically projects data into a subspace while trying to preserve the meaning of distance of data in the higher dimensional space. For this reason, words close to each other in the 2D t-SNE space are also close to each other in the higher dimensional space. We use this 2D data for visualizing distribution of words in the word2vec space (Fig. 3(a) without the color information).

As next step we apply spectral clustering on the 100 dimensional data. The resulting clusters can be visualized by coloring words with their cluster color in the 2D t-SNE space (Fig. 3). From visual observation of clusters in the 2D t-SNE space and with empirical tests we performed fine tuning the total amount of clusters in the data. We thereby find 30 clusters (Fig. 3(a)). Each cluster contains words that capture a common context or meaning. This becomes easily visible when zooming into the data and looking at individual clusters (Fig. 3(b)) to 3(e)).

3) Annotating social activity & verification: The words in each cluster contain enough information to connect the cluster to certain social activities. Nouns thereby contain information about objects that are observed with specific social activities, while verbs can directly be connected to the activity performed in the place. By combining both nouns and verbs we can thereby annotate social activities. We are intuitively aware of the meaning those words have in correspondence to activities, places, and placeness, and the background knowledge of specific urban areas reinforces this intuition. Base on this, we annotate each word cluster with a general social activity-related name.

We then verify that the annotated social activities are also common activities for people in urban areas. Through the Amazon Mechanical Turk service [22], we ask 50 participants whether those text of the group converge well on the social activities we labeled and filter those activities that have less than 75% support. We observed clusters that do not pass this threshold to have a tendency towards being unspecific and to not correlate to specific social activities. One example for this is a clusters lists place objects without giving similarities or context, with words such as 'restaurant', 'statue', 'aquarium', 'bench' , 'tent', etc. Since those words seem to be grouped by Word2Vec just by their position in sentences, there is no converge of a specific social meaning in the resulting cluster. Another cluster without specific social meaning includes words about people, such as 'person', 'man', 'woman', 'child', 'boy', 'girl', etc. Those clusters did not pass the 75% threshold, hence were rejected in our analysis. A total of 9 clusters passed the 75% threshold, which all bear meaning in terms of social activities and placeness, and which we therefore use in our subsequent analysis (Table. I). With those clusters we observed that they contain both words that point out "that something is done", as well as words that specify "where/what it is done with" – which as a result allow for connecting them to social activities.

D. Inferring land use

1) Computing the spectrum of social activities: To build an inference model, we at first quantify how strongly social activities appear at stations. As Word2Vec embeds words in a suitable place in the word embedding space given their context, we can quantify the similarity of contexts between two words through cosine similarity in that space. First, we calculate the centroid of each word cluster and define it to be the reference point for the corresponding social activity. We then calculate the cosine similarity between all words and all reference points of all social activities, to quantify how much each word corresponds to each social activity. Next, we can determine which social activities occur how strongly for each station from the frequency of words extracted from social media for that station. This can be understood as the frequencies with which any social activity occurs at any given station. Finally, we normalize on words and on stations sequentially to handle the relative gaps between the stations.

2) Building an inference model: After quantifying the occurrence of social activities for each station, we build a model to predict the function of the urban area from those social activities. For this we perform regression analysis with filtered social activities as features. However, social activities expressed in urban areas have complex, non-linear relations. One the one hand, traditional parametric regression methods, such as linear regression, are robust – but in preliminary tests they have been unable to model the complex relationships of social activities in our data. On the other hand, machine learning (ML) based, non-parametric regression methods are suitable for data in our domain, as those model relationships between social activity attributes of the stations we consider in a flexible way. We therefore select several ML based regression models to model the relation between land use and social media of those locations. The regression models we evaluate are based on k-nearest neighbor regression (KNN), support vector machine regression (SVM), regression tree (RT), and multilayer perceptron (MLP).

In order to enhance inference performance we investigate how much each social activity contributes to the regression. We expect an increased predictive performance by identifying and selecting those social activities that are most important for the regression. We capture the importance as the F-value, which we derive from univariate linear regression tests for each social activity, and which we use to quantify the contribution to the regression. By sequentially excluding social activities with low F-values we empirically determine the set of social activities with the best performance for our inference model.

E. Estimating evolving physical changes

Another important point of the proposed scheme is to estimate the physical changes in a place happening over the years from social media data. While change in land use is slow, it is an important as the actual land use might evolve to become polymorphic and different than what has been planned originally in the LULC map [23] – which is important to observe for further planning and actions from urban planners. For example, places originally dedicated as residential areas might become popular as touristic spots, and due to this, over time a different and new placeness is eventually accrued on this location. Even if there is no direct change in land use, there may be changes in placeness due to the physical development in detail: construction of new buildings, demolition of existing buildings, change of purpose of buildings, etc. Observing such changes over time can help urban planners to detect changes in the usage of a place.

TABLE II
F-VALUE FOR REGRESSION TASKS.

Social Activity	F-value
Drinking	5.468561
Watching Landscape	4.531715
Dining and dessert	3.400600
Enjoying Concerts	2.822439
Working in office	1.465334
Taking a rest at home (with animal)	1.149492
Dining and cooking	0.852771
Shopping wearings	0.148331
Enjoying Sports	0.014466

TABLE III
ERROR SCORES FOR EACH SOCIAL ACTIVITY SUBSET IN REGRESSION ANALYSIS(FROM HIGH F-VALUE SOCIAL ACTIVITY).

No of social activites	MeanAE	MedianAE	RMSE
9(total)	17.5	13.6	21.5
8	15.6	9.9	20.3
7	15.1	12.7	19.2
6	16.3	16.9	20.8
5	27.4	29.2	32.4
4	25.6	16.5	33.4
3	26.4	20.7	31.1
2	26.3	21.7	31.6
1	26.5	20.0	32.9

TABLE IV
BEST ERROR SCORE OF REGRESSION MODELS IN OUR DOMAIN.

Regressor	SVM-linear	SVM-rbf	KNN	CART	MLP
Best error score	20.4%	17.5%	29.4%	41.8%	24.0%

1) Finding social activities describing land use: We capture such development of physical changes by analyzing social activities on a yearly basis. We thereby identify which Building Use category is associated with particular social activities and observe their differences in change over time for different areas. In order to do this, we identify which social activities represent well the propensity of commercial or residential. We accumulate each area according to their commercial or residential tendency and find the social activities emphasized in each building use types. We then define the emphasized social activities as representive indicators of commercial/residential, respectively.

2) Correlating changes in physical developments from social activities: Based on the defined mapping between social activities and building use, we explore whether the distribution of social activities can sense the physical developments of urban areas over the time. We look at the physical changes over the years in each target area, and check that the social activities patterns respond correctly to the physical developments. By doing so, we can estimate from the mapped social activities the evolving physical changes in terms of what types of buildings have increased or decreased in a given area.

V. EVALUATION RESULTS & ANALYSIS

A. Overview

In this section, we evaluate how well the proposed scheme can infer the land use tendency of a place and grasp its evolving change over the time. For the former, we compare the error score between our land use inference model and a baseline model. For the latter, we compare the outcome of the proposed build use estimation method with building data, called GIS Building Information [24], as a source of detailed physical changes in a target area.

B. Accuracy of land use inference

1) Baseline model: In order to quantify the predictive performance of our social media based model, we compare it to two baseline models. Baseline performance thereby is a reference point to compare to, and usually originates form simple models, such as predicting the most common class with classification, or predicting a central tendency, like mean or median, in regression. For our regression baseline, we therefore employ both a mean model and a median model, which predict the res_ratio of any location to be mean(res_ratio) and median(res_ratio), respectively.

2) Selecting proper social activities for inferencing land use: Through univariate linear regression tests, Table. II shows which social activity has a significant effect on regression analysis. A social activity with a high F-value can have a positive effect on regression while that with a low F-value can lead to performance degradation. We calculate the error score of our model by excluding a social activity with the lowest F-value one by one. Table. III shows error scores according to the number of social activities with a high F-value. It shows that the best performance can be achieved when using 8 or 7 activities for regression analysis. We decide to perform regression analysis using 7 social activities since it performs better than the 8 social activities in M(ean)AE, RSME.

3) Evaluation: We evaluate the predictive performance of the specified ML model types for inferring res_ratio of stations from their social activity frequencies using double k-fold cross validation(CV). We use CV for the performance evaluation of the proposed ML models (SVM-linear, SVM-rbf, KNN, CART, and MLP) and use the CV once more to evaluate the prediction performance of the selected model. Table IV shows the CV evaluation results for model selection over different model types. For each model type, the result for the best hyperparameter optimization is shown, selected from evaluating an appropriate hyperparameter grid for that model. From those results, a radial support vector regression (SVM-rbf) is chosen for the proposed model.

We consider the second CV results for obtaining a prediction performance estimate of the chosen SVM-rbf model type

TABLE V
COMPARISON OF RESULTS FOR PREDICTING THE RESIDENTIAL/COMMERCIAL FRACTION PER LOCATION.

Approach	MeanAE	MedianAE	RMSE
Baseline mean model	29.5%	29.0%	33.9%
Baseline median model	29.3%	24.9%	34.6%
Our approach	15.1%	12.7%	19.2%

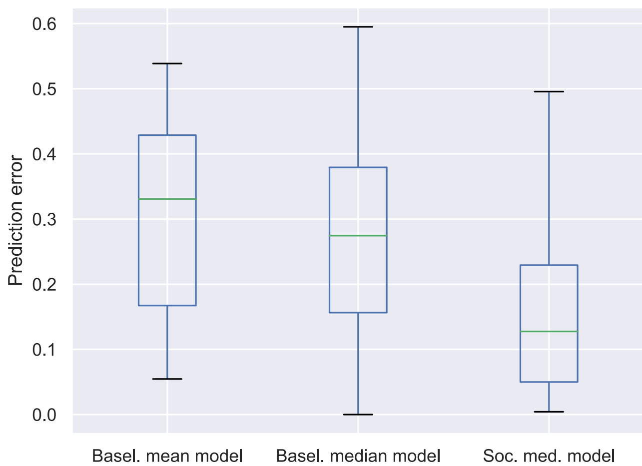


Fig. 4. Using social top 7 activities, comparison of the median absolute error of predicting the residential/commercial land usage with the baseline mean model, the baseline median model, as well as with the social media based model.

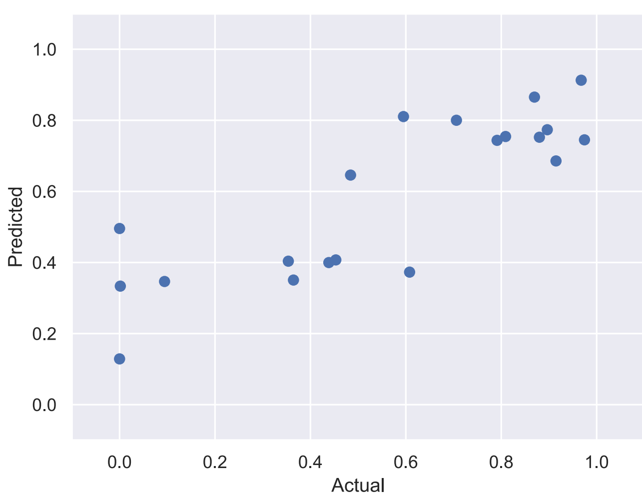
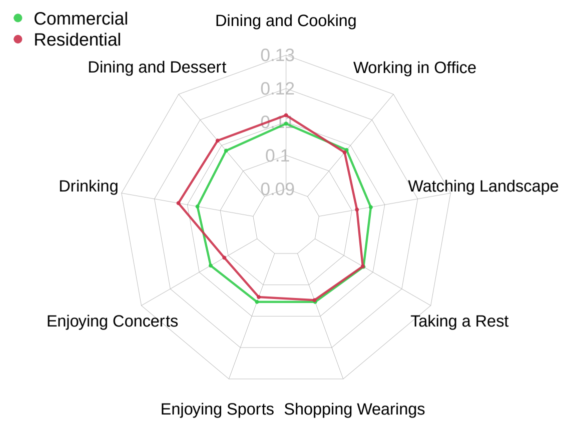


Fig. 5. Using social top 7 activities, result of predictive modeling the residential/commercial ratio of land use per location. It has 0.673 R-squared value.



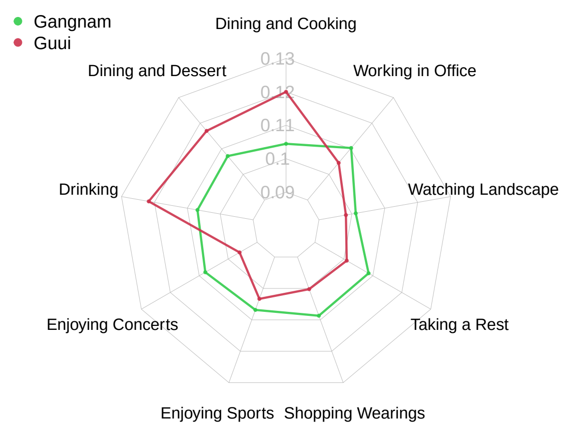


Fig. 6. *Top:* Average percentages of social activities of two groups, commercial and residential areas. *Bottom:* Percentages of social activities of two representative stations from each group.

and hyperparameterization. We then describe the performance improvements of our approach in relation to the performance of the baseline model. To quantify the prediction error of all models, we utilize the mean absolute error (MeanAE), median absolute error (MedianAE), and the root mean squared error (RMSE). Our model thereby achieves better predictive performance in inferring the land use of stations from their social activity frequencies with all those error measures (Fig. 4 and Table V). Most notably, the proposed model achieves a twice as good result as the baseline, measured in MeanAE and MedianAE (half the error of the baseline). Plotting the inferred values against the actual values of res_ratio shows that the inference error seems to be evenly distributed, without any significant patterns (Fig. 5).

C. Coverage of building use change estimation

1) Extracting general patterns of social activities: As shown in Fig. 6, we group station areas into two groups: relatively close to the commercial category and relatively close to the residential category, depending on whether the 1 exceeds 0.5. We analyze what social activities mostly appear in each group. In the residential area, food-related activities such as ”Dining and Dessert”, ”Dining and Cooking” and ”Drinking” are relatively emphasized. On the other hand, commercial areas are highlighted by more outdoor-oriented activities such as ”Enjoying Concerts”, ”Enjoying Sports” and ”Watching Landscape”. The lower part of Fig. 6 assures this finding: an area with a high commercial ratio (Gangnam Station) and one with a high residential ratio (Guui Station) clearly show what activities are more active in one category than the other.

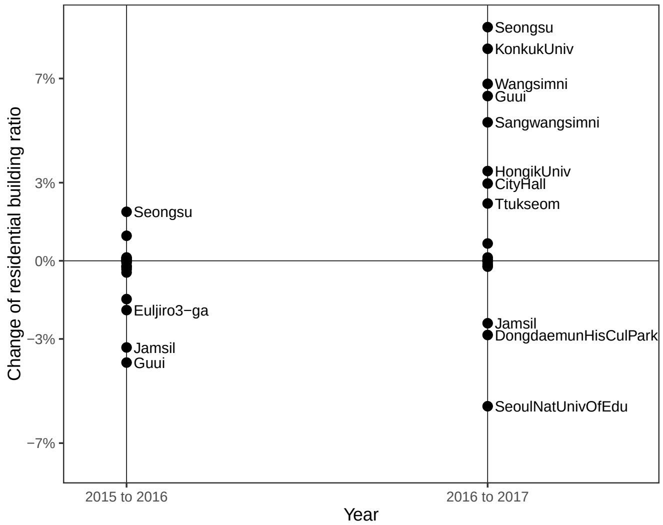


Fig. 7. Residential building ratio changes of Seoul Metro Line 2 stations between 2015 and 2016, and between 2016 and 2017.

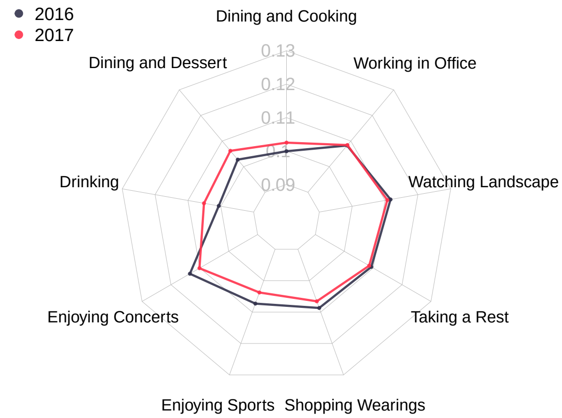
TABLE VI
DISTRIBUTION CHANGES OF SOCIAL ACTIVITIES AND RESIDENTIAL BUILDING RATIO FROM 2016 TO 2017.

Social Activity & Building	Seongsu	Wangsimni	Guui
Drinking	+0.18%	+0.47%	-0.26%
Dining and dessert	+0.15%	+0.47%	+0.14%
Dining and cooking	+0.13%	+0.58%	-0.21%
Enjoying Concerts	-0.15%	-0.27%	-0.04%
Enjoying Sports	-0.15%	-0.08%	-0.06%
Watching Landscape	-0.09%	-0.35%	+0.04%
Residential Building Ratio	+8.97%	+6.79%	+6.33%

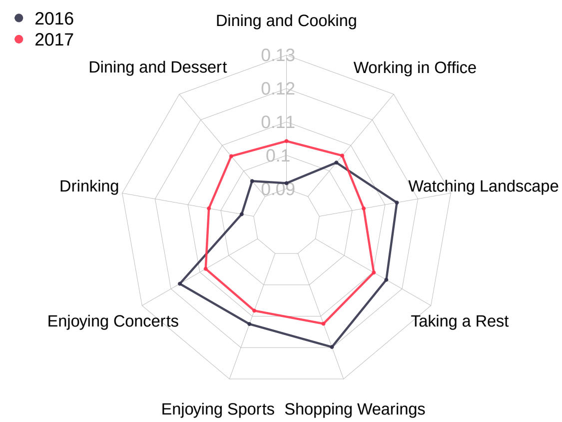
2) Evaluation : We look, in the previous section, to see which activities are related to residential area and which are inversely related to commercial area. Based on this, we estimate what kind of physical changes has occurred. However, such changes in social activities are be caused not only by changes in building information but also by various variables such as special events and street demonstrations. Therefore, even if there is no change in the building information, the distribution of the social activity may change. If a change occurs in the building information to some extent, we conjecture that the distribution of social activity also changes. For this, we fist find how much changes in building information will be correlated with the flux of social activities.

Fig. 7 shows the change in the ratio of residential buildings compared to commercial buildings between 2015 and 2016, and between 2016 and 2017. In the table, we can see that "Dining and Dessert", "Dining and Cooking" and "Drinking" increases and "Enjoying Concerts", "Enjoying Sports" and "Watching Landscape" decreases in accordance with the building ratio changes.

Based on such correlation between extracted pattern and building ratio changes, we apply this to Seoul Metro Line No.2 stations as a verification. Fig. 8 (a) and (b) show the distribution of social activities for 2016 and 2017 in the



(a) Seongsu Station from 2016 to 2017



(b) Wangsimni Station from 2016 to 2017

Fig. 8. The radial plots of (a): Seongsu Station and (b): Wangsimni Station where there exists visible changes in residential building ratio.

Seongsu station and Wangsimni station, where the change of the residential building ratio is clearly visible. In both stations, the residential building ratio has increased by more than 6.5%. According to the analysis in the previous section, the social activities related to residential areas are "Dining and Dessert", "Dining and Cooking" and "Drinking". It is consistent with our analysis because the direction in which these activities increase in both stations is observed. Fig. 9 shows how each category has changed in detail. We can see the ratio of "Detached House" and "Apartment House" which are residential buildings has increased and the ratio of "Sales Facility" and "Business Facility" which are commercial buildings has decreased.

On the other hand, Fig. 10 (a) and (b) are comparative graphs of the social activity distribution of Jamsil station and

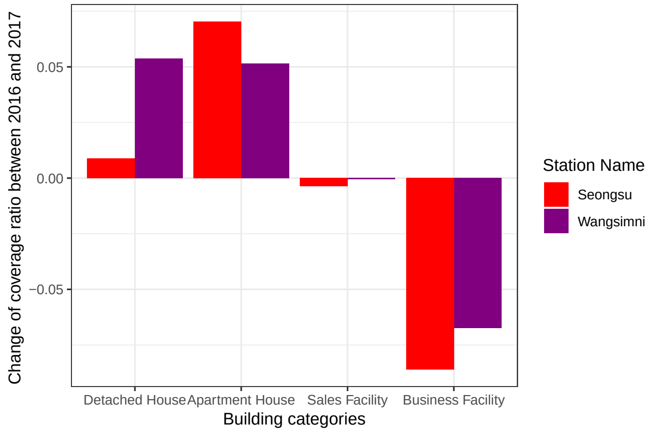


Fig. 9. The change of coverage ratio for each building category between 2016 and 2017.

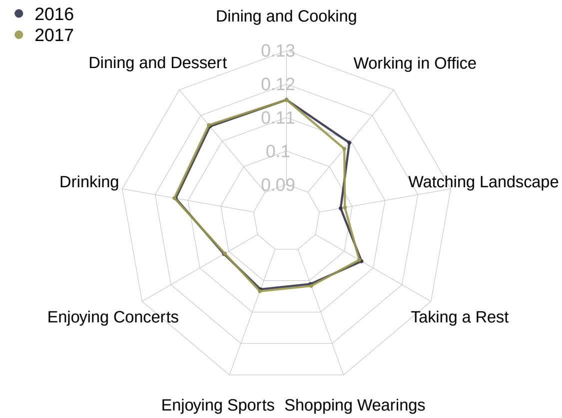
Euljiro3-ga station where there is little change in residential building ratio. It does tell that social activities do not change much when there is little change in the building use.

D. Discussion

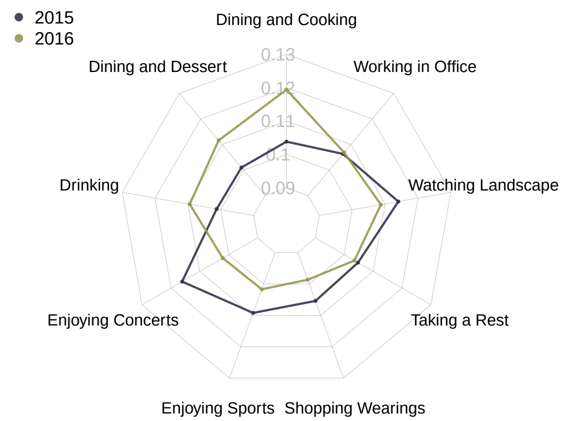
To make our approach generally applicable to any areas, we exploit several methods. We survey people living in various urban areas to determine general social activity of the city and made a numerical inference about the land use data that could be used in any urban area. However, to increase the generality of our model, there remain a few challenges to tackle. We set a regression target with a focus on the commercial and residential areas that best represent the characteristics of urban areas. For further generality, we may need to construct a regression target using attributes that might appear in cities such as parks and lakes, and did not consider the potential interrelationships between the attributes. In our approach, we found three stations out of 24 that did not have the characteristics of the urban area we specified. Most of them are dominated by educational institutions (universities) or rivers over 90%, and those outliers are excluded from regression analysis. In order for our model to be common in any city, a sophisticated regression target design that takes into account most of the attributes is essential.

It is also a challenge to improve accuracy when considering multiple attributes in inference. In particular, Since some attributes are discrete and do not have a gaussian distribution over the entire domain, making quantitative inference model is very difficult. We believe that we can mitigate this problem by using sequential ML-based classification and regression methods, and this model will capture even the most detailed details of the urban area.

In our approach, we can argue that the methodology which spreads the number of cluster using Word2Vec is a good way to show the diversity of social activities in urban areas. However, there is a limit to building social activities in social media. We reflected the human perception through surveys, but this is a weak approach because we have allowed people



(a) Jamsil Station from 2016 to 2017



(b) Euljiro3-ga Station from 2015 to 2016

Fig. 10. The radial plots of (a): Jamsil Station and (b): Euljiro3-ga Station where there is little residential building ratio change.

to see the word clusters with no weight, and only to verify the activity we annotated. Using the ML-based techniques such as attention mechanism in NLP, we can represent the importance for each words and will be able to extract more useful information from word clusters. This can lead to more flexible social activity annotation and better represent various social activities within the urban area.

Though the proposed scheme can estimate if there exist visible changes in the building over the time from the social activity analysis, it is very difficult to detect changes in an urban area more sensitively due to the nature of the social activity affected by various variables. Dealing with noise affecting changes in social activity can be an important task to support urban planning. In addition, after improving the performance through noise processing, we can expect quantitative inference about changes in a physical space over the time if we quantify the correlation between social activities and building uses.

VI. Conclusion & Future work

It is important to characterize the physical, social and cultural meaning of a place in urban design and planning. The placeness derived from social media represents the social and cultural meaning of a place, and finding a correlation with its land use can increase the availability of the cyber-physical space. For this, we design a placeness mining scheme that correlates a target area's social activities extracted from Instagram data into its land-use code. The proposed scheme also explains the physical evolution of a target place, which will give urban planners valuable clues to understand the area. The evaluation results show that the proposed scheme performs the inference of land use code with an error two times less than the baseline and estimates the building use changes over the time.

We plan to refine the inference model that can distinguish a target area in more detailed categories and apply our scheme to other major cities such as New York or Tokyo.

Acknowledgment

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