Estimating Area Characteristics Based on Geographic Object Positioning and Categories

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Abstract. This paper proposes a new method for estimating area characteristics, such as ease of parenting, by analyzing map images. Our approach utilizes map images that represent geographic object categories. This enables a machine learning model to infer area characteristics more accurately based on geographic object positioning and categories. We experimentally demonstrate the efficacy of the proposed method.

Keywords. Geographic Information, Machine Learning, Geographic Categories

1 Introduction

We often identify locations based on area characteristics in daily life such as the ease of parenting and shopping. For example, when people with young children move to a new city, they may want to determine whether the area is appropriate for raising them. In this situation, some people infer area characteristics from text-based content such as microblog posts; however, text content on specific regional characteristics that the user wants to know about may be scarce. For example, if most of the content is about shopping, it will not help users who want to know whether an area is appropriate for parenting. The primary aim of this research is to propose a machine learning model for estimating area characteristics. As training images, we use colored map images representing geographic object categories in color. Using these images instead of text data to estimate area characteristics allows a machine learning model to grasp geographical object positioning within the area. For example, in an area with one school and one

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station, a vector can only be expressed as (1, 1). However, map images can express various positional relationships between features. Thus, this study aims to develop a model capable of predicting area characteristics by learning colored map images that represent geographic object categories. The remainder of this paper is organized as follows. Section 2 discusses existing research related to our method. Section 3 describes our proposed method. Section 4 presents the results of the experiments and provides a discussion. Finally, Section 5 concludes the paper.

2 Related Work

The purpose of our method is to estimate area characteristics from map images representing geographic object categories. We organize existing research related to our study into two categories 1) estimating area characteristics using text data and 2) estimating methods of measurable area characteristics. Several previous studies have estimated area characteristics based on test data (Baral et al. 2018, Kato et al. 2009). In particular, Shoji *et al* (2018) proposed a model for predicting the atmosphere of a target area based on distributed representations of text as learning data. Our method uses map images instead of text data. Using this approach, the proposed model can learn the spatial relationships between features and estimate area characteristics. Previous studies have estimated numerical area characteristics (Bischke et al. 2019, Maggiori et al. 2016), such as the size of buildings (Hamaguchi & Hikosaka 2018). Our method proposes a machine learning model to estimate abstract area characteristics like ease of parenting and shopping.

3 Estimation Method of Area Characteristics using Map Images

3.1 Proposed Method

In this section, we describe the details of our method for estimating the area characteristics using a dataset consisting of map images and user reviews.

3.2 Colored Map Images

As training images, this study employed colored map images, which represent information on geographic object categories by color. Examples are shown in Figure 1. We created these training images based on the location information of geographic objects from OpenStreetMap[1] and represented geographic objects using Folium, a Python library. For example, blue regions represent schools, the red plots represent restaurants, and the green plots and regions represent transportation services such as bus stops and stations.

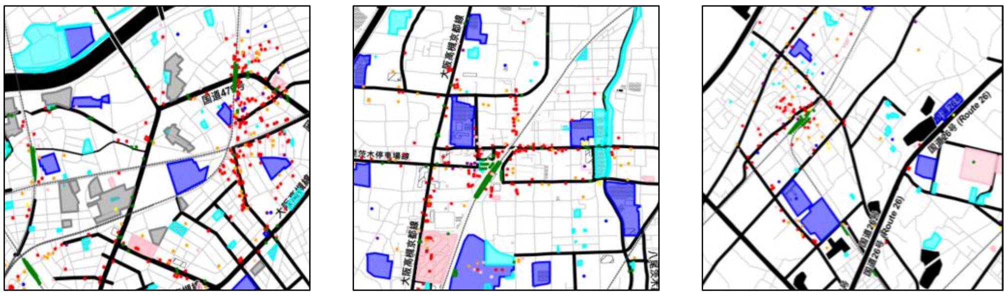

Figure 1. Examples of training images; these map images depict a part of the Kansai region in Japan.

3.3 Extraction of Area Characteristics for Training Data Set

In this paper, we employed review data of the area as labels for each colored map image. Specifically, we use the appearance rate of words that represent parenting, such as education, school, and family, as the label using the following formula:

$$P_K=\frac{t_k}{R} \quad (1)$$

Here, R denotes the total number of reviews posted for a particular area k and t_k represents the number of reviews including words related to parenting.

4 Experiments

4.1 Experiment Settings

The proposed method uses colored map images to represent geographic object categories. To evaluate the performance of the proposed method, we compared the results of the experiments using the following three map images as training images:

- Colored Map (Proposed): Images that represent object categories with color.
- Same-Colored Map: Images that represent object categories with the same color.

[1] https://www.openstreetmap.org/

- No Drawing Map: Images that do not represent geographic objects.

In this experiment, we use 1000 datasets consisting of colored map images and annotation labels. Labels were created using reviews in the LIFULL HOME'S dataset. Table 1 shows an example of the annotation labels.

Area	loccation informatioon	Review	total number of reviews	Annotation Labels
Area A	lat:32,96 lon:129,94	①There are no shops, but it is quiet and comfortable to live in.	3	0,67
		②Because I think it's good for **children** to live in nature.		
		③There are many **children** in the neighborhood, so I think raising children is easy .		

Table 1 Examples of annotation labels based on LIFULL HOME's Dataset

The dataset contained 1000 data points; 900 were used as training data, and 100 were used as test data. In this experiment, the model was evaluated by MAE and MSE for the test data. Fig.2 depicts the architecture of the neural network used in the experiments.

4.2 Results

Table 2 shows the results of the evaluation experiment. According to this result, the proposed method demonstrated higher accuracy than the other methods. These results show that representing geographic object categories is effective for estimating area characteristics through map image analysis.

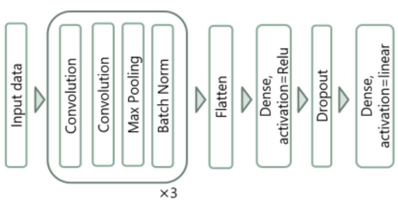

Figure 2. Architecture of the Neural Network

	MAE	MSE
Colored Map (Proposed)	0.094	0.016
Same-Colored Map	0.563	0.396
No Drawing Map	0.961	1.259

Table 2. Result of the experiment

5 Conclusion

The objective of this study is to estimate area characteristics by analyzing map images representing geographic object categories. The primary issue that we plan to address in future studies is annotation labels. Because the appearance rate of words is very simple, it is not possible for labels to reflect the characteristics of map images. Furthermore, because whether an area is suitable for parenting is very abstract, we should use indicators that clearly express regional characteristics as the label.

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