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RegNet: a neural network model for predicting regional desirability with VGI data

Abstract:

Volunteered geographic information can be used to predict regional desirability. A common challenge regarding previous works is that intuitive empirical models, which are inaccurate and bring in perceptual bias, are traditionally used to predict regional desirability. This results from the fact that the hidden interactions between user online check-ins and regional desirability haven't been revealed and clearly modelled yet. To solve the problem, a novel neural network model 'RegNet' is proposed. The user check-in history is input into a neural network encoder structure firstly for redundancy reduction and feature learning. The encoded representation is then fed into a hidden-layer structure and the regional desirability is predicted. The proposed RegNet is data-driven and can adaptively model the unknown mappings from input to output, without presumed bias and prior knowledge. We conduct experiments with real-world datasets and demonstrate RegNet outperforms state-of-the-art methods in terms of ranking quality and prediction accuracy of rating. Additionally, we also examine how the structure of encoder affects RegNet performance and suggest on choosing proper sizes of encoded representation. This work demonstrates the effectiveness of data-driven methods in modelling the hidden unknown relationships and achieving a better performance over traditional empirical methods.

Keywords: regional desirability prediction; volunteered geographic information; location-based social network

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1. Introduction

The rise of volunteered geographic information (VGI) (Goodchild 2007) has greatly influenced the manner of human interaction with the urban environment, providing new tools and datasets to study traditional research issues (Longley and Adnan 2016). For example, when a region is visited, online footprints (check-ins) may be left, and hence specific regions may be regarded as desirable regions, as a result of frequent online check-ins from users. Such correlations between regional desirability and user check-ins can be used for urban structure analysis (Cranshaw et al. 2012, Lee et al. 2014) and region recommendation (Liu et al. 2019).

A common problem affecting traditional methods is that empirical models, such as Hypertext Induced Topic Search (HITS), are traditionally used to predict regional desirability. These empirical models are intuitive and can be inaccurate in predicting desirable regions, as potential perceptual bias is introduced (Zheng et al. 2009, Zheng and Xie 2011, Liu et al. 2019). This results from the fact that the hidden interactions between user check-ins and regional desirability have not been clearly explained and precisely modelled yet, so that the empirical models based on human empirical intuition and presumed mathematical relationship are used for rough approximation.

Given the above, the aim of this work is to address the research question which deals with how to more accurately model regional desirability when the hidden interactions between user check-ins and regional desirability are still quantitatively and formulaically unknown.

The recent development of artificial neural network enables us to address this problem from a new perspective. A neural network is a collection of connected units, performing certain tasks such as classification and regression (Specht 1991, Odom and Sharda 1990). An advantage of the neural network is that it is data-driven, which means, given certain training data, the neural networks are theoretically capable of universally approximating functions (Hornik et al. 1989) and of learning the hidden unknown interactions of high-level features (LeCun et al. 2015) without prior knowledge. The neural network is hence suitable for tackling our research problem where the hidden interactive mechanisms of relevant features are still quantitatively unknown.

Specifically, in this work, a novel neural network model (called ‘RegNet’) is proposed for predicting regional desirability. RegNet takes pairs of user check-in history and regional desirability score as training data. By adjusting the network weights through backpropagation algorithm, RegNet can adaptively learn the hidden interactions of high-level features and the unknown mappings from input to output, without prior knowledge.

We conduct evaluations with real-world datasets and demonstrate that the proposed RegNet outperforms the popular state-of-the-art methods in terms of ranking quality and prediction accuracy of rating. Besides, we also examine how the structure of RegNet affects its performance and give suggestions on how to choose proper sizes of encoded representations.

The major contributions of this work are as follows:

- A novel neural network model RegNet is proposed for predicting regional desirability. The unknown hidden interactions between user check-ins and regional desirability can be adaptively modelled by RegNet. Compared with traditional empirical models, where hypothesized mathematical relationship is introduced, RegNet is data-driven and can learn the hidden interactions of high-level features and the unknown mappings from input to output. This is achieved by means of network backpropagation training and without presumed relationships. The perceptual biases are thus reduced and better prediction results are yielded.

- A structure of encoder layers is introduced for feature learning. This structure can reduce data redundancy and thus alleviate computational complexity and potential overfitting. Experiments are conducted to find how the structure of encoder affects the model performance. Suggestions are also made on how to choose proper sizes of the encoded representation.

The rest of our paper is as follows. In Section 2, the related works are summarized. In Section 3, the key problem notations are defined. In Section 4, the details of RegNet workflow are introduced. In Section 5, the experiment and evaluation are described. In Section 6, the performance and limitations of RegNet are discussed. Eventually, in Section 7, the conclusions are given.

2. Background and Related Works

The rise of location-based social networks has given rise to novel recommender systems that seek to recommend spatial-related items to users. Traditionally, the recommender systems mainly used two types of approaches: collaborative filtering and content-based filtering (Jafarkarimi et al. 2012). In Bao et al. (2015), the techniques for LBSN recommender systems were further classified into three main types: 1) content-based methods, which used information from users' profile and features of locations for recommendations (Park et al. 2007, Ramaswamy et al. 2009) ; 2) collaborative filtering methods, which inferred users' preferences from historical behaviors (Horozov et al. 2006, Ye et al. 2010, Lemire and Maclachlan 2005); 3) link analysis-based methods, where link models were used to detect informative users and desirable places (Raymond et al. 2011, Zheng et al. 2009).

In terms of recommended objectives, there are mainly two types of stand-alone location recommender systems: POI and region recommender systems. The types of items recommended by POI recommender systems are mainly individual venues that match user interests or querying requirements. Various kinds of spatiotemporal and contextual features have been incorporated in the POI recommender models (Cai et al. 2018). Particularly, the spatial effects are widely considered, which differentiates POI recommenders from other kinds of recommender systems. For example, as users are likely to visit venues nearby, such spatial effects were modelled as exponential relationships, probability distribution, or power law relationships (Yang et al. 2008, Ye et al. 2011, Kurashima et al. 2013, Liu and Seah 2015). Some works also modelled the periodicity of check-ins (Yuan et al. 2013, Gao et al. 2013), social relationships of users (Cheng et al. 2012, Gao et al. 2012) and POI tips (Yang et al. 2013). To address the variety and complexity of the features used in POI recommendation, machine learning and statistical techniques are both used for analysis (Li et al. 2016). However, there are still some challenges that undermine the effectiveness of machine learning approaches in POI recommendation, such as data bias and computational complexity (Wan et al. 2018). A recent new trend is to introduce deep neural network (DNN) into recommender systems. The DNNs are capable of learning high-order features and the unknown interactive relationships for a specific task (LeCun et al. 2015) and have been proven effective in recommending tasks. Cheng et al. (2016) jointly trained deep neural networks and wide linear models to use the advantages of both memorization and generalization, and evaluated their methodology on Google Play with good feedbacks. He et al. (2017) presented a neural network-based collaborative filtering framework for matrix factorization and recommendation. Regarding POI recommendation, Ding and Chen (2018) developed a DNN recommender system that incorporated the joint influences of co-visiting, geographical proximity and categorical correlation.

The application of POI recommender systems can be limited when users want to find spatial areas with many venue options, which is compensated by region recommender system. In Kurashima et al. (2010), the authors extracted landmarks from geo-tagged photos and estimated the probability that a user visited certain regions. A similar work was done by Sun et al. (2015) where urban landmarks were identified and travel routes were recommended accordingly. In terms of calculating regional desirability, previous works mainly used presumed empirical models, such as power law distribution (Sun et al. 2015) and Hypertext Induced Topic Search (Zheng et al. 2009, Zheng and Xie 2011, Liu et al. 2019). However, as the relations between regional desirability and user online footprints were rarely revealed, there is still a lack of convincing models that can accurately predict the interactive mechanism between user check-in and regional desirability.

Consequently, in this work, we propose a multi-layer neural network RegNet for regional desirability prediction. Given training data, the proposed RegNet is data-driven and can model the hidden unknown patterns between user check-ins and regional desirability without prior knowledge and presumed relationships, thus alleviating the inaccuracy and presumed bias introduced by intuitive empirical models and achieving better prediction results.

3. Key Problem Definition

The definition of this study's regional desirability prediction problem is given in this section. For convenience, the key notations of our RegNet are given firstly (shown in Table 1).

Table 1. RegNet Notations and Definitions

Variable	Description
p_i	A POI with identifier, category, location and rating, $p_i = (id, cat, loc, rt)$
r_i	A Region with spatial coverage, set of POIs and desirability rating, $r_i = (s, P, Rt)$
U	A Set of users, $U = (u_1, u_2, \dots, u_n)$
c	A user check-in to a venue, $c = (u, p)$
rv_i	A multi-dimension vector consisting of user visiting to

regions, $rv_i = (uv_1^i, uv_2^i, \dots, uv_n^i)$

Definition 1. POI: A POI is a venue (e.g., a hotel or a shopping place) with unique identifications. In this paper, a POI is denoted as p_i with four attributes $p_i = (id \ , cat, loc, rt)$ where id is a unique identifier, cat is the category, loc is the venue's geographical coordinates, rt is the user's rating for venue p_i's desirability.

Definition 2. Region. A region is a spatial area with coverage of POIs. A region is denoted as r_i with three attributes $r_i = (s, P, Rt)$, where *s* is the spatial coverage of r_i, *P* is the set of POIs $P = (p_1^i, p_2^i, \dots, p_m^i)$ within the spatial coverage of r_i, i.e., $p_m^i.loc \ \epsilon \ r_i.s$, *Rt* is the numerical rating of the region r_i's desirability. A region set *R* is a collection of the regions, $R = (r_1, r_2, \dots, r_n)$.

Definition 3. User Set. A user set *U* is defined as $U = (u_1, u_2, \dots, u_n)$, where u_i is a unique user in the dataset.

Definition 4. Check-in. A check-in is a record that a user *u* visits a POI *p*, denoted as $c = (u, p)$. A check-in set *C* is a collection of the check-ins, $C = (c_1, c_2, \dots, c_k)$. The frequency of check-ins to a POI p_i can imply its popularity.

Definition 5. Region-Visit Vector. Given a region r_i, a set of users *U* and check-ins *C*, a region-visit vector is denoted as $rv_i = (uv_1^i, uv_2^i, \dots, uv_n^i)$, where *n*=|*U*| is the total count of users in user dataset *U*, $uv_k^i = |subC|$, where $subC = \{e| \ \ e \ \epsilon \ C \ \ AND \ \ e.p \ \epsilon \ r_i.P \ \ AND \ \ e.u = U.u_k\}$.

Our regional desirability prediction problem can therefore be defined as below:

Research Problem: Given a user set *U*, a region set *R*, a check-in set *C*, we aim to recommend the top-k regions with the highest desirability *Rt*.

4. RegNet for Predicting Regional Desirability

In this section, the details of the proposed RegNet are given. The rationale and techniques for feature representation are given firstly, followed by an elaboration of the neural network model for region desirability prediction.

4.1 Feature Learning with Encoder

For location recommendation with VGI, the frequency of check-ins is commonly used to indicate the popularity of a location. However, for region recommendation, the regional spatial scale needs to be considered, as a large region is likely to be visited more often due to more venue amount, however, such a high frequency of visits does not necessarily indicate high regional desirability (Liu et al. 2019). Consequently, the region-visit vector $\boldsymbol{rv}_i$ (see Definition 5), is divided by regional spatial scale to construct new input feature $\boldsymbol{rv}_i'$:

$$\boldsymbol{rv}_i' = \frac{\boldsymbol{rv}_i}{|r_i.P|} \tag{1}$$

The dimension of feature $\boldsymbol{rv}_i'$ is |*U*|, which may be very large given big dataset and lead to several problems in neural network training: (1) the connections between input layer and hidden layer can be very complex, causing overfitting due to the relatively small amount of training data. (2) the large dimensionality of features can give rise to computational inconvenience and even, infeasibility. Consequently, in this work, an autoencoder for feature learning is adopted first. The autoencoder is a pair of transforming and reconstruction functions to learn feature representation, mostly in the form of neural network (Liou et al. 2008, Liou et al. 2014), with both reduction side for dimensionality reduction and reconstructing side for reconstructing the original input. By using an autoencoder, the higher abstract features with reduced dimensionality can be learned for region desirability prediction, thus reducing the computational complexity and overfitting.

An autoencoder neural network includes two structures: an encoder and a decoder (shown in Figure 1), which can be defined as two mapping functions (Vincent et al. 2010):

Figure 1. An autoencoder in the form of a fully connected neural network. The encoder transforms the input vector with multiple dimensions into a short representation, and the decoder, reversely, transforms the short representation back into vectors with the same dimension as input vector, aiming to minimize the reconstruction errors.

Encoder: The encoder $f_\theta(\mathrm{x})$ is in the form of neural network and transforms vector into a short representation (code). The mathematical formula can be illustrated as:

$$\boldsymbol{y} = f_\theta(\mathbf{x}) = s(\boldsymbol{W}\boldsymbol{x} + \boldsymbol{b}) \tag{2}$$

Where s() is a nonlinear function and the parameter $\theta = (\boldsymbol{W}, \boldsymbol{b})$ is the pair of weight matrix and bias vector.

Decoder: The representing code y is re-transformed back using another neural network to a reconstructed vector, $\mathbf{z} = g_{\theta'}(\mathbf{y})$:

$$\mathbf{z} = g_{\theta'}(\mathbf{y}) = s'(\boldsymbol{W}'\boldsymbol{y} + \boldsymbol{b}') \tag{3}$$

With parameter $\theta' = (\boldsymbol{W}', \boldsymbol{b}')$.

The training process aims to minimize the reconstruction error through backpropagation algorithm. The mean squared error is used as loss function, so the minimized reconstruction errors are defined as:

$$\arg min_{\theta,\theta'} L(\mathrm{x}, \mathrm{z}) = \frac{1}{|\boldsymbol{x}|}\Big(\mathbf{x} - \mathrm{s}'\big(\boldsymbol{W}'\big(\mathrm{s}(\boldsymbol{W}\boldsymbol{x} + \boldsymbol{b})\big) + \boldsymbol{b}'\big)\Big)^2 \tag{4}$$

In this work, an autoencoder is trained first with the input and reconstruction of $\boldsymbol{rv_i}'$. After training the autoencoder, the encoder from the autoencoder is used independently for feature learning.

4.2 Encoding-Prediction Structure

In this work, the regional desirability prediction problem is defined as a regression problem, where the regional desirability score is predicted based on the user visiting history, using the proposed neural network RegNet. The structure of RegNet is presented in Figure 2.

Figure 2. The structure of fully-connected RegNet. The scaled region-visit vector and ground-truth region rating, i.e. (rv', Rt), are fed into RegNet pairwise for neural network training.

The RegNet consists of several levels: an input layer, a neural-network encoder for feature learning, hidden layers for prediction and an output layer. The encoder network is trained from an autoencoder structure and capable of learning feature representation with reduced dimension, thus alleviating potential overfitting and computational complexity while preserving as much information as the original input. The encoder network compresses the input feature into an encoded tensor, which is then input to the hidden-layer structure for final prediction.

The workflow of RegNet can be defined as:

$$\boldsymbol{y}_i = \begin{cases} \boldsymbol{rv}' \ , & i = 0 \\ s_{i-1}(\boldsymbol{W}_{i-1}\boldsymbol{y}_{i-1} + \boldsymbol{b}_{i-1}) \ , & else \end{cases} \tag{5}$$

where $\boldsymbol{y}_i$ is the input vector of the i^{th} layer. For input layer (i.e., i=0), $\boldsymbol{y}_0$ is the network input feature $\boldsymbol{rv}'$ (see Equation 1). For encoder and other hidden layers, $s_i()$, $\boldsymbol{W}_i$, $\boldsymbol{b}_i$ are the activation function, weight matrix and offset vector for i^{th} layer respectively. For output layer, the $\boldsymbol{y}_i$ is the predicted score for regional desirability. To reduce computational cost, the stochastic gradient descent (SGD), which can be very effective for the problems with large-scale dataset (Bottou and Bousquet 2008), is adopted as the optimizer. The mean squared error is adopted as the loss function of RegNet training:

$$Loss = \frac{1}{|R|}\sum_{r_i \epsilon R}(r_i.Rt - Y_i)^2 \tag{6}$$

Where r_i is a region in R (see Definition 2), Y_i is the predicted score for r_i regional desirability prediction from RegNet (see Equation 5). The scaled region-visit vector and ground-truth region rating, i.e. $(\boldsymbol{rv}_i', \ r_i.Rt)$, are fed into RegNet pairwise for neural network training, aiming to minimize the loss function by modifying $(\boldsymbol{W}_i, \ \boldsymbol{b}_i)$, by means of the backpropagation algorithm.

5. Experiment and Evaluation

5.1 Experiment Settings

The datasets for experiment and evaluation are the same as those of Liu et al. (2019), which consist of two sources: Instagram check-ins identified as ‘food’ topic in Hong Kong from Nov 2014- Nov 2015, POIs from Foursquare. The basic description of the experimental datasets is given in Table 2. An Instagram check-in has following attributes: the check-in id, the corresponding user id, the timestamp of check-in, and the location. A POI item has following attributes: the POI identifier, the POI category, POI location and a numerical rating for POI desirability. The desirability rating is a score (0 to 10) retrieved from Foursquare platform and calculated from a wide variety of comprehensive signals derived from users’ explicit and implicit feedbacks. This rating algorithm has been validated in metropolitan areas and trusted by users for accuracy and reliability in indicating the venue desirability (Yang and Sklar 2016).

Table 2. Description of Data Sources

Data Sources	count	Key fields
Instagram check-ins	358,471	cid, uid, ctime, cloc
Foursquare POIs	32,485	vid, vcategory, vloc, vrating

The spatial regions are needed for training RegNet, so we implement DBSCAN method (Ester et al. 1996) on the Instagram check-ins for spatial clustering and the DBSCAN parameters Eps and

MinPts are set as 7 and 18 respectively. We randomly select 70% of the clustered regions as the training set and the remaining 30% as the test set for evaluation.

For regional desirability, our consideration is that a region covers many venues, so the desirability of the region should be able to reflect the general qualities of the venues within the region and user's general attitude towards that region as a whole. Consequently, for each region r_i, the desirability score $r_i.Rt$ is calculated as:

$$r_i.Rt = \frac{1}{|r_i.P|} \sum_{p_i \epsilon r_i.P} p_i.rt \tag{7}$$

$p_i.rt$ (Definition 1) is the venue rating score retrieved from Foursquare platform (vrating in Table 2). In this work, since Instagram check-ins identified as 'food' topic are used to cluster regions, the food-type venues are used for calculating regional desirability.

For RegNet, we set 35 as the dimension of the encoded representation y (Equation 2), Rectified Linear Unit (ReLU) $f(x) = max(0, x)$ as the activation function of encoder, Softsign $f(x) = \frac{x}{1+|x|}$ as the activation function of predicting hidden layers.

5.2 Evaluation Approach

Two popular measurements are used to evaluate the performance of RegNet. The first measurement is *MAE* (mean absolute error), which is to evaluate the accuracy of the predicted rating. The formula of *MAE* is as below:

$$MAE = \sum_i^n \frac{|Rt_i - Y_i|}{n} \tag{8}$$

Where Y_i, Rt_i are the predicted rating and ground-truth user rating for region r_i respectively, and n is $|R|$. Y_i and Rt_i were both normalized before calculating *MAE*. A better agreement between the system rating and user rating can be indicated with a lower *MAE*.

Another measurement nDCG (Normalized Discounted Cumulative Gain) (Järvelin and Kekäläinen 2000) is used to evaluate the ranking quality. The assumption for *nDCG* is that relevant items are more helpful when showing up in the top positions. The formula is as below:

$$nDCG_p = \sum_{i=1}^{p} \frac{2^{rel_i - 1}}{log2(i+1)} / IDCG \tag{9}$$

Where rel_i is the graded relevance if the item appearing at the i^{th} place, *IDCG* is the ideal *DCG* calculated by ranking all the items in terms of the relevance in descending order, producing the maximum possible *DCG*. A good matching between the system recommendation and user expectations can be proven with a high $nDCG_p$.

5.3 Performance Evaluation

Figure 3. The clustered food-themed regions with Instagram check-ins across Hong Kong. The majority of the regions are located in Causeway Bay, Tsim Sha Tsui, Mong Kok and Central, all of which are the major recreation and amusement areas in Hong Kong.

The clustered regions (see Section 5.1) are shown in Figure 3. It can be seen that the clustered regions are mainly located in Causeway Bay, Tsim Sha Tsui, Mong Kok and Central. The results are consistent with Hong Kong urban situation, as all of these are the famous recreation areas, where quite a number of quality restaurants and street food are located.

For each clustered region, the desirability values are respectively calculated with the comparison methods and proposed RegNet, then compared with the ground-truth for evaluation. We compare the performance of our proposed RegNet with the popular methods for regional desirability prediction: rating-by-users, rating-by-visits, HITS (Zheng and Xie 2011), HITS-based (Liu et al. 2019). For the rating-by-users, the regional desirability is proportional to the total count of visitors to the region. For the rating-by-visits, the regional desirability is proportional to the total count of check-ins into the region. The HITS (Zheng and Xie 2011) method is to predict regional desirability based on the mutual reinforcement relationship between user's travel experience (hub score) and the desirability of a region (authority score). The HITS-based (Liu et al. 2019) method is a revised model of Zheng and Xie (2011)'s method, with consideration of regional scale and user weight decay.

Figure 4. The geographical distribution of the top 5 regions with the highest desirability values respectively by HITS (Zheng and Xie 2011) (blue), HITS-based (Liu et al. 2019) (green) and proposed RegNet (red)

Figure 5. The details of the top 5 regions with the highest desirability values respectively by HITS (Zheng and Xie 2011), HITS-based (Liu et al. 2019) and proposed RegNet

The top 5 regions with the highest desirability values respectively by HITS (Zheng and Xie 2011), HITS-based (Liu et al. 2019) and proposed RegNet are geographically mapped in the Figure 4. The details of each regions are shown in Figure 5. It can be seen that regions such as Landmark Atrium-Alexandra House, Aberdeen Street-Police Married Quarters, the Peninsula are predicted with high desirability by both proposed RegNet and comparison methods.

The Table 3 lists several regions' normalized desirability value and ranking by each method. From Table 3, it can be seen the top 10 desirable regions predicted by RegNet have a good agreement with the ground truth. The region 11, 55, 75, 42 are raking at the 1st, 4th, 9th, and 10th place according to the ground truth, while predicted at 3rd, 7th, 9th, and 10th place by our RegNet. 4 out of 10 most desirable regions are predicted correctly with slight ranking inconsistency against ground truth.

Table 3. Normalized Regional Desirability Calculated by Each Method

Region ID	**Ground truth**		**rating-by-user**		**rating-by-visit**		**HITS (Zheng and Xie 2011)**		**HITS-based (Liu et al. 2019)**		**RegNet**	
	rating	rank	rating	rank	rating	rank	rating	rank	rating	rank	rating	rank
11	1.000	1	0.235	11	0.260	8	0.250	9	0.397	5	0.983	3
66	0.939	2	0.109	20	0.077	23	0.090	20	0.157	10	0.874	13

124	0.909	3	0.011	42	0.007	42	0.008	42	0.014	40	0.682	34
55	0.893	4	0.261	10	0.205	12	0.227	11	0.394	6	0.944	7
10	0.863	5	0.044	28	0.035	29	0.038	29	0.068	18	0.816	22
140	0.863	6	0.022	38	0.019	36	0.020	36	0.036	32	0.802	25
92	0.848	7	0.069	24	0.071	24	0.070	24	0.052	25	0.832	19
68	0.848	8	0.032	32	0.031	30	0.031	33	0.055	24	0.857	16
75	0.840	9	0.208	13	0.209	11	0.208	12	0.174	9	0.924	9
42	0.832	10	0.091	22	0.084	20	0.086	21	0.149	11	0.921	10
141	0.832	11	0.042	29	0.031	31	0.035	30	0.061	20	0.820	20
122	0.832	12	0.040	30	0.028	33	0.033	31	0.058	22	0.815	23
35	0.825	13	0.511	5	0.499	4	0.503	4	0.420	4	0.954	5
105	0.817	14	0.000	45	0.000	45	0.000	45	0.000	45	0.508	42

We assign different values to *p* to calculate $nDCG_p$ (Equation 9), as shown in Table 4. The results show that, as *p* increases, the $nDCG_p$ for both RegNet and comparison methods increases. With different *p* values, RegNet can stably achieve higher *nDCGs* (0.33-0.49) than the *nDCGs* of other comparison methods.

It can be expected the users care more about being recommended highly desirable regions. Particularly, with *p*=5 and 15, RegNet achieves *nDCG*=0.329 and 0.438, which are consistently higher than comparison methods (i.e., 0.255, 0.375), indicating, for the highly desirable regions, the proposed RegNet has better predictions than other methods. The above results show that RegNet can achieve better ranking quality than comparison methods and demonstrate RegNet's advantage in predicting highly desirable regions.

Table 4. Normalized Discounted Cumulative Gain for RegNet and comparison methods

$nDCG_p$	**RegNet**	**Rating-by-users**	**Rating-by-visits**	**HITS (Zheng and Xie 2011)**	**HITS-based (Liu et al. 2019)**
$nDCG_5$	0.329	0.000	0.000	0.000	0.255
$nDCG_{15}$	0.438	0.205	0.228	0.219	0.375
$nDCG_{25}$	0.456	0.281	0.300	0.294	0.384
$nDCG_{35}$	0.487	0.287	0.306	0.301	0.392
$nDCG_{45}$	0.487	0.325	0.344	0.338	0.422

The agreement between the methods' ratings and user rating (normalized to be comparable) is further measured with the MAE (Equation 8), shown in the Table 5. The user count is used as the desirability score for rating-by-users method and visit count for rating-by-visits method. The results show RegNet can achieve less MAE (0.19) than the comparison methods (around 0.53), indicating that the regional desirability ratings predicted by RegNet have better agreement and less deviation with the ground truth than the comparison methods.

The RegNet is data-driven and, given enough training data, can model the hidden unknown interactions of high-level features and approximate the unknown mapping functions from input feature to output value. In our experiment, it shows the RegNet has better performance than the traditional empirical methods, in terms of both ranking quality and prediction accuracy of rating (numerical rating agreement).

Table 5. MAE (mean absolute error) for each method

	RegNet	**Rating-by-users**	**Rating-by-visits**	**HITS (Zheng and Xie 2011)**	**HITS-based (Liu et al. 2019)**
MAE	0.193	0.528	0.534	0.531	0.532

6. Discussion

6.1 Performance Analysis

With the recent rise of VGI, region recommendation is a newly emerging research area. The empirical models are traditionally used to predict regional desirability. These models can be relatively intuitive and inaccurate. On the other hand, the massive volume of VGI provides an alternative perspective. The consideration is that the mechanism of regional desirability has already been implicitly contained by VGI, and, with proper datasets and data-driven model, the hidden patterns can be well learned without presumed relationships. Consequently, in this paper, a new neural network model RegNet is proposed for predicting regional desirability. Theoretically, the neural network has been proven to be capable of universally approximating functions (Hornik et al. 1989) and is widely used for classification and regression. The user visiting history and rating are fed into the RegNet as training data, and the hidden interactions of high-level features are learnt accordingly. The experiments demonstrate RegNet's advantage over traditional empirical models in predicting regional desirability and, in especially, recommending highly desirable regions.

Another issue to consider is how the encoder structure affects the RegNet performance. The consideration is that the encoder is a lossy data compression, which means the feature information can be lost together with the data redundancy by dimensionality reduction with encoder. Inappropriate encoder settings may cause intense information loss and the model failing to learn the hidden patterns. Consequently, comparisons are made on how the dimension of the encoded representation (y in the Equation 2) affects the method performance (shown in Figure 5). It shows that the MAEs achieved by RegNet remain relatively stable (around 0.20) with increasing encoded dimension. The MAE achieves its minimum when the dimension is 35 and increases fluctuantly as the dimension expands. An explanation can be found by examining the RegNet structure. RegNet will fail to learn the interaction of features with too few encoded dimensions, because hidden patterns can be lost if dimensionality reduction is intense. In such case, the encoded feature y becomes incapable of satisfactorily representing the original input vector x (Equation 2), leading to underfitting problem. On the other hand, the interaction of hidden layers in the regional desirability prediction phase can be over complicated, with large encoded dimensions and limited training dataset, causing RegNet performing well with training dataset and poorly with evaluation dataset, which is overfitting. A good performance can only be achieved with a proper moderate size of encoded dimension.

Figure 6. Impacts of the Encoded Dimension

6.2 Limitation and Future Work

Admittedly, predicting regional desirability with RegNet in this work has potential limitations. Firstly, the RegNet suffers from black box issue. As the RegNet approximates the mapping function from user check-ins to regional desirability, it does not necessarily give knowledge on the structure of the function being approximated or how to do parameter tuning. The network weights are not capable of inferring the form of approximated function. Further studies are needed so that the internal mechanisms between regional desirability and user online footprints can be formulaically explained. Secondly, how to select a proper region size remains challenging. To train

RegNet, spatial regions need to be clustered. A small region size may cover insufficient POIs and check-ins, making the regional rating and user check-ins unrepresentative, while a large region size may cause limited amount of total clustered regions, leading to lack of training data and overfitting. How to choose a proper region size and balance the trade-off can be a potential direction for future work. Thirdly, regarding the optimal size of encoded dimension, whether the current optimal value is a local or global optimum remains to be further investigated. Fourthly, due to data availability, our experiment was conducted in one city, which may cause limited generalization because of data bias. More cities can be included for validation in the future once the data becomes available.

7. Conclusion

The rapid development of volunteered geographic information and location-based social networks enables researchers to study traditional issues with new tools and datasets. Geo-tagged check-ins on the social media are indicative of desirable regions. To predict the regional desirability, previous works mainly used the empirical models, which can be intuitive and inaccurate with introduced perceptual bias. The underlying reason is that the mapping relationships from user check-ins to regional desirability still remain unknown so that the empirical models with presumed relationships are used for rough approximation. How to more accurately model regional desirability from user check-ins, when the hidden interactions are still quantitatively and formulaically unknown, remains a challenging research question.

Consequently, in this work, a multi-layer neural network model (RegNet) is proposed to address the aforementioned research question. Pairs of user check-in history and ground-truth regional desirability ratings are fed into RegNet and regional desirability scores are calculated as the predicted values. We implement the proposed RegNet with real-world datasets and prove the better performance of RegNet over baseline methods. Additionally, we also do sensitivity analysis on how the dimension of the encoded representation affects the performance of RegNet and find that, due to potential underfitting and overfitting issues, only with a proper moderate size of encoded dimension could a good performance be achieved. This research demonstrates the feasibility and effectiveness of data-driven methods (e.g., neural networks) in modelling the hidden unknown relationships and achieving a better performance for region desirability prediction over traditional empirical methods.

Data and codes availability statement

The data and codes that support the findings of this study are available with a DOI at

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