Regional development prediction by deep learning using time series data from Switzerland

ディープラーニングとスイスの時系列データを用いた地域発展予測に関する研究

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1. Introduction

Prediction of complex regional development process, including interaction of various interdependent factors, is significant for planners in order to make better decisions on providing infrastructure and services efficiently. Most of the existing prediction models are restricted in local scale using detailed information or do not focus on long term development. This research therefore proposes a new methodology using graph convolutional neural networks (GCN) in deep learning for regional development prediction using long term data, which is flexible and applicable on different regions.

The proposed deep learning model will explain the reciprocal relationship between population concentration and transport infrastructure development, considering the transportation network structure and transportation accessibility between different municipalities. Differences of influential factors in different municipalities and time period will also be discussed.

2. Background and literature review

(1) Interaction between transport and land use

This research is based on the theory of interaction between transport supply and land use demand.[1] This interaction is considered as a reciprocal process subject to the spatial and temporal constraints such as government budgets, technical limitation, topographical obstacles, etc.. For example, population concentration induces travel demand, and transport infrastructures might be developed in response to that demand. Conversely, transport infrastructure development can catalyze land use development and influence the movement of population.

(2) Accessibility

Existing models such as land use-transport interaction model is also based on the theory of transport supply and land use demand interaction. However, it is restricted in local scale using detailed information as inputs for travel demand forecasting model, budget model, etc. which are hardly available for a long term and regional scale. Therefore, we focus on transportation accessibility as a key factor in the proposed regional development prediction model, because it can capture the crucial effects of transport infrastructure and connect them to various information such as technology, energy and economy development.[2]

3. Application of GCN to regional development

(1) Regional development as graph structures

In regional development, the municipalities are assumed to influence each other through certain relations, and each municipality has various features being involved. Therefore, we can regard regional development as graph structures where municipalities are nodes with features and the relations among them are edges with weights.

In this research, we consider three types of edges (relations), which are physical connections by transportation links (railway and road), accessibility which assumes the relation between two municipalities to follow the assumption of gravity model, and neighboring relations assuming closer municipalities are more likely to have interactions. Regarding to the nodes, we consider four node features, which are population, transportation service accessibility (a newly defined parameter reflecting capacity and density of transportation link in each municipality) for railway (TSA-railway), TSA-road and technological and topographical difficulty of developing transport infrastructure (Diff).

(2) GCN and Shapley Additive Explanations (SHAP)

A GCN approach is used for regional development prediction. GCN is one type of deep learning applicable on non-Euclidean structured graphs that can incorporate information from neighboring connected nodes to the target node capturing both structure and node features. As we consider regional development as graph structures and with time series data available, supervised regression using GCN can be a practical and flexible method for regional development prediction.

Since deep learning model is considered as a black box and no parameter is estimated, we also apply SHAP[3] which is developed from the concept of Shapley value in cooperative game theory to fairly distribute payoff to players based on their contribution. It is also a new attempt to gain insights into the differences of influential factors in different municipalities and time period in regional development based on SHAP values.

4. Deep learning model structure

Fig. 1 shows the structure of deep learning model. The model consists of two repeating blocks where each block contains one graph convolutional layer (GraphConv) and one GraphU-net[4] layer (avoiding overfitting), a jumping knowledge[5] layer (avoiding over-smoothing) and a linear output layer.

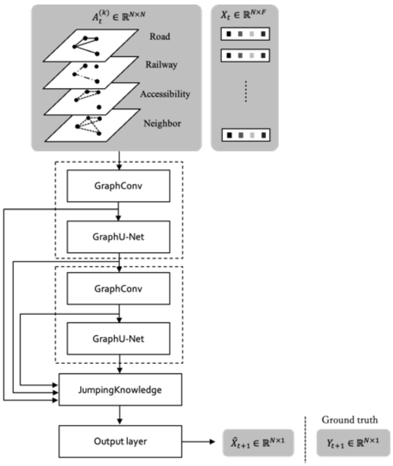

Fig. 1 Deep learning model structure

5. GraphExplainer

The algorithm of GraphExplainer[6] is shown in Fig. 2. It is developed based on SHAP to be applicable on graph structured data. By applying this to the trained model, we can find the contribution of each node feature to the prediction for target node.

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Algorithm

Input: ind_target (target node index), A (adjacency matrix), X (node feature matrix)

for ind in ind_target do
    Generate Q randomized index lists {O_1, O_2, ..., O_Q}
    Initialization: ϕ = 0, diff_shap = 0, diff = 0
    Get model output: Y = model(A, X)
    Get target output: selected = Y(ind)

    for j in {1,2, ..., Q} do
        Generate reference node feature matrix: X_ref = X(O_j)
            Get reference output: Y_ref = model(A, X_ref)
        Get reference target output: selected_ref = Y_ref(ind)
        ϕ = ϕ + gradient(X_ref) * (X − X_ref)
        diff = diff + selected − selected_ref

    ϕ_ind = ϕ/Q
    diff_shap = sum(ϕ_ind)

    if abs(diff_shap − diff) / abs(diff) > tolerance then
        Break and show error

    Output: ϕ_ind ∈ ℝ^(N×F)
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Fig. 2 Pseudocode for GraphExplainer[6]

6. Switzerland data

We collect the data in Switzerland as the model inputs. We use time series data with eight timesteps (1910, 1930, 1950, 1960, 1970, 1980, 1990 and 2000) including population, railway and road network information, origin-destination travel time for railway and road transport respectively, and Gross National Income. Map of municipality and digital elevation model in 200-meter grid are also utilized. We use 2833 municipalities where the above-mentioned information is complete.

7. Results

(1) Model performance

We pair the data into input and ground truth data, and split them into four training and two testing datasets. The prediction performance of the model is tested for population, TSA-railway and TSA-road predictions respectively. The model shows acceptable accuracy (all R2 above 0.68) for three predictions and better performance than time series analysis model.

(2) Interpretation by SHAP

Fig. 3 shows an example of visualization for TSA-railway prediction in La Chaux-de-Fonds. La Chaux-de-Fonds and Le Locle have coherent urban planning by the virtue of watchmaking industry. In the early 20th century, we can observe population of both towns tend to induce the development of railway transport in La Chaux-de-Fonds; road transport in Le Locle also contributes positively maybe due to the need of cooperation of railway and road transport. We can also infer from the negative contribution of population and TSA-railway to railway transport in 1990 that development railway transport might reach the stable state.

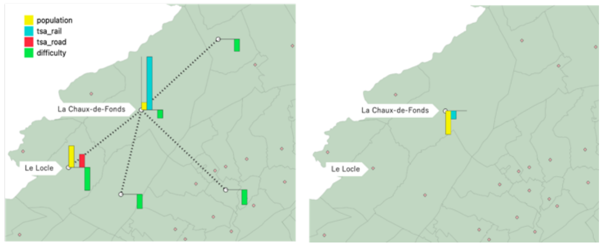

Fig. 3 SHAP values for TSA-railway prediction on La Chaux-de-Fonds in 1930 (left) and 1990 (right)

6. Conclusion

This research proposed a new method for long-term regional development prediction by deep learning, and it shows better performance than simple time series analysis model. Moreover, interpretation of the deep learning model using SHAP also shows rational results that can be confirmed in the discussion of specific municipalities. It is worth noting that this regional development prediction model is flexible to utilize various information and can also be applicable for other countries or regions.

References

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