URBAN GROWTH PREDICTIONS WITH DEEP LEARNING AND GEOSEMANTICS

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INTRODUCTION

This work outlines a novel approach for the prediction of urban growth. The method extracts semantic information of geospatial data and predicts if urban and non-urban areas are going to change in the future, using a deep neural network. The scored prediction accuracy is higher than any other urban growth prediction model. This superiority is based on two novelties: (1) The effective modeling of the geospatial configurations using semantics, (2) the use of deep learning. The proposed method is therefore an effective tool to predict one of the global challenges of urban sprawl and support the future development strategies.

EXPERIMENTS/FUNDAMENTAL OF THE PROBLEM/EXAMINATIONS

Spatial predictions are identified as one of the key aspects of Digital Earth [1]. Accordingly, spatio-temporal predictions, such as urban growth and land cover change, provide an effective tool for minimizing urban sprawl, which is a complex phenomenon that has severe environmental, social, and economical consequences. Taking the necessary measures against these negative consequences requires sound urban development strategies [2, 3]. Predictions of dynamic urban patterns have an essential role in providing optimal solutions for impact assessment of alternative scenarios and planning policies [4]. However, analysis and interpretation of these temporal, irregular urban patterns require innovative approaches.

Figure 1: Urban (dark grey) and non-urban (light grey) areas.Red areas indicate areas which changed from non-urban to urban.

The proposed methodology starts by obtaining linked data from LinkedGeoData for 2012. This data is semantically annotated vector data. The semantic information expresses the type of an geo-object such as restaurant, path, bus station as well as its geometry. OWL classes in an OWL ontology describe this semantics. The geometry can be a linestring, a point or a polygon. Afterwards, data on the imperviousness change from 2012 to 2015 is obtained from Copernicus. This data describes which non-urban areas have changed to urban areas , vice versa, as well as did not change. Thus, there are 4 different classes: (1) Urban to non-urban, (2) non-urban to urban, (3) urban no change and (4) non-urban no change. The propsed method ultimately enables to predict these changes for 2015 by utilizing the data from LinkedGeoData. For this purpose the methods transforms the obtained linked data into feature vectors. Each feature describes the spatial constellation of geo-objects of different OWL classes to a specific location. Every feature vector is than labeled with one of the four urban change classes for the corresponding location. Subsequently a deep neural network is trained and tested with these feature vectors in a 10 fold cross validation manner. Approximately 50.000 samples were used for that purpose. Finally a confusion matrix is generated in order to assess the accuracy of the predictions.

RESULTS AND DISCUSSION

The overall accuracy of the presented urban growth prediction is 87.7%. The kappa coefficient is 0.81. The results not only proof the feasibility of the method but as well as its superiority compared to other urban growth prediction models. Additionally, it demonstrates that a task such as urban growth prediction which commonly is based on remotely sensed imagery, can instead rely on geospatial semantics and therefore reveal its potential for this type of task. Furthermore deep learning has been identified as a promising tool machine learning algorithm for spatial predictions.

CONCLUSION

The presented method enables to predict the growth of urban areas and therefore provides a vital tool to control urban sprawl and support a sustainable development of cities. Additionally it provides an approach which is capable to perform spatial prediction with geospatial semantics. Several potential future works can be identified: Such as the use of advanced sensory for extracting geospatial semantics of the environment in order to increase the prediction accuracy. Within that scope Augmented Reality could be used to derive a deeper understanding of the semantics of the environment and therefore provide better spatio-temporal predictions. Another fruitful topic is the data fusion with remotely sensed imagery in order to discriminate classes more efficiently. It has to be noted that the presented approach is generic. Thus, other phenomena than urban change can be subject to such a prediction, such as real estate price development or spatial density for crime.

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