Inferring socio-economic, transport and environmental inequalities using both street network and urban image features

Stephen Law, UCL Geography, London, UK and The Alan Turing Institute, UK
Kimon Krenz, UCL Bartlett School of Architecture, Space Syntax Laboratory, UK
Alan Penn, UCL Bartlett School of Architecture, Space Syntax Laboratory, UK.
Stephen.law@ucl.ac.uk, kimon.krenz@ucl.ac.uk, alan.penn@ucl.ac.uk

Introduction

Machine learning methods have achieved human-level accuracies in many computer vision and natural language processing tasks. These techniques have led to advances in not only medical imaging, gaming and robotics but also in urban analytics. Previous research [1] has begun to apply these learning methods to estimate socio-economic indicators using urban imagery. However, limited research studied how different urban form data can be combined to improve its performance. The aims of this research is to test and explore the efficacy on combining three sources of urban data to make inferences on socio-economic, transport and environmental indicators for the case study of Greater London, UK.

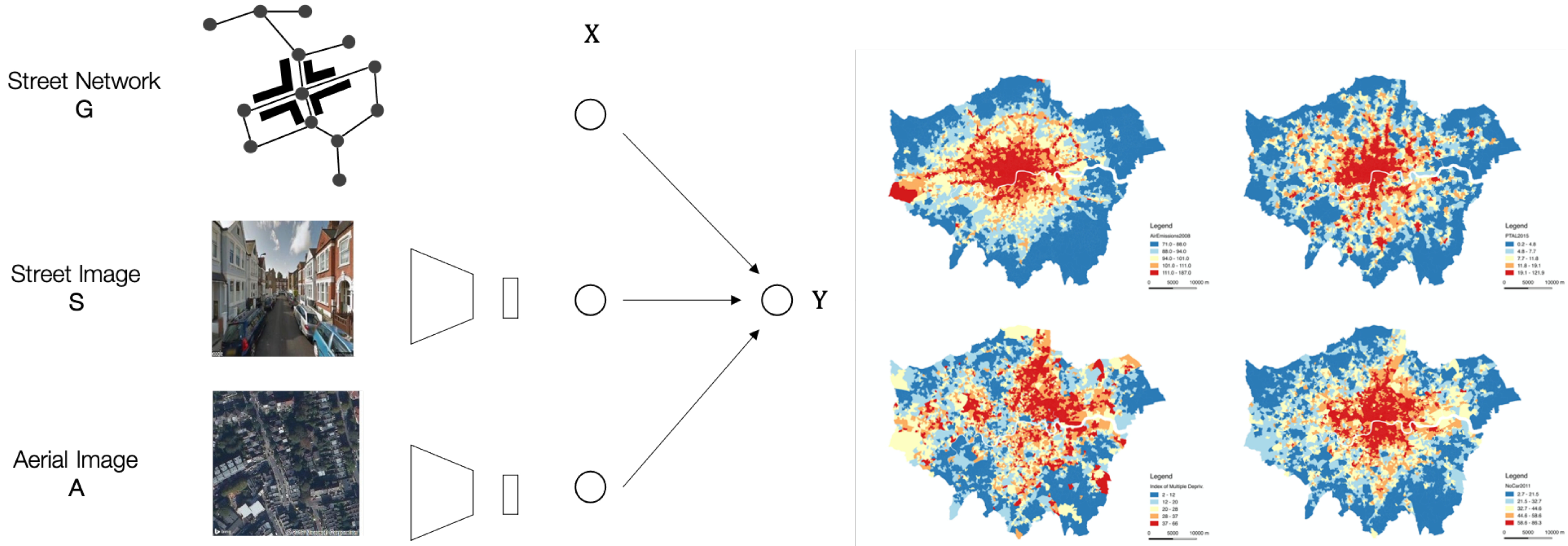

Fig 1. Method pipeline. Combining street networks, street image and aerial image data to estimate socio-economic, transport and environmental indicators

Research Approach

We differ from previous research on using a multimodal machine learning approach [2] that combines different urban form data such as street networks, street image and aerial image data to estimate indicators retrieved from the UK Census such as air emission levels, Index of Multiple Deprivation, the percentage of the population that do not use a car as a method of travel to work and Public Transport Accessibility Levels in London at the Lower Super Output Area level LSOA.

Method Pipeline

Our pipeline extracts space syntax street network features (Closeness and Betweenness) [3] from the OS ITN road network data using depthmapX, and Convolutional Neural Network visual features [4] from Google StreetView and Bing aerial images using Tensorflow/Keras in Python. These features are then concatenated to predict the four performance indicators.

Model

We explore the use of both linear and nonlinear methods to fuse street network and urban images on making inferences for the four indicators. We consider two supervised learning model. The first is a linear regressor $f_{lin}(x)$ which learns a linearly weighted combination of the features into making a prediction. The second is a Gaussian Process model which is a Bayesian approach to regression specified by a mean and covariance function $f_{GP}(x) \sim GP(m(x),k(x,x'))$ in making a prediction.

Results

We achieved an out-of-sample R2 of 63.3% (MSE 0.201) predicting the Index of Multiple Deprivation IMDScore, R2 of 80.8% (MSE 0.353) predicting Air Emissions, R2 of 69.4% (MSE 0.023) predicting public transport accessibility levels and R2 of 86.0% (MSE 0.005) predicting the percentage that do not use car as a method of travel to work in London at the LSOA level.

	Linear		NonLin (GP)	
	R2	MSE	R2	MSE
Air Emissions	69.70%	0.207	80.80%	0.201
IMD	56.20%	0.458	63.30%	0.353
NoCar	80.70%	0.007	86.00%	0.005
PTAL	66.10%	0.026	69.40%	0.023

Table 1. Regression results

Conclusions

Our research found higher predictive accuracy when including both street network and urban image data. Our research also found the use of regression methods that account for nonlinear associations achieve better results than a purely linear approach. These results suggest the use of multiple urban data can provide a good proxy of estimating socio-economic, environmental and transport outcomes.

The implication is the ability to predict urban performance indicators using easily accessible datasets without extensive surveys. This is particularly useful in data sparse context such as in the developing world and where large surveys such as the UK Census are expensive.

Further research is necessary; i. to test the extent these methods can generalises on different UK cities and across time, ii. to examine the predicted residuals on analysing under and overperforming areas and iii. to apply explainable/interpretable AI methods to examine the reliability of these models.

Data Sources

Street network data. (2020) Ordnance Survey Integrated Transport Network Data.
Social Economic data. (2011) UK Census data.
StreetView data. (2017) Google StreetView API
Aerial data. (2017) Bing Image API.

References

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