Real-time Machine Learning Prediction of an Agent-Based Model for Urban Decision-making (Extended Abstract)

Extended Abstract

Yan Zhang
Massachusetts Institute of Technology
Cambridge, Massachusetts

Arnaud Grignard
Massachusetts Institute of Technology
Cambridge, Massachusetts

Kevin Lyons
Massachusetts Institute of Technology
Cambridge, Massachusetts

Alexander Aubuchon
Northeastern University
Boston, Massachusetts

Kent Larson
Massachusetts Institute of Technology
Cambridge, Massachusetts

ABSTRACT

CityMatrix is an urban decision support system that has been developed to facilitate more collaborative and evidence-based urban decision-making for experts and non-experts. Machine learning techniques have been applied to achieve real-time prediction of an agent-based model (ABM) of city traffic. The prediction with a shallow convolutional neural network (CNN) is significantly faster than performing the original ABM, and has enough accuracy for decision-making. The result is a versatile, quick, accurate, and computationally efficient approach to provide real-time feedback and optimization for urban decision-making.

KEYWORDS

machine learning, urban decision-making, agent-based modeling, real-time feedback

ACM Reference Format:

Yan Zhang, Arnaud Grignard, Kevin Lyons, Alexander Aubuchon, and Kent Larson. 2018. Real-time Machine Learning Prediction of an Agent-Based Model for Urban Decision-making (Extended Abstract). In *Proc. of the 17th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2018), Stockholm, Sweden, July 10–15, 2018,* IFAAMAS, 3 pages.

1 INTRODUCTION

Rapid urbanization brings tremendous challenges. Currently, community engagement of urban decision-making is ineffective, uninformed, and happens in late stages. There is a the lack of rapid-prototyping tools for both experts and non-experts to explore multiple scenarios collaboratively. Designing and planning with traditional tools requires years of training, making it difficult to use these traditional tools in a public event.

CityMatrix [8] was developed to address the urban challenges above. CityMatrix is an urban decision support system with a tangible user interface, real-time feedback of multiple urban simulations, and optimized suggestions. It was designed to facilitate public engagement with multiple parties of stakeholders, both professionals and nonprofessionals. The tangible user interface (TUI) [5] and intuitive visualization allows the stakeholders explore rapidly and collaboratively the urban configurations without prior knowledge (Fig. 1). CityMatrix uses machine learning algorithms to predict multiple sophisticated urban simulations. It is a versatile, quick, accurate, and low-cost method compared to traditional options.

Proc. of the 17th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2018), M. Dastani, G. Sukthankar, E. André, S. Koenig (eds.), July 10–15, 2018, Stockholm, Sweden.

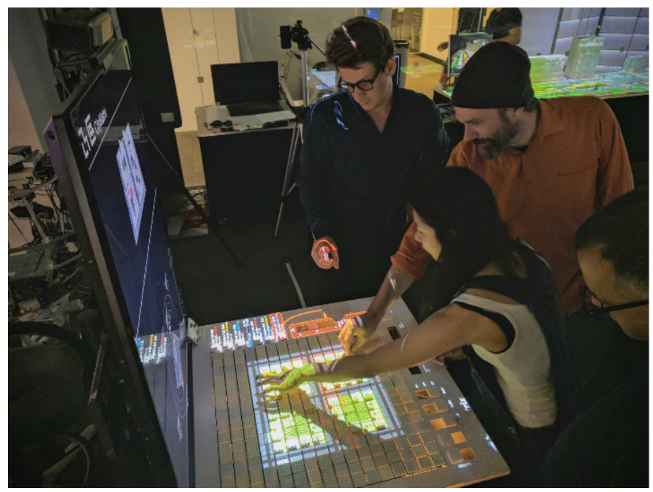

Figure 1: CityMatrix – an urban decision support system with a tangible user interface, real-time feedback of multiple urban simulations, and optimized suggestions

2 METHODOLOGY

2.1 Design of CityMatrix

Input: CityMatrix allows the users to change the layout of land-use by moving optically-tagged Lego modules. Each cell can be changed into six types of buildings, roads, and courtyards. The users can add, remove or exchange the existing bricks. The slider and selection dock on the side allows users to change urban density (Fig. 1).

Output: The real-time feedback includes heat-map visualization and a radar-chart of the urban performance, which includes density, diversity, energy, traffic, and solar performance. This helps users better understand the consequences of their decisions (Fig. 1).

Software Architecture: The CityMatrix system architecture contains four main layers and creates a loop for each move from the users: user input, urban performance evaluation, optimization suggestion, and visualization output (Fig. 2).

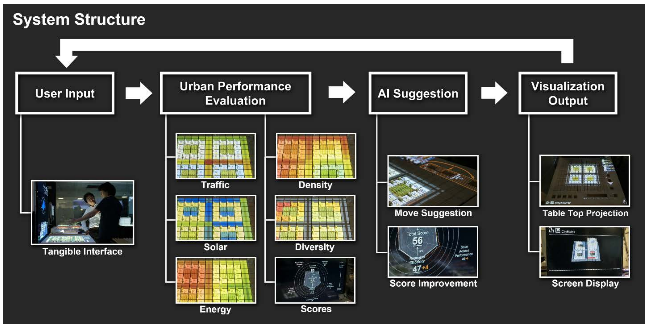

Figure 2: Software structure of CityMatrix.

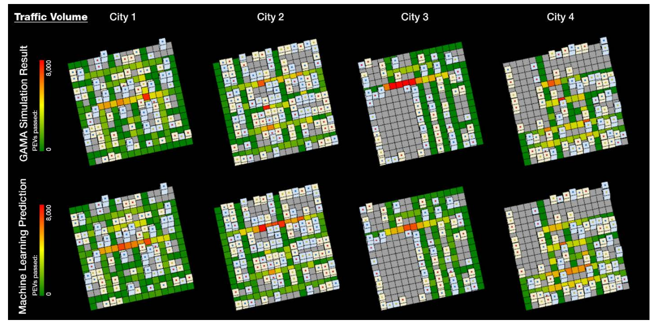

Figure 3: Comparison of the traffic volume by location for the original ABM (upper) and the predicted output (lower) of a city-configuration.

2.2 Traffic ABM Simulation

The ABM simulates the traffic volume and user wait-time in a city district, assuming all trips were performed by a highly efficient shared-mobility system composed of a fleet of autonomous vehicles.

GAMA [4][7], a programming environment for building spatially explicit agent-based simulations and visualizations [3], was used for the ABM.

The prediction model needs a training data set containing 10,000 instances of traffic simulation results to reach desired prediction precision (R2 of 0.8). A batch process takes multiple input city-configurations, runs a traffic simulation model on each of them, and provides an output for each road cell. A single traffic simulation represents 24 hours divided in steps of 1 minute. It is completed in 1 minute using a single CPU thread of 2.8 GHz with 8 GB RAM. All simulation tasks were distributed to eight computers, and the completion of 10,000 simulations took 18 hours.

2.3 ML Prediction

The 10,000 city-configurations were generated and simulated in GAMA. 7,000 were used as a training set and 3,000 used as a test set. Multiple machine learning models, different parameters and input feature combinations were tested for each algorithm to achieve the best R2 without overfitting to our training set. Our CNN, a simple, three-layer, convolutional neural network (CNN) [6] (implemented with TensorFlow [1] and Keras [2]), provided the most significant R2 and visually qualitative results when compared with the ground truth from the GAMA simulations. The architecture of the CNN contained only three convolutional layers. It is effective due to the small data input size ($19 \times 19 \times 2$ grid) and smaller dataset size (7,000 training data points).

2.4 Results

After training our models and tuning parameters to achieve the best possible accuracy, with Linear Regression, the best R2 achieved was 0.571. With CNN, the best R2 achieved was 0.86. Figure 3 shows comparisons of the GAMA traffic simulation results (upper) and the machine learning predictions (lower) of the traffic volume heat-map respectively in four different city examples. The CNN could be run on an input city-configuration in under 10 milliseconds, as opposed to the ABM model which took about 1 minute, using a computer with the same configuration.

2.5 Optimization Suggestion

Each time users make a change to the city, the server performed a random search over the possible moves from that state and provide users the most optimized move option based on the users objectives. Users set sliders to determine which aspect of the urban performance they want the algorithm to optimize, and the positions of these sliders determine the weights of these aspects.

3 CONCLUSION

3.1 Evaluation

To understand and evaluate the user-interface and the optimization suggestions functionality of CityMatrix, five pilot-user tests were conducted (group of 4, 20 users in total). Each group had users from both professional and non-professional backgrounds related to urban decision-making. Both software log data and answers to a questionnaire were collected to analyze the usability of CityMatrix.

The pattern found in the software log data analysis shows that the optimization suggestions helped stabilize and improve the total score of group's collective decisions over time. Questionnaire data provided a perspective to some of the topics about the usefulness of the system. 85% of the users found the optimization suggestions to be helpful.

3.2 Contribution

Evidence-Based Democratic Decision Making: CityMatrix was designed to promote collaborations among a broad range of stakeholders to enhance the accessibility and efficiency of public engagement events.

Real-time Simulation Prediction: A versatile, quick, accurate, and low-cost method was developed to enable real-time feedback of multiple complex simulations for stakeholders with minimized computational resources.

Optimization Suggestion: The optimization suggestion frees the users from excessive quantitative considerations and enabled them to improve the quality of their urban decisions.

REFERENCES

[1] Martín Abadi, Ashish Agarwal, Paul Barham, Eugene Brevdo, Zhifeng Chen, Craig Citro, Greg S Corrado, Andy Davis, Jeffrey Dean, Matthieu Devin, et al. 2016. Tensorflow: Large-scale machine learning on heterogeneous distributed systems. *arXiv preprint arXiv:1603.04467* (2016).

[2] François Chollet. 2017. Keras (2015). *URL http://keras. io* (2017).

[3] Arnaud Grignard and Alexis Drogoul. 2017. Agent-Based Visualization: A Real-Time Visualization Tool Applied Both to Data and Simulation Outputs. (2017).

[4] Arnaud Grignard, Patrick Taillandier, Benoit Gaudou, Duc An Vo, Nghi Quang Huynh, and Alexis Drogoul. 2013. GAMA 1.6: Advancing the art of complex agent-based modeling and simulation. In *International Conference on Principles and Practice of Multi-Agent Systems*. Springer, 117–131.

[5] Hiroshi Ishii. 2008. The tangible user interface and its evolution. *Commun. ACM* 51, 6 (2008), 32–36.

[6] Mathias Niepert, Mohamed Ahmed, and Konstantin Kutzkov. 2016. Learning convolutional neural networks for graphs. In *International Conference on Machine Learning*. 2014–2023.

[7] Patrick Taillandier, Duc-An Vo, Edouard Amouroux, and Alexis Drogoul. 2010. GAMA: a simulation platform that integrates geographical information data, agent-based modeling and multi-scale control. In *International Conference on Principles and Practice of Multi-Agent Systems*. Springer, 242–258.

[8] Yan Zhang. 2017. *CityMatrix - An Urban Decision Support System Augmented by Artificial Intelligence.* Master's thesis. Massachusetts Institute of Technology.