# Improving Urban Planning Through Agent-Based Modeling and Q-Learning

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## Challenges of Urban Planning

- Urban systems are complex
- Small local changes can cause large ripple effects
  - Phantom traffic jam

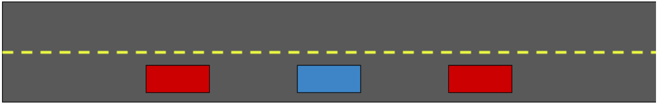

Figure 1: Highway Traffic

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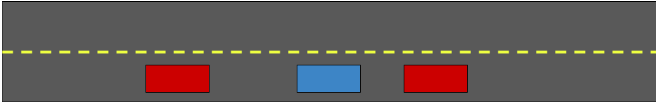

Figure 2: First Car Slows Down

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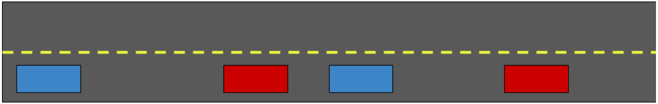

Figure 3: Second Car Also Slows Down

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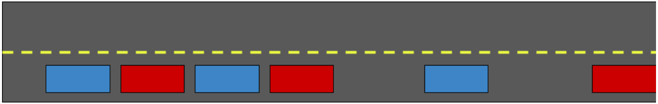


Figure 4: Phantom Traffic Jam

## Limitations of Traditional Models

- Use average and aggregate data
- Fail to capture individual decision-making
- Cannot represent emergent behavior

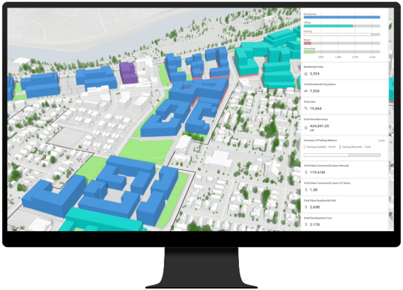


Figure 5: ArcGIS modelling Software

## What Are Agents?

- Agents are individual decision-makers (cars, people, businesses, etc.)
- Observe $\rightarrow$ decide $\rightarrow$ act
- Each follows simple rules, but their interactions produce emergent city patterns

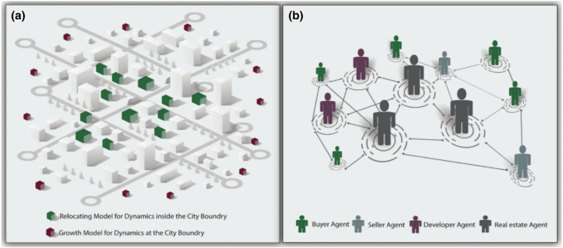



Figure 6: SmithOS: Agent-Based Modelling in Urban Planning

## Agent-Based Modeling

- Simulate interacting agents in a shared environment
- Allow planners to test changes before real-world implementation

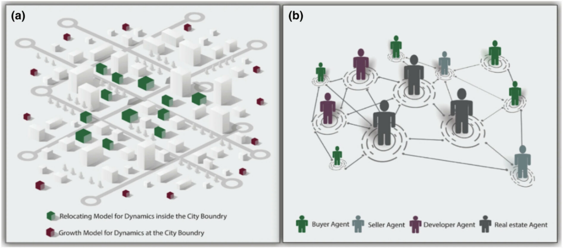



Figure 6: SmithOS: Agent-Based Modelling in Urban Planning

## Case Study: Bridge Construction in Sejong City (Yun et al., 2022)

- Simulates how a new bridge would affect citywide traffic patterns
- Used a detailed ABM with 300,000 virtual residents
- Integrated real data: demographics, road networks, bus routes, workplaces

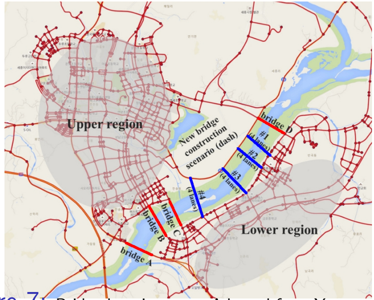



Figure 7: Bridge locations map Adapted from Yun et al. (2022)

# Bridge Map

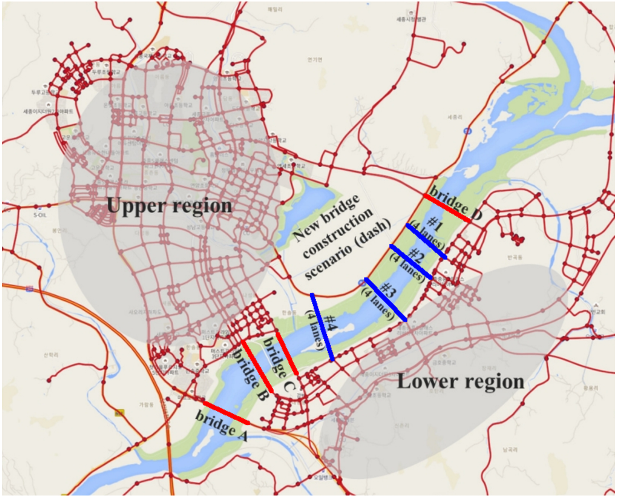



Figure 7: Bridge locations map Adapted from Yun et al. (2022)

## How the Model Worked

- Agents represented residents with daily routines (home, work, travel)
- Each agent chose transport mode (walk, drive, bus) based on probability
- Model simulated 24 hours of movement and traffic across the network

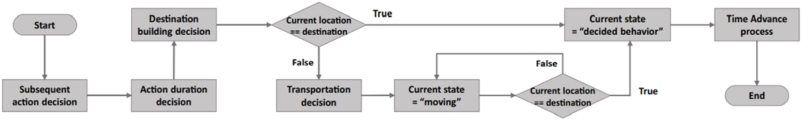
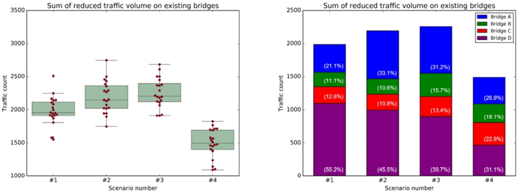



Figure 8: Agent behavioral modeling

## Findings: Bridge Placement and Traffic Dispersion

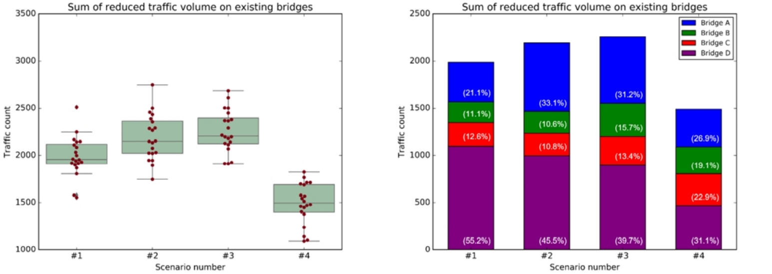
- Adding a bridge reduced congestion but effects varied by location
- Scenario 3 (mid-position bridge) achieved most balanced traffic flow
- Demonstrated ABM's value in testing infrastructure before construction




(a) Morning peak (8:00–10:00) traffic volume (b) Contribution of existing bridges to total reduction

Figure 9: Traffic reduction comparison by bridge scenario

# Traffic Reduction by Bridge Scenario




(a) Morning peak (8:00–10:00) traffic volume

(b) Contribution of existing bridges to total reduction

Figure 9: Traffic reduction comparison by bridge scenario

## Reinforcement Learning (RL)

- A type of machine learning based on trial and error
- Receives rewards or penalties for its actions
- Goal: maximize cumulative reward over time

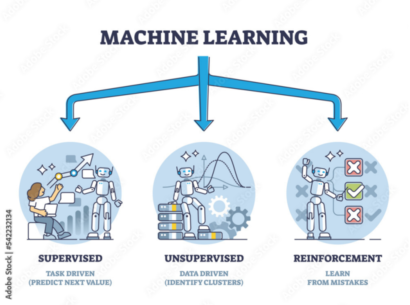



Figure 10: Branches of Machine Learning. Adobe Stock

## Components of RL

- Agent - Learns a policy to choose actions
- Policy - probabilities of different actions
- Environment - Responds to actions with new states and rewards

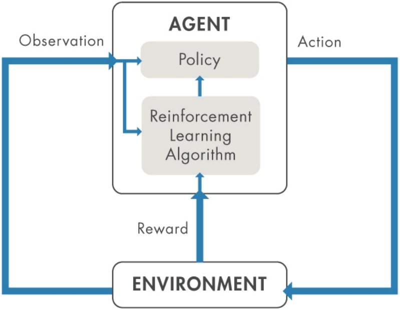
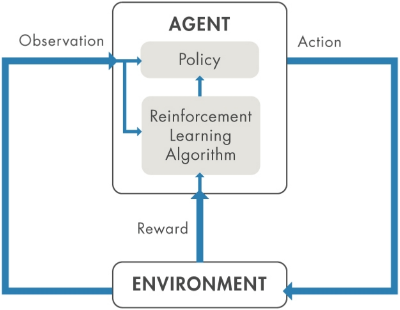



Figure 11: RL agent

## Components of RL cont.

- State - Current situation of the system
- Action - Decision the agent takes
- Reward - Feedback signal guiding learning

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## Q-Learning

- Q-Learning is a type of Reinforcement Learning where agents learn the value of actions in different states
- Uses a Q-table to store expected rewards for state-action pairs
- Updates values using the Q-learning update rule

| Q-Table | | Actions | | | | |
|---|---|---|---|---|---|---|
| | | Action 1 | Action 2 | ... | Action n-1 | Action n |
| States | State 1 | 0.789112 | 0.745642 | ... | 0.212485 | 0.256545 |
| | State 2 | 5.123455 | 5.11565 | ... | 5.156545 | 4.155612 |
| | ... | ... | ... | ... | ... | ... |
| | State n-1 | 2.156454 | 2.15567 | ... | 2.144423 | 2.454658 |
| | State n | 6.156212 | 6.154556 | ... | 6.145441 | 6.444444 |

Figure 12: Q-Table

## Q-learning update rule - SARSA

$$Q(S, A) \leftarrow Q(S, A) + \alpha(R + \gamma Q(S', A') - Q(S, A))$$

where:

- $S$: the current state
- $A$: the action taken by the agent
- $R$: the reward received for taking action $A$
- $S'$: the next state the agent transitions to
- $A'$: the best next action in state $S'$ in state $S$
- $\gamma$ (Gamma): the discount factor balancing immediate and future rewards
- $\alpha$ (Alpha): the learning rate determining how much new information influences old Q-values

## Innovative Urban Design Simulation (Glaß et al., 2023)

- Explores how agents can behave more realistically in city simulations.
- Focus area: HafenCity district in Hamburg, Germany.
- Combines Agent-Based Modeling with Reinforcement Learning to simulate pedestrian mobility.

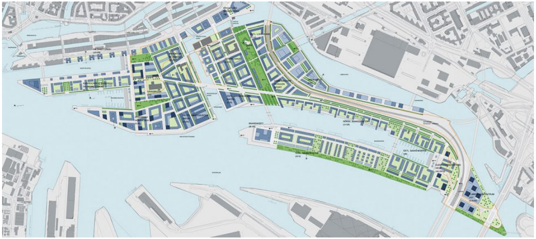

Figure 13: HafenCity waterfront redevelopment area, Hamburg

## Research Question and Method

- Question: How can agents behave more realistically to reflect citizens' mobility behavior?
- Agents modeled as pedestrians navigating between 10 real types of urban locations
- Used survey data from 130 citizens to assign "happiness scores" to each location
- Q-Learning algorithm trained agents to maximize cumulative happiness

## Results and Findings

- Agents learned to visit locations yielding higher happiness scores
- Movement paths evolved from random to realistic pedestrian routes
- Q-Learning produced plausible mobility data without massive computation

## Acknowledgements

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# Questions?

# References

Yun, T.-S., Kim, D., Moon, I.-C., & Bae, J. W. (2022). *Agent-Based Model for Urban Administration: A Case Study of Bridge Construction and its Traffic Dispersion Effect.* Applied Sciences, 12(11), 5383.

Glaß, A., Noennig, J. R., Bek, B., Glaß, R., Menges, E. K., Okhrin, I., Baddam, P., Sanchez, M. R., Senthil, G., & Jäkel, R. (2023). *Innovative Urban Design Simulation: Utilizing Agent-Based Modelling through Reinforcement Learning.* In 6th International Conference on Computational Intelligence and Intelligent Systems (CIIS 2023), Tokyo, Japan.