Multi-Agent Reinforcement Learning for Assessing False-Data Injection Attacks on Transportation Networks

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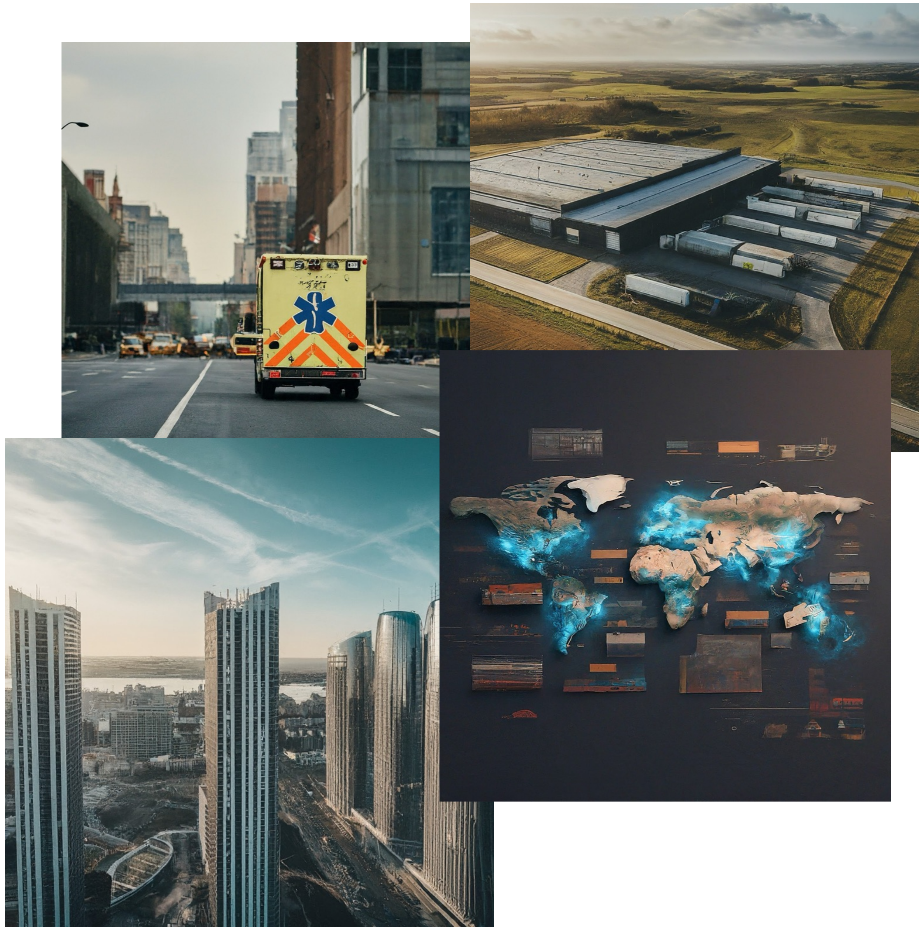
WHY TRANSPORTATION SERVICES ARE IMPORTANT?

- Provide access to:
  - Education
  - Healthcare
  - Emergency services
- Contribute to:
  - Economic growth
  - Logistic services
  - Delivery of essential goods

- Disruptions can lead to:
  - Financial losses
  - Physical damage
  - Bodily harm



Images from Gemini Advanced

VULNERABILITY OF TRANSPORTATION NETWORKS

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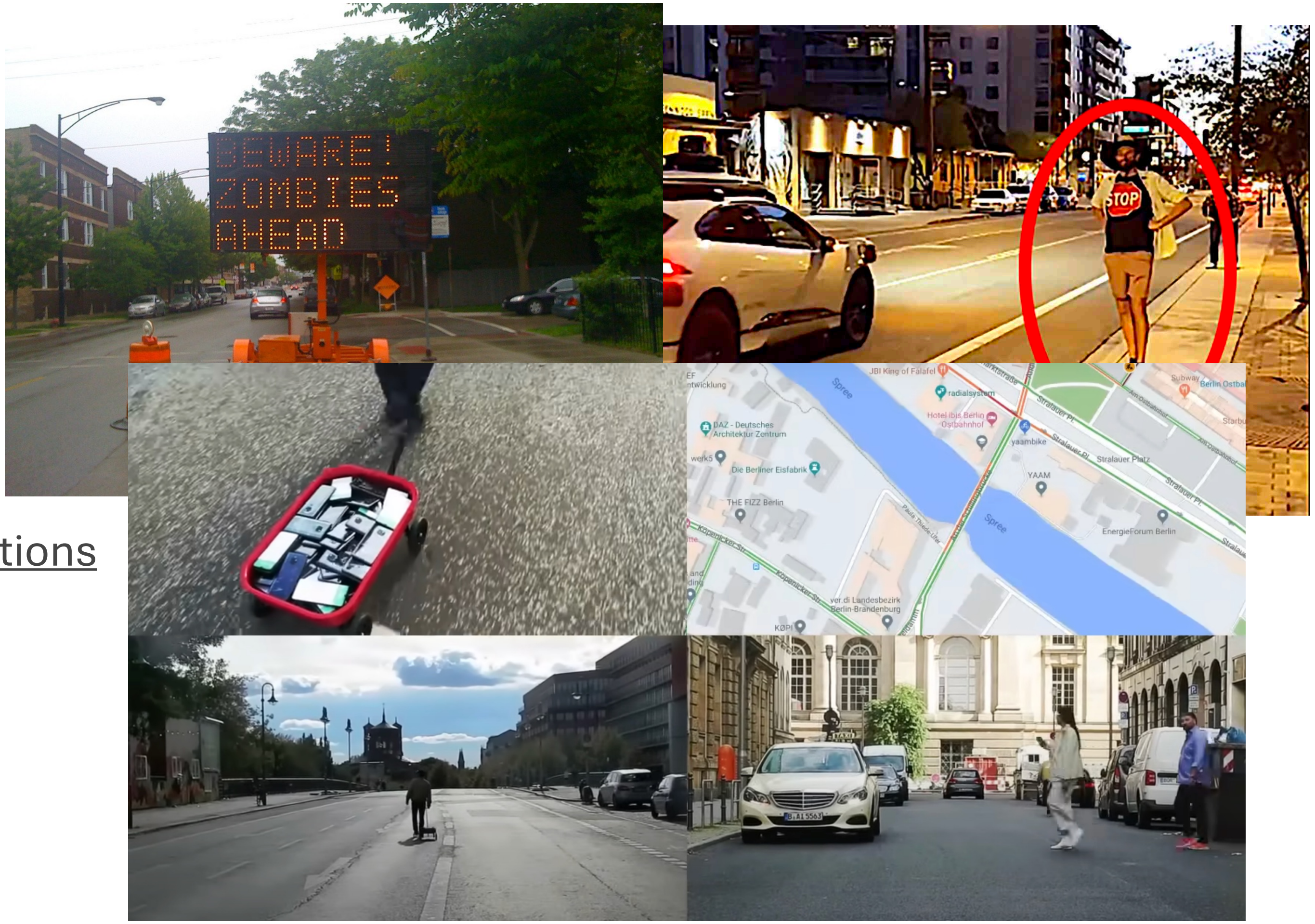
- SMS **Disinformation**
- Traffic **Sign** Manipulation
- Traffic **Signal** Manipulation
- <u>**False Data Injection** in Navigation Applications</u>



Images from https://notthebee.com/, https://9to5google.com/, and https://statescoop.com/

TRANSPORTATION NETWORK MODEL

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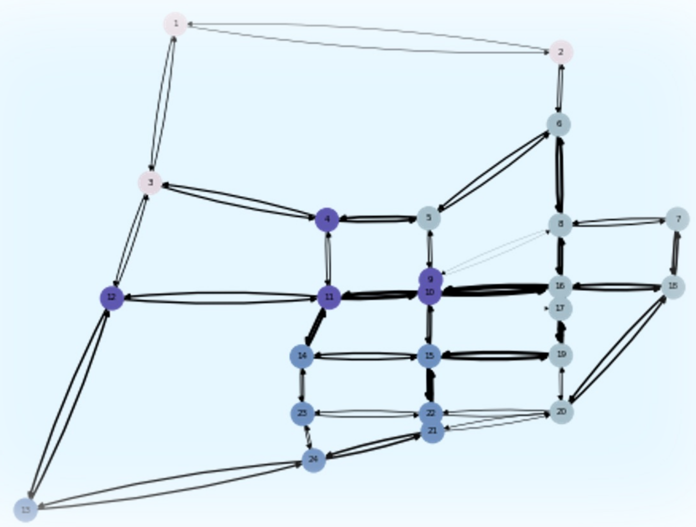
- A **directed graph** $G = \langle V, E \rangle$ defines the transportation network's roads and intersections
- **Congestion Model**
  - Each road has a given free-flow travel time
  - The more vehicles on a given road, the higher the actual travel time
- **At each intersection**, drivers take the **shortest path to their destination** based on a navigation application

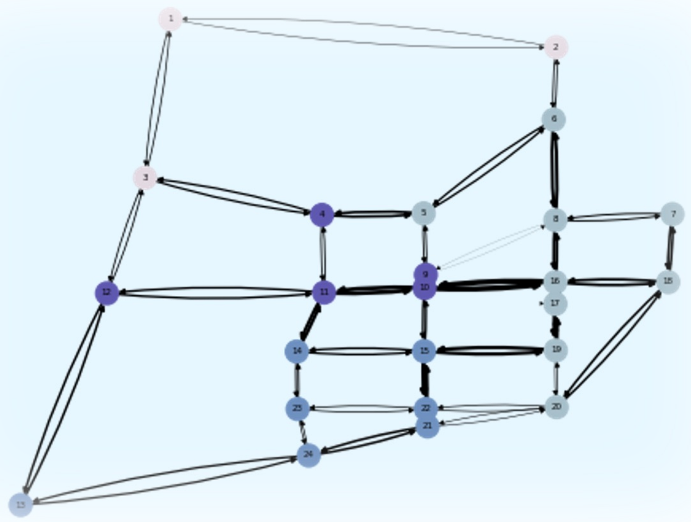


Sioux Falls, SD

FALSE DATA INJECTION (THREAT) MODEL

- The attacker has a budget to perturb perceived travel times
- The attacker perturbs perceived travel times at each step
- The drivers take a longer path due to perceived congestion

- **Strong threat model**:
  The attacker has full observation of the network
  - Vehicle locations
  - Vehicle destinations



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PROBLEM FORMULATION

- **Assessing the extent of the damage** is the prerequisite for defense
  - An attack oracle can be used to **generate worst-case** attacks for detection and mitigation schemes
- False data injection attacks may happen **over a time horizon**
- **Uncertainty** of the environment

- The attacker can manipulate observed congestion in a navigation application
  - Restricted to a **fixed budget**
  - Able to manipulate **any road link**
  - Aiming to cause **worst-case impact**

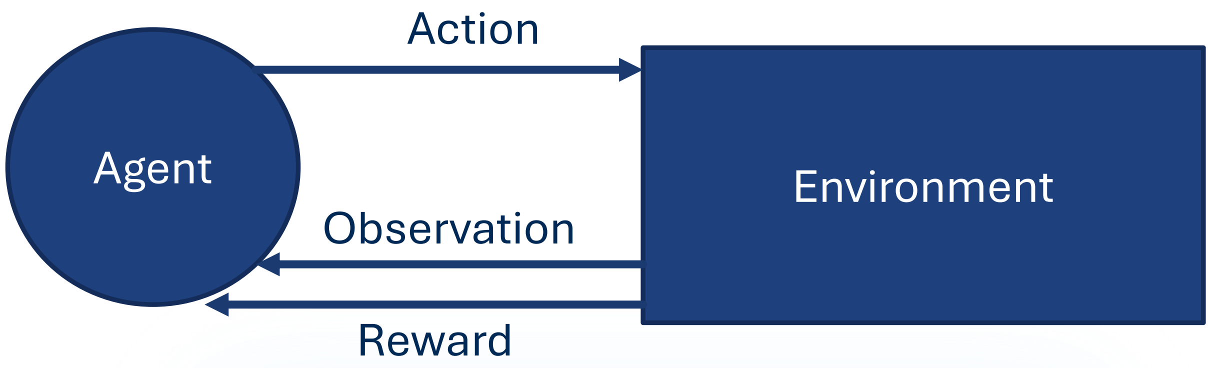
$MDP = \langle S, A, R, T \rangle$

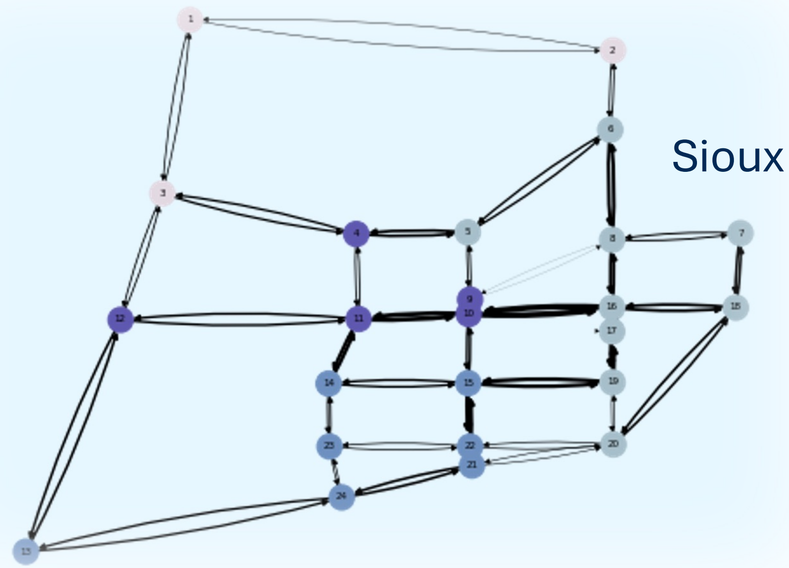
$S \mapsto$ state space
$A \mapsto$ action space
$R(s,a) \mapsto$ rewarding rule
$T(s,a) \mapsto$ transition rule

- Leading to: **Markov Decision Process (MDP)** formulation
  - Find a policy, mapping from **network state** to **perturbations**, that maximize **total travel time**

REWARD, ACTION, AND STATE SPACE

- Objective
  - Goal: maximize total travel time
  - Reward: r^t = number of vehicles in traffic
- Action Space
  - Perturb observed edge travel times restricted to a budget
  - Action space: $|a^t|_1 \leq B$ and $a_e^t \geq 0$
- State Space
  - Vehicle locations and destinations





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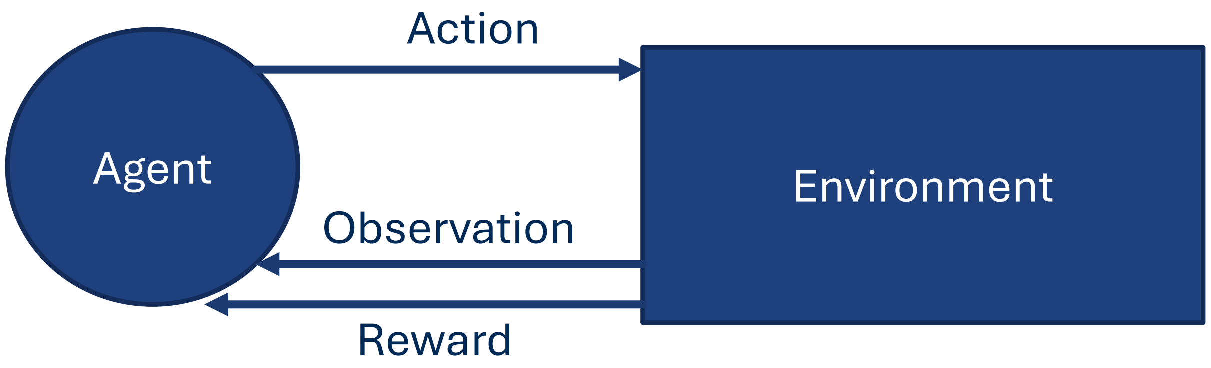
DEEP REINFORCEMENT LEARNING AS ATTACK ORACLE

- Reinforcement Learning

optimize $\pi(s^t) \mapsto a^t$

max $\mathbb{E}[\Sigma_{\tau=0}^{\infty} \gamma^\tau \cdot r^{t+\tau} | \pi]$



- **Critic**: $Q(s^t, a^t) \leftarrow r^t + \max_{a'} Q(s^{t+1}, a')$
  - Updated by gradient descent, reducing Mean Squared Bellman Error
- **Actor**: $\pi(s^t) \leftarrow \mathrm{argmax}_{a'} Q(s^{t+1}, a')$
  - Updated with gradient ascent, increasing Q

FEATURE EXTRACTION FROM COMBINATORIAL STATE

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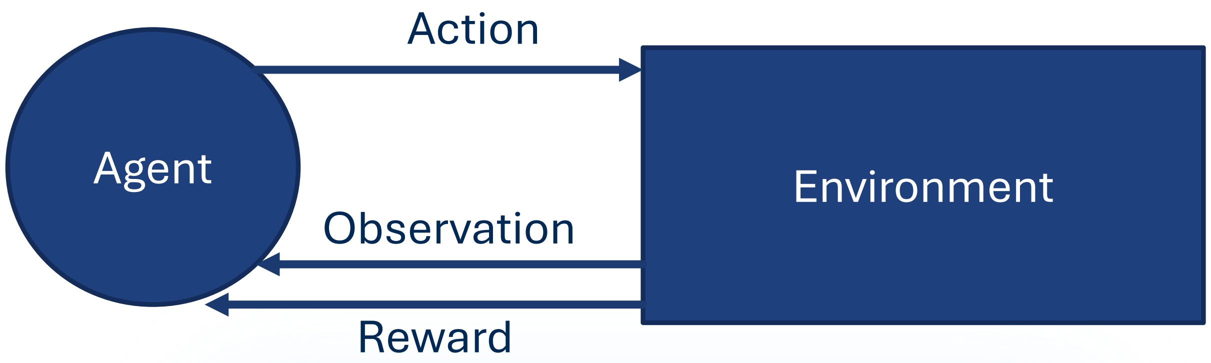
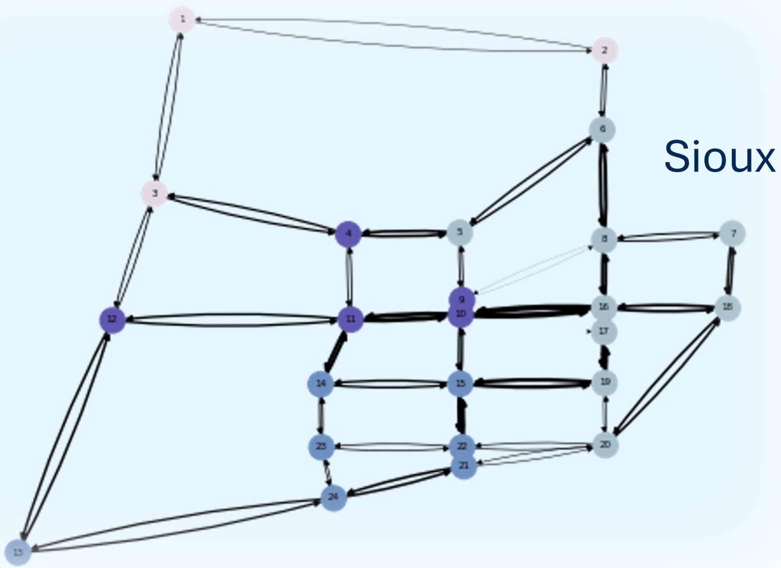
- Features for edge e
  1. Number of vehicles that are at an intersection with an unperturbed shortest path to the destination that passes through e
  2. Number of vehicles that are on an edge but will take e as the shortest path
  3. Number of vehicles that are at an intersection that will immediately take e as their shortest path without perturbation
  4. Number of vehicles currently on e
  5. Sum of remaining travel times of vehicles currently on edge e
- State represented as $|E| \times 5$ vector





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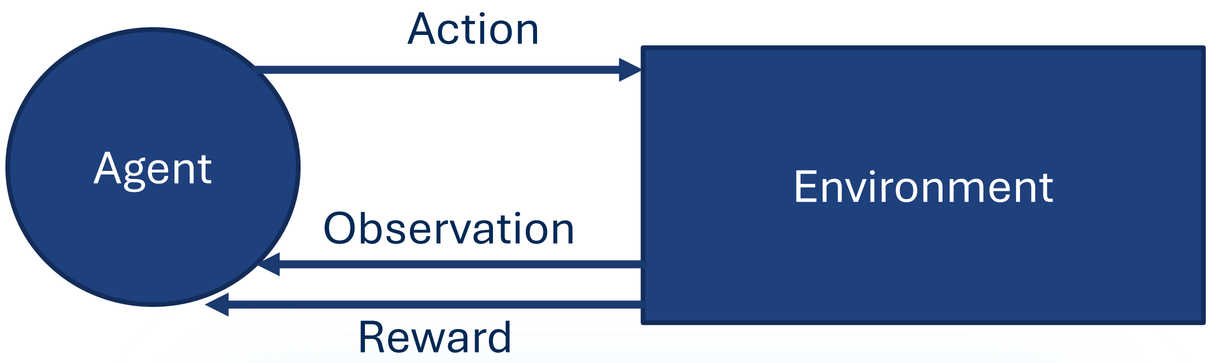
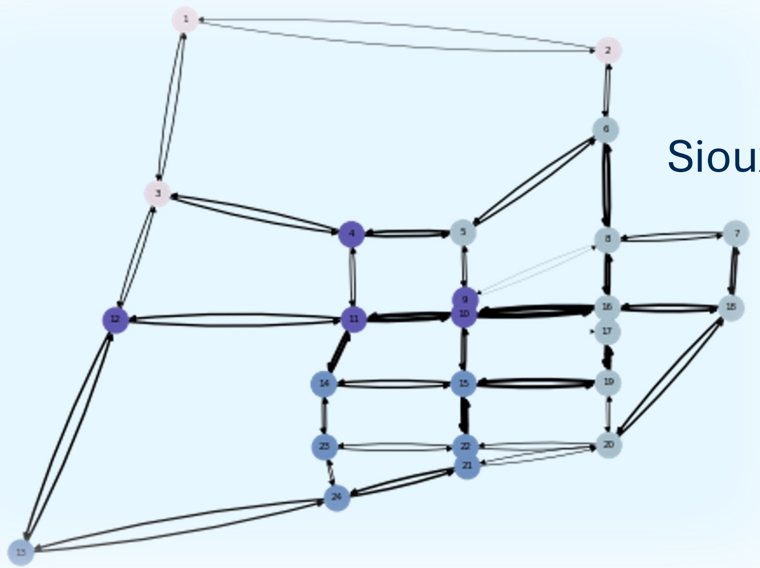
CHALLENGES FOR DEEP REINFORCEMENT LEARNING

- The attacker could output perturbations for **hundreds of city roads**
- General-purpose reinforcement learning algorithms (e.g., DDPG) are **infeasible** even for a small city
  - 24 nodes and 76 edges in Sioux Falls
  - Enormous action/observation space
- It requires **millions of samples** collected from the environment
- We need a <u>robust</u> and <u>feasible</u> attack oracle





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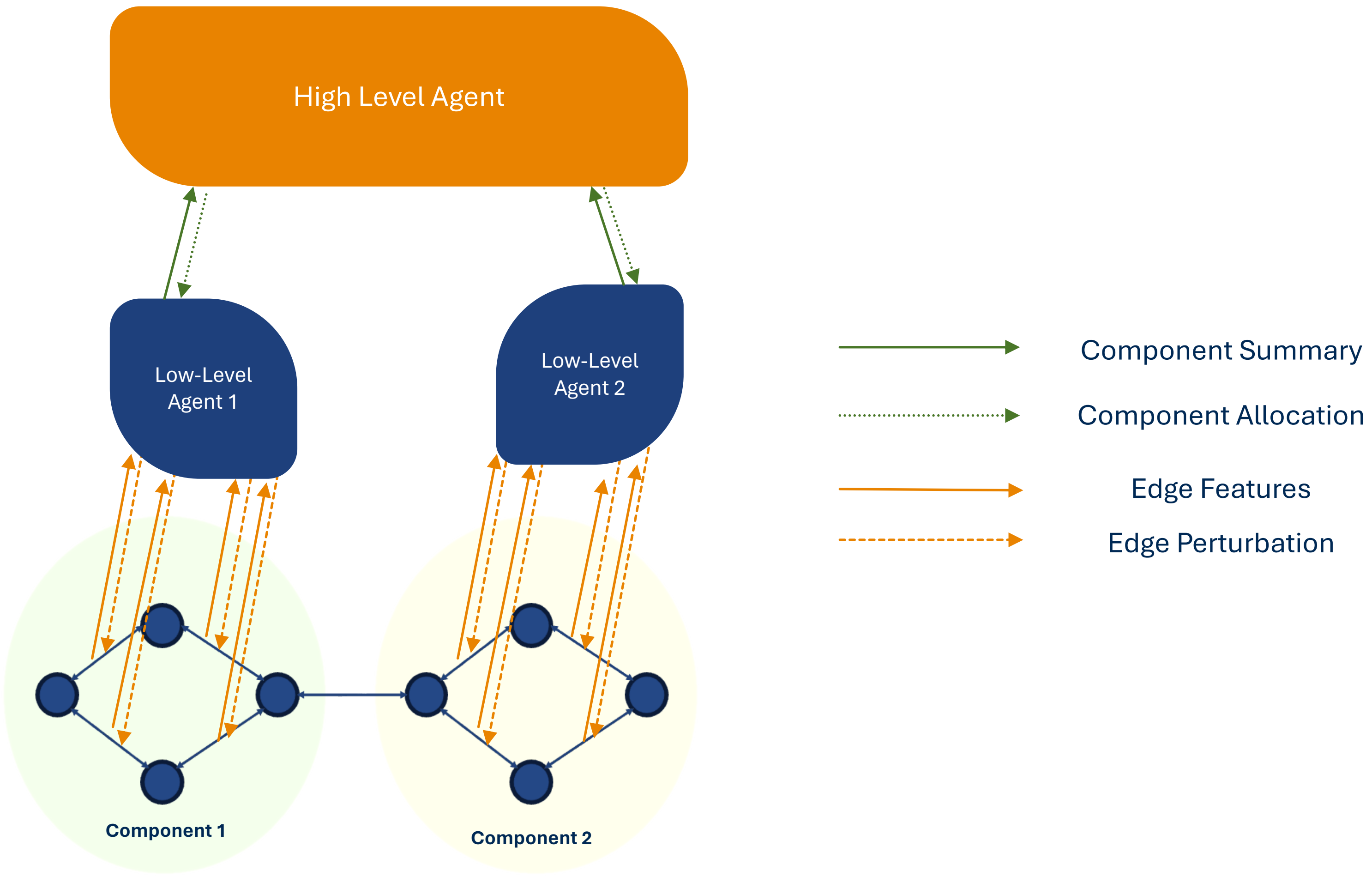
HIERARCHICAL MULTI-AGENT REINFORCEMENT LEARNING

- The idea:
  - We can **divide** the network into smaller components
  - **Low-leve**l RL agents are assigned to each component
  - A **high-level** RL agent coordinates the low-level agents

- Why a high-level coordinator?
  - The total perturbations are restricted by a budget
  - Low-level agents compete over the budget

- The high-level agent allocates the perturbation budget to the component agents
- The low-level agents distribute allocated perturbation budgets to road links

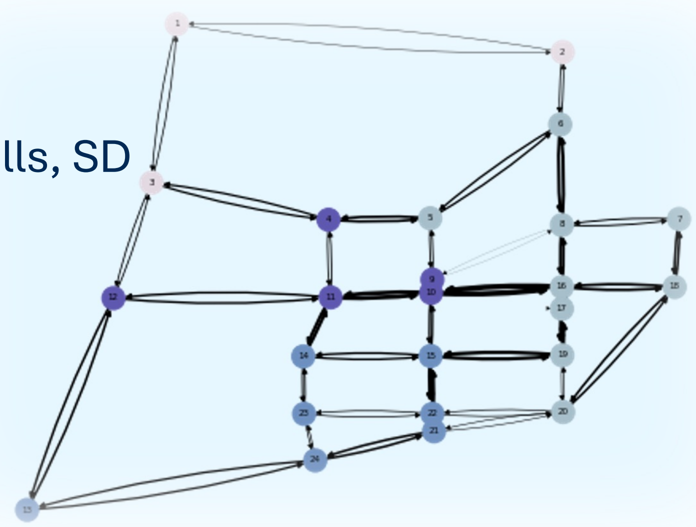
HIERARCHICAL APPROACH

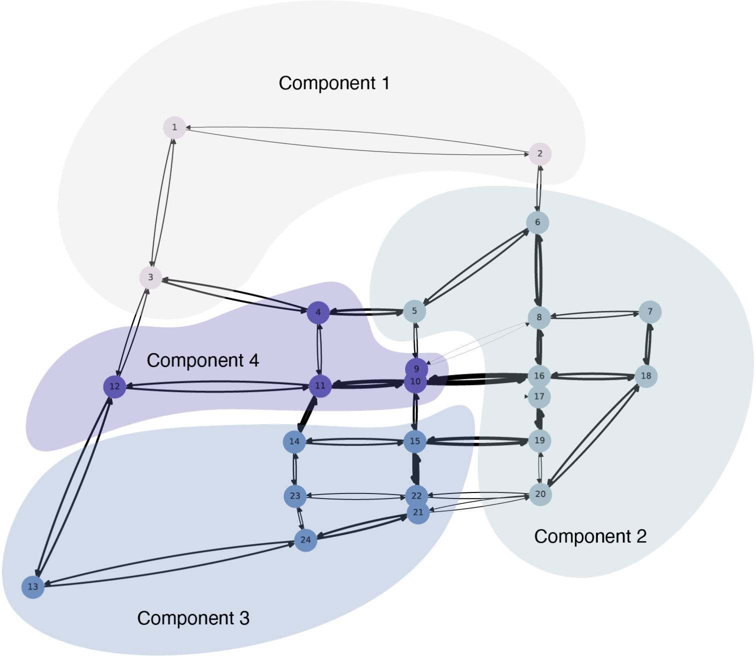


NETWORK DECOMPOSITION

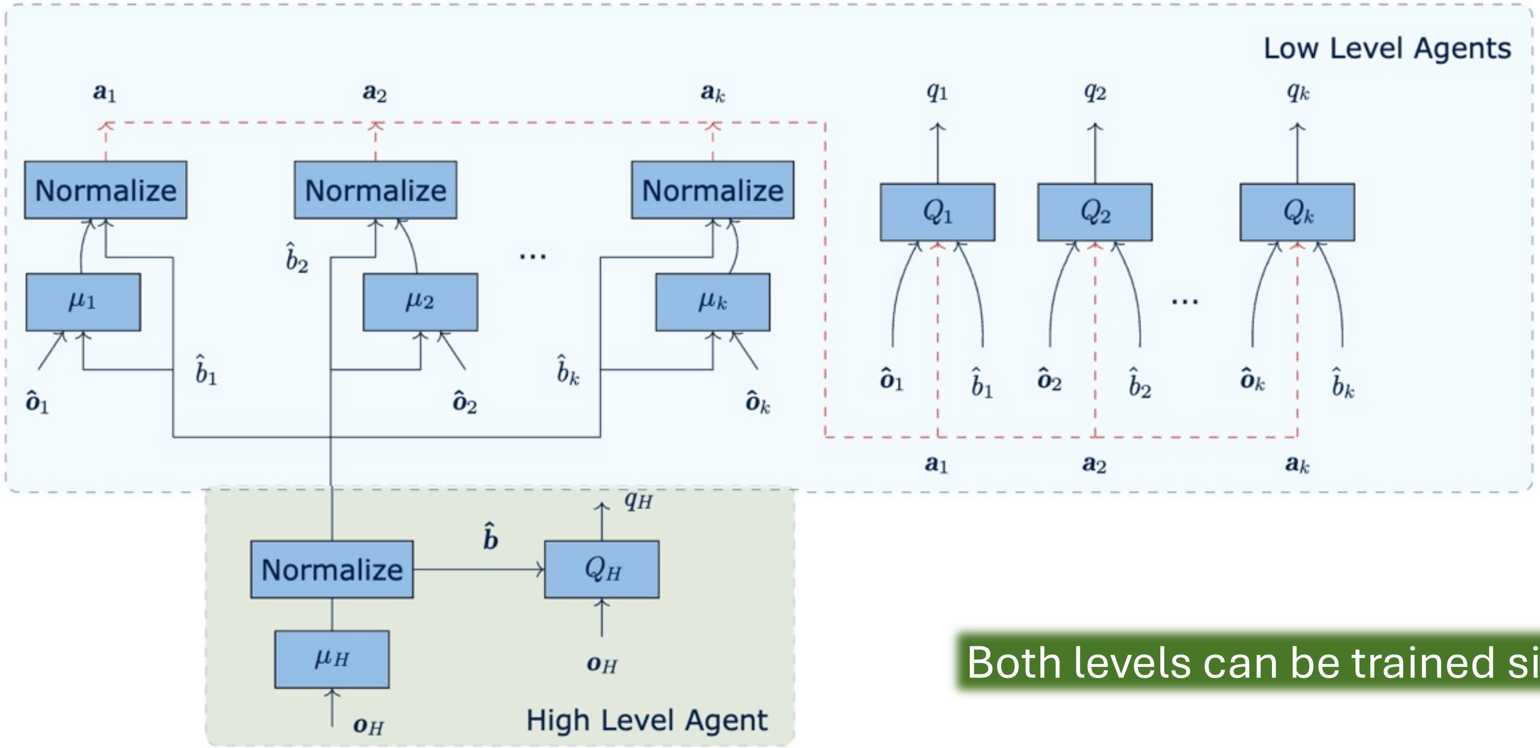
Decompose the network based on **K-means clustering** by edge distance (without congestion)

Sioux Falls, SD





DISTRIBUTED LEARNING



Both levels can be trained simultaneously.

EXPERIMENTAL SETUP

- Baselines
  - **Proportional** *(High Level)*: Allocates budget to each component based on proportion of vehicles in the component
  - **Greedy Heuristic** *(Low Level)*: Perturbs edges by proportion of vehicles that pass through that edge
  - Random actions
  - DDPG without decomposition
- Hyperparameter search
  - Grid search

EVALUATIONS

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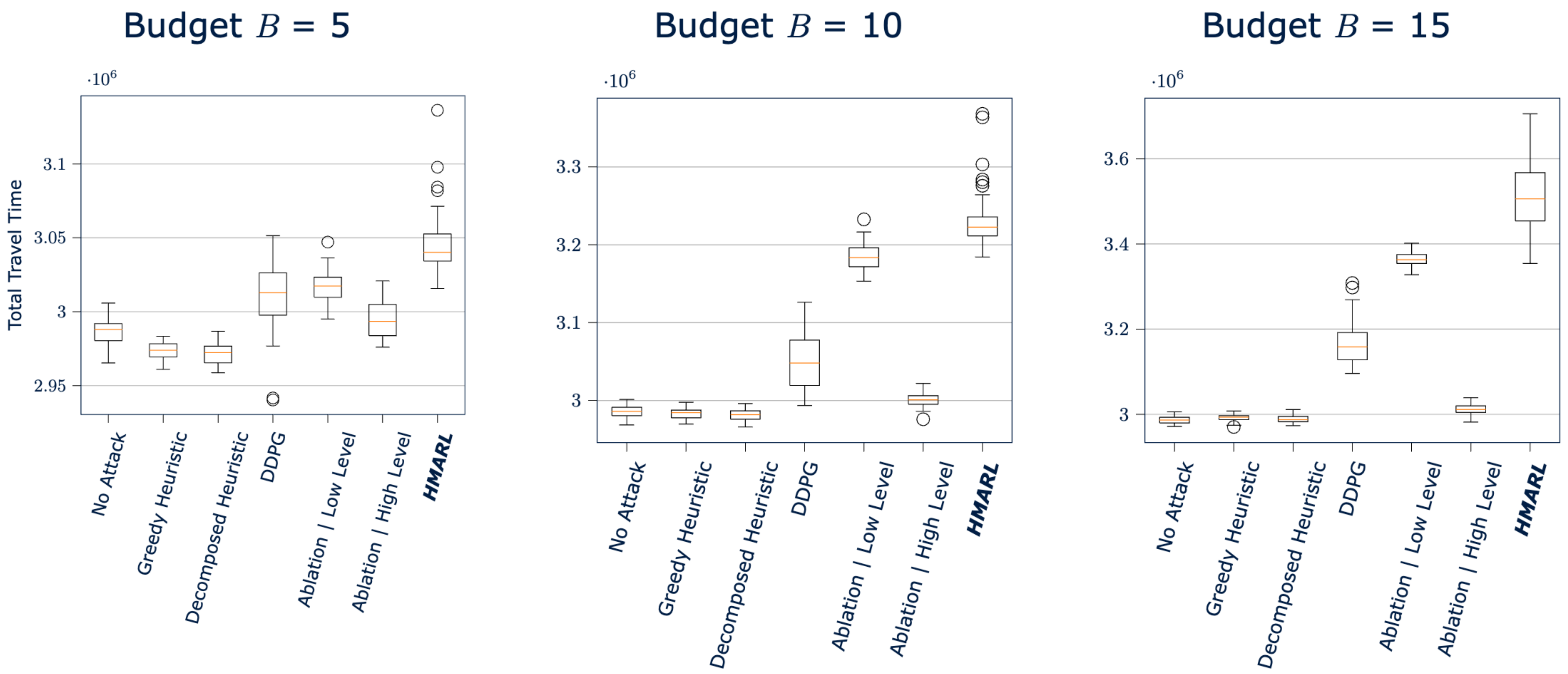

CONCLUSION

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- We discussed the importance of **resiliency** of transportation networks
- We discussed how transportation networks are **vulnerable** to various attacks.
- We introduced a **model of false-data attacks against navigation** in transportation networks
- We proposed a computational method based on **multi-agent reinforcement learning** to assess against worst-case attacks
- We demonstrated the **effectiveness** of our framework on the Sioux Falls, SD benchmark network
- We showed that a **worst-case attack can significantly increase total travel time**

THANK YOU FOR YOUR ATTENTION

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