Real-time Lane Configuration with Coordinated Reinforcement Learning

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How Often Have You Stuck In Traffic Like This?

Figure: Directionally imbalanced traffic. Congested traffic in one direction and oppose direction having less traffic.[1]

[1] https://i.dailymail.co.uk

Real-time Lane-direction Configuration with Connected Autonomous Vehicles

- What is **real-time lane-direction configuration**?

Changing the travelling direction of lanes in road segments based on real-time traffic information in short time intervals.

- Why consider this problem now?

Capabilities of Connected Autonomous Vehicles!

Difficult to Compute?

Yes! Lane-direction change in one road segment may affect traffic flow in neighboring road segments.

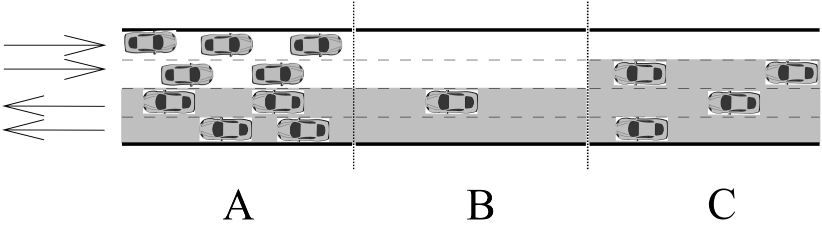


Figure: Three road segments A, B, C with different lane-configurations.

What makes lane configuration computation difficult in real-time?
Computation needs to be lightweight

Coordinated Learning-based Lane Allocation

- We propose an efficient multi-agent, scalable solution.

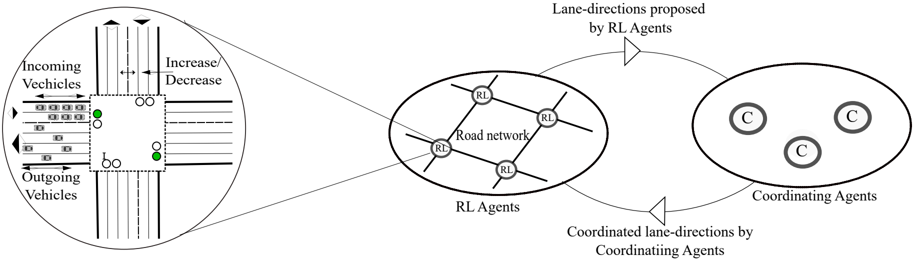


Figure: Architecture of CLLA consists of *RL Agents* that operate at the intersection level and *Coordinating Agents* who evaluate the global impact of local lane-direction changes.

Why Existing Methods Fail?

Existing approaches use mathematical programming to compute lane-direction allocation based on pre-known traffic patterns.

- Why existing methods cannot compute real-time lane-direction allocations?
  - Inability to work with real-time data
  - Computation cost is very high
  - Microscopic simulation vs Macroscopic simulation gap

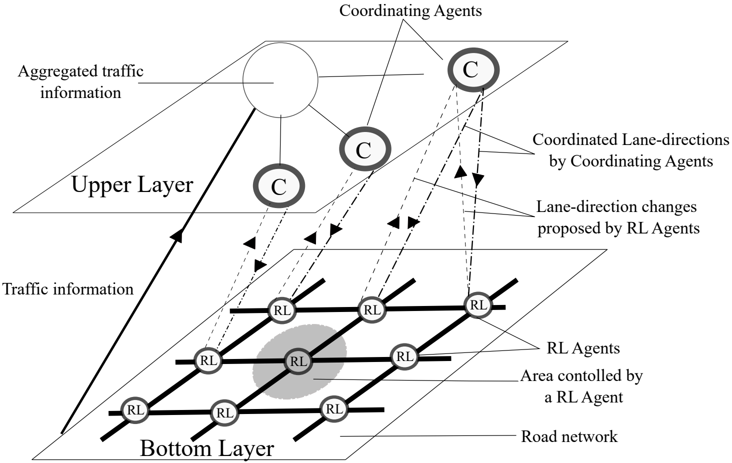
Why Multi-agent Reinforcement Learning?

- Why reinforcement learning?
  - Real-time control
  - Lack of lane-changing traffic models

- Why not a single reinforcement learning agent?
  - Exponential growth of state-space
  - Difficulty of learning

- **Coordination is the key!**
  - Network level impact of changes needs to be considered
  - Distributed RL Agents' action may conflict with each other

Coordinated Learning-based Lane Allocation



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CLLA Algorithm

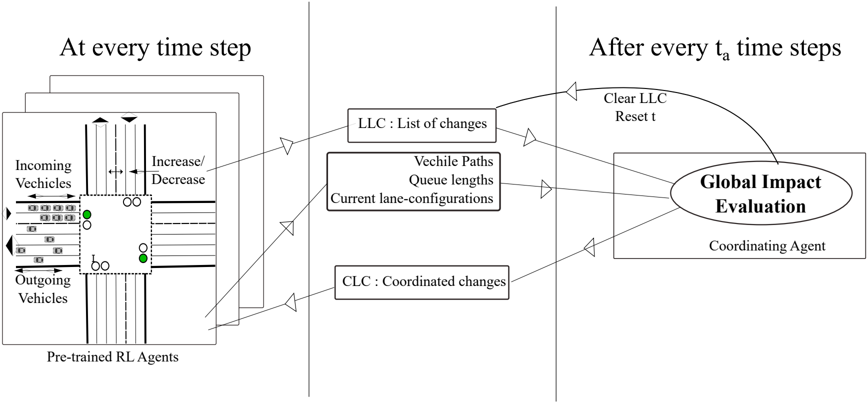

Figure: Overall CLLA algorithm with a single Coordinating Agent

Global Impact Evaluation : Complexity

Complexity

- $\mathcal{O}(m \times n)$
  - m : number of proposed changes from RL Agents
  - n : Number of neighbors per road segment
- **n** does not increase with the network size
- $\mathcal{O}(m \times n) \rightarrow \mathcal{O}(m)$
- Worst case: $\mathcal{O}(|E|)$, $|E|$: total number of road segments

Distributed Version

A distributed version can reduce the complexity further with a communication layer.

Results from Manhattan Road Network

- Simulated using SMARTS [1], a microscopic simulator
- Using one hour of New York taxi data on Manhattan road network

Baseline	Travel Time(s)	% of Vehicles with DFFT>6
no-LA	604.32	45.9
LLA	585.83	48.6
DLA	496.12	50.7
CLLA	**471.28**	**45.87**

Table: Performance of baselines evaluated using New York taxi data. **noLA** is a baseline with no lane-direction allocations, **LLA** is similar to **CLLA**, without the upper-layer coordination and **DLA** is a baseline algorithm which allocates lane-directions based on aggregated traffic demand.

Thank you
Q & A