DiffLight: A Partial Rewards Conditioned Diffusion Model for Traffic Signal Control with Missing Data

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1 Introduction

2 Our Method

3 Results

1. Introduction
2. Our Method
3. Results

Background and Motivations

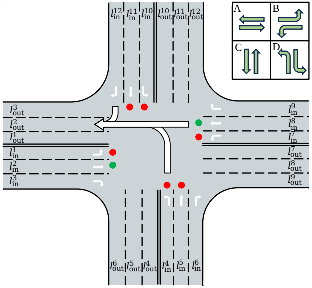
Background

- Rapid urbanization has led to increased traffic congestion and pollution.
- Conventional traffic signal control (TSC) methods struggle with dynamic real-time demands.
- Reinforcement learning (RL)-based TSC is promising but relies on complete data, which is often unavailable.

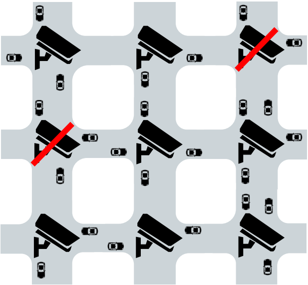
Motivations

- Sensor failures and budget constraints lead to missing data.
- Handling missing data is crucial for TSC.

Examples



(a) Illustration of an intersection and traffic signal phases.



(b) A road network with intersections that lack sensors.

Figure 1: Intersection layout and sensor limitations in traffic networks.

Challenges

- **Reward challenges in RL-based TSC.** Limited data results in partial rewards, and filling missing rewards with estimated values can harm performance by mixing real and imputed rewards.
- **Limited local intersection data.** Relying on data only from a local intersection limits the ability to capture dynamic, spatial-temporal dependencies in the traffic network for traffic data imputation and decision-making tasks.
- **Data absence from neighboring intersections.** Lack of data from adjacent intersections further impedes capturing dependencies, possibly degrading overall performance due to unobserved interactions across the network.

1 Introduction

2 Our Method

3 Results

Overview of DiffLight

Main Contributions

- **Partial Rewards Conditioned Diffusion (PRCD):** An innovative diffusion model for TSC that integrates data imputation and decision-making under incomplete data to prevent missing rewards from interfering with the learning process.
- **Spatial-Temporal Transformer (STFormer):** A tailored architecture capturing the dependencies among intersections to enhance control performance.
- **Diffusion Communication Mechanism (DCM):** A framework for sharing generated observations across intersections, improving robustness under data-missing scenarios.

Overview of DiffLight

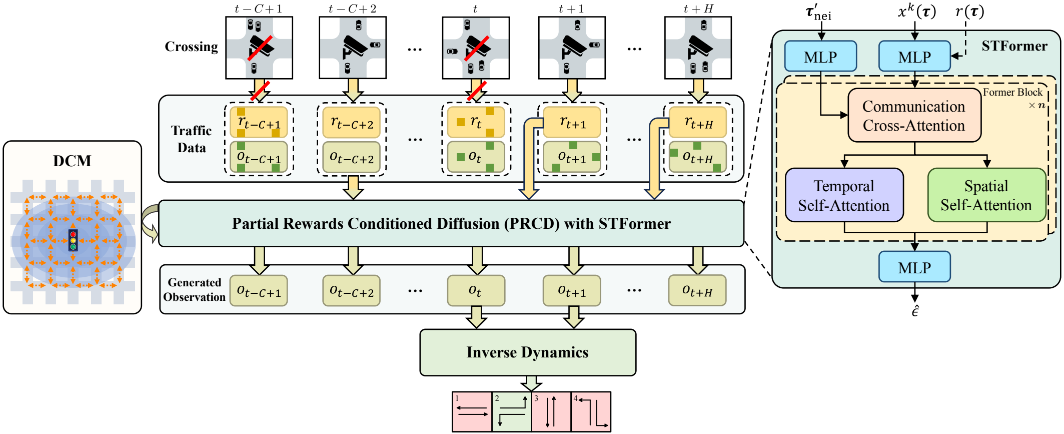


Figure 2: An overview of DiffLight.

Partial Rewards Conditioned Diffusion

Independent Data Distributions between Real and Virtual Sensors

$$p_\theta(x^0(\tau)|y(\tau)) = p_\theta(x^0(\tau_{\text{obs}})|r(\tau), y'(\tau)) \cdot p_\theta(x^0(\tau_{\text{mis}})|y'(\tau)) \tag{1}$$

Implement

$$\hat{\epsilon}_\theta(x^k(\tau), k, y'(\tau), \mathbf{c}, \mathbf{m}) := m_{\text{obs}} \odot \hat{\epsilon}_\theta(x^k(\tau), k, y'(\tau), r(\tau)) + m_{\text{mis}} \odot \hat{\epsilon}_\theta(x^k(\tau), k, y'(\tau), \phi) \tag{2}$$

Spatial-Temporal Transformer

- To address spatial-temporal dependencies in traffic signal control under missing data scenarios, we employ the STFormer architecture.
- The model consists of specialized encoder layers designed to capture both spatial and temporal dependencies within traffic networks.
- Each encoder layer includes:
    - A Communication Cross-Attention module for interaction between local and neighboring intersections.
    - Spatial and Temporal Self-Attention modules to independently model spatial and temporal correlations.

Diffusion Communication Mechanism

- DCM enables the model to propagate observation information across the network, even when data from neighboring intersections are incomplete.
- By leveraging the reverse diffusion process, DCM fills in missing data and allows intersections to make more informed decisions based on generated inputs from nearby intersections.
- We formulate DCM as follows:

$$\tau'_{\mathrm{nei}} = \begin{cases} \cup_N f_{\mathrm{nei}}(\tau^i), & k = K, \\ \cup_N f_{\mathrm{nei}}\left(\frac{1}{\sqrt{\bar{\alpha}^k}}(x^k(\tau^i) - \sqrt{1-\bar{\alpha}^k}\hat{\epsilon}_\theta(x^k(\tau), k, y'(\tau), \mathbf{c}, \mathbf{m}))\right), & k < K. \end{cases} \tag{3}$$

Examples

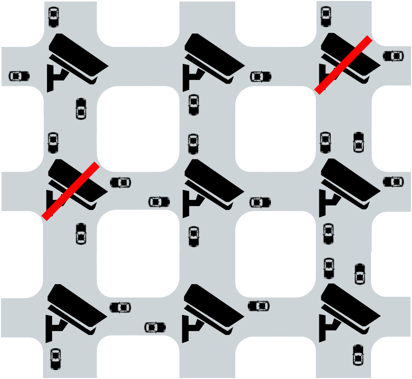


Figure 3: A road network with intersections that lack sensors.

1 Introduction

2 Our Method

3 Results

Performance under Data-Missing Scenarios

Table 1: Comparing ATT for DiffLight and baselines in random missing.

Dataset	Rate	BC	CQL	TD3+BC	DT	Diffuser	DD	DiffLight
$\mathscr{D}^1_{\mathrm{HZ}}$	10%	349.59	363.5	337.54	300.64	290.66	289.38	**286.17**±0.87
	30%	350.08	368.53	338.21	315.64	302.39	298.67	**292.81**±0.66
	50%	357.13	383.67	343.23	343.96	313.68	422.5	**304.71**±2.12
$\mathscr{D}^2_{\mathrm{HZ}}$	10%	382.45	353.23	370.16	347.25	346.82	347.77	**327.13**±1.43
	30%	388.73	352.55	376.06	360.59	366.24	364.6	**330.68**±2.63
	50%	387.77	367.38	375.32	377.79	398.23	395.61	**333.90**±2.67
$\mathscr{D}^1_{\mathrm{JN}}$	10%	320.6	299.07	315.54	308.78	272.51	**260.76**	272.18±0.93
	30%	328.97	310.8	326.37	377.39	295.09	300.49	**279.10**±2.10
	50%	355.47	322.25	351.2	439.89	324.75	517.99	**290.02**±2.18
$\mathscr{D}^2_{\mathrm{JN}}$	10%	288.42	305.86	322.44	259.3	255.12	**245.85**	247.17±1.38
	30%	297.26	308.13	330.43	263.24	271.53	256.16	**254.87**±0.69
	50%	299.44	320.17	334.78	278.22	302.28	275.2	**268.29**±0.90
$\mathscr{D}^3_{\mathrm{JN}}$	10%	301.35	291.26	281.75	257.66	246.90	**242.56**	246.65±0.94
	30%	315.03	295.61	283.24	312.56	258.83	256.95	**254.55**±0.35
	50%	326.55	301.1	292.98	382.93	272.36	351.92	**265.76**±0.01

Performance under Data-Missing Scenarios

Table 2: Comparing ATT for DiffLight and baselines in kriging missing.

Dataset	Rate	BC	CQL	TD3+BC	DT	Diffuser	DD	DiffLight
$\mathcal{D}^1_{\mathrm{HZ}}$	6.25%	338.33	317.69	332.80	300.78	302.99	395.54	**294.18**±3.36
	12.50%	346.83	317.94	332.43	310.37	305.93	483.47	**294.11**±4.34
	18.75%	350.08	319.18	333.24	306.35	307.22	572.56	**300.31**±0.31
	25.00%	354.86	328.83	341.89	381.94	328.79	836.46	**302.16**±1.23
$\mathcal{D}^2_{\mathrm{HZ}}$	6.25%	380.18	354.08	374.04	347.53	363.69	370.80	**330.40**±0.11
	12.50%	375.93	361.52	374.66	363.5	378.51	424.99	**319.11**±7.19
	18.75%	380.74	362.82	376.48	374.69	413.48	435.13	**327.61**±9.68
	25.00%	413.46	418.97	390.75	492.56	378.54	590.69	**351.21**±9.86
$\mathcal{D}^1_{\mathrm{JN}}$	8.33%	319.85	302.35	317.17	306.52	332.44	595.34	**280.75**±0.11
	16.67%	339.19	343.16	349.72	380.97	349.74	643.48	**306.06**±14.89
	25.00%	392.91	398.66	391.32	432.56	410.5	995.99	**329.67**±16.04
$\mathcal{D}^2_{\mathrm{JN}}$	8.33%	287.29	306.94	319.4	261.98	259.51	460.22	**254.13**±0.35
	16.67%	299.41	314.43	321.88	**267.67**	270.15	731.49	272.76±1.42
	25.00%	314.63	359.33	323.65	295.59	**295.21**	1049.19	325.20±26.63
$\mathcal{D}^3_{\mathrm{JN}}$	8.33%	310.44	287.25	282.46	368.2	267.64	324.42	**249.48**±0.16
	16.67%	327.7	311.89	295.07	322.96	294.27	399.67	**274.13**±2.50
	25.00%	381.37	337.33	312.44	494.04	**292.26**	409.76	342.07±16.11

Thank you for listening !

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