

LLM Powered Sim-to-real Transfer for Traffic Signal Control

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Abstract

Numerous solutions are proposed for the Traffic Signal Control (TSC) tasks aiming to provide efficient transportation and mitigate congestion waste. Recently, promising results have been attained by Reinforcement Learning (RL) methods through trial and error in simulators, bringing confidence in solving traffic congestion in cities. However, there still exists a performance gap when simulator-trained policies are deployed to the real world. This issue is mainly introduced by the system dynamic difference between the training simulator and the real-world environments. The Large Language Models (LLMs) are trained on mass knowledge and proved to be equipped with astonishing inference abilities. In this work, we leverage LLMs to understand and profile the system dynamics by a prompt-based grounded action transformation. Accepting the cloze prompt template, and then filling in the answer based on accessible context, the pre-trained LLM's inference ability is exploited and applied to understand how weather conditions, traffic states, and road types influence traffic dynamics, being aware of this, the policies' action is taken and grounded based on realistic dynamics, thus help the agent learn a more realistic policy. We conduct experiments using DQN to show the effectiveness of the proposed PromptGAT's ability to mitigate the performance gap from simulation to reality (sim-to-real).

1 Introduction

Traffic Signal Control (TSC) is a critical task aimed at improving transportation efficiency and alleviating congestion in urban areas (Zhang et al. 2020). Reinforcement Learning (RL) methods have shown promising results in tackling TSC challenges through trial and error in simulators (Ghanadbashi and Golpayegani 2022; Mei et al. 2022; Noeen et al. 2022; Ducrocq and Farhi 2023; Zang et al. 2020; Wu et al. 2020; Haydari and Yilmaz 2020), bringing hope for solving cities' traffic congestion issues. Simulation is a valuable tool for control tasks in the real world because the execution of a control skill in simulation is comparatively easier than real-world execution. However, a notable performance gap arises when deploying simulator-trained policies to real-world environments (Da et al. 2023), mainly due to differences in system dynamics between training simulators and the actual road conditions.

Grounded Action Transformation (GAT) is a framework designed to address the performance gap that arises when

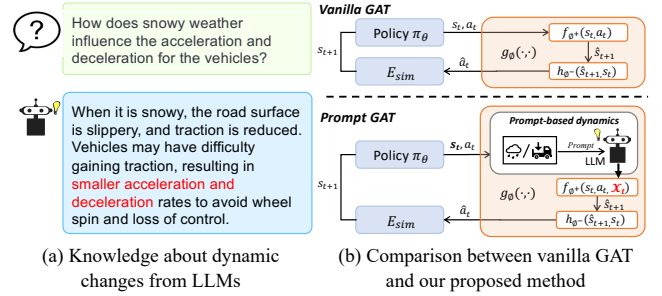


Figure 1: Integrating knowledge from LLMs into GAT. (a) LLMs have implicit human knowledge about the change in dynamics. (b) Comparisons between vanilla GAT and our proposed PromptGAT, with GAT integrating a prompt-based dynamics modeling module.

transferring policies learned in simulation to real-world scenarios (sim-to-real) (Hanna and Stone 2017). The key idea behind GAT is to induce simulator dynamics to resemble those of the real world, where policy learning takes place in simulation, and dynamics learning relies on real-world data.

The dynamics model, also known as the forward model f_{ϕ^+} , plays a crucial role in the GAT framework. It takes the current state s_t and action a_t as inputs and predicts the possible next state s_{t+1} in the real world. Traditional GAT methods focus on learning f_{ϕ^+} solely based on real-world data. While these approaches enable the forward model to be accurately fitted to real-world dynamics, it requires a substantial amount of real-world data covering the entire state distribution to achieve accurate predictions.

One limitation of conventional GAT methods is their struggle to handle unobserved states in the real world. When the policy encounters states that have not been previously observed in the real-world data, the learned forward model may predict s_{t+1} with significant errors. This is particularly evident under extreme weather conditions or rare events that are infrequently represented in the training data. In contrast, *human knowledge* allows us to infer the behavior of the system under such unique conditions. For example, we as humans understand that during extreme weather, vehicles tend to move slower with smaller acceleration and deceleration rates, and the same duration of a green traffic signal may result

in a smaller throughput. Moreover, humans can reason that adjusting the duration of green lights from the policy might be necessary to achieve a similar performance as observed in the simulation.

To leverage this implicit human knowledge for more accurate forward models, we propose a prompt-based GAT method, known as PromptGAT by introducing Large Language Models (LLMs) into the GAT framework. Specifically, as is shown in Figure 1(b), in the learning of the forward model, we design a prompt-based dynamics modeling module to better understand the real-world dynamic by asking LLMs how weather conditions, traffic states, and road types influence traffic dynamics. Through the inference ability of LLMs in profiling the system dynamics, the agent is able to learn the grounded action in GAT based on a more accurate and general forward model. This process facilitates the learning of more realistic policies and enhances the transferability of RL models from simulation to reality. In summary, the contribution of this paper is as follows:

- This paper proposes a novel method, PromptGAT, to mitigate the sim-to-real transfer problem in the context of traffic signal control by incorporating human knowledge with LLMs. To the best of our knowledge, this is the first paper bridging the performance gap between simulation and real-world settings in traffic signal control with LLMs.
- This paper provides the design of prompt generation and dynamics modeling module to understand the change of dynamics in the sim-to-real transfer. Leveraging LLMs with prompt and chain-of-thought (Wei et al. 2022), PromptGAT provides valuable insights into the system dynamics, which enhances the agent’s understanding of real-world scenarios.
- We conduct extensive experiments and case studies to validate the performance of our approach and showcase its potential impact on traffic signal control. All the experiments are conducted under a simulation-to-simulation setting with reproducible experiment settings. All the data and code can be found in the Supplementary.

2 Related Work

This section will introduce the related work from three aspects, regarding the traffic signal control methods, simulation-transfer methods, and prompt learning techniques.

Traffic Signal Control Methods Optimizing traffic signal policies to mitigate traffic congestion has posed a significant challenge within the realm of transportation. Diverse methodologies have been thoroughly investigated, encompassing rule-based methods (Dion and Hellinga 2002; Chen et al. 2020) as well as RL-based methods (Wei et al. 2019b,a, 2018) for enhancing vehicle travel time or reducing delays, most of which yielded notable enhancements over pre-existing time control techniques. Although most of the current RL-based TSC methods do not consider the sim-to-real gap problem, a few recent studies start to tackle the sim-to-real gap by modifying the simulator directly (Müller et al. 2021; Mei et al. 2022), requiring the parameters of the simulator can be easily modified to perfectly match the real world. Rather than modify the simulator, this paper proposes to modify the output actions of the policies learned in the traffic simulator.

Sim-to-real Transfer Mainly three categorized groups of literature exist in the sim-to-real transfer domain (Zhao, Queraltà, and Westerlund 2020). The first group is *domain randomization* (Tobin 2019; Andrychowicz et al. 2020), with the objective of training policies capable of adapting to environmental variations. This strategy primarily relies on simulated data and proves advantageous when dealing with uncertain or evolving target domains. The second group is *domain adaptation* (Tzeng et al. 2019; Han et al. 2019), which is dedicated to addressing the challenge of domain distribution shift by aligning features between the source and target domains. Many domain adaptation techniques focus on narrowing the gap in robotic perception (Tzeng et al. 2015; Fang et al. 2018; Bousmalis et al. 2018; James et al. 2019), in TSC, the gap mainly attributed to the dynamics rather than perception since most TSC methods directly regard the vectorized representations like lane-level number of vehicles or delays as observations. Recently, *grounding methods*, known as the third group of approaches, improves the accuracy of the simulator concerning the real world by correcting for simulator bias. Unlike system identification approaches (Cutler, Walsh, and How 2014; Cully et al. 2015) that try to learn the accurate physical parameters, Grounded Action Transformation (GAT) (Hanna and Stone 2017) induces the dynamics of the simulator to match the real world with grounded action rather than require a parameterized simulator that can be modified. It has demonstrated promising results for sim-to-real transfer in robotics. Our PromptGAT is inspired by GAT, with novel designs on leveraging LLMs to enhance action transformation.

Prompt Learning Prompt learning, first introduced by (Petrone et al. 2019), has been widely studied in NLP during these years (Jiang et al. 2020; Shin et al. 2020). Prompting means prepending instructions to the input and pre-training the language model so that the downstream tasks can be promoted. (Poerner, Waltinger, and Schütze 2019) use manually defined prompts to improve the performance of language models. To adapt LLMs for specific applications, developers often send prompts (aka, queries) to the model, which can be appended with domain-specific examples for obtaining higher-quality answers. A collection of prompt management tools, such as ChatGPT Plugin (OpenAI 2023a), GPT function API call (OpenAI 2023b), LangChain (langchain 2023), AutoGPT (Aut 2023), and BabyAGI (BabyAGI 2023), have been designed to help engineers integrate LLMs in applications and services. As far as we know, there is no exploration for prompt learning in sim-to-real transfer or traffic signal control task.

3 Method

3.1 Preliminaries

RL-based Traffic Signal Control In Traffic Signal Control (TSC), controllers determine intersection phases. Each phase comprises predefined, non-conflicting traffic movement combinations. The signal controller tends to adopt a phase that minimizes the average queue length in a certain traffic range during the next time interval Δt . The literature (Wei et al. 2018; Chen et al. 2020; Zheng et al. 2019; Wei et al. 2019b),

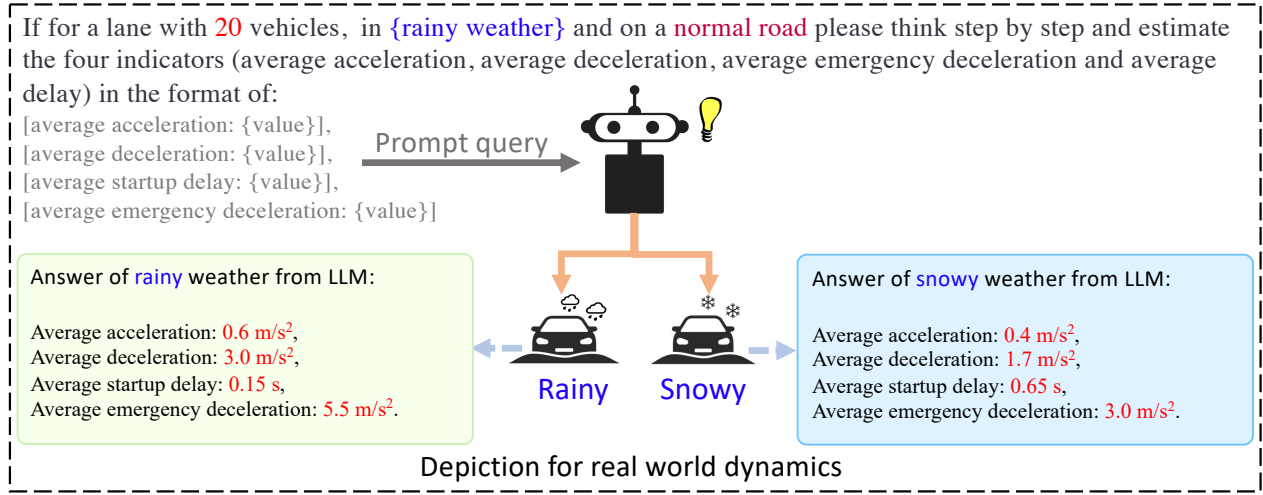


Figure 2: An example of using LLM with a prompt template for answers to depict real-world dynamics by providing traffic state (vehicle number), weather type, and road type to induce the LLM to infer based on domain knowledge. Given the same vehicle quantity and road type, we could observe that the answers under different weathers abide by the reality situation that snowy weather is more severe than rainy weather.

propose to distribute each traffic signal with an agent, responsible for choosing the actions (phases) in each time frame. It is a common practice to characterize the TSC problem in a MDP by $\mathcal{M} = \langle \mathcal{S}, \mathcal{A}, P, r, \gamma \rangle$ where \mathcal{S} denotes the system state space, \mathcal{A} denotes the set of action space, P denotes as the transition dynamics describing the probability distribution of next state $s_{t+1} \in \mathcal{S}$, r denotes the reward, and π_θ as the policy parameterized by θ and γ is the discount factor.

An RL algorithm expects to learn an optimal policy that maximizes the long-term expectation of accumulated reward which is adjusted by a discount factor γ . The discounted accumulated reward is $\mathbb{E}_{(s_t, a_t) \sim (\pi_\theta, \mathcal{M})} [\sum_{t=0}^T \gamma^{T-t} r_t(s_t, a_t)]$. We follow the past work which defines \mathcal{A} as discrete action spaces, and use Deep Q-network (DQN) (Wei et al. 2018) to optimize the RL policy. The above procedure is conducted in the simulation environment E_{sim} in previous work.

Grounded Action Transformation The Grounded Action Transformation (GAT) framework, initially introduced in the field of robotics, aims to enhance robotic learning through the utilization of real-world E_{real} trajectories to adapt and modify the simulated environment E_{sim} . Within the GAT framework, the Markov Decision Process (MDP) within E_{sim} is considered imperfect yet adjustable, allowing for its parameterization as a transition dynamic $P_\phi(\cdot|s, a)$. Based on the real-world dataset $\mathcal{D}_{real} = \{\tau^1, \tau^2, \dots, \tau^I\}$, where $\tau^i = (s_0^i, a_0^i, s_1^i, a_1^i, \dots, s_{T-1}^i, a_{T-1}^i, s_T^i)$ is a trajectory collected by executing policy π_θ in E_{real} , GAT intends to find ϕ^* that minimize differences between transition dynamics:

$$\phi^* = \arg \min_{\phi} \sum_{\tau^i \in \mathcal{D}_{real}} \sum_{t=0}^{T-1} d(P^*(s_{t+1}^i | s_t^i, a_t^i), P_\phi(s_{t+1}^i | s_t^i, a_t^i)) \quad (1)$$

where $d(\cdot)$ represents the two dynamics' discrepancy, P_ϕ stands for the simulation transition dynamics, and P^* stands for the real world transition dynamics.

For efficient determination of ϕ , the GAT takes the agent's current state s_t and action a_t predicted by the policy π_θ as input. It then produces a grounded action, denoted as \hat{a}_t , through the use of an action transformation function that is parameterized by ϕ :

$$\hat{a}_t = g_\phi(s_t, a_t) = h_{\phi^-}(s_t, f_{\phi^+}(s_t, a_t)) \quad (2)$$

which includes two specific functions: a forward model f_{ϕ^+} , and an inverse model h_{ϕ^-} , as is shown in Figure 1.

- *The forward model f_{ϕ^+}* is trained with the data from E_{real} , with the purpose of predicting the next possible state \hat{s}_{t+1} given current state s_t and action a_t :

$$\hat{s}_{t+1} = f_{\phi^+}(s_t, a_t) \quad (3)$$

- *The inverse model h_{ϕ^-}* is trained with the data from E_{sim} , with the purpose of predicting the action \hat{a}_t that brings about the given next state from the current state s_t . Specifically, the inverse model in GAT takes \hat{s}_{t+1} , the output from the forward model, as its input for the next state:

$$\hat{a}_t = h_{\phi^-}(\hat{s}_{t+1}, s_t) \quad (4)$$

Based on the state action pair $\langle s_t, a_t \rangle$ where the a_t is predicted by the policy π_θ , the grounded \hat{a}_t takes place in E_{sim} will rectify the s_{t+1} in E_{sim} close to the predicted next state \hat{s}_{t+1} in E_{real} , making the dynamics $P_\phi(s_{t+1} | s_t, \hat{a}_t)$ in simulation close to the real-world dynamics $P^*(\hat{s}_{t+1} | s_t, a_t)$. By this, the policy π_θ learned in E_{sim} with P_ϕ is close to P^* , and will have a smaller performance gap when transferred to E_{real} with P^* .

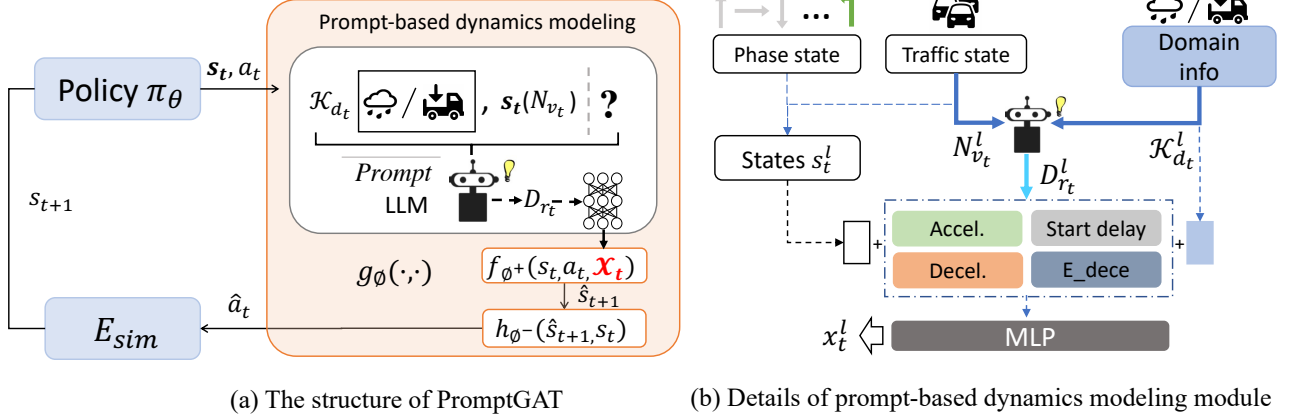


Figure 3: The overall framework of our proposed PromptGAT. (a) The structure of PromptGAT, with a prompt-based dynamics modeling integrating the knowledge of LLMs into the learning of forward model f_{ϕ^+} . (b) Details of prompt-based dynamics modeling module that infer and integrate the change of dynamics with traffic states.

3.2 Prompt-based GAT

In-context Learning for Dynamics Knowledge LLMs are known to be capable of in-context zero-shot or few-shot abilities, which adapt these models to diverse tasks without gradient-based parameter updates (Alayrac et al. 2022). This allows them to rapidly generalize to unseen tasks and even exhibit apparent reasoning abilities with appropriate prompting strategies. Here is a set of system dynamic descriptions in the natural language as in Equation (5), provided to GPT-4.0 as context. They respectively stand for the scene weather information, road condition, and lane-level traffic state:

$$\text{Context} : \langle \text{Weather} \rangle \langle \text{Road Type} \rangle \langle \text{Traffic State} \rangle \quad (5)$$

These contexts are organized and filled into the designed prompt template as in below:

$$\langle \text{Task} \rangle \langle [\text{Context}] \rangle \langle \text{Output Restriction} \rangle, \quad (6)$$

where $\langle \text{Task} \rangle$ provides task intention explanation to LLMs, and $\langle \text{Output Restriction} \rangle$ induces the LLMs to infer the possible dynamics change based on the $\langle [\text{Context}] \rangle$ provided in Equation (5) for the language model to understand the current perceptible information. As shown in Figure 2, the resulting output dynamics knowledge could be then utilized by the forward model f_{ϕ^+} .

Prompt-based Dynamics Modeling In GAT, the learning of the forward model f_{ϕ^+} and inverse model h_{ϕ^-} are crucial. The forward model $f_{\phi^+}(s_t, a_t)$ in GAT predicts the next RL state \hat{s}_{t+1} in the real world given taken action a_t and the current state s_t as in Equation (3). In the above method, direct prediction only using (s_t, a_t) omits the consideration of domain knowledge \mathcal{K}_d , such as weather or road conditions, but the state transition $s_{t+1} = T_r(s_t, a_t)$ in the real world is a joint consequence related to this perceptible domain knowledge and real-time traffic states (vehicle quantities), e.g., In the snowy days, vehicles normally act with larger startup delay than in good weather time, and for vehicles on the high occupied road, the acceleration and emergency deceleration will be lower than those on the free road that's mainly

decided by the vehicles' standard machine characteristics. Therefore, we propose leveraging the \mathcal{K}_d to provide a hint on the concrete real-world system dynamics D_r such as *acceleration*, *deceleration*, *emergency deceleration* and *startup delay* reflected by transition T_r . For $\forall s_t \in S$ on lane l , we employ LLM (GPT-4.0) to realize inference by the prompt organized in Equation (6):

$$D_{r_t}^l = \text{LLM}(\text{Prompt}(\mathcal{K}_{d_t}^l, N_{v_t}^l)) \quad (7)$$

where $\mathcal{K}_{d_t}^l = (\text{weather}, \text{road})$ and $N_{v_t}^l$ is the number of vehicles. Based on this, we incorporate the current lane state, lane level the domain knowledge $\mathcal{K}_{d_t}^l$ and dynamics knowledge $D_{r_t}^l$ from LLM together into the forward model through a fusion module of the model's network design as in Figure 3. Please note that the *road* description in $\mathcal{K}_{d_t}^l$ can vary for lanes but keep the same for the whole complete trajectory, and *weather* holds on same for one complete trajectory as well.

$$\dot{x}_t^l = \oplus \{s_t^l, D_{r_t}^l, \mathcal{K}_{d_t}^l\} \quad (8)$$

$$x_t^l = \text{ReLU}(\text{Linear}(\dot{x}_t^l)) \quad (9)$$

where \dot{x} is a temporary calculation step after the operation \oplus , which is implemented as *Concatenate*(\cdot), the derived x_t^l represents the feature space for specific lane l at time step t . The input for f_{ϕ^+} is an integrated information \mathcal{X} from all n lanes: $\mathcal{X}_t = (x_t^1, x_t^2, \dots, x_t^n)$. Now we could represent the forward model into:

$$\hat{s}_{t+1} = f_{\phi^+}(s_t, a_t, \mathcal{X}_t) \quad (10)$$

The f_{ϕ^+} is approximated by a NN (neural network) and ϕ^+ is optimized through minimizing the Mean Squared Error (MSE) loss, in the equation, the s_t^i, a_t^i, s_{t+1}^i are sampled from the trajectories collected from E_{real} :

$$\mathcal{L}(\phi^+) = \text{MSE}(\hat{s}_{t+1}^i, s_{t+1}^i) = \text{MSE}(f_{\phi^+}(s_t^i, a_t^i), s_{t+1}^i) \quad (11)$$

Different from f_{ϕ^+} , the inverse model $h_{\phi^-}(\hat{s}_{t+1}, s_t)$ predicts the grounded action \hat{a}_t^i that can lead to the same traffic

states \hat{s}_{t+1} in simulation E_{sim} . h_{ϕ^-} could be learned through the interactions within simulation with lower cost than f_{ϕ^+} , therefore in this paper, we did not incorporate the dynamics knowledge in the inverse model for a more accurate model. The h_{ϕ^-} is also approximated by NN and ϕ^- is optimized by minimizing the Categorical Cross-Entropy (CE) loss since the target a_t^i is a discrete value in traffic signal control problem defined by existing work (Wei et al. 2018):

$$\mathcal{L}(\phi^-) = CE(\hat{a}_t^i, a_t^i) = CE(h_{\phi^-}(s_{t+1}^i, s_t^i), a_t^i) \quad (12)$$

where s_t^i, a_t^i, s_{t+1}^i are sampled from the trajectories collected from E_{sim} .

Overall Algorithm In this part, we will write a clear pseudo-code in Algorithm 1 to show how the process is implemented.

Algorithm 1: Algorithm for PromptGAT

Input: Initial policy π_θ , forward model f_{ϕ^+} , inverse model h_{ϕ^-} , domain info set \mathcal{K}_d , real-world dataset \mathcal{D}_{real} , simulation dataset \mathcal{D}_{sim}

Output: Policy $\pi_\theta, f_{\phi^+}, h_{\phi^-}$

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1 Pre-train policy  $\pi_\theta$  for M iterations in  $E_{sim}$ 
2 for  $i = 1, 2, \dots, I$  do
3   Rollout policy  $\pi_\theta$  in  $E_{sim}$  and add data to  $\mathcal{D}_{sim}$ 
4   Load corresponding  $\mathcal{K}_d^i$  (weather, road condition)
5   Rollout policy  $\pi_\theta$  in  $E_{real}$  and add data to  $\mathcal{D}_{real}$ 
6   # Forward model update
7   for  $l = 1, 2, \dots, n$  do
8     Acquire  $D_r^l$  dynamics by Equation (7)
9     Feature fusion  $x_t^l$  follow Equation (8), (9)
10    Construct  $\mathcal{X}_t = (x_t^1, x_t^2, \dots, x_t^n)$ 
11    Predict  $\hat{s}_{t+1}$  by  $f_{\phi^+}$  as Equation (10)
12  end
13  Update  $f_{\phi^+}$  with Equation (11)
14  # Inverse model update
15  Update  $h_{\phi^-}$  with Equation (12)
16  # Policy training
17  for  $e = 1, 2, \dots, E$  do
18    # Policy update step
19    Improve policy  $\pi_\theta$  with reinforcement learning
20  end
21 end

```

4 Experiments

The experimental setups and results interpretation will be elaborated in this section. The implementation of PromptGAT will also be introduced based on a cross-simulator platform, Libsignal.

4.1 Experiment Settings

In this section, we introduce the overall environment setup for our experiments, commonly used metrics, important hyperparameters and model structures.

Table 1: Real-world Configurations for E_{real}

Setting	accel (m/s ²)	decel (m/s ²)	eDecel (m/s ²)	sDelay (s)	Description
V0	2.60	4.50	9.00	0.00	Default setting
V1	1.00	2.50	6.00	0.50	Lighter loaded vehicles
V2	1.00	2.50	6.00	0.75	Heavier loaded vehicles
V3	0.75	3.50	6.00	0.25	Rainy weather
V4	0.50	1.50	2.00	0.50	Snowy weather

Environment Setup In our study, we leverage the Lib-Signal (Mei et al. 2022) traffic signal control library, an open-source framework that incorporates multiple simulation environments. Our implementation involves using Cityflow (Zhang et al. 2019) as the simulation environment E_{sim} and SUMO (Lopez et al. 2018) as the real-world environment E_{real} . Throughout the paper, we consistently refer to E_{sim} and E_{real} as our default simulation and real-world environments, respectively. It is important to note that this simulation-to-simulation setting not only serves as a representative sim-to-real scenario but also allows for replicable and reproducible results in our experiments.

To simulate real-world scenarios, we consider four different configurations in SUMO, representing two types of real-world scenarios: heavy industry roads and special weather-conditioned roads, with specific parameter settings detailed in Table 1. The four configurations follows (Da et al. 2023):

- *V0: Default setting*¹. Default parameters for SUMO and CityFlow, profiling the ideal settings in E_{sim} .
- *V1 & V2: Heavy industry roads*. In this configuration, we model the situation that the commonly visited vehicles are of different types. *V1* describes roads with lighter-loaded vehicles, while *V2* represents the same roads with heavier-loaded vehicles, they also differ in startup delay.
- *V3 & V4: Special weather-conditioned roads*. Consider areas with special weather conditions, *V3* and *V4* represent rainy and snowy weather conditions, respectively.

Evaluation Metrics The primary goal of this work is to mitigate the performance gap of the trained policy π_θ in the simulation environment E_{sim} and in the real-world environment E_{real} . We calculate the performance difference Δ for commonly used traffic signal control metrics: average travel time, throughput, reward, average queue length, and average delay, and their detailed definition can be found in (Da et al. 2023). We denote their differences as ATT_Δ , TP_Δ , $Reward_\Delta$, $Queue_\Delta$, and $Delay_\Delta$. For a given metric ψ :

$$\psi_\Delta = \psi_{real} - \psi_{sim} \quad (13)$$

Since in real-world settings, policy π_θ tends to perform worse than in simulation, the values of ATT , $Queue$, and $Delay$ in E_{real} are typically larger than those in E_{sim} . Based on our goal of mitigating the gap and improving the performance of π_θ in E_{sim} , we expect that for ATT_Δ , $Queue_\Delta$, and $Delay_\Delta$, smaller values are better, while for TP_Δ and $Reward_\Delta$, larger values are better. For a fair comparison, ψ_{sim} of all methods

¹https://sumo.dlr.de/docs/Definition_of_Vehicles,_Vehicle_Types,_and_Routes.html

Table 2: The performance using **Direct-Transfer**, **Vanilla-GAT** compared with using **PromptGAT** method. The (\cdot) shows the metric gap ψ_{Δ} from E_{real} to E_{sim} and the \pm shows the standard deviation with 5 runs. The \uparrow means that the higher value for the metric indicates a better performance and \downarrow means that the lower value indicates a better performance.

Setting	Methods	Metrics				
		$ATT(\Delta \downarrow)$	$TP(\Delta \uparrow)$	$Reward(\Delta \uparrow)$	$Queue(\Delta \downarrow)$	$Delay(\Delta \downarrow)$
V1	Direct-Transfer	158.93 (47.69) ± 55.02	1901 (-77) ± 52.21	-71.55 (-32.11) ± 22.51	47.71 (21.59) ± 14.98	0.73 (0.11) ± 0.03
	Vanilla-GAT	156.10 (44.87) ± 4.81	1905 (-73) ± 13.00	-70.03 (-30.59) ± 3.80	46.61 (20.50) ± 1.97	0.71 (0.09) ± 0.01
	PromptGAT	154.97 (43.74)± 6.09	1918 (-60)± 9.62	-66.88 (-27.44)± 4.47	44.56 (18.45)± 2.96	0.71 (0.09)± 0.01
V2	Direct-Transfer	177.27 (66.03) ± 82.63	1898 (-80) ± 102.25	-87.71 (-48.27) ± 26.18	58.59 (32.47) ± 17.46	0.76 (0.14) ± 0.02
	Vanilla-GAT	180.58 (69.35) ± 11.72	1908 (-69)± 12.00	-89.69 (-50.25) ± 9.13	59.93 (33.82) ± 8.01	0.74 (0.12) ± 0.07
	PromptGAT	174.31 (63.08)± 13.11	1904 (-73) ± 21.63	-84.71 (-45.27)± 18.89	56.64 (30.53)± 12.62	0.72 (0.10)± 0.02
V3	Direct-Transfer	205.86 (94.63) ± 64.49	1877 (-101) ± 100.86	-101.26 (-61.82) ± 20.10	67.62 (41.51) ± 13.37	0.76 (0.14) ± 0.03
	Vanilla-GAT	214.29 (103.06) ± 40.59	1846 (-131) ± 56.74	-91.15 (-51.71) ± 15.13	60.93 (34.82) ± 10.10	0.73 (0.11) ± 0.02
	PromptGAT	198.48 (87.25)± 7.27	1879 (-98)± 6.02	-89.25 (-49.81)± 5.51	59.65 (33.54)± 3.70	0.72(0.10)± 0.01
V4	Direct-Transfer	332.48 (221.25) ± 109.00	1735 (-252) ± 151.91	-126.71 (-87.23) ± 14.79	84.53 (58.42) ± 9.86	0.83 (0.21) ± 0.01
	Vanilla-GAT	318.70 (207.47) ± 12.35	1750 (-227) ± 16.93	-115.01 (-75.57) ± 9.27	76.74 (50.63) ± 5.10	0.81 (0.19) ± 0.08
	PromptGAT	310.29 (199.06)± 22.57	1750 (-227)± 16.47	-113.55 (-74.11)± 6.68	75.77 (49.66)± 4.48	0.81 (0.19)± 0.01

Table 3: Overall performance in E_{sim}

Env	ATT	TP	Reward	Queue	Delay
E_{sim}	111.23± 3.5	1978± 5	-39.44± 2.23	26.11± 1.15	0.62± 0.10

in E_{sim} are trained to be similar and reported in Table 3: with the similar ψ_{sim} , we can also compare ψ_{real} from different methods to know which method performs the best.

4.2 Experimental Results and Analysis

We analyze the proposed method in the following way: First, we verify if the prompt result from Large Language Model is giving the rational inference based on the context description. Second, we compare to the Direct-Transfer to verify if PromptGAT is able to mitigate the performance. In part 3, we discuss the performance improvement competing with baseline models. Furthermore, we demonstrate our method’s contribution to the forward model’s accuracy and how it is correlated to the final E_{real} performance gap mitigation.

Prompt Intention Analysis In this section, we conduct an analysis on the verification of whether the LLM Prompt infers the expected information following the practical laws in realistic. We conduct prompts in the format of $\langle Task \rangle \langle [Context] \rangle \langle Output Restriction \rangle$ as defined in Equation (6). We first introduce the $\langle Task \rangle$ description below:

The indicators describing the traffic dynamics include the average acceleration (AC) of the vehicles (m/s²), the average deceleration (AD) (m/s²), the average emergency deceleration (AED) (m/s²) and the average startup delay (ADL) describing the average time needed for the waiting vehicles to start moving with the unit (s), and the above might vary based on weather or road type. Please assume the above indicators based on the traffic perceptive information below:

Then specifically, for the $\langle [Context] \rangle$, we have the follow-

ing implementation (the colored content is replaceable based on the actual situation, *weather*, *road*, and *traffic state (vehicle quantity)* in correspondence with Equation (5):

V1: In *sunny* day, on a *light industry road* with *8* vehicles,
V2: In *sunny* day, on a *heavy industry truck road*, *5* vehicles,
V3: In *rainy* day, on a *normal road* with *10* vehicles,
V4: In *snowy* day, on a *normal road* with *7* vehicles.

And for $\langle Output Restriction \rangle$ we design as below:

Please answer by replacing {value} in the format below:
[average acceleration: value],
[average deceleration: value],
[average emergency deceleration: value],
[average startup delay: value].

We take the real-world setting dynamics values as the ground truth and compare the LLM inferred value outputs to the ground truth to analyze their relationship, the results are shown in Figure 4. We could observe that within each sub-figure, LLM’s inference results show a similar curve across metrics, and from v1 to v4, the LLM is also reflecting the same tendency as shown by Real settings. This proves the LLM’s ability to provide a realistic inference based on the given information, thus guaranteeing the rationality to apply Prompt in our task of approximating real-world dynamics.

Ability to Mitigate the Performance Gap We first train policies using DQN in E_{sim} to well-converged as in Table 3 and apply to 4 E_{real} settings described in Table 1. This is taken as the ‘direct transfer’, which exists a large gap compared to E_{sim} training performance (Da et al. 2023). Then we leverage the proposed method PromptGAT to train policies under the same 4 settings. Following the metrics in Section 4.1, we could show a comparison in Figure 5: the center blue area is the metrics connection reported when policies are well trained in E_{sim} , these are the most ideal achievement

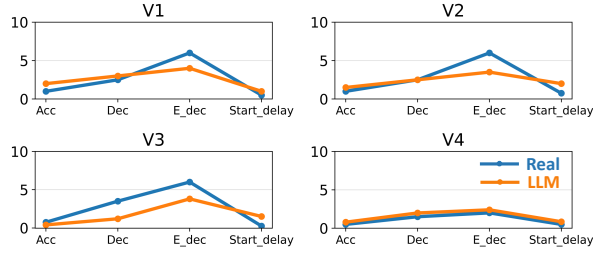


Figure 4: Comparison of LLM prompt answers and real-world settings reflects the same tendency across 4 versions.

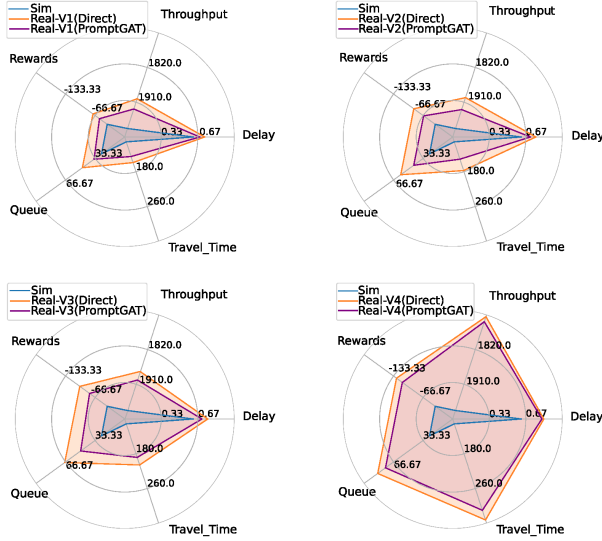


Figure 5: The performance in the E_{real} using Direct-Transfer and PromptGAT comparing to the performance in E_{sim} .

that a policy could acquire. When the well-trained policy directly applies to E_{real} , the performance is shown in the orange area, we could obviously observe that large gaps commonly exist in 4 different real-world settings. Even though the severeness varies on settings, still non of the gap is trivial. PromptGAT shows promising results by effectively shrinking the gap to a much lower level (as shown in the purple area).

Comparison to Baseline Models In this part, we analyze how the proposed PromptGAT compete with other methods at a quantity level, including Direct Transfer and VanillaGAT. We apply all 3 approaches in 4 settings and compare their performance under 5 metrics. Each performance is represented as mean value and standard deviation after conducting 5 runs of tests. As shown in Table 2 that most of the time, the PromptGAT performs better than other baselines across various settings and metrics.

4.3 Further Study and Experiment Details

In this section, we conduct a case study on setting V4 to show contribution of PromptGAT to the forward model accuracy and its relation to the performance gap mitigation in E_{real} .

Correlation Analysis We first compare the prediction error of our method to Vanilla GAT as in Figure 6 (left). Proving our method provides a better prediction of system dynamics. In order to understand how would dynamic profiling ability influence the model’s performance gap in E_{real} , we conduct correlation analysis across the metrics gap of average travel time, throughput, and waiting queue length. As shown in Figure 6 (right), the improvement of the mitigated gap (absolute values) across multiple metrics is positively correlated to the improvement of the forward model’s accuracy. This indicates PromptGAT mitigates the real-world gap by better profiling the realistic system dynamics. A more detailed analysis including p-value testing as shown in Figure 7.

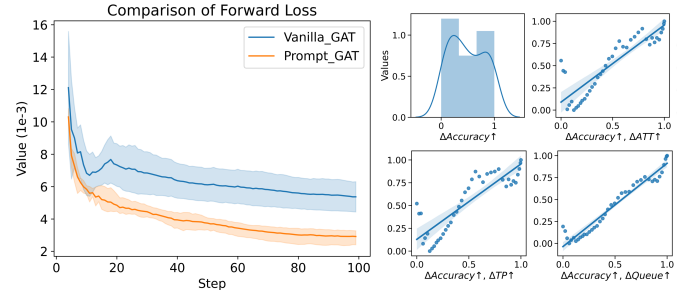


Figure 6: Left: Prediction error from the forward model using PromptGAT vs VanillaGAT, our method consistently approximates the true system dynamics and reduces the loss. Right: The correlation between improvement of accuracy and improvement of mitigated performance gap Δ in E_{real} .

The values of $\Delta_{Accuracy\uparrow}$, $\Delta_{ATT\uparrow}$, $\Delta_{TP\uparrow}$, $\Delta_{Queue\uparrow}$ indicating how much gap is mitigated, they are further definitions based on Equation (13):

$$\Delta_{\uparrow} = |\psi_{a\Delta} - \psi_{b\Delta}| \quad (14)$$

where a and b are two approaches used, here they are Vanilla-GAT and PromptGAT, respectively. Based on the absolute value of this equation, since the PromptGAT performs consistently better than Vanilla-GAT from Table 2, the larger value Δ_{\uparrow} is, the much more gap is mitigated. And since every metric has its own range, for unity, we normalized the Δ_{\uparrow} using max-min normalization. Apart from the commonly used metrics, the $\Delta_{Accuracy\uparrow}$ refers to how much accuracy (loss) has been improved.

We could observe from Figure 7 that for the relation between the accuracy improvement $\Delta_{Accuracy\uparrow}$ and each of the metrics, they are strongly correlated except for minor outlier points, which proves that, when the PromptGAT provides a better depiction inference on the system dynamics, the inverse model’s action would be better grounded to the realistic scenario, policy π will learn in a more robust way and leading to a final lower performance gap in reality. Other metrics’ mutual comparison also reflects the correctness of our method by showing a strong correlation between each other.

5 Conclusion

In this paper, we propose a prompt-based grounded action transformation method named PromptGAT in the traffic

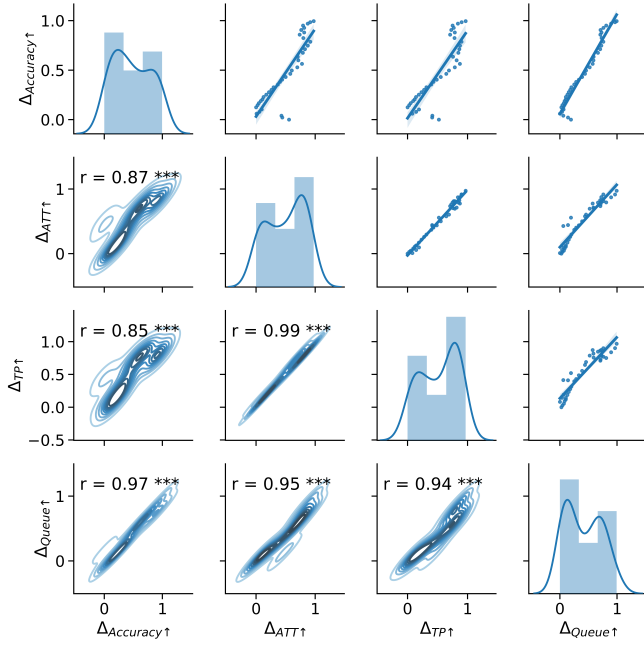


Figure 7: Correlation analysis between improvements of forward model accuracy (compared with Vanilla-GAT) and the improvements of performance in E_{real} . The value of r indicates the Pearson Correlation Coefficient, and the values with * indicating statistical significance for correlation, where *** indicates the p-value for testing non-correlation $p \leq 0.001$.

signal control domain to mitigate the sim-to-real performance gap. By leveraging the inference ability from pre-trained large language models, incorporating the perceptible domain knowledge, PromptGAT manages to better profile and depict the system dynamics in real-world settings and successfully increase the forward model’s prediction accuracy in the GAT process. Benefiting from the more accurate real-world dynamics prediction, the grounded action transformation is taken to enable the agent to perform well in the real world, further improving the model’s transferring performance. Sufficient experiments demonstrate the rationale of LLM’s inference process and prove PromptGAT has the potential to solve the police’s real-world deployment challenge. This research first leverages the LLMs to solve policies’ real-world deployment problems, cast hope for the future exploration.

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