Bayesian Meta-reinforcement Learning for Traffic Signal Control

Yayi Zou, Zhiwei Qin
DIDICHUXING AI LAB

Abstract
In recent years, there has been increasing amount of interest around meta reinforcement learning methods for traffic signal control, which have achieved better performance compared with traditional control methods. However, previous methods lack robustness in adaptation and stability in training process in complex situations, which largely limits its application in real-world traffic signal control. In this paper, we propose a novel value-based Bayesian meta-reinforcement learning framework BM-DQN to robustly speed up the learning process in new scenarios by utilizing well-trained prior knowledge learned from existing scenarios. This framework is based on our proposed fast-adaptation variation to Gradient-EM Bayesian Meta-learning and the fast-update advantage of DQN, which allows for fast adaptation to new scenarios with continual learning ability and robustness to uncertainty. The experiments on restricted 2D navigation and traffic signal control show that our proposed framework adapts more quickly and robustly in new scenarios than previous methods, and specifically, much better continual learning ability in heterogeneous scenarios.

1 Introduction
Traffic signal control in intersections takes important role in our everyday life. Efforts have been made to design systems that can react to the feedback from the environment in order to save travel time of vehicles passing through the intersections. However, traditional traffic control systems, e.g., SCATS [PR, 1992], use handcraft traffic signal plans which make them hard to find optimal control solutions in dynamic situations of intersections. Since intersection traffic signal control can be well modeled as a Markov Decision Process (MDP), it is naturally to apply reinforcement techniques to this problem, especially given the growing available traffic data (e.g., surveillance camera data) and development in deep reinforcement learning (DRL) [Lillicrap et al., 2015]. In recent years, DRL-based methods in traffic signal control have shown better performance than traditional methods [Wei et al., 2018; Wei et al., 2019; Van der Pol and Oliehoek, 2016]. However, the training process of DRL involves a lot of exploration/exploitation and thus needs a large amount of data and learning time to achieve superior performance, which is not feasible in many practical situations. Therefore, recent studies apply Meta-learning into traffic signal control [Zang et al., 2020] which utilized the common knowledge of existing tasks (referred as meta-knowledge) and learn to quickly adapt to new tasks.

Nevertheless, our empirical studies show that previous methods lack robustness in adaptation and stability in training process under more complicate settings where the available meta-knowledge from existing tasks may not be sufficient for immediate quick adaptation. These drawbacks are crucial to transportation systems where bad explorations may result in severe traffic problems. This motivates us to develop a traffic control algorithm that are able to learn robustly with only a few samples.

Our contributions come in two folds. First, we propose a Bayesian meta-learning algorithm BM-DQN with robust continual learning ability. Unlike previous methods, e.g. MetaLight [Zang et al., 2020], which learns an initial point as meta-knowledge, BM-DQN learns a prior distribution as meta-knowledge of previously learned tasks. When comes to new tasks, BM-DQN infers a task posterior based on the learned prior and data from that task. This Bayesian probabilistic foundation effectively mitigates the instability in training process and enhances its robustness in adaptation to a new task. BM-DQN alternatively performs two updates, individual update which adapts to each individual task and global update which aggregate the common knowledge learned from each individual adaptation. Specifically, we design a fast adaptation variation to effectively speeds up the adaptation process such that this meta-learning algorithm could work on DQN (since the higher update frequency in DQN requires faster adaptation ability than policy-based RL). Second, we apply BM-DQN to traffic signal control. Compared to previous methods, the Bayesian modeling adds robustness continual learning ability in the adaptation to new scenarios which is specifically important in traffic signal control. In real-world traffic signal control where only data of limited intersections is available, it is important to have robust continual learning ability especially when meta-knowledge is not sufficient yet. The success of robust continual learning on individual tasks will then help learn a better meta-knowledge. Thus, this de-
Markov decision process (MDP) lane. The control process in an intersection is modeled as a

Each entering approach has left-lane, through-lane and right-lane. Figure 1 demonstrates the a standard 4-approach intersection.

we explain as follows:

2 Markov Decision Process for Traffic Signals Control

Figure 1 demonstrates the a standard 4-approach intersection. Each entering approach has left-lane, through-lane and right-lane. The control process in an intersection is modeled as a Markov decision process (MDP) \( L = < S, A, R, \gamma > \) which we explain as follows:

- State space \( S \): Following the setting of previous work, we use current traffic flow of each lane as the states of the MDP, which includes the queue length of each lane, moving speed and so on. For a fair comparison with previous work [Zang et al., 2020], we use the queue length of each lane as state \( S \). The number of approaches and lanes determine the dimension of state space. In real world intersections with different number of entering approaches exist (e.g. three or even five) and are regarded as heterogeneous scenarios.

- Action space \( A \): As shown in Figure 1, there are eight signal phases in total. At each time step, the system chooses one phase among them to perform, so The dimension of action space for RL agent equals to the number of phases. Intersections may have only a subset of the eight signal phases available in action space known as phase setting [Zang et al., 2020]. Therefore intersections with different phase settings are regarded as heterogeneous scenarios.

- Reward \( R \): To align with previous work, we use the negative sum of queue length of all lanes as the reward. We choose travel time as the evaluation metrics defined as the average travel time that vehicles spend on approaching lanes.

- Transition Probability: Different signal phase will result in different queue length after each control step. For example, a green light phase on one direction is expected to reduce the queue length along with that direction. Note that this process is stochastic because the change in queue length is also affected by the incoming traffic which is uncertain. However, we can learn the associated probability regarding the transition in states for each action \( P(s' | s, a) \). This transition probability is called dynamics in RL. In this work, we use model-free RL which does not explicitly learn the dynamics, instead, it learns the value function regarding different states and actions which implicitly contains the information of dynamics.

3 Learning

We describe the DRL method that we apply to the single-intersection traffic signal control problem and then followed by Bayesian meta-RL.

3.1 DQN

Since the action space is discrete and with small dimension in traffic signal control problems, deep Q-learning (DQN) is an appropriate reinforcement learning algorithm to choose [Wei et al., 2019]. In Q-learning, the goal is to learn Q function defines as the sum of reward \( r_t \) discounted by \( \gamma \) at each timestep \( t \):

\[
Q(s, a) = E\sum_{t=0}^{\infty} \gamma^t r_t | s(0) = s, a(0) = a |
\]

and thus the optimal policy is \( \pi(s) = \arg \max_a Q(s, a) \). In DQN, the Q function is approximated by base learner \( f_{\theta} \) (which is a deep neural network in DQN) with input \( s \) and a dimension \( |A| \) output, each dimension corresponds to the according \( Q(s, a) \). We denote the approximate Q function as \( Q(s, a; \theta) \). The TD loss of neural network parameter \( \theta \) is

\[
L(\theta; D) = E_{s,a,r,s'\sim D} [ (y^Q - Q(s, a; \theta))^2 ]
\]

where \( y^Q \) is the target value \( r + \gamma \max_{a'} Q(s', a'; \theta^-) \). \( \theta^- \) is the parameter of target network that are only updated for every \( i \) iterations to improve stability. Double DQN [Van Hasselt et al., 2015] makes further modification and improves even more

\[
y^Q \leftarrow r + \gamma Q(s', \arg \max_a Q(s', a; \theta); \theta^-)
\]

In this paper we use Double DQN unless explicitly notified.

3.2 Bayesian Meta-reinforcement Learning

Following general meta-learning setting [Finn et al., 2017] which assumes a task distribution \( T \) where all tasks are generated from. In traffic signal control, each intersection corresponds to a task. The goal of meta-learning is to design a
meta-learner $M$ which takes data $D_i$ in a new scenario $i$ as input and output model parameters $\theta_i = M(D_i)$ with good performance for this scenario. Suppose $M$ is parameterized with $\alpha$, then the goal is to find $\alpha := \arg\min_\alpha \ E_i \ L_i[M(D_i; \alpha)]$, where $L_i$ is the expected loss function of task $i$. Notice that $M(\cdot; \alpha)$ does not need to be an explicit function, for example, it can be training rules with certain initialization [Finn et al., 2017].

The meta-learning framework can be split to meta-training phase and meta-testing phase. In meta-training phase, we are given a set of training tasks $I_{\text{train}} = \{I_1, \ldots, I_{N_{\text{train}}}\}$ sampled from task distribution $T$ and the goal is to learn a good meta-learner $M(\cdot; \alpha)$ to enhance the learning efficiency of future traffic signal control tasks. In meta-testing phase, for a new traffic intersection $t$ sampled from $T$, the meta-learner is input with data $D_t$ of this intersection and output the adapted model parameters $\theta_t = M(D_t; \alpha)$. The performance metrics of meta-learner is then evaluated by performance of adapted model parameters on sampled testing tasks $I_{\text{test}} = \{I_1, \ldots, I_{N_{\text{test}}}\}$.

Within this problem setting, [Zou and Lu, 2020] shows that model-agnostic Bayesian meta-learning is optimal under certain metrics. This method aims to learn a well-trained prior $P^*(\theta)$ of parameters in base learner $f$. Using this prior, we can get a posterior that adapts to task $i$ through Variational Inference [Kingma and Welling, 2013]. Model-agnostic meta-learning (MAML) (the base of MetaLight [Zang et al., 2020]) is a special case of model-agnostic Bayesian meta-learning by using delta distributed prior $\delta_0(\theta)$ which weakens the robustness in adaptation and uncertainty measure as we can see in experiments. Gradient-EM Bayesian meta-learning [Zou and Lu, 2020] has the advantages in traffic signal control such as computationally efficiency and allowing distributed deployment. However, it fails when directly applied to traffic signal control problem as we will see below. This motivates us to develop the BM-DQN framework.

4 Methodology

In this section, we first introduce our base learner architecture BFRAP and then introduce our proposed BM-DQN framework.

4.1 Bayesian Base-learner Architecture

As described above, a flexible base model $f$ is required to handle the scenario across heterogeneous intersections for different action space and state space in traffic signal control. We adopt FRAP++ [Zang et al., 2020] and propose a Bayesian version of this structure BFRAP.

The structures in 4-phase intersections which consists of several embedding layers and convolutional layers [Zang et al., 2020]. The parameters of the embedding layers across different lanes are shared. The number of filters in convolutional layers are also fixed. So this structure can be applied to different phase settings and different number of lanes.

In Bayesian learning, instead of learning a point estimator of the model parameter $\theta$, it learns a distribution $P(\theta)$ of the model parameters to handle uncertainty and to enhance robust continual learning ability. We assume Gaussian distribution of model parameter $P(\theta) = q(\theta; \lambda) \sim N(\mu_\lambda, \sigma_\lambda)$ in this work.

4.2 BM-DQN Framework

The goal of BM-DQN is to utilize previous learned knowledge to enhance the learning process in target intersection. To do this, we meta-learn a good prior of model parameter $P^*(\theta) = q(\theta; \Theta)$ by alternatively perform two update steps: individual update and global update. To elaborate the details, we define inner-learner $\lambda_i$ as the distribution parameter of learned posterior over task $i$, and meta-learner $\Theta$ as the distribution parameter of meta-learned prior over the task distribution $T$. During individual update, starting with some prior, the inner-learner performs Bayesian fast learning on DQN to update the posterior. During meta update, the meta-learner extracts the common knowledge over inner-learners to update the prior.

This framework is inspired by Gradient-EM Bayesian meta-learning(GEM-BML) (see Appendix and [Zou and Lu, 2020] for details). However, the original design of GEM-BML and other Bayesian meta-learning methods all focus on policy based DRL algorithms which update parameters only after each whole episode. BM-DQN improves the updating frequency by undertaking a mini-batch updating after each step in one episode which takes the advantage of fast learning in DQN. Yet, our empirical results show that the direct combination of GEM-BML and DQN does not meet our expectation. According to our analysis, it is caused by the higher update frequency requires better fast adaptation ability of the model. Therefore, we design a fast adaptation variation by adding an initial point training process during global update to enhance fast adaptation in individual update. Empirical results show that this variation largely improves the performance on traffic signal control. The framework of BM-DQN is illustrated in Algorithm 1 and we elaborate the details below.

Individual update

This step we fix the meta-learner $\Theta$ and let each inner-learner $\lambda_i$ learn from the data $D_i$ of each task $i$. As described in [Mnih et al., 2015], DQN uses a neural network with parameter $\theta$ to represent the action-state function $Q(s, a)$ in Equation (1). In traffic signal control, BFRAP follows the standard design of DQN with experience replay and target value network. In each intersection $I_i$, the agent’s experiences $e_i(t) = (s_i(t), a_i(t), r_i(t), s_i(t + 1))$ at each timestep $t$ are stored in set $D_i$. Then the learning process can be viewed as a Variational Inference of the posterior $q(\theta; \lambda_i)$ given the prior $q(\theta; \Theta)$. This is done by the gradient descent on the sampled ELBO loss:

$$\lambda_i \leftarrow \lambda_i - \alpha \nabla_{\lambda_i} \mathbb{E}_{\lambda_i(\mu_\lambda, \sigma_\lambda)} [L_{\text{ELBO}}(\mu_\lambda + \hat{\epsilon}\sigma_\lambda; D_i)]$$

where $\alpha$ is the step size, $\hat{\epsilon}$ is standard normal samples $\epsilon \sim \mathcal{N}(0, 1)$. The ELBO loss is the loss function $L$ (defined in Equation (2)) plus the KL-divergence between prior and posterior.

$$L_{\text{ELBO}}(\theta; D_i) = L(\theta; D_i) + KL[q(\theta; \lambda_i) \| q(\theta; \Theta)]$$

To speed up the learning process of this step (one gradient-step learning), we design an amortized Bayesian inference
method. We start the gradient descent at a meta-learned initial point \( \lambda \) instead of \( \Theta \). This special point is commonly sensitive for the ELBO loss function surface such that one or two gradient step would be sufficient to obtain good performance on this loss. Both \( \lambda \) and \( \Theta \) are updated in each Global update step based on the results in each individual update step.

**Global update** We then fix the posteriors and compute the update of the prior parameters \( \Theta \) by equation (7). After the adaptation in individual-level, global-level adaptation aims to aggregate the adaptation of each intersection \( I_i \) to update the initialization \( \lambda \) of inner-learner and the meta-learner (prior distribution parameter) \( \Theta \). To learn a good prior \( \Theta \) which prevents meta-level overfitting [Finn et al., 2017; Zou and Lu, 2020], the data in individual update is split into training and validation set. We perform individual update consecutively on both of them and obtain \( \lambda_{t+1}^{i,r} \) and \( \lambda_{t+1}^{i,val} \). The meta-learner \( \Theta \) and inner-learner initialization \( \lambda \) is updated as follows:

\[
\lambda \leftarrow \lambda - \gamma \sum_{i \in T_i} (\lambda_{t+1}^{i,r} - \lambda) \\
\Theta \leftarrow \Theta - \beta \nabla_{\Theta} \left\{ KL[q(\theta; \lambda_{t+1}^{i,val}) \parallel q(\theta; \Theta)] + KL[q(\theta; \lambda_{t+1}^{i}) \parallel q(\theta; \Theta)] \right\} 
\]

where \( \gamma, \beta \) are stepizes. Notice that the KL divergence of two Gaussian distributions has close form solution which is differentiable. The detail of solutions is included in Appendix. Unlike traditional MAML style framework [Yoon et al., 2018; Finn et al., 2018; Ravi and Beatson, 2018] which involves meta-update gradients over the inner-update optimization process thus leading to meta-update backProp, our method keeps the separation of meta-update and inner-update to avoid meta-update backProp while performs fast adaptation.

**Adaptation to New Scenarios** In the meta-training process of BM-DQN, we learn well-generalized prior and initialization of posterior distribution on parameters \( \theta \) in \( f \). For a new target intersection \( I_i \), we apply the learned prior parameter \( \Theta \) and posterior parameter initialization \( \lambda \) to it by running the individual update:

\[
\lambda_{t} \leftarrow \text{Individual - update}(\Theta, \lambda, D_{t}) 
\]

Then we evaluate the performance by sampling parameters \( \theta \) from the task posterior distribution \( q(\theta; \lambda_{t}) \). The meta-testing process is outlined in Alg 2.

4.3 Fast Adaptation Variation

To speed up the Gradient-based Varational Inference Subroutine, we propose a fast adaptation variation. We add an initial point training process in the meta-update phase to meta-train a good initial point \( \lambda \) for the one-step gradient training of \( \lambda_{t} \). The good initial point \( \lambda \) is trained by moving it towards the two-step trained weights \( \lambda_{t+1}^{i,val} \) at each meta-update step [Algorithm 1, line 10]. Just like Reptile, this initial point \( \lambda \) is optimized such that one or few number of gradient steps on the training of a new task model parameter \( \lambda_{t} \) will result in great performance on the ELBO loss function \( ELBO^{(i)}(\Theta, \lambda_{t}, D_{t}) \). This means one or a few number of Variational Inference gradient step will quickly produce a good approximate posterior as the prior parameter \( \Theta \) converges through the meta-update iterations.

Notice that this variation maintains the advantage of GEM-BML, i.e., the separation of meta-update and inner-update to avoid meta-update backProp which is important in scaled and potentially distributed system like traffic signal control. We show the necessity of this variation by comparing BM-DQN with GEM-BML in the experiment section (ablation experiments).

5 Related Work

In recent decades, RL-based traffic signal control has attracted widely attention from both academia and industry. Various RL algorithms have been applied to this problem, from the early tabular Q-learning and discrete state representation methods [Balaji et al., 2010; Abdulkhai et al., 2003] to current deep RL, including value based methods (e.g., deep Q-Network [Van der Pol and Oliehoek, 2016; Wei et al., 2019; Wei et al., 2018] and policy-based methods [Aslani et al., 2017].

Recently, the effort of utilizing common knowledge of intersections to enhance control has also started. A big obstacle of these direction is the lack of a universal network design for different intersection scenarios, which means that we
need to train different networks for different scenarios from the start. A recently proposed a novel network design, called FRAP, introducing convolutional layers into the architecture and makes it possible to effectively share network parameters to different intersections.

Meanwhile, meta-learning, which adapts to new task by leveraging the experience learned from similar tasks, has developed fast in recent years. In meta-reinforcement learning, model-agnostic meta-learning (MAML) [Finn et al., 2017] achieves competitive performance with good computational efficiency and becomes a leading trend. These development motivates MetaLight [Zang et al., 2020], a framework that applies FRAP and MAML into traffic signal control.

### 5.1 Bayesian Meta-learning

Further research shows that MAML is a special case of the Hierarchical Bayesian model (HBM) [Grant et al., 2018], which uses Bayesian method to utilize statistical connections between related tasks. HBM have been decently studied [Heskes, 1998] in the past, but it is until recently it has a big comeback in deep models because of its advantages in uncertainty measure and overfitting preventing [Wilson et al., 2007]. Inspired by the training scheme of MAML, a series of MAML style Bayesian meta-learning algorithms were developed [Grant et al., 2018; Yoon et al., 2018; Ravi and Beatson, 2018]. However, these methods involves optimizations over the inner-update procés during meta-update, making it hard to scale to real-world situations. Recent work GEM-BML [Zou and Lu, 2020] decouples inner-update and meta-update, thus gives high flexibility to the optimization process of inner-update and making it appropriate for distributed systems.

### 6 Experiment

We first test our algorithm on a re-designed 2D navigation RL environment, then evaluate its performance in traffic signal control environment.

#### 6.1 Restricted 2D navigation

To demonstrate the superiority of our algorithm in general RL environment, we design a restricted 2D navigation problem as follows. The restricted 2D navigation involves a set of tasks where a point agent must move to different goal positions in 2D, randomly chosen for each task within a unit square. The observation is the current 2D position and the actions are velocity commands in the range \([-0.1, 0.1]\). To make this problem suitable for value-based RL algorithms like DQN, we restricted the dimension of action space to 16, which includes 8 directions, each direction with two choice of magnitude 0.03 and 0.1. The reward is the negative squared distance to the goal, and episodes terminate when the agent is within 0.02 of the goal or at the horizon of \(H = 100\). Detailed hyperparameter settings for this problem are in Appendix.

In our evaluation, we compare adaptation to a new task with up to 3 episodes’ training and we run the same process on 40 new tasks to calculate the average performance. The results in Figure 3 show the adaptation performance after each episode of BM-DQN, GEM-BML and MAML. The results show that BM-DQN adapts to new task much quicker and achieves better performance than previous methods. It also ratified the necessity of our fast-adaptation variation to develop BM-DQN from GEM-BML.

#### 6.2 Traffic Signal Control

In this experiment, we compare our BM-DQN framework with some representative benchmarks including state-of-art MetaLight [Zang et al., 2020] (RL-based method) and Self-Organizing Traffic Light Control (SOTL) which is the representative classical transportation method [Cools et al., 2013]. The results of MAML are not included since MetaLight largely outperforms MAML. We perform experiments on both an easy setting and a challenging setting. The easy setting consists of homogeneous scenarios where the tasks in meta-testing share the same phase setting and come from the same city as the tasks in meta-training. While in challenging setting, meta-testing tasks comes from different cities with different phase setting as in meta-training. We first introduce some experiment details and then represent the results of two settings.

**Experiment details**

This experiments is conducted in a simulation platform called CityFlow [Zhang et al., 2019], one of the latest simulation environments for traffic signal control. To use the simulator, we first feed real traffic datasets into the platform then we can use the simulator as a RL environment which executes the actions and returns the state and reward in each time step.

We use the datasets provided in [Zang et al., 2020] which includes four real-world datasets from two cities in China: Jinan (JN) and Hangzhou (HZ), and two cities in the United States: Atlanta (AT), and Los Angeles (LA). The raw traffic data from two Chinese cities contains the information about the vehicles coming through the intersections, which are captured by the nearby surveillance cameras. The other raw data from American cities is composed of the full vehicle trajectories which are collected by several video cameras along the streets. Just like most intersections, the entering lanes only consist of left-lane and through-lane. The episode length is one hour. In order to build the simple and challenging settings as elaborated below, different phase settings are created. The details of phase settings are summarized in Appendix.

We compare our BM-DQN model with MetaLight [Zang et al., 2020] and GEM-BML [Zou and Lu, 2020]. For fair comparison, all models use the same Double DQN update.
Figure 3: Meta-testing results of simple settings. Each point is regarding a whole episode evaluation after each DQN training step.

Table 1: Results of different methods on simple setting. Average travel time among the whole adaptation process is reported.

| Phase Setting | 8   | 6e  | 6a  |
|---------------|-----|-----|-----|
| GEM-BML       | 119.98 | 109.57 | 294.82 |
| MetaLight     | 97.48 | 103.13 | 148.09 |
| BM-DQN        | 72.72 | 85.85  | 109.36 |

Table 2: Results of different methods on challenging setting. Average travel time among the whole adaptation process is reported.

| Phase Setting | LA-2 | Atlanta-2 | LA-1 | Atlanta-1 | Jinan-1 | Jinan-2 |
|---------------|------|-----------|------|-----------|---------|---------|
| GEM-BML       | 238.89 | 273.89 | 886.94 | 457.01 | 132.68 | 515.75 |
| MetaLight     | 157.67 | 298.91 | 889.79 | 494.36 | 173.28 | 587.72 |
| BM-DQN        | 135.14 | 675.66 | 885.27 | 192.01 | 119.50 | 549.69 |

Simple Setting: Homogeneous Scenarios

In this setting, we first perform meta-training on 25 tasks from datasets of Hangzhou. During meta-testing, we choose six homogeneous tasks also from datasets of Hangzhou whose phase settings exist in the meta-training set. The results are described in Table 1 and Figure 4. Each phase setting stands for one task. Notice that in Table 1 the average travel time among the whole adaptation process is reported, while in [Zang et al., 2020] the minimum travel time is reported. We choose these metrics because we focus on the robustness in the whole adaptation process. In Figure 4 we plot the adaptation curve during meta-testing. The model is trained in DQN scheme and we perform evaluation after each update step. The results show that our model performs better than previous work in most scenarios with better stability, but the improvement is not significant. It is within our expectation because in homogeneous setting the common knowledge of training tasks in this setting is sufficient for quick adaptation on new tasks by using point estimated meta-knowledge.

We can see that GEM-BML cannot keep a stable learning trend or adapt slowly. It is because of the high update frequency in DQN training scheme that the adaptation speed of the inner-learners can not follow up without our fast-adaptation variation. In contrast, BM-DQN maintains a more stable and faster adaptation.

Challenging Setting: Heterogeneous Scenarios

In this setting, we try to test the knowledge transfer ability not just between different phase settings but also between different cities. As described in [Zang et al., 2020], the source data may differ greatly between cities, which increasing the difficulties to adapt control policy.

For meta-training, we use the same training tasks from datasets of Hangzhou as in the simple setting. While in meta-testing we perform heterogeneous adaptation on tasks from datasets of Jinan, Atlanta, and Los Angeles. The results are presented in Table 2 and Figure 5. Compared with simple setting, BM-DQN significantly outperforms all baselines and adapts much faster and more stable. It is because under this setting the new tasks in meta-testing have a relatively different distribution from the training tasks in meta-training, which is more likely to cause meta-level overfitting [Yoon et al., 2018]. Since BM-DQN learns an effective probabilistic prior knowledge, it could enable more robust continual learning in new scenarios and mitigate the impact of meta-level overfitting.
References

[Abdulhai et al., 2003] Baher Abdulhai, Rob Pringle, and Grigoris J Karakoulas. Reinforcement learning for true adaptive traffic signal control. Journal of Transportation Engineering, 129(3):278–285, 2003.

[Aslani et al., 2017] Mohammad Aslani, Mohammad Saadi Mesgari, and Marco Wiering. Adaptive traffic signal control with actor-critic methods in a real-world traffic network with different traffic disruption events. Transportation Research Part C: Emerging Technologies, 85:732–752, 2017.

[Balaji et al., 2010] PG Balaji, X German, and Dipti Srivasan. Urban traffic signal control using reinforcement learning agents. IET Intelligent Transport Systems, 4(3):177–188, 2010.

[Cools et al., 2013] Seung-Bae Cools, Carlos Gershenson, and Bart D’Hoooge. Self-organizing traffic lights: A realistic simulation. In Advances in applied self-organizing systems, pages 45–55. Springer, 2013.

[Finn et al., 2017] Chelsea Finn, Pieter Abbeel, and Sergey Levine. Model-agnostic meta-learning for fast adaptation of deep networks. arXiv preprint arXiv:1703.03400, 2017.

[Finn et al., 2018] Chelsea Finn, Kelvin Xu, and Sergey Levine. Probabilistic model-agnostic meta-learning. arXiv preprint arXiv:1806.02817, 2018.

[Grant et al., 2018] Erin Grant, Chelsea Finn, Sergey Levine, Trevor Darrell, and Thomas Griffiths. Recasting gradient-based meta-learning as hierarchical bayes. arXiv preprint arXiv:1801.08930, 2018.

[Heskes, 1998] TM Heskes. Solving a huge number of similar tasks: a combination of multi-task learning and a hierarchical bayesian approach. 1998.

[Kingma and Welling, 2013] Diederik P Kingma and Max Welling. Auto-encoding variational bayes. arXiv preprint arXiv:1312.6114, 2013.

[Lillicrap et al., 2015] Timothy P Lillicrap, Jonathan H Hunt, Alexander Pritzel, Nicolas Heess, Tom Erez, Yuval Tassa, David Silver, and Daan Wierstra. Continuous control with deep reinforcement learning. arXiv preprint arXiv:1509.02971, 2015.

[Mnih et al., 2015] Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Andrei A Rusu, Joel Veness, Marc G Bellemare, Alex Graves, Martin Riedmiller, Andreas K Fidjeland, Georg Ostrovski, et al. Human-level control through deep reinforcement learning. nature, 518(7540):529–533, 2015.

[PR, 1992] Lowrie PR. Scats: A traffic responsive method of controlling urban traffic control/pr lowrie. Roads and Traffic Authority, 1992.

[Ravi and Beatson, 2018] Sachin Ravi and Alex Beatson. Amortized bayesian meta-learning. 2018.

[Van der Pol and Oliehoek, 2016] Elise Van der Pol and Frans A Oliehoek. Coordinated deep reinforcement learners for traffic light control. Proceedings of Learning, Inference and Control of Multi-Agent Systems (at NIPS 2016), 2016.

[Van Hasselt et al., 2015] Hado Van Hasselt, Arthur Guez, and David Silver. Deep reinforcement learning with double q-learning. arXiv preprint arXiv:1509.06461, 2015.

[Wei et al., 2018] Hua Wei, Guanjie Zheng, Huaxiu Yao, and Zhenhui Li. Intellilight: A reinforcement learning approach for intelligent traffic light control. In Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, pages 2496–2505, 2018.

[Wei et al., 2019] Hua Wei, Guanjie Zheng, Vikash Gayah, and Zhenhui Li. A survey on traffic signal control methods. arXiv preprint arXiv:1904.08117, 2019.

[Wilson et al., 2007] Aaron Wilson, Alan Fern, Soumya Ray, and Prasad Tadepalli. Multi-task reinforcement learning: a hierarchical bayesian approach. In Proceedings of the 24th international conference on Machine learning, pages 1015–1022. ACM, 2007.

[Yoon et al., 2018] Jaesik Yoon, Taesup Kim, Ousmane Dia, Sungwoong Kim, Yoshua Bengio, and Sungjin Ahn. Bayesian model-agnostic meta-learning. In Advances in Neural Information Processing Systems, pages 7343–7353, 2018.

[Zang et al., 2020] Xinshi Zang, Huaxiu Yao, Guanjie Zheng, Nan Xu, Kai Xu, and Zhenhui Li. Metalight: Value-based meta-reinforcement learning for traffic signal control. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 34, pages 1153–1160, 2020.

[Zhang et al., 2019] Huichu Zhang, Siyuan Feng, Chang Liu, Yaoyao Ding, Yichen Zhu, Zihan Zhou, Weinan Zhang, Yong Yu, Haiming Jin, and Zhenhui Li. Cityflow: A multi-agent reinforcement learning environment for large scale city traffic scenario. In The World Wide Web Conference, pages 3620–3624, 2019.

[Zou and Lu, 2020] Yayi Zou and Xiaoqi Lu. Gradient-em prototype reinforcement learning agents. IET Intelligent Transport Systems, 12(8):732–735, 2018.