Scalable Deep Reinforcement Learning for Routing and Spectrum Access in Physical Layer

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Abstract—This paper proposes a novel scalable reinforcement learning approach for simultaneous routing and spectrum access in wireless ad-hoc networks. In previous works on reinforcement learning for network optimization, the network topology is assumed to be fixed, and a different agent is trained for each transmission node—this limits scalability and generalizability. Further, routing and spectrum access are typically treated as separate tasks. Moreover, the optimization objective is usually a cumulative metric along the route, e.g., number of hops or delay. In this paper, we account for the physical-layer signal-to-interference-plus-noise ratio (SINR) in a wireless network and further show that bottleneck objective such as the minimum SINR along the route can also be optimized effectively using reinforcement learning. Specifically, we propose a scalable approach in which a single agent is associated with each flow and makes routing and spectrum access decisions as it moves along the frontier nodes. The agent is trained according to the physical-layer characteristics of the environment using a novel rewarding scheme based on the Monte Carlo estimation of the future bottleneck SINR. It learns to avoid interference by intelligently making joint routing and spectrum allocation decisions based on the geographical location information of the neighbouring nodes.

Index Terms—Routing, spectrum access, reinforcement learning, ad-hoc wireless network, distributed optimization.

I. INTRODUCTION

Routing in wireless ad-hoc networks is a complex problem involving sequential decisions in each hop in order to build a route that optimizes certain network objective. Due to the lack of centralized control, routing in wireless ad-hoc networks needs to be performed in a distributed manner. Starting from the source node, the selection of next node in each hop requires considerations of multiple often conflicting factors. This paper advocates the use of reinforcement learning for solving this complex problem.

This paper differs from myriad prior works in both the traditional routing literature and in more recent works using machine learning for network optimization in several important aspects. First, for wireless ad-hoc networks in which nodes operate in a shared wireless medium, it is important to consider the physical-layer characteristics of the transmissions. Classic works on wireless ad-hoc network routing protocols, such as [2]–[4], often abstract away the physical layer: the routing table is built based on a fixed topology; the nodes do not have complete flexibility to connect to every other node. Furthermore, the mutual interference between the transmission links and more importantly the abilities for each link to utilize different spectrum slots are not taken into account. Although more recent works [5]–[7] consider signal qualities, they utilize only heuristic rules and do not benefit from detailed physical-layer characterizations in term of the signal-to-interference-plus-noise ratio (SINR). The aim of this paper is to provide a solution to the joint routing and spectrum access problem in a large-scale network, while taking into account the physical-layer channel strengths and the interference levels in different spectrum slots. As these factors are largely determined by the geographical locations of the mobile nodes (assuming a path-loss model for wireless propagation), they motivate us to propose a new approach to routing based on the locations of each node and its neighbours and the physical-layer characteristics of the surrounding wireless environment.

This paper also explores new network objective and new methodologies for optimizing routing. As routing amounts to successive selections of nodes and spectrum slots in each hop, the number of possibilities in the overall optimization problem is combinatorial in nature; therefore finding the globally optimal route by exhaustive search is computationally prohibitive in large networks. Decentralized discrete optimization algorithms previously proposed for routing [2]–[11] are mostly heuristic in nature. On the other hand, routing is also a sequential decision making problem, in which each decision is a function of the current state of the network. Thus, routing can be modeled as a Markov decision process [12], which naturally fits into the realm of reinforcement learning. In this direction, many previous works [13]–[22] have employed the classical Q-learning [23] or deep reinforcement learning [24] to train agents to find the optimal route; see [25] for a comprehensive survey of the applications of reinforcement learning to communications and networking.

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neighbors and a \( Q \)-value table of their “fitness scores” as the potential next hop (e.g., time or number of hops to reach the destination). After training, the route is collectively determined by all the agents, each selecting the neighbor with the highest fitness scores as the next hop. However, training a distinct agent for each node limits scalability.

Secondly, most existing works assume that the network objective is cumulative along the routes, e.g., as in minimizing the transmission delay or the number of hops. While cumulative rewards fit naturally in the reinforcement learning framework, there are also important network metrics that are not cumulative in nature. In particular, assuming adaptive coding and modulation in each link, the maximum overall throughput that can be supported in a route is the minimum rate across all the hops, so it is a function of the bottleneck \( \text{SINR} \) within the data flow. Such bottleneck objective does not easily fit in the Markov decision process framework. A main objective of this paper is to show how to train a reinforcement learning agent to maximize the bottleneck objective.

To summarize, the approaches in most of the existing works in using reinforcement learning on routing for ad-hoc wireless networks are restricted by all or at least some of the following modeling and design choices:

**C.1** The network model assumes a fixed set of connections, where two nodes are either reachable or not.

**C.2** A distinct agent is associated with every node in the network and is trained specifically for this node.

**C.3** The objective is cumulative along the route.

**C.4** The same network topology must be maintained from training to testing.

Each of these modeling and design choices imposes limitations and has drawbacks. **C.1** abstracts away pivotal physical-layer characteristics of the network, thus preventing optimization of objectives such as signal-to-noise-and-interference (SINR) based quality-of-service (QoS). **C.2** requires the number of agents to scale as the network size, therefore limiting scalability and generalization capability. **C.3** does not allow the optimization of objectives such as the bottleneck link rate within a data flow. **C.4** further limits agents’ abilities to adapt to network changes. Attempting to address the limitation of **C.4**, [15] let agents explore all new neighbors opportunistically, which is essentially retraining. But as the layout of an ad-hoc network can frequently change (e.g., due to mobility), any solution designed under **C.4** is inherently insufficient. Further, to address the limitation of **C.2**, [26] proposes the use of a specific \( Q \)-function estimator [27] for the agent, allowing the same agent to be applied to different nodes. But, none of these works performs routing based on physical-layer attributes.

In this work, we recognize the critical importance of making routing decisions based on the physical-layer characteristics of the network, and moreover the importance of optimizing spectrum access jointly with routing decisions. This is because the allocation of which frequency bands to transmit for a particular link significantly affects the interference levels of all nearby links, including the previous and subsequent links in the same flow. While spectrum access has been the focus in many previous work in wireless network optimization, including conventional optimization algorithms [28]–[30], supervised learning [31], and reinforcement learning [32]–[36], all these works assume fixed wireless connections, thus do not make routing decision jointly with spectrum optimization. While there exist conventional optimization based works that focus on both routing and spectrum access [37]–[39], these works do not take advantage of learning based method. We mention here that [40] explores learning automata based optimization over wireless sensor networks that includes both routing and spectrum access, but its focus is exclusively on energy conservation.

The main contribution of this paper is a novel and scalable deep reinforcement learning approach to simultaneous routing and spectrum access for ad-hoc wireless networks based on physical-layer inputs, constraints, and objectives. We focus on the maximization of the bottleneck rate across the flow as the main task, and solve the spectrum access problem along the routing process by training a reinforcement agent to determine the suitability of different frequency bands for each link. For routing, as a main novelty, we associate one agent to each data flow from the source node to the destination. The agent executes sequential node-selection tasks along the route. Furthermore, we propose a novel \textit{Monte-Carlo} based reward estimation scheme within the conventional Q-learning strategy [23] to enable the agent to effectively learn to optimize a bottleneck objective. Throughout the paper, we propose to model the network environment via a local node density function. This is in line with the physical-layer modeling of the ad-hoc network, and more importantly, also aligns with the reinforcement learning framework which requires the environment to be stationary.

The fact that the agent takes physical-layer information as input is crucial—this allows the same agent to be used for all nodes along the route, thus providing scalability. We show that the same model parameters for the agent can also be shared across distinct data flows, or even generalized across different ad-hoc networks. Finally, the agent can also be designed to adapt to network characteristics such as the density of neighbors.

The rest of the paper is organized as follows. Section II establishes the system model and formulates the optimization problem. Section III proposes a deep reinforcement learning based approach for routing and spectrum access in wireless ad-hoc networks. The performance of the proposed method is analyzed in Section IV. As extensions, Section V incorporates delay into the objective; Section VI performs power control to further improve the data rate. Finally, conclusions are drawn in Section VII.
II. ROUTING IN AD-HOC WIRELESS NETWORK

A. Network Model

Consider a wireless ad-hoc network supporting $F$ data flows, each with a fixed source and a fixed destination node, and routed through multiple hops over a subset of $N$ intermediary relay nodes in the network. We assume that there are $B$ available frequency bands each of bandwidth $W$ Hz, and each hop uses one of the $B$ frequency bands for signal transmission and reception. We use $F$ to denote the set of data flows; $S$ and $T$ to denote the set of sources and destinations, respectively; $N$ to denote the set of relay nodes; and $B$ to denote the set of available frequency bands, with $|F| = F$, $|N| = N$, and $|B| = B$.

We assume that the environment around each node follows some statistical distribution. To this end, we characterize the ad-hoc network through a node density distribution function, and assume some local density of the neighboring nodes across each sub-region. Throughout this paper, during routing in a given network topology, the locations of the nodes are assumed to be fixed. Routing in the presence of mobility would be a much more challenging problem.

B. Routing and Spectrum Access

The task of routing is to select an ordered list of relay nodes for each flow $f \in F$. The task of spectrum access is to select a frequency band for each hop. Mathematically, we represent the route for flow $f$ as an ordered list denoted by $n(f)$:

$$n(f) = (n_0(f), n_1(f), n_2(f), \ldots n_h(f), n_{h+1}(f))$$

(1)

where $n_0(f) = s_f \in S$ represents the source node for $f$, $n_{h+1}(f) = t_f \in T$ represents the destination node for $f$, and $n_1(f), n_2(f), \ldots, n_h(f)$ are the relay nodes. We represent the spectrum access for flow $f$ as an ordered list denoted by $b(f)$, containing the frequency bands of each hop

$$b(f) = (b_0(f), b_1(f), b_2(f), \ldots b_h(f))$$

(2)

where $b_i(f) \in B$, $j = 0, \ldots, h$. Note that each hop uses only one frequency band with a fixed bandwidth.

Given $n(f)$ and $b(f)$, we have a complete description of the data flow $f$ as follows:

$$n_0(f) \xrightarrow{b_0(f)} n_1(f) \xrightarrow{b_1(f)} n_2(f) \xrightarrow{b_2(f)} \ldots n_h(f) \xrightarrow{b_h(f)} n_{h+1}(f)$$

(3)

In establishing $f$, there are $h$ routing decisions for selecting the nodes for the $h$ hops, as well as $h + 1$ spectrum access decisions for selecting the $h + 1$ transmission bands. Collectively, these routing and spectrum access decisions over all the flows are denoted as:

$$N_F = \{n(f), \forall f \in F\}$$

(4a)

$$B_F = \{b(f), \forall f \in F\}$$

(4b)

We restrict each hop of any data flow to use only one frequency band, which is already implicitly reflected in (3). We do not allow a node to transmit and receive in the same frequency band, but we do allow for the possibility that an intermediary node can serve as a relay for multiple data flows, as long as all of its incoming and outgoing hops occupy distinct frequency bands. Mathematically, this means for a flow $f$ with $h$ relays

$$b_i(f) \neq b_{i+1}(f), \forall i = 0, 1, \ldots, h - 1;$$

(5)

and if $n_i^{(f_1)} = n_j^{(f_2)}$ for some $f_1, f_2 \in F$ and some $i, j$, then

$$\{b_i^{(f_1)}, b_j^{(f_1)}, b_{j-1}^{(f_2)}, b_j^{(f_2)}\} \text{ are all distinct.}$$

(6)

Note that (6) subsumes (5).

Finally, to eliminate loops in routing (which is never helpful), we explicitly enforce that each data flow can visit an intermediary node at most once

$$n_i^{(f)} \neq n_j^{(f)}, \forall i \neq j.$$  

(7)

C. Performance Metrics

At the physical layer, the maximum transmission rate between a pair of nodes over a frequency band is characterized by the capacity of the underlying wireless channel, which is a function of the signal-to-noise-and-interference (SINR) at the receiver. In details, consider a link with transmitting node $i \in S \cup N$ and receiving node $j \in T \cup N$, over the frequency band $b \in B$ with bandwidth $W$, with $p_i$ as the transmit power of node $i$ and $\sigma^2$ as the background noise power in each frequency band, and $h_{ij,b} \in C$ as the channel strength from node $i$ to node $j$ in the band $b$, the maximum transmission rate of this link is related to the SINR as follows:

$$\text{SINR}_{(i,j,b)} = \frac{|h_{ij,b}|^2 p_i x_{i,b}}{\sum_{k \in S \cup N} |h_{kj,b}|^2 p_k x_{k,b} + \sigma^2}$$

(8a)

$$R_{(i,j,b)} = W \log \left(1 + \text{SINR}_{(i,j,b)}\right)$$

(8b)

The binary variable $x_{i,b}$ ($i \in S \cup N, b \in B$) indicates whether the node $i$ is transmitting on the band $b$ or idle, and is determined by the routing and spectrum access solution (i.e. if node $i$ is used by any route to transmit over the band $b$ or not), i.e.,

$$x_{i,b} = \begin{cases} 1 & \text{if } \exists f, k : n_k^{(f)} = i \text{ and } b_k^{(f)} = b \\ 0 & \text{otherwise.} \end{cases}$$

(9)

We assume full-buffered transmission in which the data is continuously transmitted along the route. In this case, the overall data rate for each flow is determined by its bottleneck link capacity (i.e. the minimum data rate among all its links). Specifically, consider the flow $f$ with its routing and spectrum access specified as in (3), the overall
The data rate of the flow $f$ is
\[ R^{(f)} = \min_{i=0,1,2,...,h} R_{(s_i^{(f)},n_i^{(f)},b_i^{(f)})}. \] (10)

The concept of the bottleneck link is visually illustrated in Fig. 1. We denote the set of the overall data rates of all flows to be
\[ R_F = \{ R^{(f)} \mid \forall f \in \mathcal{F} \}. \] (11)

**D. Optimization Problem Formulation**

The objective for optimal routing and spectrum access is to determine the set of solutions as in (3) for each data flow in order to optimize some global objective across all the flows in the network. The global objective is called network utility, denoted as $U(\cdot)$, which is a function of the data rates of all the flows (e.g., the sum data rates or the minimum data rate). Mathematically, the optimization problem is formulated as follows:

\[
\begin{align*}
\text{maximize} & \quad U(R_F) \\
\text{subject to} & \quad (1), (2), (4) - (11). 
\end{align*}
\] (12a, 12b)

Note that the data rates of different links both within each flow and across the flows have strong inter-dependencies due to the mutual interference. Specifically, if two links share the same frequency band, then the transmitted signal of one link appears as interference for the other link. Thus, the spectrum allocation problem is tightly coupled with the routing problem. Consequently, there is a trade-off between the data rates of different flows in the network.

We emphasize that (12) is an integer programming problem, which is highly complex, due to the above-mentioned interference terms causing the flow rates to have strong interdependencies, and due to the large number of discrete optimization variables involved. To the best of the authors’ knowledge, this formulation of routing problem (which accounts for physical-layer interference) has not been studied previously in the literature.

**E. Motivation for Reinforcement Learning**

Optimizing routing and spectrum access in even just a single data flow is already nontrivial: it involves sequential decision makings in a highly variable environment, so it can be modeled as a Markov decision process. But, because each agent can only observe local information, and further due to the lack of central infrastructure for control and communication in ad-hoc networks, the optimization across the multiple interacting flows needs to be conducted in a distributed manner, the problem of distributed routing and spectrum access over the multiple data flows belongs to the class of multi-player partially observable Markov decision process (MP-POMDP). This is a challenging problem, and it motivates the use of distributed multi-agent reinforcement learning.

Moreover, as the wireless environment is characterized by physical layer attributes modeled by continuous quantities, function approximators are required for implementing the reinforcement learning agent. This motivates us to utilize deep reinforcement learning techniques.

The novel approach taken in this paper is to let a single reinforcement learning agent optimize one flow at a time by moving along the frontier node of the flow. Then, we optimize the next flow, and do so successively, in effect letting flows compete with each other. As shown later in the paper, this would already lead to effective solutions to the problem (12) for common network utilities such as the sum rate or the minimum rate.

**III. Flow Based Deep Reinforcement Learning for Routing and Spectrum Access**

This section describes the proposed novel reinforcement learning approach for the multi-flow joint routing and spectrum-access problem.

**A. Single Agent for Multiple Nodes in a Flow**

A key innovation of this paper as compared to prior work is to associate a single reinforcement learning agent to all the nodes in each flow. The idea is that as a route is being established on a hop-by-hop basis, the agent moves along with the frontier node of the partially established route to decide the best next hop as well as the best frequency band to reach the next node from the frontier node. Compared to most prior approaches that train a different agent for each node in the network to perform either routing or spectrum access, this agent-to-flow association has the key advantage that it significantly reduces the number of parameters that need to be trained, because a single agent now works for all nodes in the flow. This improves scalability, and further
is exposed to
S4: Interference the neighbor
is exposed to
S3: Angle offset
S2: Distance from the
Neighbor to destination
S1: Distance to the neighbor

also improves generalization ability because the same agent can be used across multiple data flows and even across distinct ad-hoc networks. Fig. 2 provides a visualization of the proposed agent-to-flow association for establishing the next hop at a frontier node of a flow.

When optimizing multiple flows, we adopt a sequential ordering for establishing routes and spectrum allocation: i.e., we let one flow establish its entire route and frequency band selections before the next flow, and do so over multiple rounds to allow the interference pattern to be fully established.

B. Single Agent for Multiple Frequency Bands

We aim to develop a reinforcement learning agent to simultaneously perform routing and spectrum access for all the hops in each flow. One natural design for the agent is to aggregate features from all frequency bands, and to decide the optimal next node and frequency band combination. This, however, significantly increases the resulting state and action spaces for the agent. Furthermore, this design does not allow the agent to be generalized to scenarios with different number of frequency bands.

To reduce the state space and the action space and to achieve higher model parameter efficiency, we propose an approach of designing an agent for a single frequency band, then replicating it across \( B \) bands. The agent evaluates the suitability of the next node for all frequency bands, one band at a time, then selects the best node and frequency band combination. This process is illustrated in Fig. 3. In essence, the agent achieves equivalent state space and action space over all the frequency bands, with parameter cost of just one band.

C. Action Space and State Space

We now define the action space and the state space for the reinforcement learning agent for one frequency band. The agent’s action corresponds to selecting a next-hop node to transmit. As this paper adopts a physical-layer network model in which the connections are not predetermined, we consider a fixed number of \( c \) available neighbors with strongest channels as candidates. In addition, to ensure sufficient exploration capability, we also add one reprobe action, which means that if the agent decides none of the \( c \) strongest neighbors is a suitable next hop, it would proceed to probe the next \( c \) strongest neighbors, until a suitable next hop is found. Thus, over a single frequency band, the agent’s action space \( \mathcal{A} \) consists of \( c + 1 \) actions:

A.1 Total of \( c \) actions: one for selecting each of the \( c \) strongest neighbors.

A.2 One additional action for reprobing beyond the \( c \) strongest neighbors.

Note that if the agent chooses to reprobe, the agent stays at the current frontier node in the current time. At the next time step, the agent will explore the next \( c \) closest neighbors and collect the state information corresponding to these new set of neighbors.

The agent’s state space \( \mathcal{S} \) over one frequency band should summarize crucial factors about each of the \( c \) strongest neighbors in that frequency band as the agent moves along the frontier node. We adopt a pathless based network model in which the SINR is a function of the geographical locations of the neighbors relative to the frontier node and to the destination, as well as the interference each neighbor is subjected to. To this end, the agent gathers the following information from each neighbor to form its state:

S.1 Distance between the neighbor and the frontier node.
S.2 Distance between the neighbor and the destination.
S.3 Angle difference between the direction from the frontier node to the neighbor and the direction from the frontier node to the destination.
S.4 Total interference the neighbor is exposed to in the current frequency band.

Here, S.2 and S.3 indicate the amount of progress toward the destination node that can be made if the neighbor is chosen as the next hop, while S.1 and S.4 together allow an estimation of the SINR to the neighbor in the current frequency band. In total, the state over one frequency band is a \( 4c \)-component vector. Fig. 2 shows the four state features for each of the \( c \) closest neighbors.

Before we complete the picture by defining the agent’s reward, we next provide a brief overview of reinforcement learning, and illustrate why the standard Q-Learning needs to be modified in order to tackle the routing problem.

D. Conventional Q-Learning

Q-learning [23] is an off-policy, value-based reinforcement learning algorithm for model-free control. Q-learning
is suited for routing and spectrum access for wireless ad-hoc networks, because:

- Being a value-based algorithm, Q-learning estimates a value for each state-action pair. In the routing problem, each action corresponds to a combination of next hop node and frequency band selection. These actions can be quantitatively evaluated and compared based on the overall network objective (such as the bottleneck rate of the flow). The value-based Q-learning algorithm then allows these quantities to be mapped and learned depending on the state-action values.
- Being a model-free algorithm, Q-learning allows us to bypass explicit modeling and directly determine the optimal policy. This is useful, because in our setting, the state of the network is only partially observed by the agent, which makes the state transitions of the network difficult to model.

The conventional Q-learning algorithm is based on the following definition of the action value denoted as \( Q \):

\[
Q_\pi(s_t, a_t) = E_\pi[r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \ldots \mid s_t, a_t] \tag{13}
\]

\[
= E_\pi[r_t + \gamma Q_\pi(s_{t+1}, a_{t+1}) \mid s_t, a_t] \tag{14}
\]

where \( r_t \) is the reward at time \( t \) and \( \gamma \) is a discount factor.

Here, \( Q_\pi(s_t, a_t) \) is the expected future cumulative reward after the agent executes the action \( a_t \) from the state \( s_t \), with the expectation taken under certain policy \( \pi \). Given an estimate of \( Q_\pi(s_t, a_t) \), one can improve the policy by acting greedily with respect to \( Q_\pi(s_t, a_t) \), i.e.,

\[
\pi'(s_t) = \operatorname*{argmax}_a Q_\pi(s_t, a). \tag{15}
\]

We can then re-estimate the values of \( Q_\pi'(s_t, a_t) \) through either (13) or (14), and continue to improve the policy using (15). When the process converges, we reach an optimal policy \( \pi^* \) (and its corresponding value functions \( Q_{\pi^*}(s_t, a_t) \)). Such a process is referred to as the policy iteration, and the optimal policy takes on the following self-referential relation:

\[
\pi^*(s_t) = \operatorname*{argmax}_a Q_{\pi^*}(s_t, a). \tag{16}
\]

When estimating \( Q \) (which is commonly referred to as policy evaluation), there are two common approaches, each with its own benefits and shortcomings:

1) Monte-Carlo Estimation, corresponding to (13), which provides an unbiased estimation, but has high variance;
2) Temporal Difference Estimation, corresponding to (14), which has low variance, but is biased due to its self-referential nature.

The standard Q-learning algorithm performs the policy evaluation with temporal difference estimation, and updates the \( Q \) estimation based on the Bellman optimality equation [41] as follows:

\[
Q_{\pi}^{\text{new}}(s_t, a_t) = Q_{\pi}^{\text{old}}(s_t, a_t) + \\
\quad \alpha (r_t + \gamma \max_a Q_{\pi}^{\text{old}}(s_{t+1}, a) - Q_{\pi}^{\text{old}}(s_t, a_t)), \tag{17}
\]

where \( \alpha \) is the step size. To accelerate the algorithm,
Q-learning only performs (17) once before the policy improvement in each round of the policy iteration. (One step of the policy evaluation in a policy iteration process is also known as the value iteration process.)

There are, however, two major issues when applying the standard Q-learning algorithm to the routing and spectrum access problem for the wireless ad-hoc network. First, the conventional Q-learning assumes a reward definition \( r_{t} \) as the immediate reward that the agent receives after executing action \( a_{t} \) in state \( s_{t} \). These immediate rewards form the cumulative reward \( Q(s_{t}, a_{t}) \), which is the objective that the agent aims to optimize. However, in the routing problem, the objective (12) is determined by the bottleneck rates in the flows. Decomposing the bottleneck rate into a set of immediate rewards is not straightforward.

Secondly, even if the instantaneous rewards are redefined to account for the optimization of the bottleneck rate, the standard training process for Q-learning, which is based on temporal difference estimation, is known to suffer from high biases. In our experience for training the reinforcement learning agent for routing with the instantaneous rewards redefined to account for the bottleneck, the learned agent’s state-action value estimations are noticeably off with large positive biases throughout the state space (even when using the Double-DQN method [42]), rendering the agent incapable of producing high quality solutions for routing or spectrum access.

### E. Novel Reward and Action Value Estimation

To apply Q-learning to the routing problem, we need first to incorporate the bottleneck rate into the reward definition. The most intuitive way to do so is to set the reward to be all zero along the route until the last hop, which takes a reward value of (10), i.e., the minimum rate across all the hops in the route. However, this definition has the drawback that such a reward and the resulting Q-values for one hop could well be determined by an earlier hop, making them independent of the agent’s choice of actions. Consequently, this makes it impossible for the agent to interpret the rewards during training.

To simultaneously address the problem of decomposing the bottleneck rate to immediate rewards as well as the problem of biased estimation for temporal difference state-action value estimation, this paper proposes a novel structure for rewarding the agent. Instead of identifying an instantaneous reward \( r_{t} \) then computing \( Q \) as the cumulative sum of \( r_{t} \), we directly assign a future cumulative reward for each state-action pair. Such a new definition of future cumulative reward shares the same semantic meaning as the \( Q \) function in conventional Q-learning, but is not a result of cumulative instantaneous rewards. The main advantage of this approach is that it makes possible to optimize network objectives (such as the bottleneck rate in our case) that cannot be easily decomposed as sum of instantaneous rewards.

Specifically, at any given node, we choose to use the bottleneck link SINR from that node onwards in the route as its future cumulative reward. Note there is a one-to-one relationship between rate and SINR. More precisely, consider the data flow \( f \in \mathcal{F} \) established in (3). During training, at frontier node \( n_{f}^{(t)} \) \( (0 \leq t \leq h) \), the agent observes the state \( s_{t} \) and takes the action \( a_{t} \) (leading to node \( n_{f}^{(t+1)} \) using frequency band \( b_{f}^{(t)} \)). After the route is fully established, the state-action pairs along the route are then assigned a future cumulative reward, which we denote as \( \tilde{Q} \), defined as follows:

\[
\tilde{Q}(s_{t}, a_{t}) = \min_{i=t+1}^{h} \text{SINR}(n_{f}^{(t)}, n_{f}^{(i)}, b_{f}^{(i)})
\]  \hspace{1cm} (18)

We emphasize that \( \tilde{Q} \) plays the same role as \( Q \) value in Q-learning in that it incorporates future information (and no past information) and is used as the metric for determining the optimal actions.

In the works on classical Q-learning [23] and deep Q-learning [24], [42], [43], the target for \( Q(s_{t}, a_{t}) \) is computed based on the temporal difference estimation with bootstrapping, which can cause high biases as already mentioned. Instead, the \( Q \) defined in (18) can be computed directly based on Monte-Carlo estimation, which is unbiased. This is another crucial advantage of the proposed approach.

We note that Q-Learning is not originally designed to work with Monte-Carlo estimation. The above unconventional algorithm design, when used in conjunction with experience replay for deep reinforcement learning, does give rise to one slight technical difficulty: each time the \( Q \) is updated, it corresponds to the policy evaluation of a slightly older version of policy (from which the samples are collected for Monte-Carlo estimation). In the next section, we provide a variation to the experience replay technique to address this difficulty.

### F. Deep Q-Learning Based Routing and Spectrum Access

Since the states are continuous variables, the agent needs to be able to generalize over unseen portions of the state space \( S \). To this end, we utilize deep reinforcement learning, specifically deep Q-learning [24], in which a neural network, namely \( DQN \), is trained to predict \( Q \) values (in our case, the \( \tilde{Q} \) values) given the state-action inputs.

We format each state input for a single frequency band as a vector of length \( 4c \) (four features for each of the \( c \) strongest neighbors). These input vectors are processed with fully connected layers with non-linearities. We adopt the state-of-the-art dueling-DQN network architecture [43] for our agent, as illustrated in Fig. 4. The dueling DQN consists of two separate estimators: one for estimating the state value and the other for estimating the action advantage. Such a separation has been shown to be beneficial for the agent to learn the distinctions between actions.

The DQN is trained following the experience-replay technique as in [24], with uniform sampling from the replay
buffer. The agent follows the $\epsilon$-greedy [44] policy to gather experiences for the replay buffer. More specifically, with probability $1 - \epsilon$, the agent acts greedily according to the agent’s current estimation of $\tilde{Q}$; the action with the highest $\tilde{Q}$ value across the $B$ frequency bands is selected (as in Fig. 3). With probability $\epsilon$, the agent selects a random node as the next hop and a random frequency band to reach that node. If the selected node is not within the $\epsilon$ strongest neighbors to the agent, we store a reprobing transaction. Together, this allows us to produce a series of agent transactions for routing from the source to the destination. Once a route is fully established, we compute the rewards as defined by the onward bottleneck SINR for each node in the route, and store the corresponding (state, action, reward) tuple in the replay buffer, which is used for subsequent DQN training. Note that since the agent is trained to work in one frequency band at a time, the state is a $4c$-vector and the action is a value in $\{1, \ldots, c+1\}$. In case of greedy exploitation, we store the state vector for the frequency band in which the highest $\tilde{Q}$ is achieved; in case of random exploration, we store the state vector for the randomly chosen frequency band. The same is true for the reprobe transactions. The entire process of DQN training with experience replay is illustrated in Fig. 5.

We also propose a slight variation at the end of the training process to address the technical difficulty of using Monte-Carlo estimation for Q-learning. Normally, when training using the $\epsilon$-greedy policy, the agent always has a small (but non-zero) $\epsilon$ value, even at the end of the training process. To ensure that the policy evaluation is based on the most up-to-date policy, we set $\epsilon = 0$ at the end of training, and let the agent further collect samples and train for an extended period of time, (which we refer to as the extended training). With $\epsilon = 0$, the agent’s sampling policy reduces to the deterministic $\tilde{Q}$ value-based greedy policy. Correspondingly, the Monte-Carlo estimation from these collected samples provides the policy evaluation on this most up-to-date deterministic policy, based on which the policy improvement can be computed. As the result, the policy iteration process from the conventional Q-learning is correctly recovered\(^1\).

To showcase the generalization ability of our method, we only train the agent on one specific data flow during experience gathering. Specifically, we first use a simple closest-to-destination among the strongest neighbors heuristic to produce routes of all but one data flow. We then assign the agent to the last flow to gather experiences and conduct training. As shown later in Section IV, such lightweight training strategy is already sufficient to produce an agent that generalizes well across all data flows as well as across different ad-hoc networks. It does not need to be re-trained when the network topology changes, unlike in methods such as in [15].

G. Agent Policy Enhancements

From domain knowledge, we propose two enhancements to the agent’s policy:

- If the agent chooses a neighbor that does not have the strongest channel to the frontier node, then all neighbors with stronger channels to the frontier node are excluded for future consideration for the next hop.
- If the destination node appears within the agent’s exploration scope (i.e. one of the $c$ strongest neighbors), then the agent would not choose any neighbor which has a weaker channel to the frontier node than the destination node.

Both enhancements effectively prevent agents from taking non-essential back-and-forth hops.

H. Multi-Agent Distributed Optimization

The agent learns and acts according to $\tilde{Q}$ in (18) in order to optimize the data rate of its own flow. With each agent operating under a selfish objective, in general we do not expect the agents to collectively converge to a global network-wide optimum. Fundamentally, achieving cooperation among distributed multi-agent is always a challenging problem. If we assign selfish rewards to the agents, then there is no guarantee that they would reach a global optimum; if instead we assign all agents a common global reward, we then encounter the credit mis-assignment problem, as studied in [45], [46].

Furthermore, under the assumption that each agent only has local observations, it is helpful for the agents to coordinate their actions. However, it is challenging to engineer a messaging scheme that induces cooperation, while incurring only limited communication overhead.

\(^1\)Normally, Q-learning is regarded as a close variant to value iteration. However, if we regard each update step in Q-learning as an approximate policy evaluation, then we can still analyze Q-learning based on the policy iteration framework.
Recognizing this difficulty, in this paper, we let each agent learn independently, while being agnostic of the other agents’ actions or rewards, except through observing the surrounding interference (essentially regarding the other agents as a part of the environment). Despite its simplicity, a strategy like this can already be effective in many situations [47].

We observe that in a wireless ad-hoc network, where the major performance limiting factor is the mutual interference, routing optimization for one flow in the presence of other flows would already tend to produce an interference avoidance behavior, which benefits other data flows as well. Therefore, designing the agents to act selfishly in multiple rounds already allows every agent to adjust according to each other’s routes, thus achieving implicit cooperation to certain degree. The effectiveness of this approach is illustrated in the simulation results in Section IV.

I. Fairness Among Data Flows

In many applications, fairness among the data flows is an important design objective. We empirically observe that if routing and spectrum access are established sequentially across the data flows in multiple rounds, the data flows established relatively later tend to have better bottleneck rates. The reason is that the later flows can adjust according to the interference levels and utilize spectrum more efficiently. Therefore, to promote fairness among the data flows, we propose the following: At the end of each round, we compute the bottleneck rates for all data flows, then optimize routing and spectrum for the data flows in the next round in the decreasing order of the bottleneck rates. Flows with weak bottleneck rates in the previous round obtain the advantage of being able adjust their routes and frequency bands later in the next round, and as a result achieve better data rates. Note that such sequential routing strategy requires some level of synchronization among the flows.

IV. Simulation Results

A. Ad-hoc Network Setup

We consider wireless ad-hoc networks in a 1000m×1000m region with $F = 3$ data flows. The data flows are to be routed with $B = 8$ available frequency bands, with each band having 5MHz bandwidth. The node density profile is specified over nine equally divided sub-regions, with (6, 8, 7, 6, 5, 10, 8, 9, 6) nodes located randomly within each sub-region. We consider the short-range outdoor model ITU-1411 with a distance-dependent path-loss to model all wireless channels, over all frequency bands at 2.4GHz carrier frequency. All antennas have a height of 1.5m and 2.5dBi antenna gain. We assume a transmit power level of 30dBm for all nodes; the background noise level is at -130dBm/Hz.

We randomly generate 290,000 ad-hoc network layouts to train our agent. Among these, 20,000 layouts are used for random exploration based routing to generate the agent’s
initial experience, 250,000 layouts are used for the $\epsilon$-greedy policy based routing to train the agent, and the remaining 20,000 layouts are used for extended training with $\epsilon$ set to 0. For testing, we randomly generate 500 new ad-hoc network layouts according to the same distribution.

B. Agent and Reward Specification

We use $c = 10$ as the number of the strongest neighbors the agent explores each time. Correspondingly, the inputs to the dueling-DQN are 40-component vectors. The state inputs are processed by sequential fully-connected layers, organized into a state-value prediction branch and an action-advantage prediction branch, as in [43]. The specifications for the neural network are summarized in Table I.

This paper uses the bottleneck SINR onwards in the route as the future cumulative reward $\tilde{Q}$ assigned to each state-action pair. For practical training, we express SINR in dB scale in order to have a more suitable range of values. Further, we add a constant bias to ensure that the reward is almost always positive. This is so that this reward definition can be extended to the case in which a discount factor related to delay can later be added. Specifically, in actual training, we define the $\tilde{Q}$ function in terms of SINR as follows:

$$\tilde{Q}(s_t, a_t) = \min_{i=t,\ldots,h} 10 \log_{10} \left( \text{SINR}_{\omega^i t, \omega^{i+1} t, \omega^{i+2} t} \right) + \text{bias}. \quad (19)$$

This makes the reward much easier to learn.

C. Sum-Rate and Min-Rate Performance

We present the sum-rate and min-rate testing results for deep reinforcement learning agent (i.e., the dueling-DQN, or DDQN) as compared to a comprehensive list of benchmarks. These benchmarks are greedy in nature, since to our knowledge there currently do not exist efficient globally optimal algorithms for ad-hoc network routing based on physical-layer attributes. The benchmarks are as following:

- **Strongest neighbor**: Select the neighbor with the strongest wireless channel from the frontier node.
- **Best direction among neighbors**: Select the neighbor with the best next hop direction (i.e. the smallest angle offset between the agent-to-neighbor direction and the agent-to-terminal direction).
- **Closest to destination among neighbors**: Select the neighbor closest to the destination node. If all neighbors are further away from the destination than the agent, the agent will reprobe.
- **Least interfered among neighbors**: Select the neighbor exposed to the lowest amount of interference.
- **Largest data rate among neighbors**: Select the neighbor with the highest link capacity.
- **Destination directly**: Directly route from the source to the destination node.

These benchmarks incorporate a comprehensive set of important criteria, including but not limited to all the state features S.1--S.4.

We follow the multi-round sequential routing for all the methods. In simulations, two rounds appear to be sufficient already. For the DDQN agent, spectrum access is solved as in Section III-B. For all the benchmarks, we select the best frequency bands based on the state feature S.4. The sum-rate and min-rate results are summarized in Table II. The CDF curves of sum-rate results are presented in Fig. 6. As shown, our proposed method achieves significantly better performance than all benchmarks in both sum-rate and min-rate performances. We emphasize that this performance is achieved by re-using a single agent across all data flows, across all frequency bands, and over all testing network layouts.

To better understand how our method excels, we provide a visualization of routes formed by the DDQN agent together with selected benchmarks over a random ad-hoc network layout in Fig. 7. As shown, our agent intelligently spreads out all data flows as well as switching frequency bands for transmission to mitigate mutual interference, while still maintaining strong and properly directed links to the destination to form the routes.

To further illustrate this point, in Table III, we show the spectral efficiency in bps/Hz achieved when the number of available frequency bands varies from 2 to 8. It is clear that the DDQN agent is able to achieve higher spectrum efficiencies when more frequency bands are available. These results show that the DDQN agent is able to intelligently

| Parameters | Number of Neurons |
|------------|-------------------|
| Initial Main-Branch fully-connected layers | 1st: 150, 2nd: 150 |
| State-Value fully-connected layers | 1st: 100, 2nd: 1 (1 state value) |
| Action-Advantage fully-connected layers | 1st: 100, 2nd: 11 (11 actions) |

| Methods                      | Sum Rate | Min Rate |
|------------------------------|----------|----------|
| DDQN agent                   | 4.90     | 0.619    |
| Closest to Destination       | 1.76     | 0.238    |
| Best Direction               | 2.92     | 0.352    |
| Largest Data Rate            | 0.44     | 0.023    |
| Strongest Neighbor           | 0.43     | 0.007    |
| Least Interfered             | 0.55     | 0.040    |
| Destination Directly         | 0.02     | 0.003    |

**Table I**

**Table II**

**Table III**
Fig. 6. Cumulative distribution function of sum rate over 3 flows in 1000m × 1000m networks.

Fig. 7. Routes achieved on three data flows. Data flows are differentiated by colors, while frequency bands are differentiated by line styles. The dimension of the area is 1000m × 1000m.

TABLE III
SPECTRUM EFFICIENCY ANALYSIS FOR DDQN AGENT

| B   | Sum Rate (bps/Hz) | Min Rate (bps/Hz) |
|-----|------------------|-------------------|
| 2   | 0.066            | 0.006             |
| 4   | 0.312            | 0.032             |
| 8   | 0.984            | 0.124             |

D. Generalization Performance

1) Generalization to Different Number of Data Flows: We now investigate the generalizability of the proposed method when the number of data flows in the testing environment is different from the training set. We directly take the agent trained under the original setting and reuse it across all the data flows under the new test settings. The ad-hoc network layouts are generated under the same distribution of transmission nodes within the same area as in Section IV-A. However, the number of data flows to be routed and evaluated is set to be 2, 4, 5, and 6, which are different from the original setting of 3 data flows. The results are summarized in Table IV.

Simulation results suggest that the proposed DDQN agent still maintains the best performance among all testing approaches, although its advantage gradually decreases with the higher number of flows. The decreasing performance advantage is likely due to the fact that with the higher number of flows, the interference distribution becomes considerably different from the training setting, so the experience learned from the training set may not be as applicable. Nonetheless, routing with the DDQN agent is still the most promising approach even under these
generalized ad-hoc network settings.

2) Generalization to Larger Networks: To test the generalizability of the proposed method on larger problem instances, we directly take the agent trained under the original setting and reuse it for a much larger ad-hoc network of \( F = 10 \) data flows in a 5000m \( \times \) 5000m region, with \( B = 32 \) available frequency bands. We place larger number of \( \{19, 16, 21, 18, 14, 24, 17, 20, 19\} \) nodes over nine evenly divided sub-regions. The sum-rate results are shown in Fig. 8, which shows that our approach still significantly outperforms the benchmarks.

We notice that if we increase the number of relays nodes more aggressively, the performance of the DDQN agent drops below the strongest benchmarks tested. The potential reason is due to the fact that the DDQN agent has learned to prioritize the relatively shorter links in our simulation setting. Using shorter links is beneficial for obtaining higher direct-channel strengths, but it also leads to more nodes being active, thus more interference in the entire wireless network. As the DDQN agent is trained under the network settings as in Section IV-A, it has learned the right balance between the cost and benefit of using shorter links for achieving the optimal performance for that setting. But, when the network setting is drastically changed, the trade-off that the agent had previously learned might no longer be correct.

Nevertheless, the results presented in this subsection still illustrate that the proposed method has the capability to adapt to networks that are much larger in size, in the number of mobile nodes, and in the number of frequency bands, than the networks used for training.

E. Optimal Relaying Distance

The heart of the routing and spectrum access problem is to achieve the right balance between using nearby nodes as relays (which have strong channels) versus directly transmitting to farther-away nodes (which results in fewer number of transmissions in the network hence lower overall interference). The DDQN agent learns this balance in a data driven fashion.

For a network with a fixed node density, it is conceivable that a heuristics can be designed based on identifying an optimal relay distance, so that it can approach the performance of DDQN. Indeed, Table V shows the performance of the “closest-to-destination” benchmark, but the set of neighbors to explore is varied from 2 to 25. We see that the sum-rate and min-rate performances are the best when 4 neighbors are explored, which correspond to a medium relaying distance. Although this benchmark still does not outperform DDQN, its performance comes close. The point is, however, that this optimal number of neighbors to explore is difficult to determine in advance, while the proposed DDQN agent is able to identify the optimal number through training.

In the same vein, it is also conceivable that an optimal spectrum access heuristic can be designed. For example, we found empirically that if the agent always chooses the frequency band with the least amount of interference, it would generally work very well. In fact, the DDQN agent chooses the frequency band with the least interference about 70% of the time. Nevertheless, the proposed Q-learning based approach is still justified, because there is no easy way to come up with these heuristics, especially when the choice of the frequency band needs to be coupled with the choice of the next hop. Further, without DDQN, it is not straightforward to evaluate the optimality of these heuristics.

F. Fairness Among Flows

In the proposed DDQN, we encourage fairness between data flows by ordering the optimization of the flows in the reverse order of the data rates achieved in the previous round. To validate the achieved fairness using this approach, we provide numerical simulations of bottleneck rates achieved by each of the three flows over multiple testing layouts drawn from the same setting. The results are shown in Fig. 9. The distributions of the bottleneck rates are very close for all three data flows, indicating that fairness is achieved over the long run.

V. INCORPORATING DELAY IN THE OBJECTIVE

Up to this point, we have exclusively focused on optimizing network utilities based on the bottleneck rate of each flow. On the other hand, delay is also an important performance metric, which has been the focus of many prior routing work. As an extension of the proposed approach, in this section, we show how delay performance can be incorporated into the network objective, and propose training techniques for the reinforcement learning agent to achieve a tradeoff between the bottleneck rate and time delay—two quantities which often conflict with each other.

Similar to most prior routing works, we quantify the transmission delay of a given flow as the number of hops from the source to the destination. To incorporate the

| # of Neighbors Explored | Sum Rate (Mbps) | Min Rate (Mbps) |
|------------------------|-----------------|-----------------|
| 2                      | 4.02            | 0.430           |
| 4                      | 4.56            | 0.517           |
| 6                      | 3.79            | 0.455           |
| 8                      | 2.67            | 0.311           |
| 10                     | 1.76            | 0.238           |
| 15                     | 0.89            | 0.119           |
| 25                     | 0.33            | 0.050           |
number of hops into the reward function of the DDQN agent, we propose to augment the reward function \( \tilde{Q} \) as

\[
\tilde{Q}(s_t, a_t) = \left\{ \min_{i=t...h} 10 \log_{10} \left( \text{SINR}(n_i^f, n_{i+1}^f) \right) + \text{bias} \right\} \cdot \lambda^{h-t}
\]

(20)

where \( h - t \) is the number of hops from node \( n_{t+1} \) to the destination (i.e., remaining number of hops after executing action \( a_t \)); and \( \lambda \in (0, 1) \) is a penalizing factor. With \( \lambda \) closer to zero, the agent would prioritize more on minimizing time delays. Note that the purpose of the constant bias term is to ensure that the reward value is always positive so that it can be properly penalized by the penalty factor.

To explore such rate-delay tradeoff, we train the DDQN agent with varying values of \( \lambda \), each time from scratch. Once the agent model is trained, we evaluate its performance on the testing ad-hoc networks. The observed performance tradeoff between bottleneck rate and time delay is shown in Table VI.

As shown in the results, the tradeoff is effectively achieved as \( \lambda \) decreases from 1 to 0. Specifically, with a low value of \( \lambda \), the agent automatically learns to utilize the reprobe action more aggressively to achieve fewer number of links per data flow. These results suggest that with a properly modified reward definition and action space, the DDQN agent can achieve a desired tradeoff between objectives that conflict with each other. We note here that empirically when \( \lambda < 0.8 \), the DDQN agent reaches the destination on average faster than the Closest to destination among neighbors benchmark.

### VI. Benefit of Power Control

This paper has so far assumed that each node always transmits at its fixed power level. However, after determining the optimal routes and the set of frequency bands, the bottleneck rates can be further improved if we allow the transmission powers of the nodes to vary.

Power control among interfering links is by itself already a highly challenging optimization problem. The problem becomes even more complex if power control is performed in combination with routing and optimal spectrum access. As this paper mainly focuses on routing, we will leave optimal power control for future study. Instead, in this section, we simply apply power control after the routes and frequency bands are established.

We propose the following straightforward and computationally efficient heuristic for power control within
each flow. The heuristic is based on the fact that only the bottleneck links affect the overall data rate of the flows. Therefore, for each of the remaining links, we can decrease its transmission power as long as its transmission rate does not drop below the bottleneck rate. Decreasing these excessive transmission power levels leads to less interference, which helps improve the bottleneck rates.

In details, we fix the transmission power for the bottleneck link, then reduce the transmission powers for all other links to approximately align their link rates to the bottleneck. Specifically, consider flow \( f \in F \) with the routing and spectrum access solution as in (3), with the transmission power levels as \( \{p_0^{(f)}, p_1^{(f)}, \ldots, p_h^{(f)}\} \). We then adjust the transmission power for every node \( n_{i}^{(f)}, 0 \leq i \leq h \) as

\[
p_{i,\text{adjusted}}^{(f)} = \frac{\text{SINR}_{\text{bottleneck}}^{(f)}}{\text{SINR}_{(n_i^{(f)},n_{i+1}^{(f)},b^{(f)})}} p_{i}^{(f)}
\]  

(21)

where the SINR values are computed as in (8a), and \( \text{SINR}_{\text{bottleneck}}^{(f)} \) denotes the bottleneck SINR for \( f \).

After adjusting the powers for one flow, the bottleneck SINRs for all other flows would increase due to the reduced interference. We recompute \( \text{SINR}_{\text{bottleneck}}^{(f)} \) for all the flows, and go through all the flows successively in one round, from the data flow with highest bottleneck SINR value to the lowest.

While this method is heuristic, it is sufficient to illustrate the benefit of power control. In Table VII, we provide a comparison of achieved rates before and after power control, with the routing and spectrum access solutions already determined by the DDQN agent. As the results suggest, with even a simple power control heuristic within each data flow, the bottleneck rates can already be improved. These results show the efficacy of this simple power control method even after the routes are already fixed, as well as the potential for more sophisticated rate optimization.

### VII. Conclusion

This paper proposes a physical-layer based reinforcement learning approach to the wireless ad-hoc network routing and spectrum access problem. By training a universal agent along the different nodes in a flow and across different frequency bands, and by using the physical environment as the input, together with a novel definition of reward function that accounts for the bottleneck rate in the route, we arrive at a highly scalable algorithm for simultaneous routing and spectrum access which can be adapted to the varying network layout characteristics and generalized to larger networks. The numerical results provide insight into the optimal relaying distance in an ad-hoc network setting. We further propose methods to provide fairness, as well as extensions for incorporating delay into the optimization objective, and heuristic power control methods that can further improve the overall performance of the network.

The proposed method achieves scalability by recognizing that as long as the physical environment around each node is relatively stationary, a single agent can be trained to perform resource allocation tasks efficiently across the entire network. Thus, for ad-hoc networks, just as shown in early work [48] that the optimal scheduling strategy can be learned based on the physical environment using a universal deep learning agent, this paper shows that a universal reinforcement learning agent can learn the optimal routing and spectrum allocation strategy based on physical inputs. Together, these results show the feasibility of using machine learning to solve communication and networking problems that are otherwise difficult to tackle.

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