Make TCP Great (again?!) in Cellular Networks: A Deep Reinforcement Learning Approach

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Abstract
Can we instead of designing just another new TCP, design a TCP plug-in which can boost the performance of the existing/future TCP designs in cellular networks? To answer this question, we introduce DeepCC plug-in. DeepCC leverages deep reinforcement learning (DRL), a modern decision-making tool, to steer TCP toward achieving applications’ desired delay and high throughput in a highly dynamic network such as the cellular network. The fact that DeepCC does not try to reinvent/replace TCP but aims to boost the performance of it differentiates it from the most (if not all) of the existing reinforcement learning (RL) systems where RL systems are considered clean-slate alternative designs replacing the traditional ones.

We used DeepCC plug-in to boost the performance of various old and new TCP schemes including TCP Cubic, Google’s BBR, TCP Westwood, and TCP Illinois in cellular networks. Through both extensive trace-based evaluations and in-field tests, we show that not only DeepCC can significantly improve the performance of TCP, but also after accompanied by DeepCC, these schemes can outperform state-of-the-art TCP protocols including Aurora, Sprout, Verus, C2TCP, Copa, Indigo, Remy, PCC-Vivace, and LEDBAT in cellular networks.

1 Introduction
Nearly after 40 years from one of the earliest versions of TCP algorithm, congestion control (CC) in packet-switched networks remains a very hot and active research topic. Every year, with the new waves of technologies and improvements in the design of the packet-switched networks, new TCP designs are proposed to do a better job of controlling the congestion in the network and satisfy the new delay/throughput demands of new emerging applications (e.g. [4–7, 9, 15, 16, 18, 21, 32, 40, 55, 57]). Cellular networks with their unique characteristics (highly variable channels, radio downlink/uplink scheduling delays, deep per-user buffers, etc.) are among the networks that experience a new wave of targeted TCP designs. Emerging 5G technology which holds the promise of improved latency, throughput, and reliability for the network is another example of the new improvements which adds fuel to the fire.

After four decades of active research, there is no “the best TCP” design which can completely resolve the congestion control in the network. The reason rests on the fact that the well-known objective of maximizing the power defined as $\frac{\text{throughput}}{\text{delay}}$ [20] and its other forms, which are usually used as the main objective for CC, are proved to be nondecentralizable [27]. In other words, no distributed CC algorithm can maximize the power (or other forms of it) in the network. So, this motivated the heuristic strategy and approach toward solving the CC problem which brought up the plethora of heuristic TCP designs.

Exploring new design space (helping others instead of beating them): Interestingly, most of the TCP schemes proposed during the last four decades have a common theme in their conclusions. Most of them conclude that “… We designed a new TCP and showed that it beats the performance of other TCP schemes in the XYZ networks …”. But do we really require to replace current TCP schemes with completely new ones? Can’t we change the main design strategy and instead of proposing just another new TCP algorithm, come up with a framework that can help existing TCP schemes and boost the performance of them considering new needs or new environments?

Why a learning-based approach: A possible approach for designing a plug-in for certain TCP schemes in cellular networks is that designers manually try to tune TCP schemes’ parameters or modify their algorithm to adapt their logic to different cellular network scenarios. Although this approach is feasible, it won’t be a scalable approach. In other words, designers need to spend a lot of time on learning the logic of various TCP schemes, understanding their performance issues in different scenarios, and tune their proprietary parameters

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1 At the time of writing this paper, there are more than fifteen different TCP algorithms available at Linux Kernel stack while most of them are not used in practice.
individuals for various scenarios. That sounds pretty much time consuming and this needs to be done again for future new TCP schemes! But what if we can let machines automatically learn the behavior of TCP schemes in cellular networks and adapt them to these highly dynamic environments?

Modern decision-making tools: Generally, CC is a decision-making problem which decides that at any arbitrary time, how many packets should/can be sent to the network by a user. One of the modern tools which deals with the same class of problems i.e., the decision-making process is RL, a subcategory of machine learning (ML). Therefore, it would be a natural question to ask: Can this modern tool be leveraged to do the task of CC in a highly dynamic network such as a cellular network? And if yes, how?

These key questions and the recent advances in RL area especially the use of deep neural networks (DNN) in RL (DRL) and successful examples of applying DRL to practical scenarios such as DeepMind’s Atari and AlphaGo motivated us to design a Deep reinforcement learning plug-in for Congestion Control (DeepCC) which aims to boost the performance of the existing TCP schemes. However, the key mentioned motivations bring their own new challenges.

Improving a specific TCP scheme seems to have a straightforward procedure. First, analyze the scheme thoroughly. Second, find its problems, and then resolve them by proposing a solution. Although the procedure itself is clear, it is not clear how to really execute it even for a specific TCP scheme, let alone targeting a solution for different TCP schemes. So, one of the challenges is that how we can come up with a general plug-in without digging into the details of or tying the solution to a certain TCP algorithm.

On the other hand, unique characteristics of cellular networks such as highly variable and unpredictable channels, radio downlink/uplink scheduling delays, etc. make the cellular networks complex environments. Therefore, the task of applying RL methods in cellular networks becomes a very challenging and demanding one. For instance, very fast fluctuations of access links in cellular networks and the consideration of the history of users’ traffic and their channel qualities during the scheduling of their uplink/downlink packets at the base station (BTS) lead to not having Markov property in cellular environments. However, modeling the task as a Markov Decision Process (MDP) [47] is the foundation of solving a general RL problem.

Moreover, due to the real-time nature of the CC algorithms and the very fast fluctuations of the cellular access links, achieving operational state gathering from the network, rapid exploration of huge action space, and execution of it become very challenging.

1.1 Contributions and Summary of Results

Our key contributions in this paper are:

1. By introducing DeepCC framework, we show that the default strategy of designing "yet another new TCP" is not necessarily the best strategy toward improving TCP.

2. To the best of our knowledge, DeepCC is the first DRL-based plug-in for boosting the performance of the classic and modern TCP schemes in cellular networks.

3. We built, deployed, and evaluated DeepCC through a Linux Kernel implementation and demonstrated how a modern tool such as DRL can be employed to help the task of CC in a very complex environment such as the cellular network. The added Kernel APIs and our modular framework are open to the public and can be exploited to design more TCP plug-ins.

We showed through both in-field experiments and extensive trace-based evaluations using more than 25 LTE cellular traces that DeepCC can significantly improve the performance of different TCP schemes. For instance, when TCP Cubic [21] (the default TCP in Linux, Android, macOS, etc.) and BBR (a new TCP proposed by Google [15]) are enhanced using DeepCC, they can respectively achieve 300% and 175% lower queuing delay while they only compromise throughput about 6%. We also showed that DeepCC not only can improve the performance of various TCP, but after using DeepCC, classic TCP schemes such as TCP Illinois [32] and TCP Westwood [16] can outperform the performance of state-of-the-art schemes such as BBR [15], Sprout [55], Verus [57], PCC-Vivace [18], Indigo [56], Aurora [29], Remy [54], Copa [9], C2TCP [6], and LEDBAT [43] (detailed in section 6).

This work is by no means the end of the CC problem. Instead, we believe that it can be the start of a long journey toward the use of learning-based methods not as clean-slate alternatives but as assistant blocks in the context of CC.

2 Related Work

There is a plethora of congestion control schemes including numerous variants of TCP. Here, we briefly mention some of the related works. TCP Tahoe, TCP Reno [26], and TCP NewReno [22] are among the early AIMD-based TCP approaches that tried to use the loss of packets as the main congestion signal. TCP Cubic [21], which is today’s default TCP in most of the platforms, replaces the incremental function of classic AIMD-based approaches with a cubic function. Compound TCP [49] and TCP Illinois [32] are among the proposals which use delay and loss of packet to control the congestion. TCP Vegas [14] directly uses measured RTTs to calculate congestion window (Cwnd). BBR [15] estimates both maximum bottleneck bandwidth and minimum RTT delay of the network and uses them to calculate Cwnd. LEDBAT [43] and Copa [9] use the delay of packets to adjust the Cwnd. LEDBAT (mainly designed for background traffic) backs off to give room to another coexisted flow in the...
network, while Copa gives up achieving low delay when it detects another flow in the network!

Sprout [55], TCP Westwood [16], Verus [57], ExLL [40], and C2TCP [6] are among the end-to-end CC schemes that target cellular networks. Sprout attempts to predict the bandwidth of the cellular access link using a stochastic framework, while Verus uses a delay profile of the network to calculate Cwnd. ExLL attempts to infer the cellular bandwidth by looking into the pattern of data reception and control the Cwnd on the receiver side. C2TCP uses the design ideas behind the in-network AQM schemes such as CoDe [37] to bound the average delay of packets. TCP Westwood introduces a new fast recovery scheme and tries to choose a better slow start threshold considering the wireless nature of the bottleneck. In addition, some other TCP schemes targeting cellular networks (e.g. NATCP [7], and TG [48]) use feedback from the cellular network to do the task of CC. However, these feedback-based approaches are not deployment-ready due to the fact that they require changes in the network.

Another set of schemes try to make the TCP design an automated task done by the machines by following the clean-slate design strategy. Remy [54] attempts to prepare an offline calculated mapping from all possible events to best actions (including change in the Cwnd) by walking through all possible events in a brute-force manner. PCC-Vivace [18] proposes to use online learning techniques to choose the best sending rates. Other recent examples of machine-learning flavored clean-slate designs are Indigo [56] and Aurora [29]. Indigo [56] uses neural networks while Aurora leverages vanilla DRL to determine the sending rates and replace the TCP. We observed that these schemes perform poorly in the context of highly dynamic networks (detailed in section 6). In contrast with all these schemes, we explore new design space and philosophy which rests on helping current TCP designs instead of replacing them with new ones!

We have compared our design with most of these schemes in section 6 and showed that not only DeepCC improves the performance of TCP schemes, but also TCP schemes assisted by DeepCC can significantly outperform state-of-the-art schemes.

3 System Design Overview

3.1 The Problem of TCP in Cellular NWs

Different studies (e.g. [6, 40, 55, 57]) show that the TCP schemes, which are generally designed considering wired networks, perform poorly in cellular networks when the delay is considered as the performance metric. This problem comes from the throughput-oriented nature of most of the current TCP schemes including the most popular one TCP Cubic. Large delays will not cause serious issues for the classic throughput-oriented applications. However, emerging delay-sensitive applications such as real-time online gaming, virtual reality, augmented reality, vehicle to vehicle communications, etc. will suffer from the throughput-oriented design structures. Recently, these emerging applications and their new demands motivated the community toward a more delay-centric design [6, 9, 18, 40, 43, 55, 57]. Although throughput-oriented TCP schemes experience delay issues in cellular networks, various studies (e.g. [6, 40, 55, 57]) confirmed that throughput-oriented TCP schemes achieve very high throughput and link utilization in cellular networks. This key observation led us toward the idea of boosting the delay performance of the throughput-oriented TCP schemes without compromising their throughput that much to have the best of both worlds (very low delay and very high throughput).

3.2 The Big Picture of DeepCC

The fact that throughput-oriented TCP schemes achieve very high throughput but very large delays in cellular networks can be described as follows. Calculated Cwnds of throughput-oriented TCP (which indicate the number of in-flight packets) are usually larger than the best values of Cwnd at different times. The impact of large Cwnd values is that the user can always expect to have enough packets at BTS to fully utilize the cellular access link when the capacity of the link increases (e.g. due to good quality of channel). However, having a large number of packets at BTS makes large self-inflicted queuing delays when the capacity of the cellular link drops (e.g. due to bad quality of channel) which leads to poor delay performance of them [6, 55, 57].

Hence, the throughput-orientedness of the TCP schemes can be controlled by controlling the maximum values of the Cwnd throughout the time. More specifically, DeepCC controls the cap of the Cwnd value instead of the exact values of the Cwnd through time. This helps us consider the underlying TCP of the system as a black box and avoid controlling internal proprietary variables of different TCP schemes to have a general plug-in. This is possible thanks to the modularity of the current TCP stacks in which the TCP layer has certain inputs/outputs that are independent of the choice of the TCP schemes. The inputs are always the Ack packets (and the information that they carry) and the output is Cwnd value.

The big picture of the DeepCC plugin is shown in Fig. 1. DeepCC attempts to keep the average delay of packets below applications’ desired Targets while keeping the throughput high. To that end, the application passes its desired Target delay as a socket-option parameter to DeepCC during the TCP socket creation. The Monitor block in DeepCC periodically collects Cwnd of the system and packets’ statistics from TCP and Kernel stack. Every RTT, state generator block employs

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*Due to the lack of a publicly available code for ExLL, we couldn’t include it in our evaluations.

4To be more precise, pacing rate of the egress traffic is also another output of the TCP. However, since it is (can be) calculated in Linux stack using the Cwnd value, here, we only consider Cwnd as the output of the TCP block.
the information collected by Monitor block to generate a proper state vector declaring the state of the environment during that time period (detailed in section 4). Every new state vector leads to the execution of new action by the DRL-agent. DRL-agent considers the generated state vector, the application’s given Target, and the reward associated to the current state vector (which is generated by Reward block) to decide the proper maximum value of Cwnd ($Cwnd_{max}$) based on the previously learned behavior of the environment (detailed in section 5). At the end, the final refined Cwnd considering this maximum value will be used to send packets into the network.

A short Q.A. before going deep into the design:\footnote{Please check appendix C for more discussions}

1. Is DeepCC a plug-in for all TCP schemes without any exception? No. The current version of DeepCC stands on top of the throughput-oriented TCP to improve the delay performance of it. How to make DeepCC a plug-in for “everyone” is a good motivation for future work.

2. Why is the throughput-oriented TCP chosen as the base? Because today’s most popular and widely used TCP schemes are throughput-oriented designs (e.g. Cubic).

4 Components of DeepCC: Part I

We describe DeepCC in two separate sections. In this section, we focus on the description of the auxiliary components of DeepCC shown in Fig. 1 including Monitor, State Generator, and Reward Generator blocks and in the next section, we describe the DRL-Agent block.

4.1 Monitor Block

Every RTT, the monitor block generates digested information to be used in the state generator block. The features we use are the collectible statistics which can be measured/monitored on the fly from the network. Even though we collect traces for training, where network bandwidth is revealed, we do not directly use it as state information because when the system is running online, bandwidth is unknown in advance. We consider the following features:

- $d$: The average packets’ delay per RTT
- $n$: The number of samples used for calculation of $d$
- $p$: The average delivery rate (throughput\footnote{Throughout this paper we use delivery rate and throughput of the system interchangeably}) per RTT
- $cwnd$: The current Cwnd calculated by the underlying TCP.

In particular, Monitor block works as a shim layer and continuously gathers the required packets’ statistics by observing the incoming Ack packets. Monitor block periodically exploits generated packets’ statistics and calculates $d$, $n$, and $p$ of each time period and passes them (combined with $cwnd$) to the state generator block. Having Monitor block implemented as a shim layer in the Kernel enables us to make the process of gathering required features independent of the underlying TCP schemes.

4.2 State Generator Block

The state generator is an information processing module that manages the desired Target delay information from the application (Target) and the network dynamics coming from the monitor block and generates the input state for DRL-agent. Each time the network monitor passes the packet statistics, the state generator updates the state vector. Network dynamics in the wireless cellular environment are complicated and noisy. The learning process for DRL to extract the useful feature from the high dynamic range of state and map it to actions can be demanding. Another challenge is how the agent can effectively learn the policy of $Cwnd_{max}$ based on the features in such a highly dynamic environment. The uncertainty of the environment makes the learning harder and makes the problem setting lose Markov property. The agent is easily confused to make a decision $a_t$, if the agent only relies on the observation at time $t$. To address these issues, we use two techniques: 1) the use of filter kernel and 2) the use of recurrent structure.

**Filter kernel:** Inspired by the use of filter kernel in image processing area [13, 30, 38], first, we apply a kernel to the state so that we can reduce the feature space. We transform the delay $d$ with the Target as a kernel:

$$\kappa(d) = \begin{cases} 0 & \text{if } d > \text{Target;} \\ 1 & \text{else} \end{cases}$$

Figure 1: DeepCC framework
Now, we multiply \( p \) and \( n \) by the kernel: \( \phi(p) = p \times \kappa \) and \( \phi(n) = n \times \kappa \). Second, we encode the delay together with target (to reduce the dimensionality): \( \phi(d, \text{Target}) = \left(\left(1 - \frac{d}{\text{Target}}\right) \times \kappa, \frac{d}{\text{Target}} \times (1 - \kappa)\right) \). The observed features at time \( t \), after the above preprocessing, can be written as following vector:

\[
o_t = \left[\phi(p_t), \phi(n_t), \phi(d_t, \text{Target}), \text{cwnd}_t\right]
\]

Here, the intuition is that when system does not meet \( \text{Target} \) (i.e., \( d > \text{Target} \)), the agent should focus more on delay signal \( d \) and consider performing the action which reduces the delay.

Recurrent structure: We also use a recurrent structure \([24,41]\) to address lack of Markov property issue. Since at no time the agent has the direct knowledge of the current exact network bandwidth, the agent can only infer it like a latent variable from the observed features. Therefore, we aggregate partial information from the past and capture the dependency in the sequential data. To that end, the \( m \) history of feature vectors are concatenated to the current observed features to generate the final state. So, the final state (i.e., the input of DRL-agent block) at time \( t \) becomes the vector

\[
s_t = (o_t, o_{t-1}, ..., o_{t-m}).
\]

Then, using this state representation, we can apply the MDP style formulation.

### 4.3 Reward Generator Block

One of the important parts of any RL algorithm is the definition of the reward function which should reflect the main objective of the system. DeepCC’s objective is to keep the average delay of packets below the Target value (given by the application) while maximizing the throughput. So, DeepCC requires to have a reward function which reflects that objective correctly.

Intuitively, the RL agent is motivated to choose the actions which generate higher rewards and to avoid choosing the actions which lead to lower ones. When the environment is well-behaved (such as a game environment as in [45]) and does not show a very high random nature, the reward gained in a certain step can be considered as the result of the action chosen for that step. However, it is not necessarily the case for a dynamic and unpredictable environment such as a cellular network. For instance, when the reward function is simply defined as the throughput achieved by the system, it is not clear whether the currently gained very small reward is due to choosing a bad action by the agent or due to a very bad quality of channel in the wireless access link (which leads to low throughput). Therefore, the reward function needs to be carefully defined.

To that end, we use the following reward function where \( w(n,d) \) is the moving average of the two recent values of \( d \)

\[
(w(n,d)) = \frac{nd + n_{pre}d_{pre}}{n + n_{pre}}.
\]

\[
r(n,d,p) = \begin{cases} 
\frac{w(n,d)}{\text{Target}} \times p \times n & \text{if } d > \text{Target}; \\
\frac{w(n,d)}{\text{Target}} \times p \times n & \text{else (3)}
\end{cases}
\]

If the agent observes a high delivery rate and a high number of Acks, while it observes a bad average delay \((d > \text{Target})\), most likely, its wrong choice of action was the source of achieving bad delay response. That is why in our reward function, the agent will be penalized/rewarded in proportion with the gained delivery rate, number of received Acks, and how far the average delay is from the Target delay. Therefore, using the reward function described in Eq. 3, the agent will be motivated to first keep the average delay below \( \text{Target} \) \((d \leq \text{Target})\) (to receive less penalty). Then, it will be motivated to maximize its delivery rate and the number of received Acks (to collect more reward).

### 5 Components of DeepCC: Part II

Now, we describe the core component of DRL block: DRL-agent. DRL-agent observes a set of network statistics (given by the state generator block) and collected reward (by the reward generator block) and outputs the \( \text{Cwnd}_{\text{max}} \) value. The lower value of the \( \text{Cwnd}_{\text{max}} \) pushes the system toward being more delay-sensitive (less throughput-oriented), while the higher one pushes the system toward being more throughput-oriented (less delay-sensitive). The goal of DRL-agent is to learn the policy that makes underlying TCP gain more throughput while meeting the Target delay. The space of the action (i.e., the value of \( \text{Cwnd}_{\text{max}} \)) at different times is immense. So, letting the DRL-agent find the best values of the action in the huge space in a timely manner is not feasible. To make the exploration phase feasible and efficient, we use the \( \text{Cwnd} \) calculated by the underlying TCP to be the base to calculate the \( \text{Cwnd}_{\text{max}} \). To that end, we define a parameter \( \alpha \) which relates \( \text{Cwnd}_{\text{max}} \) value to the value of \( \text{Cwnd} \) that the DRL-agent receives periodically from the state generator block using the following equation:

\[
\text{Cwnd}_{\text{max}} = 2^\alpha \times \text{cwnd}
\]

Now, instead of searching the entire space, DeepCC only chooses the \( \alpha \) value restricted to \(-1 \leq \alpha \leq 1\). This greatly simplifies the exploration phase (and consequently lowers the convergence time), while \( \text{Cwnd}_{\text{max}} \) can still easily be increased exponentially when the DRL-agent chooses \( \alpha = 1 \) consecutively (or decreased exponentially when \( \alpha = -1 \) is chosen consecutively). We will show in section 6 that this choice leads to very good system performance.
5.1 The Learning Algorithm

Since $\alpha$ is a continuous value, it is suitable to use RL algorithms which operate in the continuous action space. Considering that, we propose to use an actor-critic algorithm based on deterministic policy gradient (DPG) algorithm [46] to train DRL-agent. DPG is an algorithm applicable to continuous action spaces. DPG consists of two components, an actor and a critic. The actor, parameterized by $\theta$, maps a state $s$ to an action $a$ by a deterministic policy $\mu_\theta(s)$. The critic, parameterized by $\phi$, $Q_\phi(s, a)$, estimates the expected cumulative reward at state $s$ given action $a$ following policy $\mu$, $Q^\mu(s, a)$. So, the performance objective of the agent is to find a policy $\mu$ that maximizes the cumulative reward defined as:

$$J(\mu) = \mathbb{E}[\sum_{t=0}^{T} \gamma r_t; \mu] \quad (5)$$

In the off-policy setting, where agent learns a target policy $\mu_\theta(s)$ by executing a different arbitrary behavior policy $\beta(s)$, the objective function in Eq. 5 can be re-written as the value function of the target policy, averaged over the state distribution of the behavior policy $(\beta(s))$:

$$J(\mu_\theta) = \int_S \beta(s) Q^\mu(s, \mu_\theta(s)) ds \quad (6)$$

In DPG, the path-wise derivative policy gradient with respect to the actor’s parameter is computed as:

$$\nabla_\theta J(\mu_\theta) \approx \mathbb{E}_{s \sim \beta}[\nabla_\theta \mu_\theta(s) \nabla_\phi Q^\mu(s, a)|_{a=\mu_\theta(s)}] \quad (7)$$

By letting the behavior policy differ from $\mu_\theta$, the off-policy formulation enables the reuse of gathered data for evaluating the above gradient more efficiently. Later, the actor applies the gradient calculated in Eq. 7 to update its parameter:

$$\theta \leftarrow \theta + \eta \nabla_\theta J(\mu_\theta) \quad (8)$$

where $\eta$ is a parameter declaring learning rate.

In DPG, the critic’s parameters are updated using well-known Q-learning algorithm [53]. Due to the sophisticated network dynamics in the cellular network, the relationship between mapping state and action is not trivial. So, in our RL design, we want to harness the power of DNN in the modeling of complex environments. Deep Deterministic Policy Gradient (DDPG) [31] is an extended version of DPG which brings DNN to the RL. That is why we use DDPG as our base model in DRL-agent and describe it as follows.

In addition to the actor and the critic components in DPG, DDPG uses DNN to do the function approximation in the actor and the critic components of DPG. Naively plugging in DNN in DPG for function approximation leads to instability issues [31]. So, DDPG incorporates two techniques to increase stability and avoid oscillation: 1) Use of two extra DNNs called target DNNs\(^{10}\) and 2) Learning with experience replay [34, 42].

**Target Networks:** The algorithm introduces an additional copy of the actor network and critic network, called the critic target network ($Q_{\theta'}(s, a)$) and actor target network ($\mu_{\theta'}(s)$). These target networks are used to make updates of the actor and the critic networks smoothly, providing a stable objective in the learning procedure. The parameters of target networks are updated slowly to improve stability (for more details, please check [34]).

**Learning with experience replay:** The actor network, $\mu_\theta(s)$, and the critic network, $Q_\phi(s, a)$, are trained by iteratively updating their parameters. At each training iteration, the transition $(s_t, a_t, r_t, s_{t+1})$ is put in a finite sized cache called replay buffer ($D$). During learning, the update of actor network happens by applying the gradient with respect to $\theta$ on mini-batch ($U(D)$) of randomly chosen samples from $D$:

$$\nabla_\theta J \approx \mathbb{E}_{(s_t, a_t, r_t, s_{t+1}) \sim U(D)}[\nabla_\theta Q_\phi(s_t, a_t)|_{s_t=s\theta; a=\mu_\theta(s\theta)} \nabla_\theta \mu_\theta(s\theta)]_{i=1}^{|U(D)|} \quad (9)$$

The critic network is updated by performing gradient descent step in Eq. 10:

$$L(\phi) = \mathbb{E}_{(s_t, a_t, r_t, s_{t+1}) \sim U(D)}[(y_t - Q_\phi(s_t, a_t))^2] \quad (10)$$

$$y_t = r_t + \gamma Q_{\theta'}(s_{t+1}, \mu_{\theta'}(s_{t+1})) \quad (11)$$

**DRL-Agent’s Learning Algorithm:** We summarize our DRL-agent learning algorithm in Algorithm 1. The algorithm has four networks: actor network, critic network, actor target network, and critic target network. At time $t$, the agent observes the state $s_t$ given by state generator block and performs action $a_t$. After action $a_t$ is executed, the agent receives the reward $r_t$ from the reward generator block and observes new state $s_{t+1}$ given by state generator block. The $(s_t, a_t, r_t, s_{t+1})$ is stored in the replay buffer $D$. We randomly sample a mini-batch of transitions from $D$ for optimizing the parameters. Then, the actor and the critic are updated (lines 8 and 9 in the Algorithm 1). At the end of this iteration, the target networks are updated (line 10 in Algorithm 1, where $\tau \ll 1$).

5.2 Batch Normalization

The loss function in our problem is non-convex, and the loss surface might have a more steep or flat region that makes the gradient descent optimization harder. Even in training with similar hyperparameter setting, when we learn with random exploration/initialization, we observe inconsistent behavior of the agent after learning for a significant amount of time, which means the agent may be trapped to some local minimum or not converge. To increase the training performance,
we adopt the Batch Normalization techniques. Batch Normalization [25] is a technique that makes the optimization landscape smoother [44]. The smoothing effect on the optimization increases the training speed and makes our DRL block less sensitive to the variation of the hyperparameter setting. The Batch Normalization technique is implemented in our actor-network as an augmented layer after each hidden layer’s output right before the non-linearity activation.

6 Evaluation

Here, we examine DeepCC plug-in by using four different TCP schemes as the underlying TCP in both in-field experiments and extensive trace-based evaluations. Without loss of generality, we chose TCP Cubic [21], TCP Westwood [16], TCP Illinois [32], and TCP BBR [15] as underlying schemes using DeepCC plug-in throughout this section. From now on, when a TCPx uses DeepCC plug-in, we add prefix character $D$ to the name of the TCPx scheme to refer to the new scheme (i.e., DCubic, DWest, Dlli, and DBBR). We, first, briefly describe the current implementation of the DeepCC plug-in and our learning approach. Then, we report the results of our trace-based evaluations comparing the performance of various TCP schemes in various cellular network conditions. Later, we conduct several experiments to deep dive into the performance analysis of DeepCC. Finally, we end this section with the results of our in-field experiments.

6.1 Implementation and Learning Approach

**Implementation:** To have a general solution which can work with various TCP schemes, we have modified Linux Kernel 4.13 and added a plug-in which works independent of the TCP scheme of the system. It can be considered as a shim layer above the TCP layer. In particular, we modify the Kernel to calculate the required statistics, provide new socket options to collect the statistics needed from the Kernel, and provide new socket options to enforce a calculated action in the Kernel. For this prototype version, we use a user-space implementation of the DRL-agent using TensorFlow [2], though putting the final learned model in the Kernel will improve the performance. The DRL-agent’s actor and critic networks are implemented using two fully-connected hidden-layers with 1000 neurons on each layer. For brevity, here, we skip the details of the implementation.

**Learning Approach:** Intentionally, to see how efficient the design can generalize the dynamic environment, we tried to keep the learning phase minimal. So, we used cellular LTE traces including more than 100,000 variations of cellular link bandwidths, as our base cellular environment and repeat that throughout the learning phase. The statistics of the base cellular environment is shown in Table 1. In addition, we used Target value of 50ms during learning\(^\text{11}\). To train the agent, we used Dell PowerEdge R730 servers with 48 cores. To observe the gradual improvements achieved during the learning, after every 30 minutes of training, we use the trained model, run an evaluation using the setting described in section 6, and gather the results of our in-field experiments.

\(^{11}\)Since we do not use the absolute value of Target in our Reward function (we use the normalized value of delay), learning phase is not that sensitive to the choice of the Target value. Results for other Target values in section 6.4.4 confirms the proposition.

| Mean | Std Deviation | Skewness | Kurtosis | [Min,Max] |
|------|--------------|----------|----------|-----------|
| 12.7875 | 11.3804     | 1.6027   | 6.5076   | [0,90]    |

Table 1: Statistics of the cellular access link capacity used during training (bandwidth units are Mbps)

![Figure 2: Average delay and utilization as a function of wall clock time for various schemes.](image)
the average delay and utilization of the scheme over the entire trace used for the learning (Totally, we trained the system over more than 2 million steps). Results are shown in Fig. 2.

While keeping average delay below the target value, DeepCC gradually learns to boost the utilization of the underlying TCP. For DeepCC, the behavior of underlying TCP is part of the dynamic nature of the environment that it observes. In other words, although the cellular environment is the same during the training of all TCP schemes, due to the different nature of these TCP schemes, DeepCC observes different environments when underlying TCP is different. That is why for different TCP schemes, DeepCC’s learning curves are different.

Results reported in section 6.3 and section 6.5 show that with the described minimal training setting, the trained model achieves good performance over real LTE cellular networks and other twenty-seven LTE cellular traces that the agent has not seen before (i.e., LTE environments with different dynamics compared to the dynamics of the LTE environment used during the training).

6.2 Traced-Based Evaluation: Setup

**Emulator**: To have more freedom to compare the performance of various schemes in a reproducible environment, we use Mahimahi [36] which is a trace-based network emulator.

**Schemes Compared**: To cover variety of TCP designs, we compared DeepCC with 13 schemes each representing different design strategy. Among them, Sprout [55], Verus [57], PCC-Vivace [18], C2TCP [6], Copa [9], and LEDBAT [43] are delay-sensitive schemes, while Cubic [21], Illinois [32], and Westwood [16] are mainly throughput-oriented schemes. In addition, Remy [54], Indigo [56], Aurora [29] and BBR [15] mainly try to maximize throughput while minimizing delay.12

**Setting**: We set the minimum RTT of the network to 20ms and the buffer size to 150KB. Throughout the evaluation, unless it is mentioned, we choose the Target value of 50ms for DeepCC.

**Cellular Traces**: We used combination of 23 new LTE cellular traces that we collected (using Saturatr [55]) and 5 LTE traces gathered in appendix B. To quantify the differences among these traces, we report statistics of some of the traces in Table 2.

In this section, we examine the performance of DeepCC in 3 different scenarios: (1) when the cellular user is in static position and does not move (stationary scenario), (2) when the cellular user is walking in crowded places (moving scenario #1), and (3) when the cellular user is riding a bus, a taxi, or driving a car (moving scenario #2).

To test over a variety of network conditions, we use a combination of publicly available cellular traces [6, 55] and new cellular traces that we collected. In particular, for the stationary scenario, we collected 5 new traces in residential buildings and crowded places and used 2 additional static traces collected in NYC by prior work [6]. For moving scenario #1, we collected and used 12 different new traces. For moving scenario #2, we collected 6 new traces while the user was riding taxi/bus and used 3 additional traces collected in Boston by prior work [55]. To quantify the differences among these traces, we report statistics of some of the traces in Table 2. Also, link capacity variations for a few first minutes of these traces are gathered in appendix B.

To highlight the improvements achieved by using DeepCC plug-in, we start by reporting the averaged queuing delay improvements (% QueueDelay(TCPx)) and averaged compromised utilization ((1 – Utilization(DTCPx))% of each scheme after using DeepCC plug-in over different scenarios in Table 3.

Table 2: Queuing delay improvements (Q.D.Imprv.) and compromised utilization (Compr.Util)

| Scheme   | Metric               | Stationary | Moving#1 | Moving#2 |
|----------|----------------------|------------|----------|----------|
| DCubic   | Compr.Util (%)       | 6.76486    | 3.22961  | 11.1933  |
|          | Q. D. Impr. (%)      | 304.192    | 328.109  | 405.2    |
| DWest    | Compr.Util (%)       | 8.32599    | 17.1448  | 16.8304  |
|          | Q. D. Impr. (%)      | 436.364    | 492.136  | 472.5    |
| DIIli    | Compr.Util (%)       | 4.35994    | 10.1299  | 9.06301  |
|          | Q. D. Impr. (%)      | 344.118    | 407.886  | 397.133  |
| DBBR     | Compr.Util (%)       | 5.74627    | 10.3102  | 9.76913  |
|          | Q. D. Impr. (%)      | 175.497    | 194.098  | 200.459  |

Table 3: Queuing delay improvements (Q.D.Imprv.) and compromised utilization (Compr.Util)

Observation 1: Table 3 shows clear improvements gained by using DeepCC plug-in for all schemes. For instance, DIIli achieves 340% lower queuing delay while it only compromises about 4% utilization compared to Illinois in the static scenario. The key takeaway is that DeepCC significantly en-
hances the delay performances of all four TCP schemes while it compromises only a few percentages of their utilization.

Now, we compare DeepCC’s performance with all other state-of-the-art schemes. Fig. 3a, Fig. 3b, and Fig. 3c show the averaged delay and utilization of all schemes over all cellular traces used in the stationary scenario, moving scenario #1, and moving scenario #2, respectively.

Observation 2: Throughput-oriented designs such as Cubic, Westwood, and Illinois intend to fill up the buffers. As expected, this leads to their good utilization, while it causes bufferbloat/delay problem for them. Verus and Sprout (which are designed for cellular networks) use white-box approach. They use the delay of packets to predict future packet arrivals or make a delay profile of the network respectively. BBR also uses a white-box approach. Modeling network in a certain way helps these schemes to perform better in terms of delay compared to Cubic, Westwood, and Illinois. However, the unpredictable nature of the cellular environment leads to inaccuracy of their network models. That’s why at the end of the day, the white-box approach cannot keep up with the dynamics of the network. Among other schemes (excluding DeepCC assisted ones!), Copa and C2TCP (which is designed for cellular networks) achieve a better trade-off between delay and throughput.

Observation 4: DeepCC helps TCP schemes to become performance frontiers and operate close to the right top region of the graphs in Fig. 3. As Table 2 and appendix B illustrate, cellular LTE traces used here are very different from each other. That being said, although in the learning phase, the agent trained over cellular LTE environment with certain statistics, results reported in Fig. 3 show that DRL-agent can achieve a good generalization of the environment and perform well for other LTE traces which she has not seen before. For more discussion on generalization, see appendix C.1.

6.4 Deep Dive

6.4.1 Fairness

To investigate the fairness property of DeepCC, we use 4 servers to send 4 separate DeepCC enhanced flows to the client (servers are connected to the client through a switch). We use Mahimahi at the client to control the client’s bottleneck link properties. Particularly, we set the client’s bandwidth to 24Mbps, the unidirectional link delay to 5ms, and the buffer size to the BDP (bandwidth-delay product).

Note that in cellular networks, flows are put into separate bearers identifying separate classes with different delay requirements to avoid a bandwidth-hungry application taking entire bandwidth from a delay-sensitive application, if both are destined to the same user. Therefore, here, we consider that flows are in the same class and have the same Target delay. We examine the case where other TCP schemes coexist in the network in section 6.4.3 and section 6.5.

We use Jain index metric [28] to quantify the fairness and compare it among various schemes with and without DeepCC. Jain index for \( n \) competing flows with rates \( f(r_1, r_2, \ldots, r_n) \) is
defined by Eq. 12. As Eq. 12 reveals, Jain Index is a number between $1/n$ (worst fairness index) and 1 (best fairness index).

$$J(r_1, r_2, \ldots, r_n) = \frac{\bar{r}^2}{\bar{r}^2} = \frac{\left(\sum_{i=1}^{n} r_i\right)^2}{n \sum_{i=1}^{n} r_i^2} \quad (12)$$

To do the evaluation, we fix number of competing flows and the scheme under the test. Then we let all flows start at the same time and give them 60s to settle down on the bottleneck link. At the end, we calculate the Jain indices. The Jain indices of various schemes with and without DeepCC are summarized in Table 4.

As Table 4 illustrates, the fairness improvements gained by using DeepCC depends on the underlying TCP. For example, TCP Cubic and TCP Westwood already achieve good fairness indices. So, DeepCC does not improve the fairness index of them that much. However, in cases of Illinois and BBR, using DeepCC can lead to tangible fairness index improvements. The bottom line is that DeepCC’s fairness property is at least as good as the underlying TCP.

### 6.4.2 Non-Cellular Bottleneck

In recent trends and cellular architectures data is pushed very close to the end-users (e.g. MEC [1], Mobile CDN, etc.), so the assumption that cellular access links are the bottleneck links in the network is valid. That being said, in this section, we investigate the performance of DeepCC in scenarios where the cellular link is not the bottleneck link. In the first scenario, we throttle the bandwidth of a wired link located in the path of the traffic from a server to a cellular client to make a non-cellular bottleneck link. In particular, we throttle the wired bandwidth from 30Mbps (which is higher than maximum cellular link’s bandwidth during the test) to 6Mbps (which is less than the cellular access link’s bandwidth during a particular period (check Fig. 4)). After 30 seconds, we roll back the bandwidth of the wired link to 30Mbps. The delay and throughput of schemes with and without using DeepCC plug-in are shown in Fig. 4 (Due to space limitation and the fact that results for BBR and Illinois are similar to the results for Cubic and Westwood, here, we only report the graphs for Cubic and Westwood). As Fig. 4 illustrates, DeepCC performs very well even when bottleneck link changes among cellular and non-cellular links.

### 6.4.3 TCP-Friendliness

Before reaching the cellular link, a flow will be likely placed in queues where other flows exist in the network. So, To investigate how DeepCC performs in the existence of other TCP schemes, we consider another scenario. First, we send a TCP Cubic flow (because Cubic is widely used as the default TCP in most of the current platforms including Windows, Linux, Android, macOS, etc.) from a server to a client and let it fill up the buffer for 30 seconds. Then, we send another flow from another server using the TCP under the test and let both flows live for the next 60 seconds\(^{14}\). To quantify the TCP friendliness, we report the difference between the average delivery rates of TCP Cubic and the scheme under the test during the last 60 seconds. Results are shown in Fig. 5. The takeaway is that DeepCC-assisted TCP schemes inherit at least the same TCP friendliness of the underlying TCP.

\(^{14}\)We use the setup similar to the one used in section 6.4.1
though in some cases (e.g. as for DWest) DeepCC can make a tangible improvement.

6.4.4 A Flexible End-to-End Scheme vs. an In-Network AQM Scheme

Here, we compare the performance of our fully end-to-end scheme with a delay-centric in-network AQM scheme CoDel [37]. We use various TCP schemes at sender combined with CoDel as AQM scheme in the network (CoDel+TCPx), While for other schemes we use normal FIFO queues.

Moreover, here, we examine the flexibility of DeepCC for providing various Target delays by varying Target delay of the system. Although we only used one Target value during the training of our model, we show that the trained model performs well for the other Targets as well. So, without loss of generality, we use one of our traces and change the Target value from 25ms to 100ms. The average delay and utilization results are shown in Fig. 6.

CoDel can improve the performance of TCP schemes very well. However, CoDel (similar to other AQM designs such as [3, 39]) requires changes in the network devices which leads to having extra CAPEX costs for the cellular network providers. On the other hand, DeepCC as a fully end-to-end and deployment-ready approach, which does not require any changes in the network, can improve classic schemes such as Westwood to even outperform the performance of new TCP schemes (e.g. BBR and Cubic) combined with a modern in-network AQM schemes such as CoDel.

6.4.5 Impact of Buffer Size on Performance

DeepCC tries to keep the average delay of packets around the desired value no matter how much buffer exists in the network. Therefore, it is expected to have very low sensitivity to the size of the buffer in the network. This property of DeepCC, which is a crucial characteristic to achieve controlled self-inflicted delays in the cellular networks, helps the loss-based TCP schemes (which normally fill up the buffer until they see a packet loss) to perform better independent of the buffer sizes in the network. To show that, we vary the buffer size from 30KB to 1MB and explore the performance of Cubic, Westwood, Illinois, BBR, and their DeepCC counterparts across various buffer sizes. Fig. 7 shows the results. As expected, the performance of schemes using DeepCC is not sensitive to the buffer size, while delay performance of Cubic, Westwood, and Illinois due to their loss-based nature, is very sensitive to the buffer size.

6.4.6 Impact of Filter Kernel on Performance

In our context, there are two fully dynamic entities: 1) cellular network itself and 2) behavior of the underlying TCP scheme which make the learning phase normally very long process. In such a dynamic environment the use of approaches such as filter kernel will guide the system toward a faster and more efficient training phase. To investigate the impact of our filter kernel (detailed in section 4.2) on the performance of DeepCC, we compare DeepCC with another version of it using different filter kernel (detailed in section 4.2) on the performance in the network.

In our context, there are two fully dynamic entities: 1) cellular network itself and 2) behavior of the underlying TCP scheme which make the learning phase normally very long process. In such a dynamic environment the use of approaches such as filter kernel will guide the system toward a faster and more efficient training phase. To investigate the impact of our filter kernel (detailed in section 4.2) on the performance of DeepCC, we compare DeepCC with another version of it using various filter kernels. The utilization and average delay of various schemes after training with and without using filter kernels is shown in Fig. 8. As expected, our results show that DeepCC using different Target values perform well for the other Targets as well.

More training using more Target values will increase the accuracy and performance of the model. However, we deliberately decided to use only one Target to see how well DRL-agent can generalize the environment.
expected, results confirm that using filter kernel in DeepCC plug-in can lead to significant performance benefits (e.g. 60% utilization improvements for DCubic).

### 6.4.7 Overhead

Having an extra module as a plug-in might arise the concern of its overhead on the system. As mentioned earlier, the current version of DeepCC is only a prototype/proof-of-concept version which is not fully implemented in the kernel (DRL-Agent block is implemented at user-space). This greatly impacts the overall overhead of the current version. However, here, we would like to show that using a plug-in, especially when that plug-in is based on a modern and (seemingly!) complicated tool such as DRL, will not necessarily lead to high overhead on the system when it is compared to the overhead of the current state-of-the-art TCP schemes (which are also implemented at user-space). To illustrate that, we use various state-of-the-art TCP schemes and send traffic from a server to a client over an arbitrary LTE trace for about 8 minutes and measure the average CPU utilization of these schemes on the sender side. To have a fair comparison, here we omit the results of the schemes that are already fully optimized and implemented in the kernel. As results reported in Fig. 9 show, DeepCC has a lower overhead compared to most of the state-of-the-art schemes, though its overhead (mainly due to its user-space DRL-Agent block) is still required to be reduced. We leave the optimization of the DRL-agent and its kernel implementation to our future work.

### 6.5 In-Field Experiments

To evaluate the performance of DeepCC in the wild with real cross-traffic and cellular packet schedulers over Internet paths, we use multiple GENI [12] servers around the US and multiple cellular clients placed in different anonymous locations and perform our tests over two different cellular network providers in the US (namely TMobile and AT&T). Considering all combinations of server-client pairs, the minRTT (measured using Ping) in our testbed spans from 30-70ms. For DeepCC, we set the Target to have 50ms delay budget for the average queuing delay.

![Figure 9: The average CPU utilization of various TCP schemes (results are mapped to a single-core CPU)](image)

![Figure 10: Performance results of various schemes over all in-field tests](image)

reporting an aggregated view of the performance across all experiments, we use the average normalized throughput, average queuing delay, and 95th percentile queuing delay. For each experiment, the throughput of each scheme is normalized to the flow achieving the highest throughput in that experiment. Each experiment lasts 15 seconds. Half of them have one flow and the other half have three flows which start at 0, 5, and 10 seconds (after the start of the experiment). The overall results are shown in Fig. 10.

The relative performance of the schemes in Fig. 10 is very close to the results reported in the trace-based evaluations done in section 6.3. DeepCC not only improves performance of the classic and modern TCP schemes dramatically but also makes them the performance frontiers outperforming state-of-the-art schemes.\(^\text{17}\)

### 7 Conclusion

In this paper, instead of adding just another TCP scheme to the huge pile of current TCP designs, we presented a new design direction toward the use of DRL systems for assisting and souping up the performance of the existing TCP designs. We demonstrated that DeepCC can significantly boost the performance of existing TCP schemes in cellular networks. We hope that DeepCC framework and the improvements that it brings to different TCP schemes motivate the community toward the design of more plug-in-based approaches benefiting

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\(^\text{16}\)For DeepCC, we set the Target to have 50ms delay budget for the average queuing delay.

\(^\text{17}\)Since both DeepCC and C2TCP require different patched Kernels, we could not include C2TCP in our in-field tests where flows are sent back-to-back. We didn’t have this problem during our traced-based tests, because we could switch from one Kernel to another one without time constraint.
current/future protocols to alleviate congestion, particularly in a highly dynamic environment such as the cellular network.

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A Background

A.1 Deep Neural Networks

DNNs enable the automatic feature extraction from raw sensory input. This property reduces the efforts of handcraft feature engineering that requires different domain knowledge. In essence, DNN can be described as a non-linear function transformation. The goal of DNN is to find the function approximation $F^*$ that models the relationship between input vector $x$ and output vector $y$. Fig. 11 declares a generic DNN.

$w$ consists of multiple layers each consisting of multiple neurons. Each neuron is a computational unit that computes the weighted sum of input values and applies a non-linear activation function to the weighted sum. The output of a neuron is passed to the connected neurons in the next layer. The computation for layer $l$ can be written as:

$$z_j^{(l)} = g(a_j^{(l)}) , \quad a_j^{(l)} = \sum_{i} w_{i,j}^{(l)} \cdot z_i^{(l-1)},$$

where $g$ is an activation function, $w$ is the connection weights, and $z_0^{(0)}$ corresponds to the input $x$. A DNN has many stages of layers: an input layer which takes the input vector $x$, more than one hidden layers, and an output layer which produces the final output. Each layer processes its input information to a higher-level of representations. The DNN allows the model to learn multiple-level abstractions of data.

The training process of a DNN is done through adjusting the value of the weights $w$ to find a set of weights, $w$, that maximizes the objective or minimizes the cost.

A.2 Reinforcement Learning

Reinforcement learning is learning how to act from interaction, by mapping a situation to action, to achieve a goal. As Fig 12 illustrates, an RL system consists of an agent (the decision-maker block) and the environment (where agent interacts with and draws observations). The reward is a feedback signal to the agent showing whether the goal is achieved.

![Figure 11: The structure of a general DNN](image-url)
The agent selects an action and the environment responds to the action and presents a new situation, and the interactions are repeated. The agent’s objective is to select a sequence of actions that maximize cumulative future rewards.

**A.2.1 RL problem setup**

The foundation of solving the general RL problem is to model the task as a Markov Decision Process (MDP) [47]. An MDP is a stochastic decision-making model, defined as a tuple \((\mathcal{S}, \mathcal{A}, \mathcal{R}, T, \gamma)\), where \(\mathcal{S}\) denotes the state space and \(\mathcal{A}\) denotes the set of actions. At each time step \(t\), the environment reveals the current state \(s_t\), and the agent chooses an actions \(a_t \in \mathcal{A}\). The environment then reveals the reward \(r_t \sim R(s_t, a_t)\) and the next state \(s_{t+1}\) as a consequence of the action. The probability function of state transition satisfies Markov property, which means the state from the environment at time \(t+1\) only depends on state and action at time \(t\), but not the history of them. The environment dynamics can be written as:

\[
T(s'|s, a) = \mathbb{P}(s_{t+1} = s'|s_t = s, a_t = a),
\]  

(14)

A policy \(\pi : \mathcal{S} \rightarrow \mathcal{A}\), specifies a mapping from any given state to an action. The learning goal of RL is to find the policy, that maximize the cumulative reward

\[
\mathbb{E}_{s_0 \sim \mathcal{S}, a_0 \sim \mathcal{A}} \left[ \sum_{t=0}^{T} \gamma^t r_t \right],
\]

(15)

where \(\gamma \in [0, 1]\) is the discount factor. The q-function is defined as the expected return taking the action \(a\) in state \(s\), and thereafter following policy \(\pi\):

\[
Q^\pi(s, a) = \mathbb{E}[\sum_{i=0}^{T} \gamma^i r_i | s_i = s, a_i = a],
\]

(16)

The optimal policy \(\pi^*\) maximizes the optimal q-function \(Q^*\). The optimal q-function corresponding to the optimal policy can be unrolled by Bellman optimal equation [11]:

\[
Q^*(s, a) = \mathbb{E}[r_1 + \gamma \max_a Q^*(s', a') | s_1 = s, a_1 = a]
\]

(17)

The optimal policy can be written as:

\[
\pi^* = \arg \max_a Q^*(s,a)
\]

A.3 Deep Reinforcement Learning

The challenge of using RL in a real-world task is how to represent the policy and the q-function effectively. The function approximations for computing \(\pi\) and \(Q(s,a)\) are indispensable, and the state representation needs to be tackled.

Deep Reinforcement Learning (DRL) is the integration of RL with DNN, where the DNN is used as function approximations in the RL framework. DRL learns the essential features directly from the raw inputs, reducing the need for specialized handcraft features used to be carefully designed previously for successful RL application. DRL enables the training in an end-to-end fashion, reaching or surpassing human-level performance.

B Sample of Cellular Traces Used During Evaluation

To have a qualitative view of the collected traces, in Fig. 13, we show the sample of link capacity variations for the cropped first few minutes of the traces reported in Table 2.

C Discussion

C.1 Generalization and Transfer Concern

Both in-field tests and traced-based evaluations in section 6 indicate that DeepCC learned the policy that performs well in diverse cellular LTE scenarios. Although performance results are promising, understanding, formulation, measurement, and improving generalization in the context of RL (and deep learning) and the question of whether a learned model can be successfully transferred are still active research topics in machine learning community [8, 10, 17, 19, 23, 35, 52].

C.2 Can we use DeepCC to resolve congestion in other networks?

DeepCC’s framework is general and can be used in different networks to boost the performance of TCP. However, the objective that we chose for the current version of DeepCC suits cellular networks and not a general network. The objective of meeting applications desired target delays is a feasible objective in today’s cellular networks due to their distinguishing key characteristics. For instance, combination of having different bearers for different QoS requirements and isolation of different clients’ traffic from each other (through using per-client separate queues at BTS) make it possible to avoid the competition among multiple flows with contradicting objectives such as achieving ultra-low latency for one flow and achieving very high throughput for another one. Another unique property of cellular networks is the existence of wireless scheduler at BTS to directly control and resolve the fairness issue among flows.
So, it can be seen that without these properties, no TCP scheme can achieve ultra-low latency for a flow when this flow coexists with a throughput-hungry flow (which is not necessarily using the same TCP scheme!).

**C.3 Setting Target Delay**

Different approaches can be used to let applications set the target delay. For instance, in one approach, instead of giving total freedom to applications to choose their target delays, they may just choose which “class” of applications they belong to. Then, based on the predefined class properties, target delays can be set at the underlying layers. As we showed in Fig. 1, DeepCC provides the packet statistics to the applications. Therefore, applications can even adjust the target (or their class) dynamically based on the reports available to them. For example, if they are not satisfied with being in a certain class, they can change their class on the go during the life of a session.

**C.4 Toward a Universal TCP?**

Compare to the clean-slate design fashion, one can imagine that the design philosophy behind DeepCC would be a better approach toward achieving the ultimate goal of having a *universal TCP*, a TCP scheme which performs as the frontier TCP in various networks and conditions and removes the need for inventing new clean-slate TCP. New application demands, new network devices, technologies or architectures will just require an update of the training models of the universal TCP. However, we think that we are still far from reaching that ultimate goal, though designs such as DeepCC will pave the way for it.

**D Exploration**

Adequate exploration in action space is crucial in our problem. The idea of exploration is to allow the agent to try different actions to improve the model. During exploration, al-
though some actions that the agent chooses have a lower return at that moment, later after the agent may discover the trajectories with better policies, might lead to a higher return. The exploration techniques add noise to the actor as if the deterministic actor selecting an action in stochastic behavior. We experimented with different types of noise including variations of Ornstein-Uhlenbeck (OU) noise [51] and variations of Gaussian noise. We observed that the uncorrelated additive Gaussian action space noise leads to better performance. Using noise ($\mathcal{N}$), the final generated action becomes $a_t = \mu_\theta(s_t) + \mathcal{N}$ (Algorithm 1, line 3).

Before using the above equation, at the cold-start of training, we use an additional exploration method, in which we enforce the agent to walk over the action space (in a piece-wise manner) for a fixed amount of steps without experiencing noise.