

A Machine Learning Approach to Routing

Asaf Valadarsky¹

Michael Schapira¹

Dafna Shahaf¹

Aviv Tamar²

¹School of Computer Science and Engineering, The Hebrew University of Jerusalem, Israel

²Dept. of Electrical Engineering and Computer Sciences, UC Berkeley, USA

ABSTRACT

Can ideas and techniques from machine learning be leveraged to automatically generate “good” routing configurations? We investigate the power of data-driven routing protocols. Our results suggest that applying ideas and techniques from deep reinforcement learning to this context yields high performance, motivating further research along these lines.

1. INTRODUCTION

Applying machine learning to computational challenges is prevalent in numerous areas in computer science (AI, computer vision, graphics, NLP, comp-bio, and beyond). Computer networking, in contrast, has largely withstood the ML tide until recently. Recent advances suggest that this might be changing [22, 32, 31].

We ask whether data-driven protocol design [22] can improve upon today’s approach in the context of the fundamental networking challenge of optimizing routing configurations. We set out to answer this question. We report below on initial results and high-level insights from this ongoing exploration.

A rich body of literature on (multicommodity [42, 21, 7, 10, 28, 15, 5]) flow optimization establishes that for any given network topology and specification of “traffic demands” between communicating end-points, optimal routing configurations can be efficiently computed for a broad variety of optimization objectives [15, 21, 42, 5, 7, 10, 28]. Unfortunately, a routing configuration that guarantees high performance for specific traffic conditions can fail miserably in maintaining good performance when traffic conditions change.

Traditional routing schemes address this challenge in two manners: (1) Optimizing routing with respect to past traffic conditions, with the hope that good routing configurations for past-observed traffic conditions will also fare well in the future, and (2) optimizing *static* routing configurations with respect to a *range* of feasible traffic scenarios [15, 10, 28, 7]. Intuitively, ML-based approaches present a third option: leveraging (implicit) information in *past* traffic conditions to learn good routing configurations for *future* conditions.

In our investigation of the power of “data-driven routing”, we contend with high-level questions regarding the relevant learning paradigm and the proper representation of the inputs and outputs.

Learning the next input or learning routing configurations directly? The main challenge in our routing context is that traffic demands are unknown to the decision maker in advance. However, a realistic assumption is that the history of traffic demands contains *some* information regarding future traffic patterns (e.g., changes in traffic across times of day, the skewness of traffic, whether certain end-hosts communicate often, etc.). A natural approach is thus to continuously observe traffic demands to learn how these evolve, and optimize routing with respect to our predictions. In machine learning terms, this is a *supervised learning* task [38].

We evaluate several supervised learning schemes for predicting traffic demands. Our preliminary results are discouraging, indicating that supervised learning might be ineffective if the traffic conditions do not exhibit very high regularity. We hence turn our attention to a different approach: applying *reinforcement learning* [44] to routing. Now, instead of attempting to learn traffic demands and optimizing routing with respect to our predictions, the goal is to directly learn a good mapping from the observed history of traffic demands to routing configurations. Our results suggest that this approach is much more promising, yet realizing effective reinforcement learning in our context requires care, as discussed next.

What should the output of the learning scheme be? We observe that the routing domain poses significant challenges to realizing the data-driven protocol design approach. A key challenge is that the natural “output” of a (general) routing scheme is a collection of rules specifying how traffic is forwarded from each source to each destination, whose naive representation involves a very large set of parameters (as opposed to, e.g., selecting a single action from a fairly small set [31, 32]). Our results indicate that this can render learning slow and ineffective. We hence devise methods for constraining the size of the output without losing “too much” in terms of expressiveness of routing configurations. We leverage ideas from the literature on hop-by-hop traffic engineering [34, 48, 15] to efficiently learn (via reinforcement learning) experimentally good routing configurations. Our preliminary findings suggest that our approach is a promising direction for improving upon today’s routing schemes.

We believe that our investigation of data-driven routing has but scratched the surface of this important subject (in terms of

identifying the right approaches and machinery, conducting more realistic simulations and real-world evaluations). Our results motivate the further exploration of this idea in a variety of contexts (data centers, WANs, ISP networks, interdomain routing, and more).

2. ROUTING MODEL

Informally, in our framework, a decision maker (network operator / automated system) repeatedly selects routing configurations for the network. Traffic conditions might vary and routing decisions are oblivious to future traffic demands. Our focus is on the conventional optimization objective of minimizing link over-utilization (a.k.a. minimizing congestion) from traffic engineering literature [15, 7, 10, 28]. We formalize our framework below.

Network. We model the network as a capacitated directed graph $G = (V, E, c)$, where V and E are the vertex and edge sets, respectively, and $c : E \rightarrow \mathbb{R}^+$ assigns a capacity to each edge. Let n denote the number of vertices in V and $\Gamma(v)$ denote vertex v 's neighboring vertices in G .

Routing. A routing strategy \mathcal{R} for the network specifies, for each source vertex s and destination vertex t how traffic from s to t that traverses v is split between v 's neighbors. Thus, a routing strategy specifies, for each vertex v and source-destination pair (s, t) a mapping from v 's neighbors to values in the interval $[0, 1]$, $\mathcal{R}_{v,(s,t)} : \Gamma(v) \rightarrow [0, 1]$, such that $\mathcal{R}_{v,(s,t)}(u)$ is the fraction of traffic from s to t traversing v that v forwards to its neighbor u . We require that for every $s, t \in V$ and $v \neq t$, $\sum_{u \in \Gamma(v)} \mathcal{R}_{v,(s,t)}(u) = 1$ (no traffic is blackholed at a non-destination), and also for every $s, t \in V$, $\sum_{u \in \Gamma(v)} \mathcal{R}_{t,(s,t)}(u) = 0$ (all traffic to a destination is absorbed at that destination).

We say that a routing strategy \mathcal{R} is *loop-free* if for every source-destination pair (s, t) and for every cycle of edges C , there must be some edge $(u, v) \in C$ such that $\mathcal{R}_{u,(s,t)}(v) = 0$ (i.e., traffic never traverses the same point twice).

Induced flows of traffic. A demand matrix (DM) D is a $n \times n$ matrix whose (i, j) 'th entry $D_{i,j}$ specifies the traffic demand between source i and destination j . Observe that any demand matrix D and a loop-free routing strategy \mathcal{R} induce a flow of traffic in the network, as explained next; Traffic from every source s to destination t is split amongst s 's neighbors according to $\mathcal{R}_{s,(s,t)}$. Similarly, traffic from s to t traversing a neighbor of s , v , is split amongst v 's neighbors according to $\mathcal{R}_{v,(s,t)}$. Loop-freeness guarantees that all traffic leaving s will reach t without cycling in the network.

How good is a traffic flow? We adopt the classical objective function of minimizing link (over)utilization (also termed congestion [15]) from traffic engineering literature [15, 10, 7, 28], though our approach can easily be extended to other objective functions. The link utilization under a specific multicommodity flow f is $\max_{e \in E} \frac{f_e}{c(e)}$, where f_e is the total amount of flow traversing edge e under flow f .

We point out that for any *given* demand matrix, computing

a multicommodity flow f that minimizes link utilization can be executed in a computationally-efficient manner via linear programming [21, 7, 15]. Our focus, in contrast, is on the realistic scenario where the DM is not known beforehand.

Routing future traffic demands. In our framework, time is divided into consecutive intervals, called “epochs”, of length δ_t (δ_t is determined by the network operator). At the beginning of each epoch t , the routing strategy \mathcal{R}^t for that epoch is decided. \mathcal{R}^t can depend only on the history of *past* traffic patterns and routing strategies (i.e., from epochs $1, \dots, t-1$).

We make two simplifying assumptions: (1) that the demand matrix is fixed within each time epoch, and (2) that demand matrices can be inferred after the fact (e.g., via network measurements). We leave the investigation of data-driven routing under more complex traffic patterns (e.g., capturing IP flows entering and leaving within each epoch) and of information-constrained routing decisions (e.g., only relying on partial information about the traffic demands) to the future. As discussed below, studying this simple setting already gives rise to interesting insights.

After selecting the routing strategy \mathcal{R}^t for epoch t , the demand matrix for epoch t , and the associated cost, in terms of maximum link-utilization, are revealed. The objective of the decision maker is to select routing strategies in a manner that consistently results in low link over-utilization.

3. WHAT TO LEARN?

Our underlying assumption is the existence of some *regularity* in the DMs, and the purpose of the investigation below is exploring ideas for how such regularity can be inferred/leveraged to optimize routing with respect to future DMs. We consider two different manifestations of regularity—embedding *deterministic* regularity into the DM sequence and drawing DMs from a *fixed probability* distribution—and two high-level learning approaches—supervised learning and reinforcement learning.

3.1 Supervised Learning Approach

Our goal is to extract “good” routing strategies from past observations. Since for a given demand matrix (DM), an optimal routing strategy is efficiently computable, a natural approach is to repeatedly try to predict (i.e., learn) the next DM and then compute an optimal routing strategy for that DM. In machine learning terms, this translates to a supervised learning problem.

Supervised learning. A supervised learning task involves a sample space \mathcal{X} and a labeling space \mathcal{Y} . An algorithm \mathcal{A} for the task is a function mapping values in \mathcal{X} to labels in \mathcal{Y} . Given a set of samples and their true labels $\{(x_i, y_i)\} \in \mathcal{X} \times \mathcal{Y}$, the goal is to identify a mapping that produces correct labels for new samples, drawn from the same distribution as the data. How good/bad a mapping fares is quantified in terms of a loss function $\mathcal{L} : \mathcal{Y} \times \mathcal{Y} \rightarrow \mathbb{R}$. Intuitively, for any pair of labels (y_1, y_2) , $\mathcal{L}(y_1, y_2)$ represents the cost of predicting, for a given sample, the label y_2 instead of the correct label y_1 .

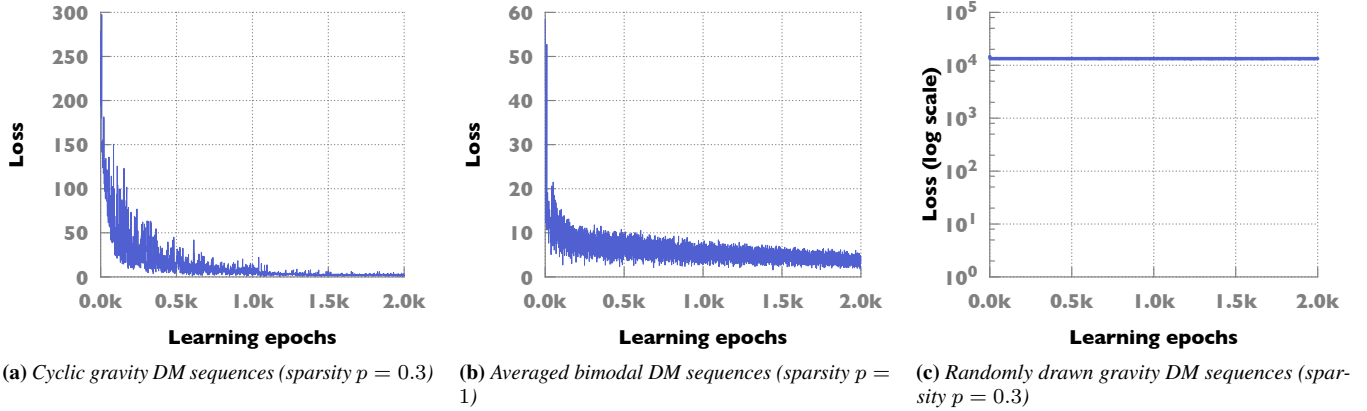


Figure 1: Representative Results for Supervised Learning (using NAR-NN with $k = 10$ and $q = 5$)

See [38] for a detailed exposition of supervised learning.

We consider the following supervised learning approach to routing: the learning algorithm observes the history of DMs up to the current epoch, and predicts the DM for the upcoming epoch. This prediction is then used to generate an optimal routing strategy with respect to the predicted DM. When is employing this scheme a good idea? To answer this question, we evaluate several supervised learning schemes for predicting the next DM on different traffic patterns.

Generating DM sequences for our experiments. We next discuss how traffic patterns are generated in our experiments. We consider two standard schemes for generating DMs: the (deterministic) gravity model [39] and the (probabilistic) bimodal model [33]. Intuitively, the former captures scenarios in which communication between end-points is proportional to their outgoing bandwidths and the latter captures scenarios in which communication end-points are divided into small flows (mice) and large flows (elephants). We also consider “sparsifications” of gravity/bimodal DMs generated by selecting, uniformly at random, a p -fraction of the communicating pairs, for some choice of $p \in [0, 1]$, and removing the traffic demands of all other pairs from consideration. We refer to p as the *sparsity* of the DM.

Our experiments require generating *sequences* of DMs, specifying a DM for each time epoch. We examine two classes of DM sequences:

Class I: DM sequences in which the next DM is *deterministically* derived from past DMs. One example for such a DM sequence is “a cycle of DMs”, in which the DM in each epoch belongs to a fixed set of q DMs, D_0, \dots, D_{q-1} such that if D_j is the DM in epoch $t - 1$ then $D_{j+1 \text{ modulo } q}$ is the DM in epoch t . D_0, \dots, D_{q-1} in our experiments are sparsified (for varied values of p) gravity/bimodal DMs (for varied values for parameters of the bimodal model). Cycles of DMs might capture, e.g., the scenario that the traffic demands at a certain time of day are rather similar across days. See discussion of such temporal consistencies in ISP networks in [16]. Another example of a DM sequence that, though more arti-

ficial, also exhibits high regularity (and so is interesting to study) is when each DM is the average of the previous q DMs (for some fixed $q > 0$). Our experiments evaluate supervised learning schemes on DM cycles of sizes $q = 5, 10, 15, 20$, and DM sequences in which each DM is the average over the previous $q = 5, 10, 15, 20$ DMs.

Class II: DM sequences in which each DM is independent of the previous DMs. The DM for each epoch is now drawn independently from a fixed probability distribution over DMs, namely sparsified gravity/bimodal DMs. We point out that such traffic patterns are commonly used in evaluations of data center architectures and protocols [24, 4, 18, 49] as traffic in data centers is often viewed as highly skewed and unpredictable [19, 17].

Supervised learning schemes. Following the recent successes of deep neural networks (DNNs) [27, 37, 40]), we evaluate 3 different DNN architectures. The input to all three architectures is the k most recent observed DMs and the output is a DM. We examine different values of k (5, 10, and 20). We use the Frobenius (or l_2) norm [20] to quantify the quality of an output with respect to the actual DM. The three architectures differ in the structure of the neural network interconnecting the input layer (representing k -long histories of DMs) and output layer (representing the next DM). We evaluate (1) *FCN*, a 3-layered fully-connected network, (2) *CNN*, a 4-layered convolutional neural-network [29], and (3) *NAR-NN*, a nonlinear auto-regressive model [11], realized via a 4-layered neural network that, for input demand matrices D_1, \dots, D_k , learns a k -vector $\alpha = (\alpha_1, \dots, \alpha_k)$ and an $n \times n$ matrix β , and outputs the DM $\sum_i \alpha_i D_i + \beta$.

Evaluation framework. We experiment with gravity and bimodal DMs of various sizes ($9 \times 9, 12 \times 12, 23 \times 23, 30 \times 30, 50 \times 50$, and 100×100) under various choices of sparsity levels $p = 0.3, 0.6, 0.9, 1$ and of values of per vertex outgoing bandwidths (ranging from 10’s of MB to 10’s of GB). We consider various DM sequence lengths for training and testing the model (ranging from a few 10’s to few 100’s of DMs). We

generate, for each choice of parameter assignment to q, p, k and sequence length, a training set of 10 DM sequences and a test set of 3 DM sequences. We define a *learning epoch* as a full traversal of the training set. We train each neural network for 2000 learning epochs.

Results. Our experimental results (for the test DM sequences) show that for DM sequences that exhibit deterministic regularity, namely, cycles of DMs and “averaged DMs”, only the *NAR-NN* performs fairly well and only for specific relations between the examined history (k) and the size of the cycle / number of DMs averaged over (q). Specifically, when $q \leq k$, *NAR-NN* well-approximates the next DM for cycles of DMs, and performs well on averaged DMs. *NAR-NN* continues to perform reasonably well on averaged DMs when $q > k$, but fails on cycles of DMs for $q > k$. All 3 architectures failed (quite miserably) to approximate the next DM for randomly generated DMs (which is not surprising, as there are no temporal correlations between DMs in the sequence).

We present representative results for *NAR-NN* on a network G with 30 vertices. We plot the loss, in terms of distance of the predicted DM from the actual DM (y-axis), over the number of learning epochs (x-axis). Figure 1b and Figure 1a show that the model succeeds in learning the next DM when using the averaged and cyclic DM sequence generation. Figure 1c demonstrates failure in learning the next DM when drawn from a probability distribution.

3.2 Reinforcement Learning Approach

We next investigate the application reinforcement learning to routing-strategy selection. Instead of attempting to learn the next DM and optimizing the routing strategy with respect to that DM, the goal now is to directly learn a good mapping from observed DMs to routing strategies.

Reinforcement learning. In the reinforcement learning framework, an agent repeatedly interacts with an environment. Time is divided into discrete time slots $t = 1, 2, 3, \dots$. At the beginning of each time slot t , the agent observes the current state s_{t-1} of the environment and selects an action a_t from a fixed set of actions. Once the agent chooses action a_t , the state of the environment changes to s_t and the agent receives a reward r_t (a numerical value) signifying how good/bad the action he took was. The goal of the agent is to learn a mapping π from the set of possible states \mathcal{S} to the space of actions \mathcal{A} (i.e., $\pi : \mathcal{S} \rightarrow \mathcal{A}$) that fares well with respect to the objective of maximizing the *expected discounted reward* $\mathbb{E}[\sum_t \gamma^t r_t]$ for a predetermined $\gamma > 0$, called the *discount factor*. See [44] for a detailed exposition of reinforcement learning.

Routing via reinforcement learning. Routing-strategy selection can be easily cast as a reinforcement learning task as follows. At the beginning of each time epoch t , the operator/system (agent) decides on a routing strategy \mathcal{R}^t for that epoch based on the routing strategies and DMs in the most recent k time epochs, which constitute the observed state of

the environment at that point. Then, the state changes as the DM for epoch t , D_t , is revealed and the reward $r_t = -\frac{c_t}{OPT_t}$ is received, where c_t is the max-link-utilization under \mathcal{R}^t for D_t and OPT_t is the optimal max-link-utilization with respect to D_t (r_t thus captures the ratio between achieved performance and optimal performance). The goal is to learn a mapping from k -long histories of DMs to routing strategies that maximizes the expected discounted reward, as formulated above. We explore the power of this approach in the following sections.

4. REPRESENTING THE OUTPUT

We observe that, in contrast to other recent applications of ML to networking [31, 32], learning routing strategies involves generating neural networks with very large output layers (containing, e.g., thousands of output nodes even for a communication network of but tens of vertices). Consider, e.g., the representation of a routing strategy described in Section 2. This representation involves $|V|^2 \cdot |E|$ variables, where $|V|$ and $|E|$ are the sizes of the network graph’s vertex set and edge set, respectively. We show below that even for constrained routing strategies of much smaller sizes, a (“vanilla”) reinforcement learning approach for predicting the complete routing strategy fails to attain good performance within reasonable time.

We restrict our attention to *destination-based* routing strategies, i.e., routing strategies in which the splitting ratios at each vertex u with respect to any destination d are the same across all possible sources s . Observe that any such routing strategy \mathcal{RS} can be represented by $|V| \cdot |E|$ values (i.e., $|V|$ times smaller than unconstrained routing strategies). We use a state-of-the-art continuous-control reinforcement-learning algorithm, TRPO [40] (also used in [31]), applied to a 3-layered fully-connected neural network, to learn the mapping π from k -long histories of DMs to a routing strategy \mathcal{RS} . The real-valued outputs generated by the deep neural network are turned into per vertex traffic-splitting ratios by applying, for each vertex in the communication network u , the softmax function [9] to the outputs corresponding to u ’s outgoing edges.

Loop-freeness of the resulting routing strategy is enforced via the following procedure: For each source-destination pair (s, t) , emulate the transmission of 1 unit of flow from s to t in consecutive iterations, as described next. s first splits the unit of flow between its neighboring vertices according to the routing strategy. Then, each neighbor splits its share of the unit of flow between its neighbors, and so on. Keep track, for each edge e , of the *total* volume of traffic f_e that traversed that edge in all iterations thus far, termed “the total flow on e ”. Continue this process until the entire unit of flow arrives at the destination t . Then, set, for each edge $e = (u, v)$, the splitting ratio on e , $R_{u,(s,t)}(v)$, to be the ratio between the total flow on e , f_e , and the sum of all total flows on edges leaving u .

Evaluation. We adapt the open-source implementation of

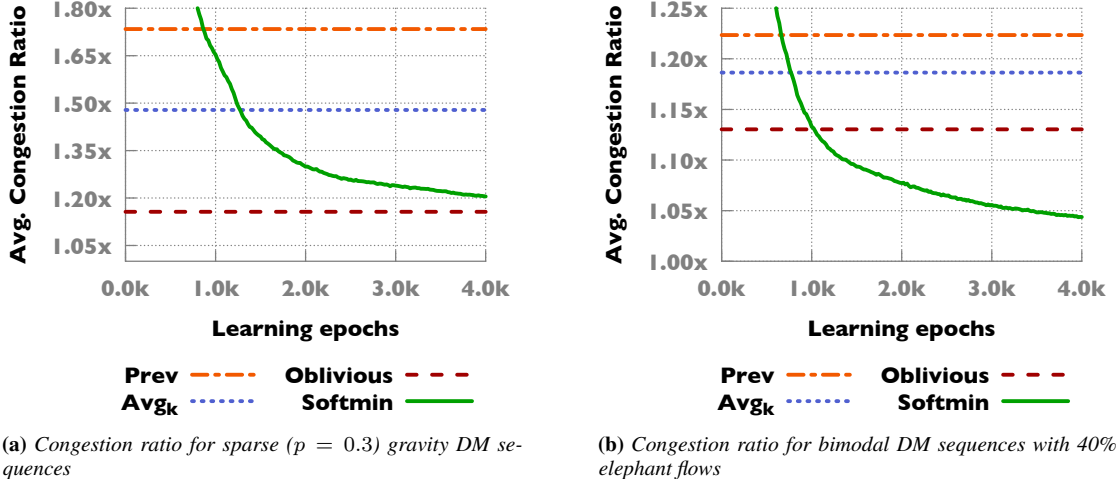


Figure 2: Representative Results for softmin-Routing

TRPO [40] provided by OpenAI [13] to the task of learning routing-strategies. We begin our evaluation with a seemingly easy target: learning the splitting ratios for a 12-vertices, 32-edges network (taken from [25]), and (sparsified) gravity DMs. We train a 3-layered fully-connected network over 7 sequences of gravity DMs of length 60 and evaluate (test) the neural network on 3 such sequences. We repeat this process for sparsity levels 0.3, 0.6, and 0.9. We use $k = 10$ (the length of the history of past DMs received as input). We compute the optimal congestion using the CPLEX [2] LP solver.

The training phase involves generating, from every sequence of DMs of length 60, 50 sequences of 10 consecutive DMs (representing ten-long histories of DMs), by grouping DMs 1 – 10, 2 – 11, etc. Training the neural network on each of these “histories of DMs” involves evaluating the neural network 30 times in parallel (and so 1,500 iterations per DM sequence and 10,500 overall). We refer to one execution of this process as a “learning epoch”.

Our results (omitted due to space constraints) suggest that this approach leads to slow and ineffective learning; e.g., even after more than 700 learning epochs, the produced routing strategies were still over 9x away from the optimum, in terms of max-link-utilization. As shown below, routing strategies that fare significantly better can be generated much quicker. We hypothesize that the large number of output parameters renders efficient learning very challenging. We thus seek a class of routing policies that can be more concisely represented yet is still rich enough to attain high performance.

5. LEARNING SOFTMIN ROUTING

We explore the following approach: instead of learning splitting ratios directly, learn *per-edge weights*, and then use these weights to generate a routing strategy. Under this approach, the output of the neural network is of size $|E|$ (as opposed to $|V|^2 \times |E|$ and $|V| \times |E|$ for unrestricted and

destination-based routing policies, respectively).

Generating forwarding rules from link weights is a classical approach to routing [15, 48, 34]. We resort to the following approach:

The $softmin_\gamma$ value for a vector of r coordinates $\alpha = (\alpha_1, \alpha_2, \dots, \alpha_r)$, for $\gamma > 0$, is the vector (also of r coordinates) $softmin_\gamma(\alpha)_i = \frac{e^{-\gamma\alpha_i}}{\sum_{i=1}^r e^{-\gamma\alpha_i}}$, $i \in 1, \dots, r$. Observe that $softmin(\alpha)$ can be regarded as a probability distribution (as the sum of all coordinates necessarily equals 1).

Consider a specific assignment of per-edge weights $w = \{w_e\}_{e \in E}$, a specific edge $(u, v) \in E$, and a specific traffic destination d . Observe that, when viewing weights as distances, w determines the length of the shortest path from vertex u to vertex d that goes through u ’s immediate neighbor v . Let $SP_w(v, u, d)$ denote this length. Given a set of such per-neighbor distances for a vertex u , the $softmin$ function can be applied to generate a probability distribution across these neighbors, which can be interpreted as u ’s splitting ratios for traffic destined for d . We refer to this scheme as “ $softmin$ -routing”. The higher the choice of γ to plug into the softmin function the closer the resulting routing scheme is to shortest path routing. We set $\gamma = 2$ in our experiments. We enforce loop-freeness of the routing strategy by applying the procedure described in Section 4.

Our reinforcement learning scheme maps k -long histories of DMs to per-edge link weights. The reward is computed by turning these weights into traffic splitting ratios and computing the max-link-utilization of the resulting routing strategy with respect to the next DM. We realize this learning scheme via a 3 layers fully-connected network.

We benchmark our results against three alternative non-ML-based approaches to computing routing strategies: (1) *Prev*: optimizing softmin routing with respect to the most recent DM, (2) *Avg_k*, optimizing softmin routing with respect to the

k most recent DMs, and (3) *Oblivious*, the optimal oblivious routing scheme [7] (which does not depend on the history of DMs at all).¹

Evaluation. We consider a communication network with 12 vertices and 32 edges.² We use the adaptation of [13] discussed in Section 4 to train a 3-layered fully-connected neural network to generate the weights for softmin routing. We train the neural network on 7 sequences of gravity and bimodal DMs of length 60 each, and tested on 3 such sequences. For gravity DM, the above process is repeated per sparsity levels 0.3, 0.6, and 0.9. For bimodal DMs the sparsity level is $p = 1$ and the percentage of large (elephant) flows amongst the communicating pairs is varied: 20/40/60% of all pairs. We set $k = 10$ and compute the optimal flow via the CPLEX [2] LP solver.

We show in Figure 2a representative results for gravity DMs and in Figure 2b representative results for bimodal based DMs. The figures plot the ratio between the performance of the resulting routing strategies (for the test DM sequences), in terms of averaged max-link-utilization (congestion), and the optimum congestion. Interestingly, oblivious routing outperforms the other two baselines. Observe that *softmin*-routing gets very close to oblivious routing’s performance for gravity DM sequences (and could perhaps outperform it with more training), and significantly outperforms oblivious routing for bimodal DM sequences.

6. RELATED WORK

Traffic engineering Traffic engineering (TE) is fundamental to networking, and hence vastly researched. Results on TE range from routing in legacy, OSPF/ECMP networks [15, 10] to datacenter networks [3] and backbone networks [23]. Softmin routing is inspired by the literature on TE via hop-by-hop routing in IP networks e.g., PEFT [48] and HALO [34]. We find softmin routing especially convenient to use as it involves fairly simple splitting traffic across next-hops and is loop-free, while still achieving high performance.

Reinforcement learning. Machine learning via deep-neural networks has proven extremely useful in executing many different tasks: machine translation [8], image recognition [27], and more. Specifically, reinforcement learning has been applied to playing computer games [36] and beating world-champions in strategic board games [43], robotics [26], 3D-

¹Observe that both *Prev* and *Avg_k* optimize softmin routing, as opposed to applying the optimal multicommodity flow computed for the input DM(s) to route the next DM. The reason is that the latter option is not well defined (and, in particular, some of the end-points communicating in the next DM might not communicate at all in the input DM). We point out that in our experimentation softmin routing is consistently within at most 5% of the optimum traffic flow with respect to any input DM and so very closely approximates this strategy.

²We also evaluated softmin-routing on larger networks, of up to 30 vertices and 102 edges, and saw the same trends as described below. However, due to time-constraints the neural network in these experiments did not fully converge. We thus defer the presentation of these results to the future.

locomotion tasks [40], and beyond. The development and optimization of reinforcement learning algorithms is thus the subject of much attention. Our algorithms rely on utilizing TRPO [40]. We leave the evaluation of other reinforcement-learning algorithms such as actor-critic-based [35] or the (very recently proposed) class of Proximal Policy Optimization algorithms [41] to future research.

ML applications to networking. Machine learning has been applied to various networking contexts including congestion control [47, 12], network bottleneck detection [45], and optimizing datacenter power consumption [1], resource allocation [31], and bitrate selection for video streaming [32]. Q-routing [30] applies Q-learning [46] to the network routing context. Under Q-routing [30], each router individually learns a mapping from packet headers to outgoing ports. This involves routers constantly exchanging information, at per packet resolution, about their latencies with respect to different destinations. Operating at per packet level, and in a decentralized fashion, poses significant challenges in terms of scalability, communication overhead, and risk of forwarding loops resulting from uncoordinated forwarding decisions at routers.

7. CONCLUSION

We initiated the study of data-driven routing. Our preliminary results from experimentation with deep reinforcement learning in this context show that extracting information from the history of traffic scenarios to generate good routing with respect to future traffic scenarios is an interesting approach. We view our results as a first step towards realizing a much broader research agenda. Optimizing routing is a keystone of networking research, investigated in a broad variety of contexts, including legacy IP networks [15], data centers [3], private backbone networks [23], overlay networks [6], publish-subscribe networks [14], and more. Applying our data-driven approach to routing protocol design to each of these settings involves careful formulation of this challenge (e.g., optimization objective, specific output) in the context of the specific environment, and an appropriate choice of machine learning approach and algorithm. We regard the pursuit of the goal of identifying in what contexts, and under what approaches, learning-based routing outperforms today’s state-of-the-art protocols, as an important and promising research agenda.

8. REFERENCES

- [1] DeepMind AI Reduces Google Data Centre Cooling Bill by 40%. <https://goo.gl/QTdU2T>.
- [2] IBM ILOG CPLEX Optimizer. <http://www-01.ibm.com/software/commerce/optimization/cplex-optimizer/index.html>.
- [3] M. Al-Fares, S. Radhakrishnan, B. Raghavan, N. Huang, and A. Vahdat. Hedera: Dynamic flow scheduling for data center networks. In *NSDI*, 2010.
- [4] M. Alizadeh, A. Greenberg, D. A. Maltz, J. Padhye, P. Patel, B. Prabhakar, S. Sengupta, and M. Sridharan. Data Center TCP (DCTCP). *ACM SIGCOMM*, 2010.
- [5] M. Allalouf and Y. Shavitt. Maximum flow routing with weighted max-min fairness. In *Quality of Service in the Emerging Networking Panorama*.
- [6] D. Andersen, H. Balakrishnan, F. Kaashoek, and R. Morris. Resilient overlay networks. 2001.
- [7] Y. Azar, E. Cohen, A. Fiat, H. Kaplan, and H. Racke. Optimal oblivious routing in polynomial time. *STOC*, 2003.

- [8] D. Bahdanau, K. Cho, and Y. Bengio. Neural machine translation by jointly learning to align and translate. *arXiv*, 2014.
- [9] C. M. Bishop. *Pattern Recognition and Machine Learning (Information Science and Statistics)*. Springer, 2006.
- [10] M. Chiesa, G. Révész, and M. Schapira. Lying your way to better traffic engineering. CoNEXT, 2016.
- [11] T. W. S. Chow and C. T. Leung. Nonlinear autoregressive integrated neural network model for short-term load forecasting. *IEE Proceedings - Generation, Transmission and Distribution*, 1996.
- [12] M. Dong, Q. Li, D. Zarchy, P. B. Godfrey, and M. Schapira. PCC: Re-architecting congestion control for consistent high performance. NSDI, 2015.
- [13] Y. Duan, X. Chen, R. Houthoofd, J. Schulman, and P. Abbeel. Benchmarking deep reinforcement learning for continuous control. ICML, 2016.
- [14] P. T. Eugster, P. A. Felber, R. Guerraoui, and A.-M. Kermarrec. The many faces of publish/subscribe. *ACM Comput. Surv.*, 2003.
- [15] B. Fortz and M. Thorup. Increasing internet capacity using local search. *Computational Optimization and Applications*, 2004.
- [16] B. Fortz and M. Thorup. Optimizing ospf/isis weights in a changing world. *IEEE J.Sel. A. Commun.*, 2006.
- [17] M. Ghodbadi, R. Mahajan, A. Phanishayee, H. Rastegarfar, P.-A. Blanche, M. Glick, D. Kilper, J. Kulkarni, G. Ranade, and N. Devanur. ProjecToR: Agile Reconfigurable Datacenter Interconnect. *SIGCOMM*, 2016.
- [18] D. Halperin, S. Kandula, J. Padhye, P. Bahl, and D. Wetherall. Augmenting data center networks with multi-gigabit wireless links. *SIGCOMM*, 2011.
- [19] N. Hamedazimi, Z. Qazi, H. Gupta, V. Sekar, S. R. Das, J. P. Longtin, H. Shah, and A. Tanwer. Firefly: A reconfigurable wireless data center fabric using free-space optics. *SIGCOMM*, 2014.
- [20] K. Janocha and W. M. Czarnecki. On loss functions for deep neural networks in classification. *CoRR*, 2017.
- [21] W. S. Jewell. *Multi-commodity Network Solutions*. 1966.
- [22] J. Jiang, V. Sekar, I. Stoica, and H. Zhang. Unleashing the potential of data-driven networking. COMSNETS, 2017.
- [23] S. Kandula, D. Katabi, B. Davie, and A. Charny. Walking the tightrope: Responsive yet stable traffic engineering. 2005.
- [24] S. Kassing, A. Valadarsky, G. Shahaf, M. Schapira, and A. Singla. Augmenting data center networks with multi-gigabit wireless links. *SIGCOMM*, 2011.
- [25] S. Knight, H. Nguyen, N. Falkner, R. Bowden, and M. Roughan. The internet topology zoo. *IEEE Journal on Selected Areas in Communications*, 2011.
- [26] J. Kober, J. A. Bagnell, and J. Peters. Reinforcement learning in robotics: A survey. *The International Journal of Robotics Research*, 2013.
- [27] A. Krizhevsky, I. Sutskever, and G. E. Hinton. Imagenet classification with deep convolutional neural networks. In *NIPS*, 2012.
- [28] P. Kumar, Y. Yuan, C. Yu, N. Foster, R. D. Kleinberg, and R. Soulé. Kulfi: Robust traffic engineering using semi-oblivious routing. *CoRR*, 2016.
- [29] Y. Lecun, L. Bottou, Y. Bengio, and P. Haffner. Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, 1998.
- [30] M. Majer, C. Bobda, A. Ahmadinia, and J. Teich. Packet routing in dynamically changing networks on chip. In *Proceedings of the 19th IEEE International Parallel and Distributed Processing Symposium (IPDPS'05) - Workshop 3 - Volume 04*, IPDPS '05, pages 154.2–, Washington, DC, USA, 2005. IEEE Computer Society.
- [31] H. Mao, M. Alizadeh, I. Menache, and S. Kandula. Resource management with deep reinforcement learning. HotNets, 2016.
- [32] H. Mao, R. Netravali, and M. Alizadeh. Neural adaptive bitrate streaming with pensive. *SIGCOMM*, 2017.
- [33] A. Medina, N. Taft, K. Salamatian, S. Bhattacharyya, and C. Diot. Traffic matrix estimation: Existing techniques and new directions. 2002.
- [34] N. Michael and A. Tang. Halo: Hop-by-hop adaptive link-state optimal routing. *IEEE/ACM Transactions on Networking*, 2015.
- [35] V. Mnih, A. P. Badia, M. Mirza, A. Graves, T. Lillicrap, T. Harley, D. Silver, and K. Kavukcuoglu. Asynchronous methods for deep reinforcement learning. ICML, 2016.
- [36] V. Mnih, K. Kavukcuoglu, D. Silver, A. Graves, I. Antonoglou, D. Wierstra, and M. A. Riedmiller. Playing atari with deep reinforcement learning. *CoRR*, 2013.
- [37] V. Mnih, K. Kavukcuoglu, D. Silver, A. A. Rusu, J. Veness, M. G. Bellemare, A. Graves, M. Riedmiller, A. K. Fidjeland, G. Ostrovski, et al. Human-level control through deep reinforcement learning. *Nature*, 2015.
- [38] M. Mohri, A. Rostamizadeh, and A. Talwalkar. *Foundations of Machine Learning*. The MIT Press, 2012.
- [39] M. Roughan, A. Greenberg, C. Kalmanek, M. Rumsewicz, J. Yates, and Y. Zhang. Experience in measuring backbone traffic variability: Models, metrics, measurements and meaning. IMW, 2002.
- [40] J. Schulman, S. Levine, P. Abbeel, M. Jordan, and P. Moritz. Trust region policy optimization. ICML, 2015.
- [41] J. Schulman, F. Wolski, P. Dhariwal, A. Radford, and O. Klimov. Proximal Policy Optimization Algorithms. *ArXiv e-prints*, 2017.
- [42] F. Shahrokhi and D. W. Matula. The maximum concurrent flow problem. *J. ACM*, 1990.
- [43] D. Silver, A. Huang, C. J. Maddison, A. Guez, L. Sifre, G. van den Driessche, J. Schrittwieser, I. Antonoglou, V. Panneershelvam, M. Lanctot, S. Dieleman, D. Grewe, J. Nham, N. Kalchbrenner, I. Sutskever, T. Lillicrap, M. Leach, K. Kavukcuoglu, T. Graepel, and D. Hassabis. Mastering the game of Go with deep neural networks and tree search. *Nature*, 2016.
- [44] R. S. Sutton and A. G. Barto. *Reinforcement learning: An introduction*. MIT press Cambridge, 1998.
- [45] H. Wang and B. Li. Lube: Mitigating bottlenecks in wide area data analytics. HotCloud, 2017.
- [46] C. J. Watkins and P. Dayan. Q-learning. *Machine Learning*, 1992.
- [47] K. Winstein and H. Balakrishnan. Tcp ex machina: Computer-generated congestion control. *SIGCOMM*, 2013.
- [48] D. Xu, M. Chiang, and J. Rexford. Link-state routing with hop-by-hop forwarding can achieve optimal traffic engineering. INFOCOM, 2008.
- [49] X. Zhou, Z. Zhang, Y. Zhu, Y. Li, S. Kumar, A. Vahdat, B. Y. Zhao, and H. Zheng. Mirror mirror on the ceiling: Flexible wireless links for data centers. *SIGCOMM*, 2012.