Edge-Compatible Reinforcement Learning for Recommendations

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Abstract

Most reinforcement learning (RL) recommendation systems designed for edge computing must either synchronize during recommendation selection or depend on an unprincipled patchwork collection of algorithms. In this work, we build on asynchronous coagent policy gradient algorithms (Kostas et al., 2020) to propose a principled solution to this problem. The class of algorithms that we propose can be distributed over the internet and run asynchronously and in real-time. When a given edge fails to respond to a request for data with sufficient speed, this is not a problem; the algorithm is designed to function and learn in the edge setting, and network issues are part of this setting. The result is a principled, theoretically grounded RL algorithm designed to be distributed in and learn in this asynchronous environment. In this work, we describe this algorithm and a proposed class of architectures in detail, and demonstrate that they work well in practice in the asynchronous setting, even as the network quality degrades.

1 Introduction

An edge system typically consists of a central hub and geographically distributed edges. The reason for having geographically distributed edges is to reduce response times between users and a web-service such as a reinforcement learning (RL) recommendation system. The benefit of faster response times comes at a cost, both for training and execution: one can no longer deploy centralized machine learning algorithms. If one naively trains independent models using local edge data, suboptimal solutions will be computed. Even if one managed to train a consistent global model, which could be updated on a regular basis (for example, every night), execution would still be a problem, since network latencies vary and temporary outages (for example, a server going offline) can occur. In real time when the algorithm needs to choose an action, it may need to consider dynamic or historical features of assets from all the edges. For example,
to recommend an item at the current edge the algorithm may need to know recent historical performance of the item from other edges. Another possibility is that all documents may not reside on all edges; for example, to recommend a document at the current edge, the algorithm may need to send a signal to an algorithm component residing on another edge, and then receive relevant document information from that remote component.

This work proposes the use of asynchronous coagent networks (Kostas et al., 2020), a type of stochastic neural network for reinforcement learning (RL), to provide recommendations while distributed over the internet. These networks provide principled, theoretically-ground learning rules for training in the distributed, edge-compatible, asynchronous recommender systems setting, where outages and variable or extreme latencies may occur.

2 Related Work

The use of machine learning to optimize recommender systems without expert human supervision dates back at least to the work of Joachims (2002), who proposed a support vector machine algorithm to optimize clickthrough rates for search engine results.

Many works have studied the RL recommendation problem. Choi et al. (2018) use biclustering to reduce the dimensionalities of the state and action spaces, thus making the problem more tractable for RL algorithms. Chen et al. (2019) propose an RL-based recommender system that scales to a large action space and that corrects for bias induced by learning from data collected based on recommendations from an earlier recommender system. Theocharous et al. (2009) study a partially-observable setting in which an algorithm must teach human students a task; they propose learning expert policies for different settings, and a switching policy that learns when to switch between these experts. Ie et al. (2019) also study the RL recommendation problem, with a particular focus on the setting in which an algorithm should consider the long-term effects of its actions. They assume that they are given the user-choice model (the model that describes how a given user will interact with a set of recommendations), and propose an algorithm, SlateQ, which makes the problem tractable under certain assumptions. Zhao et al. (2018) study the recommender systems setting in which users can provide real-time feedback. They propose an actor-critic-like learning algorithm and deep recurrent architecture to solve the problem. Theocharous et al. (2018) develop a posterior sampling for reinforcement learning algorithm that is effective at learning to give personalized recommendations. They prove a regret bound and empirically show that the algorithm is effective.

Other works study bandit problems (settings where the myopic policy is optimal) and ranking problems. Swaminathan et al. (2017) study the recommendation problem in the contextual bandit setting. They propose the pseudoinverse estimator, which estimates the performance of a policy, thus providing a method for evaluating a policy using off-policy data. Ai et al. (2018) propose a recurrent architecture and algorithm to refine and re-rank the results from another ranking
algorithm. Bello et al. (2018) study the ranking problem, and formalize it as a sequence prediction problem. They incorporate pointer networks, which are a model specialized for the ranking problem, into an algorithm designed to solve the problem. Jiang et al. (2018) point out that many popular recommender algorithms employ greedy ranking; these algorithms cannot account for biases in a slate layout and in interactions between recommendations. They propose an algorithm that uses conditional generative modeling to directly generate an entire slate of recommendations, so as to correctly account for these biases and interactions. Rhuggenaath et al. (2020) study the slate bandit setting in which rewards are not a simple function of the individual components of the slate. In other words, the authors eliminate common assumptions about the reward which make the combinatorial slate problem more feasible. They make an independence assumption about the structure of the reward function, and use this assumption to propose an algorithm with sub-linear regret with respect to the time horizon. However, none of these works address the recommender setting which we study: the setting in which the algorithm and/or data itself must be distributed and run in an asynchronous manner.

Federated learning (Qi et al., 2021) is distributed RL, but in an entirely different sense of the word “distributed” than in this paper; Section B of the supplementary material discusses this distinction in more detail.

3 Background

We study the setting in which the recommendation problem is a Markov decision process (MDP). Some problems in our setting are contextual bandits, which are MDPs with only one timestep per episode. We denote the state and action spaces as $S$ and $A$ respectively. We denote the timestep as $t$. The random variables $S_t \in S$, $A_t \in A$, and $R_t \in \mathbb{R}$ denote the state, action, and reward at time $t$, respectively. The transition function, $P : S \times A \times S \rightarrow \mathbb{R}$, gives the probability of transition to a state, given a state and action: $P(s, a, s') := \Pr(S_{t+1} = s' | S_t = s, A_t = a)$. We write the reward discount parameter as $\gamma \in [0, 1]$. The agent is parameterized by $\theta \in \Theta$, where $\Theta$ is the feasible set. The agent’s goal is to maximize the objective $J : \Theta \rightarrow \mathbb{R}$, which is defined as $J(\theta) := \mathbb{E}[\sum_{t=0}^{\infty} \gamma^t R_t | \theta]$; where “given $\theta$” means that an agent parameterized by $\theta$ chooses the actions. Policy gradient algorithms are a popular class of RL algorithms that aim to maximize the objective by performing stochastic gradient ascent using estimates of the objective’s derivative, $\nabla J(\theta)$.

3.1 Asynchronous Coagent Networks

We propose a unified distributed training and execution approach based on asynchronous coagent networks (Kostas et al., 2020). Coagent networks are a type of asynchronous stochastic neural network that are comprised of conjugate agents, or coagents, operating asynchronously in continuous time. Each coagent is an RL algorithm learning and acting cooperatively with the other coagents.
in its network. During a coagent’s execution, it takes as input the state of the environment and the outputs from the other coagents (not necessarily the whole state space or the outputs of all other coagents, it could take a small subset of the union of these spaces), and computes some output, which the coagent continuously outputs until its next execution. The output of the coagent is fed into other coagents and/or the network’s output (i.e., action). A coagent’s probability (mass and/or density) of updating at any time can be a deterministic or stochastic function of its input and the state of the environment. For example, one coagent might be designed to execute at 10 Hz, another coagent might be designed to execute each microsecond with a probability of $10^{-7}$, and a third might execute at times based on some (stochastic or deterministic) function of the environment’s state and/or the outputs of the coagents.

During training, each coagent computes a local gradient; the gradient rules are straightforward to derive (Kostas et al., 2020). The asynchronous coagent policy gradient theorem states that if each coagent updates its parameters using its local gradient, then the entire network will be updated as if the global policy gradient was computed. The theory holds for asynchronous networks where the units in the neural network do not execute simultaneously or at the same rate. See Section 4.2 for an example of this class of algorithm, and see Section A of the supplementary material for more intuition about the central result that enables the class of asynchronous recommender algorithms that we propose. The asynchronous nature of training and execution makes the approach natural for distributed implementations and particularly for our edge setting.

4 Approach

4.1 Architecture

We propose an architecture in which every edge has its own coagents that compute recommendations scores for each of its items. In addition, each edge has a coagent that decides how to combine the computations of adjacent edges. The learning algorithm accounts for all network delays in a theoretically-grounded way. For example, it will account for the situation where it had to give a suboptimal recommendation due to a delay and how that delay and suboptimal recommendation should influence the follow-up recommendation.

Figure 1 shows a high-level view of the architecture we propose. Figure 2 demonstrates how this architecture can be distributed in the edge setting; see the captions for more details.

4.2 Example Algorithm

In this setting, time is continuous: no global syncing of the algorithm is ever necessary for action selection. Each component of the network (coagent) simply executes (computes its action) whenever a new signal reaches it.

The following update describes a simple example asynchronous coagent
Figure 1: A high-level view of our recommendation architecture. The small empty square represents a coagent or group of coagents. At a given time-step, for each document, the network takes user attributes (including the query, if applicable) and document attributes as inputs. These observations are processed, and a scalar or vector is computed for the document. The parameters used to generate each document’s scalar or vector are the same (that is, the parameters are shared across the network). The recommendation generation component takes these scalars as input (one per document) and outputs a recommendation. The recommendation generation process may be a simple fixed algorithm: a sorting of scalars (one per document) may be effective if the user choice model can be assumed to be a cascade (Craswell et al., 2008) or logit model (Ie et al., 2019). A softmax could be used (similar to the approach of Chen et al. (2019)) for more efficient exploration.

Figure 2: Each user/document computation may take place on a different edge, and the final computation which computes the recommendation takes the results and computes the action (recommendation) on the local edge. Connections for the local edge and edge 2 are visualized as arrows; connections for edge n and the hub are not visualized, but the process is the same as for edge 2. Since some results may not arrive until after the recommendations must be displayed to the user (in other words, at any given time, the algorithm may not be able to communicate completely with itself and/or may not be able to access some documents), the algorithm must learn to achieve the best result it can for each recommendation, given the limitations of the edge setting.
learning algorithm based on REINFORCE (Williams, 1992). Let \( \Theta_i \) be the feasible set for coagent \( i \), \( \theta_i \in \Theta_i \) be the parameters of coagent \( i \), \( \alpha \) be the step size, and \( G_t \) be the return (that is, the cumulative discounted reward) up to time \( t \in \mathbb{R} \) (notice that because time is continuous, \( t \) does not take a value in the integers, as is typical in RL, but instead takes a value in the reals). Let \( \mathcal{U}_i \) be the output space of the \( i^{th} \) coagent, and let \( \mathcal{X}_i \) be the space of inputs to the \( i^{th} \) coagent (a subset of \( S \times \mathcal{U}_1 \times \mathcal{U}_2 \times \cdots \times \mathcal{U}_m \), where \( m \) is the number of coagents). Let the random variable \( X_i^t \in \mathcal{X}_i \) be the inputs to the coagent at time \( t \), and the random variable \( U_i^t \in \mathcal{U}_i \) be the action (output) of the coagent at time \( t \). Let \( n \) denote the number of times a coagent executes during a sequence of interactions with the environment. Let \( \pi_i : \mathcal{X}_i \times \mathcal{U}_i \times \Theta_i \to \mathbb{R} \) be the policy of the \( i^{th} \) coagent, which gives the probability of an output \( u \in \mathcal{U}_i \) given an input in \( x \in \mathcal{X}_i \) and a set of parameters in \( \theta_i \in \Theta_i \): \( \pi_i(x, u, \theta_i) := \Pr(U_i^t = u | X_i^t = x, \theta_i) \).

Let \( t_1, t_2, \ldots, t_n \) be the times of the coagent’s first execution, second execution, \( \ldots \), and \( n^{th} \) execution. The update each coagent will follow after a sequence of environment interactions is:

\[
\theta_i \leftarrow \theta_i + \alpha \sum_{t \in \{t_1, t_2, \ldots, t_n\}} \gamma^t G_t \left( \frac{\partial \ln (\pi_i(X_i^t, U_i^t, \theta_i))}{\partial \theta_i} \right).
\]

In practice, a more sophisticated policy gradient algorithm than this simple variant of REINFORCE may be used.

5 Results

In this section, we give results demonstrating that the algorithm and architecture proposed learn effectively in the asynchronous edge setting. Note that these results are not intended to demonstrate state-of-the-art results for the standard RL recommender-system setting (and, since no other algorithm we are aware of can be used in our asynchronous setting, there is no baseline to compare against). Instead, these results show that the proposed algorithm can learn and function effectively in this setting.

All experiments were conducted using a set of simulators developed from the MSLR-WEB10K dataset (Qin and Liu, 2013). See Section C of the supplementary material for simulator details. All learning curves are plotted from 30 runs (i.e., 30 trials), and all error bars show the standard deviation (between runs). See Section D of the supplementary material for more plot details.

5.1 Asynchronous Bandit Simulations

In this section, we demonstrate that the algorithm can function in the asynchronous edge setting, as described above. We created different versions of the simulator based on an unreliability parameter. An unreliability of 0.0 means that the network is fully synchronous, and an unreliability of 1.0 means that
Figure 3: Asynchronous edge setting results. These demonstrate that the algorithm can continue to learn effective recommendation strategies in an increasingly asynchronous edge setting. Note that these results do not indicate that the algorithm is performing worse given more unreliability. Rather, as the unreliability increases, the environment is becoming more challenging, degrading the agent’s ability to access documents and to communicate with itself; even an optimal policy would have progressively lower return as unreliability increases. These results demonstrate that our algorithm can learn effective recommendation strategies even in harsh, extremely asynchronous conditions.
Figure 4: RL results. Similar to the results above, these results demonstrate that the algorithm can learn effective recommendation strategies in an increasingly asynchronous edge setting.

the network is fully asynchronous (which would make communication between edges, and thus recommendations, impossible). More generally, an unreliability of $p \in [0, 1]$ means that, with probability $p$, each document/query pair will not compute a scalar in time to respond to the local edge before it must display results to the user (and so that document will be unavailable to the algorithm for that timestep). The results are shown in Figure 3; they demonstrate that the algorithm can continue to learn effective recommendation strategies in an increasingly harsh asynchronous edge setting.

5.2 Asynchronous RL Simulations

Next, we added a temporal aspect to the simulation; see Section C.1 of the supplemental material for details. The results are displayed in Figure 4. These results demonstrate that the algorithm learns effective recommendation strategies in this setting even as network quality degrades. As in Section 5.1, note that the results do not indicate that the algorithm is getting worse in more asynchronous settings. Rather, the problem and environment are becoming more difficult as the problem becomes more asynchronous (such that even the optimal policy would result in lower returns), and the algorithm is learning effective recommendation strategies despite this fact.

6 Summary and Conclusions

In this paper, we propose a distributed class of RL recommender algorithms and architectures based on asynchronous coagent networks. This class of algorithms
is designed to learn and function in an asynchronous edge recommender setting using principled and theoretically-grounded learning rules. Using simulations based on real-world data, we show that this approach works well in practice, even when the asynchronous edge setting interferes with the ability of the algorithm to access documents and to communicate with itself.

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Tao Qin and Tie-Yan Liu. Introducing LETOR 4.0 datasets. CoRR, abs/1306.2597, 2013. URL http://arxiv.org/abs/1306.2597.
A Asynchronous Learning Rule Intuition

Kostas et al. (2020) prove the asynchronous coagent policy gradient theorem. Intuitively, this theorem states that if each coagent ignores the complexity of the setup (that is, that it is a coagent embedded in an asynchronous continuous-time network of coagents, and the whole network is interacting with an environment) and simply runs an unbiased policy gradient algorithm, treating its inputs as the state space, its outputs as the action space, and the (discounted sum of) rewards between the coagent’s executions as the rewards between timesteps, then the network as a whole will follow an unbiased policy gradient. See the work of Kostas et al. (2020) for a more formal description, and see Section 4.2 for an example of this kind of algorithm.

B Federated Learning

Federated learning (Qi et al., 2021) is distributed RL, but in an entirely different sense of the word “distributed” than in this paper. Federated learning algorithms allow for the distribution of the training of a model among different parties, typically for the purpose of keeping the training data private. Typically, for federated learning algorithms, copies of a model are distributed to multiple parties to be run on different (private) data, and the resulting model update (e.g., a gradient) is then computed based on the information the different parties send back. Most federated learning algorithms are in fact synchronous in the terminology of this paper, since action selection must occur synchronously. Unlike asynchronous coagent networks, federated learning does not aim to distribute a single instance of a model over a network or run asynchronously for the purpose of computing actions.

So while the distributed nature of federated learning algorithms might sound superficially similar to asynchronous coagent networks, in fact the meanings and motivations behind the “distributed” natures of these two classes of algorithms are entirely orthogonal and unrelated.

C Simulator Details

The simulator is based on approximately 235,000 query-url pairs drawn from the MSLR-WEB10K dataset (Qin and Liu, 2013). The dataset provides relevance scores for each query-url pair; these scores take a value in \{0, 1, 2, 3, 4\}, where 0 is the least relevant and 4 is the most relevant. We use these scores as rewards: for a given query, when the agent selects a given document, the corresponding relevance (in \{0, 1, 2, 3, 4\}) is the reward. All features are normalized to the range \([-1, 1]\).

For each timestep (which corresponds to a whole episode for the bandit setting), the simulator randomly selects a query. The simulator then presents the agent with five possible documents to recommend (prepossessing to narrow down
the options for the agent is a well-established technique, see, for example, the work of Ie et al. (2019). To make the problem interesting, and to incentivize non-myopic behavior (see the RL simulator variant below), the simulator tries to select documents with a large range of relevance. Specifically, it selects documents with the following priority: 4, 0, 2, 3, 1. So, if documents of all relevances exist for the query, then the five documents will have the five different possible relevances. In the case where the simulator does not contain a document with a given relevance for the query, the simulator loops back to the beginning of the priority list above to find replacement document(s). For example, if a document with relevance 2 cannot be found, an extra document with relevance 4 will be provided, since 4 is at the beginning of the priority list above. Another example: if documents cannot be found with relevance 4 or 2, then the simulator will provide an extra document with relevance 0 and an extra document with relevance 3 (since those are the two highest priority relevance scores after 4 and 2).

C.1 RL Simulator Details

For the RL variety of the simulator, we added a temporal aspect to the simulation, inspired by the problem described by Ie et al. (2019). In this setting, a dimension is added to the state space which represents some aspect of the user’s internal state; below, we refer to this as the user state (USE). Similar to the experiments described by Ie et al. (2019), recommending a low relevance document (that is, a non-myopic document) stochastically increases the USE over the course of an episode. Specifically, the USE starts each episode with a value of 0, and, on timestep $t$, stochastically increases by a random variable $B_t$ when a document with relevance 0 or 1 is recommended, where $B_t$ is sampled from $U(\{0.0, 0.4, 0.8\})$, where $U$ denotes the discrete uniform distribution. If the USE is greater than or equal to 0.8, the reward given for each timestep is multiplied by ten for the duration of the episode. Episodes last for five user-system interactions. The result is that a less myopic policy that focuses on increasing the USE in addition to making good myopic recommendations will be more effective than even the optimal myopic policy. As in the work by Ie et al. (2019), the increase of the USE might represent nudging the user’s interests towards higher-value types of documents. Alternatively, the increase of the USE might represent increased interest or trust in the recommender system, the advantages of showing more diverse recommendations, or other similar benefits that can be gained from making non-myopic recommendations.

D Plot Details

Because of the highly stochastic nature of recommender systems and the resulting highly stochastic returns, for readability, each plotted data point is the running average of the previous 10,000 episodes (or, in the case of the first 10,000 episodes, each data point is simply the average of the first 10,000 episodes so as to avoid extreme noise at the beginning of each plot).
E Algorithm and Architecture Details

All coagent algorithms use a learning rule based on REINFORCE (Williams, 1992) (see Section 4.2). While more sophisticated, lower-variance learning algorithms may be used in practice, the simple asynchronous coagent version of the REINFORCE learning rule is sufficient for the purposes of this work (to illustrate the fact that these algorithms can be distributed and run asynchronously, even in poor network conditions). The learning rule is also principled in that it is unbiased (unlike most more-sophisticated policy gradient algorithms).

All coagent architectures used two-fully connected layers of 32 coagents each for each document. That is, there are 64 coagents per document, $64 \times 5 = 320$ distinct coagents, and 64 sets of unique coagent weights (since weights are shared across the five documents, see Figure 1). Each coagent uses binary (discrete) actions, and uses a linear basis (including a bias feature). Each coagent used softmax action selection with no temperature parameter.

Document selection (“Recommendation Generation” in Figures 1 and 2) is based on a simple “vote” across the network. Specifically, an integer for each document is computed between 0 and 32 (from the 32 second-layer coagents outputting binary actions), and the document with the greatest integer is that which is recommended. Ties are broken by choosing the document at random from the documents that are tied. Within the theoretical framework of Kostas et al. (2020), this document selection portion of the network can be viewed as a coagent with no learnable parameters.