1 Algorithm descriptions

We note that the decision procedure of a wide range of policy networks could be efficiently represented as high-fidelity tree shaped symbolic policy. In this tree structure, one basic component — the condition node, has three key properties: the condition, $a_{LEFT}$, and $a_{RIGHT}$, and could be written equivalent to one basic boolean operation, $\text{condition} \ast a_{LEFT} \ast a_{RIGHT}$, as explained in Figure[1].

A careful and delicate “DRL behavior dataset” is to be generated and processed, which we specify below. Once having generated the DRL behavior dataset, one could then apply one of the current symbolic regression benchmarks to parse out a symbolic rule that best fit the DRL behavior data.

We now specify how we build the DRL behavior dataset and process into a symbolic regression friendly format. In general, the symbolic regression algorithms are able to evolve into an expression that maps a vector $x \in \mathbb{R}^d$ into a scalar $y \in \mathbb{R}^1$, where $d$ is the dimensionality of the input vector. To do so, they require a dataset that stacks $N_{\text{Data}}$ samples of $x$ and $y$, into $X \in \mathbb{R}^{N_{\text{Data}} \times d}$ and $y \in \mathbb{R}^{N_{\text{Data}} \times 1}$, respectively. Given these input/output sample pairs, i.e., $(X, y)$, a symbolic expression that faithfully fit the data can be reliably recovered. The overview of our symbolic distillation algorithm is provided in Table[1] and equivalently in Figure[2].

The genetic mutation is guided by a measure termed program fitness. It is an indicator of the population of genetic programs’ performances. The fitness metric driving our evolution is simply the MSE between the predicted action and the “expert” action (teacher model’s action). We use the fitness metric to determine the fittest individuals of the population, essentially playing a

Table 1: Symbolic distillation algorithm.
survival of the fittest game. These individuals are mutated before proceeding to following evolution rounds. We specifically follow 5 different evolution schemes, either one picked stochastically. They are:

- **Crossover**: Requires a parent and a donor from two different evolution tournaments. This scheme replaces (or) inserts a random subtree part of the donor into a random subtree part of the parent. This mutant variant carries forth genetic material from both its sources.

- **Subtree Mutation**: Unlike crossover which brings “intelligent” subtrees into the parent, subtree mutation instead randomly generates it before replacing its parent. This is more aggressive as compared to the crossover counterpart and reintroduce extinct functions and operators into the population to maintain diversity.

- **Hoist Mutation**: Being a bloat-fighting mutation scheme, hoist mutation first selects a subtree. Then a subtree of that subtree is randomly chosen and hoists itself in the place of the original subtree chosen.

- **Point Mutation**: Similar to subtree mutation, point mutation also reintroduces extinct functions and operators into the population to maintain diversity. Random nodes of a tree are selected and replaced with other terminals and operators with the same arity as the chosen one.

- **Reproduction**: An unmodified clone of the winner is directly taken forth for the proceeding rounds.

### 2 Experimental Settings

In our training regime, the configured link bandwidth is between $100 - 500$ pps, latency $50 - 500$ ms, queue size $2 - 2981$ packets, and a loss rate between $0 - 5\%$. In the MiniNet emulation, the link bandwidth is between $0 - 100$ mbps, latency $0 - 1000$ ms, queue size $1 - 10000$ packets, and a loss rate upto $8\%$. The MiniNet configuration is from its default setting, and we adopt this mismatch to purposely explore the model’s robustness.

### 3 Extended Discussions

**The Interpretability.** The simple form of distilled symbolic rules provides more insights for networking researchers of what are the key heuristic for TCP CC. Moreover, our success of using symbolic distillation for CC also paves the possibility of applying it to other systems and networking applications such as traffic classification and CPU scheduling tasks.
def solve_policy_as_symbolic_tree(x, y):
    # input is a list of pairs of teacher behaviors:
    # x: numerical state
    # y: action
    # output: a symbolic tree with condition nodes and action nodes
    root = new_action_node(depth=0)  # initialize the root node as an action node
    unsolved_action_nodes = {root}
    loop_cnt = 0
    while (unsolved_action_nodes is not empty) and (loop_cnt < max_cnt):
        loop_cnt += 1
        node = sample(unsolved_action_nodes).pop()  # randomly sample an unsolved action node
        # First check if the actions under the current total_condition is near deterministic.
        y_subset = y[node.total_condition]  # select slices that satisfy total_condition
        if entropy(y_subset) < entropy_threshold:
            # If a single action fits under the current total_condition, then resolve and close this branch
            node.policy = mean(y_subset)
        else:
            if node.depth < max_depth:
                # If max depth is not met, branch on this node by
                # a randomly guessed
                # condition, and mark new child nodes as unsolved
                replace_action_node_with_new_condition_node(node)
                unsolved_action_nodes.add([node.a_LEFT, node.a_RIGHT])
            else:
                # If the current node is already too deep, then stop branching further.
                uniform_0_1 = rand()  # sample from a uniform distribution [0,1]
                if uniform_0_1 > p_SR:
                    # With probability p_SR, directly solve this node using Symbolic_Regression.
                    x_subset = x[node.total_condition]
                    node.policy = Symbolic_Regression(x_subset, y_subset)
                elif uniform_0_1 > p_SR + p_default_action:
                    # With probability p_default_action, set to default action to de-noise teacher behavior.
                    node.policy = default_action
                else:
                    # Otherwise, remove a subtree containing this node, then renew the searches.
                    node_father = sample(node.father_nodes_list)
                    remove_subtree(node_father)
                    node_father = new_condition_node()
                    unsolved_action_nodes.add([node_father.a_LEFT, node_father.a_RIGHT])
    return root

Figure 2: The pseudo-code for the algorithm in Table 1.

Need for Branching. The branched training of multiple symbolic models, each in different training
regimes, is designed to ease the optimization process. It does not directly enforce similarity between
solutions for the grouped states — therefore not causing brittleness. This is assured as the symbolic
model within any branch does not directly perform the same action for all scenarios within its regime,
but contains multiple operations within itself to map states to actions based on the network state
observed. Also, during the inference/deployment stage, we use the branch-decider network which
chooses branches based on the observed state, not the bandwidths or latencies (in fact, these measures
are unavailable to the controller agent and cannot be observed).

Checklist

The checklist follows the references. Please read the checklist guidelines carefully for information on
how to answer these questions. For each question, change the default [TODO] to [Yes], [No], or
[N/A]. You are strongly encouraged to include a justification to your answer, either by referencing
the appropriate section of your paper or providing a brief inline description. For example:
• Did you include the license to the code and datasets? [Yes]
• Did you include the license to the code and datasets? [No] The code and the data are proprietary.
• Did you include the license to the code and datasets? [N/A]

Please do not modify the questions and only use the provided macros for your answers. Note that the Checklist section does not count towards the page limit. In your paper, please delete this instructions block and only keep the Checklist section heading above along with the questions/answers below.

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper’s contributions and scope? [Yes]
   (b) Did you describe the limitations of your work? [Yes] See Section 5 in main text.
   (c) Did you discuss any potential negative societal impacts of your work? [Yes] See Section 5 in main text.
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes]

2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? [N/A] We did not include theoretical results.
   (b) Did you include complete proofs of all theoretical results? [N/A]

3. If you ran experiments...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [No] Our codes and data will be fully released upon acceptance.
   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes]
   (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [Yes]
   (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [No]

4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...
   (a) If your work uses existing assets, did you cite the creators? [Yes]
   (b) Did you mention the license of the assets? [N/A] The assets we used are open-source. The license information is available online.
   (c) Did you include any new assets either in the supplemental material or as a URL? [N/A]
   (d) Did you discuss whether and how consent was obtained from people whose data you’re using/curating? [Yes] The data we are using is open source.
   (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [No] Our data does not include personally identifiable information or offensive content.

5. If you used crowdsourcing or conducted research with human subjects...
   (a) Did you include the full text of instructions given to participants and screenshots, if applicable? [N/A]
   (b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [N/A]
   (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [N/A]