Asynchronous Reinforcement Learning Framework and Knowledge Transfer for Net Order Exploration in Detailed Routing

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***Abstract*—The net orders in detailed routing are crucial to routing closure, especially in most modern routers following the sequential routing manner with the rip-up and reroute scheme. In advanced technology nodes, detailed routing has to deal with complicated design rules and large problem sizes, making its performance more sensitive to the order of nets to be routed. In literature, the net orders are mostly determined by simple heuristic rules tuned for specific benchmarks. In this work, we propose an asynchronous reinforcement learning (RL) framework to automatically search for optimal ordering strategies and a transfer learning (TL) algorithm to improve performance. By asynchronous querying, the router, pre-training the RL agents, and finetuning with the TL algorithm, we can generate high-performance routing sequences to achieve a 26% reduction in the DRC violations and a 1.2% reduction in the total costs compared with the state-of-the-art detailed router.**

***Index Terms*—Physical design, detailed routing, reinforcement learning, transfer learning, policy distillation**

I. Introduction

Routing is a critical and time-consuming step in physical design [1]. Its solution impacts timing, power, and yield [2]. Routing is usually divided into global routing and detailed routing, with the former planning the rough routing regions and the latter finishing the actual interconnections [3]. Unlike global routing, detailed routing needs to handle plenty of design rules on a large grid graph. With feature sizes scaling down with the technology nodes, the routing grids become increasingly denser, leading to more complicated design rules from manufacturing, such as parallel-run spacing, end-of-line spacing, corner-to-corner spacing, and minimum area [4], [5]. Meanwhile, the grid graph for detailed routing is much larger than that of global routing, indicating larger solution space. As a result, detailed routing is becoming the most time-consuming step in advanced technology nodes [4].

While routing has been studied for several decades with many fundamental algorithms proposed, e.g., Lee's algorithm, A* search, negotiation-based rip-up and reroute scheme, etc., most of the attention has been paid to global routing for a long time [3], [6], [7]. In the past few years, with advanced technology nodes coming to the stage, the importance of detailed routing has been realized. Various aspects of detailed routing have been investigated. For example, pin access issues have been discussed in [8]–[10]. Ahrens et al. explored specific data structures for efficient detailed routing [11]. Manufacturing constraints have also been explored in [12]–[14], such as lithography-friendly routing algorithms.

In recent ISPD contests [4], [5], detailed routing has been raised as a fundamental challenge in the backend design with practical benchmarks and realistic design rules. The contests largely stimulate the researches in detailed routing and several high-performance and robust routers have been proposed [15]–[19]. Sun et al. [20] proposed a valid pin access pattern generalization with a via-aware track assignment to minimize the overlaps between the wire segments. TritonRoute [15] adopted integer linear programming (ILP) for parallel intra-layer routing. DRAPS [18] developed an A*-interval-based path search algorithm to handle complicated design rules. Dr.CU [16], [17], [21] proposed an optimal correct-by-construction path search algorithm and a two-level sparse data structure for runtime and memory efficiency. RDTA [19] developed an analytical approach to solve the track assignment problem following the global routing guides. Attention router explored reinforcement learning to solve the analog routing problem at a small scale [22].

Among the aforementioned detailed routers, most of them substantially follow the sequential routing strategy with the negotiation-based rip-up and reroute scheme [16]–[18], [20]. The parallelism is usually obtained by routing a batch of nets far away enough from each other simultaneously. This means the routing order of nets is critical to the performance of the algorithm. Currently, the net ordering strategy is usually determined by simple heuristics. For instance, some net ordering indicators are listed here: 1) the number of pins in a net; 2) the number of DRC violations caused by a net [23]; 3) the region size covered by a net [17]; 4) the distance from a certain point [24]. In addition, the net order may change according to the current routing status and historical penalties during the rip-up and reroute stage [3]. The performance of these ordering strategies may vary from design to design and from router to router as well. Therefore, a generic way to search for a good ordering strategy is desired to achieve high-performance routing.

The preliminary version has been presented at the Design, Automation and Test in Europe (DATE) Conference 2021. This work was supported by the National Natural Science Foundation of China (61874002, 62034007), Beijing Municipal Natural Science Foundation (2017ZX02315001), the National Key Research and Development Program of China (2019YFB2205005).

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To find a good ordering strategy, in this work, we formulate the strategy search problem into a reinforcement learning (RL) task to automatically learn from the designs. The major contributions can be summarized as follows.

- We develop an asynchronous reinforcement learning framework to learn the ordering strategy in sequential detailed routing. By developing a customized neural network architecture, we can apply the learned model to different designs.
- We propose a transfer learning algorithm that can adapt the pre-trained policy to target designs by finetuning small, clipped regions for better performance.
- Experimental results on ISPD 2018 & 2019 contest benchmarks [4], [5] demonstrate that the ordering strategy obtained from our framework generalizes well. Compared with the state-of-the-art detailed router Dr.CU 2.0 [17], the DRC violations and the total costs are reduced by 14 % and 0.7 %, respectively. With transfer learninng, we can reduce the DRC violations and the total costs by 26 % and 1.2 %, respectively.

The rest of this paper is organized as follows. Section II explains the background of routing, reinforcement learning, transfer learning, and problem formulation. Section III presents the RL framework details. Section IV explains the transfer learning algorithm. Section V reports the experimental results on ISPD contest benchmarks. Finally, Section VI concludes the paper.

II. Preliminaries

In this section, we introduce the background on VLSI routing, reinforcement learning, and problem formulation.

A. Design Rules

More design rules are introduced in the advanced technology nodes. Meanwhile, three fundamental and representative design rules need to be considered [4]. (1) Short: a via or wire segment of a net should not overlap with any object of another net. (2) Spacing: the spacing between two objects should satisfy the minimum distances. There are several different types of such requirements, e.g., end-of-line spacing, parallel-run spacing, and cut spacing. (3) Minimum area: a metal polygon should have an area larger than the minimum threshold. Typical objectives for routing are to minimize the total wirelength and the DRC violations.

B. Sequential Detailed Router

In year 2018 and 2019, the ISPD contest was organized on detailed routing [4], [5]. Dr.CU [17] won the first place in the ISPD 2019 contest and is open source. In this work, we adopt Dr.CU as the target detailed routing framework for studying, while the methodology can work on other routers as well. Fig. 2 illustrates its routing flow, which is a typical procedure for most sequential routing algorithms as well. Given a placed netlist, routing guides, routing tracks, and design rules, it first assigns access points for each pin. Then it starts the rip-up and reroute (RRR) iterations to accomplish the routing. During the RRR iterations, if the router encounters congestion or DRC violations when trying to route a net, it rips up the net and the conflicted nets, leaving them for the next iteration to reroute. With enough iterations, the router can achieve convergence. Finally, it performs a post-routing refinement stage to reduce DRC violations. It needs to be noted that within each RRR iteration, Dr.CU also exploits parallelism between nets far away from each other, such that there will be no interaction when simultaneously solving the routing problem of each net. This does not change the sequential nature of the algorithm, i.e., routing in a net-by-net manner, as it does not determine the routing of different nets at the same time. The solution quality of sequential routers like Dr.CU is highly correlated to the order of nets to be routed. Fig. 1 shows the distribution of solution quality with random net ordering routed by Dr.CU. Although the wirelength does not change much, the order affects both via count and the number of DRC violations. Thus, the ordering strategy needs to be carefully designed for high-quality routing across various benchmarks.

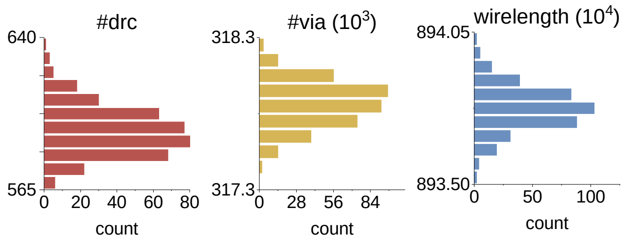


Fig. 1: Distribution of solution quality with random net ordering (300 iterations). The relative standard deviation of the number of DRC violations, the number of vias, and wirelength is 1.95 %, 0.04 %, and 0.008 %. Their ranges are 70.00, 845.00, and 4996.31, respectively.

Dr.CU sorts nets by the routing region sizes (half-perimeter of the bounding box) of each net in descent order. In other words, nets covering large routing regions are routed first. However, we observe that the routing region sizes of different nets can be very similar, leading to random orders between these nets, and eventually causing high variations in the final violations. For example, Fig. 3 shows that 5293 nets have the same routing region size, accounting for 14.4 % of the total number of nets in benchmark `ispd18_test3`. Therefore, there is a potential to improve the routing performance by developing an ordering strategy considering more features, which will be explained in detail in Section III-A and Table I.

C. Reinforcement Learning

Machine Learning (ML) is an effective practical tool to optimize a design in the absence of suitable models for optimization. One of the main obstacles in using supervised ML-based techniques for solving routing problems, especially the net ordering problems, is the lack of golden labeled datasets to learn. One way to overcome this problem is to use a reinforcement learning approach. RL has been successfully applied in many applications. A typical RL problem can be considered as training an agent to interact with an environment. As illustrated

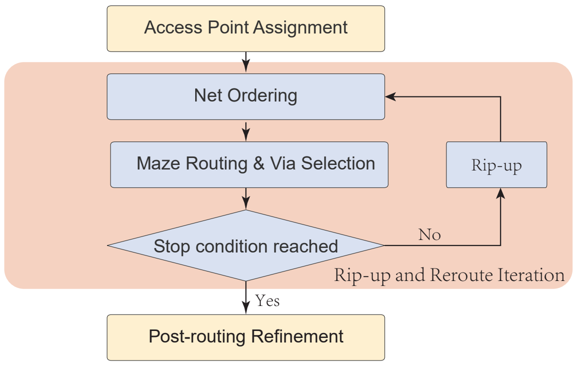


Fig. 2: Routing Flow.

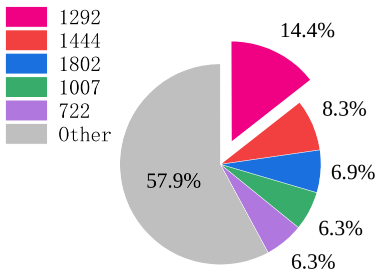


Fig. 3: Distribution of the net routing region sizes in `ispd18_test3`.

in Fig. 4, at each step t, the agent g observes a state $s_t \in \mathcal{S}$, takes an action $a_t \in \mathcal{A}$ based on s_t, receives a reward $r_t \in \mathcal{R}$, and then the state stochastically transits to the next state s_{t+1}. The objective is to learn a policy $\pi(a_t|s_t)$ that maximizes the expected cumulative reward $R = \sum_{i=0}^{\infty} \gamma^i r_{t+i}$, starting from any state s, where scalar $\gamma \in (0, 1]$ is a discount rate.

In this work, we define the environment as the router, and the design to be routed, the agent as a net order planner that ranks the nets based on the features (state). The net ordering result is the action, and the reward is positively related to the solution quality, e.g., total wirelength and DRC violations.

D. Problem Formulation

We define the net ordering problem in detailed routing as follows.

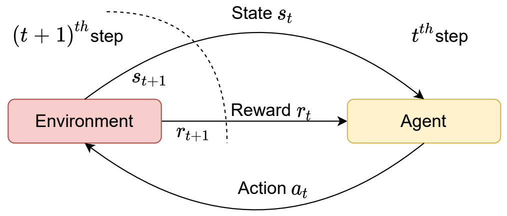


Fig. 4: Environment and agent system of reinforcement learning.

TABLE I: Features of Each Net.

Feature	Dimension	Description
Size	1	The size of the routing region (half-perimeter of bounding box).
Degree	1	Number of nets with conflicts in its routing region.
Count	1	The number of times it has been routed/rerouted.
Cost	1	The weighted sum of violations on it.
Via	1	Number of via on it.
WL	1	Wirelength.
LA	16	Layer assignment.

Problem 1 (Net ordering)**.** *Given a set of nets N, train a net ordering policy that can generate a ranking score s_i for each net $n_i \in N$ used by a sequential detailed router. The following metrics should be optimized simultaneously: (1) the total wirelength of all nets, (2) the number of the total used vias, (3) the number of DRC violations.*

We further define the transfer learning problem to adapt the net ordering policy to a target design.

Problem 2 (Transfer learning)**.** *Given a target design with a set of nets N and a pre-trained policy for net ordering, finetune the net ordering policy with small clipped regions of the target design. The performance metrics, as mentioned earlier, after routing the target design can be optimized.*

III. Reinforcement Learning Framework

In this section, we first define the state space, action space, reward, and the basic RL setup. Then we explain the dedicated RL techniques for our routing problem.

A. Basic RL Setup

We define the state space, action space, and reward as follows:

State space $\mathcal{S}$: A state s is the collective representation of features for all nets. Table I summarizes the seven features for each net. The first feature is the size of its routing region. The second feature is its degree, which denotes the number of nets whose routing region overlaps with it. The third feature is the number of times routed/rerouted so far. The remaining four features are its costs information, including the violations cost, wirelength, number of vias, and metal layers assignment.

Action space $\mathcal{A}$: An action a is a real number vector. Each number is defined as an ordering score of a net.

Reward $\mathcal{R}$: Given the ordering scores (action a), the environment (router) will provide its feedback (i.e. evaluation metrics). The agent receives a reward according to the environment's feedback. The reward r is defined as:

$$r = -c + c_o \tag{1}$$

Where c and c_o are the total cost of all nets achieved by the agent's action a and Dr.CU's default strategy. The total cost c is defined as:

$$c = \sum_{i=1}^{4} w_i x_i \tag{2}$$

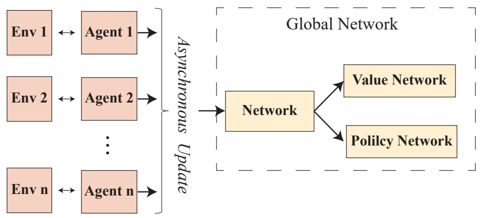


Fig. 5: The A3C Framework with asynchronous parallel agents and global network.

Where $x_i|i \in \{1,2,3,4\}$ are the evaluation metrics used in the ISPD Contests, including short violation, spacing violation, number of vias, and wire length, $w_i|i \in \{1,2,3,4\}$ are the weights of the above metrics. The objective of the agent is to learn a policy to maximize the reward.

B. Asynchronous Advantage Actor-Critic (A3C) Algorithm

Expensive query to the environment is a typical challenge in RL, leading to slow convergence and unaffordable training time. We adopt an A3C method [25] with multiple actor-critic (AC) agents running in parallel. This asynchronous reinforcement learning framework can be defined as follow.

Definition 1. *Given m independent environments (designs), the corresponding m agents are trained in parallel to get a policy π that maximizes the rewards.*

As shown in Fig. 5, each agent of A3C has a local copy of the policy and value networks. It performs actions in its environment to explore the solution space with a different policy. Different agents update the global network asynchronously during the training. A3C maintains a policy $\pi(a_t|s_t;\theta)$ and an estimate of the value function $V(s_t;\theta_v)$, where θ and θ_v are the global shared parameter vector. Algorithm 1 illustrates how each actor is updated. After initialization, each agent takes a copy of the global shared network, with parameters θ' and θ'_v (line 5), and then runs the policy for $t_{\max}$ steps or until a terminal state is reached. Finally, the agent computes the gradients in its process (line 17-18) and then updates the global share network asynchronously.

Algorithm 1 Update each A3C actor [25]

```
Require: Global shared parameter vectors $\theta$, and $\theta_v$
 1: Initialize thread step counter $t \leftarrow 1$
 2: Define thread-specific copy of weights $\theta', \theta'_v$
 3: for $T = 1,..,T_{max}$ do
 4:     $d\theta \leftarrow 0$ and $d\theta_v \leftarrow 0$          ▷ Reset gradients
 5:     $\theta' = \theta$ and $\theta'_v = \theta_v$
 6:     Get state $s_t$
 7:     $t_{start} = t$
 8:     repeat
 9:         Find action $a_t$ according to policy $\pi$
10:         Sort nets according action $a_t$
11:         Receive reward $r_t$ and new state $s_{t+1}$ from router
12:         $t \leftarrow t+1$
13:     until terminal $s_t$ or $t - t_{\text{start}} == t_{\max}$
14:     Return $R = \begin{cases} 0 & \text{for terminal } s_t \\ V(s_t, \theta'_v) & \text{for non-terminal } s_t \end{cases}$
15:     for $i = t-1, ..., t_{start}$ do
16:         $R \leftarrow r_i + \gamma R$
17:         $d\theta \leftarrow d\theta + \nabla_{\theta'} \log \pi(a_i|s_i;\theta')(R - V(s_i;\theta'_v))$
18:         $d\theta_v \leftarrow d\theta_v - \partial(R - V(s_i;\theta'_v))^2 / \partial\theta'_v$
19:     end for
20:     Perform asynchronous update of $\theta$ using $d\theta$ and of $\theta_v$ using $d\theta_v$
21: end for
```

C. Network Architecture

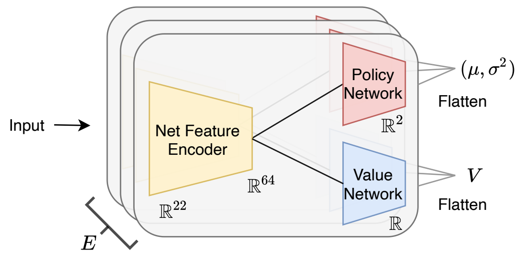
We need two models in the A3C framework, a policy network and a value network. The policy network takes the state s and outputs two arrays (μ, σ^2) that represent a normal distribution $\boldsymbol{p} \sim N(\mu, \sigma^2)$ over the actions. We pick the action by sampling from this normal distribution $\boldsymbol{p}$. We denote $\pi(a|s)$ as the probability of the sampled action a given state s. The value network outputs the value function $V(s)$ (the expected return in rewards for state s and action a), which is used to determine how advantageous it is in a particular state. Intuitively, the policy network tells us the ordering scores of the nets and the value network evaluates the scores in the sense of future rewards.

Fig. 6 plots the network architecture of the two models. We design the models in a special way so that the policy model can be used across different designs with different numbers of nets. To decouple the network architecture from the number of nets in design, we introduce a net-wise feature encoding network that encodes the features of each net independently. We then concatenate the encoded features for the policy and value networks. For example, given a design with E nets, the encoder will encode the $\mathbb{R}^{E\times 22}$ input feature tensor into an $\mathbb{R}^{E\times 64}$ tensor. The policy network takes this tensor and generates an array of ordering scores for all nets, i.e., $\mathbb{R}^{E\times 2}$ (mean and variance of the probability distribution for each net). We then sample from a normal distribution for each net to get its ordering score. In our implementation, μ is modeled by a linear layer and σ^2 by a softplus layer. The value network flattens the feature tensor and feeds into a fully connected layer with $E \times 64$ hidden units to obtain a scalar at the output.

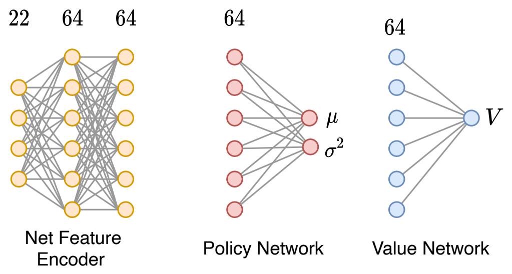
The major benefit of such a network architecture is that the policy network can be shared across different designs, as we essentially perform net-wise modeling with the ordering score of each net dependent on its features only. While it is true that using a more complicated model that correlates the features of multiple nets may help to explore better policy, current architecture still has enough expressive power to verify the main idea of using RL in solving the net ordering problem. We leave the exploration of complicated models in the future. For example, we can determine the ranking score of a net by multiple related nets. This requires the model to be able to learn the correlation of features between multiple nets.

D. Mismatch Penalty

General RL framework initializes the neural networks in a random manner, which may cause slow convergence in our problem, especially when obtaining the reward from the



(a) Architecture of the policy and value networks, where E denotes the number of nets. The net feature encoder encodes the features of each net.



(b) Network Configuration.

Fig. 6: Network structure.

environment (i.e., running the router) is very time-consuming. On the other hand, we do have the prior knowledge to this problem that the default ordering strategy of using routing region sizes in Dr.CU is a generally good policy compared with a random one. Incorporating such knowledge has the potential to speed up training. Hence, Equation (1) is modified to:

$$r = -c + c_o - \frac{\alpha}{k}\sum_{i=1}^{k} \Delta {a_i}^2 \tag{3}$$

Where Δa is the difference between the predicted ordering scores and the sizes of routing regions, α is a user-defined parameter, and k is the number of nets to be routed. The parameter α is positive only at the early training steps and then set to zero. The detailed setup can be found in Section V. Fig. 7 compares the learning speeds of the two reward function defining methods. The results show that the method of adding a mismatch penalty tends to learn faster. As we only apply the mismatch penalty at the early stage of the training, it will speed up the training, but not limit the exploration space to the heuristic ordering strategy used in Dr.CU. In other words, the agent is free to generate different orders from that in Dr.CU.

IV. Transfer Learning Algorithm

In this section, we first introduce the transfer learning algorithm based on policy distillation. In the end, we summarize the overall flow of our TL algorithm.

We assume a reasonably good policy is available. Our task is to mine the knowledge from the pre-trained policy and adapt to a target design to improve the performance.

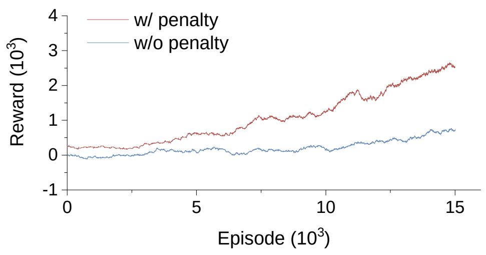


Fig. 7: Comparison of two reward functions. The curves represent the moving average reward of the last 1000 episodes (one episode includes four RRR iterations according to the setting of Dr.CU). We train the agents for 15 000 episodes and the maximum training time is within 24 hours. Mismatch penalty enables faster reward increase.

A. Policy Distillation Algorithm

In the previous section, we aim at training a general RL policy to solve the net ordering tasks of multiple designs, which is essentially a multi-task learning problem. However, it is not always easy to achieve good generality across a wide range of designs. On designs with unique characteristics, a generally good policy may not capture the unique design styles and eventually fails to result in high solution quality. If we can customize the policy for each design with low overhead, there is an opportunity to improve the performance further. To reduce the overhead of customization, we finetune the well-trained policy from the previous section using a small region clipped from the target design instead of training from scratch. In this way, we can minimize the transfer learning overhead by repeatedly routing the target design when the agents interact with the environment. The key for transfer learning is to effectively transfer the knowledge from the source domain (i.e., the pre-trained policy) to the target domain (i.e., for routing the target design).

Policy distillation is a transfer learning approach that distills the knowledge from a teacher network to a student network. Typical RL policy distillation frameworks transfer the teacher policy in a supervised learning paradigm. Specifically, a student policy is learned by minimizing the Kullback-Leibler (KL) divergence of actions between the teacher policy π^S and student policy π^T [26]. As explained in Section III-C, one action a is sampled from the normal distribution $\boldsymbol{p}$ from the policy network, so the policy distillation can be completed by optimizing the per-time-step KL divergence between the distributions of the teacher and the student over actions:

$$L_{KL}(D, \theta^S) = \sum_{t=1} \boldsymbol{p}_t^T \log \frac{\boldsymbol{p}_t^T}{\boldsymbol{p}_t^S}, \tag{4}$$

where $\boldsymbol{p}_t^T$ is the normal distribution from the teacher network at step t, $\boldsymbol{p}_t^S$ is the distribution from the student network of this step, θ^S denotes the parameters of the student policy network, and D is a set of distributions from the teacher network.

B. Policy Transfer Flow

As our network structure in Section III-C is decoupled with the number of nets, different designs' action spaces can

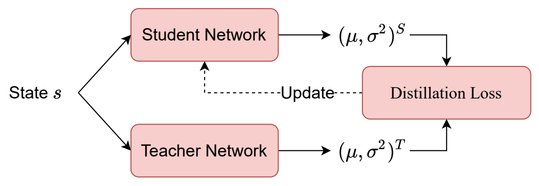


Fig. 8: Distillation procedure.

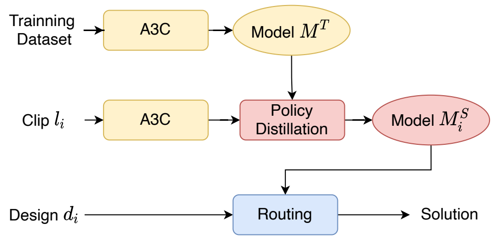


Fig. 9: Overall flow.

be considered as the same dimensions. Hence, the student network can directly mimic the action pattern of the teacher network.

Based on the above observation, we propose a policy distillation flow to transfer knowledge between designs. As illustrated in Fig. 8, the distribution $\boldsymbol{p}$ of the teacher network from a source design (environment) E^T is used as our supervision to update the student network of target design (environment) E^S. This procedure is performed by minimizing Equation (4) over student policy network parameters θ^S for E^S, θ^S including the net feature encoder, value layer, and policy layer. The input to both the teacher and the student networks is the state s of environment E^S. It means that we want to transfer the expertise from the environment E^T towards the current state. Symbol D is a set of distributions from the teacher network in one batch.

Suppose we have already had a reasonably good policy for most designs. We want to use the knowledge from the policy to improve the performance of a particular design further. In the proposed transfer learning approach, we first select a clip from the target design because training on a complete design is not affordable, mainly when the design contains tens of thousands of nets. Given a representative clip, we observe that training can significantly reduce the training time without much performance loss. Then, we train the student network by interacting with the clip (environment) E^S for a certain amount of steps, e.g., 1000 steps in the experiments. Afterward, we start performing policy distillation.

C. Overall Flow

Fig. 9 shows the overall flow. The A3C algorithm is first used to train on multiple designs to obtain the pre-trained model M^T. For each input design d_i to be routed, we select a clip l_i from it. The policy distillation is performed to guide the model M_i^S, which is trained on the clip l_i. After a certain period of training, the best model for clip l_i is selected. Finally, the input design d_i is routed under the guidance of model M_i^S.

The overall routing flow is summarized in Algorithm 2, given that the RL model M_i^S to determine the net ordering. We first extract features for each net to be routed within each routing iteration and then obtain the ordering scores using the RL policy (line 9). After that, we leverage Dr.CU to finish each RRR iteration (line 10-19). More specifically, we schedule all batches at the beginning of an RRR iteration (line 10) by sorting the nets according to the scores and dividing them into batches. Nets within a batch that do not conflict with each other can be routed parallel to reduce the runtime [16]. If the

Algorithm 2 Overall routing flow using RL model

```
Require: A set of nets $N$ in design $t_i$, RL model $M_i^S$, and
    various design rules for a router
Ensure: Routing solution with optimized solution quality
 1: Define $M$ as the maximum number of iterations of RRR.
 2: Define $S$ as the set of nets' ordering scores.
 3: $i \leftarrow 0$
 4: while $i < M, N \neq \emptyset$ do
 5:     $i \leftarrow i + 1$
 6:     for all net $n \in N$ do
 7:         Extract net features $f_n$
 8:     end for
 9:     Use the RL policy $\pi$ and features $F$ to get the ordering
    scores of all nets $S$
10:     batch list $B = \textbf{Scheduler}(N, S)$
11:     for all $b \in B$ do
12:         Run maze routing, via selection and post-routing
    in multiple threads
13:     end for
14:     Calculate the total cost
15:     for all $n \in N$ do
16:         if $n$ meet constraints then
17:             Pop $n$ from $N$
18:         else
19:             Rip-up $n$
20:         end if
21:     end for
22: end while
```

RRR stopping criteria are not met, the iterations will continue until the maximum number of iterations is reached. We keep the same settings as Dr.CU except for the net ordering.

V. Experimental Results

A. Experimental Setup

We define our environment using the OpenAI Gym interface with Dr.CU 2.0 [17] as the detailed router, and implement our RL agent network in PyTorch. All the experiments ran on a 64-bit Linux machine with two 20-core Intel Xeon@2.1 GHz CPUs and 64 GB RAM.

The latest design benchmarks available to academics are the ISPD 2018 and ISPD 2019 Initial Detailed Routing Contests [4], [5] benchmarks, which have 20 designs. We experiment on those benchmarks. The detailed information of the benchmarks

Algorithm 3 Clip Selection

```
1: Define $H_C$ and $W_C$ as the initial width and height of a clip $C$, and $N_C$ as the step size.
2: while the number of nets in clip $C$ is smaller than 500 do
3:     Divide the benchmarks into clips with sizes of $H_C \times W_C$
4:     Choose the clip with the highest pin density as the candidate clip $C$
5:     Project pins outside the clip $C$ to the boundary
6:     $W_C \leftarrow W_C + N_C$
7:     $H_C \leftarrow H_C + N_C$
8: end while
9: Add the clip $C$ into the training dataset
```

is shown in Table II. We can see that benchmarks have quite different problem sizes, and technology nodes (32/45/65 nm).

As the benchmarks are large, we select clips with suitable scales and add them to the training dataset. The procedure of clip selection is described in Algorithm 3. The idea is to select a dense clip including around 500 nets because we observe this is an affordable scale to invoke the router during training repeatedly. We first divide a benchmark into fixed-size clips (line 3) and then choose the densest one in terms of pins (line 4). We then project the pins outside the clip to its boundary (line 5). If the number of nets in the clip exceeds 500, we add it to the training dataset. Otherwise, we expand the clip to include more nets and repeat the above steps.

B. Asynchronous Advantage Actor-Critic

In this subsection, we verify the effectiveness of the A3C framework. We set the discount factor $\gamma = 0.99$, the coefficient for the value loss $\beta = 0.25$, entropy cost $\eta = 0.001$, and learning rate to 0.001. We also set $\alpha = 0.1$ for the first 100 training episodes and reduce to 0 afterward. A standard non-centered RMSProp is used as the gradient ascent optimizer. The neural network weights are initialized randomly. We use eight AC agents to train in parallel, and the maximum training time is set to 24 hours (around 8000 episodes).

According to Dr.CU [17], the runtime of routing one of these benchmarks varies from two minutes to five hours. Ideally, it is expected to train and test a RL model on one technology node only. However, considering that most designs in Table II are in the 32 nm node, while the ones in 45/65 nm nodes are either too small or large, we choose a training dataset mixed with designs in 32 nm and 45 nm nodes, and test on the remaining to validate the framework. To balance the runtime overhead and universality of the generated model, `ISPD18_test3/5/6/7` are selected as benchmarks in the training dataset and the remaining sixteen as the test dataset. Due to `ISPD18_test7`'s large size, we choose two clips from it containing 7 and 26 violations to put in the training dataset. In conclusion, the training dataset contains {two regions clipped from `ISPD18_test7`, `ISPD18_test3/5/6`}. These training benchmarks have moderate and diverse sizes that can keep reasonable training time but also complicated enough to represent the real routing challenges.

TABLE II: Characteristics of ISPD 2018 & 2019 Contest Benchmarks.

	benchmarks	#std	#net	Die size (mm^2)	Tech. node (nm)
ISPD18	test1	8879	3153	0.20×0.19	45
	test2	35 913	36 834	0.65×0.57	45
	test3	35 973	36 700	0.99×0.70	45
	test4	72 094	72 401	0.89×0.61	32
	test5	71 954	72 394	0.93×0.92	32
	test6	107 919	107 701	0.86×0.53	32
	test7	179 865	179 863	1.36×1.33	32
	test8	191 987	179 863	1.36×1.33	32
	test9	192 911	178 857	0.91×0.78	32
	test10	290 386	182 000	0.91×0.87	32
ISPD19	test1	8879	3153	0.148×0.146	32
	test2	72 094	72 410	0.873×0.589	32
	test3	8283	8953	0.195×0.195	32
	test4	146 442	151 612	1.604×1.554	65
	test5	28 920	29 416	0.906×0.906	65
	test6	179 881	179 863	1.358×1.325	32
	test7	359 746	358 720	1.581×1.517	32
	test8	539 611	537 577	1.803×1.708	32
	test9	899 341	895 253	2.006×2.151	32
	test10	899 404	895 253	2.006×2.151	32

Table III and Table IV summarize the results of the training and testing datasets. We compare the wirelength, number of vias, DRC violations, total cost, and runtime between our RL framework and Dr.CU [17]. The violation values here are a summation of all the DRC violations mentioned in Equation (1). In the training dataset, with similar wirelength and number of vias, we can achieve 13% fewer DRC violations compared with the default policy in Dr.CU. The total cost only has small improvements. This is because the cost is dominated by wirelength due to its large scale according to its definition in the contests. The results on the training dataset indicate that our RL framework and training techniques are able to learn good policies from the benchmarks. We also observe around 6 % runtime overhead, which mostly comes from the feature extraction and the system integration between the `Python`-based RL agent and the `C++`-based Dr.CU implementation. In the testing dataset, our policy can achieve an average of 14 % improvement in violations and 0.7 % in total cost without degradation in wirelength and number of vias. The results on the testing dataset demonstrate that the policy learnt from the training dataset can generalize to unseen benchmarks and achieve high-quality solutions on average.

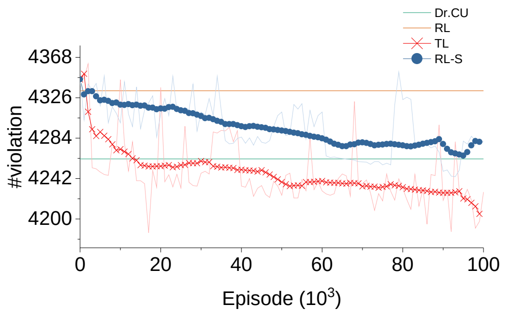
One needs to mentioned that on large benchmarks like `ISPD19_test7-10` in 32 nm technology node, the RL policy can reduce the violations by 40 % to 50 %, which is rather promising. However, we observe that there are also outliers like `ISPD18_test4` and `ISPD19_test4` where the violations increase by 15 % and 46 %, respectively. The results of all the remaining benchmarks are either improved or within a comparable range. We speculate that the two outliers contain special features not in our training dataset or state space, causing unusual behaviors. `ISPD19_test4` is in 65 nm technology node with 6 metal layers, while the designs in the training dataset are in 45/32 nm technology nodes with 9 metal layers. These differences probably reduce the generalization performance of the RL policy in these two designs. At this point, we have obtained a model that can perform well in most design, and further improvement will be completed in transfer learning.

C. Transfer Learning via Policy Distillation

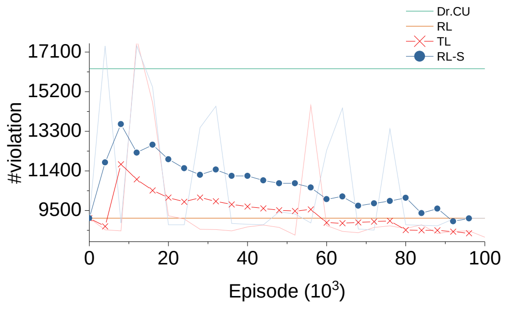
In this subsection, we design experiments to illustrate the effectiveness of the policy distillation algorithm. We obtained a generally good model in previous experiments, but there are some outliers like `ISPD18_test4` and `ISPD19_test4`. This result indicates that the knowledge gained in the training dataset has insufficient generalization capabilities. Therefore, we transfer the knowledge from the pre-trained policy to the student network for each design via policy distillation. One challenge is that the routing of each design is time-consuming in the testing dataset. As we mentioned before, for each design d_i to be tested, we select a clip l_i from it for interaction. The clip l_i must have sufficient representation. We select a clip containing about 500 nets from the region with the highest pin density such that the routing can be finished within 1 minute by Dr.CU. Pin density is a straightforward metric for clip selection. We leave the exploration of more complicated clipping strategies to the future. In the following experiments, we maintain consistent hyper-parameters of the network structures across all designs.

The student agents are trained with the clip l_i only and perform policy distillation after 1000 episodes. We set the maximum time for the entire training to three hours (assume the maximum time available for transfer learning, equivalently around 3000 episodes). Finally, the model is evaluated with the design d_i. Table IV shows the comparison of wirelength, number of vias, number of DRC violations, and total costs between Dr.CU, the RL algorithm [27], and the transfer learning algorithm. By enabling transfer learning, we can further reduce the average number of DRC violations by 12% and the average total cost by 0.5% compared with the RL algorithm, while other metrics remain almost the same as the RL algorithm. Note that these numbers are an extra improvement from the RL algorithm. Compared with Dr.CU, the TL algorithm can contribute to 26% reduction of DRC violations and 1.2% reduction of total cost.

To further verify the performance of the model with additional training iterations, we also train the model for 100 K episodes on `ISPD19_test2` and `ISPD19_test8`, and show the training curves in Fig. 10. As routing an entire design to obtain the number of DRC violations is time-consuming, we only sample every 1000 and 4000 episodes for these designs, respectively. We can see that the performance of the TL curves continues to improve and gradually saturates at 60 K to 100 K episodes. We also plot the curves of training from scratch using the RL algorithm as 'RL-S' in the figure. Compared with the RL-S curve, the TL curve drops much faster, indicating the effectiveness of the proposed transfer learning technique compared with training from scratch. We also observe that the #violation of the average TL and RL-S curves can go much higher than that of the RL curve between 0 to 20 K episodes. This is because the performance oscillates greatly at the beginning of the training iterations, several extremely poor points cause large average number of violations. With the training continuing, the performance gradually converges and becomes more stable.



(a) `ISPD19_test2`



(b) `ISPD19_test8`

Fig. 10: The performance with additional training iterations on `ISPD19_test2` and `ISPD19_test8`. The raw TL/RL-S results are shown in light red/blue, and the average TL/RL-S results are shown in the blue/green by taking an average of 25 data points around each point.

In the previous section, we observe that the numbers of DRC violations for `ISPD18_test2/4/10` and `ISPD19_test2/4/5/6` are larger than Dr.CU's results. With our transfer learning technique, `ISPD18_test4` and `ISPD19_test2` can outperfrom Dr.CU, while the results for `ISPD18_test2/10` and `ISPD19_test4/5/6` are still not as good as Dr.CU, especially that the results of `ISPD18_test10` and `ISPD19_test4/5/6` are far from expected. One possible reason lies in insufficient training, and the teacher network guides the student networks in the wrong direction. To verify that, we continue the training iterations of transfer learning on these designs and report the numbers of DRC violations with the intermediate policies, as shown in Fig. 11. Each model is trained for 100 K to 140 K episodes (around 100 hours to 140 hours). Similar to that in Fig. 10, we only sample every 500, 1000, and 2000 episodes for each of the four designs mentioned above according to their sizes, respectively. We compare the transfer learning curves with the results of Dr.CU and the RL algorithm as well as the results of training from scratch ('RL-S'). Fig. 11 shows that in the first 3000 episodes (about three hours), the model's performance improves slowly. When the training continues, the performance of the models keeps improving, even though

TABLE III: Experimental Results on the Training Dataset (Comparison between Dr.CU [17] and RL [27]).

Absolute Values

		Wirelength (10^7)		#via (10^6)		#vio		Cost (10^7)		T (s)	
	Design	Dr.CU	RL	Dr.CU	RL	Dr.CU	RL	Dr.CU	RL	Dr.CU	RL
ISPD18	test3	0.894	0.894	0.318	0.318	361	342	0.529	0.528	172	189
	test5	2.870	2.870	0.966	0.965	393	388	1.648	1.648	610	638
	test6	3.700	3.701	1.481	1.481	95	63	2.151	2.150	756	793
	test7	6.727	6.728	2.403	2.403	792	735	3.884	3.881	1466	1576

Relative Ratios

		Wirelength		#via		#vio		Cost		T	
	Design	Dr.CU	RL	Dr.CU	RL	Dr.CU	RL	Dr.CU	RL	Dr.CU	RL
ISPD18	test3	1.000	1.000	1.000	1.000	1.000	0.947	1.000	0.998	1.000	1.099
	test5	1.000	1.000	1.000	0.999	1.000	0.987	1.000	1.000	1.000	1.046
	test6	1.000	1.000	1.000	1.000	1.000	0.663	1.000	1.000	1.000	1.049
	test7	1.000	1.000	1.000	1.000	1.000	0.928	1.000	0.999	1.000	1.075
	Min.	1.000	1.000	1.000	0.999	1.000	0.663	1.000	0.998	1.000	1.046
	Max.	1.000	1.000	1.000	1.000	1.000	0.987	1.000	1.000	1.000	1.099
	Geo. Mean	1.000	1.000	1.000	1.000	1.000	0.870	1.000	0.999	1.000	1.067

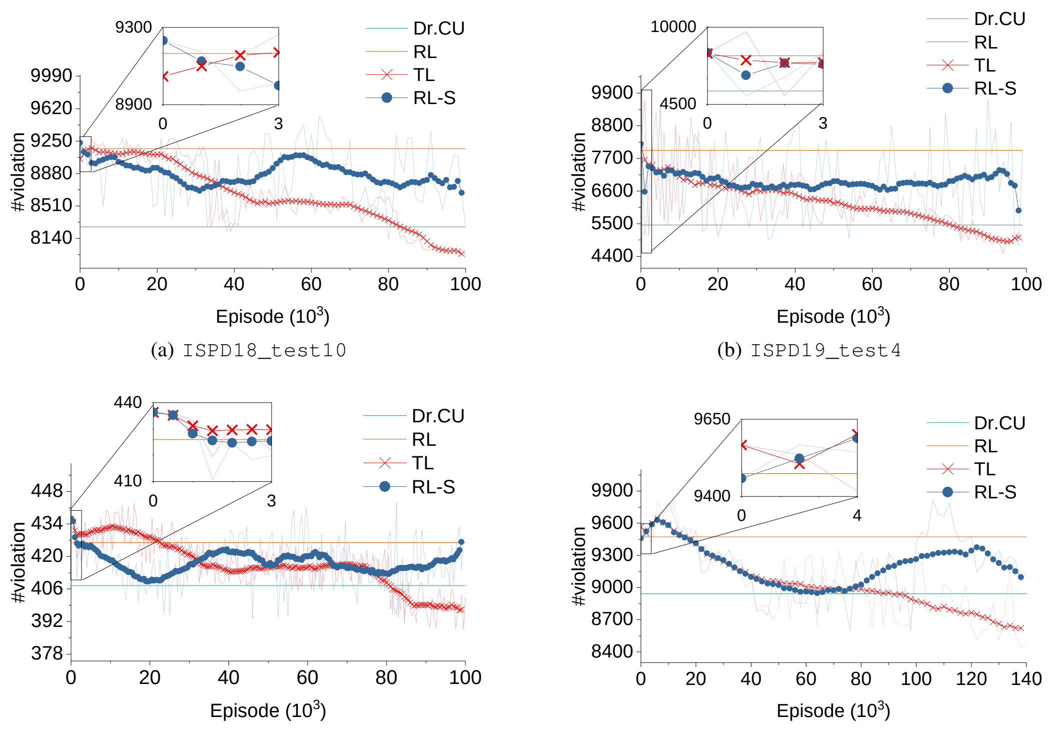
TABLE IV: Experimental Results on the Testing Dataset (Comparison between Dr.CU [17], RL [27], and TL).

Absolute Values

		Wirelength (10^7)			#via (10^6)			#vio			Cost (10^7)			T (s)		
	Design	Dr.CU	RL	TL	Dr.CU	RL	TL	Dr.CU	RL	TL	Dr.CU	RL	TL	Dr.CU	RL	TL
ISPD18	test1	0.05	0.05	0.05	0.03	0.03	0.03	1	0	0	0.03	0.03	0.03	9	10	10
	test2	0.81	0.81	0.81	0.33	0.33	0.33	1	4	4	0.47	0.47	0.47	125	136	137
	test4	2.70	2.70	2.70	0.73	0.73	0.73	507	584	487	1.52	1.52	1.52	696	745	727
	test8	6.76	6.76	6.76	2.41	2.41	2.41	819	756	753	3.90	3.90	3.90	1474	1541	1548
	test9	5.69	5.69	5.69	2.41	2.41	2.41	139	54	9	3.33	3.33	3.33	1196	1260	1240
	test10	7.04	7.04	7.04	2.59	2.59	2.60	8271	9165	8915	4.45	4.50	4.49	2244	2373	2315
ISPD19	test1	0.07	0.07	0.07	0.04	0.04	0.04	1121	1110	1045	0.10	0.10	0.09	102	109	106
	test2	2.56	2.56	2.56	0.79	0.79	0.79	4262	4333	4253	1.65	1.66	1.65	1499	1610	1625
	test3	0.09	0.09	0.09	0.06	0.07	0.07	167	96	77	0.07	0.06	0.06	52	54	54
	test4	3.13	3.13	3.13	1.03	1.03	1.03	5455	7968	7949	2.04	2.17	2.17	1548	1653	1665
	test5	0.49	0.49	0.49	0.15	0.15	0.15	408	426	436	0.30	0.30	0.30	154	163	165
	test6	6.78	6.78	6.78	1.99	1.99	1.98	8944	9474	9363	4.23	4.26	4.25	3158	3340	3374
	test7	12.72	12.72	12.71	4.81	4.81	4.80	11649	7798	7577	7.90	7.71	7.69	7812	8338	8379
	test8	19.56	19.56	19.55	7.33	7.33	7.32	16291	9128	8676	12.06	11.70	11.67	11089	11870	11855
	test9	29.73	29.73	29.72	12.19	12.20	12.17	34632	16745	16015	19.03	18.14	18.10	15225	15967	15681
	test10	29.46	29.45	29.45	12.48	12.49	12.49	32743	18150	17522	18.86	18.13	18.10	16156	17108	17335

Relative Ratios

		Wirelength			#via			#vio			Cost			T		
	Design	Dr.CU	RL	TL	Dr.CU	RL	TL	Dr.CU	RL	TL	Dr.CU	RL	TL	Dr.CU	RL	TL
ISPD18	test1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.000	0.000	1.000	1.000	1.000	1.000	1.111	1.111
	test2	1.000	1.000	1.000	1.000	1.000	1.000	1.000	4.000	4.000	1.000	1.000	1.000	1.000	1.088	1.096
	test4	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.152	0.961	1.000	1.000	1.000	1.000	1.070	1.045
	test8	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.923	0.919	1.000	1.000	1.000	1.000	1.045	1.050
	test9	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.388	0.065	1.000	1.000	1.000	1.000	1.054	1.037
	test10	1.000	1.000	1.000	1.000	1.000	1.004	1.000	1.108	1.078	1.000	1.011	1.009	1.000	1.057	1.032
ISPD19	test1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.990	0.932	1.000	1.000	0.900	1.000	1.069	1.039
	test2	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.017	0.998	1.000	1.006	1.000	1.000	1.074	1.084
	test3	1.000	1.000	1.000	1.000	1.167	1.167	1.000	0.575	0.461	1.000	0.857	0.857	1.000	1.038	1.038
	test4	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.461	1.457	1.000	1.064	1.064	1.000	1.068	1.076
	test5	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.044	1.069	1.000	1.000	1.000	1.000	1.058	1.071
	test6	1.000	1.000	1.000	1.000	1.000	0.995	1.000	1.059	1.047	1.000	1.007	1.005	1.000	1.058	1.068
	test7	1.000	1.000	0.999	1.000	1.000	0.998	1.000	0.669	0.650	1.000	0.976	0.973	1.000	1.067	1.073
	test8	1.000	1.000	0.999	1.000	1.000	0.999	1.000	0.560	0.533	1.000	0.970	0.968	1.000	1.070	1.069
	test9	1.000	1.000	1.000	1.000	1.001	0.998	1.000	0.484	0.462	1.000	0.953	0.951	1.000	1.049	1.030
	test10	1.000	1.000	1.000	1.000	1.001	1.001	1.000	0.554	0.535	1.000	0.961	0.960	1.000	1.059	1.073
	Min.	1.000	1.000	0.999	1.000	1.000	0.995	1.000	0.000	0.000	1.000	0.857	0.857	1.000	1.038	1.030
	Max.	1.000	1.000	1.000	1.000	1.167	1.167	1.000	4.000	4.000	1.000	1.064	1.064	1.000	1.111	1.111
	Geo. Mean	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.856	0.734	1.000	0.993	0.988	1.000	1.065	1.062



(a) `ISPD18_test10` (b) `ISPD19_test4`

(c) `ISPD19_test5` (d) `ISPD19_test6`

Fig. 11: The performance of policy distillation with additional training iterations on outlier designs, where 'RL-S' represents the training results from scratch. The raw TL/RL-S results are shown in light red/blue, and the average TL/RL-S results are shown in the blue/green by taking an average of 25 data points around each point. We also zoom on the first ∼3000 episodes to show the results at the beginning of the additional training iterations.

with some turbulence. At around 80 K to 100 K episodes, the performance of the TL algorithm approaches Dr.CU and eventually outperforms the latter with extra iterations. The best results in Fig. 11 can achieve approximately 4%, 17%, 6%, and 6% fewer DRC violations compared to Dr.CU, respectively. This experiment explains the reasons for the outliers in Table IV, and they can be resolved by continuing the policy distillation training until convergence. We also observe that the transfer learning technique eventually leads to better convergence than training from scratch on these designs.

VI. Conclusion

In this paper, we propose an asynchronous reinforcement learning framework to search for high-quality net ordering strategies in detailed routing automatically. We propose highly extensible agent models and mismatch penalty to enable efficient exploration of good policies. Experiments on ISPD 2018 & 2019 contest benchmarks demonstrate that our framework is able to learn an ordering policy that reduces the number of violations by 14 % on unseen benchmarks, compared with the state-of-the-art detailed router. We also propose a transfer learning algorithm to further improve the agent models' performance based on policy distillation. The models after transfer learning can reduce the number of violations by 26 % on the testing designs. This study can enlighten techniques to automatically search for better routing solutions during design space exploration with extra computing resources or explore effective heuristics for routing.

The future work includes improving the agent network architecture to consider the correlation between multiple nets and expanding the state space to consider more features. We also plan to explore techniques [28] to handle the staleness between global and local agents in the asynchronous reinforcement learning framework.

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