Generating sub-optimal synthesis transformation sequences ("synthesis recipe") is an important problem in logic synthesis. Manually crafted synthesis recipes have poor quality. State-of-the-art machine learning (ML) works to generate synthesis recipes do not scale to large netlists as the models need to be trained from scratch, for which training data is collected using time consuming synthesis runs. We propose a new approach, Bulls-Eye, that fine-tunes a pre-trained model on past synthesis data to accurately predict the quality of a synthesis recipe for an unseen netlist. This approach on achieves 2x-10x run-time improvement and better quality-of-result (QoR) than state-of-the-art machine learning approaches.

Index Terms—Logic synthesis, Deep Learning, Graph Neural Networks

I. INTRODUCTION

There is a growing academic and industry interest in using machine learning (ML) techniques in design automation problems. Several problems in electronic design automation (EDA), such as logic synthesis, placement and routing, and VLSI testing are combinatorial optimization problems that require sequential decision-making to achieve the target objective. Logic synthesis, the first step in an EDA flow, applies a sequence of synthesis transformations (i.e., a "synthesis recipe") to an and-inverter-graph (AIG) representation of a Boolean function to minimize its size or depth. For instance, the transformation heuristics in ABC, a leading academic synthesis tool, include steps like balance, refactor, rewrite, etc. In this work, we focus on ML-guided search for "good" logic synthesis recipes; a problem that has received much recent attention.

Traditionally, EDA engineers choose from a set of handcrafted synthesis recipes, for instance, resyn2 or compress2rs based on intuition and experience. Yet, the space of all synthesis recipes is vast; recent work has shown ML-guided exploration of this vast solution space can yield synthesis recipes that are tailored for each design and outperform handcrafted recipes in terms of quality-of-result (QoR). In these papers, finding a good synthesis recipe is formulated as a classification problem—which seeks to distinguish good "angel" recipes from bad "devil" recipes—or as a Markov decision process (MDP) that is solved using reinforcement learning (RL). However, the prior work is deficient on two fronts: (1) scalability to large designs; and (2) generalizability to previously unseen netlists. Typically, models are trained from scratch, requiring significant training time and a large number of synthesis runs for large unseen designs; and leaving prior experience untapped. For this reason, in [12], “benchmarks were excluded from the experimentation which showed significant training times, being large circuits”.

The underlying issue is that ML methods rely on high-quality labeled data (or reward signals for RL)—in logic synthesis, the input features are AIGs and synthesis recipes, and the resulting QoRs are labels/rewards. For each new design, prior work obtains labels/rewards (i.e., QoRs) by synthesizing the design using a large number of synthesis recipes; however, this is prohibitively time-consuming for large designs. An alternative is to use fewer synthesis runs, or even a model trained on previously seen designs, but this results in lower quality synthesis recipes.

In this paper, we propose a new logic ML-guided synthesis solution that addresses these limitations and scales to large designs on which existing state-of-the-art (SOTA) solutions fail or time-out. Bulls-Eye has two key ideas: (1) few-shot learning: fine-tuning a base model trained on previously seen designs using only a few training samples from the new design; and (2) active learning: fine-tuning can be further improved by intelligently picking the synthesis recipes for which we obtain QoRs/labels a limited synthesis run budget. We illustrate these ideas using Bulls-Eye, a framework that uses a graph convolutional network (GCN) as a QoR predictor, and simulated annealing (SA) to search the design space. The core ideas proposed are general and apply to other ML-guided synthesis frameworks also. To summarize, our key contributions are:

- **Bulls-Eye**: an active few-shot learning approach that transfers knowledge from a base model trained on past data to train a new model that predicts the QoR of a synthesis run for an unseen netlist; and uses simulated annealing to find an optimized synthesis recipe for the new netlist.

- **Scalability to large benchmarks**: Bulls-Eye’s base model can be learned on small designs for which training data is easy to generate; and transferred using only a few, smartly selected synthesis runs (i.e., "shots") to large, unseen netlists. Bulls-Eye produces high-quality synthesis recipes for benchmarks on which SOTA methods fail or time-out.

- Bulls-Eye achieves better QoR with 2x-10x run-time speed-up and more than 7x speed-up on large benchmarks.
TABLE I: Work on ML-based synthesis recipe generation

| Prior work | Input Features | ML techniques | Max. nodes considered | Model transferability |
|------------|----------------|---------------|-----------------------|-----------------------|
| 9          | MIG            | GCN, RL       | ≤2000                 | ×                     |
| 7          | Flow encoding  | CNN           | 44045                 | ×                     |
| 6          | AIG encoding   | RL            | 176938                | †                     |
| 10         | AIG+state encoding | GCN, RL | 30003                 | ×                     |
| 8          | AIG+state encoding | GCN, RL | 2675                  | ×                     |
| 5          | AIG+state encoding | GCN, CNN | 32060                 | ×                     |
| Bulls-Eye  | AIG+recipe encoding | GCN,CNN | 114771                | ✓                     |

† DRILLS claims the model can be reused, without empirical evaluation

compared to conventional approaches. Compared to prior SOTA, Bulls-Eye achieves better QoR with an average 1.04x (vs. [8]) and 11.21x (vs. [7]) run-time speedup.

II. PRELIMINARIES AND RELATED WORK

A. Logic Synthesis

Logic synthesis transforms a hardware design in a high-level abstraction (e.g., register-transfer level) to a gate-level netlist, ultimately mapping to a user-specified technology library. Typically, logic synthesis tries to minimize the circuit level area and meet a specific delay constraint. Logic synthesis is performed in a series of steps: (1) the design is converted to a generic netlist-level representation (e.g., AIG), (2) the netlist undergoes heuristics-based optimization to implement the same functionality using fewer gates and/or reduced depth which correlates to a reduction in the final area and delay of design [2], (3) technology mapping of the generic netlist using standard cells, and (4) post-mapping optimizations. Consistent with prior works, we focus on the pre-technology mapping optimization of generic gate-level netlists.

ABC [4] is the current state-of-the-art framework for optimizing AIG-based netlists. AIGs are directed acyclic graphs (DAGs) and ABC’s synthesis transformation heuristics perform local sub-graph-level optimization to reduce the AIG structure. ABC’s well-known transformations are refactor, rewrite, re-substitute (these reduce the nodes), and balance (for depth-reduction). For M unique synthesis transformations, \( \{ T_1, T_2, \ldots, T_M \} \) in a synthesis recipe \( S \), the possible number of synthesis recipes of length \( L \) is \( M^L \) (with repeatable transformation). This indicates that the search space of possible synthesis recipes is huge. The problem of optimal synthesis recipe generation for a given AIG is:

\[
\text{argmin}_S \text{QoR}(G(AIG, S))
\]

where \( G \) is the synthesis function defined as \( G : AIG \times S \rightarrow AIG \) and QoR is a function that evaluates the quality of the synthesis (i.e., lower number of nodes/depth of AIG is better).

B. Prior work

We summarize prior work on ML for logic synthesis in Table I. Recent enhancements in logic synthesis have built on recent successes of supervised learning and RL approaches for solving sequential decision making problems [1], [11] in an attempt to find good synthesis recipes in the vast space of possible recipes. In [6–9], authors generate optimal synthesis by formulating the problem as an MDP and training a policy gradient agent over a collection of synthesis runs on a set of benchmarks. During inference, the trained agent (in exploit phase) predict the best synthesis recipe for a given AIG. Authors in [6, 9] use handcrafted features from AIGs (i.e. number of AND and NOT gates, depth, number of primary inputs and outputs) to represent AIG state. Zhu et al. use handcrafted features with GCN embedding of AIG to represent current AIG state [7]. These works show results that improve upon handcrafted recipes like resyn2. In an alternate approach, Yu et al. classify an unseen synthesis recipe as good (“angel”) or bad (“devil”) by training a model on the results corresponding to a set of recipes for a design [5]. However, the trained model is design specific; a model trained on one design cannot be reused for another.

III. PITFALLS OF EXISTING APPROACHES

Black-box optimization techniques (e.g., simulated annealing or RL methods in prior work) need feedback in terms of the cost (or reward) of actions; in the logic synthesis context, the action is a synthesis recipe \( S \) and the cost/reward is \( G(AIG, S) \), obtained by synthesizing AIG using \( S \). Typically a large number of cost/reward evaluations, or equivalently, synthesis runs, are required to obtain good solutions. The biggest challenge here is that even a single synthesis run for modern complex system-on-chip (SoC) designs can require several hours or days, which limits the number of synthesis runs that can be performed in a limited time budget, and consequently, the amount of training data that can be collected and the fraction of design space that can explored. A black-box optimizer can cover in a limited time. Hence, although RL-based approaches have shown promise in generating good quality synthesis recipes, they cannot scale up to industrial-sized benchmarks [7, 8]. These observations indicate the following key questions computationally-efficient ML-enhanced logic synthesis:

- How can we predict the best synthesis recipe for a new, unseen netlist using only a limited or budgeted number of synthesis runs of that netlist?
- Given a budget, which synthesis recipes should be selected to train an accurate model for the new netlist?
- How can we efficiently leverage past information, specifically, synthesis runs on previously seen netlists to improve solution quality?

We next present Bulls-Eye, that solves the key roadblocks towards computationally efficient ML-guided logic synthesis.

IV. THE BULLSEYE FRAMEWORK

To reduce the cost of running actual synthesis during black-box optimization, Bulls-Eye trains a QoR predictor, \( \hat{\Phi}(AIG, S, \theta) \), which predicts the QoR for a given AIG synthesized using an L-length synthesis recipe \( S \). We now seek to solve the following problem:

\[
\text{argmin}_S \hat{\Phi}(AIG, S, \theta)
\]

\( \hat{\Phi} \approx \text{QoR}(G(AIG, S)) \)
where $\theta$ represents the QoR predictor’s model parameters, and $\epsilon$ represents model noise that we also seek to minimize.

A. Insights from ML domain

Unlike ML application in computer vision, the diversity of circuit characterization in terms of size, complexity, functionalities is not well studied and understood. We borrow two important insights from core ML community to solve our problem of learning proxy model with limited data.

**Insight 1**: In computer vision, various deep learning networks learn robust embeddings and are pre-trained on large dataset like Imagenet [12]. The pre-trained models are fine-tuned later for specific applications.

This helps us adopt a similar strategy and study its applicability in EDA. Large circuit designs have smaller known IP designs as building blocks; therefore pre-training a model using labelled data on small sized IP designs followed by fine-tuning can help predict important parameters of downstream tasks. Thus, a one-time training with labelled data on small IP designs (varied functionality) can be a qualitative QoR predictor.

**Insight 2**: Few-shot learning [13] learns a hypothesis function with limited labeled data of target task; however abundant labeled data is available for different tasks. Effectively, it uses transfer learning approach for classification/regression task using limited labeled data of target task.

This insight guide us in our problem context for solving the problem of data scarcity, knowledge transfer and picking best-possible synthesis scripts (few-shots) to generate the labelled data. We solve this problem in three steps, illustrated in Figure 2. First we train a zero-shot QoR predictor using prior synthesis data; as we show, it is sufficient to use small benchmarks to train this zero-shot model. Next we fine-tune the zero-shot model using a small number of smartly selected synthesis runs of the AIG being optimized; and we deploy the fine-tuned QoR predictor within a black-box SA optimizer.

B. Zero-Shot QoR predictor (Fig. 1)

We assume that a design house has access to data from previously synthesized designs or can quickly generate data by running synthesis on small designs. We also developed OpenABC-D [14]), an open-source automated synthesis data generation framework used to generate data and train our Zero-shot predictor.

In this work, we adopt a GCN-based architecture for the predictor (Figure 1). GCNs have been used in RL-based approaches as well [7], [9], but with different architectures. Our predictor architecture is shown in Figure 1 and contains two parallel paths. The first path takes an AIG as input and create an AIG embedding of the network; the second path extract features from synthesis recipe and outputs a “synthesis recipe embedding”. We now describe the “AIG embedding” network and recipe embedding network:

1) AIG embedding: We leverage GCN to represent the original AIG graph. GCN can learn and extract key features from DAG structures; particularly subgraph structures that can be optimized via various synthesis transformations. GCNs make our model generalize over different AIGs structures. For AIG embedding, we consider two features for each node: type and # inverter in fan-in. The type of node can be primary input (PI), primary output (PO) or internal node. As shown in Figure 1, we encode nodetype and pass it via a linear layer. The initial node level features pass through two consecutive GCN layers aggregating local neighbourhood information based on connectivity. We use batch-norm followed by ReLU operation after each GCN layer. The graph level embedding is a readout like global pool operation on all node embeddings. We choose concatenation of average pooling and max pooling to produce the AIG embedding $h_{AIG}$. Formally, the embeddings are

$$
\mathbf{h}_{AIG} = \frac{1}{N} \sum_{i=1}^{N} \mathbf{h}_i + \max_{i=1}^{N} \mathbf{h}_i
$$

where $N$ is the number of nodes in AIG.

Fig. 1: Architecture for QoR prediction. GCN: Graph convolutional layer. FC: fully connected layers. BN: Batch normalization layer.
defined as follows:

\[ h_u^k = \sigma(W_k \times \sum_{u \in N(u)} h_{u-1}^k + b_k), k \in [1, 2] \]

\[ h_{AIG} = \frac{1}{|V|} \sum_{u \in V} \max_u h_u^k \]

where \( h_u^k \) is GCN embedding generated by \( k \)-th layer of node \( u \). \( W_k \) and \( b_k \) are GCN parameters and \( \sigma \) is non-linear ReLU activation. \( N(\cdot) \) denotes 1-hop neighbors.

2) Synthesis recipe embedding: In our work, we consider a fixed length synthesis recipe \( L \). We numerically encode the recipe using available synthesis transformation and pass it through a linear layer. Next, a set of one-dimensional convolutional neural networks (CNNs) with different kernel length extract features to produce "synthesis recipe embedding" \( h_{\text{recipe}} \). Mathematically, it can be shown as follows:

\[ h_{\text{recipe}} = \text{concat}_{i}(b_i + \sum_{j=1}^{j=M} s_{kl}W_l^{i}), i \in [1, 4] \]

where \( M \) is kernel length and \( (W_i, b_i) \) are filter parameters.

The Bulls-Eye zero-shot predictor is created by concatenating AIG and synthesis recipe embeddings followed by four fully connected layers that output a QoR prediction (Figure 2). Assuming a training dataset, \( D_{\text{train}} \), comprising AIGs \( (g_i) \), synthesis recipes \( (s_i) \), and labels represented by number of nodes \( (y_i) \)—normalized to respective samples of design in the dataset—the graph-based regression learns a parameterized function \( \hat{F}(\cdot; \theta_{\text{ZS}}) \) by minimizing the loss function

\[ \mathcal{L}(y, \hat{y}) = \frac{1}{|D_{\text{train}}|} \sum_{(g_i, s_i) \in D_{\text{train}}} \|y - \hat{F}(g_i, s_i; \theta_{\text{ZS}})\|_2^2 \].

C. Fine-tuning QoR predictor (9)

One can use the zero-shot model to predict QoR of different synthesis recipes on a new AIG. However, the accuracy of the model might be low if the features of the new AIG are different from prior data. To address this problem, we propose to fine-tune the zero-shot model using a limited number, \( n_{\text{budget}} \), of synthesis runs on the new AIG, where \( n_{\text{budget}} \) is specified by the designer depending on the amount of time they are willing to spend.

Fine-tuning the zero-shot predictor avoids the need to train a model from scratch for each new design, which was a critical roadblock for prior work. This strategy has been successful in a variety of other domains, for example, image classification [15], but has not been explored for ML-guided synthesis.

The next question we seek to answer is: How should the synthesis budget \( n_{\text{budget}} \) be used?

We explore two solutions. The first solution, that we refer to as FT+R fine-tunes the zero-shot model using randomly selected synthesis recipes. However, the aim of the designer is to pick best synthesis recipes giving wide variations in the synthesis output. This problem can be mapped similarly to an active learning problem where label generation is a costly operation and therefore needs careful picking of data points. Inspired by active learning approach [16], we propose a smarter solution, FT+A. Here, we cluster the embeddings of the synthesis recipes used to train the zero-shot model (recall that each recipe has its own embedding denoted by \( h_{\text{recipe}} \)) into \( n_{\text{budget}} \) clusters, and pick the cluster heads as our candidates. The intuition behind this idea is that the cluster heads represent maximally diverse and informative points in the solution space. We synthesize the unseen AIG using the recipe cluster heads, generate labels and fine-tune \( \hat{F}(\cdot; \theta_{\text{ZS}}) \) to produce a high-quality QoR predictor.

D. Black-box Optimization (9)

Although Bulls-Eye (the zero-shot and fine-tuned predictors) can be used in a wide variety of black-box approaches (e.g., evolutionary algorithms), we focus on SA adopted in [17]. A good QoR predictor provides fast and accurate feedback to the optimizer by estimating the QoR of a synthesis recipe for an AIG. As we will show in our experimental evaluation, QoR predictor aided SA can substantially explore the synthesis recipe space in a given time span. Algorithm 2 outlines the flow for generating synthesis recipes. The terminology in Algorithm 2 is based on the SA literature; readers can peruse [17] for more background.
Algorithm 2: Simulated Annealing based recipe generator

**Data:** Initial temperature ($T_{\text{initial}}$); Max. oracle queries: $Q_{\text{max}}$; Fine-tuned QoR predictor $\hat{F}(\cdot; \theta^A_{FT})$; Design: ($AIG_U$)

**Result:** Node optimized synthesis recipe: $s^* \in M^L$

$t \leftarrow T_{\text{initial}}, Q \leftarrow 0, s^* \leftarrow \text{RANDOMRECIPE}()$

while $Q < Q_{\text{max}}$

$s_{\text{next}} \leftarrow \text{NEIGHBOUR}(T, s^*)$ \quad \triangleright Neighbour recipes

$\Delta E \leftarrow \text{ENERGY}(s_{\text{next}}, \hat{F}(\cdot; \theta^A_{FT})) - \text{ENERGY}(s^*, \hat{F}(\cdot; \theta^A_{FT}))$ \quad \triangleright Energy down\no{nodes}↓

if $\Delta E < 0$ or RANDOM() < $\text{ACCEPT}(T, \Delta E)$

then $s^* \leftarrow s_{\text{next}}$

$T \leftarrow \text{COOLING}(T, s^*)$; $Q \leftarrow Q + 1$ \quad \triangleright Annealing schedule

return $s^*$ \quad \triangleright Best synthesis recipe

V. DATA GENERATION AND ANALYSIS

For wider access and reproducible, we focus on open source EDA platforms as key to advancing ML research in EDA. Thus, we develop OpenABC-D framework (Figure 3): an end-to-end large-scale data generation framework for augmenting ML research in circuit synthesis and making it freely available. We applied the OpenABC-D framework on a set of open source designs to generate dataset for training our Bulls-Eye predictor.

A. Data Generation

To produce the OpenABC-dataset, we use 44 open source designs with a wide range of functions. In the absence of a preexisting dataset like ImageNet [15] that represents many classes of designs, we hand-curated designs of different functionalities from MIT LL labs CEP [19], OpenCores [18], IWLS [28], ISCAS [23], [29], MCNC [22] and EPFL benchmarks [24]. These benchmarks include more complex and functionally diverse compared to only ISCAS [23], [29] and EPFL [24] benchmarks that are used in prior work and represent large, industrial-sized designs. In the context of EDA, functionally diverse IPs should have diverse AIG structures (e.g., tree-like, balanced, and skewed) that mimic the distribution of real hardware designs. Table II summarizes the structural characteristics of the data before synthesis (without optimizations). These designs are functionally diverse – bus communication protocols, computing processors, digital signal processing cores, cryptographic accelerators and system controllers.

| Benchmark   | Characteristics |
|-------------|------------------|
| Primary Inputs (PI), Primary outputs (PO) |

![Fig. 3: OpenABC-D framework](image-url)

TABLE II: Open source design characteristics (unoptimized).
-z, refactor -z and balance transformations, consistent with prior works [6]–[8]. The synthesis recipes were prepared by randomly sampling from the set of synthesis transformations, assuming a uniform distribution. We ran synthesis with \textit{abc} using server-grade Intel processors for 200,000+ computation hours to generate the labeled data. We analyzed the top $k$ synthesis recipes (in terms of node optimization) by varying $k = 15$, 75 and 150 (1% to 10%). We found that the commonality of the top performing recipes across any two designs is less than 30% (Figure 4). This indicate that the AIG structures of designs are diverse and synthesis recipes perform differently across them.

B. Preprocessing for ML

This stage involves preparing the circuit data for use with any ML framework. We use pytorch-geometric APIs to create data samples using AIG graphs, synthesis recipes, and number of nodes and delay of synthesized AIGs. The dataset is available using a customized dataloader for easy handling for preprocessing, labeling, and transformation. We create a script that helps partition the dataset (e.g., into train/test) based on user specified learning tasks.

VI. EXPERIMENTAL SETUP AND EVALUATION

As we discussed in Section I, Bulls-Eye illustrates ideas of fine-tuning, active learning, and scalability for ML-guided logic synthesis. We focus our experimental evaluation on characterizing Bulls-Eye in these dimensions.

A. Setup

We evaluate the efficacy of the Bulls-Eye predictor and the quality of the recipes found using Bulls-Eye on OpenABC-dataset. We emphasize that our work scales to larger designs compared to prior work.

For assessing quality of a recipe, we use the following metrics for comparison. These metrics provide a qualitative indicator on number of nodes optimized in AIG and relative improvement compared to baselines:

- Reduction factor (%): This metric depicts a ratio of number of nodes optimized post synthesis to number of nodes in original netlist. This is denoted by:

  $$rf(\%) = \frac{N_{\text{original}} - N_{\text{synthesized}}}{N_{\text{original}}} \times 100\%$$

- Relative Improvement (%): This metric measures relative performance of reduction factor of a proposed technique compared to baseline technique. This is denoted by:

  $$RI(\%) = \frac{rf_{\text{proposed}} - rf_{\text{baseline}}}{rf_{\text{baseline}}} \times 100\%$$

We use these metrics to compare the synthesis output quality using recipes generated by simulated annealing with Bulls-Eye QoR predictor. As an intermediate result, we also evaluate the quality of the Bulls-Eye QoR predictors. For this, we use a reference set of 1500 recipes and corresponding synthesis results as the ground-truth QoR. We draw from this reference set the various train/test recipe splits for evaluation.

In our experiment, we train the zero-shot predictor on 18 small designs ($\leq 30k$ nodes, upper half of Table II), and fine-tune and evaluate it on 26 designs (10 large designs with 41k–114k nodes) from the OpenABC dataset. We evaluate the predictor on designs from prior works for comparisons to the SOTA.

To train our models, we use mean-square error (MSE) as the loss function and normalized number of nodes as labels (normalized across each benchmark). The hyperparameters used include Adam optimizer, learning rate of 0.01 and batch size of 64. During fine-tuning, we set the learning rate to 0.01 for fully connected layers and 0.001 for GCN and 1-D convolution layers. We perform experiments on a 2.9GHz Intel Xeon CPU with 384GB RAM and NVIDIA V100 GPU. We train the zero-shot model for 80 epochs with a runtime of about 12 hours as a one-time effort. This relatively low one-time effort is because we only use small netlists to train the zero-shot predictor; surprisingly, we find it transfers well to new and unseen large netlists. Once the model zero-shot model trained, it can be directly used or fine-tuned for any new design. We perform fine-tuning for 20 epochs that takes
TABLE III: GCN architecture. I: Input dimension, L1, L2: dimension of GCN layers; f: # filters, k: kernels, s: stride, # I: #FC layers

| AIG Embedding | Recipe Encoding | FC Layers |
|---------------|-----------------|-----------|
| L1 | L2 | Pool | I | #f | k | s | # I | arch |
| 4 | 64 | 64 | Max+Mean | 60 | 4 | 12,15,18,21 | 3 | 4 | 190-512-512-512-1 |

less than 200 seconds for each new design that we evaluate, including the large designs.

B. Evaluating QoR predictor

1) Experiment design: We first examine how well the predictors enables accurate QoR prediction by comparing different variants of the Bulls-Eye predictor. We evaluate and compare their predictions on the reference set of randomly selected synthesis recipes (for which we have actual synthesis results). We capture this as the predictor’s Commonality factor, which is defined as $\frac{n(P \cap A)}{n(P)}$, where $A$ denotes top k% performing synthesis recipes (actual) and $P$ denotes top k% synthesis recipes (predicted). As mentioned earlier, we use 9 large benchmarks from OpenABC-D framework and 17 benchmarks from SOTA works for evaluation. The models are:

- **Standalone** QoR predictor is trained from scratch using $n_{budget}$ samples from synthesizing the target design.
- **Zero-shot (ZS)** QoR predictor is trained only on small designs from the OpenABC-D synthesis dataset.
- **Fine-tuning + random (FT + R)** QoR predictor, which is fine-tuned on randomly chosen $n_{budget}$ recipes and corresponding synthesis results as fine-tuning (calibration) data.
- **Fine-tuning + active (FT + A)** QoR predictor, which is prepared by fine-tuning on synthesis data from $n_{budget}$ most-informative recipes (generated from k-means clustering of the 1500 reference set recipe embeddings).

2) Analysis of Results: Figure 5 presents the performance of all QoR predictors using commonality factor as the metric across various top-k% values. For example, Figure 5(d) shows that Bulls-Eye using fine-tuning and active learning achieves 0.46 for top-5% on the bp-be design. This indicates 46% of top 5% performing synthesis recipes (out of 1450) on bp-be is common with top 5% synthesis recipes predicted by QoR predictor. Generally, we observe fine-tuned QoR predictors yield better results (better commonality factor for every top k%) compared to standalone and zero-shot predictors. A high commonality factor denotes that the model can infer better QoR achieving recipes successfully; pre-trained predictors are indeed beneficial as the basis for fine-tuning QoR predictor.

C. QoR of Bulls-Eye generated recipes

1) Experiment design: A good QoR predictor accurately predicts the quality of a synthesis recipe for a given design to provide good feedback in an optimization scheme. Bulls-Eye uses QoR predictors in lieu of actual synthesis runs as the backend engine (“evaluator”) of an SA-based recipe generator. For a fair evaluation, we set two baselines to compare the quality of recipes generated using a QoR predictor: 1) $k$-repeat application of SA-generated recipe using actual synthesis runs as the evaluator 2) resyn2*: repeated application of resyn2 synthesis recipe. In our experiments, we set resyn2 as starting seed for simulated annealing and $k = 25$. For a fair performance evaluation, we set a threshold of 1000 calls to evaluator of simulated annealing and compare runtime speed up of QoR predictor versus conventional actual synthesis. We compare Bulls-Eye on two definitive aspects: 1) Run-time speedup of simulated annealing using Bulls-Eye predictor instead of actual synthesis, 2) Relative performance improvement of Bulls-Eye compared to resyn2* for same runtime. We set the initial temperature $T_{start} = 7250$ and distorted Cauchy-Lorentz distribution as visiting distribution as part of simulated annealing.

2) Analysis of Results: We compare QoR of synthesis output using Bulls-Eye generated recipes to our baselines and SOTA prior work [7], [8] in Table IV. This shows synthesis output using Bulls-Eye generated recipes achieve better QoR compared to conventional SA and resyn2* with 2.94x average runtime speedup. Red and Blue denotes top-2 performing recipes. Our results show Bulls-Eye generated recipes using finetuning perform better than SOTA on 9 out of 10 benchmarks (Table IV). Compared to [7] and [8], our best predictor ($FT + A$) achieves better rf % (around 4%) with a 11.20x and 1.04x run-time speed-up, respectively. Our ($FT + R$) predictor achieves better rf % than [7] and [8] (2.7% and 1.35%) with 12x and 1.10x run-time speed-up, respectively. The zero-shot predictor ZS obtains almost similar QoR, however achieving a huge run-time speed-up over prior work (45x and 4x compared to [7], [8] respectively). This shows that our zero-shot predictor is indeed helpful for prediction on unseen netlists. The prediction quality improved
TABLE IV: Reduction factor (%) obtained by our work and prior works

| Design          | Nodes | Baseline | SOTA | Bulls-Eye | RI w.r.t. resyn2* (%) | RI w.r.t. S_A1_k (%) |
|-----------------|-------|----------|------|-----------|-----------------------|---------------------|
| apex1           | 1577  | 26.44    | 29.93| 35.89     | 28.66                 | 28.97               |
| sinc            | 5452  | 34.12    | 34.46| 40.7      | 35.69                 | 35.33               |
| max             | 2865  | 1.19     | 1.50 | 1.29      | 1.29                  | 1.29                |
| log2            | 1572  | 20.08    | 20.58| 22.56     | 20.45                 | 20.63               |
| c5315           | 1613  | 20.08    | 20.58| 22.56     | 22.75                 | 23.94               |
| bc0             | 1592  | 44.40    | 45.03| 51.14     | 48.98                 | 53.39               |
| c7552           | 2198  | 35.53    | 36.08| 38.58     | 36.26                 | 37.31               |
| c7552           | 2198  | 35.53    | 36.08| 38.58     | 36.26                 | 37.31               |
| daulu           | 1735  | 39.77    | 39.96| 46.51     | 42.31                 | 45.71               |
| mainpla         | 5346  | 34.12    | 34.46| 40.7      | 35.69                 | 35.33               |
| resyn2         | 57247 | 28.88    | 33.42| 40.7      | 28.92                 | 33.42               |
| log2           | 32090 | 7.97     | 8.57 | 9.63      | 8.58                  | 9.63                |
| max            | 2665  | 1.19     | 1.50 | 1.29      | 1.29                  | 1.29                |
| multiplier      | 27062 | 9.27     | 9.71 | 10.49     | 9.7    | 10.15               |
| sin              | 5416  | 7.42     | 7.75 | 8.23      | 7.88                  | 8.3               |
| sqrt            | 24618 | 21.05    | 21.05| 22.62     | 21.64                 | 22.67               |
| square          | 18484 | 14.47    | 17.8  | 19.73     | 8.73                  | 19.73              |
| aes-secworks   | 40778 | 7.40     | 7.54 | 7.74      | 7.87                  | 7.87               |
| aes-secrypt    | 45850 | 8.01     | 8.16 | 8.16      | 8.16                  | 8.16               |
| bbpe           | 82514 | 4.92     | 5.18 | 5.34      | 5.34                  | 5.34               |
| ethernet       | 67164 | 3.30     | 3.44 | 3.46      | 3.48                  | 3.48               |
| ecc_2crypt     | 114771| 9.18     | 9.37 | 11.15     | 11.11                 | 11.11              |
| pipsrc         | 82945 | 7.40     | 7.54 | 7.74      | 7.54                  | 7.54               |
| tinyRocket      | 52315 | 21.30    | 21.80| 22.64     | 22.03                 | 22.22              |
| vgbounding     | 105334 | 1.62   | 1.64   | 1.71      | 1.67                  | 1.72               |
| shapex         | 47840 | 6.72     | 6.89 | 9.35      | 9.26                  | 9.26               |

Time (in s) - 5.338 3932.8 3932.8 1494.6 1738.0 5296.0 1250.53 1333.91

† Runtime scaled on our machine based on data provided by authors [8] for synthesis runs during training. Total training runtime will be higher than reported here.

TABLE V: Reduction factor (%) obtained by our work on large benchmarks

| Design          | Nodes | Baseline | SOTA | Bulls-Eye | RI w.r.t. resyn2* (%) | RI w.r.t. S_A1_k (%) |
|-----------------|-------|----------|------|-----------|-----------------------|---------------------|
| div             | 57247 | 28.88    | 29.93| 35.89     | 28.66                 | 28.97               |
| log2            | 32090 | 7.97     | 8.57 | 9.63      | 8.58                  | 9.63                |
| max             | 2665  | 1.19     | 1.50 | 1.29      | 1.29                  | 1.29                |
| multiplier      | 27062 | 9.27     | 9.71 | 10.49     | 9.7    | 10.15               |
| sin              | 5416  | 7.42     | 7.75 | 8.23      | 7.88                  | 8.3               |
| sqrt            | 24618 | 21.05    | 21.05| 22.62     | 21.64                 | 22.67               |
| square          | 18484 | 14.47    | 17.8  | 19.73     | 8.73                  | 19.73              |
| aes-secworks   | 40778 | 7.40     | 7.54 | 7.74      | 7.87                  | 7.87               |
| aes-secrypt    | 45850 | 8.01     | 8.16 | 8.16      | 8.16                  | 8.16               |
| bbpe           | 82514 | 4.92     | 5.18 | 5.34      | 5.34                  | 5.34               |
| ethernet       | 67164 | 3.30     | 3.44 | 3.46      | 3.48                  | 3.48               |
| ecc_2crypt     | 114771| 9.18     | 9.37 | 11.15     | 11.11                 | 11.11              |
| pipsrc         | 82945 | 7.40     | 7.54 | 7.74      | 7.54                  | 7.54               |
| tinyRocket      | 52315 | 21.30    | 21.80| 22.64     | 22.03                 | 22.22              |
| vgbounding     | 105334 | 1.62   | 1.64   | 1.71      | 1.67                  | 1.72               |
| shapex         | 47840 | 6.72     | 6.89 | 9.35      | 9.26                  | 9.26               |

Fig. 6: BullsEye performance compared to resyn2* and conventional simulated annealing

VII. DISCUSSION AND INSIGHTS

We proposed Bulls-Eye as a solution for ML-guided synthesis recipe generation that scales on large designs. Bulls-Eye uses few-shot learning and active learning to build upon models pre-trained on historical synthesis data, particularly given a limited synthesis run budget for new, unseen designs. Our framework generates better synthesis recipes compared to prior techniques, with an average 2.94x run-time speed-up and up to 10.2x speed-up (on large benchmarks) compared to conventional black-box approaches. We have made our code and associated dataset available to the community at: [https://github.com/NUYU-MLDA/OpenABC](https://github.com/NUYU-MLDA/OpenABC)
## TABLE VI: Timing complexity of baseline and Bulls-Eye framework.

| Design  | resyn2 (s) | Baseline (SA14k) | Time taken (s) | Speedup |
|---------|------------|------------------|----------------|---------|
|         |            | SA | synth | total | SA | synth | total | FT | SA | synth | total | FT | SA | synth | total |
| apex1   | 0.4        | 216.5 | 13.2 | 229.7 | 35.5 | 11.3 | 46.8 | 48.3 | 30.2 | 13.5 | 92.0 | 53.1 | 37.6 | 15.9 | 106.6 |
| bc0     | 0.3        | 235.2 | 11.2 | 246.4 | 36.9 | 9.8  | 46.7 | 47.2 | 30.2 | 12.3 | 84.7 | 46.5 | 37.5 | 9.1  | 93.0  |
| c1355   | 0.2        | 135.3 | 5.4  | 140.7 | 37.5 | 5.5  | 43.0 | 40.1 | 28.0 | 4.9  | 73.0 | 44.1 | 26.1 | 5.2  | 75.4  |
| c26322  | 0.5        | 287.1 | 16.5 | 303.6 | 32.6 | 17.5 | 50.1 | 49.6 | 33.0 | 19.1 | 101.7 | 54.5 | 32.3 | 16.5 | 103.3 |
| c2688   | 1.5        | 298.3 | 60.5 | 988.8 | 23.7 | 57.4 | 81.1 | 51.2 | 38.7 | 61.6 | 151.5 | 56.4 | 23.5 | 70.5 | 150.3 |
| c7552   | 0.3        | 358.8 | 17.0 | 375.8 | 29.3 | 18.3 | 47.6 | 46.9 | 39.2 | 21.1 | 150.9 | 99.6 | 23.2 | 17.7 | 140.5 |
| dalu    | 0.4        | 267.7 | 9.2  | 276.9 | 27.7 | 9.2  | 36.9 | 47.5 | 40.0 | 13.9 | 128.4 | 82.0 | 43.1 | 12.7 | 137.7 |
| i10     | 0.5        | 342.5 | 21.4 | 346.0 | 33.7 | 17.0 | 50.7 | 48.6 | 35.2 | 20.5 | 154.3 | 108.4 | 40.4 | 23.2 | 172.0 |
| k2      | 0.3        | 308.7 | 13.6 | 322.3 | 38.1 | 12.1 | 43.0 | 53.6 | 46.7 | 14.5 | 134.9 | 92.9 | 62.2 | 15.1 | 170.2 |
| manupla | 0.8        | 567.4 | 47.3 | 614.6 | 70.2 | 4.4  | 76.6 | 99.4 | 30.7 | 49.2 | 179.2 | 109.3 | 29.8 | 45.8 | 184.9 |
| div     | 12.7       | 6554.4 | 291.9 | 6846.2 | 115.0 | 250.2 | 365.8 | 104.7 | 171.7 | 208.2 | 556.6 | 115.2 | 37.9 | 104.5 | 152.4 |
| log2    | 11.0       | 7614.2 | 587.5 | 8201.7 | 110.6 | 70.3 | 569.4 | 750.3 | 121.6 | 165.0 | 571.0 | 857.6 | 172.0 | 10.9 | 96.6  |
| max     | 0.7        | 397.9 | 22.5 | 420.4 | 30.2 | 17.0 | 47.2 | 57.8 | 30.2 | 23.4 | 132.3 | 86.5 | 27.3 | 23.3 | 159.2 |
| multiplier | 8.2      | 5359.1 | 487.2 | 5846.3 | 58.7 | 394.8 | 453.5 | 97.9 | 117.9 | 457.4 | 673.2 | 107.7 | 58.4 | 20.2 | 80.6  |
| sin     | 1.9        | 1216.4 | 342.6 | 1559.0 | 63.4 | 85.6 | 149.0 | 52.4 | 34.3 | 110.8 | 197.5 | 57.6 | 26.5 | 89.8 | 173.9 |
| sqrt    | 7.4        | 4460.3 | 340.6 | 4800.9 | 39.9 | 294.1 | 334.0 | 110.5 | 61.7 | 340.0 | 512.2 | 121.5 | 55.1 | 346.6 | 523.2 |
| aes     | 8.7        | 3913.0 | 345.6 | 4258.6 | 58.7 | 313.8 | 372.5 | 100.4 | 23.5 | 360.9 | 484.7 | 110.4 | 44.6 | 273.3 | 428.3 |
| log2    | 11.0       | 7614.2 | 587.5 | 8201.7 | 110.6 | 70.3 | 569.4 | 750.3 | 121.6 | 165.0 | 571.0 | 857.6 | 172.0 | 10.9 | 96.6  |
| div     | 12.7       | 6554.4 | 291.9 | 6846.2 | 115.0 | 250.2 | 365.8 | 104.7 | 171.7 | 208.2 | 556.6 | 115.2 | 37.9 | 104.5 | 152.4 |

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Fig. 7: QoR at various times from recipes by simulated annealing using different evaluators: actual synthesis ($B$) and proxy predictors ($ZS$ and $FT + A$)