GCN-RL Circuit Designer: Transferable Transistor Sizing with Graph Neural Networks and Reinforcement Learning

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Bio

Hanrui Wang is a PhD student at MIT HAN Lab. His research interest is the intersection of computer architecture and efficient machine learning. He received his B.Eng. from Fudan University in 2018, and M.S. from MIT in 2020.
AI is Revolutionizing EDA

• Fast: 🔝
  • Inference of an AI model is fast thanks to well-optimized libraries (e.g. cuDNN)
  • Can be accelerated by GPUs and AI accelerators

• Accurate: 🎯
  • Data-driven
  • With enough data, performance of AI models can exceed traditional methods
  • Enable continuous learning with newly obtained data
AI is Revolutionizing EDA

• AI for Physical Design & Manufacture:
  • “DreamPlace”\(^1\) for placement
  • “LithoGAN”\(^2\) for lithography modeling
  • “Google’s Chip Design AI”\(^3\) for floorplanning

• AI for Circuit Design
  • “Circuits-GNN”\(^4\) for RF circuits
  • “Learning to Design Circuits”\(^5\) for Analog IC
  • “Analog and Digital Circuits Classifier”\(^6\) for sub-circuits classification

• AI for System-Level Modeling & Optimization
  • “PowerNet”\(^7\) for power modeling
  • “Resource Management with RL”\(^8\) for many-core resources management
  • “Combine Evolutionary with Deep Learning”\(^9\) for Interface Optimization

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\(^1\)Lin, Y., Dhar, S., Li, W., Ren, H., Khelany, B., & Pan, D. Z. DREAMPlace: Deep learning toolkit-enabled GPU acceleration for modern VLSI placement. In DAC 2019
Analog IC is Labor Intensive for Design & Porting

• Analog IC Design
  • **Manual** schematic design
  • **Manual** transistor sizing
  • **Manual** layout design
  • Lacks Automation & Labor Intensive
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• Analog IC Porting
  • Inherit schematic
  • **Manual** transistor sizing again
  • **Manual** layout design again
  • **Large** Overhead & Effort

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**Schematic Design**

**Transistor Sizing**

**Layout Design**
GCN-RL Circuit Designer

- AI for higher analog IC design efficiency
GCN-RL Circuit Designer

• Target at the challenging transistor sizing problem
  • Large design space
  • Complex trade-offs
GCN-RL Circuit Designer

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• Leverage Graph Convolutional Neural Networks (GCN)
  • Circuit is a graph
  • Involve graph information into optimization loop
GCN-RL Circuit Designer

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• Leverage Graph Convolutional Neural Networks (GCN)
  • Circuit is a graph
    • Involve graph information into optimization loop

• Transfer learning to reduce design porting overhead
  • Between technology nodes
  • Between different circuit topologies
GCN-RL Circuit Designer: What is GCN?

- Graph Convolutional Neural Networks (GCN) [Kipf et al, 2017]
  - Each node aggregates information from neighbors
  - The more layers, the larger receptive field of each node
GCN-RL Circuit Designer Overview

• Step 0: We have a target circuit and a simulator as environment
One Optimization Iteration Contains 6 Steps

- **Step 1**: Environment embeds the topology into a graph whose nodes are components (transistor, resistor) and edges are wires.
One Optimization Iteration Contains 6 Steps

- Step 2: The environment generates a state vector for each component and passes them to the RL agent.
One Optimization Iteration Contains 6 Steps

- Step 3: The RL agent processes the graph and states, and generates the sizes (W/L, R, C, etc.) for each node.
One Optimization Iteration Contains 6 Steps

- Step 4: The environment refines the sizes to meet circuit requirements such as transistor matching
One Optimization Iteration Contains 6 Steps

- Step 5: Simulator simulates the circuit with the generated sizes
One Optimization Iteration Contains 6 Steps

- Step 6: Compute a reward (FoM) value and feed it to RL agent to update policy
Many Iterations Later

- After many iterations, we get the sizes with high FoM and a trained RL agent
Knowledge Transfer to Other Technology and Topology

- **Inherit** the trained RL agent to design circuits in other technology nodes and topologies.
GCN RL Agent: Actor-Critic Algorithm

- **Actor**: Generates actions (sizes)
- **Critic**: Estimates reward (FoM) and guides the actor to generate actions with high reward
GCN RL Agent: GCN Model

- Actor Input: graph and states on each node
GCN RL Agent: GCN Model

- First GCN layer: multiply input features with the same weight matrix for each node to get hidden features
GCN RL Agent: GCN Model

• First GCN layer: for each node, accumulate hidden features with neighbors to get aggregated features
GCN RL Agent: GCN Model

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GCN RL Agent: GCN Model

- Stack multiple GCN layers, each has one FC and one aggregation operation
GCN RL Agent: GCN Model

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GCN RL Agent: GCN Model

• After several GCN layers, each node has a **large** receptive field
• After the last GCN layer: output actions (sizes) with a unique FC for each node
• Critic is similar but the last layer outputs estimated FoM
GCN-RL Enables Knowledge Transfer

- Bayesian Optimization & Evolutionary Search cannot transfer knowledge
Evaluations

Two-Stage TIA

Two-Stage Voltage Amp

Three-Stage TIA

Low-Dropout Regulator
Experiment Setups

• Figure of Merits (FoM):
  • Weighted sum of multiple normalized performance metrics such as bandwidth, power, and gain

• Baselines:
  • Human Expert Design
  • Random Search
  • Evolutionary Search (ES)
  • Bayesian Optimization (BO)
  • MACE (multi-objective version of BO)
  • NG-RL (Non-graph RL, no GCN layer aggregation)
### GCN-RL Achieves the Highest FoMs

<table>
<thead>
<tr>
<th>Method</th>
<th>Two-TIA</th>
<th>Two-Volt</th>
<th>Three-TIA</th>
<th>LDO</th>
</tr>
</thead>
<tbody>
<tr>
<td>Human</td>
<td>2.32</td>
<td>2.02</td>
<td>1.15</td>
<td>0.61</td>
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<tr>
<td>Random</td>
<td>2.46±0.02</td>
<td>1.74±0.06</td>
<td>0.74±0.03</td>
<td>0.27±0.03</td>
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<tr>
<td>ES</td>
<td>2.66±0.03</td>
<td>1.91±0.02</td>
<td>1.30±0.03</td>
<td>0.40±0.07</td>
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<tr>
<td>BO</td>
<td>2.48±0.03</td>
<td>1.85±0.19</td>
<td>1.24±0.14</td>
<td>0.45±0.05</td>
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<tr>
<td>MACE</td>
<td>2.54±0.01</td>
<td>1.70±0.08</td>
<td>1.27±0.04</td>
<td>0.58±0.04</td>
</tr>
<tr>
<td>NG-RL</td>
<td>2.59±0.06</td>
<td>1.98±0.12</td>
<td>1.39±0.01</td>
<td>0.71±0.05</td>
</tr>
<tr>
<td>GCN-RL (Ours)</td>
<td>2.69±0.03</td>
<td>2.23±0.11</td>
<td>1.40±0.01</td>
<td>0.79±0.02</td>
</tr>
</tbody>
</table>

- GCN-RL consistently achieves the **highest FoMs with small variances**.
Learning Curves

Two-Stage Voltage Amplifier

Low-Dropout Regulator

- GCN-RL has highest FoMs and **fastest convergence speed**
Transfer between Tech Nodes on Three-Stage TIA

- GCN-RL achieves much higher FoM after 200 steps
Transfer between Two-Stage and Three-Stage TIA

- GCN-RL with transfer achieves highest FoM
- **Graph information is critical** for knowledge transfer
GCN-RL Circuit Designer

- AI for EDA achieves **high** performance with **less** human labor
- GCN-RL consistently achieves highest FoMs
- GCN-RL has transfer learning ability
  - Between technology nodes
  - Between topologies

Area: Design, Machine Learning/AI
Session: Learning to Yield
Fri. July 24, 2:00pm to 3:00pm

https://gcnrl.mit.edu
Questions