Assessment of Reinforcement Learning for Macro Placement

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GitHub: https://github.com/TILOS-Al-Institute/MacroPlacement
Why MacroPlacement?

- **June 2021**: Google Brain *Nature* paper proposed RL-based macro placer
  - Claimed superior or comparable macro placement solutions compared to human experts, in under six hours
  - Did not release code or data as had been committed
- **January 2022**: Google Research open-sourced Circuit Training (*CT*)
  - “reproduces the methodology published in the *Nature* 2021 paper”
  - No dataset, and insufficient code to reproduce the *Nature* results
- **March 28, 2022**: “Stronger Baselines” manuscript posted during ISPD-22
  - States shortcomings of the Nature paper
  - Also lacks code and dataset to reproduce results or confirm claims
- **MacroPlacement**: open, transparent assessment of *Nature*, *CT*
  - Goal: resolve controversy; foster calm discussion and scientific progress
  - **June 2022**: *MacroPlacement* repository open-sourced


**Circuit Training (CT): Important Surprises and Gaps**

- **Surprise:** CT uses placement information from its input
  - *Nature* paper does not mention this
  - Ablation: use of placement info reduces routed wirelength by 7-10%

- **CT optimizes proxy cost during training**
  - RL agent places hard macros on gridded canvas
  - Stdcell clusters placed using force-directed (FD) placer
  - Proxy cost \((R)\) is then evaluated:
    \[
    R = \text{Wirelength} + \gamma \times \text{Density} + \lambda \times \text{Congestion}
    \]

- **Gap:** key elements hidden behind plc_client APIs
  - FD placer, proxy cost calculation
  - We reverse-engineered these and released as open source

- **Thanks** to the TensorFlow Agents team for open-sourcing the grouping and training flows in the CT repository, and to Google Brain engineers for extensive Q&A and checking!
Scope of *MacroPlacement*

- **Code**: Includes open-source implementation of missing, blackbox elements of CT
- **Missing elements**: Format translators, *Baselines for comparison* (simulated annealing, human expert)
- **Blackbox elements**: force-directed placement, proxy cost components

- **Modern benchmarks**: Open testcases on open enablements
  - Enablements: SKY130HD+FakeStack, *NanGate45*, ASAP7+FakeRAM

- **Reproducible results with commercial synthesis, place and route evaluation flow**
  - Cadence Genus iSpatial physical synthesis flow and Cadence Innovus P&R flow
  - Synopsys Design Compiler Topographical physical synthesis flow
  - Major changes in EDA vendor policies allow us to share our Tcl scripts in GitHub for research purposes! ⇐ *Kudos and thanks to Cadence and Synopsys!!!*

- **Extensive documentation and data**: See FAQs, Docs, “Our Progress”

*Simulated annealing is implemented following the description in the “Stronger Baselines” manuscript*
CT, SA and Human results for Modern Benchmarks

*Normalized routed wirelength, proxy cost, and TNS → Lower values are better*

- Normalized routed wirelength, proxy cost, and TNS → Lower values are better
- All data is normalized to CT results
- More details: Table 1 of our paper

For postRouteOpt metrics, Human outperforms CT for macro-heavy BlackParrot, MemPool Group
Macro Placement Solutions: Ariane133

- **Ariane133** with **68%** utilization, **1.3ns** target clock period on **NG45**

  - **CT**
  - **CMP**: Innovus Concurrent Macro Placer
  - **AutoDMP**: DREAMPlace based macro placer from **Nvidia Research**
  - The **human** macro placement is from **Dr. Jinwook Jung** of IBM Research
  - postRouteOpt metrics in Table 1 of our paper

*Nature* implements Ariane133 on a different enablement
CT, SA and RePIAce Comparison on ICCAD04 Benchmarks

Proxy Cost: RePIAce beats SA, and SA beats CT

- Data is normalized based on CT
- Table 6 of our paper gives raw data

HPWL: RePIAce beats SA and SA beats CT in most of the testcases

In terms of proxy cost, SA outperforms CT and in terms of HPWL, SA produces better result than CT in 16 out of 17 cases
Conclusions

- **MacroPlacement** = open, transparent assessment and implementation
  - Source code for CT’s missing and blackbox elements
  - Modern, macro-heavy testcases on open enablements
  - Commercial evaluation flow with all runscripts
  - Baselines cited in Nature: human expert, simulated annealing
  - Extensive documentation: FAQs, “Our Progress”, and more

- **CT benefits from placement information in incoming physical synthesis netlist**

- **Baselines (SA and Human experts) outperform CT**
  - For 17 ICCAD04 designs and 4 out of 6 modern testcases, SA generates better proxy cost than CT
  - For large macro-heavy designs, human experts outperform CT in terms of Nature Table 1 metrics

- “There is no substitute for source code (and data)”

Please see the long video and our FAQs in GitHub for more information!!!

https://github.com/TILOS-AI-Institute/MacroPlacement
FAQ: Runtimes (Wall Times) of Different Macro Placers

<table>
<thead>
<tr>
<th>Design</th>
<th>CT (Hours)</th>
<th>CMP (Hours)</th>
<th>RePIAce (Hours)</th>
<th>SA (Hours)</th>
<th>AutoDMP (Hours)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ariane-NG45</td>
<td>32.31</td>
<td>0.05</td>
<td>0.06</td>
<td>12.50</td>
<td>0.29</td>
</tr>
<tr>
<td>BlackParrot-NG45</td>
<td>50.51</td>
<td>0.33</td>
<td>2.52</td>
<td>12.50</td>
<td>0.71</td>
</tr>
<tr>
<td>MemPool-NG45</td>
<td>81.23</td>
<td>1.97</td>
<td>*N.A.</td>
<td>12.50</td>
<td>1.73</td>
</tr>
</tbody>
</table>

- CT: only includes CT training time
- SA: stopped after 12.5 hours automatically
- CMP: only the runtime of `place_design -concurrent_macros` command
- Resources used:
  - CT: Training and evaluation jobs run on (8 NVIDIA-V100 GPU, 96 CPU thread, Memory: 354 GB) machine and 13 collector jobs on each of two (96 CPU thread, Memory: 354 GB) machines
  - SA: 320 parallel jobs where each job used 1 thread
  - RePIAce: used 1 thread
  - CMP: Innovus launched with 8 threads
  - AutoDMP: run on NVIDIA DGX-A100 machine with two GPU workers

*RePIAce run for MemPool Group did not complete
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