Adaptive FPGA Placement Optimization via Reinforcement Learning

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Reinforcement Learning & CAD

































Large solution space \rightarrow Use heuristics



With human-in-the-loop:

• Slow

•Simple heuristics, limited tool parameters (to keep tractable)

•Tune for average case (can't investigate every benchmark design)

CAD Tool Development: Reinforcement Learning (RL)



- •Human out of the loop!
- •Learn better heuristics: exploit more information, more parameters
- •Online adaptation \rightarrow better than average case



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FPGA Placement



FPGA Placement

FPGA:

- Pre-fabricated programmable blocks and routing
- Can implement wide range of designs

Placement Considerations:

- Key step for timing (no later fix up)
 - Routing architecture dependent
- Many legality constraints
- Discrete optimization
- Large designs (millions of netlist primitives)



Simulated Annealing (SA) Placement

- Modify placement by making 'moves'
- Accept/Reject move based on:
 - Cost change
 - Temperature (hill climbing)





Many possible types of moves!



Many possible types of moves!



Simple: random swap



Many possible types of moves!



Simple: random swap



Many possible types of moves!









Many possible types of moves!









Many possible types of moves!



Simple: random swap



Smart: directed move to 'good' location (wirelength, timing)



Complex: Analytic



Many possible types of moves!



Complex: Analytic





Many possible types of moves!











Many possible types of moves!











Many possible types of moves!



Complex: Analytic

Many considerations:

- Frequencies of different moves
- Situation dependent?

99) 199) Move 'strength' vs run-time





Many possible types of moves!



Move 'strength' vs run-time





RL Move Generator

Actions: moved different block types Reward:

- Accepted: -Δcost
- Rejected: 0

Agent:

- Estimates value of actions
- Selects action to take



Action/Move



• Values of action are not stationary!



Move



Values of action are not stationary!



Values of action are not stationary!



Values of action are not stationary!



Action Selection: Exploration vs Exploitation

- ε-greedy: Mostly greedy (exploit), occasionally random (explore)
- ε: fraction of exploratory moves



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Conclusion

- RL-enhanced Simulated Annealing based FPGA Placer
 - RL agent controlled move generator
 - Learns on-line what types of moves are productive
 - Improves run-time/quality trade-offs
 - Particularly at low run-times



Future Work

- More types of moves
- •Other reward formulations (e.g. cost run-time)?
- •Agent:
 - •Less greedy action selection (soft-max)?
 - Use more state information: Circuit & Optimizer statistics
- •Learn:
 - Off-line agent training
 - Other RL algorithms (e.g. Temporal Difference Learning, Policy Gradients)
- Explore RL elsewhere in CAD flow



Thanks!

Questions?

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Backup



Exploration vs Exploitation: Critical Path Delay





Quality/Run-time Comparison: Critical Path



Estimating Action Values: Time Scale



Reinforcement Learning (RL) for CAD: Challenges

Long CAD Run-times

• Must exploit limited experience

Long delayed rewards

- Core challenge of RL
- CAD has well defined objectives

Nested black-box optimization

- CAD optimization already difficult to interpret/debug
- Nested optimization makes interpretability more challenging

