Al and ML with OpenROAD: Some Possibilities!

ECE 260C, Spring 2025 Andrew B. Kahng

Optimization

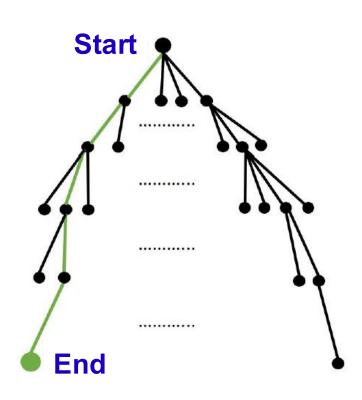
IC Design

AI/ML (?)

Automation (EDA)



Design Optimization Lives in a Box



- Start to End: expensive!
 - O(year) for product
 - O(weeks) for SP&R and Opt
- Goal: best possible End
- Constraint: stay in "Box" {compute}
 - X {licenses}
 - X {people}
 - X {weeks}



Designers always need more leverage!

"Machine Learning in EDA": Why

- A. You need models to have predictions
- B. You need predictions to leverage in exploration
- C. What you can't predict, you guardband
- D. What you don't explore, you leave on the table
- E. C and D are bad for product quality and schedule

"Moore's Law slowdown" -> in an Era of Optimization



"Machine Learning in EDA": What

Predict

 Will RouteOpt finish with clean signoff, <1000 DRVs by tomorrow night?

Classify

 Out of these 50 floorplans + budgets, which 3 should go into trial SP&R?

Estimate

 How many hold buffers will tool eventually add into this post-CTS layout?

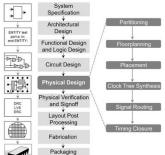
Guide / advise

 What P&R tool setup/script will obtain the best QOR within next 36 hours?

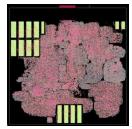


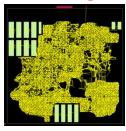
What's Different (and Difficult) for AI/ML?

1. Changing abstractions, formats, and the design itself



and Testing

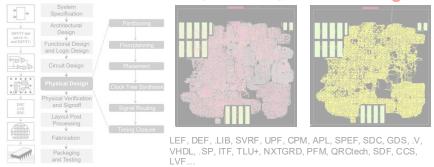




LEF, DEF, .LIB, SVRF, UPF, CPM, APL, SPEF, SDC, GDS, .V, VHDL, .SP, ITF, TLU+, NXTGRD, PFM, QRCtech, SDF, CCS, LVF...

What's Different (and Difficult) for AI/ML?

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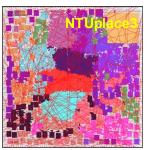
2. Long chains of distinct, intractable discrete optimizations

- "Practical optimization" = metaheuristics on top of metaheuristics
- Scale, multimodality, dynamism, diversity
 → 1000s of hidden commands and options in a commercial placer!
- Objectives are ad hoc
- Trajectories are chaotic
- Outcomes have distributions



Outcomes Heavily Mediated by Heuristics!

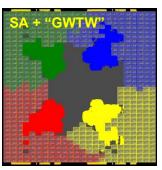


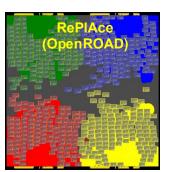


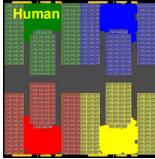


- "ibm01" from ISPD-2002, "Bookshelf" format
- 12.7K instances
- FengShui ~2005; NTUplace3 ~2008; RePlAce ~2018
- "CT-Ariane133 X4", protobuf format [link]
- 532 macros, 332K cells in TSMC 7nm
- AlphaChip 2024, SA/GWTW 1983/1994; RePlAce 2020-









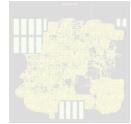
"ibm01" thanks: Prof. Patrick Madden, Binghamton Univ.

What's Different (and Difficult) for AI/ML?

1. Changing abstractions, formats, and the design itself







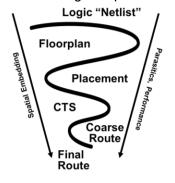
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 → 1000s of hidden commands and options in a commercial placer!
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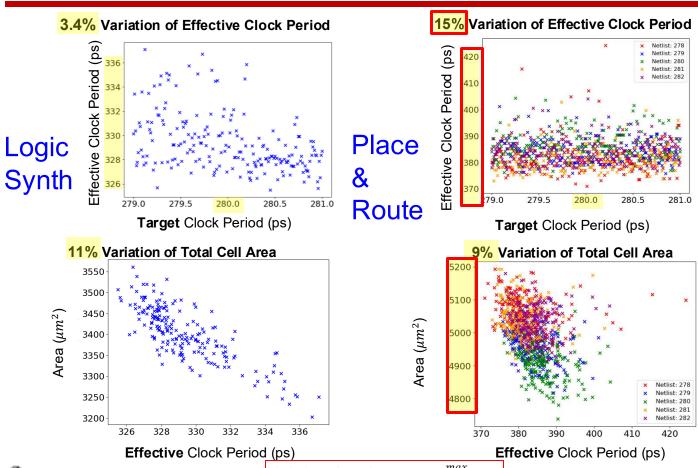
3. Loops are expensive (often, fatally so)

Design process must "converge" both spatial embedding **and** performance



How?

With Chained Chaotic Optimizations ?!?



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Variation of metrics: $100 \times (\frac{max}{min} - 1)$

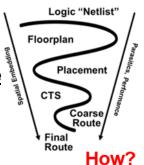
Implications for Optimization in IC Design

- Predictions today are Constructive
 - · Quick-and-dirty, under the hood

Catechism:

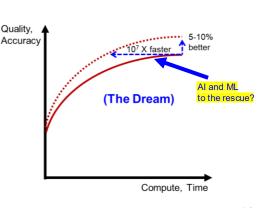
- A. You need **models** to have predictions
- B. You need predictions to leverage in exploration
- C. What you can't predict, you guardband
- D. What you don't explore, you leave on the table

- Optimizations today are <u>Iterative</u>
 - "Construct by Correction"



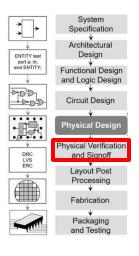


- "Construct by Corrections ...
 - ... that are Correct by Construction"

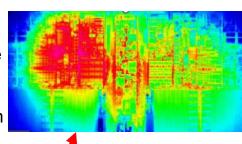


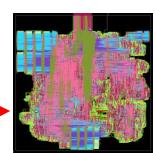


Signoff in Design: Optimize Max, not Sum!



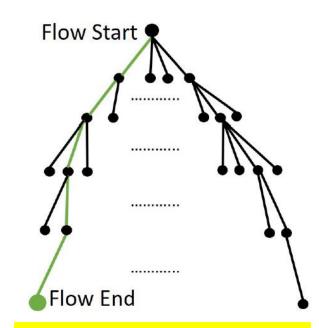
- Signoff is a defined business interface
- Establishes "Who pays for the scrap?"
- Golden, foundry-qualified tools perform signoff analyses and simulations
 - Typically with very long batch runtimes
- Many design steps must optimize "max"
 - · Max timing path delay determines max frequency
 - · Max wiring congestion determines routing feasibility
- Inverse problems galore
 - Worst-case stimuli → e.g., "rogue wave in power grid"
 - "Whack-a-mole", "ping-pong" are in the lexicon of design → can new Al foundation models help?





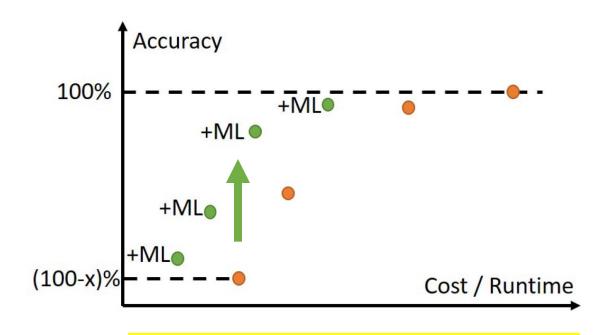
4-Stage "Roadmap" of ML in EDA

- Mechanization and Automation
- Orchestration of Search and Optimization
- Pruning via Predictors and Models
- 4. From Reinforcement Learning through Intelligence



Huge space of tool, command, option trajectories through design flow

No-Brainer: Shift Accuracy-Cost Tradeoffs

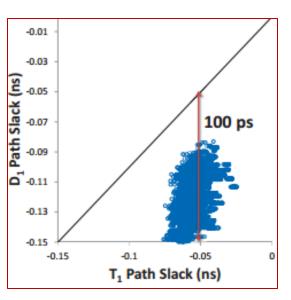


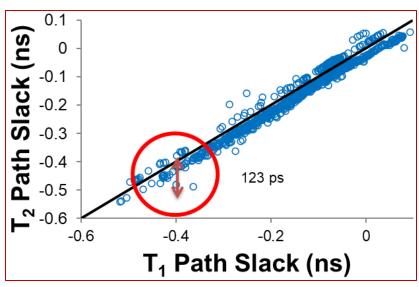
Tagline: "It's Just Physics!"



ML to Fix Timing Miscorrelation

UCSD, DATE-2014





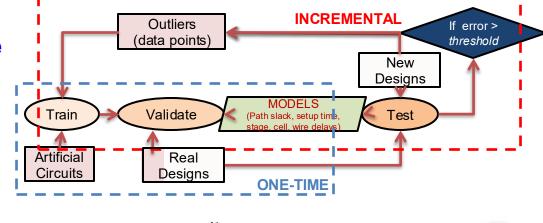
D = non-signoff timer (e.g., in P&R tool)
T = "golden" timer (e.g., signoff-qualified)

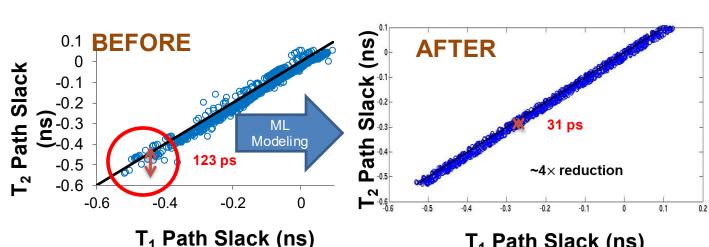
- Can you explain the slack miscorrelation?
- What is the impact of the miscorrelation?



"gt1-gt2": ML to Erase Miscorrelation

Can also erase miscorrelation between D, T



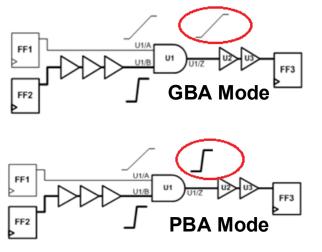


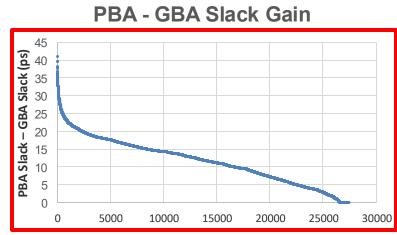
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15

T₁ Path Slack (ns)

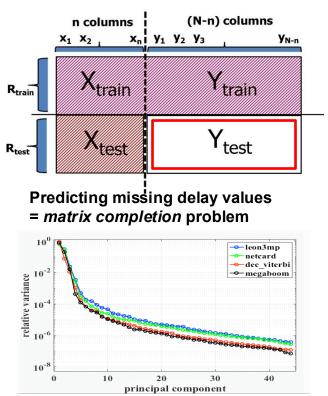
- PBA (Path-Based Analysis) is less pessimistic but more expensive than GBA (Graph-Based Analysis)
- ML to predict PBA timing from GBA timing
 - → Better and faster outcomes from P&R, Opt



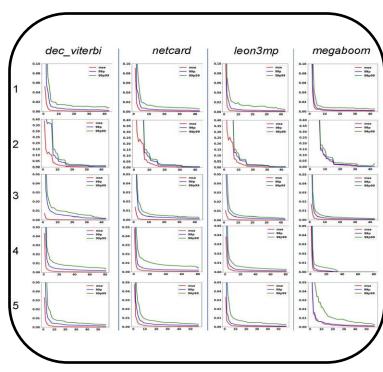


Endpoint Index

Timing at "Unobserved Corners" UCSD, DATE19



PCA: low-dimensional modeling task



STA at few *known corners* → predict timing at all *unknown corners*

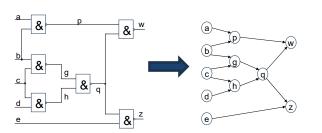
"It's Just Physics!"



A Call-Out: Semiconductor Design Data

Many types

- Formal specs
- HDLs
- Graphs
- Hierarchies
- Tabular data
- Images



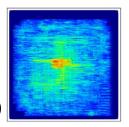
// Memory Write Block
// Write Operation: When we_0 = 1, cs_0 = 1
always @ (address_0 OF cs_0 OF we_0 OF data_0
OF address_1 OF cs_1 OF we_1 OF data_1)
begin: MEM_WRITE
if (cs_0 && we_0) begin
 mem[address_0] <= data_0;
end else if (cs_1 && we_1) begin
 mem[address_1] <= data_1;
end
end

IC data characteristics

- · Constantly changing
 - · technologies, designs, tools, ...
- Non-standard forms (even, "Tower of Babel")
- No massive redundancy
- Different shapes and scales
- No "Zipf's Law"



· Who owns, and who can use, what data?





Thanks: Igor Markov, Synopsys

A Call-Out: Semiconductor Design Data

Proprietary

- Designs
- Technologies
- Design methods
- EDA tools

Expensive

E.g., design flows take weeks to run

Closer to physics → harder to access

- Materials
- Equipment
- Process, Devices

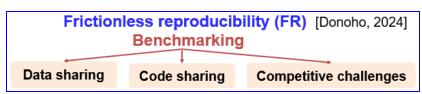


Semiconductor Design Data: Well-Lamented Gaps

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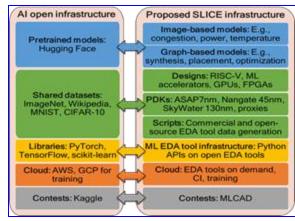


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https://slice-ml-eda.github.io/

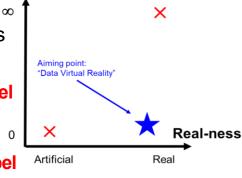
A Call to Action: Must Develop "Proxies" "if it can't be shared, need a proxy!"

Cost

Democratization Requires Proxies

- Proprietary PDK (Process Design Kit) data
- Commercial EDA End-User License Agreements
 - No benchmarking (!)
 - Copyrighted command language → Tower of Babel
 - report timing, report checks, report timing analysis, check timing, ...
 - Copyrighted report formats → more Tower of Babel
 - ^ and v vs. r and f, *** vs. === , ...
 - Can't share/upload ML data or models!

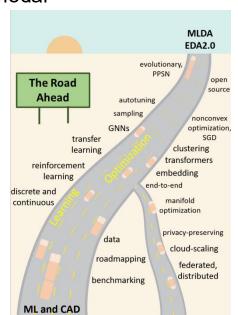
- Foundation Models will require Data, which will require Proxies!
 - Tech files, device models, "safe names", design enablements / tool setups, sharable results and metrics, ... ("journey of a thousand miles ...")





Er, EDA Foundation Models?

- Physics
- Logic
- Circuits
- Multimodal



Towards Foundation Models for Scientific Machine Learning: Characterizing Scaling and Transfer Behavior

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Wahid Bhimji wbhimji@lbl.gov Lawrence Berkeley National Lab Peter Harrington pharrington@lbl.gov Lawrence Berkeley National Lab

Dmitriy Morozov dmorozov@lbl.gov Lawrence Berkeley National Lab

> Amir Gholami amirgh@berkeley.edu ICSI, UC Berkeley

Kurt Keutzer keutzer@eecs.berkeley.edu UC Berkeley

Michael W. Mahoney mmahoney@stat.berkeley.edu LBNL, ICSI, and UC Berkeley

???

"Foundation Models for CAD/EDA", 202?

"ML for CAD/EDA", 2020 talk, paper

Possibilities With OpenROAD

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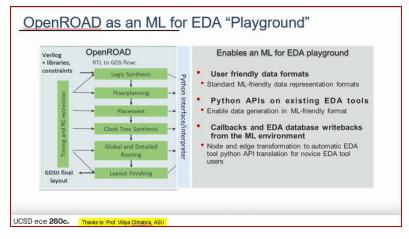
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Kahng ECE 260C SP2

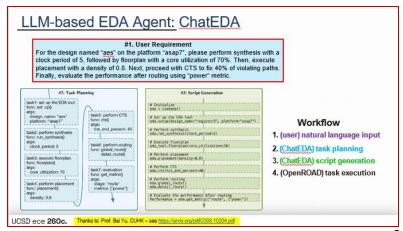
Have seen examples in lectures ...



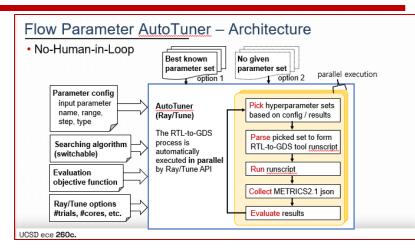
Lecture 1: CircuitOps (ASU, Nvidia)

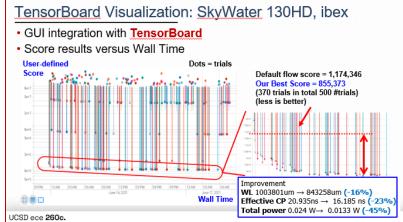


Lecture 1: ChatEDA (CUHK)



Lecture 1: AutoTuner (UCSD)





Lecture 1: METRICS (UCLA, UCSD)



METRICS2.1: Standard Naming!

https://github.com/ieee-ceda-datc/datc-rdf-Metrics4ML

- Problem: "Tower of Babel" (names, formats that are all different and proprietary)
- Solution: "METRICS"
- General and extensible
- · Syntax and semantics to support future addition of new metrics
- No ambiguity!!!
- · Any desired measurement must map to a unique METRICS2.1 metric
- · Every METRICS2.1 metric must map to a unique interpretation as a measurement
- Two-way mapping is crucial to avoid future confusion
- · Can also capture the same metric at different stages of the design flow
- Free, open and frictionless agnostic to EDA provider

UCSD ece 260c.

METRICS2.1 Examples

https://github.com/ieee-ceda-datc/datc-rdf-Metrics4ML

Sample metrics

Metric	Description			
timing setup wns	Setup worst negative slack in the design			
timingsetupwnsclock;clk_a	Setup worst negative slack for clock "clk_a" in the design			
timing_setup_wns_analysis_view:s	Setup worst negative slack for analysis view "slow"			
power_total	Total power consumption			
power leakage	Total leakage power			
power leakage clock	Total leakage power in the clock network			

Many applications: data for machine learning, CI/CD infrastructure for software quality, ...

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- Lecture 2: The PDN Chicken-Egg (Arm, UMN, UCSD)
- Critical cells want to be near each other.
 Supplying extra power to this hotspot will force the cells apart.
- Can ML predict the "convergence point"?

Template-based PDN Synthesis in Floorplan and Placement Using Classifier and CNN Techniques

Vidya A. Chhabria¹, Andrew B. Kahng², Minsoo Kim², Uday Mallappa², Sachin S. Sapatnekar¹, and Bangqi Xu²

¹University of Minnesota; ²University of California, San Diego

pdngen Improvements / Problem Statements

- Automatic connectivity rules (add_pdn_connect)
- Create rules automatically for defining grid connectivity based on layers used, instances present, etc.
- Edge connectivity
 - Enable the power grid to connect to edge ports for macros, right now
 this is only possible on pad cells and standard cells, for macros we only
 connect from the top which requires macros use lower metals for power
 and routing. This is not a huge problem in nodes with a large number of
 metal layers, but for sky130, ihp130, etc, this imposes a large penalty.
- Power grid reinforcement (eco power grid)
 - Later in most flows, after detailed placement, it may be possible to
 determine if additional wires are needed to ensure IR drop stays within
 limits based on the power requirements of those areas. On the opposite
 side, it maybe possible to prune the grid if IR drop is not an issue and
 free up routing resources. [cf. https://arxiv.org/abs/2110.14184]
- Automatic power grid definition (hard)
 - Given an IR drop goal, create a power grid that meets this requirement based on the parasitic resistances and estimated power (either from placement or good guesses)

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(What can/should the flow do with such a prediction?)

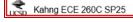
Other examples: useful skew vs. synthesis; multi-bit FF clustering vs. place/opt; ...

₹ UCSD

Lecture 13: BlobPlace (UCSD, POSTECH)

"Oracle" clusters – do they exist?

- "Oracle" clustering: hypothetical "optimal" clustering → generates "best" BlobPlace sol.
- "Is there a clustering of a netlist that can lead the "best" final placement ?" - Bodhi
- Spatial proximity ?
- Timing paths?
- Avoid hot spots ?
- Or ...?
- Amenable to ML if these clusters do exist!







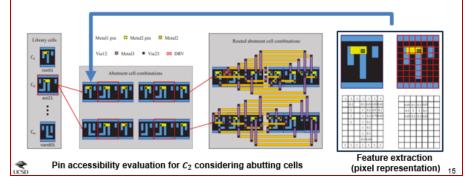


Examples: Lectures 7, 15

Lectures 7, 15: Pin Access (UCSD)

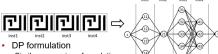
ML for Pin Access Analysis?

- Pin accessibility prediction (PAP): pattern recognition
 - Predict DRV occurrences due to bad pin accessibility [YuFCHT20ISPD]
 - . "Close the loop": use PAP for placement refinement
- Pin access generation : pattern generation
 - Can we learn the pin access pattern from well-established tools?
 - Try Generative Adversarial Network (GAN) or diffusion models ?
 - "Close the loop": replace the default pin access engine in OpenROAD



Cluster-Based Access Pattern Selection

- · Instance ordering
- Sort instances in the cluster according to x coordinate of the lower-left corner
- · Graph construction
- Vertex = access pattern
- Shortest path from s to t is the best pattern combination



- · Similar as previous formulation
- No iteration

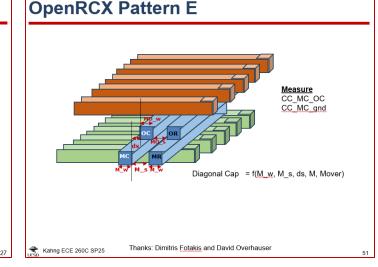
Kahng ECE 280C SP25 Thanks: Dr. Banggi Xu



 Lecture 12: RCX Model Creation (Athena/Nefelus)

(2.5D) Extraction Model Creation

- Determine the characteristics of the process from the foundry technology information (e.g. itf or ict file)
 - Layer specs, wire shape, dielectrics stack, WEE tables, Thickness tables, Rho tables, ...
- Create a large number of patterns of interconnect and transistor-level test structures
 - Interconnect-level test structures differ from transistor-level structures
- Run each pattern through a golden reference extractor
- Field solver requires proper shape, enlargements, thickness and dielectrics
- · Based on golden reference results, build extraction models
- Verify model results versus test results and design layouts



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Thanks: Dimitris Fotakis and David Overhauser

....

ML Target #1: "Virtual Buffering"

- Motivation: Netlist changes during ERC fix, timing fix (+ MBFF clustering, CTS, scan stitch, hold fix, antenna fix, etc.) how many netlists are there during P&R?!?
 - Topology changes require accesses to GPU memory → slowdown of GPU-accelerated placers
- Goal: Predict future netlist changes, account for them during placement to avoid "buffer surprise"
 - E.g., pre-allocate space that will be used by buffers, upsizes

Theme: Prediction for Prevention ("doomed runs" etc.)

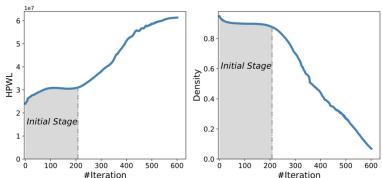
Comment 1: What is the ACCURACY requirement? E.g., costs of FP, FN

Comment 2: "Acting on a prediction changes what is being predicted, so BE CAREFUL WHAT YOU ASK FOR (from ML)" ("BCWYAF")



ML Target #2: Placement Initialization

- Analytical placement = nonlinear optimization, sensitive to initial solutions
- Goal: reduce #iterations, improve placement QoR



Theme: ML for Warm Start e.g., as in BlobPlace's seeded blob placement

Comment 1: What are challenges? representation, embedding, model architecture, training, scalability, generalization (transfer, fine-tuning, ...) across designs and technologies, data



ML Target #3: Handoffs at Interstices

- Co-evolutions, Co-optimizations are often at arm's length
- Interstices = opportunities for "Conditioning Magic" via ML

Co-optimizations

- Netlist Backend
- Hierarchy Floorplan
- Floorplan SP&R
- Synthesis P&R
- Place Route
- GRoute DRoute

"Magic"

- Netlist
- Netlist Partitioning
- Block shaping + boundaries
- Placement screens
- Route screens
- Route guides
- Corners + endpoint SDCs
- Constraints
- Tool/engine recipes

Placement Tomography

Netlist

Tomograph

Themes: Initialization, TAT, Sampling

from Chaos to Autotuning

+ Modern Compute (cloud, multicore)

Comment 1: Key concept = "Tomography"

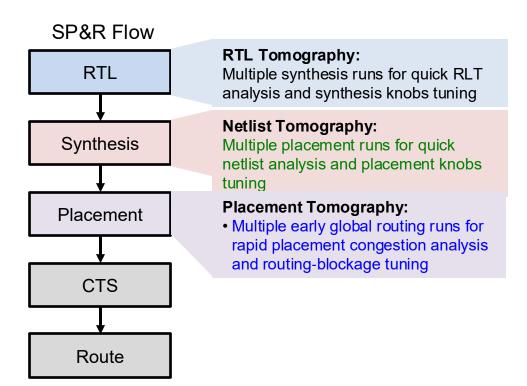
ISPD-2024 paper, slides



Concept of "Tomography"

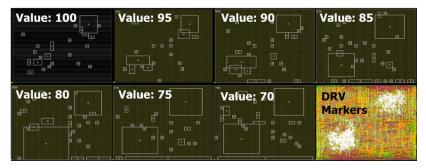
Tomography = multiple cross-sectional **views** of a solid object

 IDEA: Use many quick tool (GPU, proxy) runs and parallel execution to extract multiple views/reports in one unit of time



Placement Tomography (ICCAD24) Link

 Placement Tomography: Use routing blockage with varying routing-resource values → generate multiple congestion views



- ICCAD24 method has three main elements
 - DRVNet model: predicts layer-wise DRV hotspots
 - **BlkgComp** model: compares two routing blockage configurations

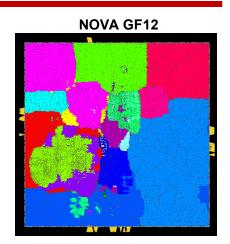
RL Agent: uses DRVNet, BlkgComp to sample routing blockages for #DRVs

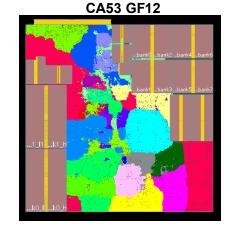
mitigation

Tech	Design	Method	#DRV	WL	WNS	TNS	Power
				(mm)	(ns)	(ns)	(mW)
GF12	NOVA	No Blkg	1,242	1.000	-0.562	-782	1.000
		Human	403	0.994	-0.655	-707	0.994
		Ours	442	0.990	-0.475	-186	0.994
	LDPC	No Blkg	1,739	1.000	-0.583	-632	1.000
		Human	345	0.990	-0.472	-604	0.980
		Ours	346	0.990	-0.438	-717	0.980
	CA53	No Blkg	3,316	1.000	-0.369	-1,495	1.000
		Human	942	0.992	-0.615	-783	0.986
		Ours	902	0.991	-0.454	-696	0.986

Can Also Try Netlist or RTL Tomography!

- Multiple views of a netlist
 - Slightly perturb the floorplan or SDC
 - Run each through place or placeopt
- Analyze placement runs
 - Instances in congested regions
 - Failing endpoints
- Set available placement knobs
 - Placement blockage
 - Cell padding
 - Soft guides
 - •
- How about RTL tomography?



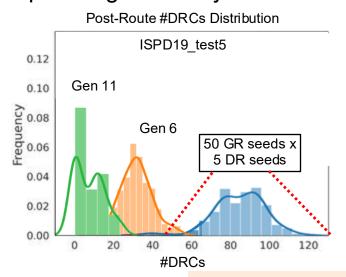


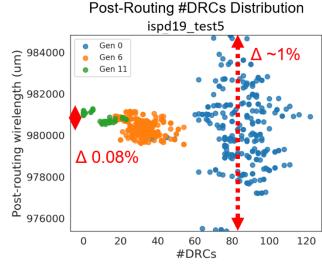
ML Target #4: Evolution in Optimizers

- Example/Observation: global routing solution (route guides) sets the detailed router's initial solution space
- Can we create "good" GR solutions from "not-good" solutions?

• UCSD "genetic / adaptive multi-start metaheuristic" using patching-based hybridization

Post-Routing #DRCs Distribution





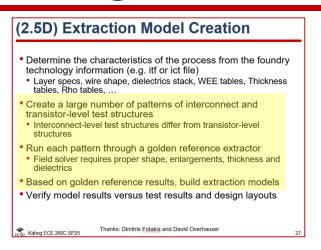
AMS, CAMS

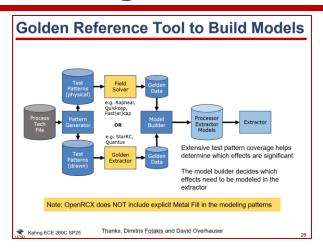
* Kahng ECE 260C SP25

Theme: "Parallel Problem Solving from Nature"

Learn-to-Optimize, Adaptive Learning, Multi-fidelity BO, Evolutionary Optimization, Reinforcement Learning, ... (+ metaheuristics)

ML Target #5: "The Analog Hole"





- Field solvers, golden tools, patterns, ... Can we skip this?
- Idea: build OpenRCX table from massive post-P&R def, spef

Theme: "It's Just Physics" could mean "No More Secrets" !!!

Comment 1: There is massive data in standard tool reports, outputs

Comment 2: ML can help "bypass" PDK data for material, device, BEOL ...



AI, ML (+ OpenROAD): Some Takeaways

What's Different (and Difficult)

- Layers of hierarchy, abstractions and boundaries in any given instance of "design problem"
- "Construct by correction" in chained chaotic, discrete (+ high-stakes) optimization (how to use predictions?)
- Extreme multiscale in space, time
- Infinite variety of possible layouts, shapes, constraints, designs
- Data is unavailable \rightarrow proxies needed (+ privacy-preservation, obfuscation, trust/verification etc.)

Many Opportunities

- Full-stack proxy data generation will unblock many next steps! ("#1 with a bullet")
- "Stubs and supports" for physical modeling and design of digital twins, 3D heterogeneous integration
- Fast and accurate optimization of multiphysics behavior without detailed PDE simulations
- Leverage datasets, insights, models developed for other engineering and design domains?
- Pathfinding (from materials to systems) into the "beyond-everything" future
- [Opportunities in RTL-to-GDSII: see Lecture Slides, Example ML Targets, and Themes!]

Trajectories of Connecting Silos

- Materials + Mechanical sciences + EE/CS + Optimization + AI
- Electrical-Thermal → Mechanical → Aging/Reliability/Noise → ...
- Digital (HW + SW) → Analog → Mechanical → (hydraulic, thermal, magnetic, fluidic) → ...

