



# AI: Trailblazing the Future: Innovative Chip Design in the era of Pervasive AI

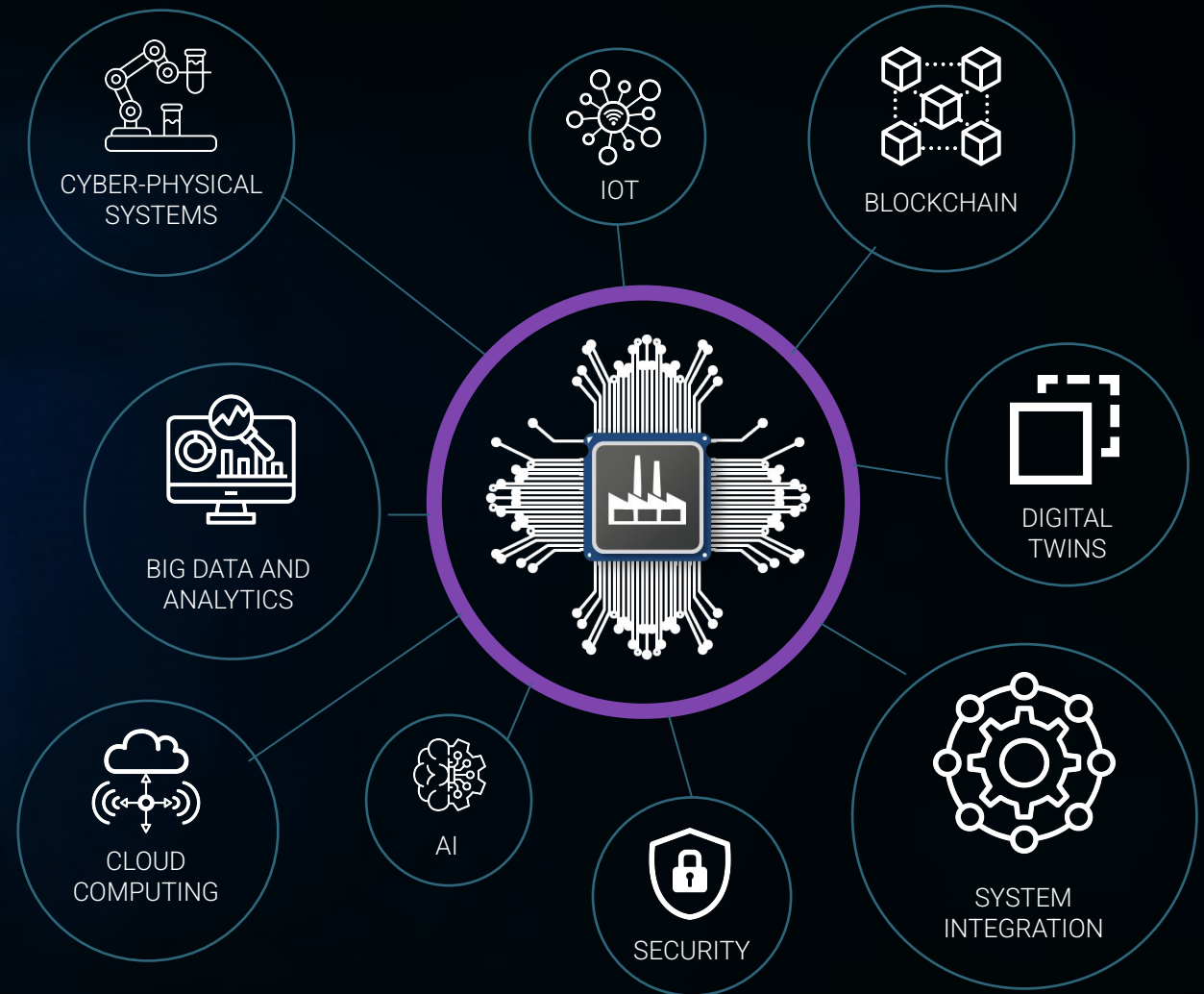
**Sudipto Kundu**

R&D Scientist, Technology Product Group

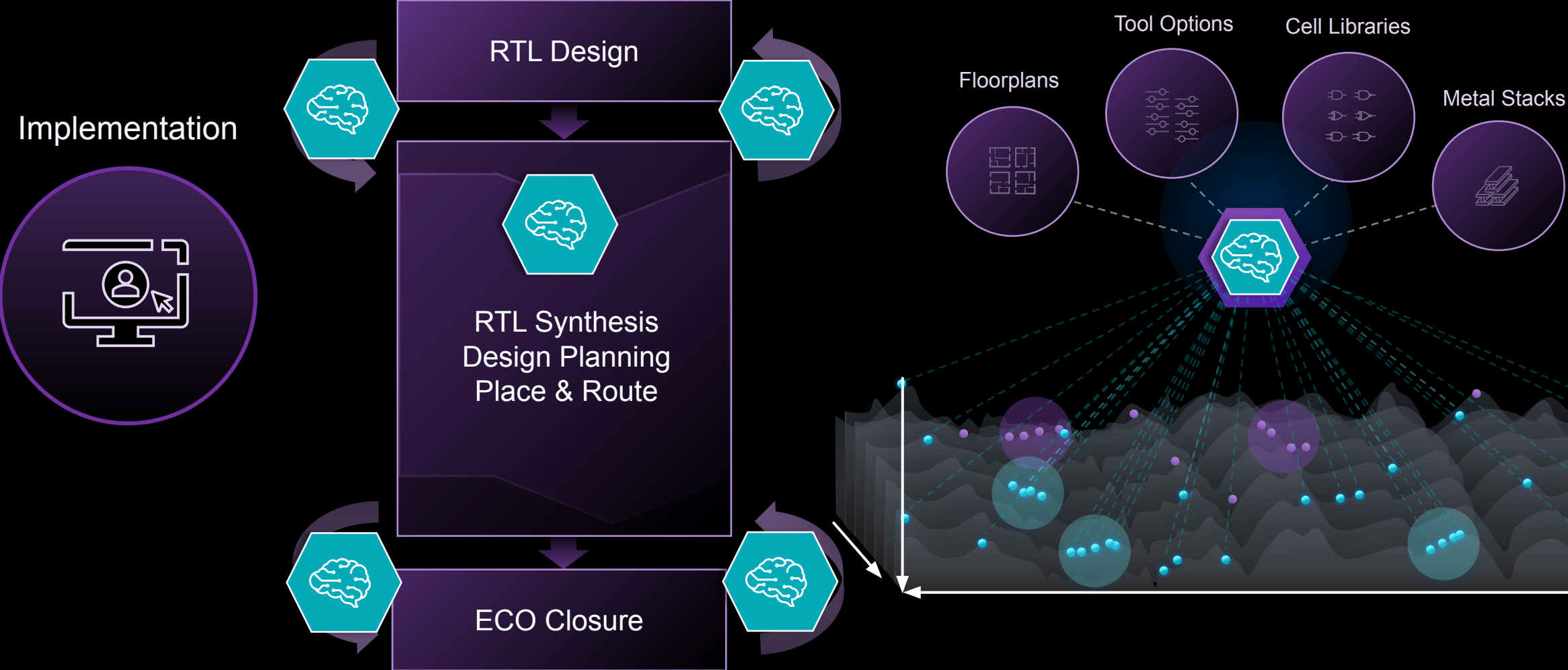
Mar, 2025

# The Fourth Industrial Revolution – Powered by Silicon

Complexity of Chip Design growing exponentially



# EDA Workflow Offers Opportunities for AI



# Chip Design Workflows Have Large Search Spaces

Architectural Design

Structural Design

Logic Design

Layout Design

System Architecture

Design Capture


Verification

Implementation

Signoff


Test & Silicon Lifecycle Mgmt.

Silicon Manufacturing



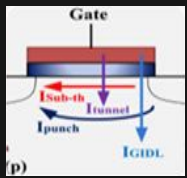
Performance

- Frequency, WNS, TNS,...
- CTS latency,...



Area

- Die area, std cell area,...
- Area by cell VT,...



Power Leakage

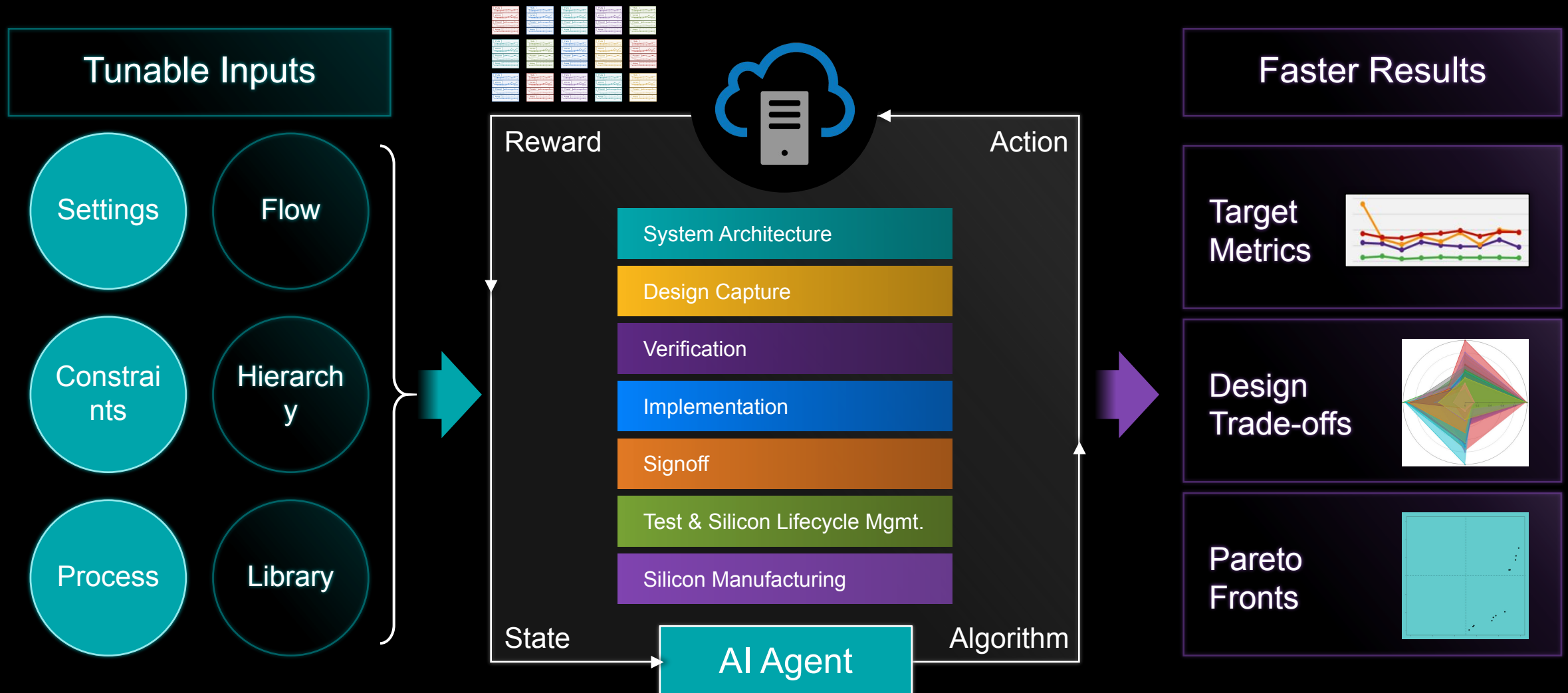
- Leakage
- Leakage by cell type, by VT,...

Source : SV SNUG '23 Proceedings

Example :  $10^{25}$  for latest Arm CPU

## Can AI Help?

# Digital Implementation: Applying AI to Navigate Chip Design Solution Space



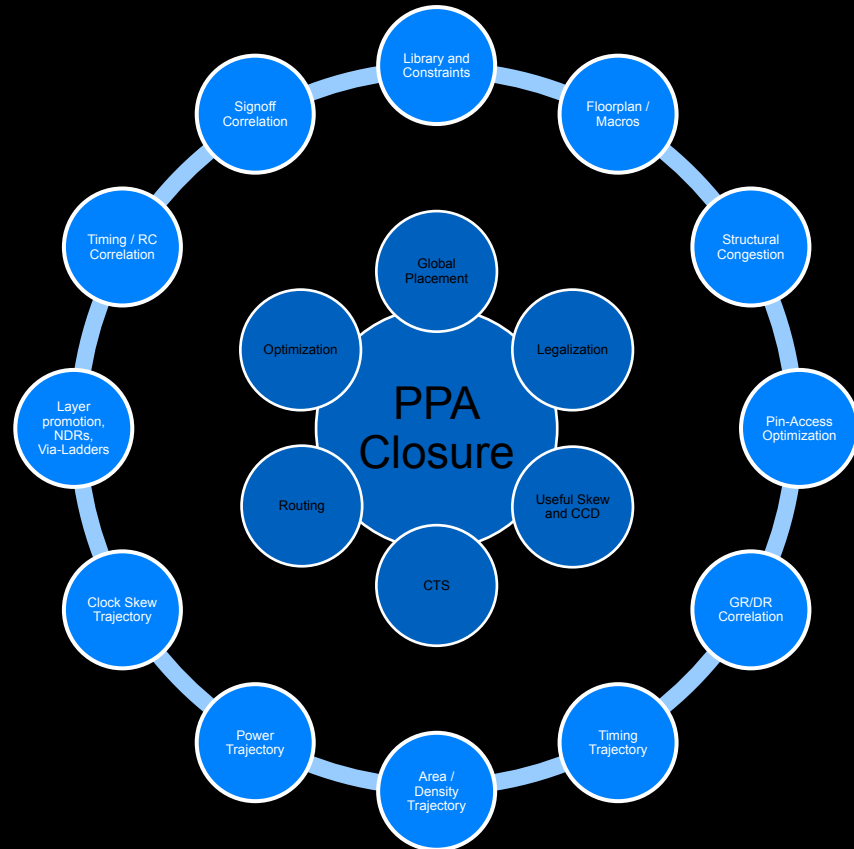
# What's next in AI for EDA ?

## EDA R&D perspective

- Design Learning Driven Auto-Convergence
  - Graduate from point AI/ML applications
  - EDA tools become a fully learning-driven system to drive end-end convergence
  
- Auto-convergence to target different user personas
  - “Virtual” designers
  - “Green” designers
  - “Expert” designers

# AI inside Physical Design Subsystems

## EDA R&D perspective

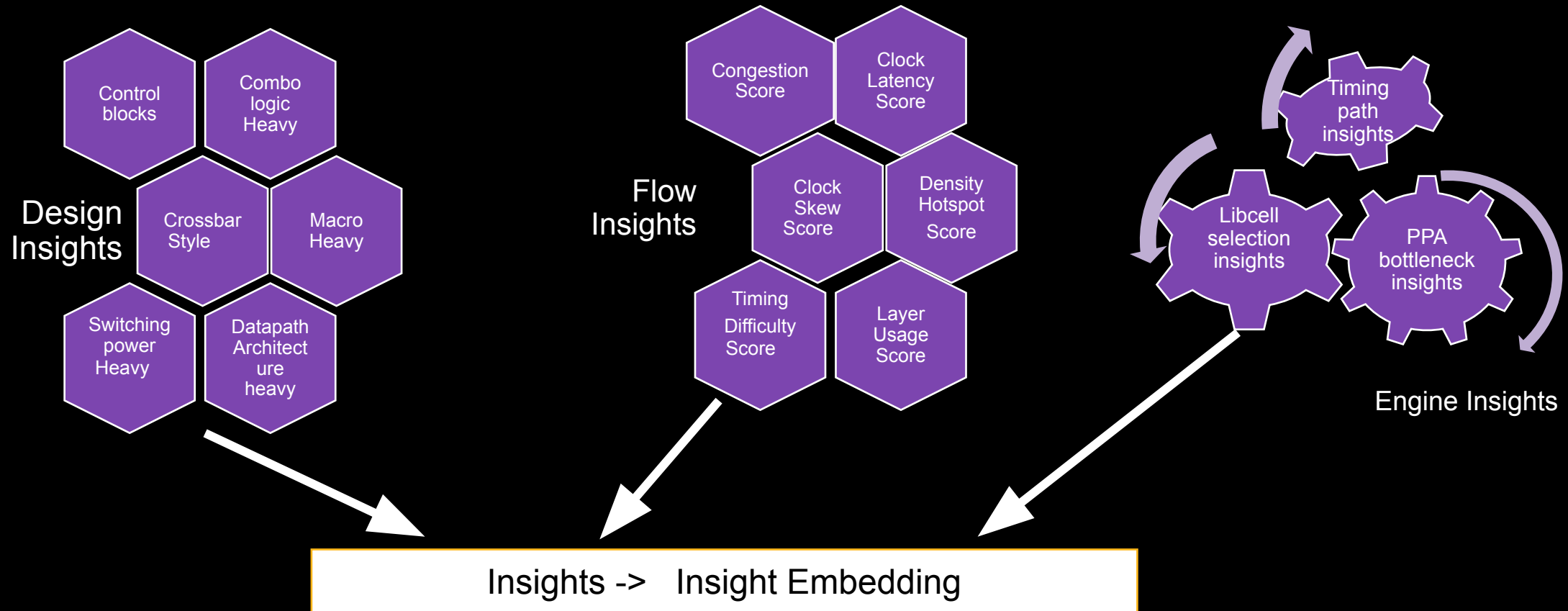


- Complex workflow with many subsystems
  - ❖ Same engine runs multiple times.
  - ❖ Opportunity to learn from initial invocation
  - ❖ Learning from one subsystem pass down to next subsystem.
  - ❖ Auto discovery of trend and patterns
  - ❖ Self recovery of PPA trajectory anomalies
- Pilot Learning using small sample execution
  - ❖ Formulate small problem and build knowledge Model
  - ❖ Example-1 : Fast solver iteration in placement
  - ❖ Example-2: Fast netlist optimization on top timing paths
  - ❖ Leverage ML models for parameter optimization within the flow

# Deep Insights – Catalysts for AI in EDA

EDA R&D perspective

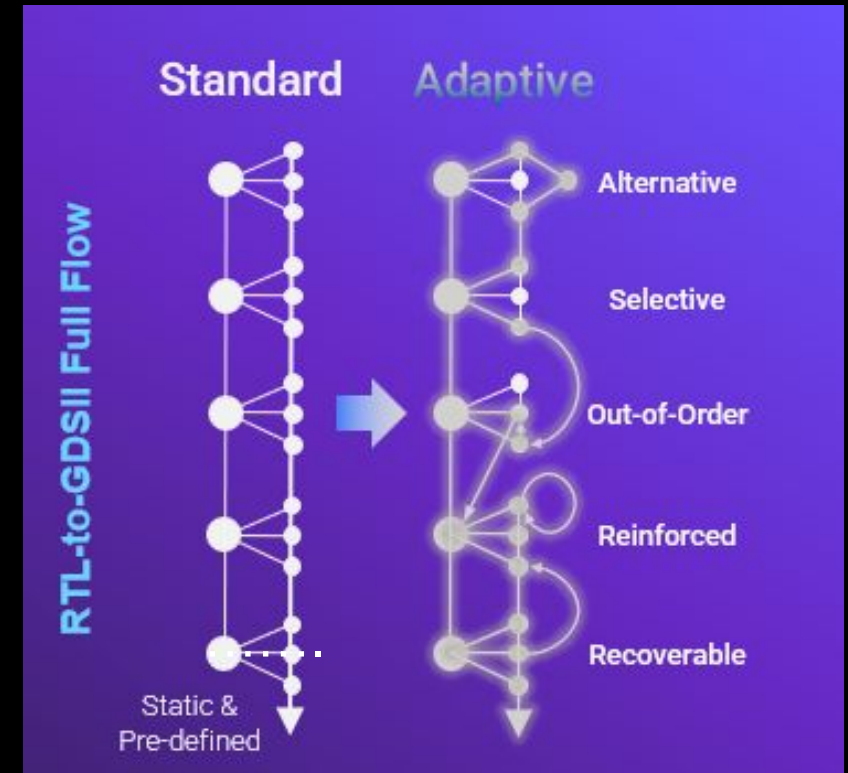
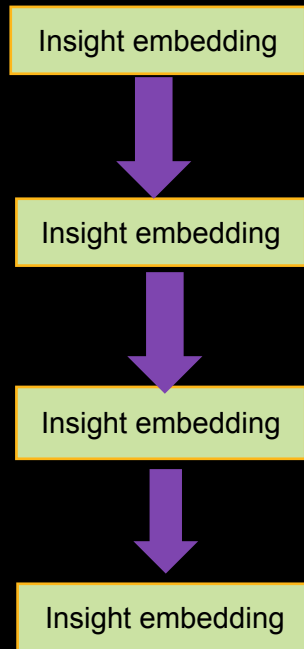
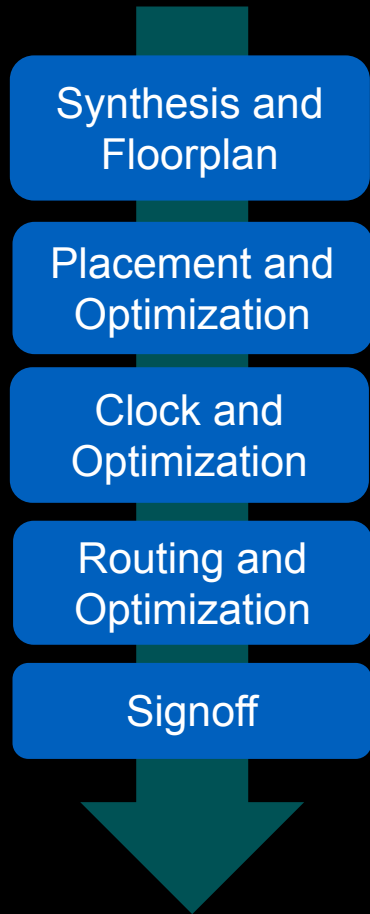
- Build deep netlist insights to drive AI recommendation





# Design Insight based Physical Design Flow

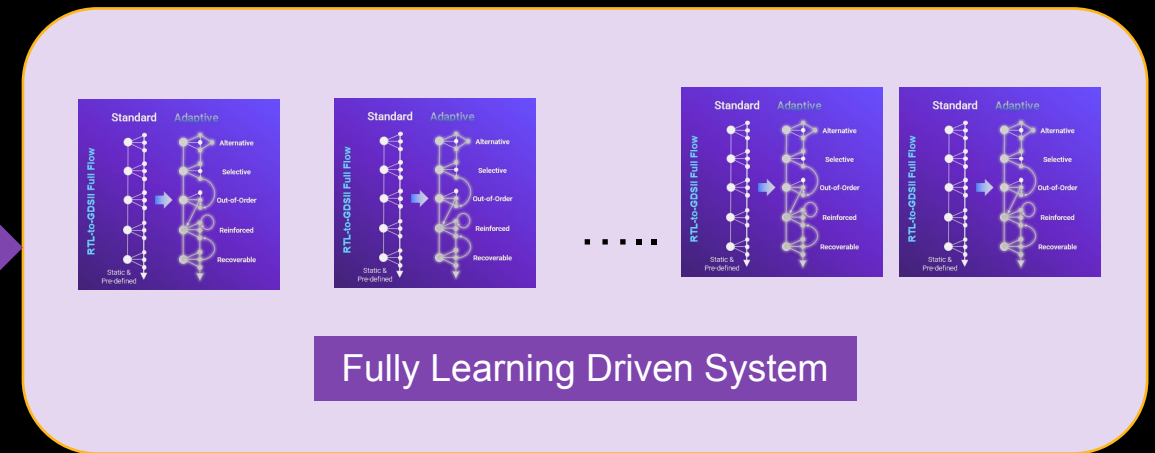
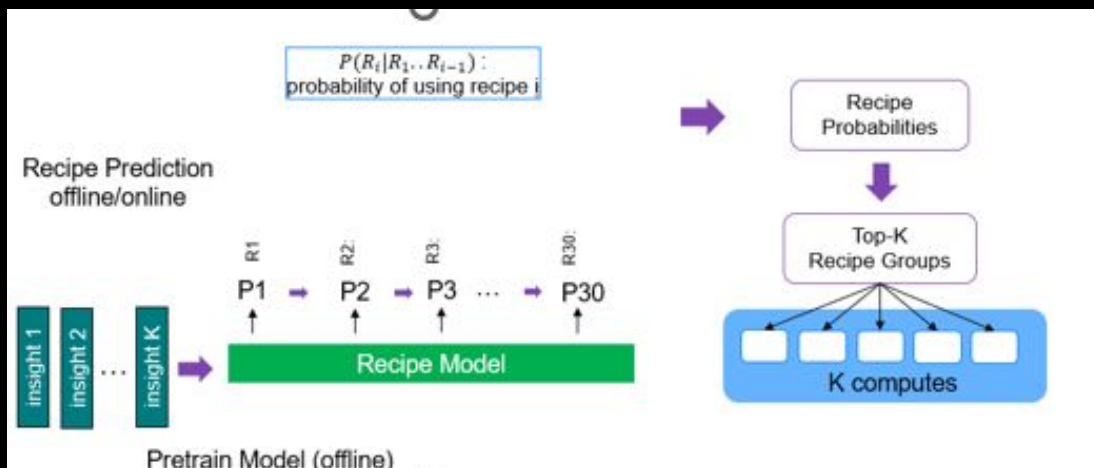
Transitioning from Black Box AI



Insight Embedding -> Action Prediction

# Design Insight Assisted Solution Space Navigation

- Train offline AI models for Top K recipe group prediction
  - ❖ Driven by insight embeddings.
- Given apriori run with insights -
  - ❖ predict group of recipes for exploration.



# Experimental Result

## Total-Power Benefit

Design	Default Baseline	Human Baseline	Offline Prediction	Improvement ( $\Delta\%$ )
D1 (3nm)	49.67	47.08	42.93	13.57%
D2 (3nm)	55.45	53.04	49.18	11.31%
D3 (2nm)	2076.16	2065.07	2058.80	0.84%
D4 (2nm)	437.36	431.08	428.54	2.02%
D5 (5nm)	71.12	68.62	64.81	8.87%

- ❖ Insight Inspired Recipe model shows superior PPA over manually tuned baseline

# Summary

## Key Takeaways

- AI everywhere : Within a single run, across parallel runs
- Learning driven subsystems generate deep design, flow and engine insights.
- Pilot learning within run using small samples within subsystem domain.
- Insights inspired AI models to generate action recommendation within run and across runs.



**AI,**  
The Only Way  
Forward

**SYNOPSYS**<sup>®</sup>

Thank you