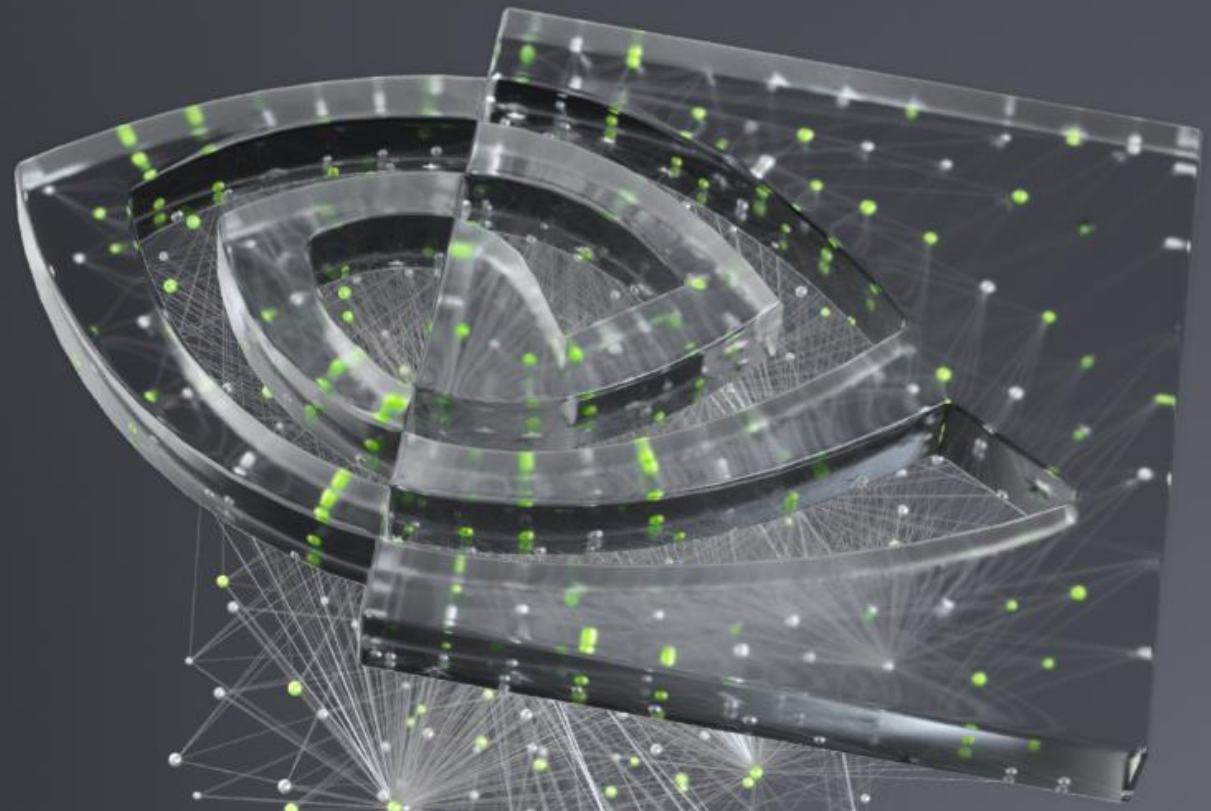


EMBRACING MACHINE LEARNING IN EDA

TRADITIONAL ALGORITHMS VERSUS MACHINE LEARNING APPROACHES

ISPD 2022

Haoxing (Mark) Ren

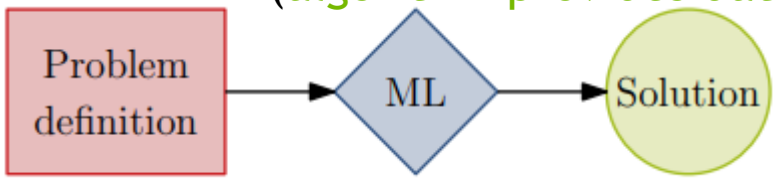
COMPARE ML AND EDA ALGORITHMS

	EDA Algorithms	ML
	Placement, route, synthesis, CTS, simulations, etc	Supervised, unsupervised, reinforcement learnings, etc
Pros	Known optimality, robust, less training data, good interpretability, Solve an abstracted problem efficiently	GPU parallel computing, easy to design, end-to-end training on complex problem, Solve any problem by learning from its data
Cons	Oversimplification of dynamic, complex problems	Rely too much on data, not leveraging the mechanics of the problem

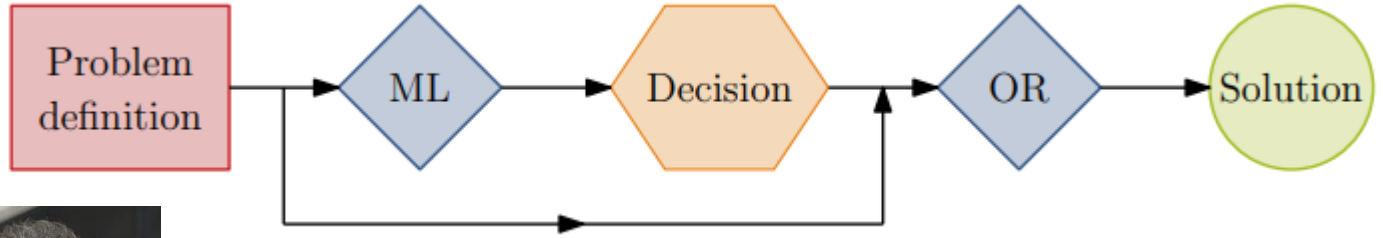
Integrate ML with EDA Algorithms, but how?

ML FOR COMBINATORIAL OPTIMIZATION METHODOLOGY

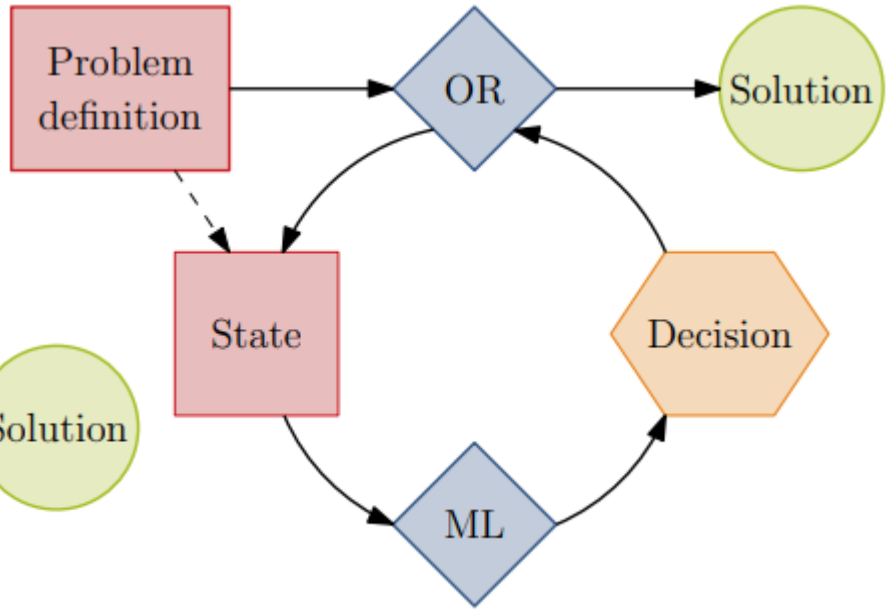
1. End-to-end learning
(algorithm provides data only)



2. Learning to configure algorithms
(coarse-grain integration)

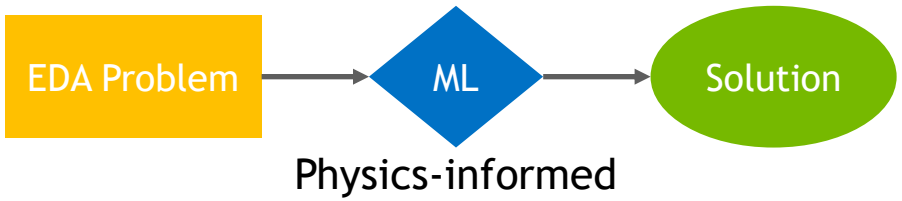


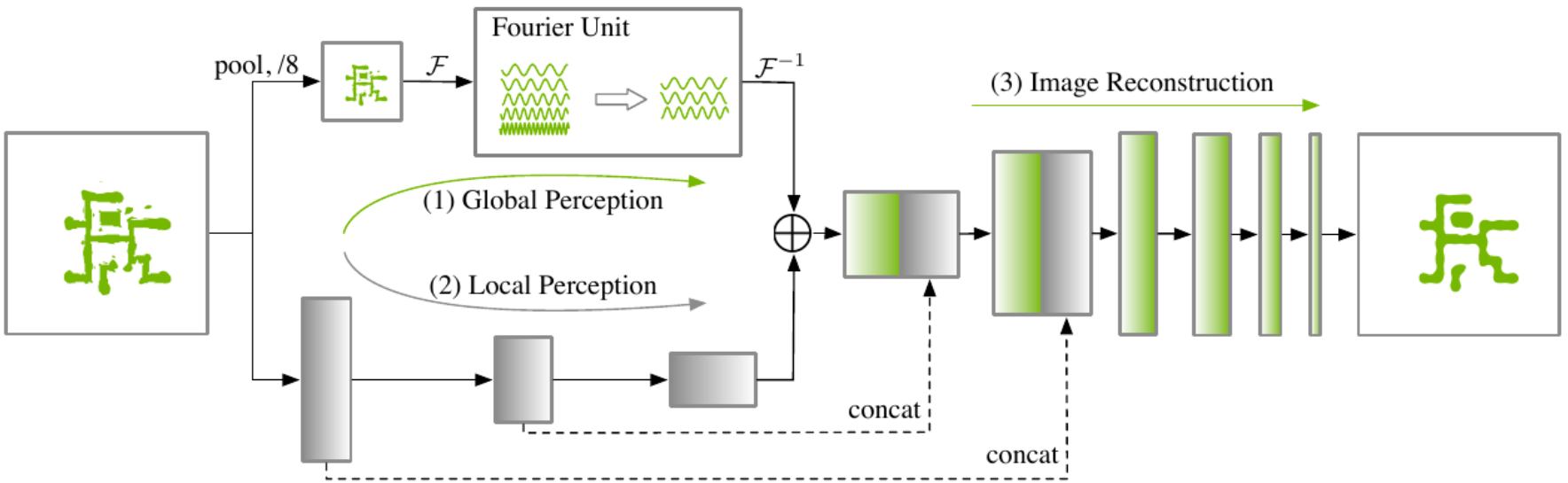
3. Machine learning alongside optimization algorithms
(fine-grain integration)



Yoshua Bengio et al, Machine Learning for Combinatorial Optimization: a Methodological Tour d'Horizon, 2020

END-TO-END LEARNING WITH INNER MECHANICS

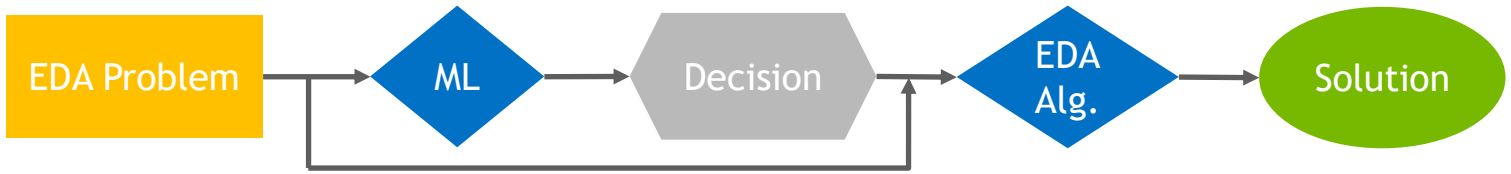




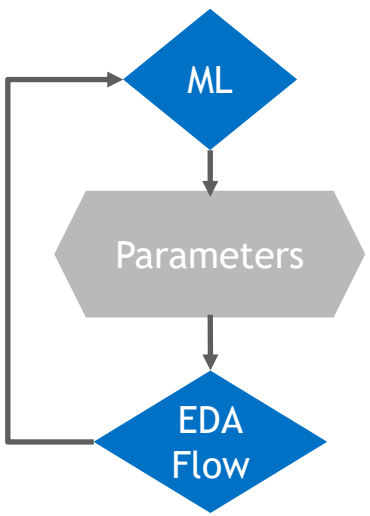
Haoyu Yang et al, Generic Lithography Modeling with Dual-band Optics-Inspired Neural Networks, DAC 2022

COARSE-GRAIN INTEGRATION

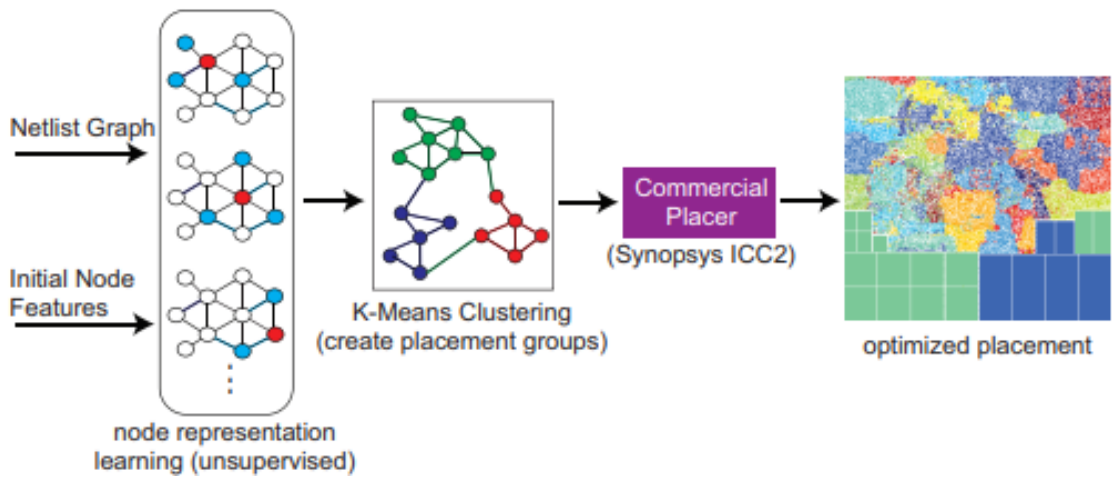
Learning to configure EDA algorithms



Flow parameter tuning



Placement clustering

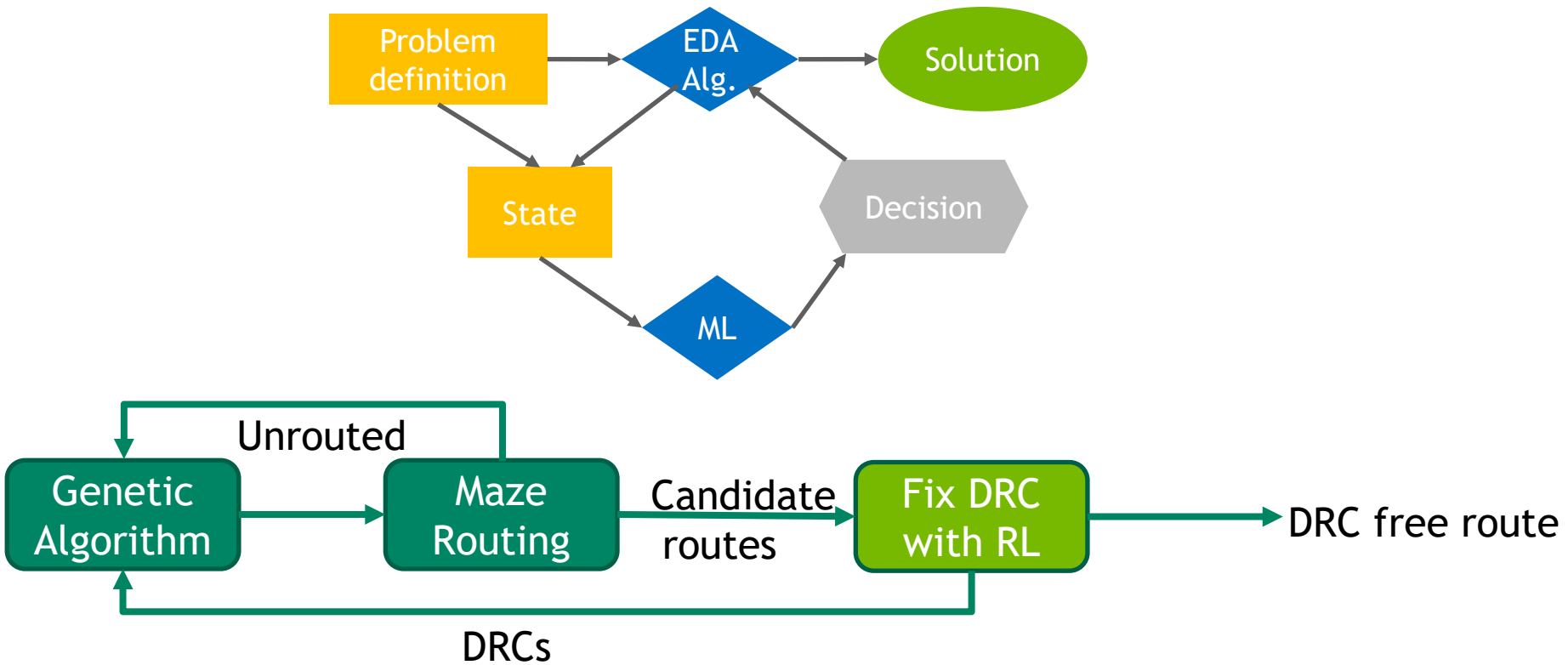


Z. Xie et al., "FIST: A Feature-Importance Sampling and Tree-Based Method for Automatic Design Flow Parameter Tuning", DATE 2021

Yi-Chen Lu et al., "The Law of Attraction: Affinity-Aware Placement Optimization using Graph Neural Networks", ISPD 2021

FINE-GRAIN INTEGRATION

ML alongside EDA algorithms

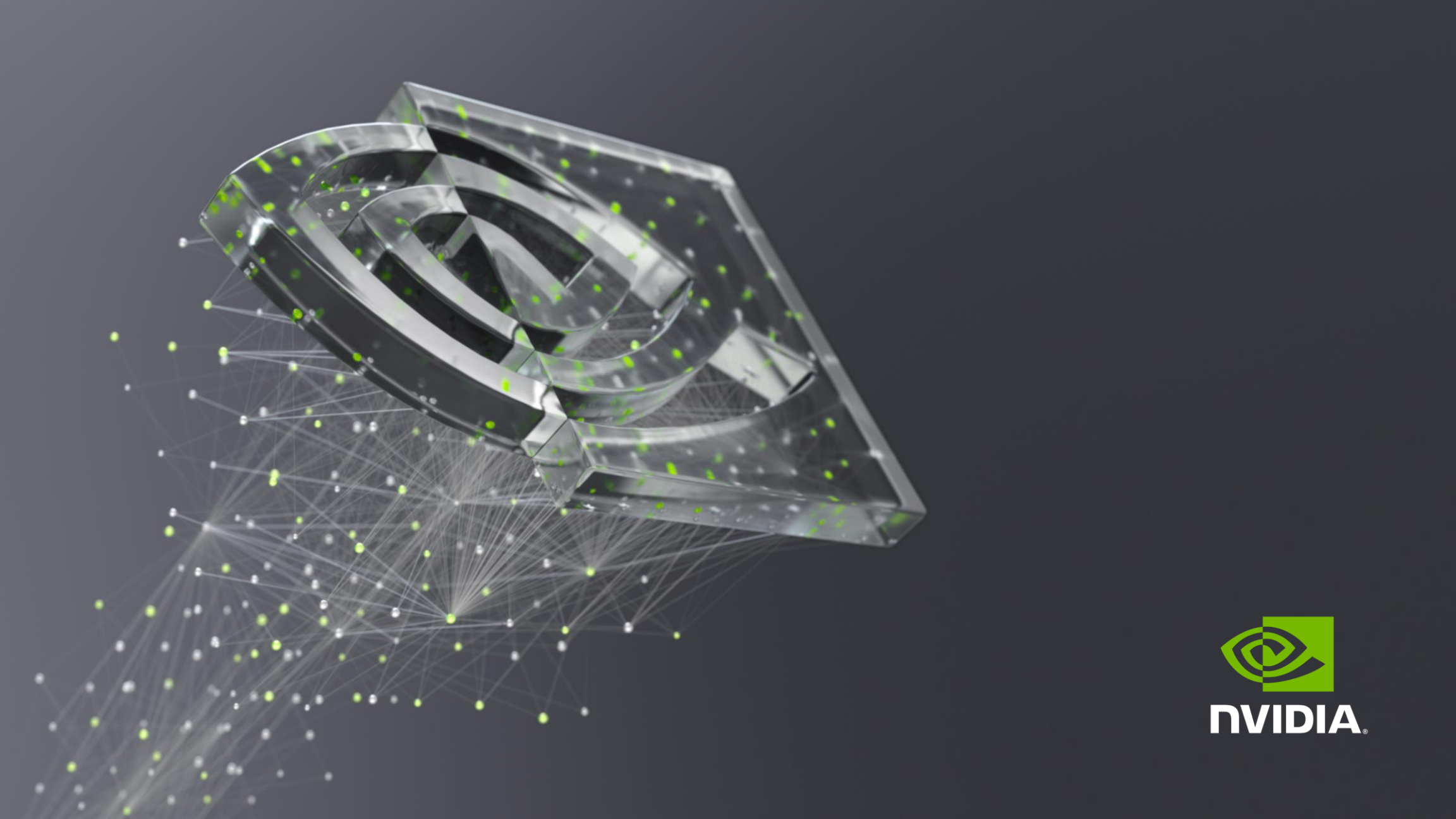


Ren et al, Standard Cell Routing with Reinforcement Learning and Genetic Algorithm in Advanced Technology Nodes, ASPDAC 2021

SUMMARY

ML and EDA algorithms both have advantages and disadvantages.

Three methodologies to integrate ML with EDA algorithms.


NVIDIA