NSF IUCRC
Alternative Sustainable &
and Intelligent Computing

D4: Automatic Routability Predictor Development Using Neural Architecture Search

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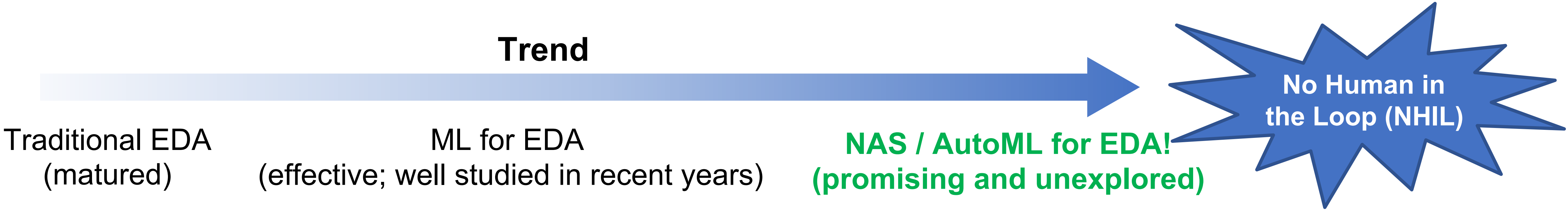
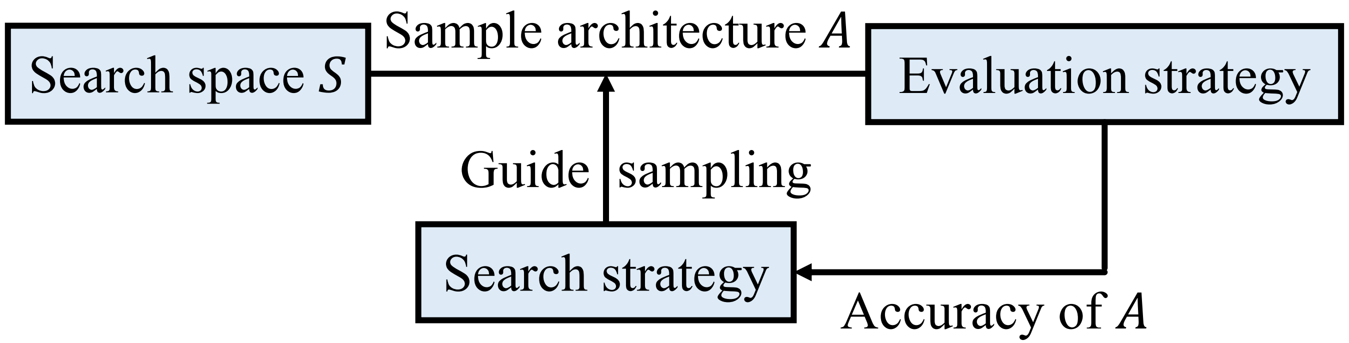
Motivation: Why NAS / AutoML for EDA

- Machine learning (ML) for EDA
  - Enable early-stage predictions
- However, the development of ML models still:
  - Require strong ML expertise and tremendous engineering effort
  - Prolong the development cycle of the ML-based models in EDA
- Neural Architecture Search (NAS) / AutoML for EDA
  - Enable design automation of ML models without human interventions
  - Outperform state-of-the-art manual CNN designs in computer vision



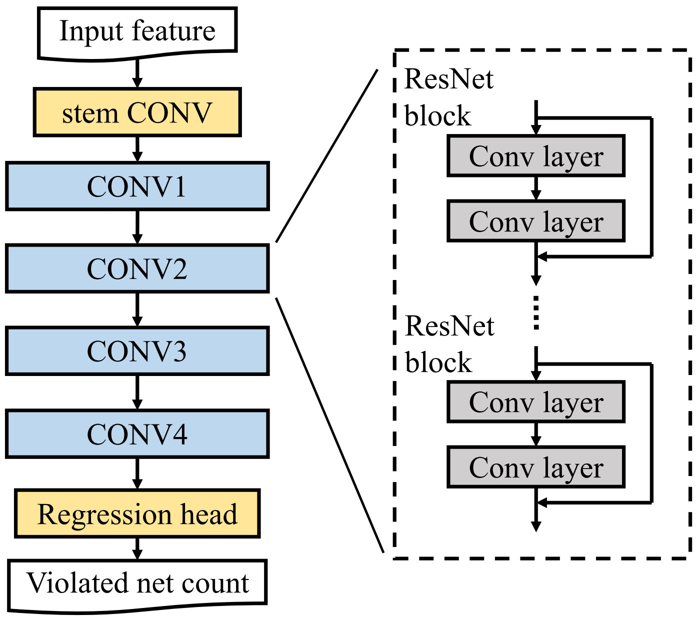
Preliminary: NAS and AutoML

- Neural Architecture Search (NAS) aims to automatically explore efficient yet high-performance CNN models without human interventions.
- It includes three major components:
  - Search space: the candidate architectures that can be explored in NAS.
  - Evaluation strategy: the way to evaluate the candidate architecture in the search space.
  - Search strategy: the method adopted to explore the search space.

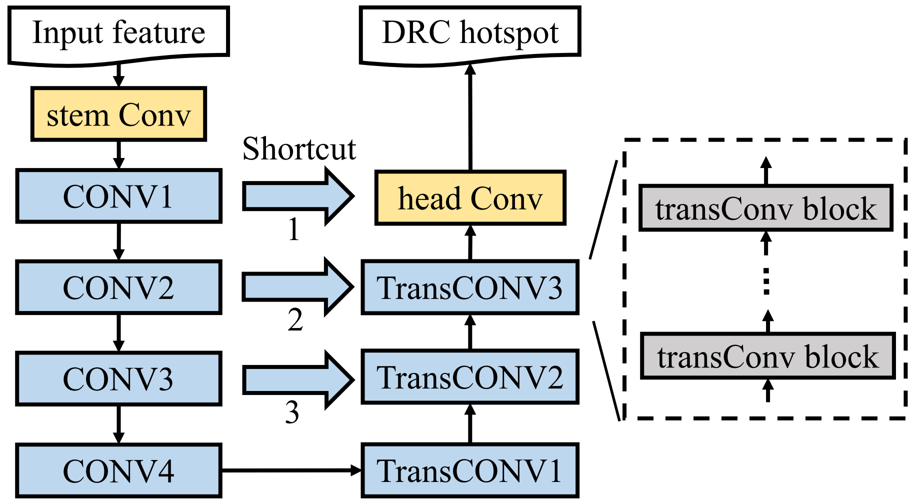


Search Space for Violated Net Count Prediction & DRC Hotspots Detection

- We search for the hyperparameters in all CONV blocks.
- We further insert 3 searchable TransCONV blocks and 3 optional shortcut connections for DRC hotspots detection.



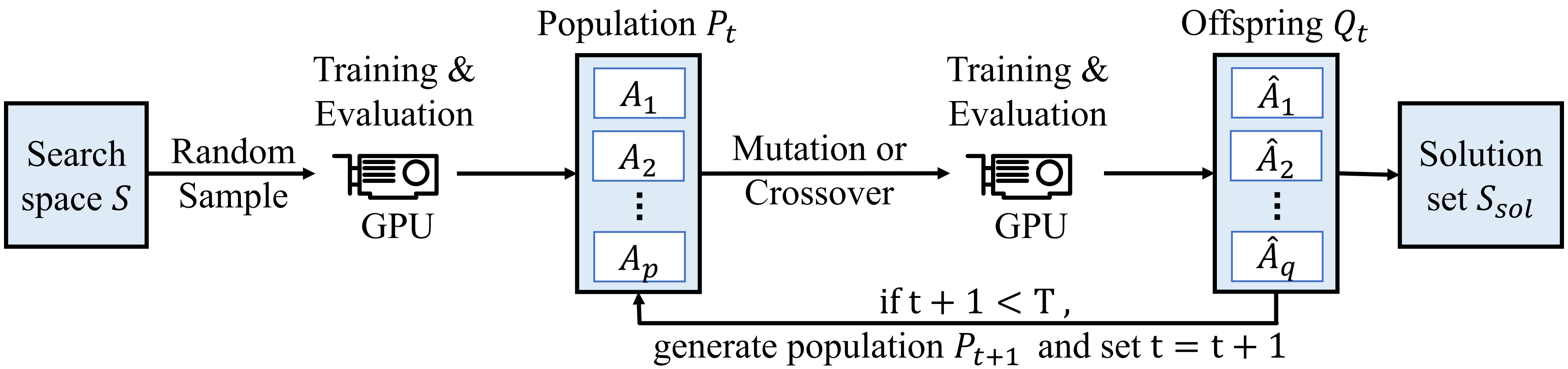
Space for violated net count prediction



Space for DRC hotspots detection

Evolutionary-based Search Strategy

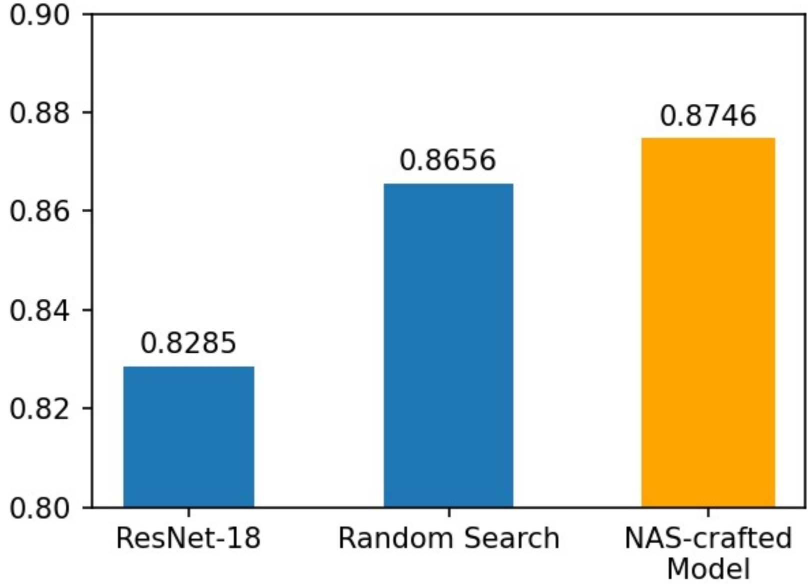
- The flow of evolutionary-based search strategy
  - Initial the first population by random sampling
  - Mutate and crossover to generate offspring
  - Update the next population from the population and offspring
  - Terminate after T iterations



Violated Net Count Prediction Results

- Our NAS-crafted model outperforms both ResNet-18 (ML baseline) and Random Search (NAS baseline)
- It also improves accuracy of the best layout, reducing designers' effort to reach the best solution.

Kendall's τ in cross-validation



Rank of the best layout in prediction

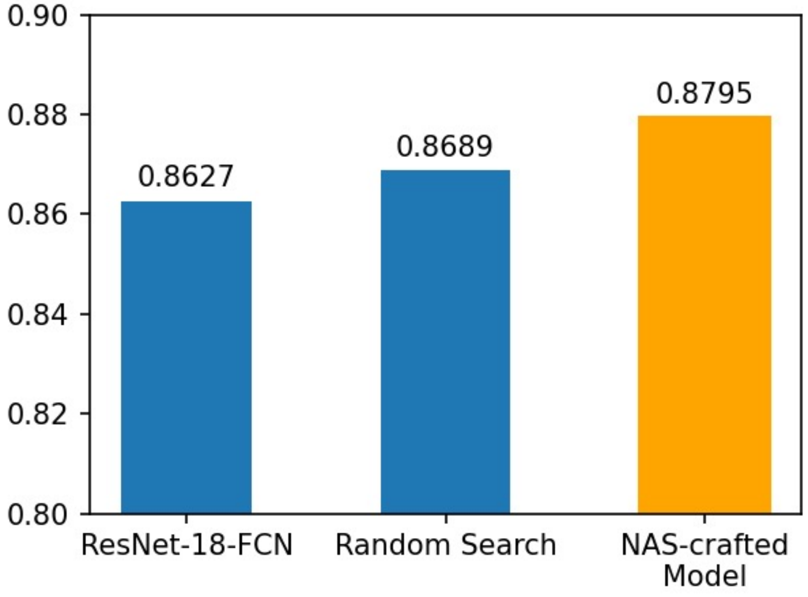
Design	#Nets	ResNet-18	**Searched**
usb_phy	835	1	**1**
des	1 K	2	**1**
wb_dma	6 K	4	**4**
aes_core	34 K	19	**9**
b18	105 K	4	**3**
Avg all 61	20 K	4.1	**3.1**

Outperform by 1.0 position!

DRC Hotspots Detection Results

- Our NAS-crafted model outperforms both ResNet-18-FCN (ML baseline) and Random Search (NAS baseline)
- It yields improvement for any design in our target dataset.

ROC-AUC in cross-validation



Hotspots detection accuracy (FPR=10%)

Design	#Nets	ResNet-18-FCN TPR	**Searched TPR**	ResNet-18-FCN AUC	**Searched AUC**
usb_phy	835	23.9%	**27.5%**	0.719	**0.775**
des	1.5 K	46.1%	**56.5%**	0.851	**0.887**
wb_dma	6 K	51.5%	**53.8%**	0.801	**0.818**
aes_core	34 K	80.9%	**86.2%**	0.809	**0.956**
b18	105 K	40.6%	**43.0%**	0.768	**0.790**
Avg all 61	20 K	46.0%	**50.5%**	0.809	**0.832**

4.5% higher

2.8% higher

Summary of Research Outcome

- **What we present**:
  - An evolutionary-based NAS method that automates the design of ML models for **routability** prediction
- **Result: higher accuracy & efficiency**
  - For violated net count prediction, **5.6% higher Kendall's $\boldsymbol{\tau}$** than the ResNet-18
  - For DRC hotspots detection, **1.95% higher ROC-AUC** than the ResNet-18-FCN
  - Developing CNN models with **0.3 days** for the whole search process
  - **Promising recent results** on larger search space & automatic feature selection
- **Our outcome:**
  - Paper [pdf] submitted to DAC 2021
  - Project has been released [code*]

* Email us for full code access: zhiyao.xie@duke.edu