Stronger NAS with Weaker Predictors

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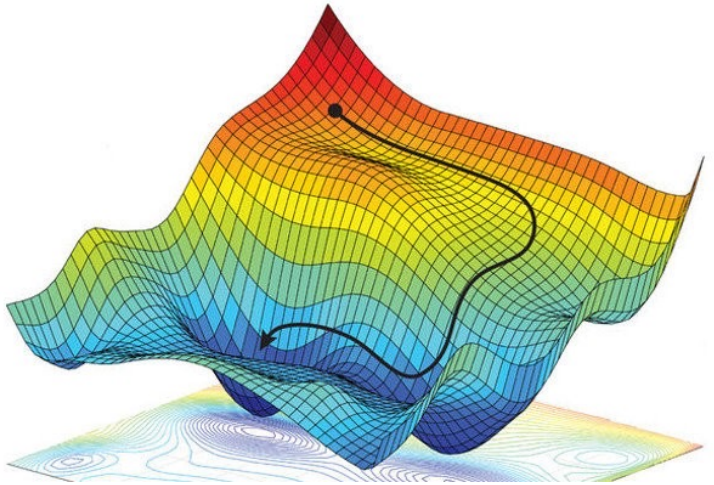
Neural Architecture Search (NAS)

- **Objective of Neural Architecture Search**

Find the neural architecture x^* with the highest performance $f(x)$ given the search space X

$$x^* = \underset{x \in X}{\operatorname{argmax}} f(x)$$



$f: X \rightarrow P$

Previous NAS Approaches

- **A naïve solution**
  - Estimate the performance mapping $f(x)$ through the full search space
    - *prohibitively expensive*
- **Predictor-based NAS [1]**
  - Learns a proxy predictor $\tilde{f}(x)$ to approximate $f(x)$ by sampling some architecture-performance pairs
    - *significantly reduces the training cost.*
  - In general, predictor-based NAS can be re-cast as a bi-level optimization problem:

$$x^* = \underset{x \in X}{\operatorname{argmax}} \tilde{f}(x|S),\ s.t.\ \tilde{f} = \underset{S, \tilde{f} \in \tilde{F}}{\operatorname{argmin}} \sum_{s \in S} L(\tilde{f}(s), f(s))$$

[1] Wei Wen, Hanxiao Liu, Hai Li, Yiran Chen, Gabriel Bender, Pieter-Jan Kindermans "Neural Predictor for Neural Architecture Search." *In European Conference on Computer Vision (ECCV), 2020.*

Previous: Predictor-based NAS

Sampling stage:

$$S \subset X$$

Learning stage:

$$x^* = \arg\max_{x \in X} \tilde{f}(x|S)$$

$$\text{s.t. } \tilde{f} = \arg\min_{S, \tilde{f} \in \tilde{\mathcal{F}}} \sum_{s \in S} \mathcal{L}(\tilde{f}(s), f(s))$$

Proposed: WeakNAS

Sampling stage:

$$\tilde{P}^k = \{\tilde{f}_k(s) | s \in X \setminus S^k\}$$

$$S^{k+1} = \{s_i\}_{i=1}^{M} \cup S^k,$$

$$\text{where } \tilde{f}_k(s_i) \in \text{Top}_N(\tilde{P}^k),$$

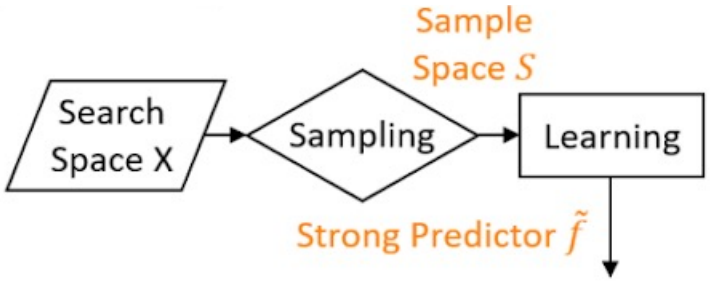
Learning stage:

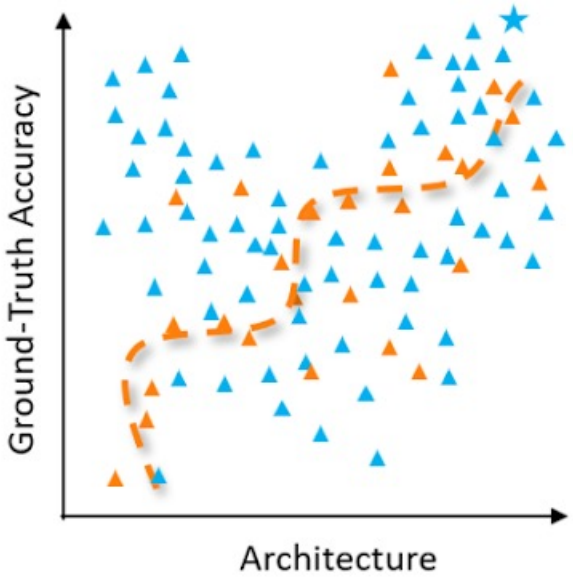
$$x^* = \arg\max_{x \in X} \tilde{f}(x|S^{k+1})$$

$$\text{s.t. } \tilde{f}_{k+1} = \arg\min_{\tilde{f}_k \in \tilde{\mathcal{F}}} \sum_{s \in S^{k+1}} \mathcal{L}(\tilde{f}(s), f(s))$$

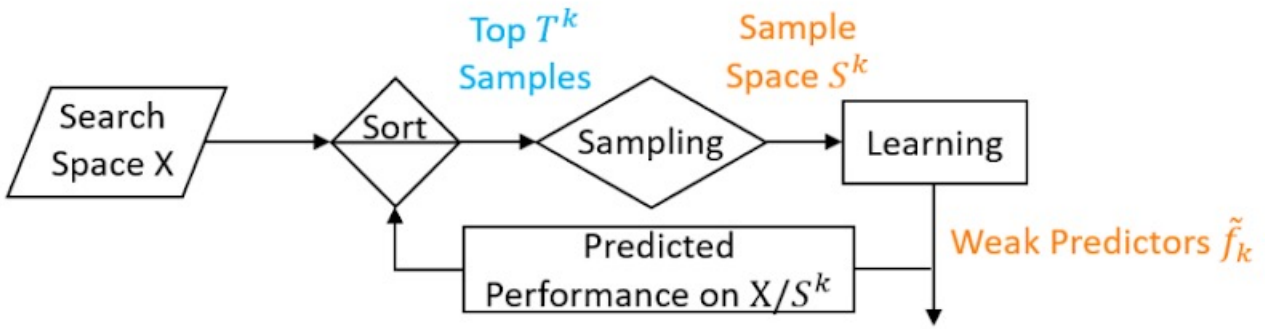
WeakNAS ***jointly evolve*** the Sampling stage & Learning stage

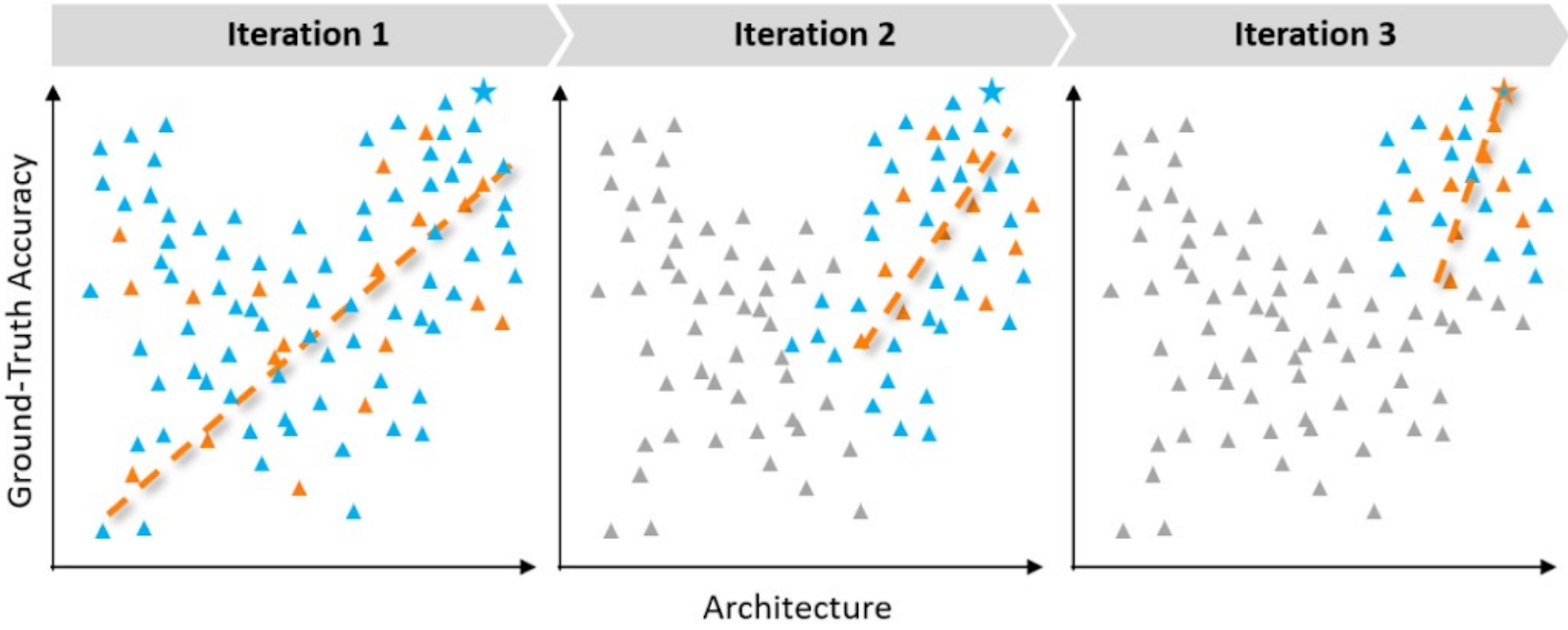
Previous: Predictor-based NAS





Proposed: WeakNAS



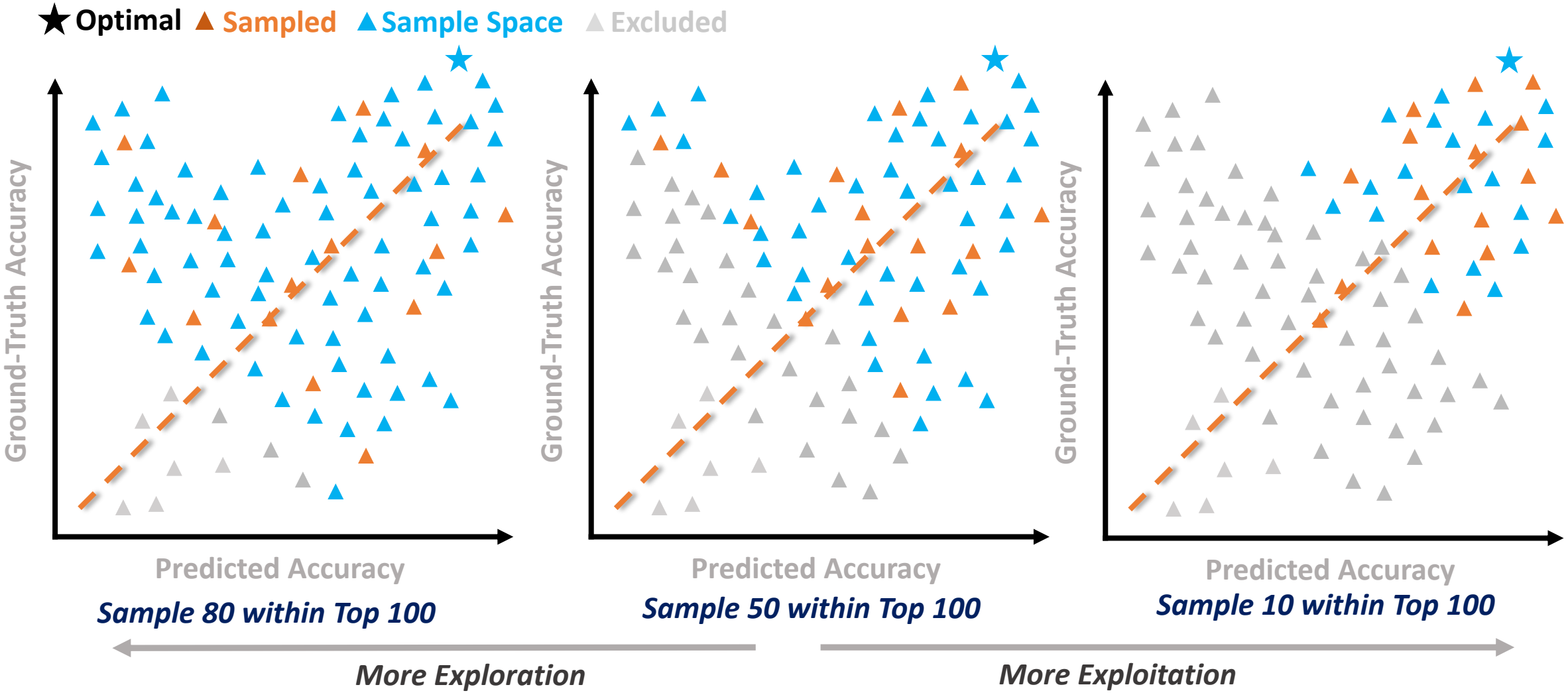


★ Optimal ▲ New Sampled ▲ Sample Space ▲ Excluded

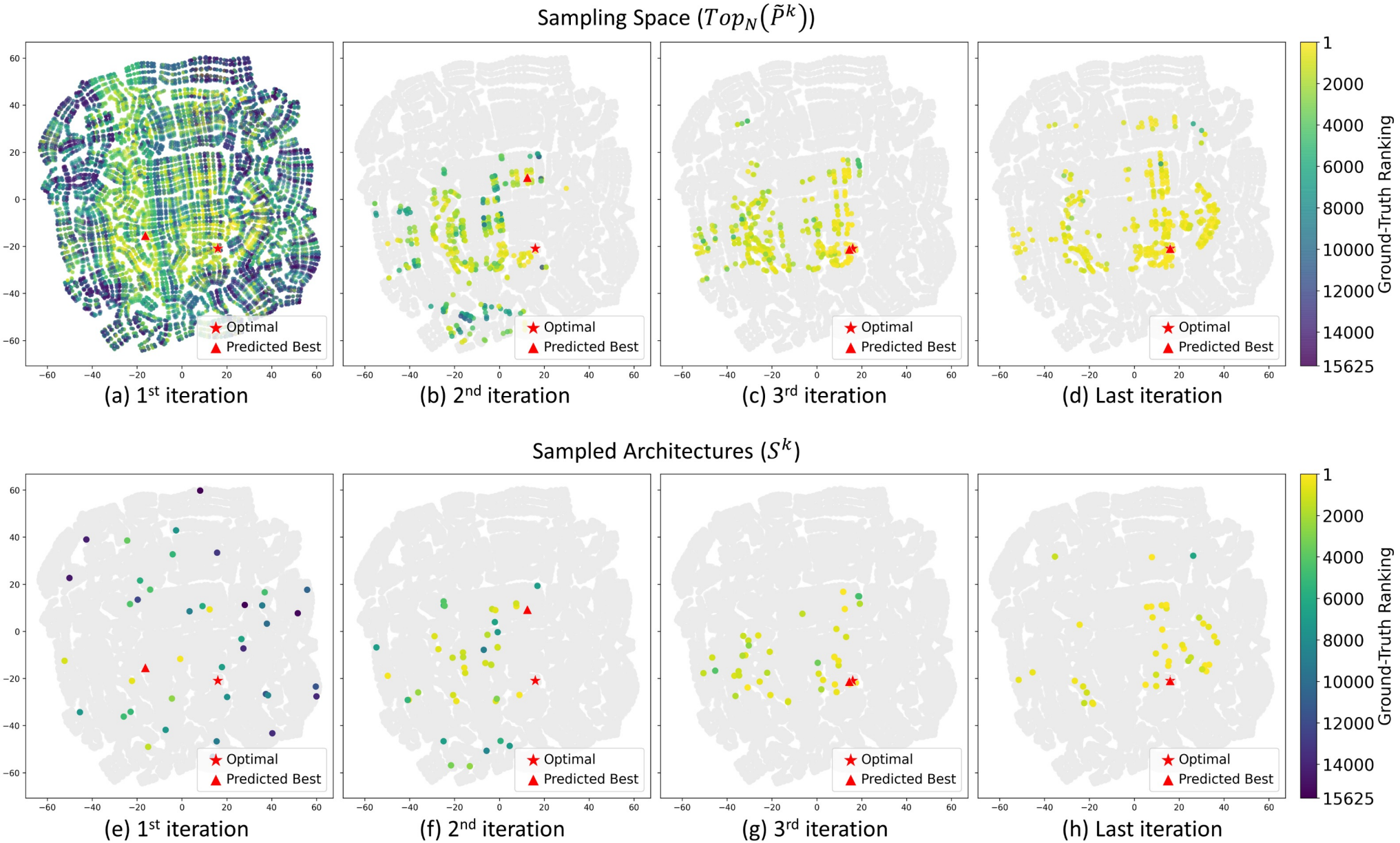
Exploitation-exploration trade-off

Uniformly sample M samples within Top N predictions by $\tilde{f}$

$\boldsymbol{\varepsilon = M/N}$ control the Exploitation-exploration trade-off

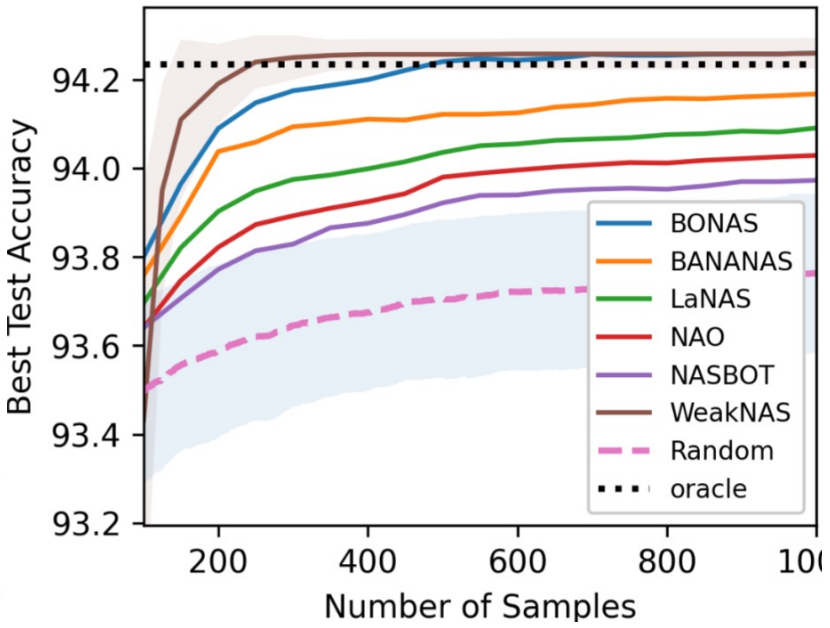


Search Dynamics (t-SNE Visualization)



Comparsion to SoTA on NAS-Bench-101

Method	#Queries	Test Acc.(%)	SD(%)	Test Regret(%)	Avg. Rank
Random Search	2000	93.64	0.25	0.68	1750.0
NAO [2]	2000	93.90	0.03	0.42	168.1
Reg Evolution [14]	2000	93.96	0.05	0.36	85.0
Semi-NAS [20]	2000	94.02	0.05	0.30	42.1
Neural Predictor [7]	2000	94.04	0.05	0.28	33.5
WeakNAS	**2000**	**94.26**	**0.04**	**0.06**	**1.6**
Semi-Assessor [42]	1000	94.01	-	0.31	47.1
LaNAS [21]	1000	94.10	-	0.22	14.1
BONAS [19]	1000	94.22	-	0.10	3.0
WeakNAS	**1000**	**94.25**	**0.04**	**0.07**	**1.7**
arch2vec [41]	400	94.10	-	0.22	14.1
WeakNAS	**400**	**94.24**	**0.04**	**0.08**	**1.9**
LaNAS [21]	200	93.90	-	0.42	168.1
BONAS [19]	200	94.09	-	0.23	18.0
WeakNAS	**200**	**94.18**	**0.14**	**0.14**	**5.6**
Optimal	-	94.32	-	0.00	1.0



Comparsion to SoTA on ImageNet (MobileNet Search Space)

Model	Queries(#)	Top-1 Acc.(%)	Top-5 Acc.(%)	FLOPs(M)
Proxyless NAS[47]	-	75.1	92.9	-
Semi-NAS[20]	300	76.5	93.2	599
BigNAS[42]	-	76.5	-	586
FBNetv3[43]	20000	80.5	95.1	557
OFA[36]	16000	80.0	-	595
LaNAS[21]	800	80.8	-	598
WeakNAS	**1000**	**81.3**	**95.1**	**560**
	800	**81.2**	**95.2**	**593**

Thanks!

Code: https://github.com/VITA-Group/WeakNAS