NAS-Bench-101: Towards Reproducible Neural Architecture Search

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Motivation

Neural architecture search (NAS) methods are notoriously difficult to reproduce and compare:

1. **Different search spaces** and **training procedures**
    - Implicit biases imposed by search space and training, different NAS methods optimized for different setups
    - Cannot separate benefit of NAS from the careful design of the search space and training procedures

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Neural architecture search (NAS) methods are notoriously difficult to reproduce and compare:

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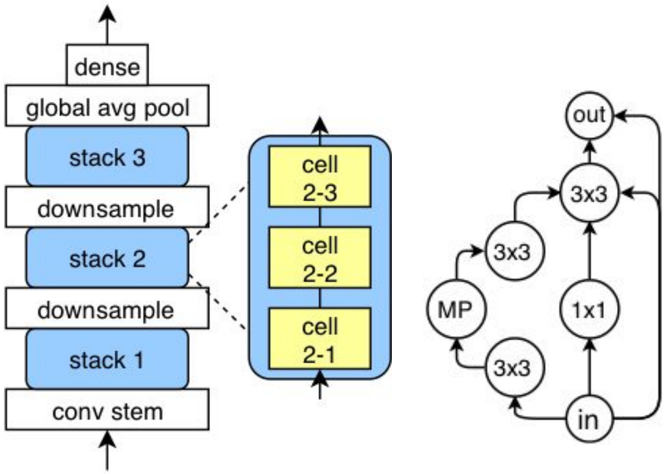
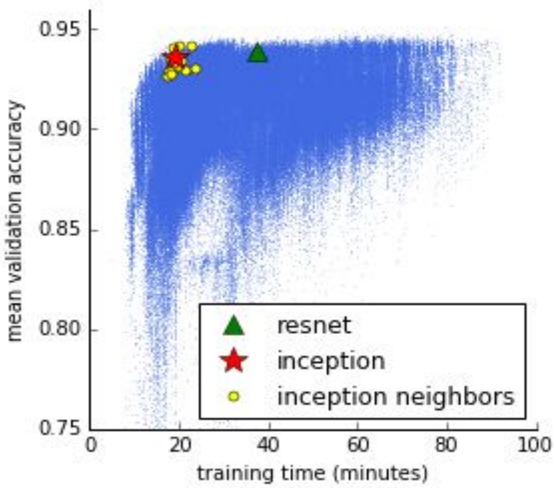
    - Implicit biases imposed by search space and training, different NAS methods optimized for different setups
    - Cannot separate benefit of NAS from the careful design of the search space and training procedures
2. **Compute cost** limits number of trials and makes methods inaccessible to most researchers

NAS-Bench-101

- General search space of directed acyclic graphs for cell-based NAS methods
- Exhaustively trained & evaluated all models on CIFAR-10 to create a queryable dataset

~423K <u>unique</u> cells
* 4 epoch budgets
* 3 repeats
= **~5M <u>total</u> models** trained





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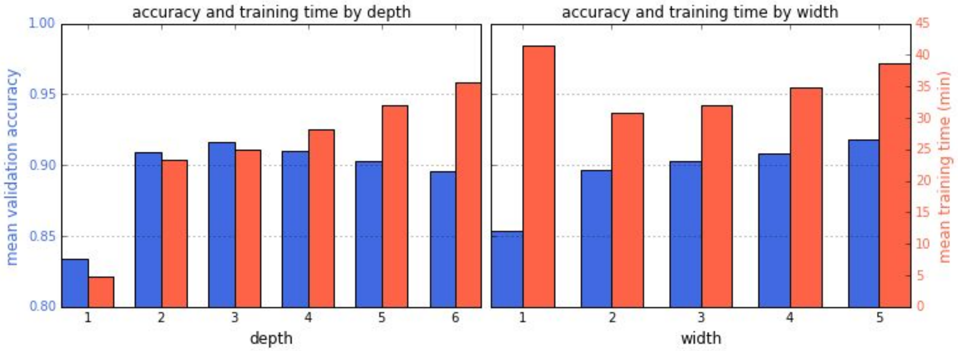
Enables:

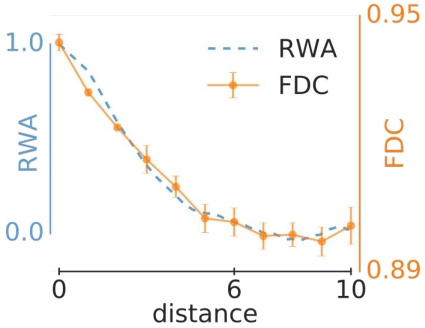
1) Studying the landscape of a neural architecture search space as a discrete optimization space

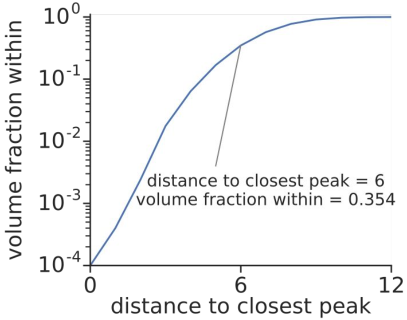
2) Efficient benchmarking of NAS methods by separating the process of **searching for models** (cheap) from **evaluating the models** (expensive)

Aggregate Analysis of Search Space

- Search space exhibits *locality*: similar architectures often have similar performance
- Randomly selecting top model is extremely unlikely, but many models within short edit-distance away

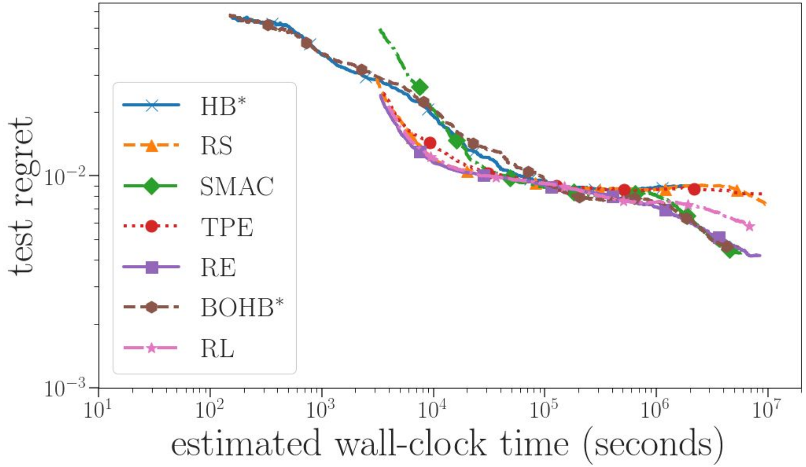


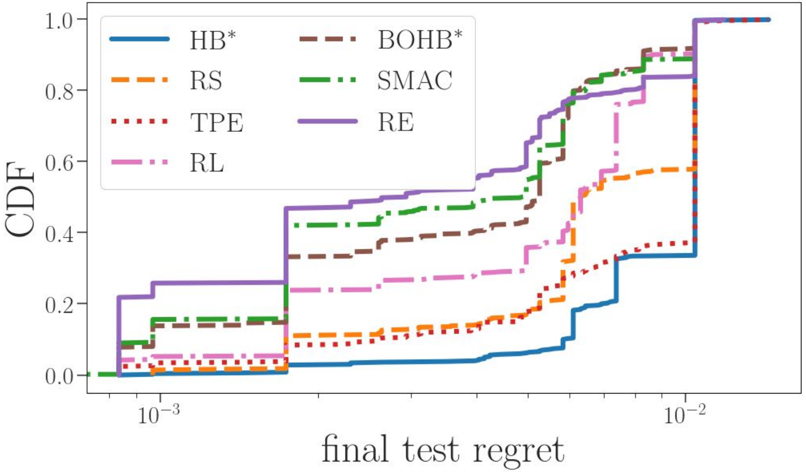




Benchmarking

- Querying dataset enables running entire NAS experiments in seconds
- Can investigate the robustness of NAS methods across random repeats
- Results suggest that conclusions may generalize to larger spaces





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Dataset and code available at:
https://github.com/google-research/nasbench