AutoML: Neural Architecture Search

Part 2: One-shot Neural Architecture Search

Bernd Bischl   Frank Hutter   Lars Kotthoff
Marius Lindauer   Joaquin Vanschoren

The One-Shot Model

One-shot models: convolutional neural fabrics [Saxena and Verbeek. 2017]

- A one-shot model is a big model that has all architectures in a search space as submodels
  - This allows weights sharing across architectures
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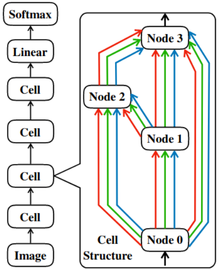
One-shot models for cell search spaces

- Directed acyclic multigraph to capture all (exponentially many) cell architectures
  - The nodes represent tensors
  - The edges represent computations (e.g., 3x3 conv, 5x5 conv, max pool, ...)
  - The results of operations on multiple edges between two nodes are combined (addition/concatenation)



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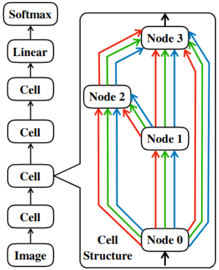
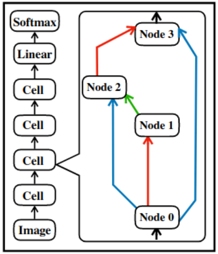
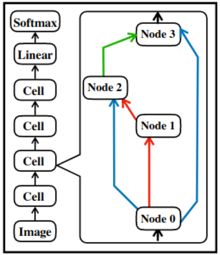
- Individual architectures are subgraphs of this multigraph
  - Weights for the operation on an edge are shared across all (exponentially many) architectures that have that edge







Training the one-shot model – standard SGD [Saxena and Verbeek. 2017]

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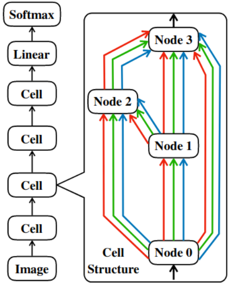

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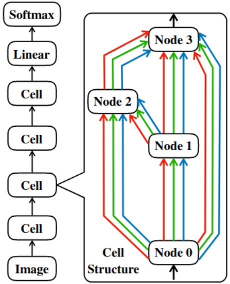
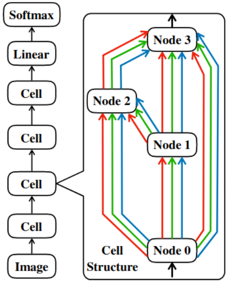
- Potential issue: co-adaptation of weights
  - Weights are implicitly optimized to work well on average across all architectures
  - They are not optimized specifically for the top-performing architecture



Training the one-shot model – DropPath [Bender et al. 2018]

- To avoid coadaptation of weights, we can use DropPath, a technique analogous to Dropout [Srivastava et al., 2014]:



One-shot model

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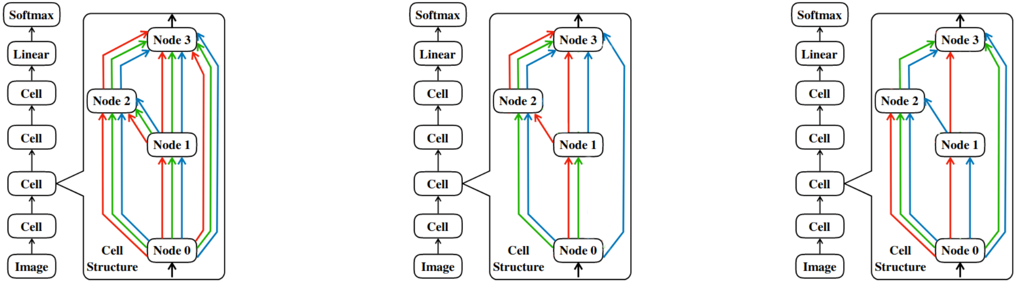

One-shot model

Architecture for batch 1

Architecture for batch 2

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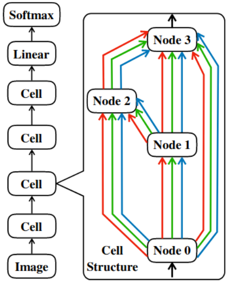
  - ScheduledDropPath: starts with $p = 0$ and increases p linearly to p_{max} at the end of training



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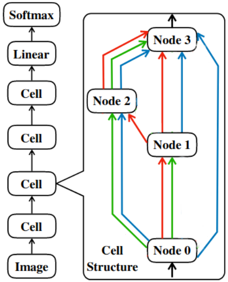

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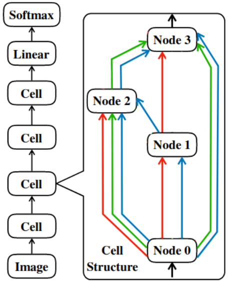

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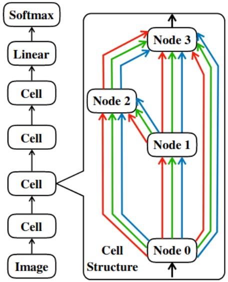

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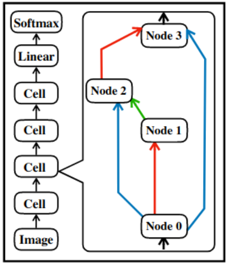
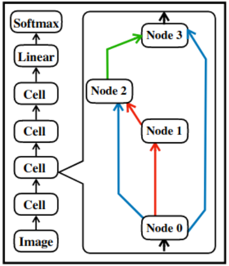


Architecture for batch 1



Architecture for batch 2

Training the one-shot model – Sampling

- At each mini-batch iteration during the training of the one-shot model sample a single architecture from the search space
  - **Random Search with Weight Sharing** [Li and Talwalkar. 2020] ⟶ sample from uniform distribution
  - **ENAS** [Pham et al. 2018] ⟶ sample from the learned policy of a RNN controller
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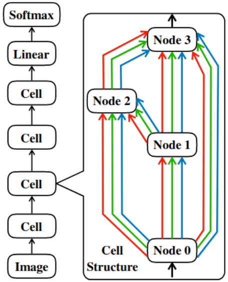

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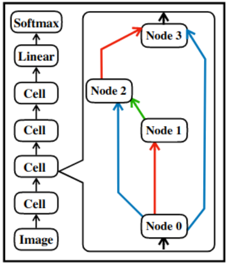

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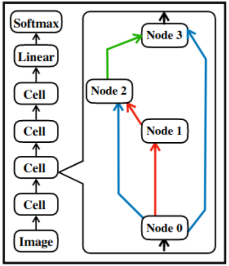

Architecture for batch 2

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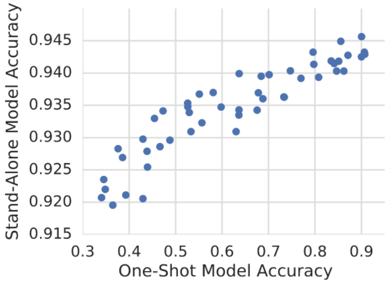
- **Pitfall:** the correlation between architectures evaluated with the one-shot weights and retrained from scratch (stand-alone models) should be high
- If not, **selecting the best architecture based on the one-shot weights** is sub-optimal.



From [Bender et al. 2018]

Questions to Answer for Yourself / Discuss with Friends

- Repetition:
  How are the weights shared in the one-shot model?
- Repetition:
  What is the difference between Random Search with Weight Sharing and ENAS?
- Discussion:
  What migth be some downsides of using the one-shot model for NAS?

AutoML: Neural Architecture Search (NAS)

Part 1: Search Spaces, Blackbox Methods, Speedup Techniques, and Best Practices

Bernd Bischl   Frank Hutter   Lars Kotthoff
Marius Lindauer   Joaquin Vanschoren

Outline

AutoML: Neural Architecture Search (NAS)

Overview

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Neural Architecture Search (NAS)

- Goal: automatically find neural architectures with strong performance
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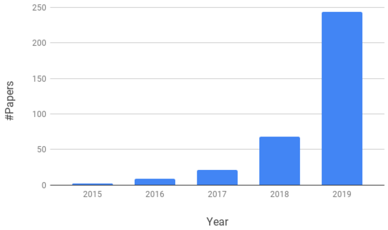

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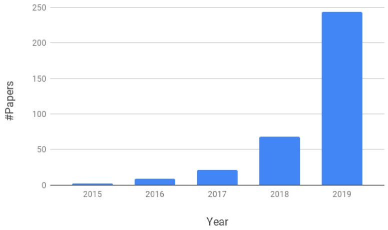
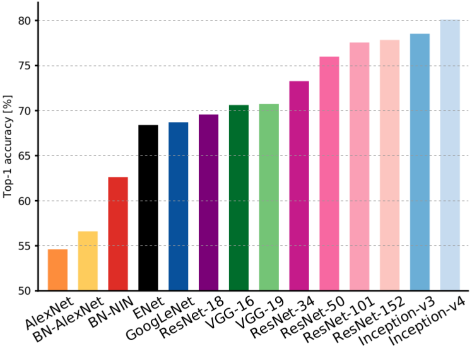
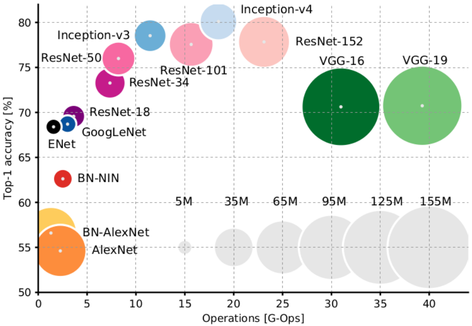
- Initially extremely expensive
- By now several methods promise low overhead over a single model training



Motivation for NAS

- Performance improvements on various tasks due to novel architectures
- Can we automate this design process, potentially discovering new components/topologies?

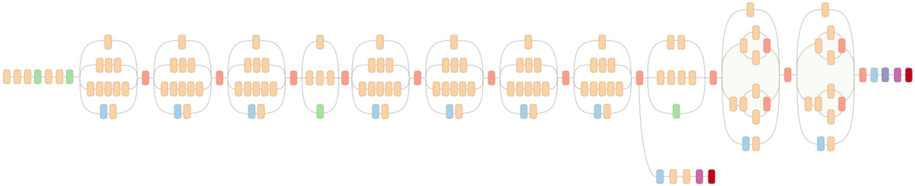




[Canziani et al. 2017]

Motivation for NAS

- Manual design of architectures is time consuming
- Complex state-of-the-art architectures are a result of years of trial and errors by experts



Inception-v3 [Szegedy et al. 2015]

Motivation for NAS

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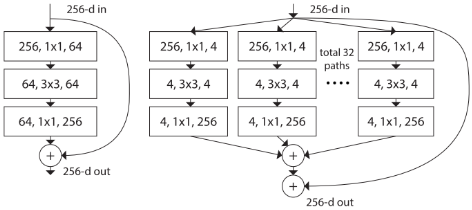
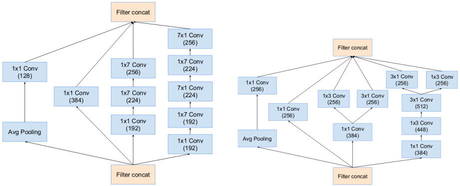
  - Main pattern: Repeated blocks with same structure (topology)

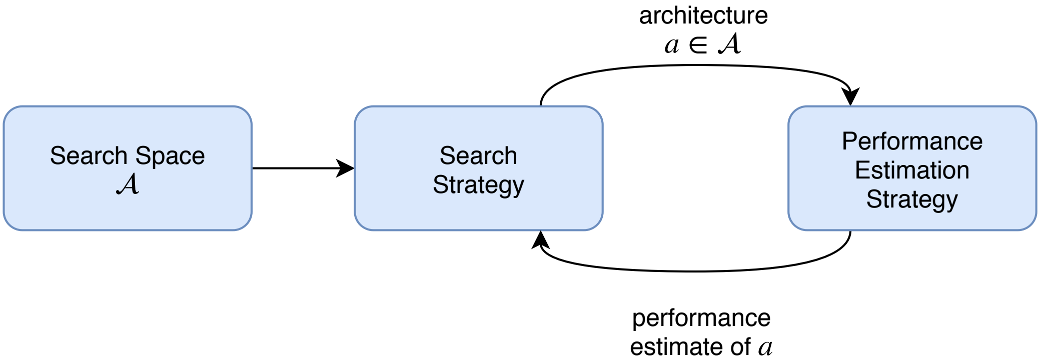


ResNet/ResNeXt blocks
[He et al. 2016; Xie et al. 2016]



Inception-v4 blocks [Szegedy et al. 2016]

NAS components [Elsken et al. 2019]



- Search Space: the types of architectures we consider; micro, macro, hierarchical, etc.
- Search Strategy: Reinforcement learning, evolutionary strategies, Bayesian optimization, gradient-based, etc.
- Performance Estimation Strategy: validation performance, lower fidelity estimates, one-shot model performance, etc.

Questions to Answer for Yourself / Discuss with Friends

- Repetition:
  List three major components of NAS methods.
- Discussion:
  Is there a problem for which you would like to apply NAS yourself?

Outline

AutoML: Neural Architecture Search (NAS)

Search Spaces

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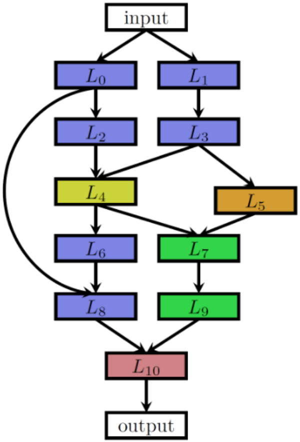
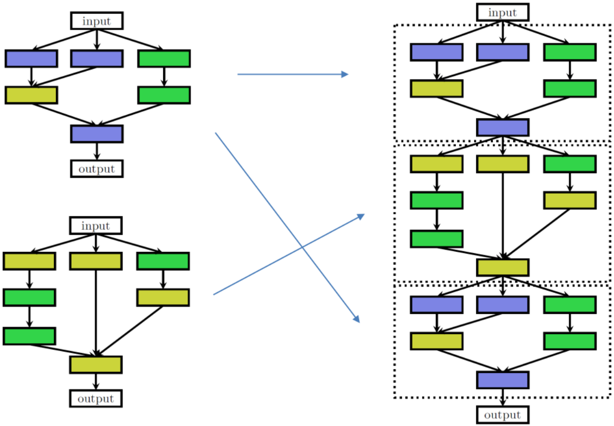
Basic Neural Architecture Search Spaces

Chain-structured space
(different colours:
different layer types)



More complex space
with multiple branches
and skip connections

Cell Search Spaces [Zoph et al. 2018]

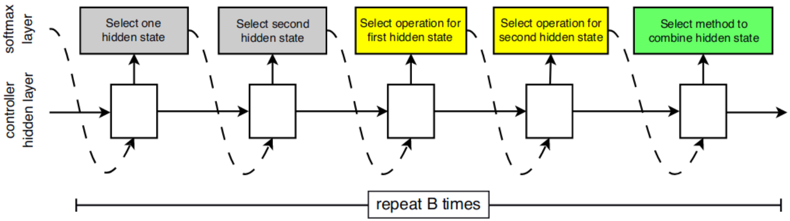


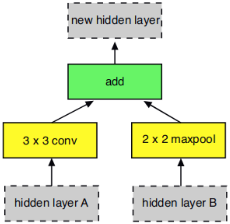
Two possible cells

Architecture composed of stacking together individual cells

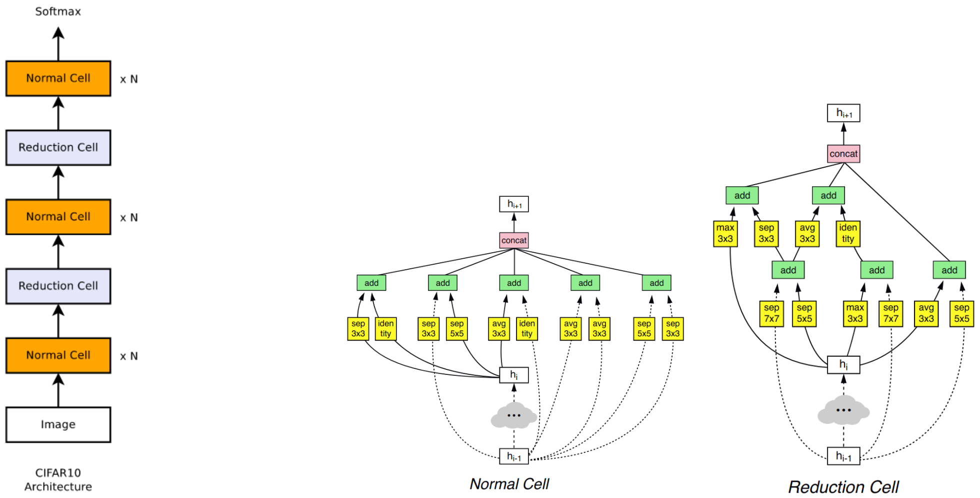
Details on Cell Search Spaces [Zoph et al. 2018]

- 2 types of cells: normal and reduction cells
- For each type of cell: B blocks, each with 5 choices
  - Choose two previous feature maps (from this cell)
  - For each of these, choose an operation (3×3 conv, max-pool, etc.)
  - Choose a merge operation to combine the two results (concat or add)





Example of an architecture sample with B=5



Source: [Zoph et al. 2018]

Pros and Cons of Cell Search Space

What are some pros and cons of the cell search space compared to the basic one?

Please think about this for a few minutes before continuing.

Pros and Cons of Cell Search Space

Pros:

- Reduced search space size; speed-ups in terms of search time.
- Transferability to other datasets (e.g., cells found on CIFAR-10 transfer to ImageNet)
- Stacking repeating patterns is proven to be a useful design principle (ResNet, Inception, etc.)

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Cons:

- Still need to (manually) determine the *macro* architecture, i.e., the way in which cells are connected.
- Limiting if different cells work better in different parts of the network
  - E.g., different spatial resolutions may favour different convolutions

Hierarchical representation of search space [Liu et al. 2017]

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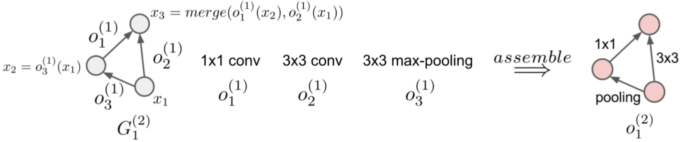

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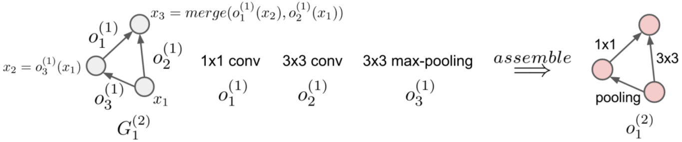
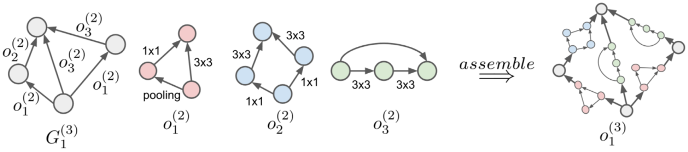


  - Level-3 motivs: combinations of level-2 motivs



Pros and Cons of Hierarchical Search Space

What are some pros and cons of a hierarchical search space compared to the cell search space?

Please think about this for a few minutes before continuing.

Pros and Cons of Hierarchical Search Space

Pros:

- Flexibility of constructing building blocks and reusing them many times
  - like a cell search space
- Flexibility of using different building blocks in different parts of the network
  - like a basic search space
- Ability to reuse building blocks at various levels of abstraction
  - again, this pattern has been used in manual design, e.g., in Inception nets

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Cons:

- Larger than cell search space
- Vastly more expressive than cell search space $\rightarrow$ potentially much harder to search

Questions to Answer for Yourself / Discuss with Friends

- Repetition:
  What are some pros and cons of the cell search space compared to the basic one?
- Repetition:
  Explain the way in which level-3 motivs in the hierarchical search space use level-2 motivs.
- Repetition:
  What are some pros and cons of the hierarchical search space compared to the other ones?

Outline

AutoML: Neural Architecture Search (NAS)

Blackbox Optimization Methods

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NAS as Hyperparameter Optimization

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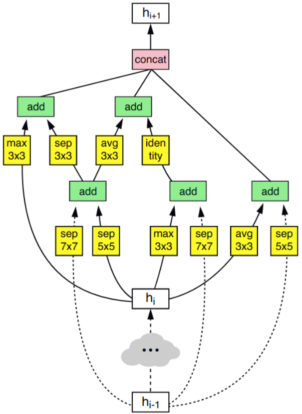
  - 2 categorical choices of hidden states
    - ★ For block N, the domain of these categorical variables is $\{h_i, h_{i-1}, \text{output of block } 1, ..., \text{output of block } N-1\}$
  - 2 categorical variables choosing between operations
  - 1 categorical variable choosing the combination method
  - Total number of hyperparameters for the cell: 5B (with B=5 by default)



Reduction Cell

NAS as Hyperparameter Optimization

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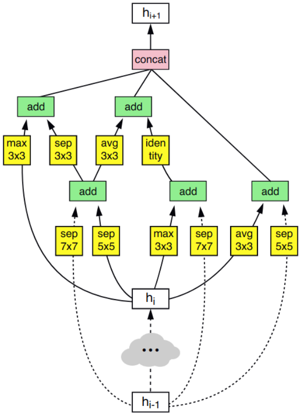
  - Total number of hyperparameters for the cell: 5B (with B=5 by default)
- In general: one may require conditional hyperparameters
  - E.g., chain-structured search space
    - ★ Top-level hyperparameter: number of layers L
    - ★ Hyperparameters of layer k conditional on L $\geq$ k



Reduction Cell

Early Work on Neuroevolution (already since the 1990s)

[Kitano. 1990; Angeline et al. 1994; Stanley and Miikkulainen. 2002; Bayer et al. 2009; Floreano et al. 2008]

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- Typical approach:
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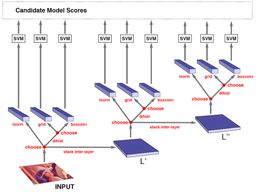
- Mutations include adding, changing or removing a layer

Early Work on Bayesian Optimization (since 2013)

- With TPE [Bergstra et al. 2011]:
  - Joint optimization of a vision architecture with 238 hyperparameters [Bergstra et al. 2013]
  - State-of-the-art performance on 3 disparate problems:
    - Face matching, face identification, and object recognition



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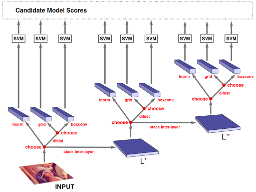

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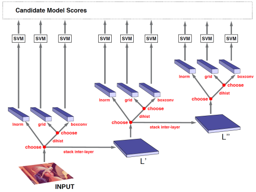

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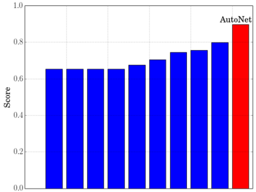
      54491 data points, 5000 features, 18 classes
    - First automated deep learning (Auto-DL) method to win a machine learning competition dataset against human experts



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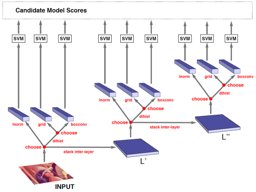

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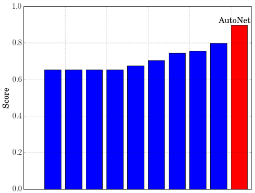
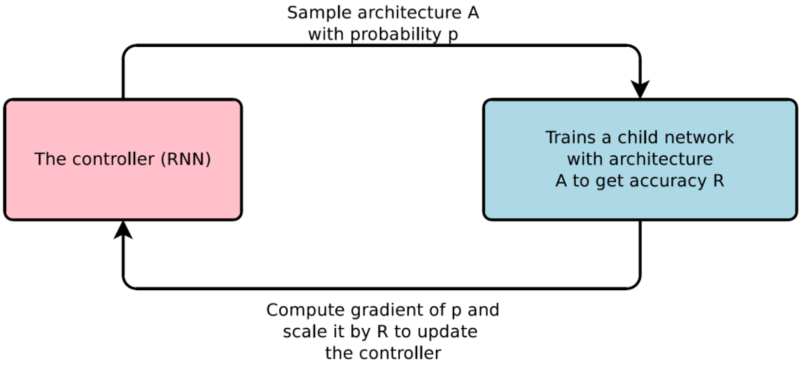


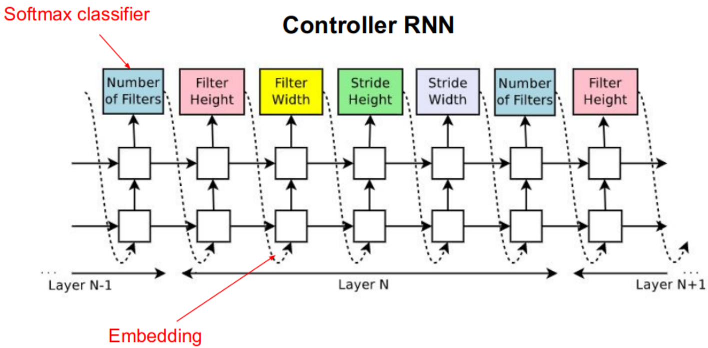
- With Gaussian processes:
  - Arc kernel [Swersky et al. 2013]

Reinforcement Learning [Zoph and Le. 2016]



- Use RNN ("Controller") to generate a NN architecture piece-by-piece
- Train this NN ("Child Network") and evaluate it on a validation set
- Use Reinforcement Learning (RL) to update the parameters of the Controller RNN to optimize the performance of the child models

Learning CNNs with RL [Zoph and Le. 2016]



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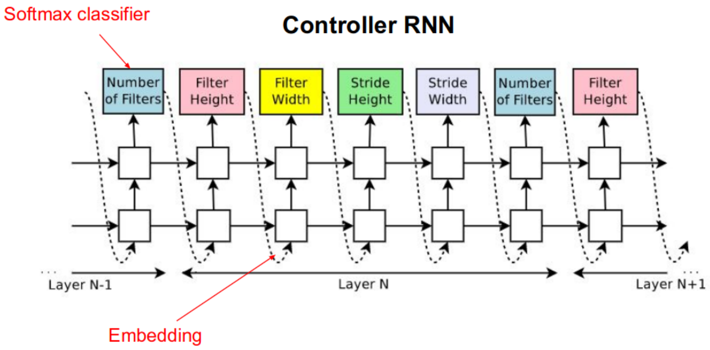

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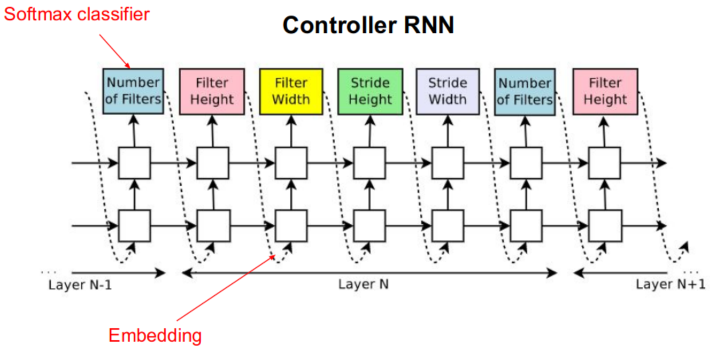
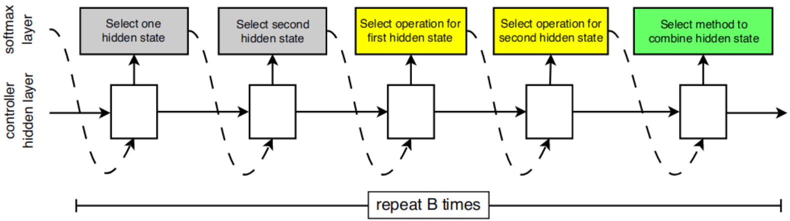


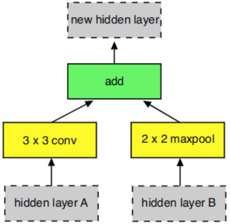
- For a fixed number of layers, select:
  - Filter width/height, stride width/height, number of filters
- Large computational demands (800 GPUs for 2 weeks, 12.800 architectures evaluated)
- State-of-the-art results for CIFAR-10 & Penn Treebank architecture

  → Brought NAS into the limelight

Learning CNN cells with RL [Zoph et al. 2018]

- 2 types of cells: normal and reduction cells
- For each type of cell: B blocks, each with 5 choices
  - Choose two previous feature maps (from this cell)
  - For each of these, choose an operation (3×3 conv, max-pool, etc.)
  - Choose a merge operation to combine the two results (concat or add)





Learning CNN cells with evolution [Real et al. 2018]

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  - Choose two previous feature maps (from this cell)
  - For each of these, choose an operation (3$\times$3 conv, max-pool, etc.)
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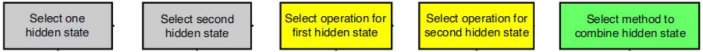
- Evolution simply tackles this as a HPO problem with 2$\times$5$\times$B variables:



Regularized/Aging Evolution [Real et al. 2018]

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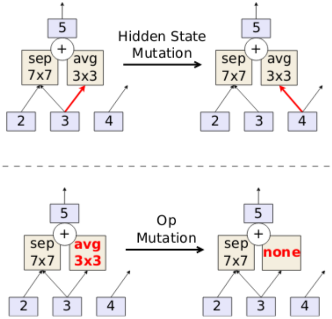

Different types of mutations in cell search space

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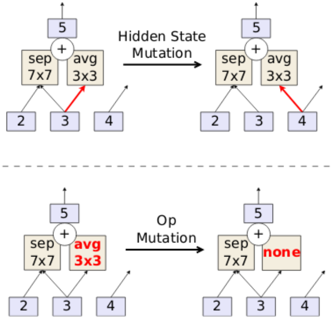

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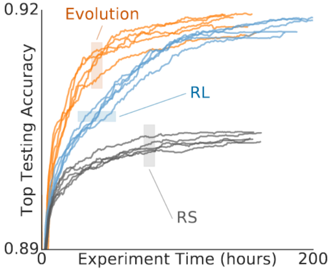

State-of-the-art performance in apples-to-apples comparison $\rightarrow$ AmoebaNet

Bayesian Optimization (BO)

- Encode the architecture space by categorical hyperparameters (like regularized evolution)
- Strong performance with tree-based models
  - TPE [Bergstra et al. 2013]
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  - BANANAS [White et al. 2019]
- BO is very competitive, has been shown to outperform RL [Ying et al. 2019]

Current State of the Art: Differential Evolution

- Comprehensive experiments on a wide range of 12 different NAS benchmarks
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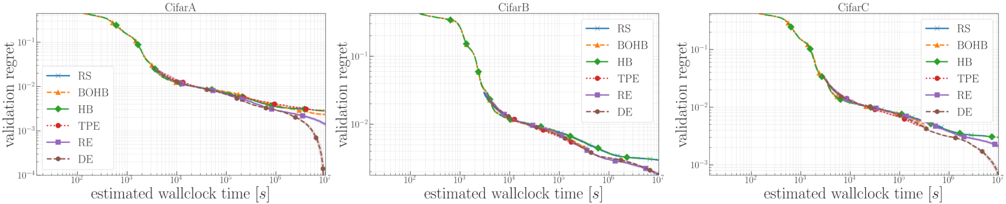
- Comprehensive experiments on a wide range of 12 different NAS benchmarks [Awad et al. 2020]
- Results:
  - Regularized evolution is very robust, typically amongst best of the methods discussed so far
  - Evolution variant of differential evolution is yet better; most efficient and robust method



Questions to Answer for Yourself / Discuss with Friends

- Repetition:
  What are some pros and cons of using black-box optimizers for NAS?
- Repetition:
  How can NAS be modelled as a HPO problem?
- Discussion:
  Given enough resources, will blackbox NAS approaches always improve performance?
- Discussion:
  Why does discarding the oldest individual (rather than the worst) help in regularized/aging evolution?
- Transfer:
  How would you write NAS with the hierarchical search space as a HPO problem?

Outline

AutoML: Neural Architecture Search (NAS)

Speedup Techniques

Bernd Bischl   Frank Hutter   Lars Kotthoff
Marius Lindauer   Joaquin Vanschoren

Overview of NAS Speedup Methods

- Multi-fidelity optimization
- Learning curve prediction
- Meta-learning across datasets
- Network morphisms & weight inheritance
- Weight sharing & the one-shot model

NAS Speedup Technique 1: Multi-fidelity optimization

- Analogous to multi-fidelity optimization in HPO
  - Many evaluations for cheaper fidelities (less epochs, smaller datasets, down-sampled images, shallower networks, etc)
  - Fewer evaluations necessary for more expensive fidelities

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- Compatible with any blackbox optimization method
  - Using random search: ASHA [Li and Talwalkar. 2019]
  - Using Bayesian optimization: BOHB [Zela et al. 2018]
  - Using differential evolution: DEHB [Awad et al. under review]
  - Using regularized evolution: progressive dynamic hurdles [So et al. 2019]

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  - Using regularized evolution: progressive dynamic hurdles [So et al. 2019]
- Often used for joint optimization of architecture & hyperparameters
  - Auto-Pytorch [Mendoza et al. 2019; Zimmer et al. 2020]
  - "Auto-RL" [Runge et al. 2019]

NAS Speedup Technique 2: Learning Curve Prediction

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  - Can use features of the architecture as input (just like hyperparameters as inputs)

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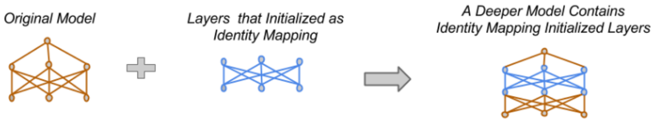
- Compatible with any blackbox optimization method
  - Using random search and Bayesian optimization: [Domhan et al. 2015]
  - Using reinforcement learning: [Baker et al. 2018]

NAS Speedup Technique 3: Meta-Learning

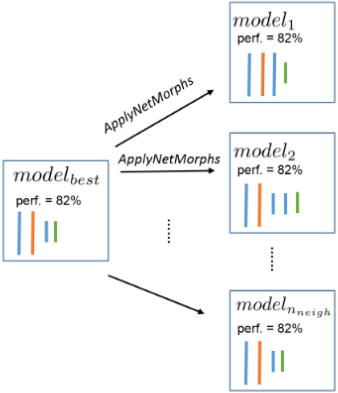
- Lots of work on meta-learning for HPO
- Only little work on meta-learning for NAS
  - Find a set of good architectures to initialize BOHB in Auto-Pytorch [Zimmer et al. 2020]
  - Learn RL agent's policy network on previous datasets [Wong et al. 2018]
  - Learn neural architecture that can be quickly adapted [Lian et al. 2019; Elsken et al. 2019]

NAS Speedup Technique 4: Network Morphisms

- Network Morphisms [Chen et al. 2016; Wei et al. 2016; Cai et al. 2017]
  - Change the network structure, but not the modelled function
  - I.e., for every input the network yields the same output as before applying the network morphisms operations
  - Examples: “Net2DeeperNet”, “Net2WiderNet”, etc.



Network Morphisms Allow Efficient Moves in Architecture Space



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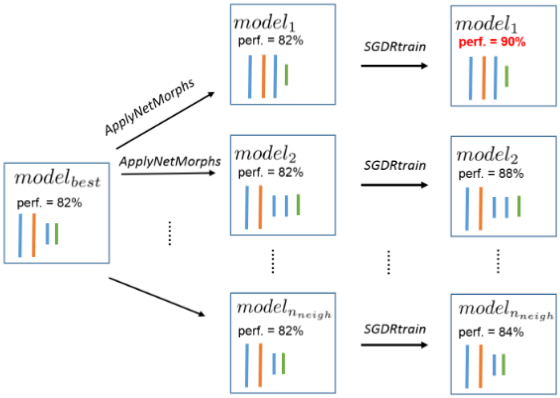

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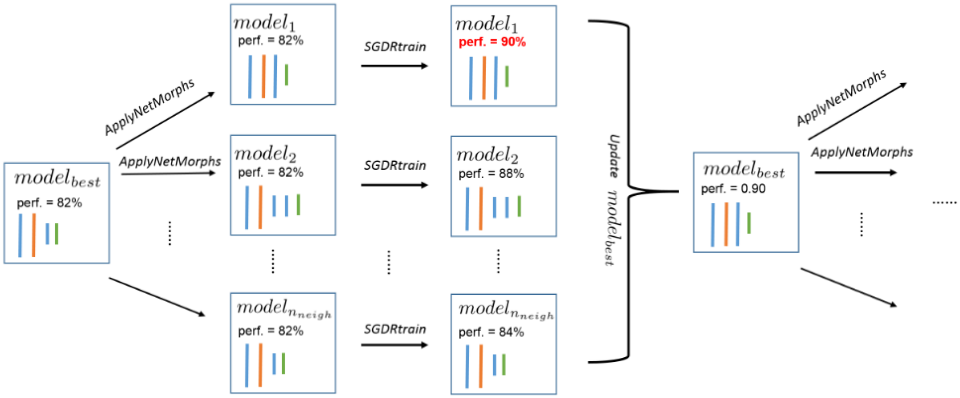

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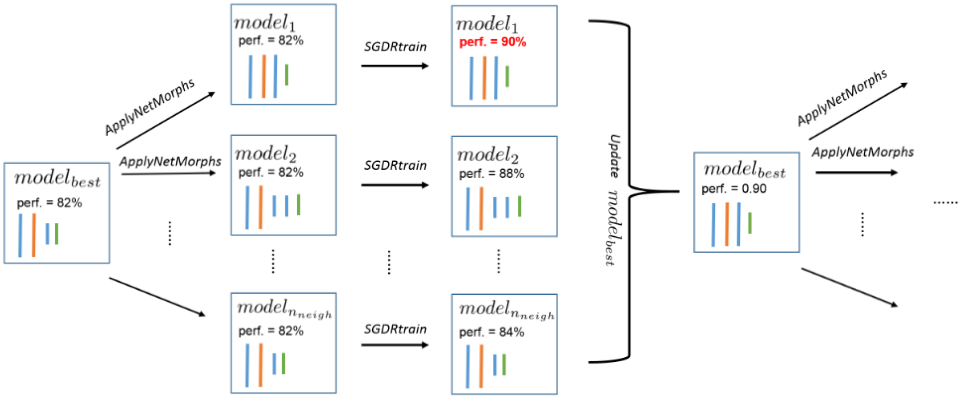
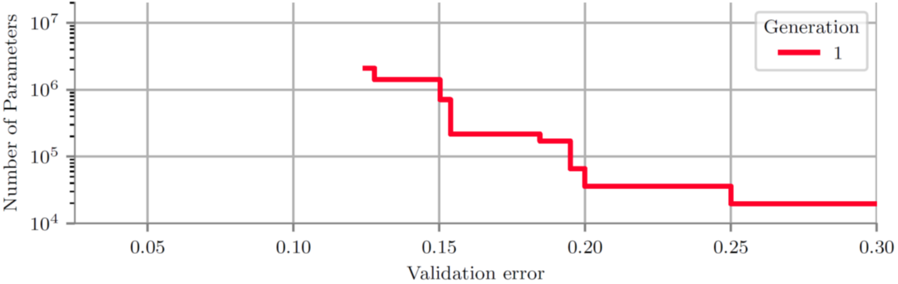


Weight inheritance avoids expensive retraining from scratch

[Real et al. 2017; Cai et al. 2018; Elsken et al. 2017; Cortes et al. 2017; Cai et al. 2018; Elsken et al. 2019]

Network Morphisms for Multi-objective NAS [Elsken et al. 2019]

- To trade off error vs. resource consumption (e.g, #parameters):
  - Maintain a Pareto front of the two objectives
  - Evolve a population of Pareto-optimal architectures over time



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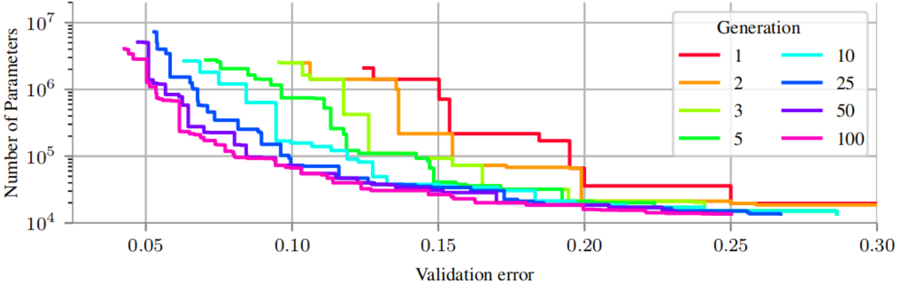
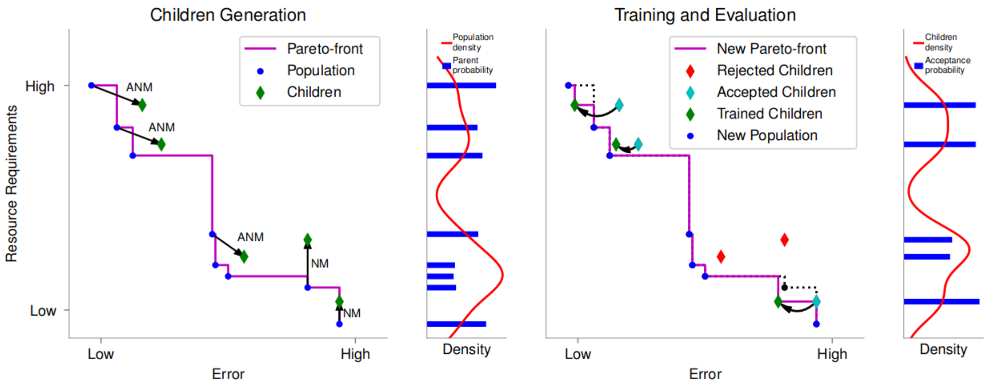


Network Morphisms for Multi-objective NAS [Elsken et al. 2019]

- LEMONADE: Lamarckian Evolution for Multi-Objective Neural Architecture Design
- Weight inheritance through approximate morphisms (ANMs)
  - Dropping layers, dropping units within a layer, etc (function not preserved perfectly)



NAS Speedup Technique 5: Weight Sharing and One-shot Models

[Pham et al. 2018; Bender et al. 2018]

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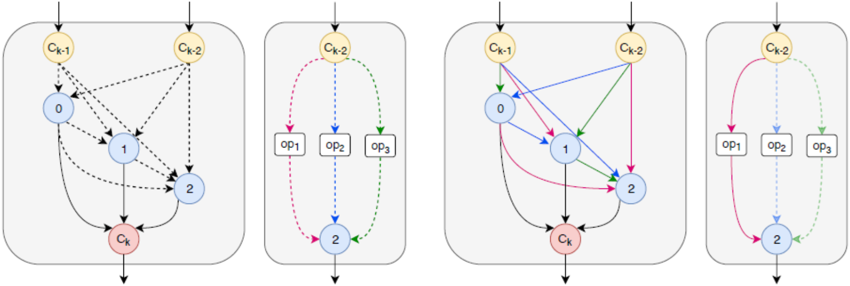
- All possible architectures are subgraphs of a large supergraph: the one-shot model
- Weights are shared between different architectures with common edges in the supergraph
- Search costs are reduced drastically since one only has to train a single model (the one-shot model).

NAS Speedup Technique 5: Weight Sharing and One-shot Models

[Pham et al. 2018; Bender et al. 2018]

- The one-shot model can be seen as a directed acyclic multigraph
  - ⇒ Nodes - latent representations.
  - ⇒ Edges (dashed) - operations.



(a) One-shot search **(b)** Final evaluation

- Architecture optimization problem: Find optimal path from the input to the output

Questions to Answer for Yourself / Discuss with Friends

- Repetition:
  List five methods to speed up NAS over blackbox approaches
- Repetition:
  Which speedup techniques directly carry over from HPO to NAS?
- Discussion:
  Why do network morphisms and the one-shot model only apply to NAS, and not to HPO?

Outline

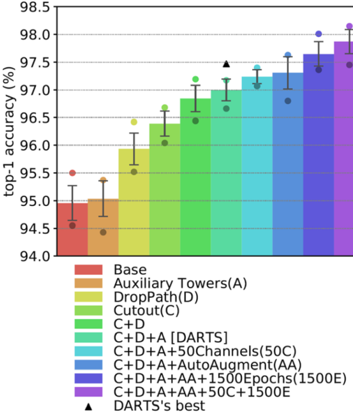
AutoML: Neural Architecture Search (NAS)

Issues and Best Practices in NAS Research

Bernd Bischl Frank Hutter Lars Kotthoff
Marius Lindauer Joaquin Vanschoren

Issues in NAS Research & Evaluations

- Most NAS methods are extremely difficult to reproduce and compare [Li and Talwalkar. 2019]
- For benchmarks used in almost all NAS papers:
  - Training pipeline matters much more than neural architecture



[Yang et al. 2020]

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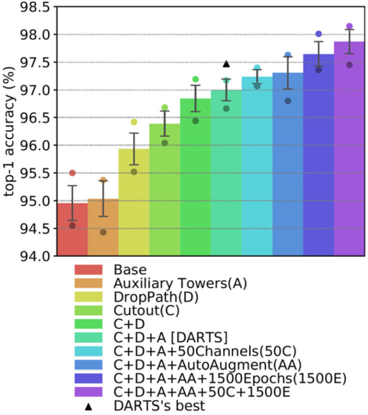

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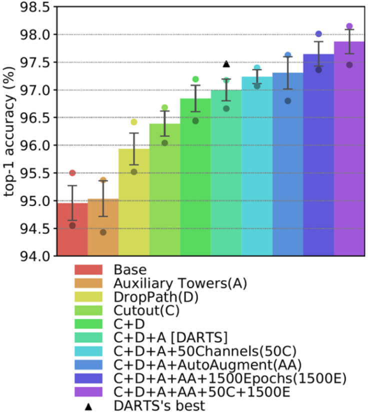
→ We emphasize concepts, not published performance numbers



[Yang et al. 2020]

Building a Scientific Community for NAS

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  - NAS-Bench-101 [Ying et al. 2019]
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  - Finally enables empirical comparisons without confounding factors
- First NAS workshop at ICLR 2020

Best Practice Checklist for NAS Research [Lindauer and Hutter. 2020]

- Best practices for releasing code
  - Code for the training pipeline used to evaluate the final architectures
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- Note that the easiest way to satisfy the first three is to use existing NAS benchmarks

Definition: NAS Benchmark [Lindauer and Hutter. 2020]

A NAS benchmark consists of a dataset (with a predifiend training-test split), a search space, and available runnable code with pre-defined hyperparameters for training the architectures.

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  - Did you perform multiple runs of your experiments and report seeds?
  - Did you use tabular or surrogate benchmarks for in-depth evaluations?

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- We believe the community would benefit a lot from:
  - Clean NAS benchmarks for new applications
    - Including all details for the application. No need to also develop a new method.
  - Open-source library of NAS methods to compare methods without confounding factors
    - First version already developed: NASlib [Zela et al, under review]

NAS-Bench-101: The First NAS Benchmark [Ying et al. 2019]

- Dataset: CIFAR-10, with the standard training/test split
- Runnable open-source code provided in Tensorflow
- Cell-structured search space consisting of all directed acyclic graphs (DAGs) on V nodes, where each possible node has L operation choices.

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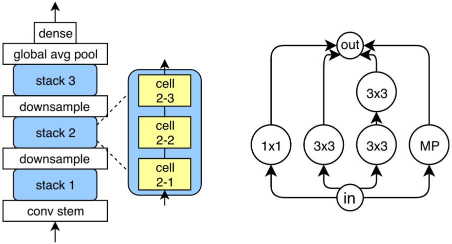
- To limit the number of architectures, NAS-Bench-101 has the following constraints:
  - $L = 3$ operators:
    - 3×3 convolution - 1×1 convolution - 3×3 max-pooling
  - $V \leq 7$ nodes
  - A maximum of 9 edges



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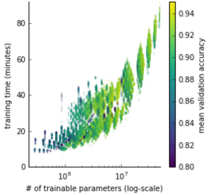
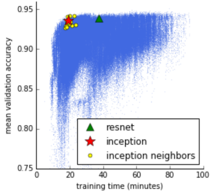
- Around 423k unique cells
  - 4 epoch budgets: 4, 12, 36, 108
  - 3 repeats
  - around 5M trained and evaluated models
  - 120 TPU years of computation
  - the best architecture mean test accuracy: 94.32%





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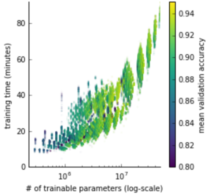
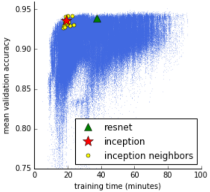
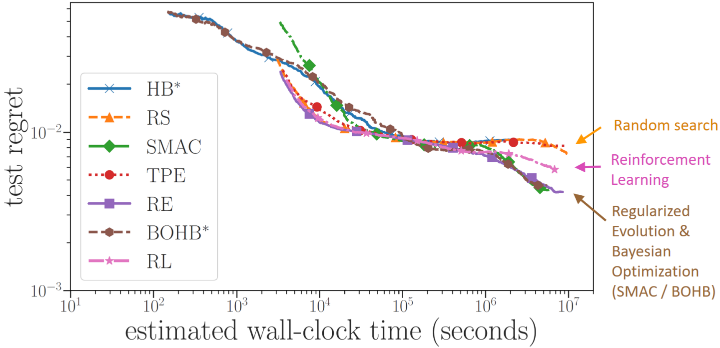


- Given an architecture encoding A, budget E_{stop} and trial number, one can query from NAS-Bench-101 the following quantities:
  - training/validation/test accuracy
  - training time in seconds
  - number of trainable model parameters



Evaluation of Blackbox NAS Methods on NAS-Bench-101 [Ying et al. 2019]

- RL outperforms random search
- BO and regularized evolution perform best, better than RL



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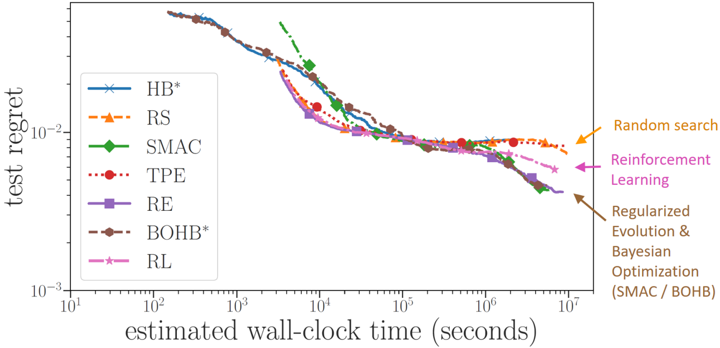

- Note that the BO method SMAC [Hutter et al. 2011] predated RL for NAS [Zoph and Le. 2017] by 6 years
  - Only now, benchmarks like NAS-Bench-101 allow for efficient comparisons

Questions to Answer for Yourself / Discuss with Friends

- Repetition:
  For the most common NAS search space, how important is the NAS component compared to the importance of the training pipeline used?
- Repetition:
  Why do we need proper benchmarking of NAS algorithms?
- Repetition:
  What does a NAS benchmark consist of?
- Repetition:
  List all best practices for NAS you remember.

Further Reading

Survey on NAS: [Elsken et al. 2019]