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Neural Architecture Search: A Survey

Thomas Elsken THOMAS.ELSKEN@DE.BOSCH.COM
Bosch Center for Artificial Intelligence
71272 Renningen, Germany
and University of Freiburg

Jan Hendrik Metzen JANHENDRIK.METZEN@DE.BOSCH.COM
Bosch Center for Artificial Intelligence
71272 Renningen, Germany

Frank Hutter FH@CS.UNI-FREIBURG.DE
University of Freiburg
79110 Freiburg, Germany

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Abstract

Deep Learning has enabled remarkable progress over the last years on a variety of tasks, such as image recognition, speech recognition, and machine translation. One crucial aspect for this progress are novel neural architectures. Currently employed architectures have mostly been developed manually by human experts, which is a time-consuming and error-prone process. Because of this, there is growing interest in automated *neural architecture search* methods. We provide an overview of existing work in this field of research and categorize them according to three dimensions: search space, search strategy, and performance estimation strategy.

Keywords: Neural Architecture Search, AutoML, AutoDL, Search Space Design, Search Strategy, Performance Estimation Strategy

1. Introduction

The success of deep learning in perceptual tasks is largely due to its automation of the feature engineering process: hierarchical feature extractors are learned in an end-to-end fashion from data rather than manually designed. This success has been accompanied, however, by a rising demand for *architecture engineering*, where increasingly more complex neural architectures are designed manually. *Neural Architecture Search* (NAS), the process of automating architecture engineering, is thus a logical next step in automating machine learning. Already by now, NAS methods have outperformed manually designed architectures on some tasks such as image classification (Zoph et al., 2018; Real et al., 2019), object detection (Zoph et al., 2018) or semantic segmentation (Chen et al., 2018). NAS can be seen as subfield of AutoML (Hutter et al., 2019) and has significant overlap with hyperparameter optimization (Feurer and Hutter, 2019) and meta-learning (Vanschoren, 2019). We categorize methods for NAS according to three dimensions: search space, search strategy, and performance estimation strategy:

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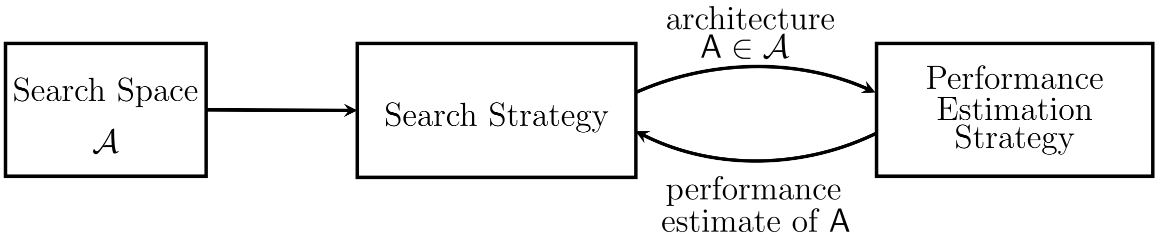

Figure 1: Abstract illustration of Neural Architecture Search methods. A search strategy selects an architecture A from a predefined search space $\mathcal{A}$. The architecture is passed to a performance estimation strategy, which returns the estimated performance of A to the search strategy.

- **Search Space.** The search space defines which architectures can be represented in principle. Incorporating prior knowledge about typical properties of architectures well-suited for a task can reduce the size of the search space and simplify the search. However, this also introduces a human bias, which may prevent finding novel architectural building blocks that go beyond the current human knowledge.

- **Search Strategy.** The search strategy details how to explore the search space (which is often exponentially large or even unbounded). It encompasses the classical exploration-exploitation trade-off since, on the one hand, it is desirable to find well-performing architectures quickly, while on the other hand, premature convergence to a region of suboptimal architectures should be avoided.

- **Performance Estimation Strategy.** The objective of NAS is typically to find architectures that achieve high predictive performance on unseen data. *Performance Estimation* refers to the process of estimating this performance: the simplest option is to perform a standard training and validation of the architecture on data, but this is unfortunately computationally expensive and limits the number of architectures that can be explored. Much recent research therefore focuses on developing methods that reduce the cost of these performance estimations.

We refer to Figure 1 for an illustration. The article is also structured according to these three dimensions: we start with discussing search spaces in Section 2, cover search strategies in Section 3, and outline performance estimation methods in Section 4. We conclude with an outlook on future directions in Section 5.

2. Search Space

The search space defines which neural architectures a NAS approach might discover in principle. We now discuss common search spaces from recent works.

A relatively simple search space is the space of *chain-structured neural networks*, as illustrated in Figure 2 (left). A chain-structured neural network architecture A can be written as a sequence of n layers, where the i'th layer L_i receives its input from layer $i-1$ and