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HANNA: Hardware-Aware Neural Network Analysis

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Neural Architecture Search (NAS) is the deep-learningspecific variant of model selection. The goal of NAS is discovering those network topologies that have good task accuracy, i.e., that are most effective.

NAS spaces are vast:

- many degrees of freedom (layers, connectivity, ...);
- many options for each degree of freedom.

Several **stochastic and probabilistic algorithms** to explore NAS spaces have been proposed:

- Evolutionary Algorithms;
- Reinforcement Learning;
- Gradient-Based Learning;
- Bayesian Methods;
- Random Network Generation.

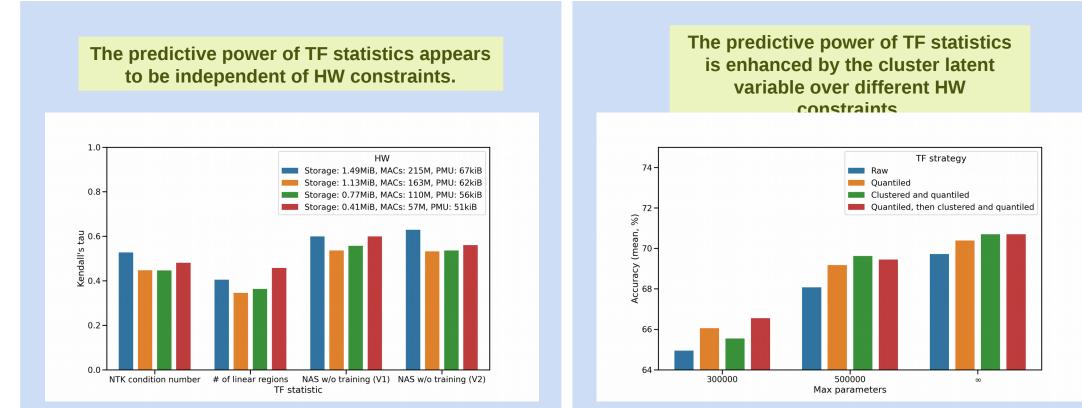
They **require training candidate networks** for several epochs: this is **time-consuming and computationally expensive**.

When thinking to a **DNN** f_{λ} as a computer program, we model it as a computational graph G_{λ} . To design better HW for DNNs, we need to answer the following question: "What are the features shared by good programs?" Similarly, to design better DNNs for constrained HW, we need to answer the following question: "What are the features shared by good HW-constrained programs?" We analyse data sets of network topologies (e.g., NAS-Bench-201) whose task accuracy is known. We quantify the similarity between programs using distances between graphs:

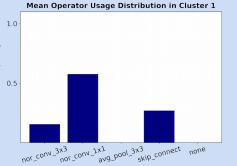
 $k_{\lambda_1,\lambda_2} \coloneqq k(G_{\lambda_1},G_{\lambda_2}).$

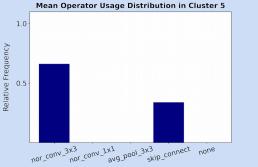
"How can we discriminate clusters of bad programs from clusters of good programs when accuracy is not known?" Training-free (TF) statistics measure properties of DNNs before any epoch of training is run. The hypothesis is that good values of TF statistics correlate with good task accuracy:

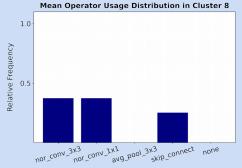
 $s(f_\lambda) \propto a(f_\lambda) \, .$



Effective HW-constrained programs use nondestructive operators (e.g., no pooling).







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