# Task-Adaptive Neural Network Retrieval with Meta-Contrastive Learning

**Anonymous Author(s)**
Affiliation
Address
email

## Abstract

Most conventional Neural Architecture Search (NAS) approaches are limited in that they only generate architectures without searching for the optimal parameters. While some NAS methods handle this issue by utilizing a supernet trained on a large-scale dataset such as ImageNet, they may be suboptimal if the target tasks are highly dissimilar from the dataset the supernet is trained on. To address such limitations, we introduce a novel problem of *Neural Network Search* (NNS), whose goal is to search for the optimal pretrained network for a novel dataset and constraints (e.g. number of parameters), from a model zoo. Then, we propose a novel framework to tackle the problem, namely *Task-Adaptive Neural Network Search* (TANS). Given a model-zoo that consists of network pretrained on diverse datasets, we use a novel amortized meta-learning framework to learn a cross-modal latent space with contrastive loss, to maximize the similarity between a dataset and a high-performing network on it, and minimize the similarity between irrelevant dataset-network pairs. We validate the effectiveness and efficiency of our method on ten real-world datasets, against existing NAS/AutoML baselines. The results show that our method instantly retrieves networks that outperform models obtained with the baselines with significantly fewer training steps to reach the target performance, thus minimizing the total cost of obtaining a task-optimal network. Our code and the model-zoo are available here.

## 1 Introduction

*Neural Architecture Search* (NAS) aims to automate the design process of network architectures by searching for high-performing architectures with RL [46, 47], evolutionary algorithms [28, 7], parameter sharing [3, 27], or surrogate schemes [24], to overcome the excessive cost of trial-and-error approaches with the manual design of neural architectures [31, 14, 16]. Despite their success, existing NAS methods suffer from several limitations, which hinder their applicability to practical scenarios. First of all, the search for the optimal architectures usually requires a large amount of computation, which can take multiple GPU hours or even days to finish. This excessive computation cost makes it difficult to efficiently obtain an optimal architecture for a novel dataset. Secondly, most NAS approaches only search for optimal architectures, without the consideration of their parameter values. Thus, they require extra computations and time for training on the new task, in addition to the architecture search cost, which is already excessively high.

For this reason, supernet-based methods [4, 23] that search for a sub-network (subnet) from a network pretrained on large-scale data, are attracting more popularity as it eliminates the need for additional training. However, this approach may be suboptimal when we want to find the subnet for a dataset that is largely different from the source dataset the supernet is trained on (e.g. medical images or defect detection for semiconductors). This is a common limitation of existing NAS approaches, although

Submitted to 35th Conference on Neural Information Processing Systems (NeurIPS 2021). Do not distribute.

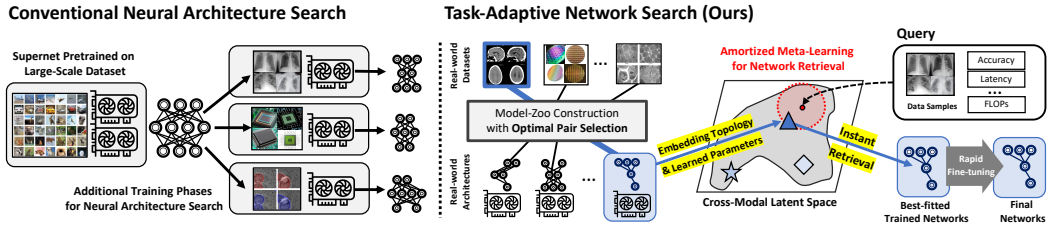



Figure 1: **Comparison between conventional NAS approaches and our method**: Conventional supernet-based NAS approaches (Left) sample subnets from a fixed supernet trained on a single dataset. TANS (Right), on the other hand, can dynamically select the best-fitted neural networks that are trained on diverse datasets, adaptively for each query dataset with the meta-learned cross-modal latent space.

the problem did not receive much attention due to the consideration of only a few datasets in the NAS benchmarks (See Figure 1, left). However, in real-world scenarios, NAS approaches should search over diverse datasets with heterogeneous distributions, and thus it is important to *task-adaptively* search for the architecture and parameter values for a given dataset. Recently, MetaD2A [18] has utilized meta-learning to learn common knowledge for NAS across tasks, to rapidly adapt to unseen tasks. However it does not consider parameters for the searched architecture, and thus still requires additional training on unseen datasets.

Given such limitations of NAS and meta-NAS methods, we introduce a novel problem of *Neural Network Search* (NNS), whose goal is to search for the optimal pretrained networks for a given dataset and conditions (e.g. number of parameters). To tackle the problem, we propose a novel and extremely efficient task-adaptive neural network retrieval framework that searches for the optimal neural network with both the architecture and the parameters for a given task, based on cross-modal retrieval. In other words, instead of searching for an optimal architecture from scratch or taking a sub-network from a single super-net, we *retrieve* the most optimal network for a given dataset in a task-adaptive manner (See Figure 1, right), by searching through the model zoo that contains neural networks pretrained on diverse datasets. We first start with the construction of the model zoo, by pretraining state-of-the-art architectures on diverse real-world datasets.

Then, we train our retrieval model via amortized meta-learning of a cross-modal latent space with a contrastive learning objective. Specifically, we encode each dataset with a set encoder and obtain functional and topological embeddings of a network, such that a dataset is embedded closer to the network that performs well on it while minimizing the similarity between irrelevant dataset-network pairs. The learning process is further guided by a performance predictor, which predicts the model's performance on a given dataset.

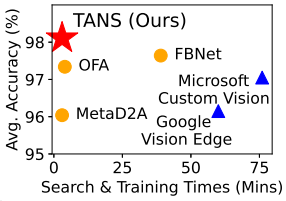



Figure 2: Comparison with NAS (orange) & AutoML (blue) baselines on 5 Real-world Datasets

The proposed *Task-Adaptive Network Search* (TANS) largely outperforms conventional NAS/AutoML methods (See Figure 2), while significantly reducing the search time. This is because the retrieval of a trained network can be done instantly without any additional architecture search cost, and retrieving a task-relevant network will further reduce the fine-tuning cost. To evaluate the proposed TANS, we first demonstrate the sample-efficiency of our model zoo construction method, over construction with random sampling of dataset-network pairs. Then, we show that the TANS can adaptively retrieve the best-fitted models for an unseen dataset. Finally, we show that our method significantly outperforms baseline NAS/AutoML methods on **real-world datasets** (Figure 2), with incomparably smaller computational cost to reach the target performance. In sum, our main contributions are as follows:

- We consider a novel problem of *Neural Network Search*, whose goal is to search for the optimal network for a given task, including both the architecture and the parameters.
- We propose a novel cross-modal retrieval framework to retrieve a pretrained network from the model zoo for a given task via amortized meta-learning with constrastive objective.
- We propose an efficient model-zoo construction method to construct an effective database of dataset-architecture pairs, considering both the model performance and task diversity.
- We train and validate TANS on a newly collected large-scale database, on which our method outperforms all NAS/AutoML baselines with almost no architecture search cost and significantly fewer fine-tuning steps.

## 2 Related Work

**Neural Architecture Search** *Neural Architecture Search* (NAS), which aims to automate the design of neural architectures, is an active topic of research nowadays. Earlier NAS methods use non-differentiable search techniques based on RL [46, 47] or evolutionary algorithms [28, 7]. However, their excessive computational requirements [29] in the search process limits their practical applicability to resource-limited settings. To tackle this challenge, one-shot methods share the parameters [27, 3, 22, 39] among architectures, which reduces the search cost by orders of magnitude. The surrogate scheme predicts the performance of architectures without directly training them [24, 45, 33], which also cuts down the search cost. Latent space-based NAS methods [24, 33, 41] learn latent embeddings of the architectures to reconstruct them for a specific task. Recently, supernet-based approaches, such as OFA [4], receive the most attention due to their high-performances. OFA generates the subnet with its parameters by splitting the trained supernet. While this eliminates the need for costly re-training of each searched architecture from scratch, but, it only trains a fixed-supernet on a single dataset (ImageNet-1K), which limits their effectiveness on diverse tasks that are largely different from the training set. Whereas our TANS task-adaptively retrieves a trained neural network from a database of networks with varying architectures trained on diverse datasets.

**Meta-Learning** The goal of meta-learning [34] is to learn a model to generalize over the distribution of tasks, instead of instances from a single task, such that a meta-learner trained across multiple tasks can rapidly adapt to a novel task. While most meta-learning methods consider few-shot classification with a fixed architecture [35, 12, 32, 25, 20, 17], there are a few recent studies that couple NAS with meta-learning [30, 21, 9] to search for the well-fitted architecture for the given task. However, these NAS approaches are limited to small-scale tasks due to the cost of roll-out gradient steps. To tackle this issue, MetaD2A [18] proposes to generate task-dependent architectures with amortized meta-learning, but does not consider parameters for the searched architecture, and thus requires additional cost of training it on unseen datasets. To overcome these limitations, our method retrieves the best-fitted architecture with its parameters for the target task, by learning a cross-modal latent space for dataset-network pairs with amortized meta-learning.

**Neural Retrieval** Neural retrieval aims to search for and return the best-fitted item for the given query, by learning to embed items in a latent space with a neural network. Such approaches can be broadly classified into models for image retrieval [13, 8, 40] and text retrieval [43, 5, 38]. Cross-modal retrieval approaches [19, 44, 36] handle retrieval across different modalities of data (e.g. image and text), by learning a common representation space to measure the similarity across the instances from different modalities. To our knowledge, none of the existing works is directly related to our approach that performs cross-modal retrieval of neural networks given datasets.

## 3 Methodology

We first define the Neural Network Search (NNS) problem and propose a meta-contrastive learning framework to learn a cross-modal retrieval space. We then describe the structural details of the query and model encoders, and an efficient model-zoo construction strategy.

### 3.1 Problem Definition

Our goal in NNS is to search for an optimal network (with both architectures and parameters) for a dataset and constraints, by learning a cross-modal latent space over the dataset-network pairs. We first describe the task-adaptive network retrieval with amortized meta-contrastive learning.

#### 3.1.1 Meta-Training

We assume that we have a database of neural networks (model zoo) pretrained over a distribution of tasks $p(\tau)$ with each task $\tau = \{D^\tau, M^\tau, s^\tau\}$, where $D^\tau$ denotes a dataset, $M^\tau$ denotes a neural network trained on the dataset, and $s^\tau$ denotes a set of auxiliary constraints for the network to be found (e.g. number of parameters or the inference latency). Then, our goal is to learn a cross-modal latent space for the dataset-network pairs $(D^\tau, M^\tau)$ while considering the constraints $s^\tau$ over the task distribution $p(\tau)$, as illustrated in Figure 1. In this way, a meta-trained model from diverse $(D^\tau, M^\tau)$ pairs, will rapidly generalize on an unseen dataset $\tilde{D}$; $D^\tau \cap \tilde{D} = \emptyset$ by retrieving a well-fitted neural network on the dataset that satisfies the conditions $s^\tau$.

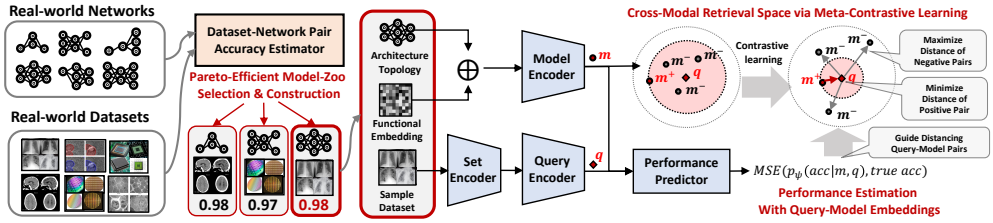



Figure 3: **Illustration for overall framework of our proposed method (TANS)**: We first construct our model-zoo with pareto-optimal pairs of dataset and network, rather than exhaustively train all possible pairs. We then embed a model and a dataset with a graph-functional model and a set encoder. After that, we meta-learn the cross-modal retrieval network over multiple model-query pairs, guided by our performance predictor.

**Task-Adaptive Neural Network Retrieval** To learn a cross-modal latent space for dataset-network pairs over a task distribution, we first introduce a novel task-adaptive neural network retrieval problem. The goal of task-adaptive retrieval is to find an appropriate network $M^\tau$ given the query dataset $D^\tau$ for task $\tau$. To this end, we need to calculate the similarity between the dataset-network pair $(D^\tau, M^\tau) \in \mathcal{Q} \times \mathcal{M}$, with a scoring function $f$ that outputs the similarity between them as follows:

$$\max_{\boldsymbol{\theta},\boldsymbol{\phi}} \sum_{\tau \in p(\tau)} f(\boldsymbol{q}, \boldsymbol{m}), \quad \boldsymbol{q} = E_Q(D^\tau; \boldsymbol{\theta}) \quad \text{and} \quad \boldsymbol{m} = E_M(N^\tau; \boldsymbol{\phi}), \tag{1}$$

where $E_Q : \mathcal{Q} \to \mathbb{R}^d$ is a query (dataset) encoder, $E_M : \mathcal{M} \to \mathbb{R}^d$ is a model encoder, which are parameterized with the parameter $\boldsymbol{\theta}$ and $\boldsymbol{\phi}$ respectively, and $f_{sim} : \mathbb{R}^d \times \mathbb{R}^d \to \mathbb{R}$ is a scoring function for the query-model pair. In this way, we can construct the cross-modal latent space for dataset-network pairs over the task distribution with equation 1, and use this space to rapidly retrieve the well-fitted neural network in response to the unseen query dataset.

We can learn such a cross-modal latent space of dataset-network pairs for rapid retrieval by directly solving for the above objective, with the assumption that we have the query and the model encoder: $Q$ and $M$. However, we further propose a contrastive loss to maximize the similarity between a dataset and a network that obtains high performance on it in the learned latent space, and minimize the similarity between irrelevant dataset-network pairs, inspired by Faghri et al. [11], Engilberge et al. [10]. While existing works such as Faghri et al. [11], Engilberge et al. [10] target image-to-text retrieval, we tackle the problem of cross-modal retrieval across datasets and networks, which is a nontrivial problem as it requires task-level meta-learning.

**Retrieval with Meta-Contrastive Learning** Our *meta-contrastive learning* objective for each task $\tau \in p(\tau)$ consisting of a dataset-model pair $(D^\tau, M^\tau) \in \mathcal{Q} \times \mathcal{M}$, aims to maximize the similarity between positive pairs: $f_{sim}(\boldsymbol{q}, \boldsymbol{m}^+)$, while minimizing the similarity between negative pairs: $f_{sim}(\boldsymbol{q}, \boldsymbol{m}^-)$, where $\boldsymbol{m}^+$ is obtained from the sampled target task $\tau \in p(\tau)$ and $\boldsymbol{m}^-$ is obtained from other tasks $\gamma \in p(\tau); \gamma \neq \tau$, which is illustrated in Figure 3. This meta-contrastive learning loss can be formally defined as follows:

$$\begin{aligned} \mathcal{L}_m(\tau; \boldsymbol{\theta}, \boldsymbol{\phi}) &= \mathcal{L}(f_{sim}(\boldsymbol{q}, \boldsymbol{m}^+), f_{sim}(\boldsymbol{q}, \boldsymbol{m}^-); \boldsymbol{\theta}, \boldsymbol{\phi}) \\ \boldsymbol{q} = E_Q(D^\tau; \boldsymbol{\theta}),\ \boldsymbol{m}^+ &= E_M(M^\tau; \boldsymbol{\phi}),\ \boldsymbol{m}^- = E_M(M^\gamma; \boldsymbol{\phi}). \end{aligned} \tag{2}$$

We then introduce $\mathcal{L}$ for the meta-contrastive learning:

$$\max \left( 0, \alpha - \log \frac{\exp(f_{sim}(\boldsymbol{q}, \boldsymbol{m}^+))}{\exp\left(\sum_{\gamma \in p(\tau), \gamma \neq \tau} f_{sim}(\boldsymbol{q}, \boldsymbol{m}^-)\right)} \right), \tag{3}$$

where $\alpha \in \mathbb{R}$ is a margin hyper-parameter and the score function $f_{sim}$ is the cosine similarity. The contrastive loss promotes the positive $(\boldsymbol{q}, \boldsymbol{m}^+)$ embedding pair to be close together, with at most margin $\alpha$ closer than the negative $(\boldsymbol{q}, \boldsymbol{m}^-)$ embedding pairs in the learned cross-modal metric space. Note that, similar to this, we also contrast the query with its corresponding model: $\mathcal{L}_q(f_{sim}(\boldsymbol{q}^+, \boldsymbol{m}), f_{sim}(\boldsymbol{q}^-, \boldsymbol{m}))$, which we describe in the supplementary material in detail.

With the above ingredients, we minimize the meta-contrastive learning loss over a task distribution $p(\tau)$, defined with the model $\mathcal{L}_m$ and query $\mathcal{L}_q$ contrastive losses, as follows:

$$\min_{\boldsymbol{\phi},\boldsymbol{\theta}} \sum_{\tau \in p(\tau)} \mathcal{L}_m(\tau; \boldsymbol{\theta}, \boldsymbol{\phi}) + \mathcal{L}_q(\tau; \boldsymbol{\theta}, \boldsymbol{\phi}). \tag{4}$$

**Meta-Performance Surrogate Model** We propose the meta-performance surrogate model to predict the performance on an unseen dataset without directly training on it, which is highly practical in real-world scenarios since it is expensive to iteratively train models for every dataset to measure the performance. Thus, we meta-train a performance surrogate model $a = S(\tau; \boldsymbol{\psi})$ over a distribution of tasks $p(\tau)$ on the model-zoo database. This model not only accurately predicts the performance $a$ of a network $M^\tau$ on an unseen dataset $D^\tau$, but also guides the learning of the cross-modal retrieval space, thus embedding a neural network closer to datasets that it performs well on.

Specifically, the proposed surrogate model $S$ takes a query embedding $\boldsymbol{q}^\tau$ and a model embedding $\boldsymbol{m}^\tau$ as an input for the given task $\tau$, and then forwards them to predict the accuracy of the model for the query. We train this performance predictor $S(\tau; \boldsymbol{\psi})$ to minimize the mean-square error loss $\mathcal{L}_s(\tau; \boldsymbol{\psi}) = (s^\tau_{\text{acc}} - S(\tau; \boldsymbol{\psi}))^2$ between the predicted accuracy $S(\tau; \boldsymbol{\psi})$ and the true accuracy $s^\tau_{\text{acc}}$ for the model on each task $\tau$, which is sampled from the task distribution $p(\tau)$. Then, we combine this objective with retrieval objective in equation 4 to train the entire framework as follows:

$$\min_{\boldsymbol{\phi}, \boldsymbol{\theta}, \boldsymbol{\psi}} \sum_{\tau \in p(\tau)} \mathcal{L}_m(\tau; \boldsymbol{\theta}, \boldsymbol{\phi}) + \mathcal{L}_q(\tau; \boldsymbol{\theta}, \boldsymbol{\phi}) + \lambda \cdot \mathcal{L}_s(\tau; \boldsymbol{\psi}), \tag{5}$$

where $\lambda$ is a hyper-parameter for weighting losses.

### 3.1.2 Meta-Test

By leveraging the meta-learned cross-modal retrieval space, we can instantly retrieve the best-fitted pretrained network $M \in \mathcal{M}$, given an unseen query dataset $\tilde{D} \in \tilde{\mathcal{Q}}$, which is disjoint from the meta-training dataset $D \in \mathcal{Q}$. Equipped with meta-training components described in the previous subsection, we now describe the details of our model at inference time, which includes the following: amortized inference, performance prediction, and task- and constraints-adaptive initialization.

**Amortized Inference** Most existing NAS methods are slow as they require several GPU hours for training, to find the optimal architecture for a dataset $\tilde{D}$. Contrarily, the proposed *Task-Adaptive Network Search* (TANS) only requires a single forward pass per dataset, to obtain a query embedding $\tilde{\boldsymbol{q}}$ for the unseen dataset using the query encoder $Q(\tilde{D}; \boldsymbol{\theta}^*)$ with the meta-trained parameters $\boldsymbol{\theta}^*$, since we train our model with amortized meta-learning over a distribution of tasks $p(\tau)$. After obtaining the query embedding, we retrieve the best-fitted network $M^*$ for the query based on the similarity:

$$M^* = \max_{M^\tau} \{ f_{sim}(\tilde{\boldsymbol{q}}, \boldsymbol{m}^\tau) \mid \tau \in p(\tau) \}, \tag{6}$$

where a set of model embeddings $\{\boldsymbol{m}^\tau \mid \tau \in p(\tau)\}$ is pre-computed by the meta-trained model encoder $E_M(M^\tau; \boldsymbol{\phi}^*)$.

**Performance Prediction** While we achieve the competitive performance on unseen dataset only with the previously defined model, we also use the meta-learned performance predictor $S$ to select the best performing one among top $K$ candidate networks $\{\tilde{M}_i\}_{i=1}^K$ based on their predicted performances. Since this surrogate model with module to consider datasets is meta-learned over the distribution of tasks $p(\tau)$, we predict the performance on an unseen dataset $\tilde{D}$ without training on it. This is different from the conventional surrogate models [24, 45, 33] that additionally need to train on an unseen dataset from scratch, to predict the performance on it.

**Task-adaptive Initialization** Given an unseen dataset, the proposed TANS can retrieve the network trained on a training dataset that is highly similar to the unseen query dataset from the model zoo (See Figure 4). Therefore, fine-tuning time of the trained network for the unseen target dataset $\tilde{D}$ is effectively reduced since the retrieved network $M$ has task-relevant initial parameters that are already trained on a similar dataset. If we need to further consider constraints $s$, such as parameters and FLOPs, then we can easily check if the retrieved models meet the specific constraints by sorting them in the descending order of their scores, and then selecting the constraint-fitted best accuracy model.

## 3.2 Encoding Datasets and Networks

**Query Encoder** The goal of the proposed query encoder $E_Q(D; \boldsymbol{\theta}) : \mathcal{Q} \rightarrow \mathbb{R}^d$ is to embed a dataset $D$ as a single query vector $\boldsymbol{q}$ onto the cross-modal latent space. Since each dataset $D$ consists of $n$ data instances $D = \{X_i\}_{i=1}^n \in \mathcal{Q}$, we need to fulfill the permutation-invariance condition over

the data instances $X_i$, to output a consistent representation regardless of the order of its instances. To satisfy this condition, we first individually transform $n$ randomly sampled instances for the dataset $D$ with a continuous learnable function $\rho$, and then apply a pooling operation to obtain the query vector $\boldsymbol{q} = \sum_{X_i \in D} \rho(X_i)$, adopting Zaheer et al. [42].

**Model Encoder** To encode a neural network $M^\tau$, we consider both its architecture and the model parameters trained on the dataset $D^\tau$ for each task $\tau$. Thus, we propose to generate a model embedding with two encoding functions: 1) topological encoding and 2) functional encoding.

Following Cai et al. [4], we first obtain a topological embedding $\boldsymbol{v}_t^\tau$ with auxiliary information about the architecture topology, such as the numbers of layers, channel expansion ratios, and kernel sizes. Then, our next goal is to encode the trained model parameters for the given task, to further consider parameters on the neural architecture. However, a major problem here is that directly encoding millions of parameters into a vector is highly challenging and inefficient. To this end, we use functional embedding, which embeds a network solely based on its input-output pairs. This operation generates the embedding of trained networks, by feeding a fixed Gaussian random noise into each network $M^\tau$, and then obtaining an output $\boldsymbol{v}_f^\tau$ of it. The intuition behind the functional embedding is straightforward: since networks with different architectures and parameters comprise different functions, we can produce different outputs for the same input.

With the two encoding functions, the proposed model encoder generates the model representation by concatenating the topology and function embeddings $[\boldsymbol{v}_t^\tau, \boldsymbol{v}_f^\tau]$, and then transforming the concatenated vector with a non-linear function $\sigma$ as follows: $\boldsymbol{m}^\tau = \sigma([\boldsymbol{v}_t^\tau, \boldsymbol{v}_f^\tau]) = E_M(M^\tau; \boldsymbol{\phi})$. Note that, the two encoding functions satisfy the injectiveness property under certain conditions, which helps with the accurate retrieval of the embedded elements in a condensed continuous latent space. We provide the proof of the injectiveness of the two encoding functions in Section C of the supplementary file.

### 3.3 Model-Zoo Construction

Given a set of datasets $\mathcal{D} = \{D_1, \ldots, D_K\}$ and a set of architectures $\mathcal{M} = \{M_1, \ldots, M_N\}$, the most straightforward way to construct a model zoo $\mathcal{Z}$, is by training all architectures on all datasets, which will yield a model zoo $\mathcal{Z}$ that contains $N \times K$ pretrained networks. However, we may further reduce the construction cost by collecting $P$ dataset-model pairs, $\{D, M\}_{i=1}^P$, where $P \ll N \times K$, by randomly sampling an architecture $M \in \mathcal{M}$ and then training it on $D \in \mathcal{D}$. Although this works well in practice (see Figure 6 (d)), we further propose an efficient algorithm to construct it in a more sample-efficient manner, by skipping evaluation of dataset-model pairs that are certainly worse than others in all aspects (memory consumption, latency, and test accuracy). We start with an initial model zoo $\mathcal{Z}_{(0)}$ that contains a small amount of randomly selected pairs and its test accuracies. Then, at each iteration $t$, among the set of candidates $C_{(t)}$, we find a pair $\{D, M\}$ that can expand the currently known set of all Pareto-optimal pairs w.r.t. all conditions (memory, latency, and test accuracy on the dataset $D$), based on the amount of the Pareto front expansion estimated by $f_{zoo}(\cdot; \mathcal{Z}_{(t)})$:

$$\{D, M\}_{(t+1)} = \underset{(D,M) \in C_{(t)}}{\arg\max} \; f_{zoo}(\{D, M\}; \mathcal{Z}_{(t)}) \tag{7}$$

where $f_{zoo}(\{D, M\}; \mathcal{Z}) := \underset{\hat{s}_{acc}}{\mathbb{E}} \left[ g_D(\mathcal{Z} \cup \{D, M, \hat{s}_{acc}\}) - g_D(\mathcal{Z}) \right]$, $\hat{s}_{acc} \sim S(\{D, M\}; \boldsymbol{\psi}_{zoo})$ with parameter $\boldsymbol{\psi}_{zoo}$ trained on $\mathcal{Z}$, and the function $g_D$ measures the volume under the Pareto curve, also known as the Hypervolume Indicator [26], for the dataset $D$. We then train $M$ on $D$, and add it to the current model zoo $\mathcal{Z}_{(t)}$. For the full algorithm, please refer to Section A of the supplementary file.

## 4 Experiments

In this section, we conduct extensive experimental validation against conventional NAS methods and commercially available AutoML platforms, to demonstrate the effectiveness of our proposed method.

### 4.1 Experimental Setup

To construct a model zoo consisting of a large number of dataset-network pairs, we collect 119 real-world datasets from Kaggle*, and divide the datasets into two non-overlapping sets for meta-train

*https://www.kaggle.com/

Table 1: **Performance of the searched networks on 10 real-world datasets.** We report the averaged accuracy on ten unseen datasets over 3 different runs with 95% confidence intervals.

| Target Dataset | Method | Params (M) | Search Time (GPU sec) | Training Time (GPU sec) | Speed Up | Accuracy (%) |
|---|---|---|---|---|---|---|
| Averaged Performance | MobileNetV3 [15] | 4.00 | - | 257.78±09.77 | 1.00× | 94.20±0.70 |
| | PC-DARTS [39] - 500 Epochs | **3.54** | 1100.37±22.20 | 5721.13±793.71 | 0.04× | 79.22±1.69 |
| | DrNAS [6] - 500 Epochs | 4.12 | 1501.75±43.92 | 5659.77±403.62 | 0.04× | 84.06±0.97 |
| | FBNet-A [37] | 4.3 | - | 293.42±57.45 | 0.88× | 93.00±1.95 |
| | OFA [4] | 6.74 | 121.90±0.00 | 226.58±03.13 | 0.74× | 93.89±0.84 |
| | MetaD2A [18] | 6.56 | 2.59±0.13 | 345.39±28.36 | 0.74× | 95.24±1.14 |
| | **TANS (Ours)** - 10 Epochs | 5.51 | 0.002±0.00 | 40.19±03.06 | - | 95.17±2.20 |
| | **TANS (Ours)** - 50 Epochs | 5.51 | **0.002±0.00** | **200.93±11.01** | **1.28×** | **96.28±0.30** |
| Colorectal Histology Dataset (Easy) | MobileNetV3 [15] | **4.00** | - | 577.18±04.15 | 1.00× | 96.23±0.07 |
| | PC-DARTS [39] - 500 Epochs | 4.02 | 2062.42±49.14 | 12124.18±1051.16 | 0.04× | 96.17±0.68 |
| | DrNAS [6] - 500 Epochs | 4.12 | 4183.20±188.60 | 11355.18±1352.62 | 0.04× | 97.51±0.13 |
| | FBNet-A [37] | 4.3 | - | 696.00±295.19 | 0.83× | 95.43±0.57 |
| | OFA [4] | 6.74 | 121.90±0.00 | 537.61±03.52 | 0.88× | 96.40±0.52 |
| | MetaD2A [18] | 5.93 | 2.58±0.12 | 784.45±79.32 | 0.73× | 96.57±0.56 |
| | **TANS (Ours)** - 10 Epochs | 4.95 | 0.001±0.00 | 98.56±04.24 | - | 96.87±0.21 |
| | **TANS (Ours)** - 50 Epochs | 4.95 | **0.001±0.00** | **492.81±21.19** | **1.17×** | **97.67±0.05** |
| Food Classification Dataset (Hard) | MobileNetV3 [15] | 4.00 | - | 235.57±07.57 | 1.00× | 87.52±0.78 |
| | PC-DARTS [39] - 500 Epochs | **3.62** | 1018.49±6.31 | 6323.40±938.83 | 0.03× | 55.42±2.46 |
| | DrNAS [6] - 500 Epochs | 4.12 | 1276.38±0.00 | 5079.89±161.05 | 0.04× | 61.45±0.68 |
| | FBNet-A [37] | 4.3 | - | 251.24±3.31 | 0.94× | 84.33±1.41 |
| | OFA [4] | 6.74 | 121.90±0.00 | **190.86±03.48** | 0.75× | 87.43±0.59 |
| | MetaD2A [18] | 8.23 | 2.60±0.23 | 324.62±34.97 | 0.72× | 89.72±1.53 |
| | **TANS (Ours)** - 10 Epochs | 5.07 | 0.002±0.00 | 40.59±04.84 | - | 93.11±0.24 |
| | **TANS (Ours)** - 50 Epochs | 5.07 | **0.002±0.00** | 202.93±24.21 | **1.16×** | **93.71±0.24** |

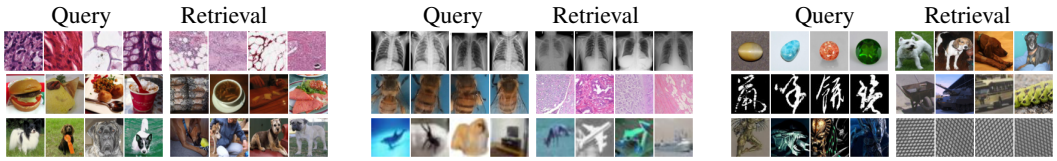



Figure 4: **Retrieved examples for meta-test datasets.** We visualize the dataset used for pretraining the retrieved model with the unseen query dataset. For more examples, see Section D in supplementary file.

and meta-test. We then adjust each dataset to have up to 20 classes, yielding 140/10 datasets for meta-train/meta-test, respectively. We use randomly sampled 80/20% instances for each dataset as a training and test set. For evaluating datasets, we use 10 real-world datasets, which are Colorectal Histology, Drawing, Dessert, Chinese Characters, Speed Limit Signs, Alien vs Predator, COVID-19, Gemstones, and Dog Breeds, downloaded from Kaggle. We strictly verified that there is **no dataset-, class-, and instance-level overlap** between the training datasets in the model zoo and the test datasets, while some datasets may contain semantically similar classes. We arbitrarily sample 100 architecture candidates from the OFA space and construct our model-zoo with all 14,000 dataset-model pairs, and also construct model-zoos with smaller sizes using our algorithm described in Section 3.3. For baseline models, we consider a pretrained neural network [15] as well as ones searched by several efficient NAS methods [39, 6, 4, 18] and AutoML platforms that are commercially available. For detailed descriptions of the experimental setup, please see Section D of the supplementary file.

### 4.2 Experimental Results

**Meta-test Results** We compare 50-epoch accuracy between TANS and the existing NAS methods on 10 novel real-world datasets. For a fair comparison, we train PC-DARTS [39] and DrNAS [6] for 10 times more epochs (500), as they only generate architectures without pretrained weights, so we train them for a sufficient amount of iterations. For FBNet and OFA (weight-sharing based methods) and MetaD2A (data-driven meta-NAS method), which provide the searched architectures as well as pretrained weights from ImageNet-1K, we fine-tune them on the meta-test query datasets for 50 epochs. As shown in Table 1, we observe that TANS outperforms all baselines, with incomparably smaller search time and relatively smaller training time. Conventional NAS approaches such as PC-DARTS and DrNAS repeatedly require large search time for every dataset, and thus are inef-

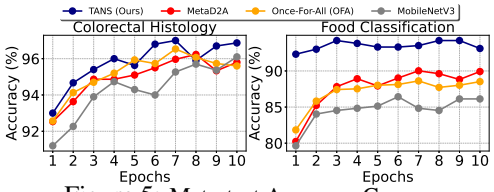
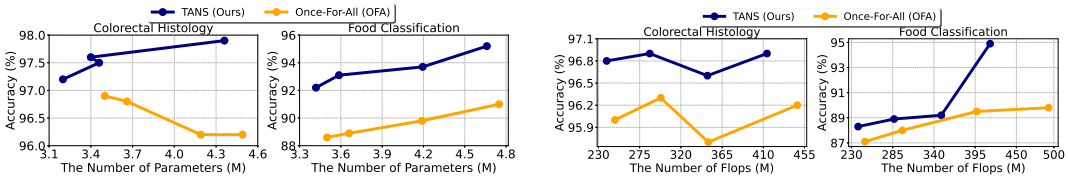
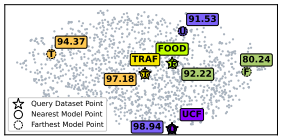


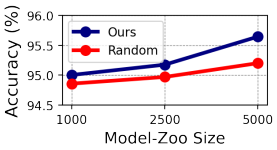

Figure 5: Meta-test Accuracy Curves




(a) Number of Parameters (b) FLOPs




(c) The Cross-Modal Latent Space




(d) Model-Zoo Size

| Method (1/20 Model-Zoo) | Averaged Acc. |
|---|---|
| TANS (Ours) | 95.07% |
| TANS w Random Init. | 74.89% |
| TANS w ImageNet | 94.84% |
| **TANS w MetaD2A Arch.** | **95.38%** |

(e) Ablation Study on Archi. & Param.

Figure 6: **In-depth analysis of TANS:** Performance plot regarding constraints, such as (a) the number of parameters and (b) FLOPs. (c) Visualization for the cross-modal latent space using T-SNE. (d) Model-zoo with different sizes. (e) Ablation study on architecture and parameter information.

ficient for this practical setting with real-world datasets. FBNet, OFA, and MetaD2A are much more efficient than general NAS methods since they search for subnets within a given supernet, but obtain suboptimal performances on unseen real-world datasets as they may have largely different distributions from the dataset the supernet is trained on. In contrast, our method achieves almost zero cost in search time, and reduced training time as it fine-tunes a network pretrained on a relevant dataset. In Figure 5, we show the test performance curves and observe that TANS often starts with a higher starting point, and converges faster to higher accuracy.

In Figure 4, we show example images from the query and training datasets that the retrieved models are pretrained on. In most cases, our method matches semantically similar datasets to the query dataset. Even for the semantically-dissimilar cases (right column), for which our model-zoo does not contain models pretrained on datasets similar to the query, our models still outperform all other base NAS models. As such, our model effectively retrieves not only task-relevant models, but also potentially best-fitted models even trained with dissimilar datasets, for the given query datasets. We provide detailed descriptions for all query and retrieval pairs in Section D of the supplementary file.

We also compare with commercially available AutoML platforms, such as Microsoft Azure Custom Vision [1] and Google Vision Edge [2]. For this experiment, we evaluate on randomly chosen five datasets (out of ten), due to excessive training costs required on AutoML platforms. As shown in Figure 2, our method outperforms all commercial NAS/AutoML methods, with a significantly smaller total time cost. We provide more details and additional experiments, such as including real-world architectures, in Section D of the supplementary file.

**Analysis of the Architecture & Parameters** To see that our method is effective in retrieving networks with both optimal architecture and relevant parameters, we conduct several ablation studies. We first report the results of base models that only search for the optimal architectures. Then we provide the results of the network retrieved using a variant of our method which does not use the topology (architecture) embedding, and only uses the functional embedding $v_f^\tau$ (Tans w/o Topol). As shown in Table 2, TANS w/o Topol outperforms base NAS methods (except for MetaD2A) without considering the architectures, which shows that the performance improvement mostly comes from the knowledge transfer from the weights of the most relevant pretrained networks. However, the full TANS obtains about 1% higher performance over TANS w/o Topol., which shows the importance of the architecture and the effectiveness of our architecture embedding. In Figure 6 (e), we further experiment with a version of our method that initializes the retrieved networks with both random weights and ImageNet pre-trained weights, using 1/20 sized model-zoo (700 models). We observe that they achieve lower accuracy over TANS on 10 datasets, which again shows the importance of retrieving relevant tasks' knowledge. We also construct the model-zoo by training on the architectures found by an existing NAS method (MetaD2A), and see that it further improves the performance of TANS.

Table 2: Effects of Topology

| Model | Averaged Acc. |
|---|---|
| FBNet-A [37] | 93.00±1.95 |
| OFA [4] | 93.89±0.84 |
| MetaD2A [18] | 95.24±1.14 |
| TANS w/o Topol. | 95.24±0.21 |
| TANS (Ours) | **96.28±0.30** |

**Contraints-conditioned Retrieval** TANS can retrieve the network for the given dataset while considering additional constraints, such as the number of the parameters or the computations (in

FLOP). This is practically important since we may need a network with less memory and computation overhead depending on the hardware device. This can be done by filtering networks that satisfy the given conditions among the candidate networks retrieved. For this experiment, we compare against OFA that performs the same constrained search, as other baselines do not straightforwardly handle this scenario. As shown in Figure 6, we observe that the network retrieved with TANS consistently outperforms the network searched with OFA under varying parameters and computations constraints. Such constrained search is straightforward with our method since our retrieval-based method allows us to search from the database consisting of networks with varying architectures and sizes.

**Effectiveness of the Meta-performance Predictor** The role of the proposed performance predictor is not only guiding the model and query encoder to learn the better latent space but also selecting the best model among retrieval candidates. To verify its effectiveness, we measure the performance gap between the top-1 retrieved model w/o the predictor and the model with the highest scores selected using the predictor among retrieved candidates. As shown in Figure 7, there are $1.5\%p$ - $8\%p$ performance gains on the meta-test datasets. The top-1 retrieved model from the model zoo with TANS may not be always optimal for an unseen dataset, and our performance predictor remedies this issue by selecting the best-fitted model based on its estimation.

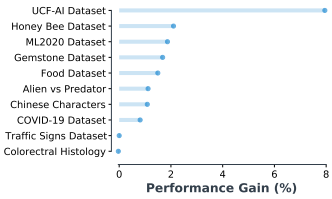


Figure 7: Performance Gain

**Retrieval Performance** We also verify whether our model successfully retrieves the same paired models when the correspondent **meta-train** datasets are given (we use unseen instances that are **not used** when training the encoders.) For the evaluation metric, we use recall at $k$ (**R@$k$**) which indicates the percentage of the correct models retrieved among the top-$k$ candidates for the unseen query instances, where $k$ is set to 1, 5, and 10. Also, we report the mean and median ranking of the correct network among all networks for the unseen query. In Table 3, the largest parameter selection strategy shows poor performances on the retrieval problem, suggesting that simply selecting the largest network is not a suitable choice for real-world tasks. In addition, compared to cosine similarity learning, the proposed meta-contrastive learning allows the model to learn significantly improved discriminative latent space for cross-modal retrieval. Moreover, without our performance predictor, we observe that TANS achieves slightly lower performance.

Table 3: Retrieval Performance

| Model | Performance of The Same Pair Retrieval | | | | |
|---|---|---|---|---|---|
| | R@1 | R@5 | R@10 | Mean | Median |
| Random | 2.14 | 2.86 | 8.57 | 69.04 | 70.0 |
| Largest Parameter | 3.57 | 7.14 | 10.00 | 51.85 | 52.0 |
| TANS + Cosine | 9.29 | 12.86 | 22.14 | 46.02 | 38.0 |
| TANS + Hard Neg. | 72.14 | 84.29 | 88.57 | 4.86 | 1.0 |
| **TANS + Contrastive** | **80.71** | **96.43** | **99.29** | **1.90** | **1.0** |
| TANS w/o Predictor | 80.00 | **96.43** | 97.86 | 2.23 | **1.0** |

**Analysis of the Cross-Modal Retrieval Space and the Model-Zoo** We further examine the learned cross-modal space and the model zoo. We first visualize the meta-learned latent space in Figure 6 (c) with randomly sampled 1,400 models among 14,000 models in the model-zoo. We observe that the network whose embeddings are the closest to the query dataset achieves higher performance on it, compared to networks embedded the farthest from it. For example, the accuracy of the closet network point for UCF-AI is $98.94\%$ while the farthest network only achieves $91.53\%$. To further show the efficiency of our model-zoo, we show that using a smaller model zoo up to 1/10 the size of the original, only incurs a small performance drop compared to the full model zoo with 14,000 networks in Figure 6 (d). Furthermore, a model zoo constructed using our efficient construction algorithm yields models with higher performance on average, compared with random sampling. Note that the model-zoo is constructed is only once, and we do not need additional search procedures for each task regardless of the number of the queries (tasks).

## 5 Conclusion

We propose a novel Task-Adaptive Neural network Search framework (TANS), that instantly retrieves a relevant pre-trained network for an unseen dataset, based on the cross-modal retrieval of dataset-network pairs. We train this retrieval model via amortized meta-learning of the cross-modal latent space with contrastive learning, to maximize the similarity between the positive dataset-network pairs, and minimize the similarity between the negative pairs. We train our framework on a model zoo consisting of diverse pretrained networks, and validate its performance on ten unseen datastes. The results show that the proposed TANS rapidly searches and trains a well-fitted network for unseen datasets with almost no architecture search cost and significantly fewer fine-tuning steps to reach the target performance, compared to other NAS methods. We discuss the **limitation and the societal impact** of our work in the supplementary file.

# References


[1] Microsoft azure custom vision. https://www.customvision.ai/.

[2] Google automl vision edge. https://cloud.google.com/vision/automl.

[3] Andrew Brock, Theodore Lim, James M. Ritchie, and Nick Weston. SMASH: one-shot model architecture search through hypernetworks. In *6th International Conference on Learning Representations, ICLR 2018, Vancouver, BC, Canada, April 30 - May 3, 2018, Conference Track Proceedings*, 2018.

[4] Han Cai, Chuang Gan, Tianzhe Wang, Zhekai Zhang, and Song Han. Once for all: Train one network and specialize it for efficient deployment. In *International Conference on Learning Representations*, 2020.

[5] Wei-Cheng Chang, Felix X. Yu, Yin-Wen Chang, Yiming Yang, and Sanjiv Kumar. Pre-training tasks for embedding-based large-scale retrieval. In *8th International Conference on Learning Representations, ICLR 2020, Addis Ababa, Ethiopia, April 26-30, 2020*, 2020.

[6] Xiangning Chen, Ruochen Wang, Minhao Cheng, Xiaocheng Tang, and Cho-Jui Hsieh. Dr{nas}: Dirichlet neural architecture search. In *International Conference on Learning Representations*, 2021.

[7] Yukang Chen, Gaofeng Meng, Qian Zhang, Shiming Xiang, Chang Huang, Lisen Mu, and Xinggang Wang. RENAS: reinforced evolutionary neural architecture search. In *IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2019, Long Beach, CA, USA, June 16-20, 2019*, pages 4787–4796. Computer Vision Foundation / IEEE, 2019.

[8] A Francis Saviour Devaraj, G Murugaboopathi, Mohamed Elhoseny, K Shankar, Kyungbok Min, Hyeonjoon Moon, and Gyanendra Prasad Joshi. An efficient framework for secure image archival and retrieval system using multiple secret share creation scheme. *IEEE Access*, 8: 144310–144320, 2020.

[9] Thomas Elsken, Benedikt Staffler, Jan Hendrik Metzen, and Frank Hutter. Meta-learning of neural architectures for few-shot learning. In *2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition, CVPR 2020, Seattle, WA, USA, June 13-19, 2020*, pages 12362–12372. IEEE, 2020.

[10] Martin Engilberge, Louis Chevallier, Patrick Pérez, and Matthieu Cord. Finding beans in burgers: Deep semantic-visual embedding with localization. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2018.

[11] Fartash Faghri, David J. Fleet, Jamie Kiros, and Sanja Fidler. VSE++: improving visual-semantic embeddings with hard negatives. In *British Machine Vision Conference 2018, BMVC*, 2018.

[12] Chelsea Finn, Pieter Abbeel, and Sergey Levine. Model-agnostic meta-learning for fast adaptation of deep networks. In *International Conference on Machine Learning (ICML)*, 2017.

[13] Albert Gordo, Jon Almazán, Jerome Revaud, and Diane Larlus. End-to-end learning of deep visual representations for image retrieval. *International Journal of Computer Vision*, 124(2): 237–254, September 2017.

[14] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *2016 IEEE Conference on Computer Vision and Pattern Recognition, CVPR*, 2016.

[15] Andrew Howard, Mark Sandler, Grace Chu, Liang-Chieh Chen, Bo Chen, Mingxing Tan, Weijun Wang, Yukun Zhu, Ruoming Pang, Vijay Vasudevan, et al. Searching for mobilenetv3. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 1314–1324, 2019.

[16] Andrew G. Howard, Menglong Zhu, Bo Chen, Dmitry Kalenichenko, Weijun Wang, Tobias Weyand, Marco Andreetto, and Hartwig Adam. Mobilenets: Efficient convolutional neural networks for mobile vision applications. *arXiv preprint arXiv:1704.04861*, 2017.

[17] Hae Beom Lee, Hayeon Lee, Donghyun Na, Saehoon Kim, Minseop Park, Eunho Yang, and Sung Ju Hwang. Learning to balance: Bayesian meta-learning for imbalanced and out-of-distribution tasks. In *International Conference on Learning Representations (ICLR)*, 2020.

[18] Hayeon Lee, Eunyoung Hyung, and Sung Ju Hwang. Rapid neural architecture search by learning to generate graphs from datasets. In *International Conference on Learning Representations*, 2021.

[19] Kuang-Huei Lee, Xi Chen, Gang Hua, Houdong Hu, and Xiaodong He. Stacked cross attention for image-text matching. In *Computer Vision - ECCV 2018 - 15th European Conference, Munich, Germany, September 8-14, 2018, Proceedings, Part IV*, volume 11208 of *Lecture Notes in Computer Science*, pages 212–228. Springer, 2018.

[20] Kwonjoon Lee, Subhransu Maji, Avinash Ravichandran, and Stefano Soatto. Meta-learning with differentiable convex optimization. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2019.

[21] Dongze Lian, Yin Zheng, Yintao Xu, Yanxiong Lu, Leyu Lin, Peilin Zhao, Junzhou Huang, and Shenghua Gao. Towards fast adaptation of neural architectures with meta learning. In *8th International Conference on Learning Representations, ICLR 2020, Addis Ababa, Ethiopia, April 26-30, 2020*, 2020.

[22] Hanxiao Liu, Karen Simonyan, and Yiming Yang. Darts: Differentiable architecture search. In *In International Conference on Learning Representations (ICLR)*, 2019.

[23] Zhichao Lu, Kalyanmoy Deb, Erik Goodman, Wolfgang Banzhaf, and Vishnu Naresh Boddeti. Nsganetv2: Evolutionary multi-objective surrogate-assisted neural architecture search. In *European Conference on Computer Vision*, pages 35–51. Springer, 2020.

[24] Renqian Luo, Fei Tian, Tao Qin, Enhong Chen, and Tie-Yan Liu. Neural architecture optimization. In *Advances in neural information processing systems (NeurIPS)*, 2018.

[25] Alex Nichol, Joshua Achiam, and John Schulman. On first-order meta-learning algorithms. *arXiv preprint arXiv:1803.02999*, 2018.

[26] Krzysztof Nowak, Marcus Märtens, and Dario Izzo. Empirical Performance of the Approximation of the Least Hypervolume Contributor. In Thomas Bartz-Beielstein, Jürgen Branke, Bogdan Filipič, and Jim Smith, editors, *Parallel Problem Solving from Nature – PPSN XIII*, Lecture Notes in Computer Science, pages 662–671, Cham, 2014. Springer International Publishing. ISBN 978-3-319-10762-2. doi: 10.1007/978-3-319-10762-2_65.

[27] Hieu Pham, Melody Y. Guan, Barret Zoph, Quoc V. Le, and Jeff Dean. Efficient neural architecture search via parameter sharing. In *Proceedings of the 35th International Conference on Machine Learning, ICML 2018, Stockholmsmässan, Stockholm, Sweden, July 10-15, 2018*, volume 80 of *Proceedings of Machine Learning Research*, pages 4092–4101. PMLR, 2018.

[28] Esteban Real, Alok Aggarwal, Yanping Huang, and Quoc V Le. Regularized evolution for image classifier architecture search. In *Proceedings of the aaai conference on artificial intelligence*, volume 33, pages 4780–4789, 2019.

[29] Pengzhen Ren, Yun Xiao, Xiaojun Chang, Po-Yao Huang, Zhihui Li, Xiaojiang Chen, and Xin Wang. A comprehensive survey of neural architecture search: Challenges and solutions, 2020.

[30] Albert Shaw, Wei Wei, Weiyang Liu, Le Song, and Bo Dai. Meta architecture search. In *Advances in Neural Information Processing Systems 32: Annual Conference on Neural Information Processing Systems 2019, NeurIPS 2019, December 8-14, 2019, Vancouver, BC, Canada*, pages 11225–11235, 2019.

[31] Karen Simonyan and Andrew Zisserman. Very deep convolutional networks for large-scale image recognition. In *3rd International Conference on Learning Representations, ICLR 2015, San Diego, CA, USA, May 7-9, 2015, Conference Track Proceedings*, 2015.

[32] Jake Snell, Kevin Swersky, and Richard Zemel. Prototypical networks for few-shot learning. In *Advances in neural information processing systems (NIPS)*, 2017.

[33] Yehui Tang, Yunhe Wang, Yixing Xu, Hanting Chen, Boxin Shi, Chao Xu, Chunjing Xu, Qi Tian, and Chang Xu. A semi-supervised assessor of neural architectures. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 1810–1819, 2020.

[34] Sebastian Thrun and Lorien Pratt, editors. *Learning to Learn*. Kluwer Academic Publishers, Norwell, MA, USA, 1998. ISBN 0-7923-8047-9.

[35] Oriol Vinyals, Charles Blundell, Timothy Lillicrap, Daan Wierstra, et al. Matching networks for one shot learning. In *Advances in neural information processing systems (NIPS)*, 2016.

[36] Sijin Wang, Ruiping Wang, Ziwei Yao, Shiguang Shan, and Xilin Chen. Cross-modal scene graph matching for relationship-aware image-text retrieval. In *IEEE Winter Conference on Applications of Computer Vision, WACV 2020, Snowmass Village, CO, USA, March 1-5, 2020*, pages 1497–1506. IEEE, 2020.

[37] Bichen Wu, Xiaoliang Dai, Peizhao Zhang, Yanghan Wang, Fei Sun, Yiming Wu, Yuandong Tian, Peter Vajda, Yangqing Jia, and Kurt Keutzer. Fbnet: Hardware-aware efficient convnet design via differentiable neural architecture search. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 10734–10742, 2019.

[38] Lee Xiong, Chenyan Xiong, Ye Li, Kwok-Fung Tang, Jialin Liu, Paul N. Bennett, Junaid Ahmed, and Arnold Overwikj. Approximate nearest neighbor negative contrastive learning for dense text retrieval. In *International Conference on Learning Representations*, 2021.

[39] Yuhui Xu, Lingxi Xie, Xiaopeng Zhang, Xin Chen, Guo-Jun Qi, Qi Tian, and Hongkai Xiong. Pc-darts: Partial channel connections for memory-efficient architecture search. In *International Conference on Learning Representations (ICLR)*, 2020.

[40] Chenggang Yan, Biao Gong, Yuxuan Wei, and Yue Gao. Deep multi-view enhancement hashing for image retrieval. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2020.

[41] Shen Yan, Yu Zheng, Wei Ao, Xiao Zeng, and Mi Zhang. Does unsupervised architecture representation learning help neural architecture search? *Advances in Neural Information Processing Systems*, 33, 2020.

[42] Manzil Zaheer, Satwik Kottur, Siamak Ravanbakhsh, Barnabas Poczos, Ruslan R Salakhutdinov, and Alexander J Smola. Deep sets. In *Advances in Neural Information Processing Systems (NIPS)*, 2017.

[43] Weinan Zhang, Xiangyu Zhao, Li Zhao, Dawei Yin, Grace Hui Yang, and Alex Beutel. Deep reinforcement learning for information retrieval: Fundamentals and advances. In *Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 2468–2471, 2020.

[44] Liangli Zhen, Peng Hu, Xu Wang, and Dezhong Peng. Deep supervised cross-modal retrieval. In *IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2019, Long Beach, CA, USA, June 16-20, 2019*, pages 10394–10403. Computer Vision Foundation / IEEE, 2019.

[45] Dongzhan Zhou, Xinchi Zhou, Wenwei Zhang, Chen Change Loy, Shuai Yi, Xuesen Zhang, and Wanli Ouyang. Econas: Finding proxies for economical neural architecture search. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 11396–11404, 2020.

[46] Barret Zoph and Quoc V. Le. Neural architecture search with reinforcement learning. In *International Conference on Learning Representations (ICLR)*, 2017.

[47] Barret Zoph, Vijay Vasudevan, Jonathon Shlens, and Quoc V Le. Learning transferable architectures for scalable image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 8697–8710, 2018.

## Checklist

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes]
   (b) Did you describe the limitations of your work? [Yes]
   (c) Did you discuss any potential negative societal impacts of your work? [Yes]
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes]
2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? [N/A]
   (b) Did you include complete proofs of all theoretical results? [N/A]
3. If you ran experiments...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [Yes]
   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes]
   (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [Yes]
   (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [Yes]
4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...
   (a) If your work uses existing assets, did you cite the creators? [Yes]
   (b) Did you mention the license of the assets? [N/A]
   (c) Did you include any new assets either in the supplemental material or as a URL? [Yes]
   (d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? [Yes]
   (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [Yes]
5. If you used crowdsourcing or conducted research with human subjects...
   (a) Did you include the full text of instructions given to participants and screenshots, if applicable? [N/A]
   (b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [N/A]
   (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [N/A]