Meta Architecture Learning

Albert Shaw[1], Wei Wei[2], Weiyang Liu[1], Le Song[1,3], Bo Dai[1,2]

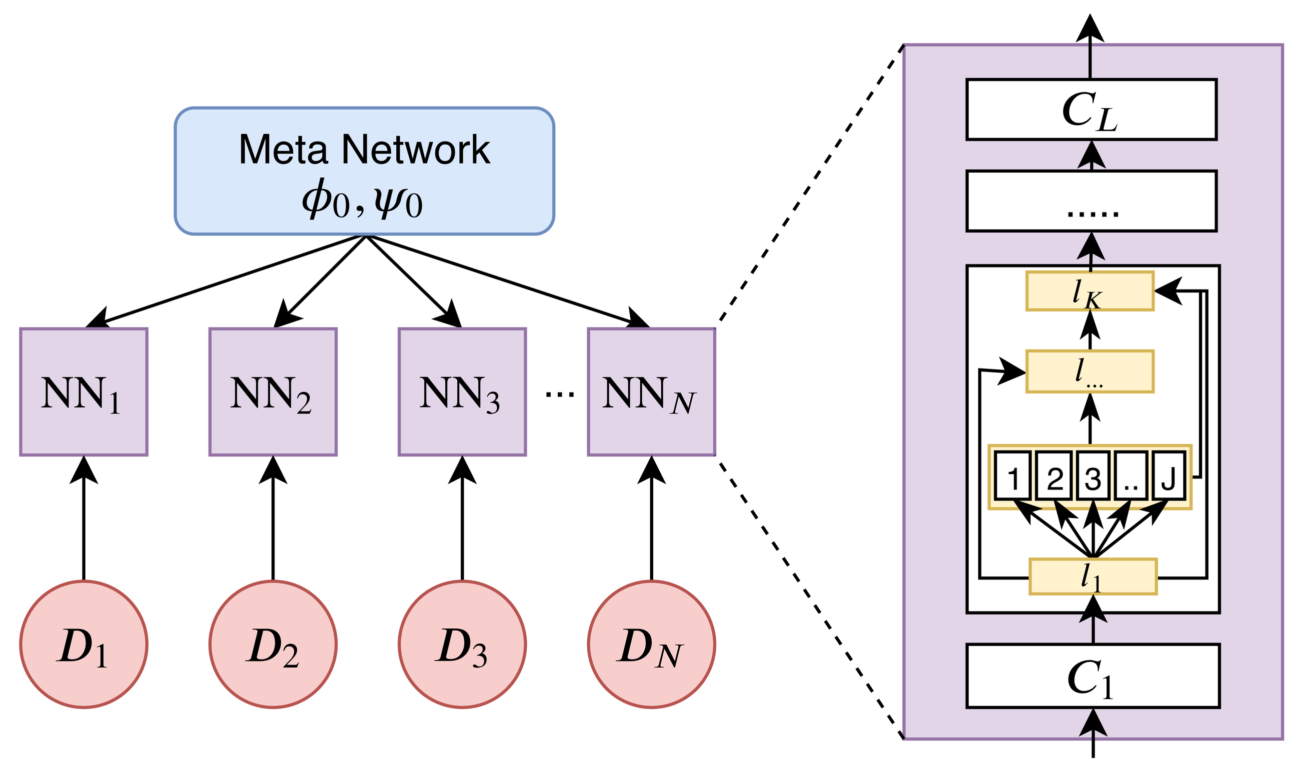
Motivation

While developing techniques to automatically search the space of Neural Network architectures has become a large focus of recent efforts, existing methods can only learn the architecture for a single task at a time. We approach the problem of neural architecture search using Bayesian and Meta-learning techniques to simultaneously learn the architecture and weight distribution for multiple tasks at once.

Main Contribution:

- We propose a Bayesian inference view of architecture learning.
- We derive a variational inference method to learn the architectures of an entire set of tasks simultaneously using the optimization embedding technique to design the parameterization of the posterior.
- Demonstrates a concrete algorithm for Meta Architecture Search that can use a prior trained over multiple tasks to find competitive models for new unseen datasets with just quick adaptation.

Bayesian View of Architecture Search



We consider NAS as an operation selection problem.

$$x_k = \sum_{i=1}^{k-1} \left(z_{i,k}^\top \mathcal{A}_i(\theta)\right) \circ x_i := \sum_{i=1}^{k-1}\sum_{l=1}^{L} z_{i,k}^l \phi_i^l(x_i;\theta),$$

Assume the probabilistic model as

$$\theta \sim \mathcal{N}(\mu, \sigma^2),$$
$$z_{i,k} \sim \mathcal{C}ategorial(\alpha_{i,k}),\; k = 1, \ldots, K,$$
$$y \sim p(y|x;\theta,z) \propto \exp\left(-\ell\left(f(x;\theta,z), y\right)\right),$$

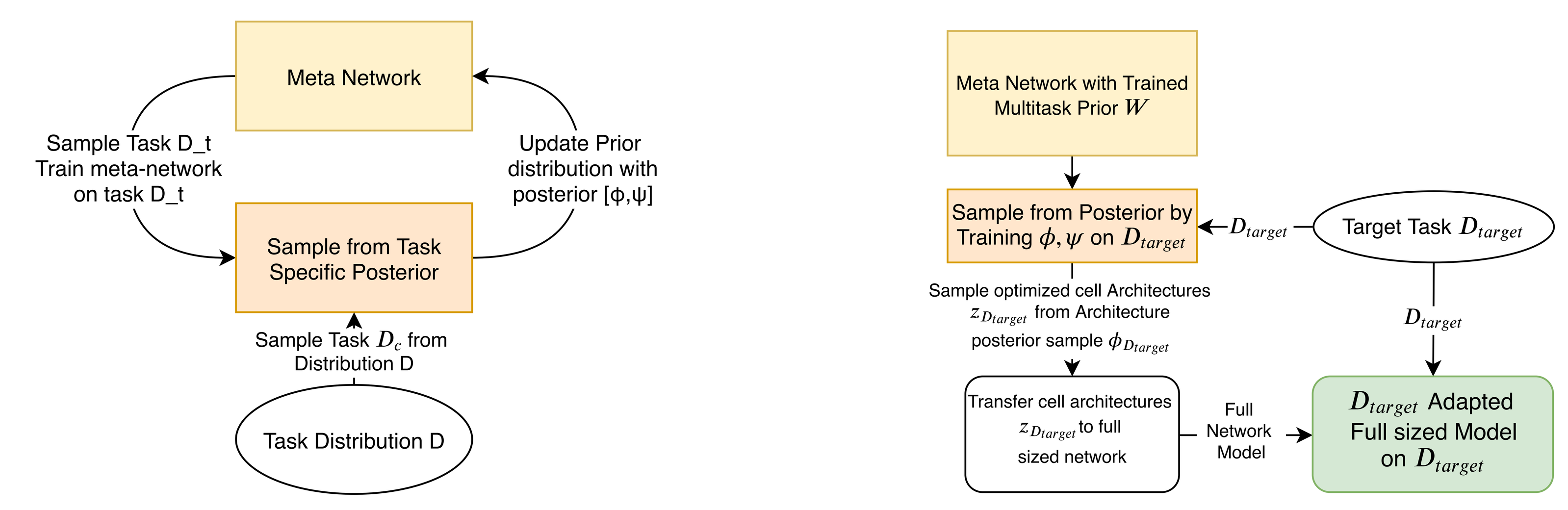
We can estimate the parameters $W(\mu,\sigma,\alpha)$ via MLE.

$$\max_W \widehat{\mathbb{E}}_{x,y}\left[\log \int p(y|x;\theta,z)\, p(z;\alpha)\, p(\theta;\mu,\sigma)\, dz d\theta\right].$$

Extended to the meta-learning setting with many tasks $\mathcal{D}_t$ and weight and architecture priors (μ,σ,α) are shared between all the tasks,

$$\max_W \widehat{\mathbb{E}}_{\mathcal{D}_t}\widehat{\mathbb{E}}_{(x,y)\sim\mathcal{D}_t}\left[\log \int p(y|x;\theta,z)\, p(z;\alpha)\, p(\theta;\mu,\sigma)\, dz d\theta\right]$$

Meta Architecture Search and Adaptation



(a) Meta Architecture Search (b) Quick Architecture Adaptation

Variational Inference by Optimization Embedding

We consider the ELBO, since the MLE is intractable due to the integral.

$$\widehat{\mathbb{E}}_{\mathcal{D}}\left[\max_{\phi_{\mathcal{D}},\psi_{\mathcal{D}}} \underbrace{\widehat{\mathbb{E}}_{x,y}\mathbb{E}_{\xi,\epsilon}\left[-\ell\left(f\left(x;\theta_{\mathcal{D}}(\epsilon,\psi), z_{\mathcal{D}}(\xi,\phi)\right), y\right)\right] - \log\frac{q_\phi(z|\mathcal{D})}{p(z;\alpha)} - \log\frac{q_\psi(\theta|\mathcal{D})}{p(\theta;\mu,\sigma)}}_{L(\phi_{\mathcal{D}},\psi_{\mathcal{D}};W)}\right].$$

We approximate $q(z|\mathcal{D})$ with the Gumbel-Softmax distribution.
We follow the parametrized CVB derivation for embedding the optimization procedure for (ϕ,ψ) deriving the explicit form of the parameters $\phi_{\mathcal{D}}$ and $\psi_{\mathcal{D}}$. Denoting the $\widehat{g}_{\phi_{\mathcal{D}},\psi_{\mathcal{D}}}(\mathcal{D}, W) = \frac{\partial \widehat{L}}{\partial(\phi_{\mathcal{D}},\psi_{\mathcal{D}})}$ where $\widehat{L}$ is the stochastic approximation for $L(\phi_{\mathcal{D}},\psi_{\mathcal{D}};W)$, we have

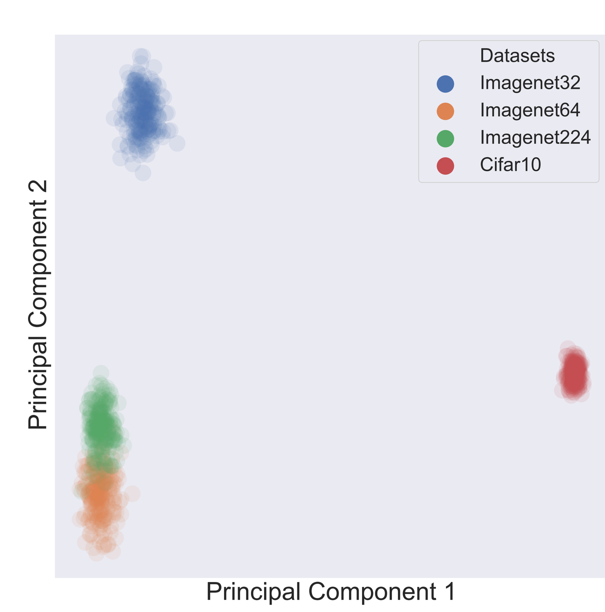
$$\left[\phi_{\mathcal{D}}^t, \psi_{\mathcal{D}}^t\right] = \eta_t \widehat{g}_{\phi_{\mathcal{D}},\psi_{\mathcal{D}}}(\mathcal{D}, W) + \left[\phi_{\mathcal{D}}^{t-1}, \psi_{\mathcal{D}}^{t-1}\right],$$

We can initialize $(\phi^0,\psi^0) = W$ which is shared across all the tasks. After T optimization steps, we obtain $(\phi_{\mathcal{D}}^T, \psi_{\mathcal{D}}^T)$, which leads to $\left(\theta_{\mathcal{D}}^T(\xi,\psi_{\mathcal{D}}^T), z_{\mathcal{D}}(\xi,\phi_{\mathcal{D}}^T)\right)$. In other words, we derive the concrete parameterization of $q(\theta|\mathcal{D})$ and $q(z|\mathcal{D})$ automatically by unfolding the optimization steps.

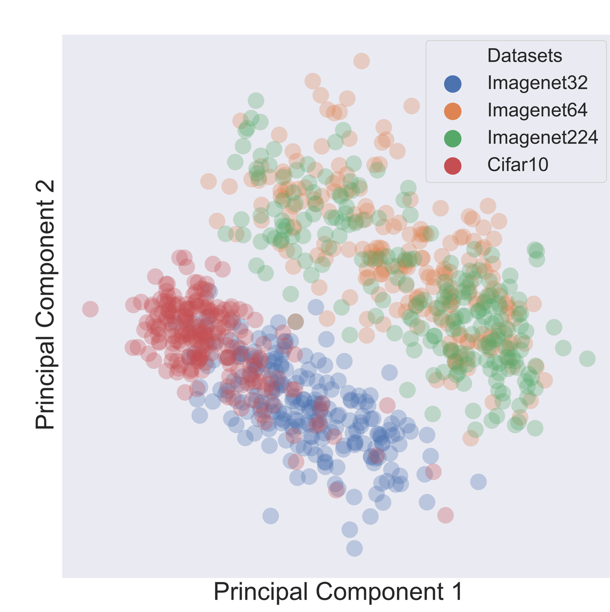
$$\max_{W,V} \widehat{\mathbb{E}}_{\mathcal{D}}\widehat{\mathbb{E}}_{x,y}\mathbb{E}_{\xi,\epsilon}\left[-\ell\left(f\left(x;\theta_{\mathcal{D}}^T(\epsilon,\psi), z_{\mathcal{D}}^T(\xi,\phi)\right), y\right) - \log\frac{q_{\phi_{\mathcal{D}}^T}(z|\mathcal{D})}{p(z;\alpha)} - \log\frac{q_{\psi_{\mathcal{D}}^T}(\theta|\mathcal{D})}{p(\theta;\mu,\sigma)}\right].$$

which can be optimized by stochastic gradient ascent for learning W.

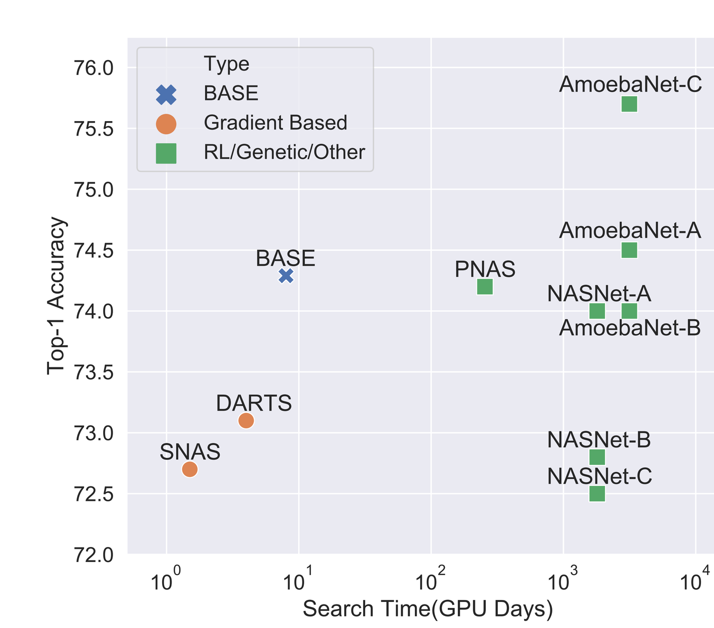
Meta Architecture Search and Adaptation



PCA of weights



PCA of architecture



`Imagenet` Acc vs Search Time

Bayesian meta-Architecture SEarch (BASE) Algorithm

Initialize meta-network parameters W_0.
for $e = 1, \ldots, E$ **do**
  Sample C tasks $\{\mathcal{D}_c\}_{c=1}^C \sim \mathcal{D}$.
  for $\mathcal{D}_c$ in $\mathcal{D}$ **do**
    Sample $\{x_t, y_t\}_{t=1}^T \sim \mathcal{D}_c$.
    Let $\phi_c^0, \psi_c^0 = W_{e-1}$.
    for $t = 1, \ldots, T$ **do**
      Sample $\xi \sim \mathcal{G}(0,1)$.
      Update $\left[\phi_c^t, \psi_c^t\right] = \left[\phi_c^{t-1}, \psi_c^{t-1}\right] - \eta\nabla_{\phi_c^{t-1},\psi_c^{t-1}}\widehat{L}(f(x_t;\phi_c^{t-1},\psi_c^{t-1},\xi), y_t)$.
  Update $W_e = W_{e-1} + \lambda\frac{1}{C}\sum_{c=1}^C\left(\left[\phi_c^T, \psi_c^T\right] - W_{e-1}\right)$.

Classification Accuracy on `CIFAR10`

Architecture	Top-1 Test Error	Params (M)	Search Time (Gpu Days)
DenseNet-BC	3.46	25.6	-
NASNet-A + cutout	**2.65**	3.3	1800
AmoebaNet-A + cutout	3.34 ± 0.06	3.2	3150
AmoebaNet-B + cutout	2.55 ± 0.05	**2.8**	3150
Hierarchical Evo	3.75 ± 0.12	15.7	**300**
DARTS (1st order)	3.00 ± 0.14	3.3	1.5
DARTS (2nd order)	**2.76** $\pm$ **0.09**	3.3	4
SNAS (single-level)	2.85 ± 0.02	**2.8**	1.5
ENAS + cutout	2.89	4.6	**0.5**
PNAS	3.41 ± 0.09	3.2	225
SMASH	4.03	16	1.5
BASE(Multi-task Prior)	3.18	**3.22**	8
BASE(`Imagenet32`)	3.00	3.29	**0.04 Adap / 8 Meta**
BASE(`CIFAR10`)	**2.83**	3.07	0.05 Adap / 8 Meta

Classification Accuracy on `Imagenet`

Architecture	Top-1 Err	Top-5 Err	MACs (M)	Search Time (GPU Days)
NASNet-A	26.0	8.4	564	1800
NASNet-B	27.2	8.7	**488**	1800
NASNet-C	27.5	9.0	558	1800
AmoebaNet-A	25.5	8.0	555	3150
AmoebaNet-B	26.0	8.5	555	3150
AmoebaNet-C	**24.3**	**7.6**	570	3150
PNAS	25.8	8.1	588	**225**
DARTS	**26.9**	**9.0**	595	4
SNAS	27.3	9.2	**522**	**1.5**
BASE (Multi-task Prior)	26.12	8.52	**544**	**0 Adap / 8 Meta**
BASE (`Imagenet`)	**25.71**	**8.08**	559	0.04 Adap / 8 Meta

[1]Georgia Institute of Technology, [2]Google Research, [3]Ant Financial

Mailto: ashaw596@gatech.edu