# Meta Architecture Learning

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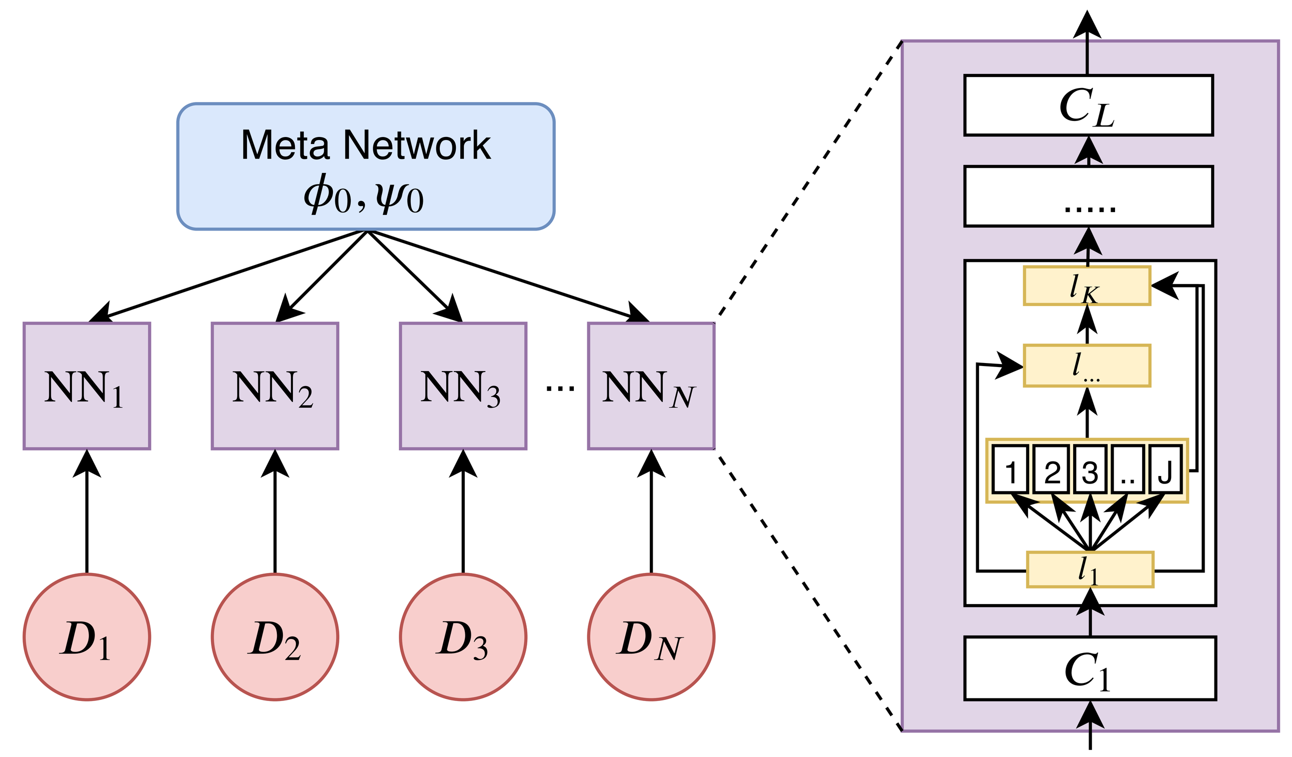
## Motivation

Recent work has increasingly shown that the optimal architectures can vary between even similar tasks. On new datasets, NAS is often individually run for each task which can be quite costly. With Meta Architecture Search, we aim to learn task-agnostic representations that will be used to speed up the process of architecture search on a large number of tasks.

**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 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

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

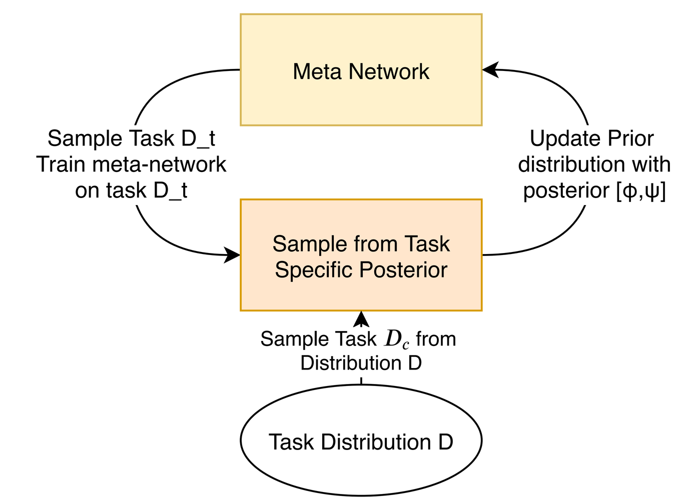
$W(\mu, \sigma, \alpha)$ can be estimated via Maximum Likelihood Estimation (MLE).

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

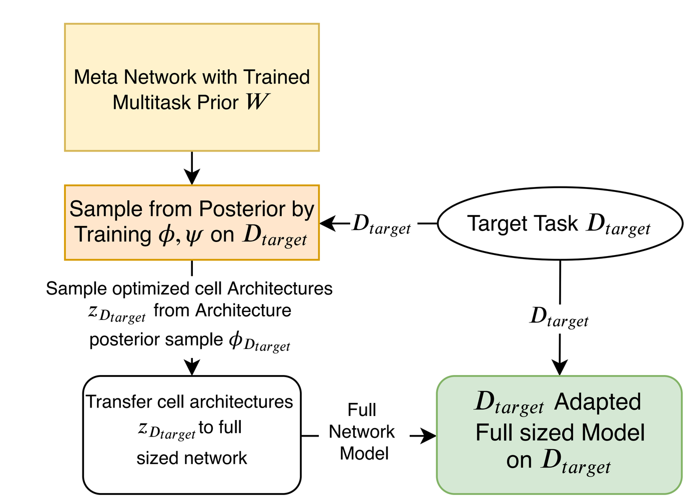
We extend this to the meta-learning setting with many tasks $\mathcal{D}_t$. Weight and architecture priors $(\mu, \sigma, \alpha)$ are shared between all tasks.

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

## Meta Architecture Search and Adaptation




(a) Meta Architecture Search




(b) Quick Architecture Adaptation

## Variational Inference by Optimization Embedding

**Variational Bayesian Inference**: Since the Maximum Likelihood Estimation (MLE) is intractable due to the integral over latent variable $z$, we consider optimizing the Evidence Lower Bound (ELBO).

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

**Optimization Embedding**: With this objective, we follow the parameterized Coupled Variational Bayes derivation for embedding the optimization procedure for $(\phi, \psi)$.

$$\left[\phi_\mathcal{D}^t, \psi_\mathcal{D}^t\right] = \eta_t \hat{g}_{\phi_\mathcal{D},\psi_\mathcal{D}}(\mathcal{D}, W) + \left[\phi_\mathcal{D}^{t-1}, \psi_\mathcal{D}^{t-1}\right] \quad \text{where} \quad \hat{g}_{\phi_\mathcal{D},\psi_\mathcal{D}}(\mathcal{D}, W) = \frac{\partial \widehat{L}}{\partial(\phi_\mathcal{D}, \psi_\mathcal{D})}$$

$\widehat{L}$ is the stochastic approximation for $L(\phi_\mathcal{D}, \psi_\mathcal{D}; W)$

We initialize $(\phi^0, \psi^0) = W$ where $W$ 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 parameterization of $q(\theta|\mathcal{D})$ and $q(z|\mathcal{D})$ by unfolding the optimization.

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

## Result Tables

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 ± 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 |

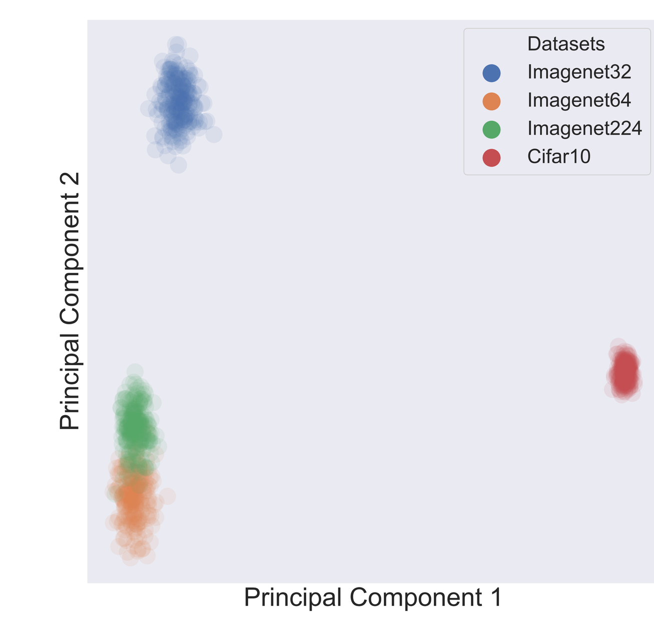
Classification Accuracy on Imagenet

| 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 |

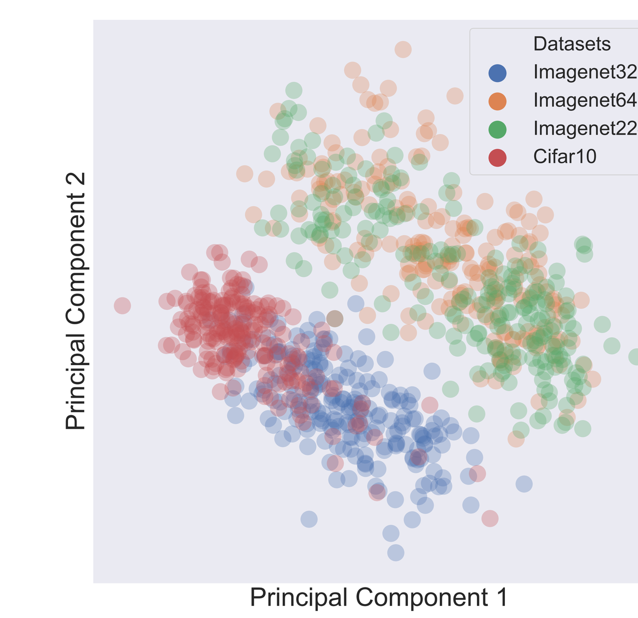
## Bayesian meta-Architecture SEarch (BASE) Algorithm

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

## Meta Architecture Search and Adaptation

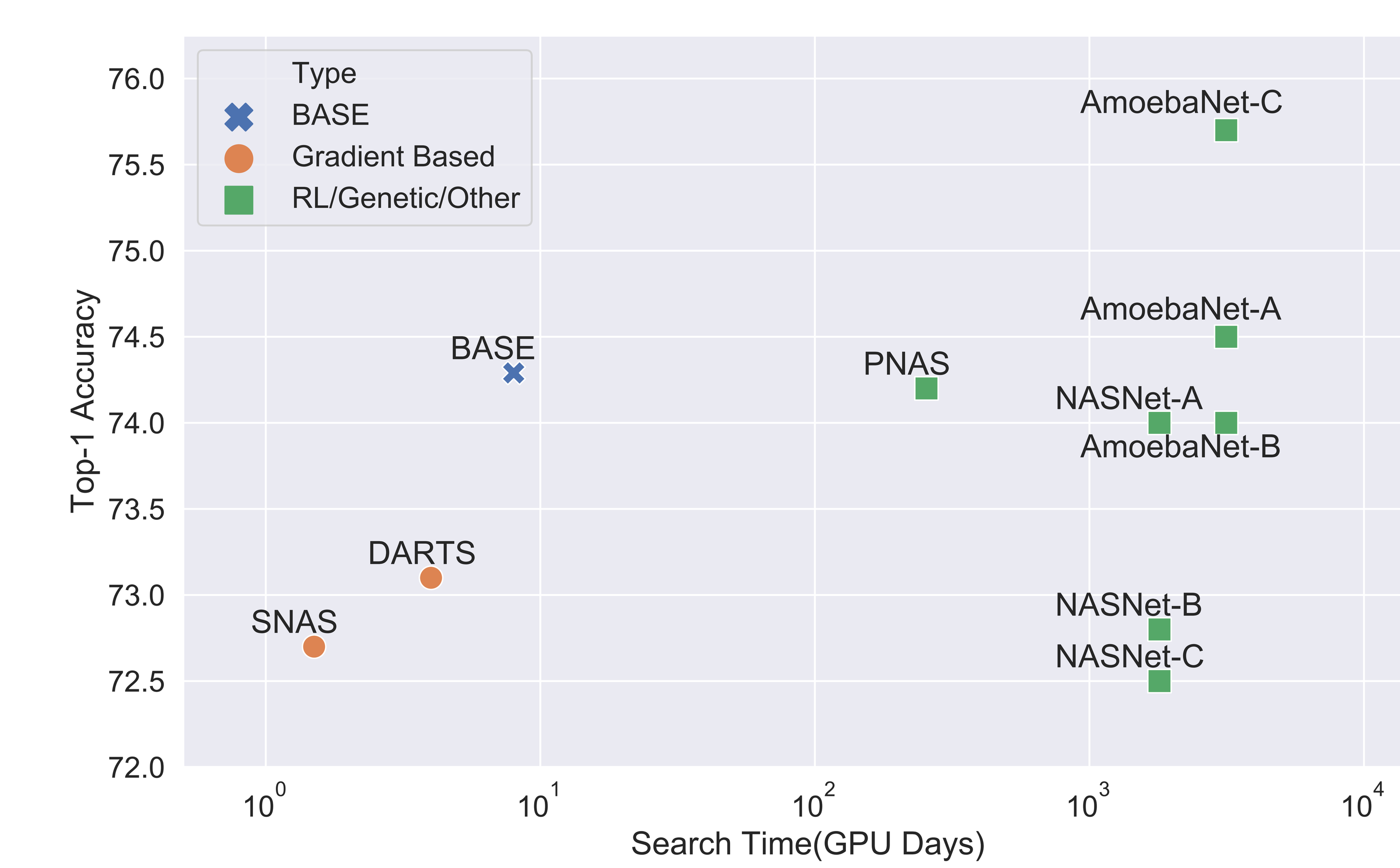



PCA of weights




PCA of architecture

## Imagenet Accuracy vs Search Time

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