

# Gradient-Free Supervised and Unsupervised Learning with Rewards

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## Abstract

*We develop a method for policy architecture search and adaptation via gradient-free optimization which can learn to perform autonomous driving tasks. By learning from both demonstration and environmental reward we develop a model that can learn with relatively few early catastrophic failures. We first learn an architecture of appropriate complexity to perceive aspects of world state relevant to the expert demonstration, and then mitigate the effect of domain-shift during deployment by adapting a policy demonstrated in a source domain to rewards obtained in a target environment. We show that our approach allows safer learning than baseline methods, offering a reduced cumulative crash metric over the agent’s lifetime as it learns to drive in a realistic simulated environment. A full version of this paper [2] and videos can be found in <https://saynaebrahimi.github.io/corl.html>*

## 1. Introduction

Deep architectures have become popular as function approximators to represent action-selection policies. Common approaches to learn the parameters of such models include reinforcement learning and/or learning from demonstration: both learn model parameters to maximize expected reward, mimic human behavior, and/or achieve implicit goals. However, the design of policy architectures, especially in a deep learning paradigm, remains relatively unexplored. Architectures are typically selected through a combination of intuition and/or trial and error.

Learning to learn, including the learning of learning architectures, is a long-articulated goal of AI, and many meta-learning and lifelong learning schemes have been proposed (e.g., [6] offered seminal views; see [5] for a survey).

We investigate policy architecture search using gradient-free optimization and learn optimal policy structure for autonomous driving tasks. We propose a model which learns jointly from demonstration and optimization, with the goal of safe training: minimizing the amount of damage a vehi-

cle incurs to learn a threshold level of performance. We base our approach on exploration-based schemes due to their ability to optimize model weights and architecture hyperparameters, leverage expert demonstrations, and adapt to reward obtained in new domains. We believe that a model which can initialize from demonstration, and learn an optimal policy from that foundation, is likely to achieve higher performance while maintaining the constraint of safe training, compared to models which must randomly search through action space during initial learning, or which learn from a reasonably safe demonstration but cannot further optimize performance based on environmental reward.

Often, deep models which learn to perform in one domain fail to perform well when deployed in another setting, such as differing weather or lighting conditions. We show that our method can effectively and safely adapt a model demonstrated in one environment but deployed in a visually different environment based on the reward signal in the latter domain, even when the agent is initialized far from initial demonstrations. Our approach leverages only target domain reward, and makes no assumptions about domain alignment, explicit or implicit, nor assumes any demonstration supervision in the target domain.

To achieve these goals, we present a gradient-free optimization algorithm inspired by [4] with a modification in noise generation that results in estimating the gradients more efficiently and accurately (Sec. 2.1). We then apply this algorithm to search over variable length architectures. Next, we combine our gradient-free policy search with demonstrations to learn a better policy that adapts to the new environment by receiving rewards as feedback (Sec. 2.3). We experimentally show that our architecture search model finds a policy on the GTA game environment that outperforms previously published methods (e.g., [1]) in end-to-end steering prediction from demonstrations, and that it can be efficiently adapted to learn to drive in previously unseen scenarios (Sec. 3). Our model reduces the number of crashes incurred while learning to drive, compared to baselines based only on reward or demonstration but not both, or compared to previously proposed fixed architectures that

were not optimized for the domain.

## 2. Approach

We propose a learning-to-learn model which includes architecture optimization, parameter learning, and representation adaptation over different time scales. Our approach can be summarized by the following two steps. (1) Given expert demonstration, search over architectures and parameters to find a policy that best mimics performance by monitoring the obtained accuracy and number of parameters. (2) Having learned from demonstration, adapt the model to the reward provided by the target environment. In both steps, it is essential to derive a function approximator that optimizes an objective function. We use a gradient-free optimization algorithm [4] that maximizes a parametrized reward function using gradient estimation to perform architecture search (Sec. 2.2) and policy learning (Sec. 2.3).

### 2.1. Gradient-free optimization algorithm

Let  $F(\cdot)$  be our objective function parametrized by  $\theta$  which is an  $n$ -dimensional vector.  $F$  can be the reward that an environment provides for an agent when it executes a policy with parameters  $\theta$ ; our goal is to maximize the expected reward by perturbing the policy parameters, denoted as  $\hat{\theta}$ , by moving in particular directions. The parameter estimate update can be performed using a general stochastic form:

$$\hat{\theta}_{t+1} = \hat{\theta}_t + \alpha_t \nabla_{\hat{\theta}} y(\hat{\theta}) \quad (1)$$

where  $y(\cdot)$  is an approximation of the objective function (i.e.  $y(\cdot) = F(\cdot) + \text{noise}$ ) and  $\nabla_{\hat{\theta}} y(\hat{\theta})$  is the gradient of objective estimate that can be approximated by any gradient estimator in the family of finite difference methods. The gradient is estimated in a randomly chosen direction by perturbing all the elements of  $\hat{\theta}_t$  to obtain two measurements of  $y(\cdot)$  as follows:

$$y_t^{(+)} = F(\hat{\theta}_t + c_t \Delta_t) + \epsilon_t^{(+)} \quad (2)$$

$$y_t^{(-)} = F(\hat{\theta}_t - c_t \Delta_t) + \epsilon_t^{(-)} \quad (3)$$

where  $\Delta_t \in R^n$  is a vector of  $n$  mutually independent randomly perturbed variables taken from a zero-mean distribution. While there is no restriction for it to have a specific type of distribution, we use Laplace distribution, as it tends to choose orthogonal directions in the long run. Other recent efforts [7] utilized Gaussian noise to sample mirrored projections.  $c_t$  is a small positive number and  $\epsilon_t^{(+)}$  and  $\epsilon_t^{(-)}$  are the noise associated with evaluating  $F(\cdot)$  such that:  $E(\epsilon_t^{(+)} - \epsilon_t^{(-)} | \{\theta_1, \theta_2, \dots, \theta_t\}, \Delta_t) = 0$ . The gradient estimate can then be computed as:

$$\nabla_{\hat{\theta}_t} y(\hat{\theta}_t) = \left[ \frac{y_t^{(+)} - y_t^{(-)}}{2 c_t \Delta_{t1}} \quad \dots \quad \frac{y_t^{(+)} - y_t^{(-)}}{2 c_t \Delta_{tn}} \right]^T \quad (4)$$

Parameter estimates can be updated by replacing the gradients in Eq. 1 with those found in Eq. 4.

### 2.2. Learning an optimal initial policy from demos

Inspired by [7] we have used a recurrent neural network to sequentially generate the description of layers of an architecture from a given design space defined by the user. The RNN acts as a controller which generates the architecture description defined by its hyper-parameters chosen from a pre-defined search space. Our model uses the demonstrations to provide the reward function, ((i.e.,  $F$  above), to train the RNN. Unlike backpropagation which suffers from gradient vanishing while training RNNs, gradient-free algorithms do not have such an issue [4]. Our RNN controller specifies three types of layers: convolutional, fully connected, and max-pool which can have inter-layer dropouts. For the reward signal, we use the negative value of *total* loss function. At the last layer of the network, we regress to three real-valued numbers, each having a mean-squared loss. The total loss is the sum of all three losses. We use a novel reward function (Eq. 5) that not only results in the minimum total loss but also grows the architecture as long as the loss keeps decreasing.

$$R = R_1 - \lambda (R_1) R_2 \quad (5)$$

where  $R_1$  is the negative of the minimum loss (or maximum accuracy in a classification problem) on the validation set for the last 5 epochs and  $R_2$  is the total number of parameters in the child network.  $\lambda$  is the Lagrange parameter defined as a function of the first sub-reward in a ReLU-based fashion.

### 2.3. Adapting policy to a new domain

As confirmed experimentally below, it is well known that a policy learned from behavioral cloning can perform poorly when evaluated on inputs with a domain shift relative to the demonstration supervision. To overcome this, we further use the gradient-free search algorithm described in Sec. 2.1 to adapt a driving policy learned from demonstration in a source domain based on rewards in a target domain. We experiment with the setting where the driving domain attributes are substantially different than provided as demonstration.

In the driving scenario, we wish to learn to drive with optimal or near-optimal performance, using the reward function in target domain which is composed of two factors (we receive +1 if obeyed and 0 if violated): 1) No crashes with other objects 2) Staying within the lane lines if they are available in the driving scene. We have used the lane reward function and accident detection function defined in [3] source code as a *paths.xml* file.



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