Random Network Distillation as data selection method

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Random Network Distillation (RND) is used as a data selection method. It is optimized and benchmarked with respect to its ability of reducing the size but maintain necessary information of a data set to train a neural network.

The concept arises from the idea that the stochastic nature of a randomly initialized neural networks will act to sufficiently separate unique points from a data pool in their high-dimensional representation space. With this approach, it appears that training a neural network onto the representations of a random network can resolve unique points in a sample of data such that a minimal data-set can be constructed for neural network training. The goal of this application is similar in nature to that of core-set approaches [2] albeit using the model itself to provide information on uniqueness of training data in an unsupervised manner. Figure 1 outlines graphically the process by which Random Network Distillation filters points from a data pool into a target set.

During the data selection, the target network will remain untrained while the predictor network will be iteratively re-trained to learn the representations produced by the target network. Theoretically, this should mean that the error between the predictor network and the target network will provide a measure of whether a point has already been observed. During the procedure, the points are selected for the target set in a greedy fashion, that is, the distance between target and predictor is computed on all data points in the point cloud and the one with the largest distance is chosen.

The method first was introduced in 2018 by Burda et al. in [1] as curiosity driven exploration technique in reinforcement learning. Transferring the iterative nature of reinforcement learning to data set selection, the recursive training process of RND is studied as a continual learning problem. The structure of RND in figure 1, is made of three main components, which are checked for optimization opportunities. The re-training procedure is optimized using a loss-aware reservoir re-training method inspired by [3]. The comparison of high-dimensional representations inside the RND process are an essential part and the distance metric is optimized. The random initialization of neural networks is optimized by pre-training using a contrastive loss function [4].
Finally, the method is bench-marked on standard data sets as MNIST, CIFAR10 and some regression tasks.

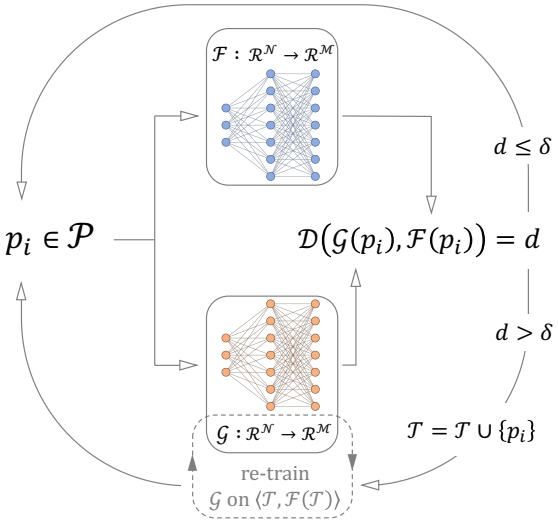

Figure 1: Workflow of RND. A data point p, is passed into the target network, $\mathcal{F}$ and the predictor network $\mathcal{G}$, in order to construct the representations $\mathcal{F}(p)$ and $\mathcal{G}(p)$. A distance, d is then computed using the metric $D(\mathcal{F}(p), \mathcal{G}(p))$. If $d > \delta$, the point p will be added to the target set $\mathcal{T}$ and the predictor model retrained on the full set T . If $d \leq \delta$, it is assumed that a similar point already exists in $\mathcal{T}$ and is therefore discarded. In our notation, $\langle \mathcal{T}, \mathcal{F}(\mathcal{T}) \rangle$ denotes the function set with domain $\mathcal{T}$ and image $\mathcal{F}(\mathcal{T})$.

References

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