Dataset Distillation

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Knowledge distillation

Teacher

- high-capacity model
- good performance

Student

- more compact model
- not as good performance as the teacher but better than if it was trained without it

By transferring knowledge, one hopes to benefit from the student's compactness while suffering only minimal degradation in performance [1], [4].

Dataset Distillation

1. pick an original dataset e.g. MNIST
2. select a specific architecture and initial weights
3. synthesize new smaller dataset using the selected architecture and weights
4. train the model on this small dataset
5. evaluate the model on the test set of the original dataset

Problems

Problem:

- Why not just remember the final trained weights instead of the initial ones?
- If we have fixed init weights the created dataset encodes the information of both training dataset and the init weights = it looks like noise

Solution:

- init weights are from a distribution D
- create such examples that work for multiple sampled init weights

Uses

Advantages:

- compressed representation
- faster training - only couple GD steps
- fine-tune pre-trained weights to new dataset
- dataset poisoning = fine-tune the model to predict trash
- how much can we compress the information of the dataset?
- can we train the model by synthetic images that are not on the natural image manifold?

Compressed representation:

- architecture
- init weights distribution
- learned learning rate
- created small train dataset

Algorithm

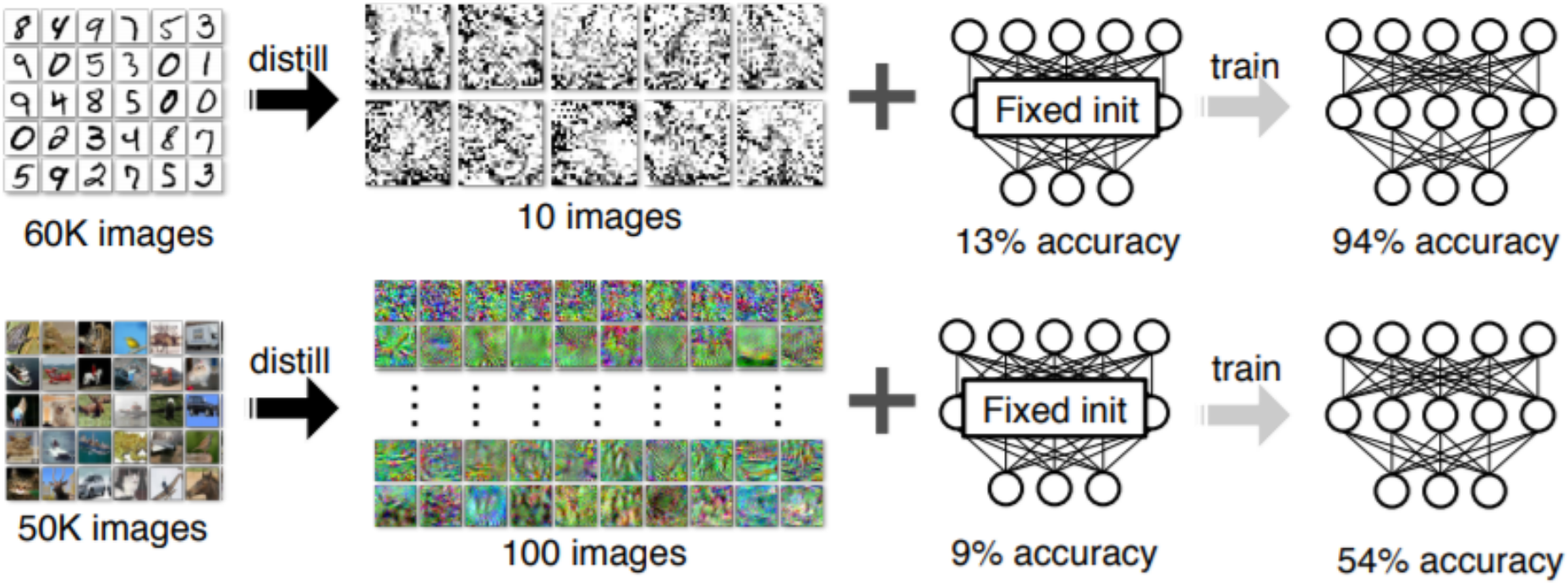
Algorithm 1 Dataset Distillation

Input: $p(\theta_0)$: distribution of initial weights; M: the number of distilled data
Input: α: step size; n: batch size; T: the number of optimization iterations; $\tilde{\eta}_0$: initial value for $\tilde{\eta}$

Initialize $\tilde{\mathbf{x}} = \{\tilde{x}_i\}_{i=1}^{M}$ randomly, $\tilde{\eta} \leftarrow \tilde{\eta}_0$
for each training step $t = 1$ to T **do**
    Get a minibatch of real data $\mathbf{x}_t = \{x_{t,j}\}_{j=1}^{n}$
    Sample a batch of initial weights $\theta_0^{(j)} \sim p(\theta_0)$
    for each sampled $\theta_0^{(j)}$ **do**
        Compute updated parameter with GD: $\theta_1^{(j)} = \theta_0^{(j)} - \tilde{\eta}\nabla_{\theta_0^{(j)}}\ell(\tilde{\mathbf{x}}, \theta_0^{(j)})$
        Evaluate the objective function on real data: $\mathcal{L}^{(j)} = \ell(\mathbf{x}_t, \theta_1^{(j)})$
    end for
    Update $\tilde{\mathbf{x}} \leftarrow \tilde{\mathbf{x}} - \alpha\nabla_{\tilde{\mathbf{x}}}\sum_j \mathcal{L}^{(j)}$, and $\tilde{\eta} \leftarrow \tilde{\eta} - \alpha\nabla_{\tilde{\eta}}\sum_j \mathcal{L}^{(j)}$
end for

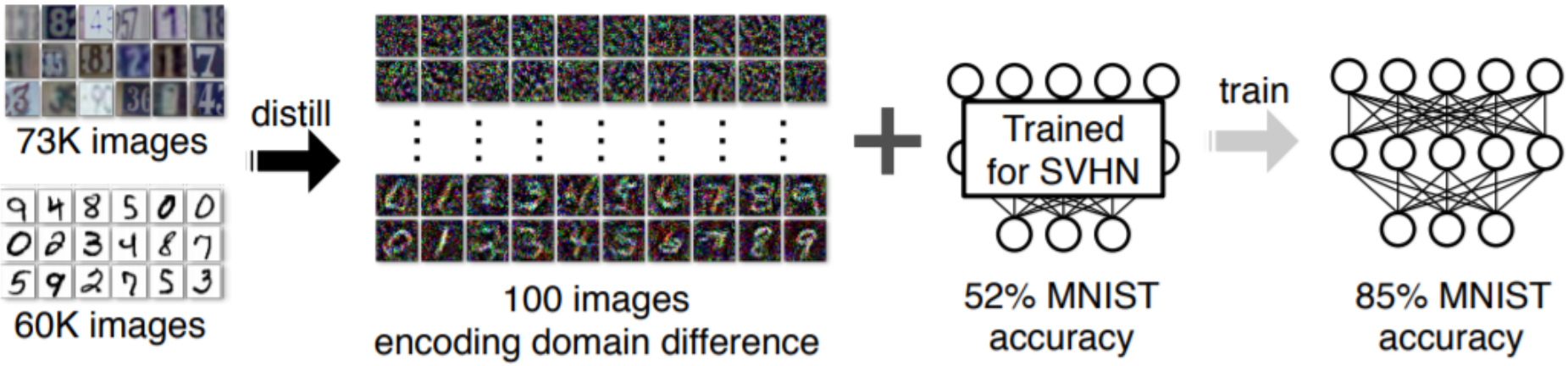
Output: distilled data $\tilde{\mathbf{x}}$ and the optimized learning rate $\tilde{\eta}$

Results

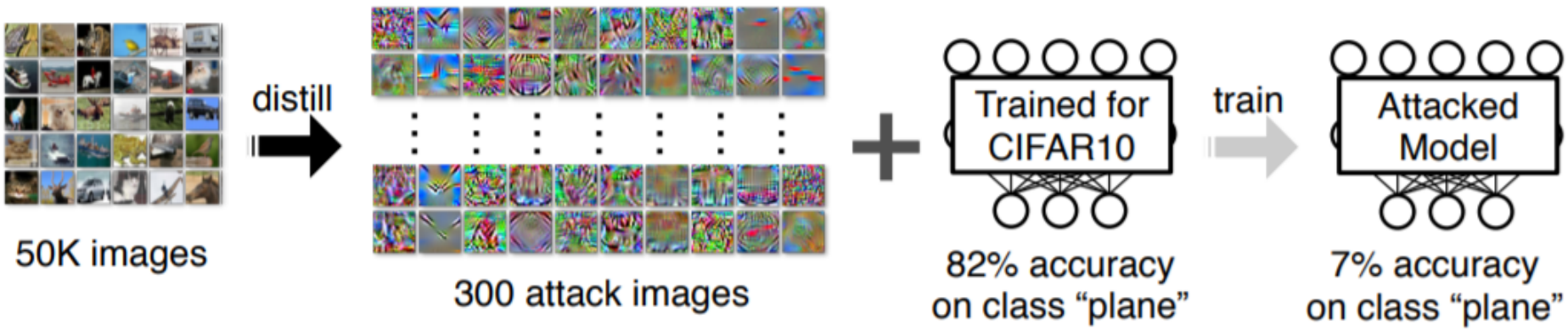


(a) Dataset distillation on MNIST and CIFAR10

Results

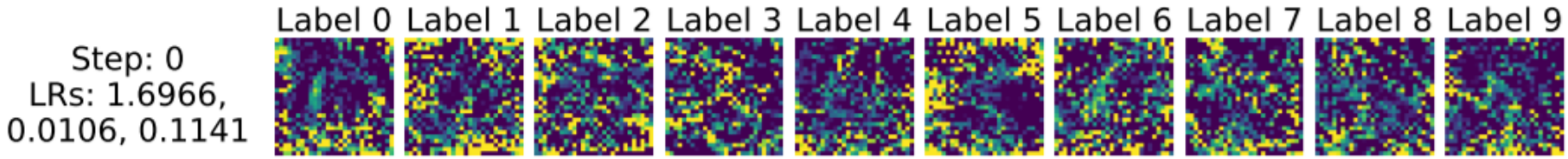


(b) Distillation for classifiers pre-trained on SVHN to perform well on MNIST

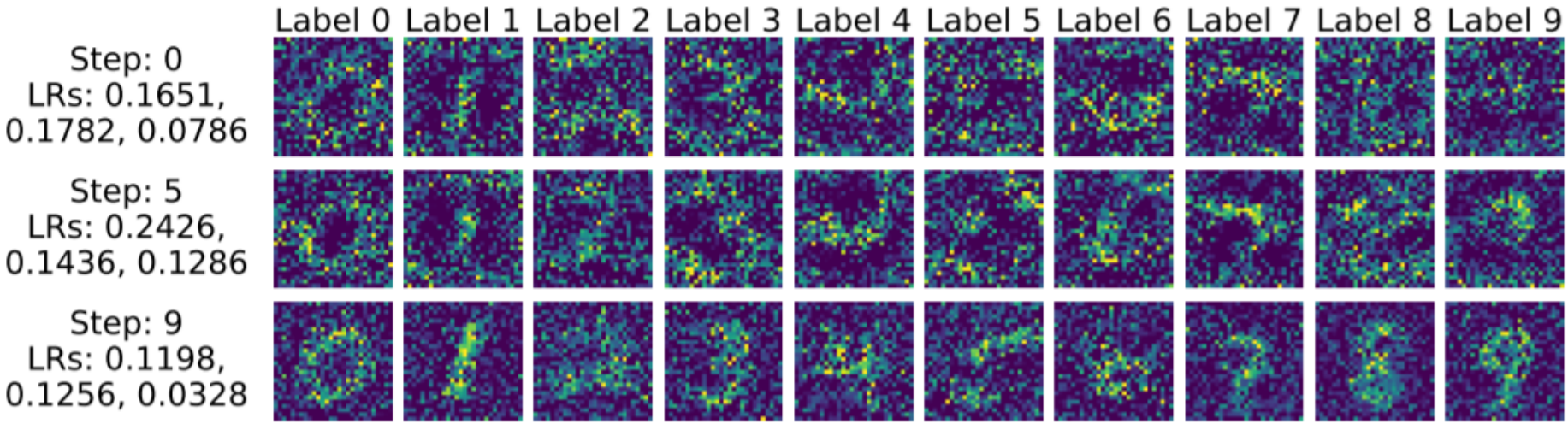


(c) Distillation for a malicious objective on well-trained CIFAR10 classifiers

Results

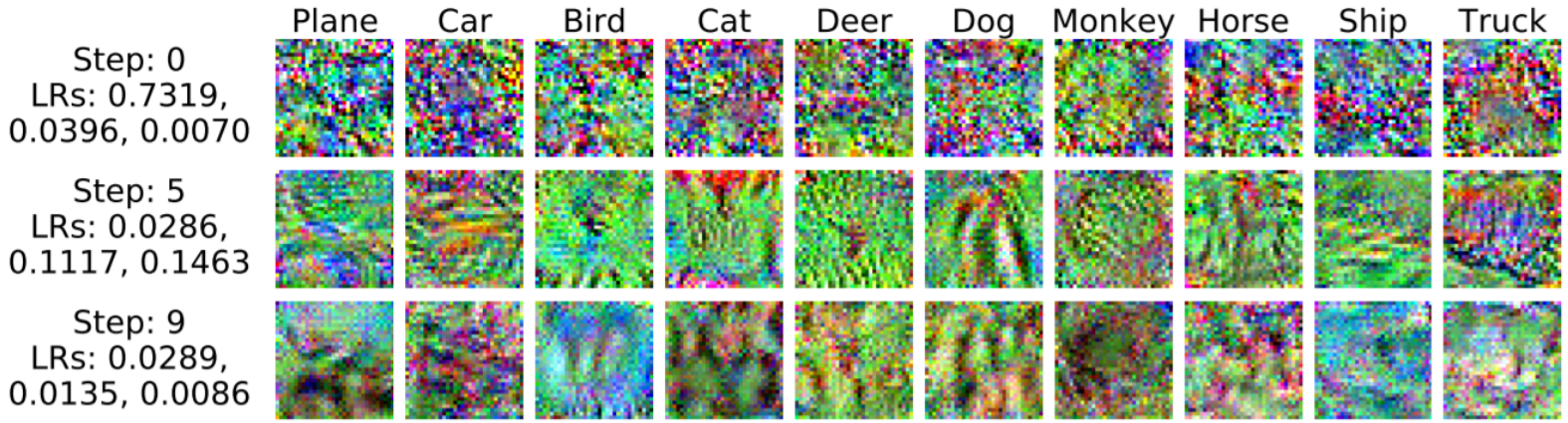


(a) MNIST. These images train networks with a particular initialization from 12.9% test accuracy to 93.76%.

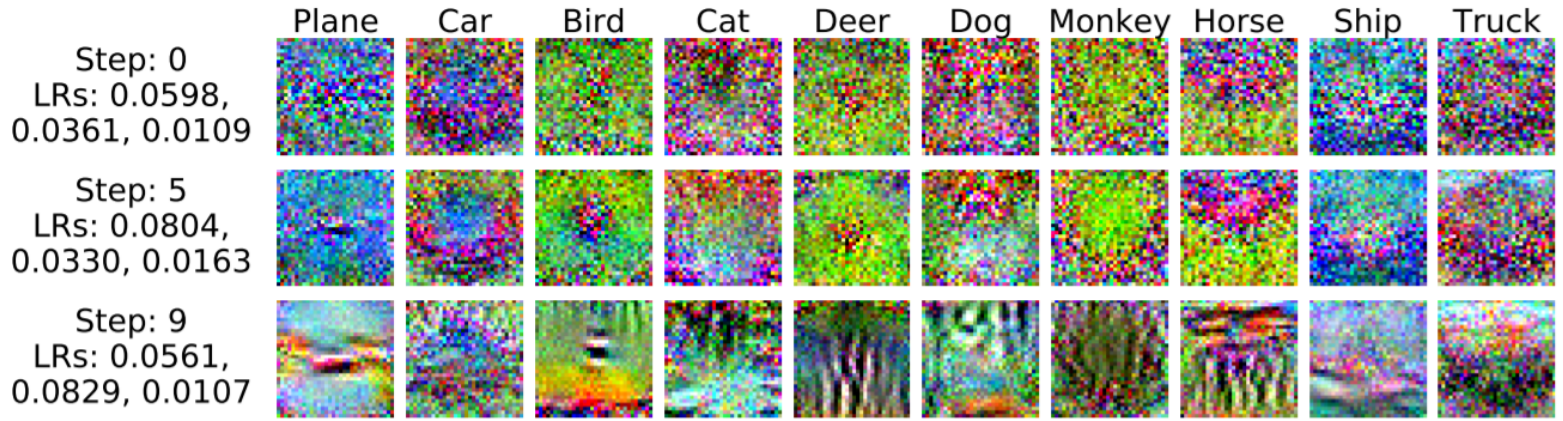


(a) MNIST. These images train networks with unknown initialization to 79.50% $\pm$ 8.08% test accuracy.

Results



(b) CIFAR10. These images train networks with a particular initialization from 8.82% test accuracy to 54.03%.



(b) CIFAR10. These images train networks with unknown initialization to $36.79\% \pm 1.18\%$ test accuracy.

Experiments

N = number of synthesized images per category

Baselines:

- **Random real images**: N randomly sampled training images per category.
- **Optimized real images**: We sample sets of real images as above, and choose on the top 20% sets that perform the best
- **k-means**: For each category, we use k-means to extract N cluster centroids
- **Average real images**: We compute the average image of all the images in each category, which is reused in different GD steps.

Results

	Ours		Baselines		
	Fixed init.	Random init.	Used as training data in same number of GD steps		
			Random real	Optimized real	k-means
MNIST	**96.6%**	79.5% ± 8.1%	68.6% ± 9.8%	73.0% ± 7.6%	76.4% ± 9.5%
CIFAR10	**54.0%**	**36.8% ± 1.2%**	21.3% ± 1.5%	23.4% ± 1.3%	22.5% ± 3.1%

	Used as data for K-NN classification	
Average real	Random real	k-means
77.1% ± 2.7%	71.5% ± 2.1%	**92.2% ± 0.1%**
22.3% ± 0.7%	18.8% ± 1.3%	29.4% ± 0.3%

Figure: Focus on random init.
MNIST with only 1 image per class = similar performance to Average image.
CIFAR with 10 images per class = improvement over baselines.

Sources

1. Belagiannis, Vasileios, Azade Farshad, and Fabio Galasso. "Adversarial Network Compression." arXiv preprint arXiv:1803.10750 (2018). Accessible from: https://arxiv.org/abs/1803.10750

2. Wang, Tongzhou, et al. "Dataset Distillation." Arxiv preprint. 2018. Accessible from: https://arxiv.org/abs/1811.10959v1

Sources

4. Breiman, Leo, and Nong Shang. "Born again trees." ps (1996). Accessible from: https://www.stat.berkeley.edu/~breiman/BAtrees.pdf

5. Hinton, Geoffrey, Oriol Vinyals, and Jeff Dean. "Distilling the knowledge in a neural network." arXiv preprint arXiv:1503.02531 (2015). Accessible from: https://arxiv.org/pdf/1503.02531.pdf