Dataset Distillation with Infinitely Wide Convolutional Networks

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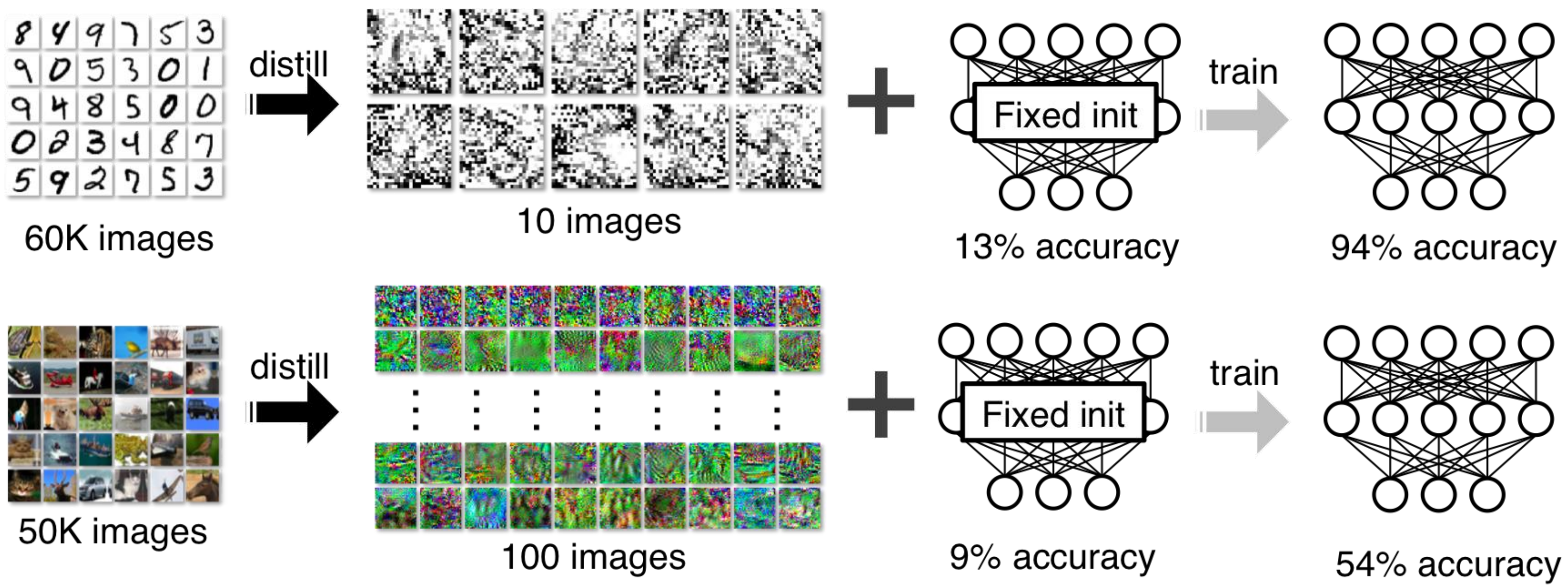
What is data distillation?



Dataset distillation on MNIST and CIFAR10

[2]

Applications

Distillation method.Recap

Ridge Regression

$$\min_{w} \|Xw - y\|_2^2 + \lambda \|w\|_2^2$$

$$w^* = \left(X^\top X + \lambda I\right)^{-1} X^\top y$$

$$y_{\text{new}} = X_{\text{new}} w^*$$

Kernel Ridge Regression

$$\min_{w} \|K_{XX} w - y\|_2^2 + \lambda w^\top K_{XX} w$$

$$w^* = (K_{XX} + \lambda I)^{-1} y$$

$$y_{\text{new}} = K_{X_{\text{new}} X} w^*$$

Distillation method.KIP

$$L(X_s, y_s) = \frac{1}{2} \left\| y_t - K_{X_t X_s} (K_{X_s X_s} + \lambda I)^{-1} y_s \right\|_2^2$$

Algorithm 1: Kernel Inducing Point (`KIP`)

Require: A target labeled dataset (X_t, y_t) along with a kernel or family of kernels.

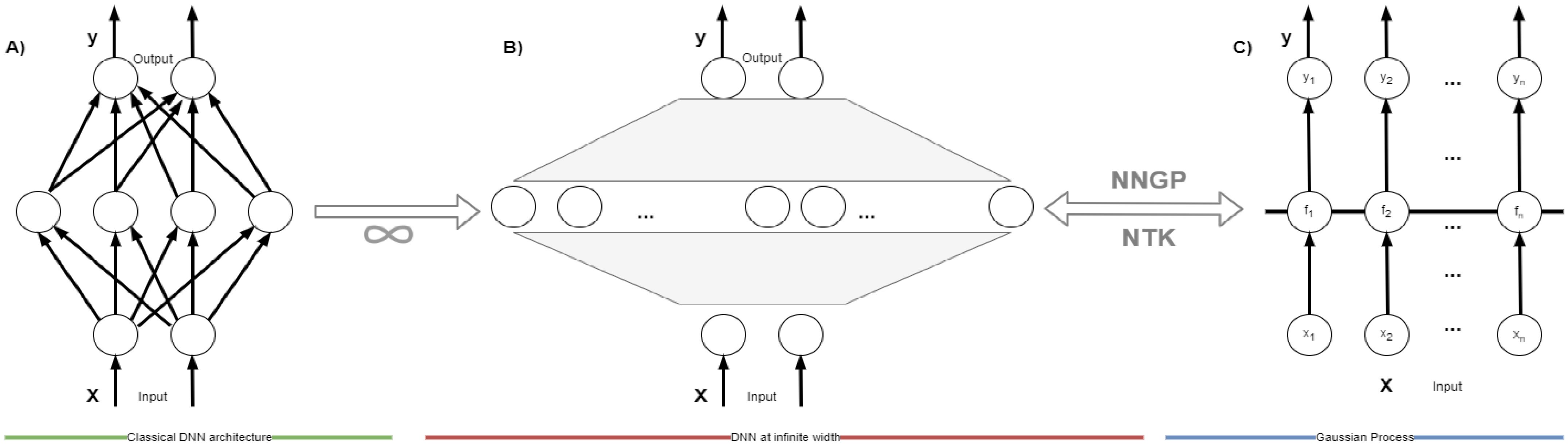
1: Initialize a labeled support set (X_s, y_s).
2: **while** not converged **do**
3: Sample a random kernel. Sample a random batch $(\bar{X}_s, \bar{y}_s)$ from the support set. Sample a random batch $(\bar{X}_t, \bar{y}_t)$ from the target dataset.
4: Compute the kernel ridge-regression loss given by (7) using the sampled kernel and the sampled support and target data.
5: Backpropagate through $\bar{X}_s$ (and optionally $\bar{y}_s$ and any hyper-parameters of the kernel) and update the support set (X_s, y_s) by updating the subset $(\bar{X}_s, \bar{y}_s)$.
6: **end while**
7: **return** Learned support set (X_s, y_s)

Distillation method.Algorithm

1) Forward pass: compute kernels by batch partition
2) Backward pass:

$$\frac{\partial L}{\partial X_s} = \frac{\partial L}{\partial (K(X_s, X_s))} \frac{\partial K(X_s, X_s)}{\partial X_s} + \frac{\partial L}{\partial (K(X_t, X_s))} \frac{\partial K(X_t, X_s)}{\partial X_s}$$

Infinitely Wide Convolutional Networks



Neural Tangents [lib] [paper]

Preprocessing.ZCA-regulized

1) flatten the features for each train image and

then standardize each feature across the train dataset.

2) feature-feature covariance matix $C = U\Sigma U^T$,

3) Let $W_\lambda = U\phi_\lambda(\Sigma)U^T$ where ϕ_λ: μ to $(\mu + \lambda\overline{\mathrm{tr}}C)^{-1/2}$, $\overline{\mathrm{tr}}(C) = \mathrm{tr}(C)/\mathrm{len}(C)$.

4) New features: standardize + @ W_lambda

(if lambda = 0 -> standadrt ZCA = I cov matrix)

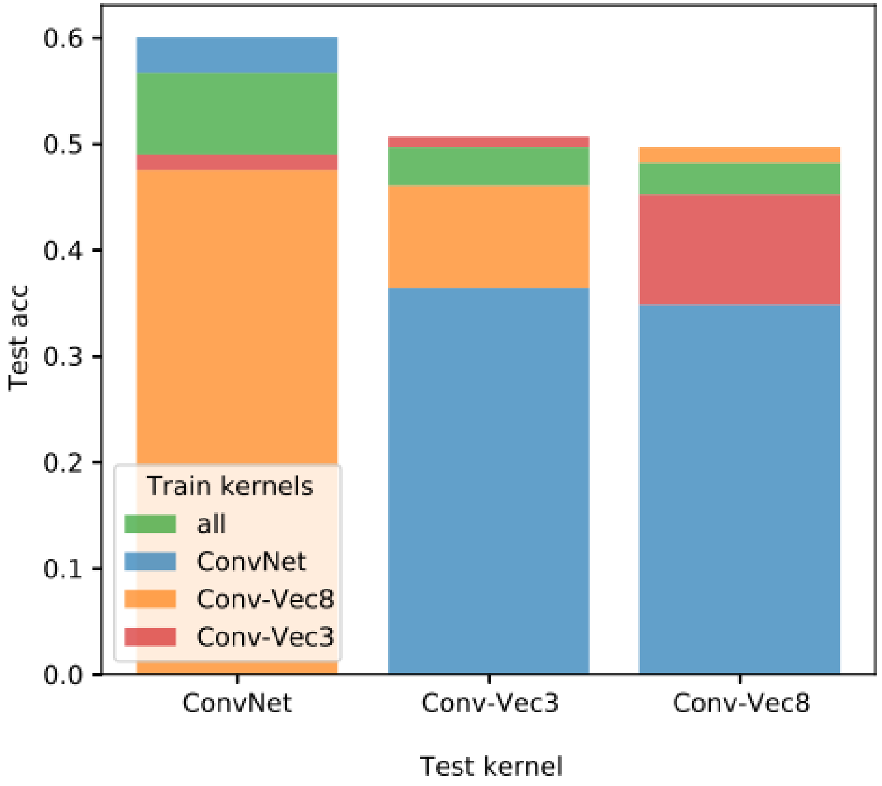
Experiments.KIP vs ALL

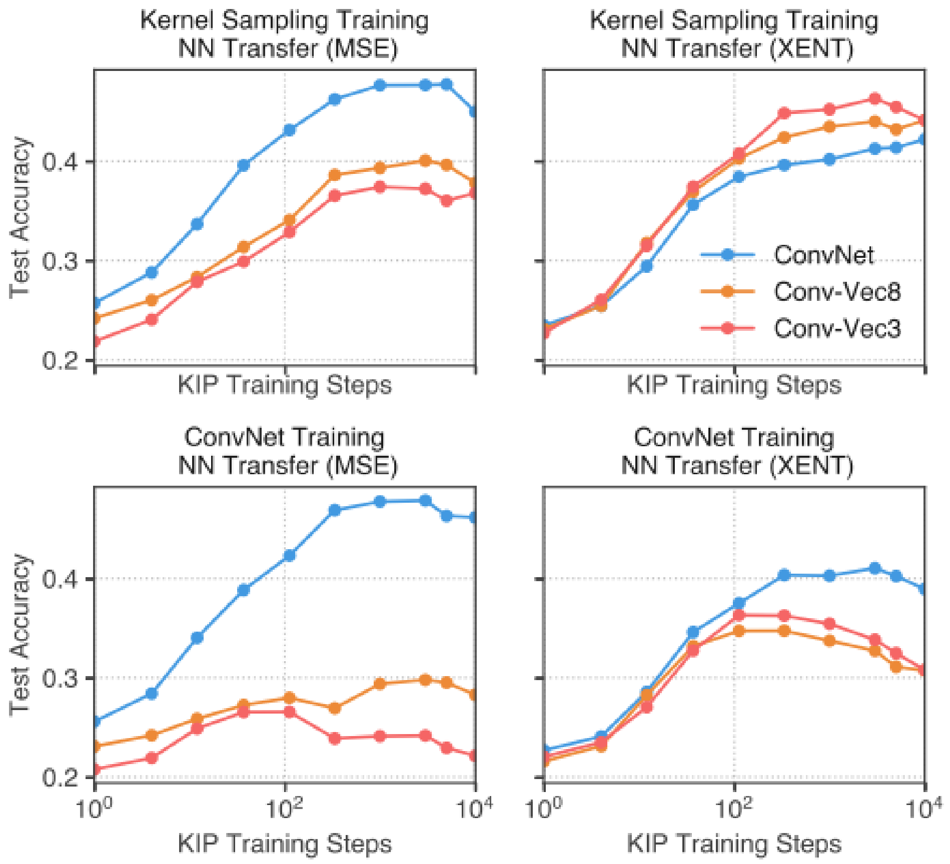
Table 1: **Comparison with other methods.** The left group consists of neural network based methods. The right group consists of kernel ridge-regression. All settings for KIP involve the use of label-learning. Grayscale datasets use standard channel-wise preprocessing while RGB datasets use regularized ZCA preprocessing.

	Imgs/ Class	DC[1]	DSA[1]	KIP FC[1] aug	LS ConvNet[2,3]	KIP ConvNet[2] no aug	KIP ConvNet[2] aug
MNIST	1	91.7±0.5	88.7±0.6	85.5±0.1	73.4	**97.3±0.1**	**96.5±0.1**
	10	97.4±0.2	97.8±0.1	97.2±0.2	96.4	**99.1±0.1**	**99.1±0.1**
	50	98.8±0.1	99.2±0.1	98.4±0.1	98.3	**99.4±0.1**	**99.5±0.1**
Fashion-MNIST	1	70.5±0.6	70.6±0.6	-	65.3	**82.9±0.2**	76.7±0.2
	10	82.3±0.4	84.6±0.3	-	80.8	**91.0±0.1**	88.8±0.1
	50	83.6±0.4	88.7±0.2	-	86.9	**92.4±0.1**	91.0±0.1
SVHN	1	31.2±1.4	27.5±1.4	-	23.9	62.4±0.2	**64.3±0.4**
	10	76.1±0.6	79.2±0.5	-	52.8	79.3±0.1	**81.1±0.5**
	50	82.3±0.3	**84.4±0.4**	-	76.8	82.0±0.1	**84.3±0.1**
CIFAR-10	1	28.3±0.5	28.8±0.7	40.5±0.4	26.1	**64.7±0.2**	63.4±0.1
	10	44.9±0.5	52.1±0.5	53.1±0.5	53.6	**75.6±0.2**	**75.5±0.1**
	50	53.9±0.5	60.6±0.5	58.6±0.4	65.9	78.2±0.2	**80.6±0.1**
CIFAR-100	1	12.8±0.3	13.9±0.3	-	23.8	**34.9±0.1**	33.3±0.3
	10	25.2±0.3	32.3±0.3	-	39.2	47.9±0.2	**49.5±0.3**

+ ZCA, + label-learning, +- aug

Experiments.Kernels Choice



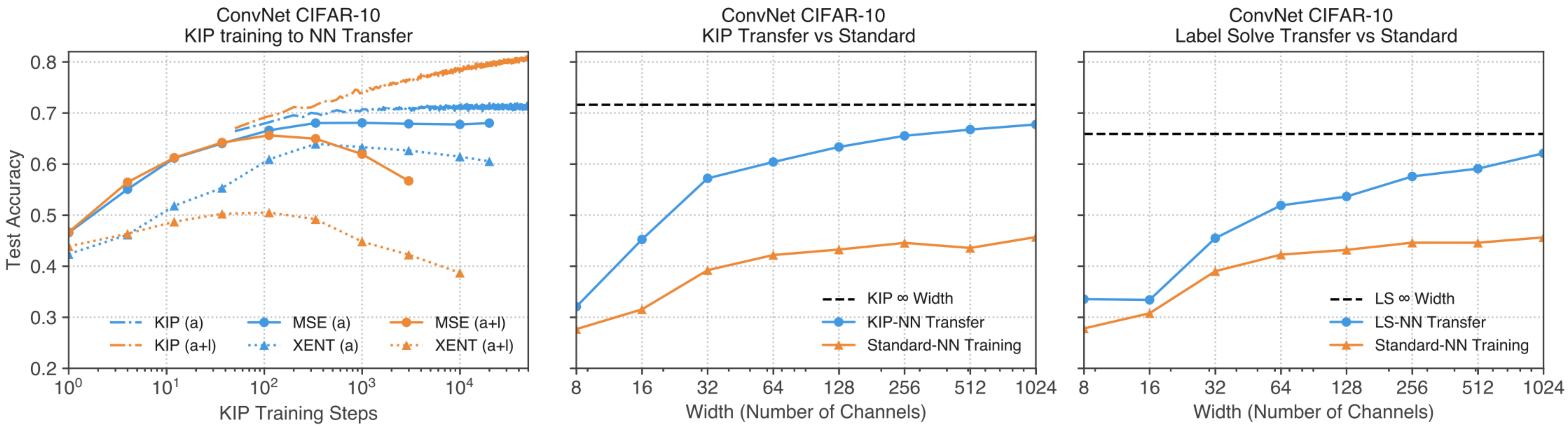


Experiments.Transfer

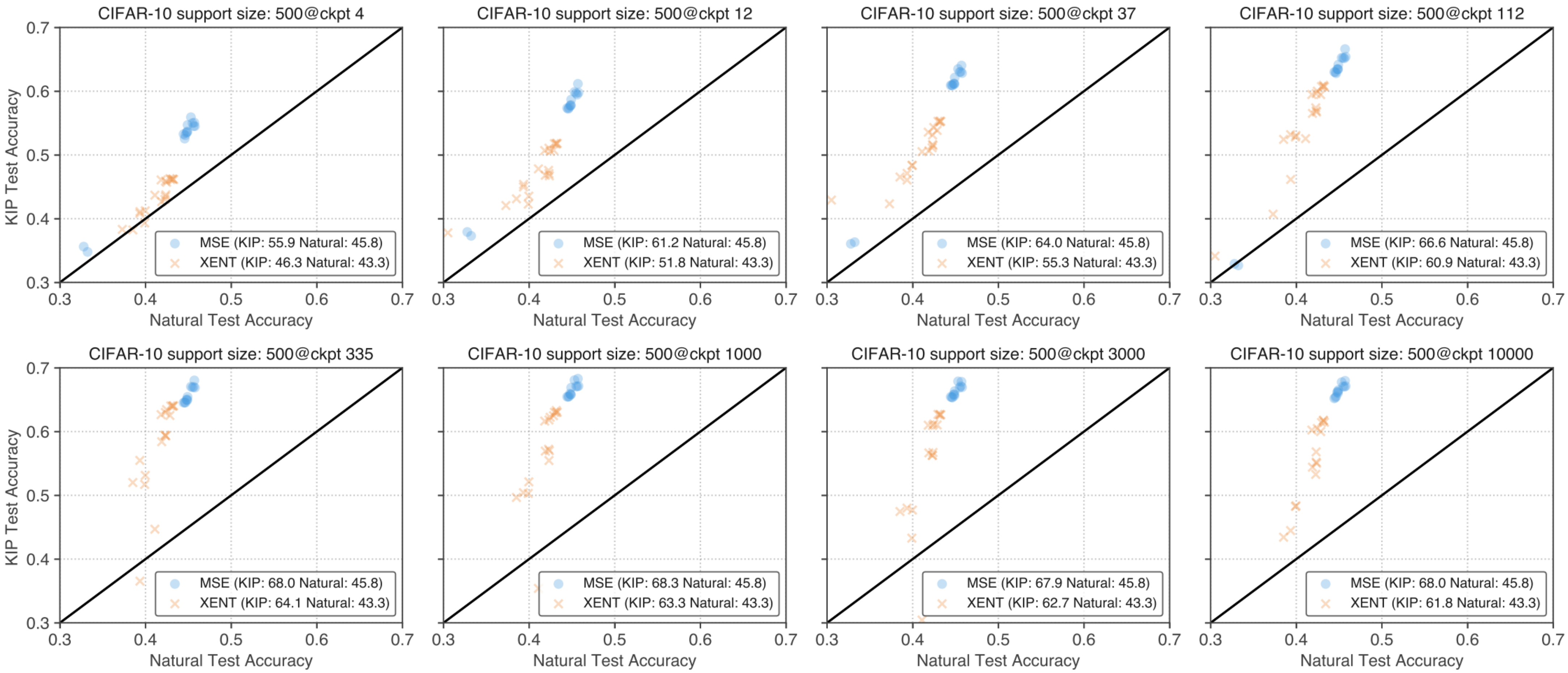
	Imgs/Class	DC/DSA	KIP to NN	Perf. change	LS to NN	Perf. change
MNIST	1	**91.7±0.5**	90.1±0.1	-5.5	71.0±0.2	-2.4
	10	**97.8±0.1**	97.5±0.0	-1.1	95.2±0.1	-1.2
	50	**99.2±0.1**	98.3±0.1	-0.8	97.9±0.0	-0.4
Fashion-MNIST	1	70.6±0.6	**73.5±0.5***	-9.8	61.2±0.1	-4.1
	10	84.6±0.3	**86.8±0.1**	-1.3	79.7±0.1	-1.2
	50	**88.7±0.2**	88.0±0.1*	-4.5	85.0±0.1	-1.8
SVHN	1	31.2±1.4	**57.3±0.1***	-8.3	23.8±0.2	-0.2
	10	**79.2±0.5**	75.0±0.1	-1.6	53.2±0.3	0.4
	50	**84.4±0.4**	80.5±0.1	-1.0	76.5±0.3	-0.4
CIFAR-10	1	28.8±0.7	**49.9±0.2**	-9.2	24.7±0.1	-1.4
	10	52.1±0.5	**62.7±0.3**	-4.6	49.3±0.1	-4.3
	50	60.6±0.5	**68.6±0.2**	-4.5	62.0±0.2	-3.9
CIFAR-100	1	13.9±0.3	**15.7±0.2***	-18.1	11.8±0.2	-12.0
	10	**32.3±0.3**	28.3±0.1	-17.4	25.0±0.1	-14.2

ZCA preprocessing, +- aug, * - best with trained labels

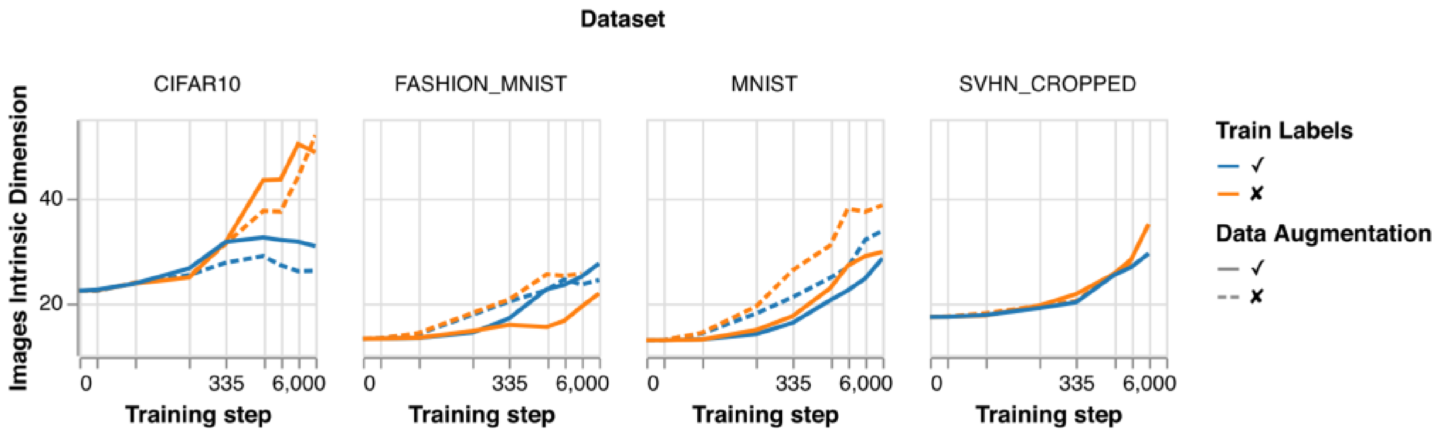
Experiments.Transfer

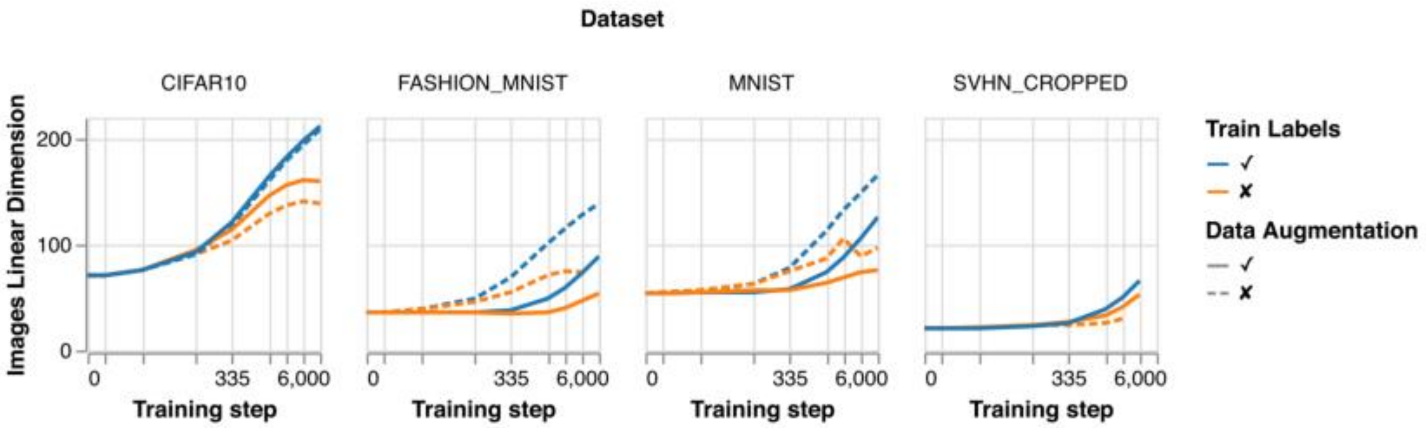


Experiments.Hyperparameters



Experiments.Datasets Dims

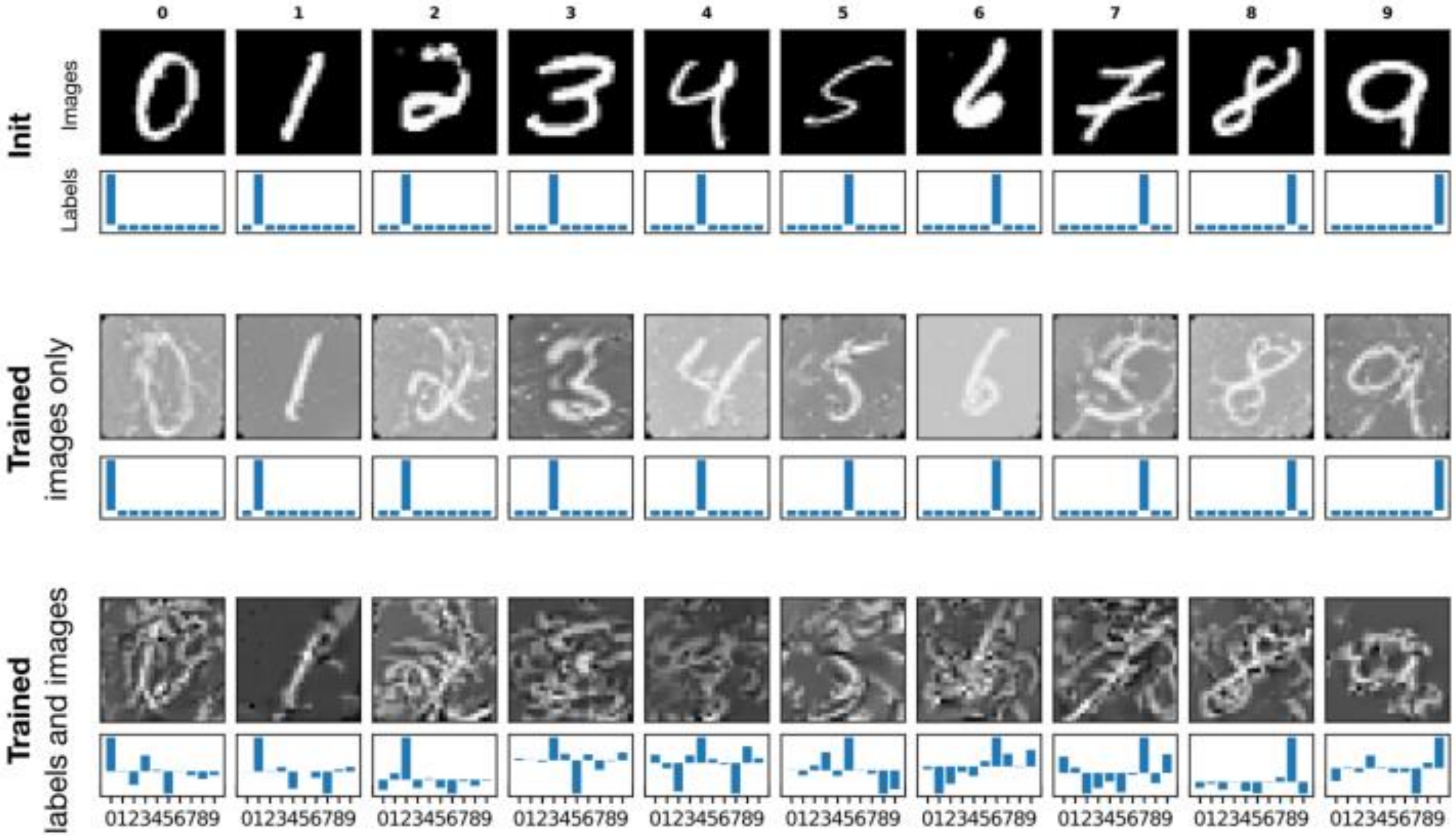




Experiments.Learned Images

CIFAR-100

Experiments.Learned Images



MNIST

Papers

- [2] Wang, T., Zhu, J., Torralba, A. and Efros, A. Dataset Distillation, 2018.