Evaluating the Robustness of Generative Teaching Networks

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Overview

1. Generative Teaching Networks

2. Robustness Performance Tests

3. Conclusion

Generative Teaching Networks

Meta-Learning

Meta-Learning is about ”learning to learn”.

There are generally 3 components to Machine-Learning..
The **environment**, the learner **model** and the learning **algorithm**.

Generative Teaching Networks

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algorithm: *fixed*
model architecture: *fixed*
model parameters: *learned*

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Generative Teaching Networks (GTN) aim to learn an environment and algorithm parameters via meta-learning for rapid training of a variety of different kinds of deep neural network architectures.

traditional ML	Generative Teaching Networks
environment: *`fixed`*	environment: *`learned`*
algorithm: *`fixed`*	algorithm: *`learned`*
model architecture: *`fixed`*	model architecture: *`random`*
model parameters: *`learned`*	model parameters: *`learned`*

GTN Algorithm

Algorithm Generative Teaching Networks

initialize $G_{\boldsymbol{\omega}}$
for $\mathtt{2000\ times}$ **do**
  sample $D_{\boldsymbol{\theta}}$
  for $\mathtt{64\ times}$ **do**
    $\mathsf{z} = (\mathsf{z}_x, \mathsf{z}_y) \sim$ sample randomly
    $\mathsf{x} \leftarrow G_{\boldsymbol{\omega}}(\mathsf{z})$
    $\hat{\mathsf{y}} \leftarrow D_{\boldsymbol{\theta}}(\mathsf{x})$
    $\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} - \lambda \nabla_{\boldsymbol{\theta}} \mathcal{L}(\hat{\mathsf{y}}, \mathsf{z}_y)$
  end for
  $\boldsymbol{\omega} \leftarrow \boldsymbol{\omega} - \gamma \nabla_{\boldsymbol{\omega}} \mathcal{L}(D_{\boldsymbol{\theta}}(\mathsf{x}_{train}), \mathsf{y}_{train})$
end for

Meta-Loop

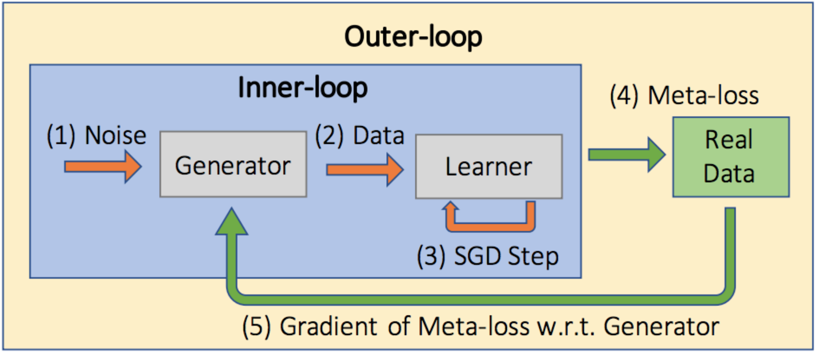

Figure 1: Generative Teaching Networks meta-loop [1]

Full Curriculum:
In addition to the weights of the generator G, the full ordered set of 64 latent vectors $\mathbf{z}^{(i)} \in \mathbb{R}^{138}$ and learning rates $\lambda^{(i)}$ (and weight decay parameters) are learned for $i \in [1, \ldots, 64]$.

GTN - Results

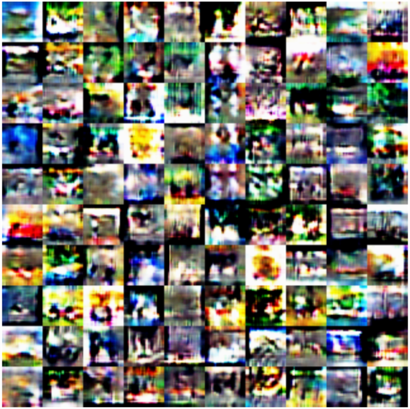

Figure 2: CIFAR10 Generator examples [1]

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$\rightarrow$ debugging & interacting with code was very difficult.

Training Models

GTN trained on *'base_larger'*.

learner type
'base'
'base_fc'
'base_larger'
'base_larger2'
'base_larger3'
'base_larger3_global_pooling'
'base_larger4'
'base_larger4_global_pooling'
'linear'

Training Models

GTN trained on `'base_larger'`.

Criteria: mean accuracy over 5 independently trained networks should be ≥ 0.7.

learning algorithm / *learner type*	`10_gtn`	`vanilla`	`gtn`
`'base'`	0.16	0.95	0.22
`'base_fc'`	0.97	0.98	0.98
`'base_larger'`	0.97	0.98	0.98
`'base_larger2'`	0.12	0.96	0.16
`'base_larger3'`	0.72	0.97	0.91
`'base_larger3_global_pooling'`	0.11	0.96	0.12
`'base_larger4'`	0.09	0.11	0.09
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Robustness Performance Tests

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Overview of robustness tests:

- Noise corruption
- Blurring
- FGSM-attack
- LBFGS-attack

Robustness Performance Tests

For all experiments, two GTN models (based on *'base_larger'*, *'base_larger3'*) have been trained. For each GTN model and for each learner type, 5 independent models have been trained for the full 64 cycles (*gtn*). The same has been done for only 10 cycles for comparison (*10_gtn*). Also, each learner type has been trained for one epoch ($\sim$390 update steps) on the training set (*vanilla*). All tests are performed on unseen test data.

Noise Corruption

$$\tilde{x} = \text{clip}[\,x + \beta z\,]\,, \quad z \sim \mathcal{N}(0, I)$$

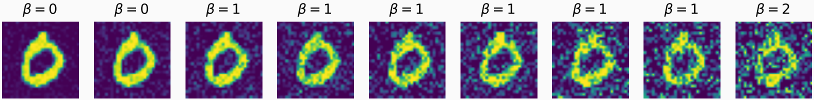
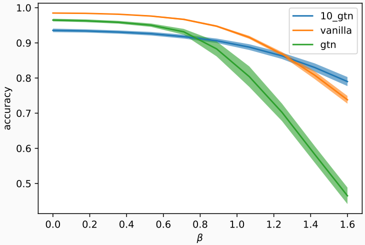


Figure 3: Noise corruption of varying strength β.

Noise Corruption - Results

GTN trained with *'base_larger'*



GTN trained with *'base_larger3'*

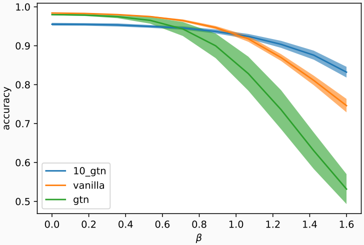


Figure 4: Accuracies of trained models under varying input noise corruption.

Blurring

$$\tilde{x} = \text{gaussian\_blur}_{\beta}(x)$$

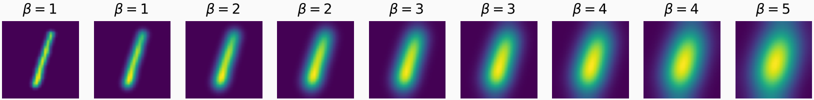


Figure 5: Gaussian-blur filter applied with varying Gaussian kernel std β.

Blurring - Results

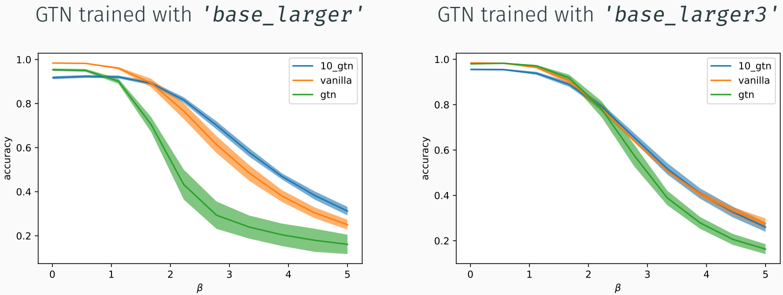


Figure 6: Accuracies of trained models under varying Gaussian-blur filters.

FGSM-Attack

$$\mathsf{x} \leftarrow \mathsf{x} + \beta\, \mathrm{sign}\left(\nabla_{\mathsf{x}} \mathcal{L}(D(\mathsf{x}), y)\right)$$
$$\mathsf{x} \leftarrow \mathrm{clip}[\,\mathsf{x}\,]$$

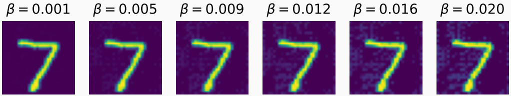


Figure 7: Results after 30 steps of FGSM-attack with varying β.

FGSM-Attack - Results

GTN trained with *'base_larger'* GTN trained with *'base_larger3'*

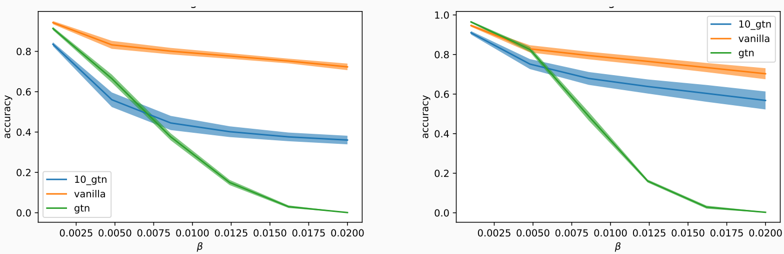


Figure 8: Accuracies of trained models under FGSM-attack with varying strengths.

LBFGS-Attack

$$\mathbf{x} \leftarrow \mathbf{x} + \varepsilon \left(\nabla_{\mathbf{x}} \mathcal{L}(D(\mathbf{x}), y) - \frac{1}{\beta} \nabla_{\mathbf{x}} \|\mathbf{x} - \mathbf{x}^0\|_2 \right)$$

$$\mathbf{x} \leftarrow \mathrm{clip}[\,\mathbf{x}\,]$$

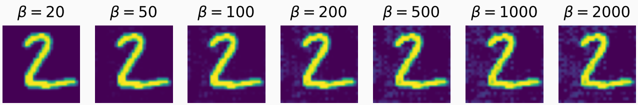
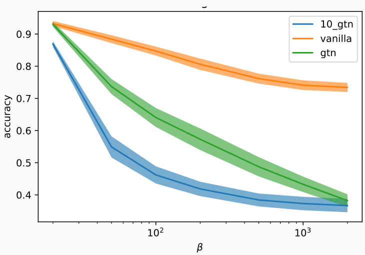


Figure 9: Results after 30 steps of LBFGS-attack with varying β.

LBFGS-Attack - Results

GTN trained with `'base_larger'`   GTN trained with `'base_larger3'`



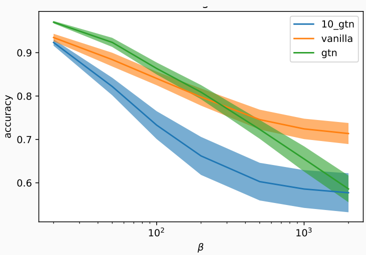


Figure 10: Accuracies of trained models under LBFGS-attack with varying strengths.

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- models trained with GTNs are less robust than vanilla trained models
- however, number of testable architectures was limited due to shortcomings
- MNIST is a fairly simple task $\rightarrow$ more datasets are needed to be conclusive
- GTNs are likely to improve over time

Questions?

References

Felipe Petroski Such et al. *Generative Teaching Networks: Accelerating Neural Architecture Search by Learning to Generate Synthetic Training Data*. 2019. arXiv: 1912.07768 [cs.LG].