Adversarial Transform Networks

Learning to Generate Adversarial Examples

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arXiv:1703.0938

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https://qdata.github.io/deep2Read/

Outline

- Create a network which learns how to generate adversarial networks given a model
- Generate either untargeted or targeted examples
- Current approaches include using optimizers, fast single-step gradients, and iterative variants of gradient-based techniques

Adversarial Transformation Networks

Network, Optimization, and Inference

- Focus on targeted, white-box ATNs
- ATNs transforms an input into an adversarial example against a target network or set of networks. θ is the parameter vector of g, f is the target network

$$g_{f,\theta}(x) : x \in X \to x'$$

- To find $g_{f,\theta}$, solve following optimization where L_X is a loss function on the input space and L_Y is a loss function on the output space to avoid learning identity function

$$\text{argmin}_{\theta} \Sigma_{x_i \in X} \beta L_X(g_{f,\theta}(x_i), x_i) + L_Y(f(g_{f,\theta}(x_i)), f(x_i))$$

- Inference does not require any further gradient calculations or access to f, so generation is very quick

Adversarial Transformation Networks

Loss Function and Reranking

- L_X was picked to be L_2 loss
- L_Y determines whether ATN is targeted; define L_Y to be following equation, where t is the target class, $y = f(x)$, $y' = f(g_f(x))$, and r is a reranking function

$$L_{Y,t}(y', y) = L_2(y', r(y, t))$$

- r reranks y such that $y_k < y_t, \forall k \neq t$ and attempts to keep most of structure from y to minimize distortions; defined where $\alpha > 1$ and *norm* rescales output to be valid probability distribution

$$r_\alpha(y, t) = norm(\{\alpha max(y) \text{ if } k = t, y_k \text{ otherwise}\})$$

Adversarial Transformation Networks

Example Generation

- Two approaches of generating examples
  - Perturbation ATN (P-ATN): Similar to He et al. 2015, set $g_f(x) = \tanh(x + G(x))$, where $G(x)$ is the core function of g_f; easy to generate small, but effective, perturbations
  - Adversarial Autoencoding (AAE): Similar to standard autoencoders, attempt to reconstruct input subject to regularization (L_Y) and noise
- For both approaches, enforce that x' is in X by restricting x' to valid input range of f; adding a tanh function in the last layer sufficiently restricts the range to $[-1, 1]$

MNIST Experiments

Procedure

- Train 5 separate models with varying architectures (combinations of fully connected and convolution layers) and weight initializations on MNIST
  - Baseline accuracy around 98.5-99.1 percent
- Attempt to create an autoencoding ATN using previously detailed process
- During training of ATN, weights of classifier model are frozen
- Empirically set $\alpha = 1.5$ for reranking

MNIST Experiments

Optimizing Beta

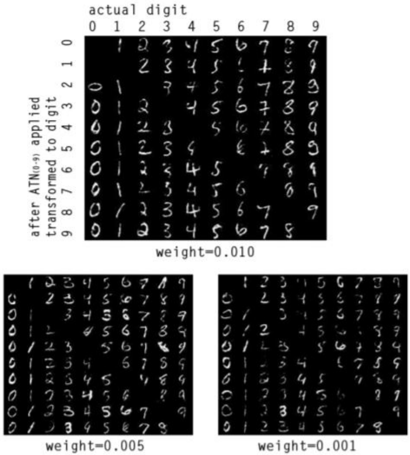
- Vary β on one various ATN architectures, find average accuracy on all 10 targets (all trained on original model of 5x5 conv, 5x5 conv, FC, FC); 1 separate network for each target
  - Row 1: classifier labeled x' as t
  - Row 2: classifier labeled x' as t that kept previous argmax(y) in second
  - Row 3: argmax(y) in second place

	β: 0.010	0.005	0.001
ATN$_a$ FC $\to$ FC$\to$28x28 Image	**69.1%**	**84.1%**	**95.9%**
	91.7%	93.4%	95.3%
	63.5%	78.6%	91.4%
ATN$_b$ (3x3 Conv)$\to$ (3x3 Conv) $\to$ (3x3 Conv) $\to$ FC $\to$ 28x28 Image	**61.8%**	**77.7%**	**89.2%**
	93.8%	95.8%	97.4%
	58.7%	74.5%	86.9%
ATN$_c$ (3x3 Conv)$\to$ (3x3 Conv)$\to$(3x3 Conv) $\to$ Deconv: 7x7 $\to$ Deconv: 14x14 $\to$ 28x28 Image	**66.6%**	**82.5%**	**91.4%**
	95.5%	96.6%	97.5%
	64.0%	79.7%	89.1%

MNIST Experiments

Optimizing Beta

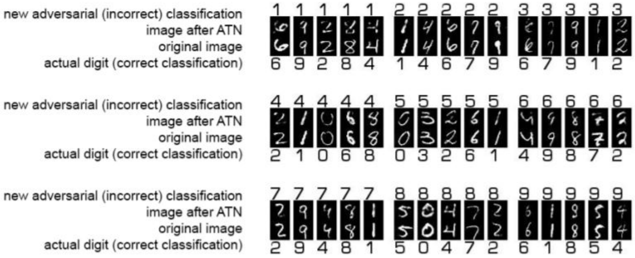
- Smaller beta values more easily fool networks, but at a cost of losing similarity to original input image



MNIST Experiments

Key Observations

- Transformation maintains empty space; no salt-and-pepper type noise
- In majority of generated examples, shape does not drastically change; by training output to maintain rank except for the top-output, this should be true
- Vertical components seem to be emphasized in some digits (especially if $t = 1$)
- Novel aspect of ATN is the rank preservation



ATN Extensions

Multiple Networks

- ATN trained on one classifer generated examples which did not generalize well to other classifiers, even those with similar architectures
- ATN trained while minimizing L_Y for three classifiers performed better on all three classifiers and also two outside classifiers

	Classifier_p*	Classifier_{a0}	Classifier_{a1}	Classifier_{a2}	Classifier_{a3}
1st Place Correct	82.5%	15.7%	16.1%	7.7%	28.9%
2nd Place Correct (Conditional)	96.6%	84.7%	89.3%	85.0%	81.8%
2nd Place Correct (Unconditional)	79.7%	15.6%	16.1%	8.4%	26.2%

β		Classifier_p*	Classifier_{a0}	Classifier_{a1}*	Classifier_{a2}*	Classifier_{a3}
0.010	1st Place Correct	89.9%	37.9%	83.9%	78.7%	70.2%
	2nd Place Correct (Conditional)	96.1%	88.1%	96.1%	95.2%	79.1%
	2nd Place Correct (Unconditional)	86.4%	34.4%	80.7%	74.9%	55.9%
0.005	1st Place Correct	93.6%	34.7%	88.1%	82.7%	64.1%
	2nd Place Correct (Conditional)	96.8%	88.3%	96.9%	96.4%	73.1%
	2nd Place Correct (Unconditional)	90.7%	31.4%	85.3%	79.8%	47.2%

ATN Extensions

Inside Information

- Since treating classifier as white-box, may be helpful to look at more inside information than just outputs and error derivatives
- Look at hidden unit activations (for practicality, only for penultimate FC layer)
- Increased conditional success of second position

ATN Extensions

Parallel and Serial ATNs

- First, take 1000 random images from MNIST test set, then apply each ATN for each digit separately; track how many ATNs can successfully transform each image
- Next, sequentially apply all 10 ATNs on images
- In parallel application, 283/1000 were transformed successfully; in serial application, 741/1000 were transformed successfully
  - Likely because each transformation diminished underlying original image, so only a few pixels needed to be added to change top class to target
- Order preservation was not maintained in serial application

ImageNet Experiments
Procedure

- Use state-of-the-art Inception ResNet (IR2)
- Trained both AAE and P-ATNs against IR2
- 5 separate architectures for IR2
  - IR2-Base-Deconv (AAE, P-ATN)
  - IR2-Resize-Conv (AAE)
  - IR2-Conv-Deconv (AAE)
  - IR2-Conv-FC (P-ATN)

  The use of FC layer makes AAE too slow, so only P-ATN used FC layer
- All 5 architectures were trained with same hyperparameters for 4 separate targets (binoculars, soccer ball, volcano, zebra) for a total of 20 ATNs
- Hyperparameters found using grid search using only volcano target

ImageNet Experiments

Results

- AAE more successful than P-ATN
- P-ATN tends to preserve most of image at cost of small area with high perturbation, while AAE distributes changes across image
- AAEs, however, can produce checkerboard patterns, a common problem in image generation
- For AAEs, many high frequency patterns are replaced by high frequencies which encode adversarial signal

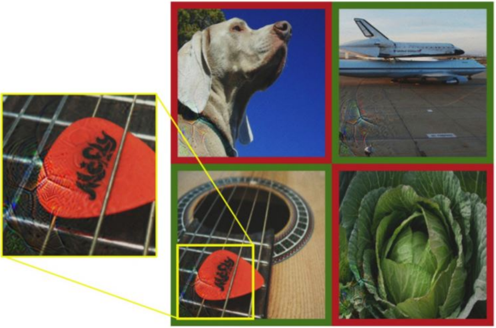
Table 8. IL2 ATN Performance

	P-ATN Target Class Top-1 Accuracy			
	Binoculars	Soccer Ball	Volcano	Zebra
IR2-Base-Deconv	66.0%	56.5%	0.2%	43.2%
IR2-Conv-FC	**79.9%**	**78.8%**	0.0%	**85.6%**
	AAE ATN Target Class Top-1 Accuracy			
	Binoculars	**Soccer Ball**	**Volcano**	**Zebra**
IR2-Base-Deconv	**83.0%**	**92.1%**	88.1%	**88.2%**
IR2-Resize-Conv	69.8%	61.4%	**91.1%**	80.2%
IR2-Conv-Deconv	56.6%	75.0%	87.3%	79.1%

ImageNet Experiments

Results

- AAE produces more diverse adversarial examples, which may be useful for adversarial training
- P-ATNs sometimes produces the same perturbation in the same place for all input examples (similar to DeepDream)



Summary

- ATNs are a fundamentally different approach then previous gradient descent based approaches for generating adversarial examples
- ATNs are efficient to train, fast to execute, and produces diverse examples; may allow for more robust models in future by improving adversarial training procedures

References

- https://arxiv.org/pdf/1703.09387.pdf