On Saliency Maps and Adversarial Robustness

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Overview

- ***Robustness and Interpretability*** are important parameters for DNNs

- ***Early works:*** focusing solely on either robustness or interpretability

- **Recent works:** started exploring relation between these notions

    - Robust DNNs exhibit high interpretability

    - DNNs with robust explanations are inherently robust

- ***Our contributions:*** explore new tangible relationship between a saliency maps and adversarial perturbations

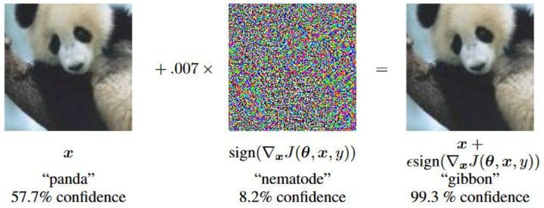
    - propose a new method (SAT) that uses the saliency map while training to improve networks robustness.

    - Experimented on widely used datasets

    - Show that the improvement becomes more pronounced when a better saliency map is used

    - Exploit bounding boxes or segmentation masks as weak saliency to efficiently improve model's robustness

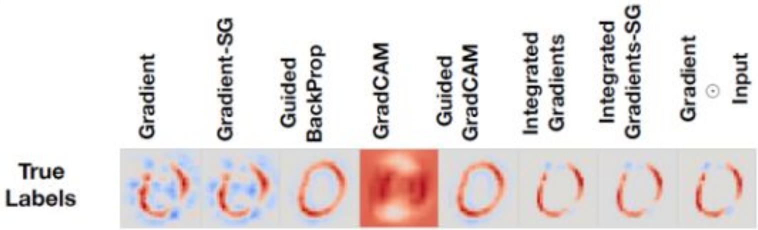
Adversarial Robustness



- **Adversarial Attacks:**
  - Adding imperceptible perturbations to input leading to wrong model predictions.
  - E.g FGSM (Goodfellow et al. 2015), PGD (Madry et al 2018.), stAdv (Xiao et al. 2018)

- **Adversarial Training:**
  - Make models robust by augmenting training data with adversarial perturbations.
  - Popular ones: PGD-AT (Madry et al. 2018) and TRADES (Zhang et al. 2019)

Interpretability



- **Backpropagation based:** importance of each pixel by backpropagating the class score error to the input image

  - E.g Guided Backprop (Springenberg et al. 2015), SmoothGrad (Smilkov et al 2017.), Integrated Gradients (Sundararajan et al. 2017)

- **Activation Based:** use linear combinations of activations of convolutional layers

  - E.g CAM (Zhou et al. 2016), GradCAM (Selvaraju et al 2017.), GradCAM++ (Chattopadhyay et al. 2018)

Coupling Robustness and Interpretability

- **Zhang et al. 2018:** Robust models are more biased towards image shape than its texture and evince more interpretable saliency maps

- **Etmann et al. 2019:** quantified above behavior of robust models by considering the alignment between saliency map and the image as the metric for interpretability

- **Dombrowski et al. 2019, Ghorbani et al. 2019 :** Do robust and interpretable saliency maps imply adversarial robustness ?

Our Work- Can saliency maps be used to induce robustness ?

- **Motivation:** humans tend to learn new tasks in a robust fashion when provided with explanations during their learning phase
  - Eg. a medical student

- **Our hypothesis:** a DNN model that is trained with explanations is less easily fooled by adversarial perturbations.

Saliency Based Adversarial Training : Motivation

- An adversarial perturbation,**e**, which is intended as a perturbation to input **x** which results in a change of predicted label, can be modeled as follows:

$$\arg\max_i \Phi^i(x+e) \neq \arg\max_i \Phi^i(x) \tag{5}$$

$$\iff \exists j \neq i^* : \Phi^j(\mathbf{x}+e) > \Phi^{i^*}(\mathbf{x}+e) \tag{6}$$

$$\iff \exists j \neq i^* : e^T \cdot (\nabla_{\mathbf{x}}\Phi^j(\mathbf{x}) - \nabla_{\mathbf{x}}\Phi^{i^*}(\mathbf{x})) > \Phi^{i^*}(\mathbf{x}) - \Phi^j(\mathbf{x}) \tag{7}$$

Adversarial perturbation definition

$$\arg \inf_{e \in \mathbb{R}^d} \{\|e\| : \arg\max_i \Phi^i(x+e) \neq \arg\max_i \Phi^i(x)\}$$

Etmann et al. 2019

$$\Phi^i(\mathbf{x}+e) \approx \Phi^i(\mathbf{x}) + e^T \cdot \nabla_{\mathbf{x}}\Phi^i(\mathbf{x})$$

Saliency Based Adversarial Training : Motivation

$$\exists j \neq i^* : e^T \cdot (\nabla_{\mathbf{x}} \Phi^j(\mathbf{x}) - \nabla_{\mathbf{x}} \Phi^{i^*}(\mathbf{x})) > \Phi^{i^*}(\mathbf{x}) - \Phi^j(\mathbf{x})$$

The infimum over **llell**, which provides a minimal perturbation to change the class label, is achieved by choosing **e** as a multiple of $\nabla_x(\Phi^j(x) - \Phi^{i*}(x))$.

- The direction of adversarial perturbation then becomes

$$\nabla_x(\Phi^j(x) - \Phi^{i*}(x)).$$

- This perturbation direction depends on two quantities:

(i) $\nabla x \Phi^{i*}(x)$ the saliency map for the true class **i***

(ii) $\nabla x \Phi^j(x)$, the saliency map of **x** for class **j** for which the infimum of **e** is attained.

Case of Binary Classifiers

- A binary classifier **h : x→ {−1,1}** given by: **h=sign(Φ(x,θ))**, where **Φ(x,θ))** represents the logit of the positive class.
- Let **Φ'(x)** denotes the logit of negative class, then

$$P(y=+1|\mathbf{x}) = \frac{1}{1+\exp^{-\Phi(\mathbf{x},\theta)}} \qquad P(y=-1|\mathbf{x}) = \frac{1}{1+\exp^{-\Phi'(\mathbf{x},\theta)}}$$

$$P(y=-1|\mathbf{x}) = 1 - P(y=+1|\mathbf{x}) = \frac{1}{1+\exp^{\Phi(\mathbf{x},\theta)}}$$

- Thus, logit score of the negative class is −Φ(x,θ)
- So, the direction of adversarial perturbation $\nabla_x(\Phi^j(x)-\Phi^{i*}(x))$ becomes $-\nabla x\Phi^{i*}(x)$
- **The negative of saliency map, gives us the direction of adversarial perturbation in case of binary classifier**

Case of Multi-class Classifiers

$$\nabla_{\mathbf{x}}(\Phi^{j}(\mathbf{x}) - \Phi^{i^*}(\mathbf{x}))$$

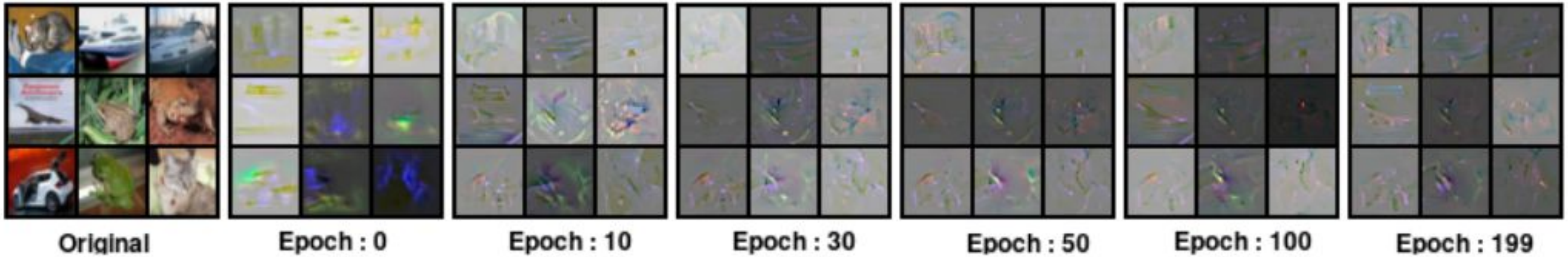
- The multi-class case would require finding the class **j** for which the infimum of **||e||** is attained.
- To avoid this computational overhead, we rely on $\nabla_x \Phi^{i*}(x)$ alone, and simply propose the use of $-\nabla_x \Phi^{i*}(x)$ as the direction of perturbation.

This is a reasonable approximation. Why?

- Consider the multi-class setting as k binary classification problems
- For each individual problem, corresponding logit score of the negative class is $-\nabla_x \Phi^{i*}(x)$
- Assuming that each of the classes **!= i*** is equally likely to be the **j** that minimizes **||e||**
- Approximate average direction of the perturbations across the k binary classification problems.

Saliency based Adversarial Training: Algorithm

- $-\nabla_x\Phi^{i*}(x)$ is given to us in form of saliency map, **s.**
- **We don't have any intermediate perturbations.**
- While adversarial training, during the initial phases, the perturbations computed by the attack methods are random. But with training, they become more class-discriminative.



Saliency based Adversarial Training: Algorithm

To generate intermediate perturbations, we mimic the above observation

- We choose the **ith** component **δ^t[i]** of perturbation as
- Note that saliency map, **s,** can be converted in range {-1,1} by using thresholds.

$$\delta^t[i] = \begin{cases} \mathbf{z}[i], & \text{with probability } \alpha^t \\ -\mathbf{s}[i], & \text{with probability } 1 - \alpha^t \end{cases}$$

where $\mathbf{z} \in \{-1, 1\}^d$ is sampled randomly, and $0 < \alpha < 1$. D

Leveraging bounding- boxes and segmentation masks

- When additional annotations such as bounding boxes or segmentation masks are available in a dataset,our approach considers these as weak saliency maps for the methodology.

We generate the weak saliency from bounding boxes or segmentation masks as:

$$\tilde{\mathbf{s}}[i] = \begin{cases} 1, & \text{if } \mathrm{i}^{\mathrm{th}} \text{ pixel lies inside bbox or seg masks} \\ -1, & \text{otherwise} \end{cases}$$

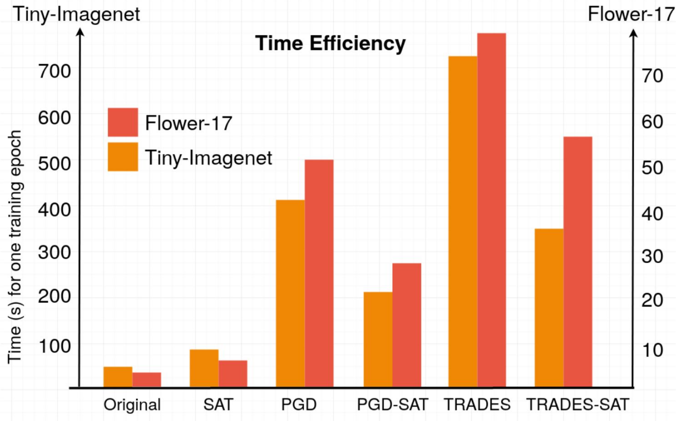
Robustness Results on Tiny-Imagenet and Flower-17

Method	Tiny-Imagenet			FLOWER-17		
	$\epsilon = 1/255$	$\epsilon = 2/255$	$\epsilon = 3/255$	$\epsilon = 1/255$	$\epsilon = 2/255$	$\epsilon = 3/255$
Original	1.04	0.4	0.0	63.2	48.01	34.2
Original + Uniform-Noise	9.45	2.32	0.77	64.56	50.43	36.2
SAT	**9.79**	**2.46**	**0.77**	**66.17**	**52.94**	**38.93**
PGD	18.91	14.34	11.37	72.38	70.4	70.3
PGD + Uniform-Noise	19.57	15.49	11.66	73.52	72.79	72.71
PGD-SAT	**20.56**	**16.38**	**12.91**	**78.67**	**75.73**	**75.00**
TRADES	18.45	16.76	11.09	74.56	73.89	73.67
TRADES + Uniform-Noise	19.96	16.13	12.58	76.47	74.26	74.0
TRADES-SAT	**20.04**	**16.45**	**12.96**	**79.41**	**77.94**	**77.20**

The above table shows results on Tiny-Imagenet and Flower-17 datasets where the given bounding boxes and segmentation masks are used as saliency maps. The value of ϵ denotes the maximum l_∞ perturbation allowed in 5-step PGD attack. (More the ϵ, stronger the attack)

Time efficiency of training procedure

- PGD-SAT and TRADES-SAT require much less training time when compared to their vanilla counterparts, while achieving superior performance at the same time.
- In case of vanilla SAT, we observe an increase in robustness without much increase in training time.



Using better saliency maps for training (Cifar-100)

- The saliency maps used in this study were SmoothGrad, Guided Grad-CAM++ and Integrated Gradients.
- **Better explanations improves performance of our trained models.**

Notations **X-Y-Z** (Resnet10-Std.-GBP)
X: Model architecture (Resnet10)
Y: Training procedure (Std.)
Z: Saliency method (GBP)

Method	PGD $\frac{1}{255}$	PGD $\frac{2}{255}$	PGD $\frac{3}{255}$	PGD $\frac{4}{255}$
Original	25.83	7.76	3.35	1.94
Original + Uniform-Noise	33.15	13.50	6.01	3.22
SAT				
Resnet-10 — Std. — GBP	20.53	7.52	3.5	2.12
Resnet-10 — Std. — S.Grad	**39.22**	**19.89**	**9.44**	**4.49**
Resnet-10 — Std. — G.G.CAM++	21.46	8.00	3.53	2.23
Resnet-10 — Std. — I.Grad	36.2	5.43	7.28	3.37
Resnet-10 — Adv. — GBP	34.29	14.73	6.84	4.22
Resnet-10 — Adv. — S.Grad	**40.01**	**21.2**	**10.96**	**4.85**
Resnet-10 — Adv. — G.G.CAM++	34.07	13.18	5.85	3.09
Resnet-10 — Adv. — I.Grad	37.56	16.45	7.55	4.31

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Honeywell
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