Deep Learning for Computer Vision

Adversarial Robustness

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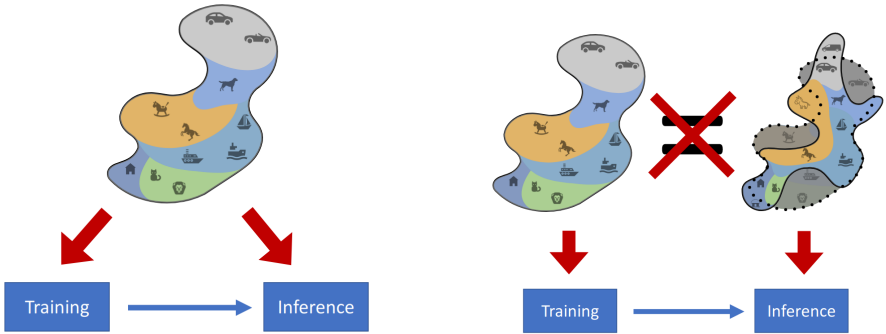
Limitation of Supervised Machine Learning

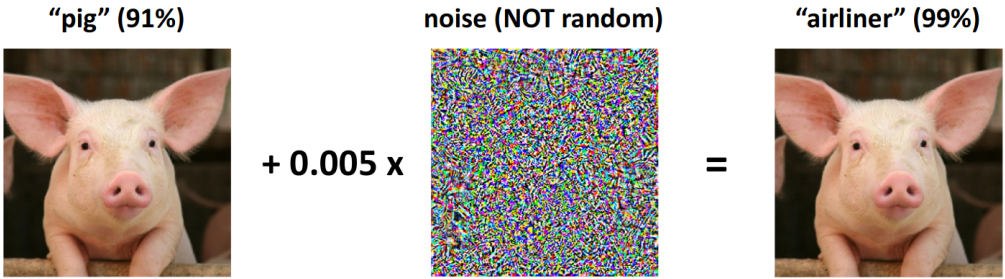
- In reality, the distributions we use ML on are often **NOT** the ones we train it on
- Whenever there is a distribution shift, Deep Neural Networks tend to perform poorly



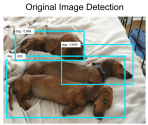
Credit: https://adversarial-ml-tutorial.org/

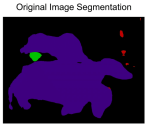
Adversarial Examples

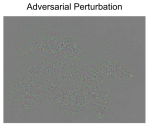
- Examples indistinguishable from original input which leads to wrong predictions
- $\delta^* = \arg\inf_\delta \|\delta\|_p$ such that $f(x+\delta) \neq f(x)$

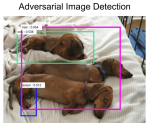


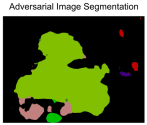
Supervised Frameworks are Vulnerable to Adversarial Attacks[1]







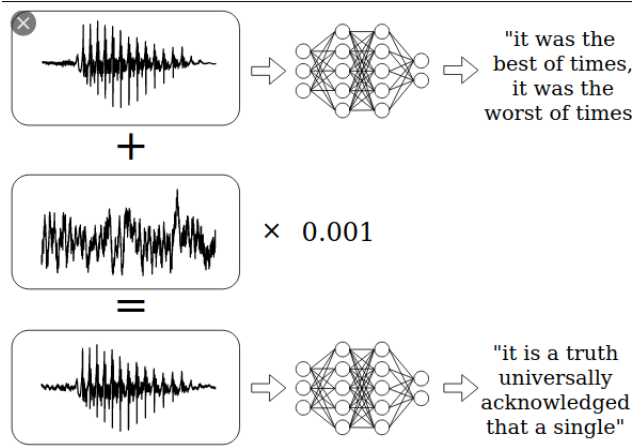




Original Input	Connoisseurs of Chinese film will be pleased to discover that Tian's meticulous talent has not withered during his enforced hiatus.	Prediction: **Positive (77%)**
Adversarial example [Visually similar]	**Aonnoisseurs** of Chinese film will be pleased to discover that Tian's meticulous talent has not withered during his enforced hiatus.	Prediction: **Negative (52%)**
Adversarial example [Semantically similar]	Connoisseurs of Chinese **footage** will be pleased to discover that Tian's meticulous talent has not withered during his enforced hiatus.	Prediction: **Negative (54%)**

[1] Xie et al, Adversarial Examples for Semantic Segmentation and Object Detection, ICCV 2017

Supervised Frameworks are Vulnerable to Adversarial Attacks [2]



[2] Carlini et al, Audio Adversarial Examples: Targeted Attacks on Speech-to-Text, 2018

Taxonomy of Adversarial Attacks

On basis of Threat Model

- **White Box Attacks:** attacker has access to model's parameters.
- **Black Box Attacks:** attacker has no access to model's 'parameters, i.e., it a different model or no model at all to generate adversarial images

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On basis of Objective

- **Untargeted Attacks:** aim is to enforce the model to misclassify adversarial image
- **Targeted Attacks:** aim is to get the image classified as a specific target class, different from the true class

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On basis of Distance Metrics

- L_0: total number of pixels that differ between clean and adversarial images
- L_2: squared difference between pixel values of clean and adversarial images
- L_∞: maximum pixel difference between clean and adversarial images

White-box Adversarial Attacks[3]

Fast Gradient Sign Method (FGSM)

- Computes an adversarial image by adding a pixel-wise perturbation of magnitude in the direction of gradient

[3] Goodfellow et al, Explaining and Harnessing Adversarial Examples, ICLR 2015

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- Computes an adversarial image by adding a pixel-wise perturbation of magnitude in the direction of gradient
- **Single step method:** very efficient in terms of computation time:

$$x_{adv} = x + \epsilon \cdot \text{sign}(\nabla_x \mathcal{L}(x, y_{true})$$

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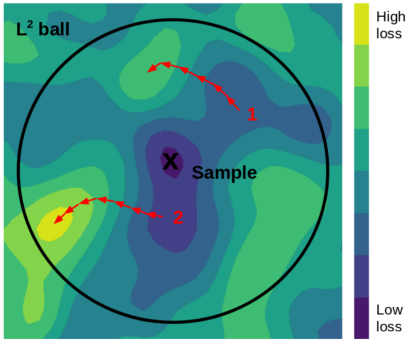
- In case of **targeted attack**, direction is negative gradient with respect to target class:

$$x_{adv} = x - \epsilon \cdot \text{sign}(\nabla_x \mathcal{L}(x, y_{target})$$

where x is clean input image, x_{adv} is corresponding adversarial image, $\mathcal{L}$ is classification loss, y_{true} is actual label, y_{target} is target label and ϵ is L_∞ budget

[3] Goodfellow et al, Explaining and Harnessing Adversarial Examples, ICLR 2015

White-box Adversarial Attacks[4]



Projected gradient descent with restart. 2nd run finds a high loss adversarial example within the L² ball. Sample is in a region of low loss.

Projected Gradient Descent (PGD)

- "Complete" method as it does not consider constraints on amount of time and effort

$$x_{adv}^{0} = x$$

$$x_{adv}^{t+1} = \text{Proj}\{x_{adv}^{t} + \epsilon \cdot \text{sign}(\nabla_x \mathcal{L}(x_{adv}^{t}, y_{true})\}$$

where **Proj**{.} projects the updated adversarial sample into the ϵ neighborhood and a valid range

Credit: Oscar Knagg, TowardsDataScience

[4] Towards Deep Learning Models Resistant To Adversarial Attack — Madry et al 2017

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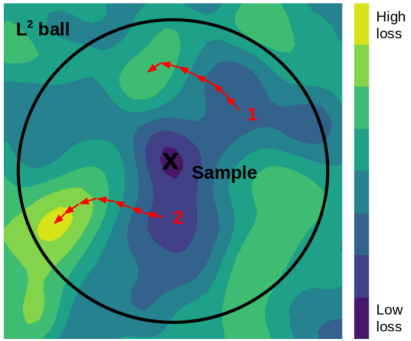

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- In case of L_2, update is as follows:

$$x_{adv}^{t+1} = \text{Proj}\{x_{adv}^{t} + \epsilon \cdot \frac{\nabla_x \mathcal{L}(x_{adv}^{t}, y_{true})}{\|\nabla_x \mathcal{L}(x_{adv}^{t}, y_{true})\|_2}\}$$

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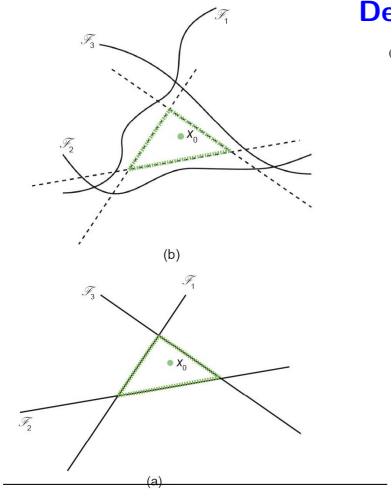

DeepFool

- For affine classifier, $f(x) = w^T x + b$, minimum perturbation to change the class of example x_0 is distance from the decision boundary hyperplane $\mathcal{F} = \{x : w^T x + b = 0\}$, i.e., $\frac{-f(x_0)}{\|w\|_2^2} \cdot w$

[5] Seyed-Mohsen et al, DeepFool: A Simple and Accurate Method to Fool Deep Neural Networks, CVPR 2016

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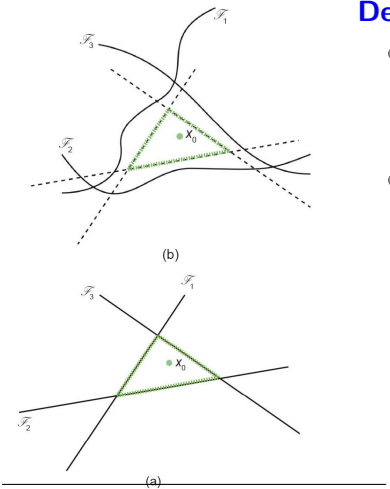

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- For a general differentiable classifier, assuming f is linear around x_t', iteratively compute perturbation δ_t:

$$\arg\min_{\delta_t} \|\delta\|_2 \text{ subject to } f(x_t') + \nabla_x f(x_t')^T \delta_t = 0$$

Runs until $f(x_t') \neq f(x_0)$

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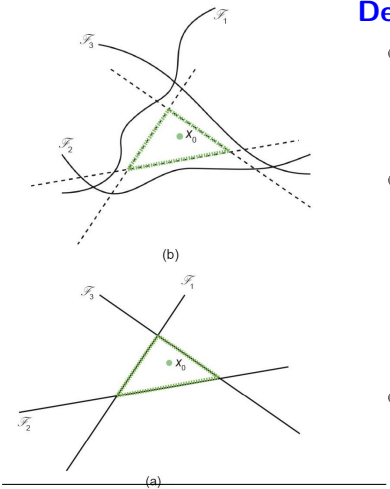

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  Runs until $f(x'_t) \neq f(x_0)$
- **Multi-class classifiers:** Compute distance from x_0 to surface of a convex polyhedron formed by decision boundaries between all classes

[5] Seyed-Mohsen et al, DeepFool: A Simple and Accurate Method to Fool Deep Neural Networks, CVPR 2016

White-box Adversarial Attacks[6]

Carlini and Wagner (C&W) attack

- Optimization-based adversarial attack that can generate adversarial samples using:

$$\min_{\delta} D(x, x+\delta) \text{ such that } f(x+\delta) = t$$

subject to $x + \delta \in [0, 1]$; $D(.,.)$ is L_0 ,L_2 and L_∞ distance measures

[6] Carlini and Wagner, Towards Evaluating the Robustness of Neural Networks, arXiv 2016

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- To ensure $x + \delta$ yields a valid image (i.e., $x + \delta \in [0, 1]$), it introduces a new variable, κ, to substitute as follows:

$$\delta = \frac{1}{2}[\tanh(\kappa) + 1] - x$$

such that $x + \delta = \frac{1}{2}[\tanh(\kappa) + 1]$ which always resides in the range of the optimization process

[6] Carlini and Wagner, Towards Evaluating the Robustness of Neural Networks, arXiv 2016

White-box Adversarial Attacks[7]

Jacobian-based Saliency Map Attack

- Fool DNNs with small L_0 perturbations; compute Jacobian matrix of logits $f(x)$ before softmax layer:

$$\nabla_x f(x) = \frac{\partial f(x)}{\partial x} = \left[\frac{\partial f_i(x)}{\partial x_j}\right]_{i \in \{1,2..M_{out}\}; j \in \{1,2..M_{in}\}}$$

  where M_{in} is input dimension and M_{out} is output dimension

[7] Papernot et al, The Limitations of Deep Learning in Adversarial Settings, EuroS&P 2016

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- Jacobian matrix - how input pixels affect logits; **adversarial saliency map** $S(x, y_{true})$ - to select pixels that should be perturbed to obtain desired changes in logits

$$S(x_j, y_{true})[i] = \begin{cases} 0 & \text{if } \frac{\partial f_{y_{true}}(x)}{\partial x_j} \leq 0 \text{ or } \sum_{i \neq y_{true}} \frac{\partial f_i(x)}{\partial x_j} > 0 \\ \frac{\partial f_{y_{true}}(x)}{\partial x_j} \left| \sum_{i \neq y_{true}} \frac{\partial f_i(x)}{\partial x_j} \right| & \text{otherwise} \end{cases}$$

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- Finally, perturb element with highest value of $S(x, y_{true})[i]$ to increase/decrease logit outputs of target/other class significantly

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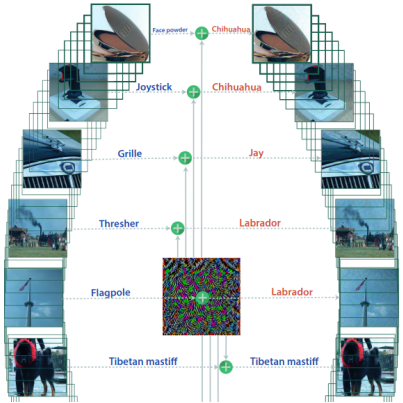
White-box Adversarial Attacks[8]



Universal Adversarial Attack

- One perturbation for all examples

[8] Moosavi-Dezfooli et al, Universal Adversarial Perturbations, CVPR 2017

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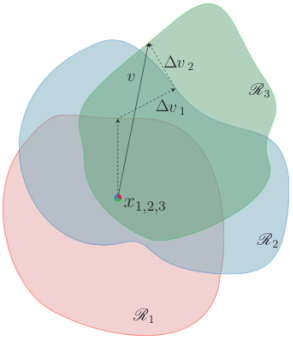

Universal Adversarial Attack

- One perturbation for all examples
- For each x_i, compute minimal perturbation that sends $x_i + v$ to decision boundary

$$\text{Initialize } v = 0$$

$$\Delta v_i = \arg\min_r \|r\|_2 \text{ s.t } f(x_i + v + r) \neq f(x)$$

$$v = \mathcal{P}_{p,\epsilon}(v + \Delta v_i)$$

$$\mathcal{P}_{p,\epsilon}(v) = \arg\min_{v'} \|v - v'\|_2 \text{ subject to } \|v'\|_p \leq \epsilon$$

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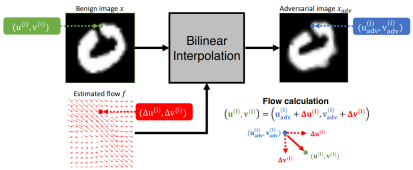
Non-L_p White-box Adversarial Attacks [9] [10]

Spatially Transformed Adversarial Attacks



$$f^* = \arg\min_f \mathcal{L}_{adv}(x, f) + \tau \mathcal{L}_{flow}(x, f)$$

$\mathcal{L}_{adv}$ encourages generated examples to be misclassified; $\mathcal{L}_{flow}$ ensures that spatial transformation distance is minimized

[9] Xiao et al, Spatially Transformed Adversarial Examples, ICLR 2018

[10] Laidlaw et al, Functional Adversarial Attacks, NeurIPS 2019

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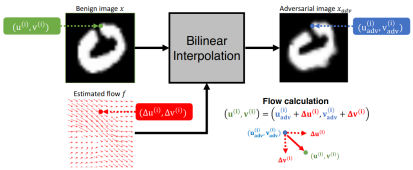

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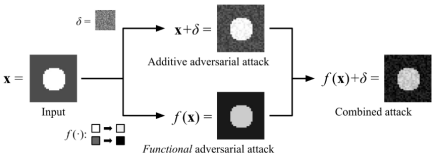
Functional Adversarial Attacks



- A single function to be used to perturb input features to produce an adversarial example
- E.g. attack applied on colors of an image can change all red pixels simultaneously to light red.

[9] Xiao et al, Spatially Transformed Adversarial Examples, ICLR 2018

[10] Laidlaw et al, Functional Adversarial Attacks, NeurIPS 2019

Black-box Adversarial Attacks: Gradient Estimation-based [11]

Zeroth-Order Optimization (ZOO)

- Need to estimate gradients of target DNN in order to produce an adversarial image
- But now, target model can only be queried to obtain probability scores of all classes; how?

$$\mathcal{L}(x, y) = \max\{\max_{i \neq y_{true}} \log\left[f_i(x)\right] - \log\left[f_{y_{true}}(x)\right] - k\}$$

[11] Chen et al, ZOO: Zeroth Order Optimization Based Black-Box Attacks to Deep Neural Networks without Training Substitute Models, AISecW 2017, Cheng et al, Query-efficient Hard-label Black-box Attack: An Optimization-based Approach, 2018

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- To estimate gradient:

$$\frac{\partial f(x)}{\partial x} \approx \frac{f(x + he_i) - f(x - he_i)}{2h}$$

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Opt-Attack

- Target model can only be queried to obtain true label (hard-label setting); now, how?

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- A coarse-grained search to initially find a decision boundary and then finetune the solution using Binary Search

[11] Chen et al, ZOO: Zeroth Order Optimization Based Black-Box Attacks to Deep Neural Networks without Training Substitute Models, AISecW 2017, Cheng et al, Query-efficient Hard-label Black-box Attack: An Optimization-based Approach, 2018

Black-box Adversarial Attacks: Gradient-Free[12]

Greedy Local-Search

- Create a neighborhood consisting of all images that are different from previous round's image by one pixel only

[12] Nina Narodytska et al, Simple Black-box Adversarial Perturbations for Deep Networks, 2016

Black-box Adversarial Attacks: Gradient-Free[12]

Greedy Local-Search

- Create a neighborhood consisting of all images that are different from previous round's image by one pixel only
- Initially, a pixel location is randomly selected, and perturbation is added to it

[12] Nina Narodytska et al, Simple Black-box Adversarial Perturbations for Deep Networks, 2016

Black-box Adversarial Attacks: Gradient-Free[12]

Greedy Local-Search

- Create a neighborhood consisting of all images that are different from previous round's image by one pixel only
- Initially, a pixel location is randomly selected, and perturbation is added to it
- Calculate importance of pixel by observe change in classification accuracy after adding noise

[12] Nina Narodytska et al, Simple Black-box Adversarial Perturbations for Deep Networks, 2016

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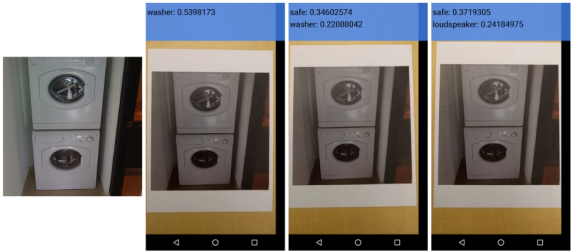
- The next pixel location is chosen among pixels lying within a square whose side length is $2p$
- Use these importance to approximate the loss function's gradient

[12] Nina Narodytska et al, Simple Black-box Adversarial Perturbations for Deep Networks, 2016

Need for Adversarial Defenses: Adversarial Examples in Physical World [13]

- Poses a serious security threat to services using modern day Deep Learning models
- E.g. TensorFlow Camera Demo app to classify clean and adversarial generated images
- A clean image (b) recognized correctly as a "washer" when perceived through camera, while adversarial images (c) and (d) are misclassified



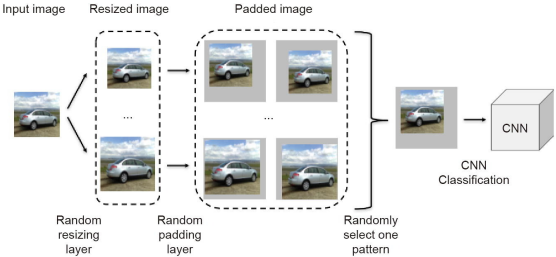
(a) Image from dataset (b) Clean image (c) Adv. image, $\epsilon = 4$ (d) Adv. image, $\epsilon = 8$

[13] Alexey Kurakin et al, Adversarial Examples in the Physical World, ICLRW 2017

Adversarial Defenses: Randomization [14] [15]

Random Input Transformation

- Two random transformations—random resizing and padding—to mitigate adversarial effects at inference time



[14] Xie et al, Mitigating Adversarial Effects through Randomization, 2017

[15] Liu et al, Towards Robust Neural Networks via Random Self-Ensemble, ECCV 2018

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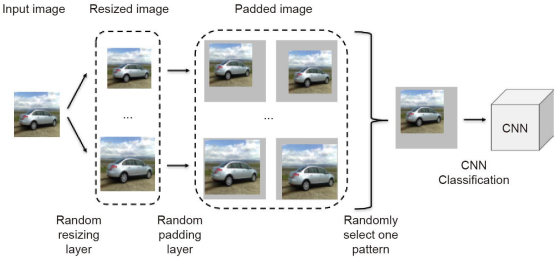
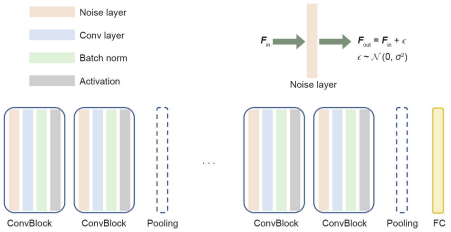


Random Noising

- Adds a noise layer before each convolution layer in both training and testing phases
- Ensembles prediction results over random noises to stabilize DNN's outputs

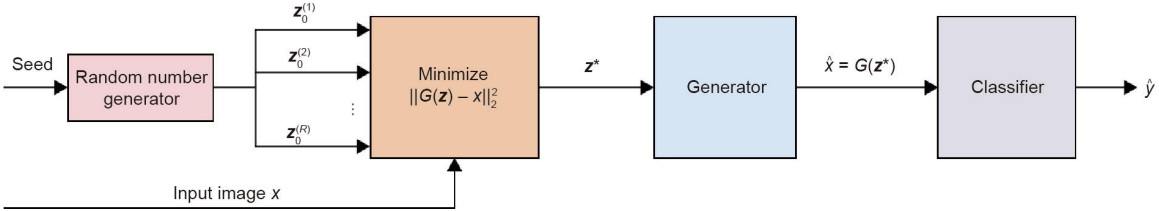


[14] Xie et al, Mitigating Adversarial Effects through Randomization, 2017

[15] Liu et al, Towards Robust Neural Networks via Random Self-Ensemble, ECCV 2018

Adversarial Defenses: Input Cleansing/Reconstruction [16]

Defense-GAN



- Trains a generator to model distribution of benign images

[16] Samangouei et al, Defense-GAN: Protecting Classifiers AgainstAdversarial Attacks Using Generative Models, ICLR 2018

Adversarial Defenses: Input Cleansing/Reconstruction [16]

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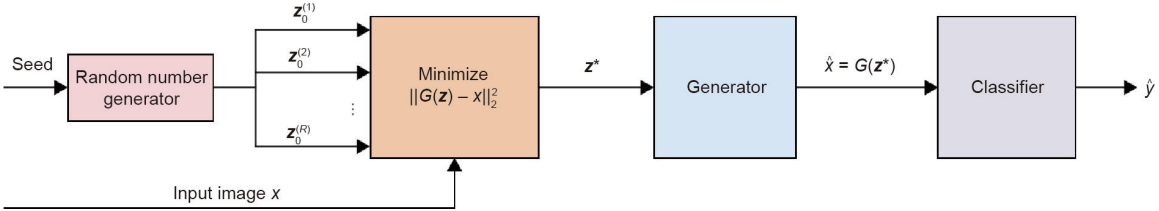

- Trains a generator to model distribution of benign images
- In the testing stage, cleanses an adversarial input by searching for a close image, and feeds this benign image into the classifier

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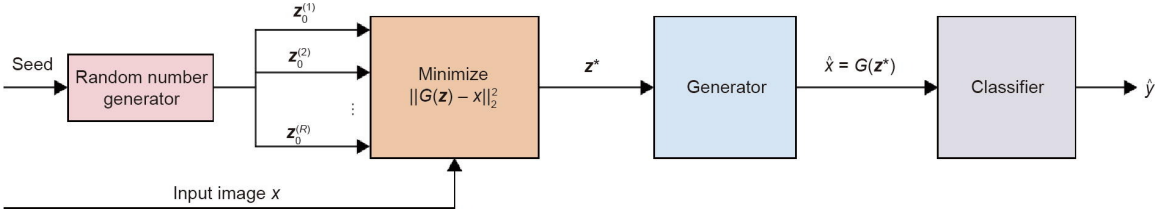
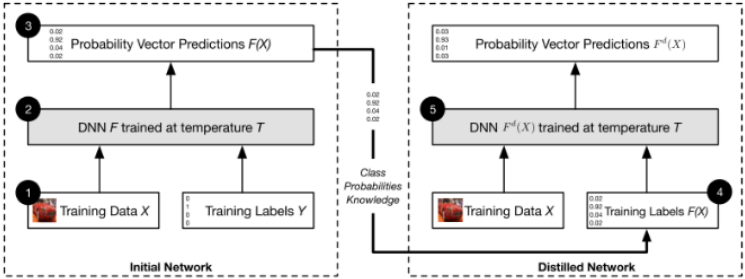


- Trains a generator to model distribution of benign images
- In the testing stage, cleanses an adversarial input by searching for a close image, and feeds this benign image into the classifier
- Other similar methods: PixelDefend, MagNet, APE-GAN, etc

[16] Samangouei et al, Defense-GAN: Protecting Classifiers AgainstAdversarial Attacks Using Generative Models, ICLR 2018

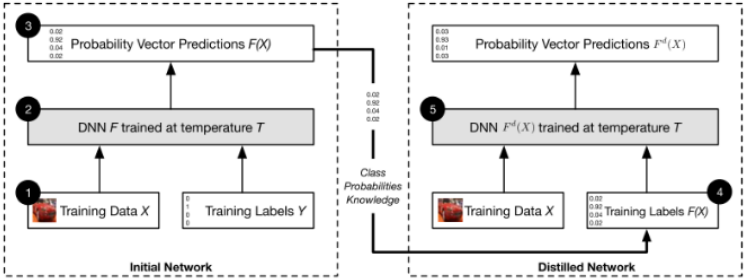
Adversarial Defenses: Network Distillation [17]



- Probability of classes produced by first DNN used as inputs to train second DNN

[17] Papernot et al, Distillation as a Defense to Adversarial Perturbations against Deep Neural Networks, arXiv 2016

Adversarial Defenses: Network Distillation [17]



- Probability of classes produced by first DNN used as inputs to train second DNN
- Using high-temperature softmax reduces model sensitivity to small perturbations

[17] Papernot et al, Distillation as a Defense to Adversarial Perturbations against Deep Neural Networks, arXiv 2016

Adversarial Defenses: Adversarial Training [18]

PGD/FGSM Adversarial Training

- Simply add PGD/FGSM attack inside your training loop
- "Ultimate data augmentation"
- Create specific perturbations that best fool our model and classify them correctly
- Most popular and widely opted; current SOTA

Regular Training

$$\min_{\theta} \mathcal{L}(x, y; \theta)$$

Adversarial Training

$$\min_{\theta} \max_{\delta \in \Delta} \mathcal{L}(x + \delta, y; \theta)$$

[18] Goodfellow et al, Explaining and Harnessing Adversarial Examples, ICLR 2015, Madry et al, Towards Deep Learning Models Resistant To Adversarial Attack, 2017

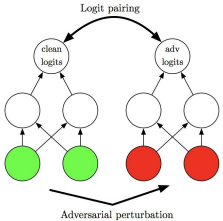
Adversarial Defenses: Adversarial Training [19], [20]

Adversarial Logit Pairing

- Encourages similarity between logits of clean x and adversarial x_{adv} examples

$$\mathcal{L}_{alp} = \mathcal{L}_{ce} + \frac{\lambda}{N} \cdot \sum_{i=1}^{N} D(f(x^i), f(x^i_{adv}))$$

D encourages logits to be similar; e.g. L_2 loss



[19] Kannan et al, Adversarial Logit Pairing, 2018

[20] Zhang et al, Theoretically Principled Trade-off between Robustness and Accuracy", ICML 2019

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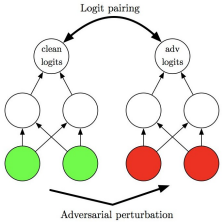


TRADES

- Decompose prediction error for adversarial examples as sum of natural error and boundary error

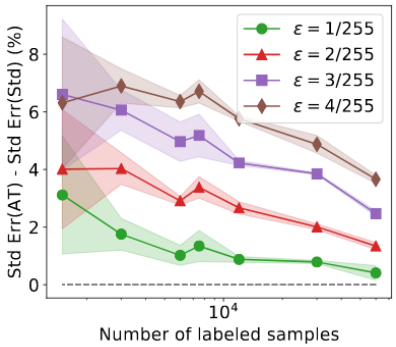
$$\min_f \mathbf{E} \left\{ \mathcal{L}(f(x), y_{true}) + \max_{\delta \in \Delta} \frac{\mathcal{L}(f(x), f(x+\delta))}{\lambda} \right\}$$

- While ALP uses PGD adversarial examples, TRADES computes x_{adv} as $\max_{\delta \in \Delta} \mathcal{L}(f(x), f(x+\delta)$
- ALP enforces L_2 loss while TRADES uses classification-calibrated loss

[19] Kannan et al, Adversarial Logit Pairing, 2018

[20] Zhang et al, Theoretically Principled Trade-off between Robustness and Accuracy", ICML 2019

Tradeoff between Robust and Clean Accuracy[21]

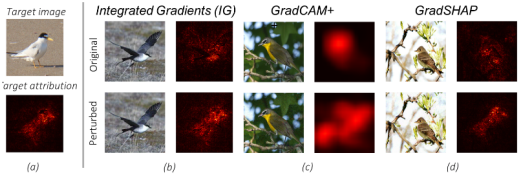


- Adversarial robustness comes at a cost of decreased clean/standard accuracy
- Gap decreases with increase in training set size; tradeoff should disappear with infinite data
- Recent methods like IAT, AVMixup reduce this tradeoff by increasing train set size

[21] Tsipras et al, Robustness May Be at Odds with Accuracy, ICLR 2019, Lamb et al, Interpolated Adversarial Training: Achieving Robust Neural Networks Without Sacrificing Too Much Accuracy, AISec 2019, Lee et al, Adversarial Vertex Mixup: Toward Better Adversarially Robust Generalization, CVPR 2020

Other Notions of Robustness[22]

- **Attributional Robustness:** Robustness of attributions (explanations/ saliency maps)



- **Unseen Natural Corruptions:** Robustness to common occurring distribution shifts like fog, blur, snow, etc.

[22] Hendrycks et al, Benchmarking Neural Network Robustness to Common Corruptions and Perturbations, 2019, Singh et al, Attributional Robustness Training using Input-Gradient Spatial Alignment, ECCV 2020

Homework

Readings

- Adversarial Machine Learning Tutorials: Tutorial 1, Tutorial 2 and Tutorial 3
- Opportunities and Challenges in Deep Learning Adversarial Robustness: A Survey
- Adversarial Machine Learning Reading List from beginner to advanced.
- PyTorch and TensorFlow Libraries/Implementations: MadryLab, Cleverhans and Advertorch

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Pouya Samangouei, Maya Kabkab, and Rama Chellappa. "Defense-GAN: Protecting Classifiers Against Adversarial Attacks Using Generative Models". In: *International Conference on Learning Representations*. 2018.

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