CS182/282A: Designing, Visualizing and Understanding Deep Neural Networks

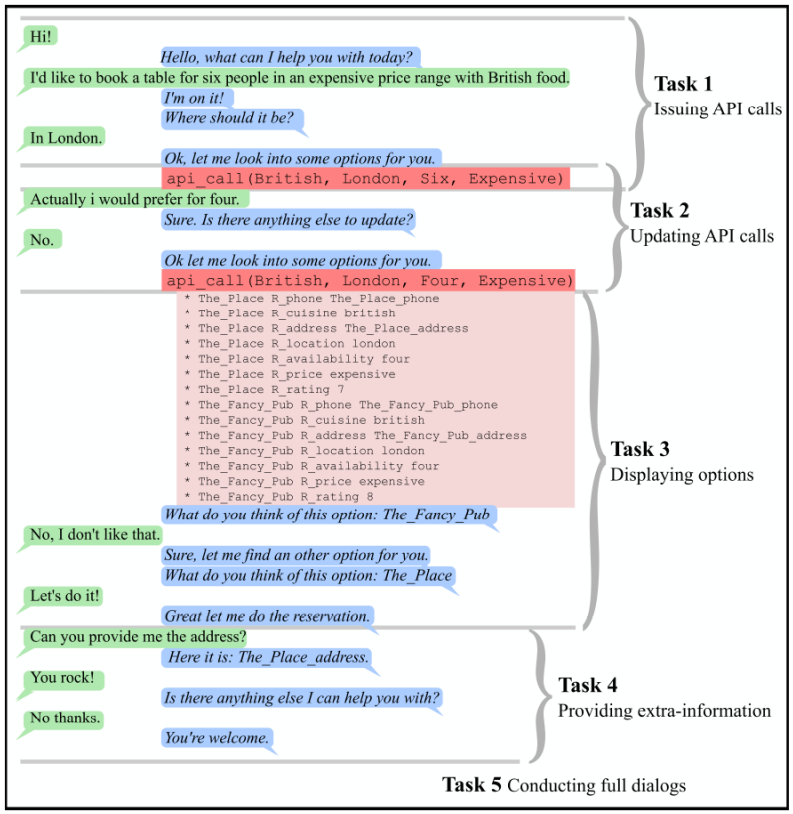
John Canny

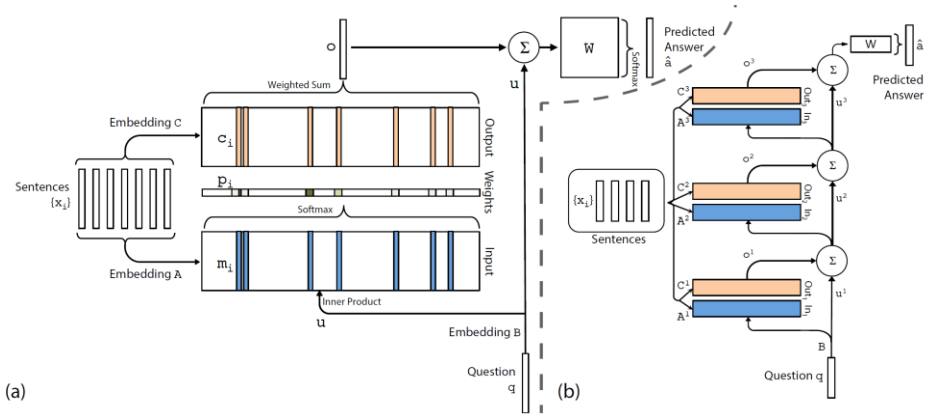
Spring 2019

Lecture 16: Adversarial Networks

Slides from Bo Li and Dawn Song

Last Time: Goal-directed dialog





Last Time: GPT and BERT

GPT and BERT are transformer-based language models trained on a large dataset of natural language and then fine-tuned for particular tasks.

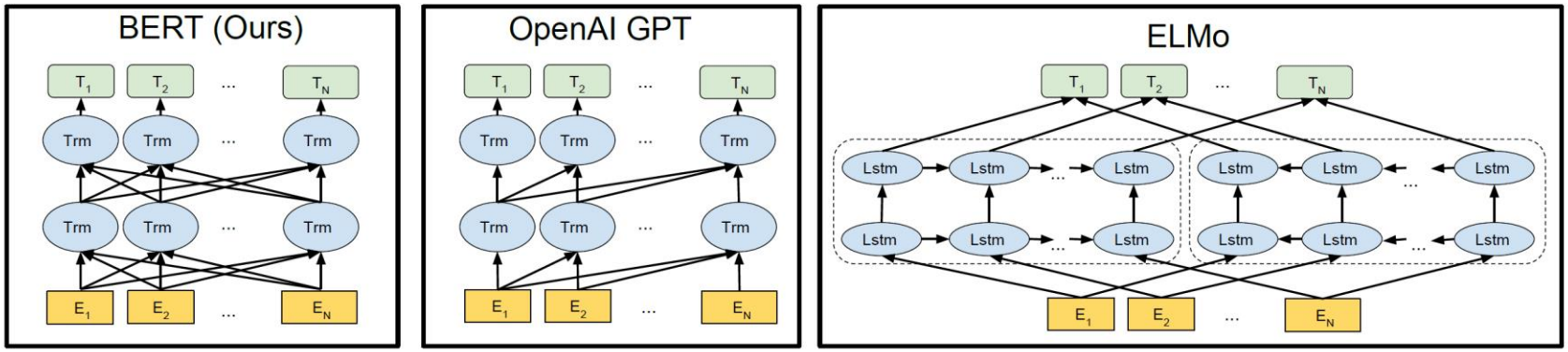
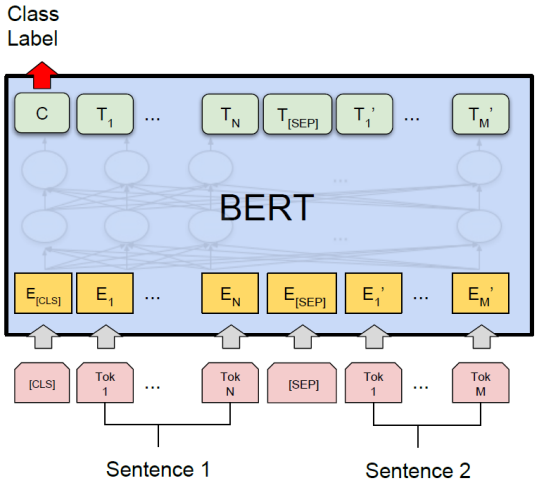


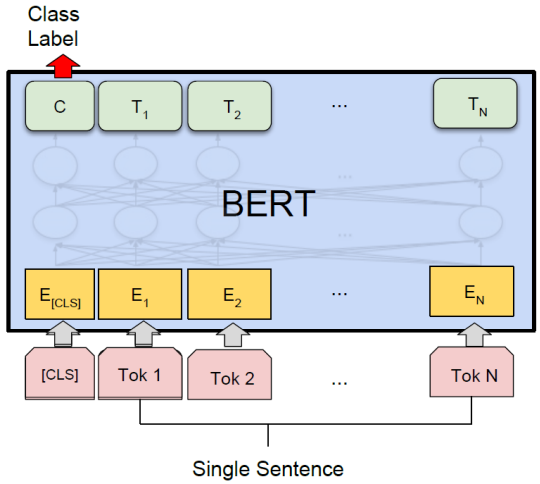
Figure 1: Differences in pre-training model architectures. BERT uses a bidirectional Transformer. OpenAI GPT uses a left-to-right Transformer. ELMo uses the concatenation of independently trained left-to-right and right-to-left LSTM to generate features for downstream tasks. Among three, only BERT representations are jointly conditioned on both left and right context in all layers.

They have improved the state-of-the-art for many NLP tasks.

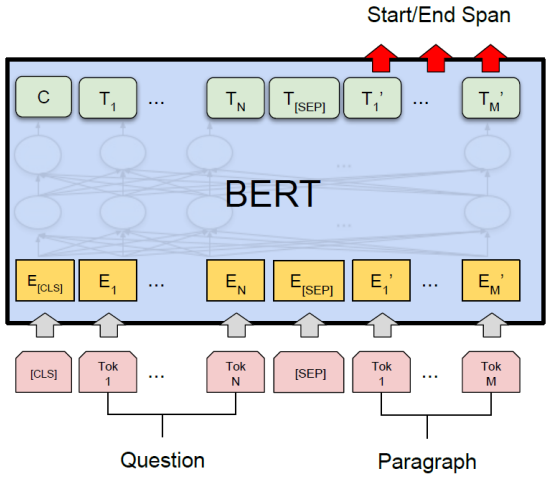
BERT Task specialization



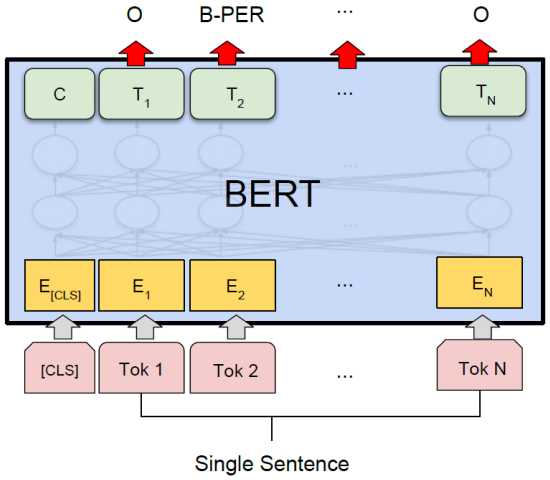
(a) Sentence Pair Classification Tasks:
MNLI, QQP, QNLI, STS-B, MRPC,
RTE, SWAG



(b) Single Sentence Classification Tasks:
SST-2, CoLA



(c) Question Answering Tasks:
SQuAD v1.1



(d) Single Sentence Tagging Tasks:
CoNLL-2003 NER

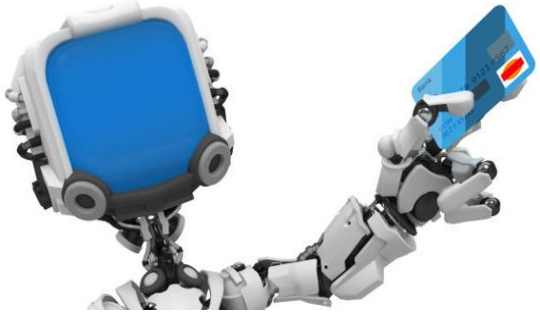
Machine Learning in Physical World

Autonomous Driving

Healthcare

Smart City

Malware Classification



Fraud Detection

Biometrics Recognition

Security & Privacy Problems

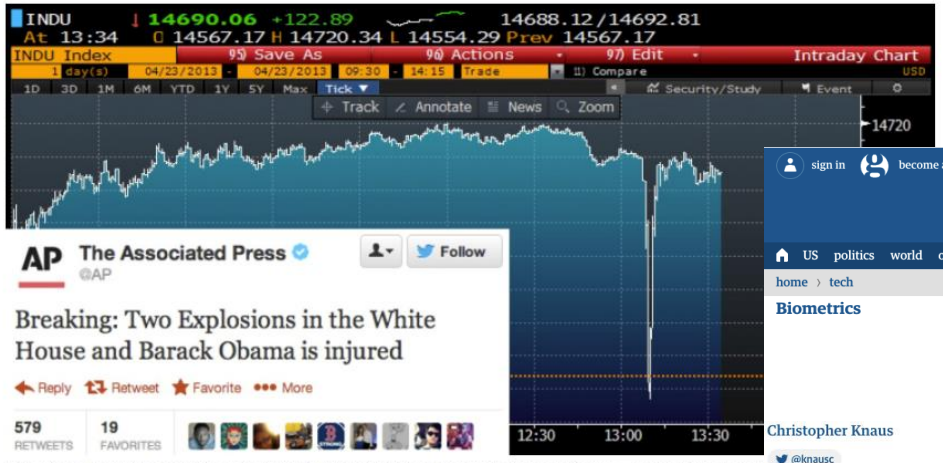
Sections

The Washington Post

WorldViews

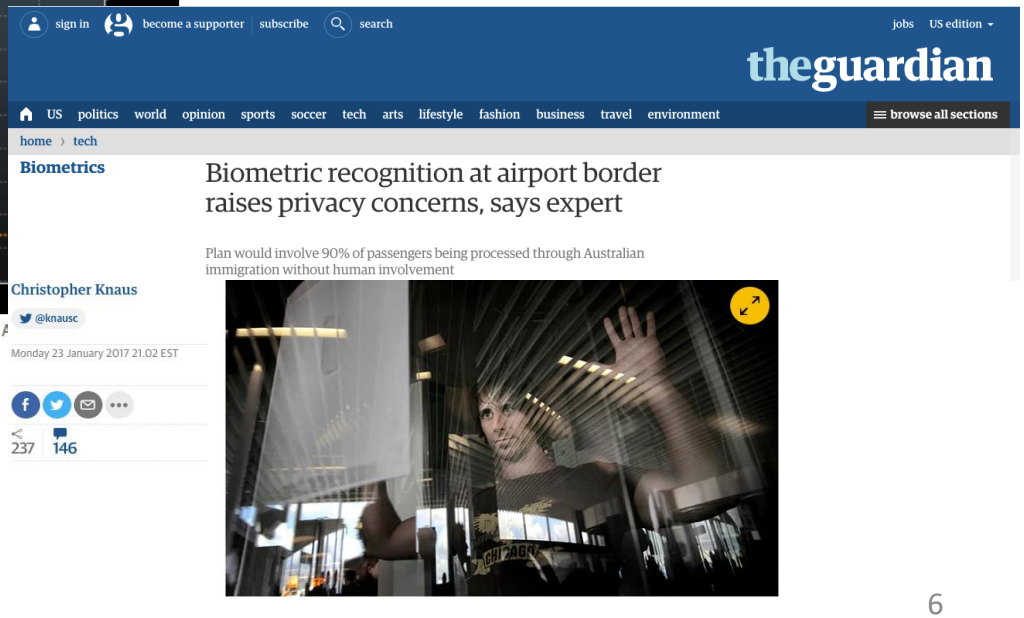
Syrian hackers claim AP hack that tipped stock market by $136 billion. Is it terrorism?

By Max Fisher April 23, 2013



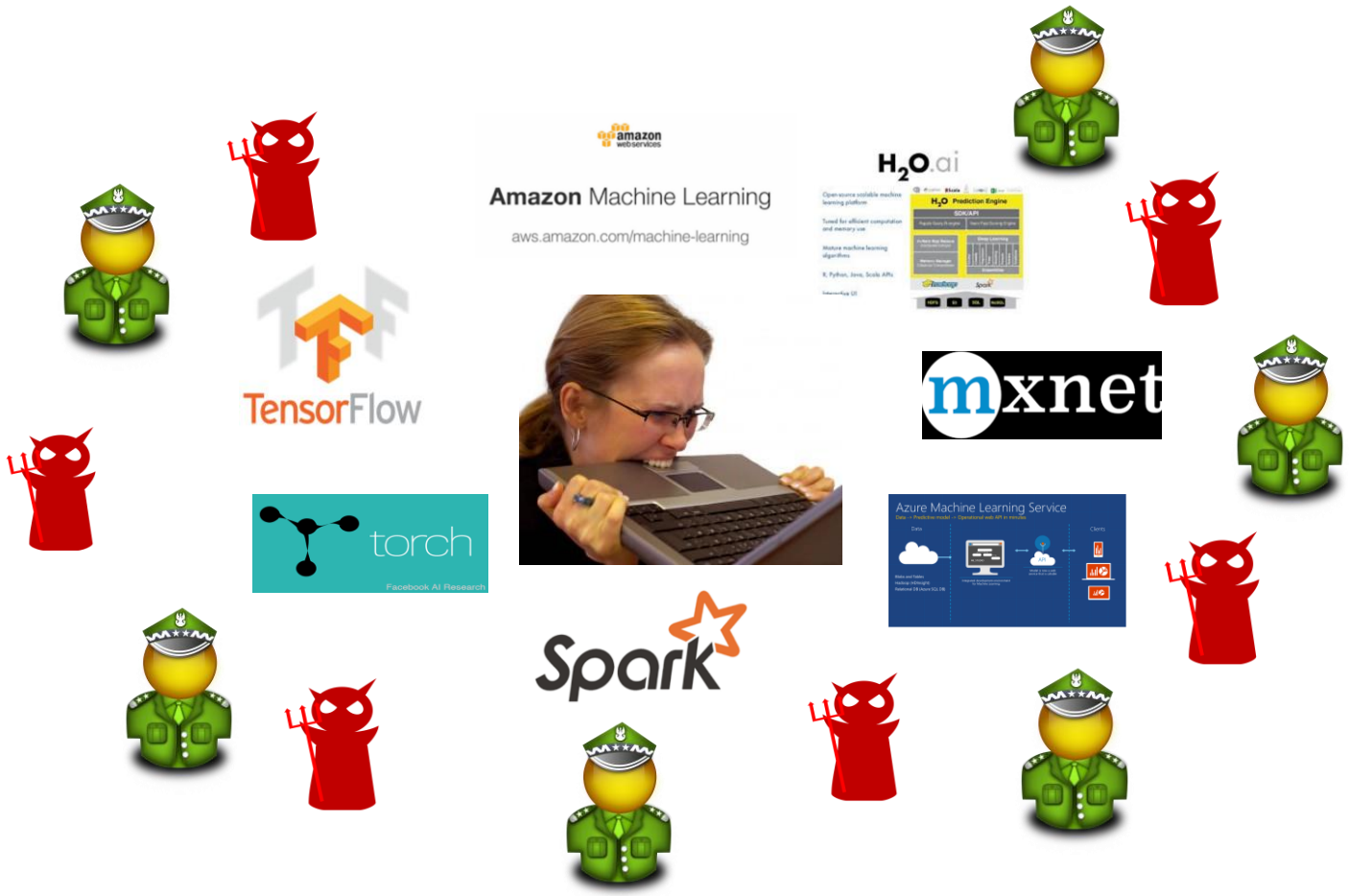
This chart shows the Dow Jones Industrial Average during Tuesday afternoon's drop, caused by a fake A

Security Problems



Privacy Concerns

We Are in Adversarial Environments

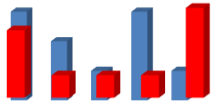


While cybersecurity R&D needs are addressed in greater detail in the NITRD Cybersecurity R&D Strategic Plan, some cybersecurity risks are specific to AI systems. ***One key research area is "adversarial machine learning"****, that explores the degree to which AI systems can be compromised by "contaminating" training data, by modifying algorithms, or by making subtle changes to an object that prevent it from being correctly identified….*

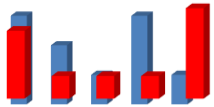
- National Science and Technology Council
2016

Perils of Stationary Assumption

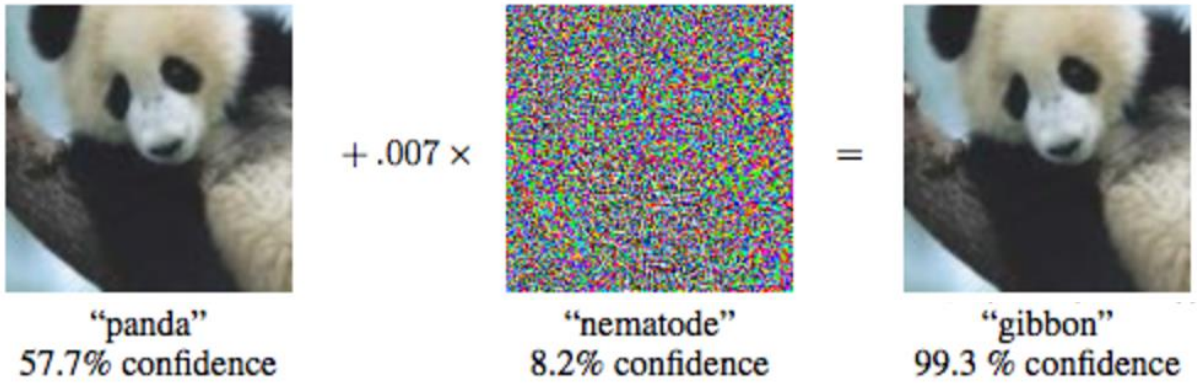
Traditional machine learning approaches assume

Training Data 

≈

Testing Data 

Adversarial Examples



$$\boldsymbol{\eta} = \epsilon \text{sign}(\nabla_x J(\boldsymbol{\theta}, \mathbf{x}, \mathbf{y}))$$

FGSM attack

Goodfellow, Ian J., Jonathon Shlens, and Christian Szegedy. "Explaining and harnessing adversarial examples." *ICLR 2015.*

Li, Bo, Yevgeniy Vorobeychik, and Xinyun Chen. "A General Retraining Framework for Scalable Adversarial Classification." ICLR. (2016).

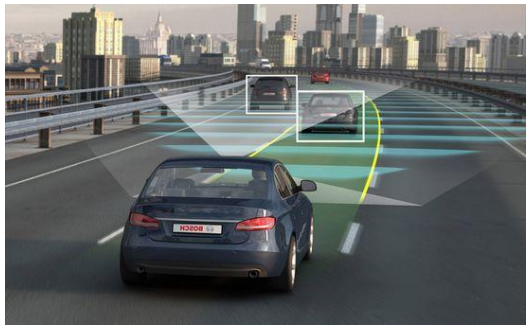
Optimization Based Attack

$$\begin{aligned} \text{minimize} \quad & \mathcal{D}(x, x+\delta) \\ \text{such that} \quad & C(x+\delta) = t \\ & x+\delta \in [0,1]^n \end{aligned} \qquad \begin{aligned} \text{minimize} \quad & \mathcal{D}(x, x+\delta) + c \cdot f(x+\delta) \\ \text{such that} \quad & x+\delta \in [0,1]^n \end{aligned}$$

	Best Case				Average Case				Worst Case			
	MNIST		CIFAR		MNIST		CIFAR		MNIST		CIFAR	
	mean	prob	mean	prob	mean	prob	mean	prob	mean	prob	mean	prob
Our L_0	8.5	100%	5.9	100%	16	100%	13	100%	33	100%	24	100%
JSMA-Z	20	100%	20	100%	56	100%	58	100%	180	98%	150	100%
JSMA-F	17	100%	25	100%	45	100%	110	100%	100	100%	240	100%
Our L_2	1.36	100%	0.17	100%	1.76	100%	0.33	100%	2.60	100%	0.51	100%
Deepfool	2.11	100%	0.85	100%	–	-	–	-	–	-	–	-
Our L_∞	0.13	100%	0.0092	100%	0.16	100%	0.013	100%	0.23	100%	0.019	100%
Fast Gradient Sign	0.22	100%	0.015	99%	0.26	42%	0.029	51%	–	0%	0.34	1%
Iterative Gradient Sign	0.14	100%	0.0078	100%	0.19	100%	0.014	100%	0.26	100%	0.023	100%

[Carlini, Wagner, Towards robustness of neural networks. 2017]

Autonomous Driving is the Trend…



However, What We Can See Everyday…

The Physical World Is… Messy

Varying Physical Conditions (Angle, Distance, Lighting, …)

Physical Limits on Imperceptibility

Fabrication/Perception Error (Color Reproduction, etc.)

Digital Noise (What you want) | What is printed | What a camera may see

Background Modifications*

Image Courtesy, OpenAI

[Evtimov, Eykholt, Fernandes, Kohno, Li, Prakash, Rahmati, and Song, *2017*]

An Optimization Approach To Creating Robust Physical Adversarial Examples

$$\underset{\delta}{\operatorname{argmin}}\ \lambda||\delta||_p + J(f_\theta(x+\delta), y^*)$$

Perturbation/Noise Matrix

Lp norm (L-0, L-1, L-2, …)

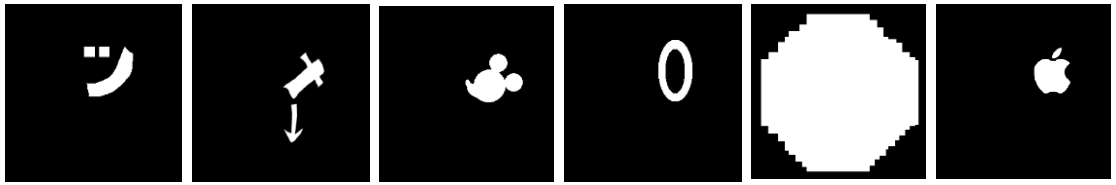
Loss Function

Adversarial Target Label

$$\underset{\delta}{\operatorname{argmin}}\ \lambda||\delta||_p + \frac{1}{k}\sum_{i=1}^{k} J(f_\theta(x_i+\delta), y^*)$$

Optimizing Spatial Constraints (Handling Limits on Imperceptibility)

$$\underset{\delta}{\operatorname{argmin}}\ \lambda||M_x \cdot \delta||_p + \frac{1}{k}\sum_{i=1}^{k} J(f_\theta(x_i + M_x \cdot \delta), y^*)$$



Subtle Poster

Camouflage Sticker

Mimic vandalism

"Hide in the human psyche"

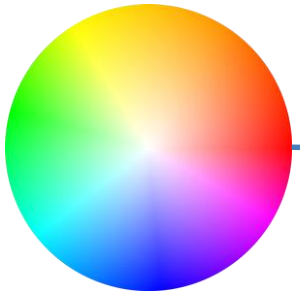
Handling Fabrication/Perception Errors

$$\underset{\delta}{\operatorname{argmin}}\ \lambda||M_x \cdot \delta||_p + \frac{1}{k}\sum_{i=1}^{k} J(f_\theta(x_i + M_x \cdot \delta), y^*) + NPS(M_x \cdot \delta)$$

$$NPS(\delta) = \sum_{\hat{p} \in \delta} \prod_{p' \in P} |\hat{p} - p'|$$

P is a set of printable RGB triplets

Color Space

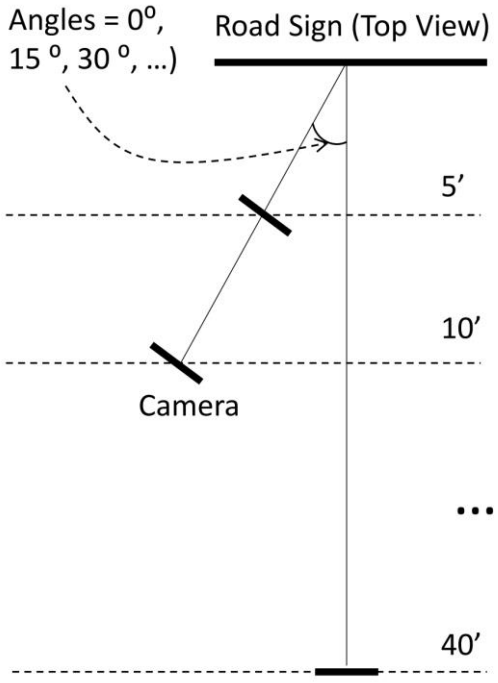


Sampled Set of RGB Triplets

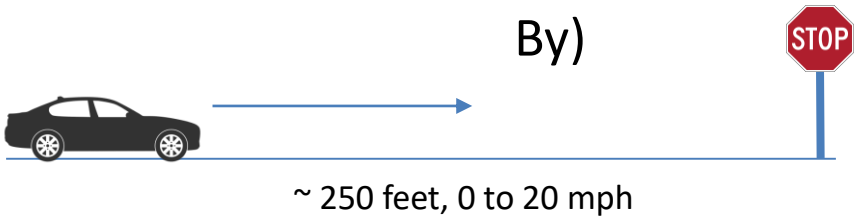
NPS based on Sharif et al., “Accessorize to a crime,” CCS 2016

How Can We Realistically Evaluate Attacks?

Lab Test (Stationary)



Field Test (Drive-By)



Record video

Sample frames every k frames

Run sampled frames through DNN

Subtle Poster

Lab Test Summary (Stationary)

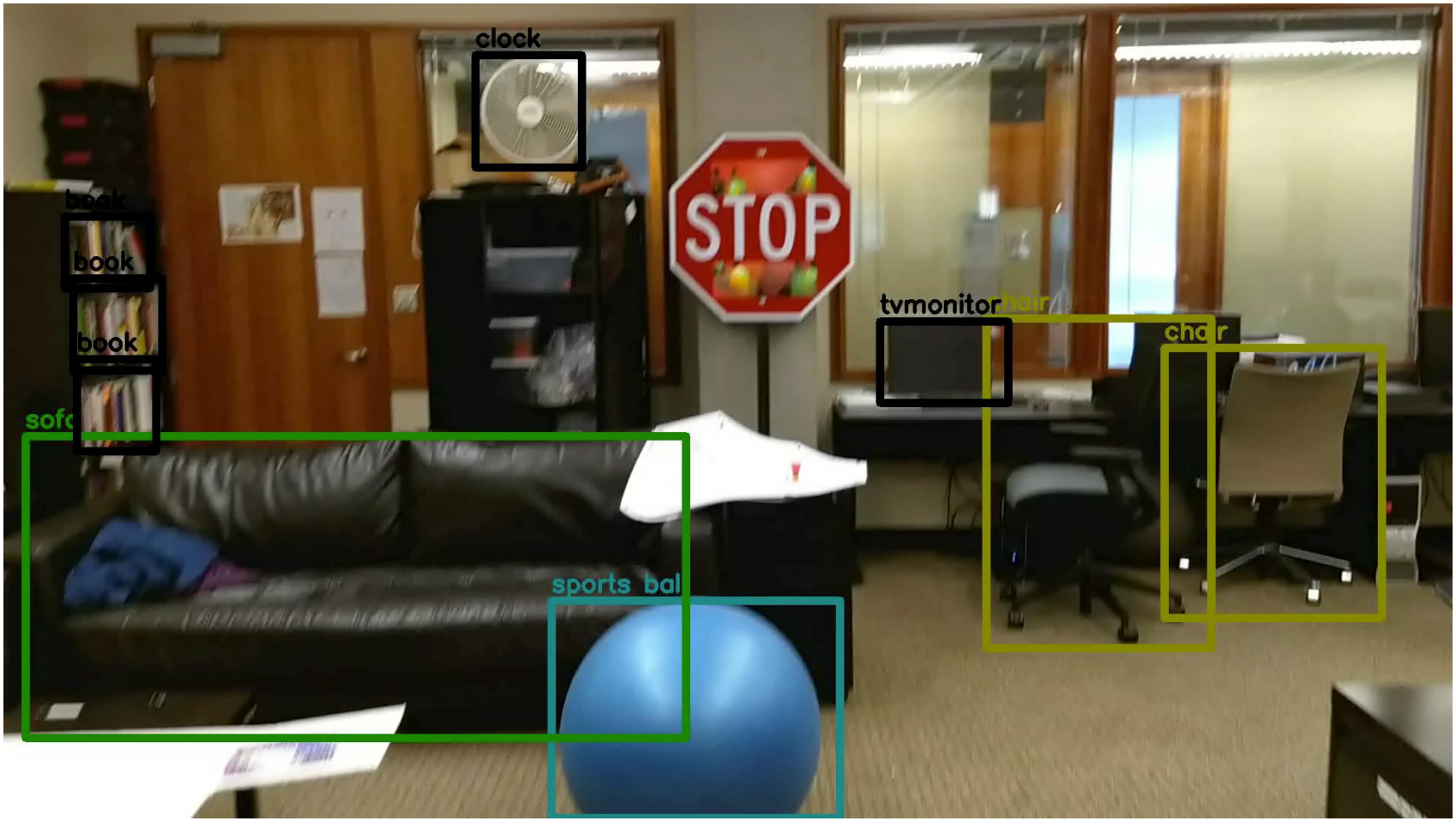
Target Class: Speed Limit 45

GTSRB*-CNN

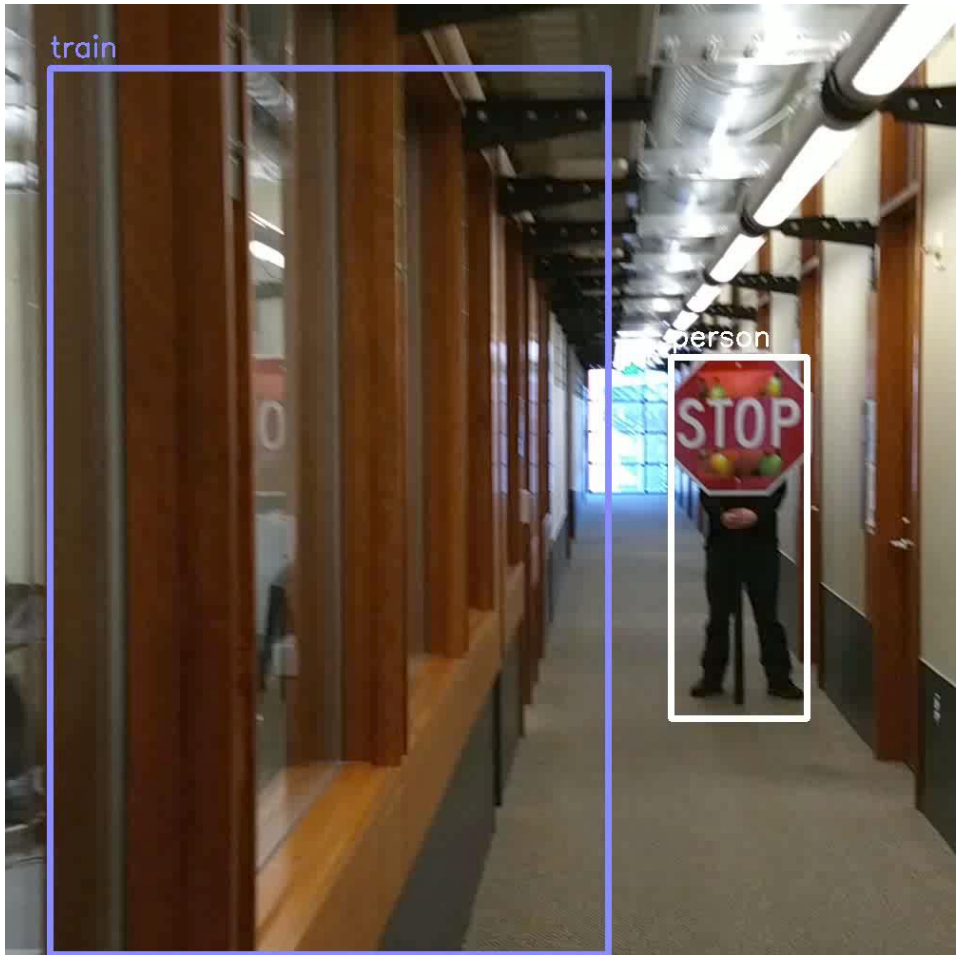
Art Perturbation

Subtle Perturbation

Physical Attacks Against Detectors



Physical Attacks Against Detectors



Adversarial Examples in Physical World

Adversarial perturbations are possible in physical world under different conditions and viewpoints, including the distances and angles.

Different approaches to optimize the objective

- Fast approaches
  - Fast gradient sign ($d = ||\cdot||_\infty$): $x^* = x + B\text{sgn}\left(\nabla_x \ell(f_\theta(x), y)\right)$
  - Fast gradient ($d = ||\cdot||_2$): $x^* = x + B\left(\frac{\nabla_x \ell(f_\theta(x), y)}{||\nabla_x \ell(f_\theta(x), y)||_2}\right)$
- Iterative approaches
  - E.g., use a SGD optimizer, such as Adam, to optimize

$$\min_{x^*} \ell(f_\theta(x^*), y^*) + \lambda d(x, x^*)$$

- Optimization

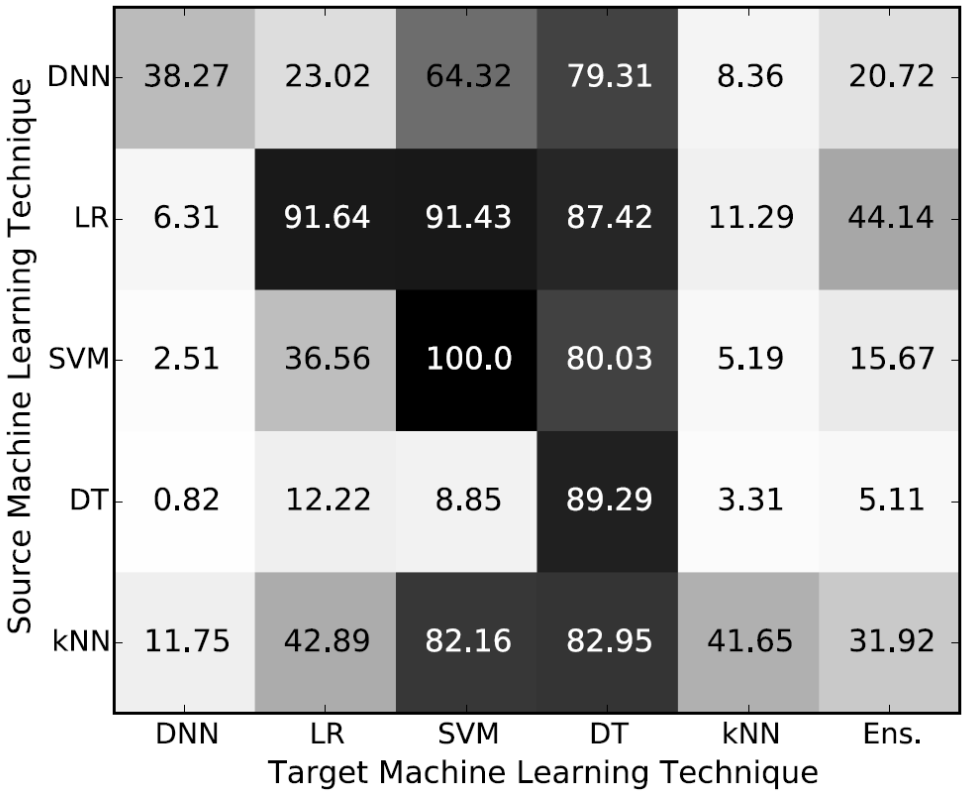
$$\underset{\delta}{\text{argmin}}\ \lambda||\delta||_p + J(f_\theta(x+\delta), y^*)$$

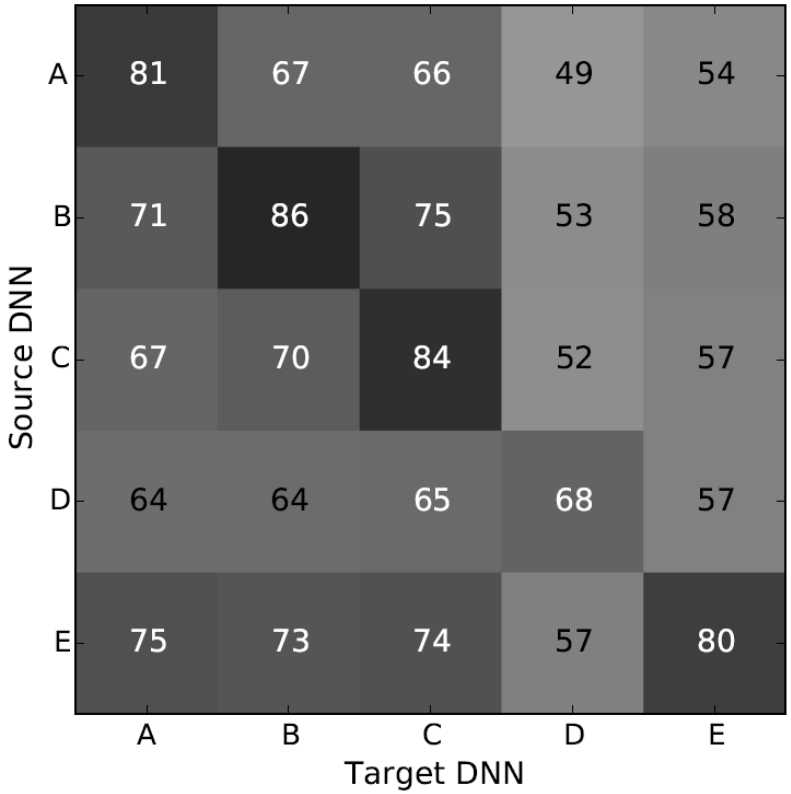
- **Need to know model f_θ**

A General Framework for Black-box attacks

- Zero-Query Attack
  - Random perturbation
  - Difference of means
  - *Transferability-based attack*
    - Practical Black-Box Attacks against Machine Learning
    - Ensemble transferability-based attack
- Query Based Attack
  - Finite difference gradient estimation
  - Query reduced gradient estimation
  - Results: similar effectiveness to whitebox attack
  - A general active query game model

Transferability





Adversarial examples are generated to fool the Source Learning method. The table shows their success at fooling the target learning method.

Papernot, McDaniel, Goodfellow, Transferability in Machine Learning: from Phenomena to Black-Box Attacks using Adversarial Samples. 2016
Xiao, Li, Malware Evasion Attacks Based on Generative Adversarial Networks (GANs), 2017.

Targeted vs Non-targeted

- Non-targeted adversarial examples
  - The goal is to mislead the classifier to predict **any labels** other than the ground truth
  - Most existing work deals with this goal

- Targeted adversarial examples
  - The goal is to mislead the classifier to predict a **target label** for an image
  - **Harder!**

Ground truth: running shoe

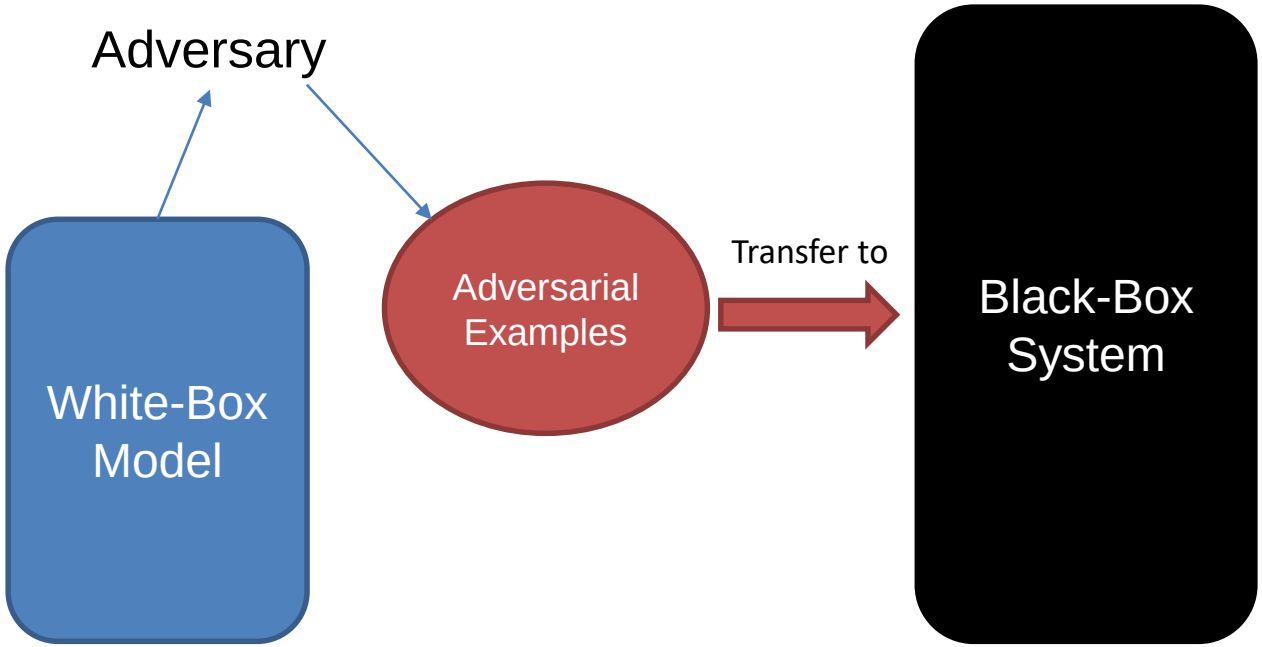
VGG16	**Military uniform**
ResNet50	Jigsaw puzzle
ResNet101	Motor scooter
ResNet152	Mask
GoogLeNet	Chainsaw

Targeted Adversarial Example's Transferability Among Two Models is Poor!

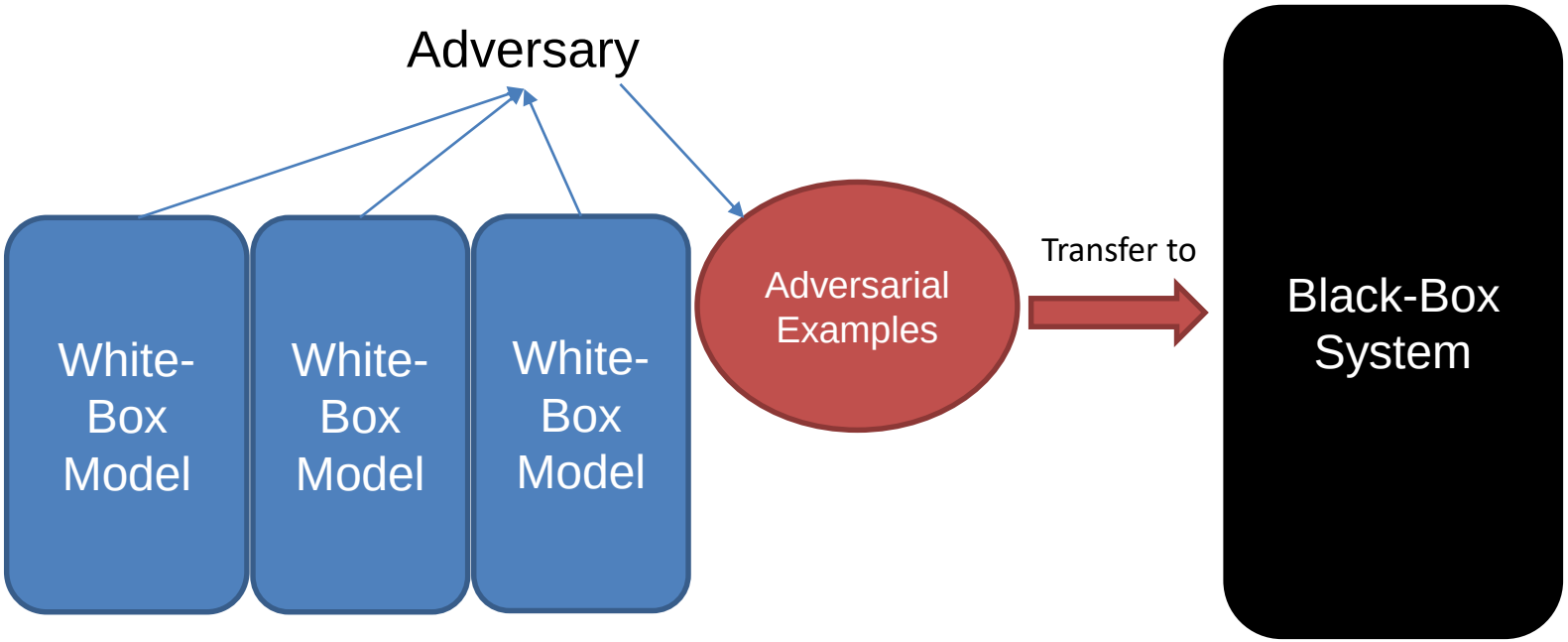
	ResNet152	ResNet101	ResNet50	VGG16	GoogLeNet	Incept-v3
ResNet152	100%	2%	1%	1%	1%	0%
ResNet101	3%	100%	3%	2%	1%	1%
ResNet50	4%	2%	100%	1%	1%	0%
VGG16	2%	1%	2%	100%	1%	0%
GoogLeNet	1%	1%	0%	1%	100%	0%
Incept-v3	0%	0%	0%	0%	0%	100%

Only 2% of the adversarial images generated for VGG16 (row) can be predicted as the targeted label by ResNet50 (column)

Black-box Attacks Based On Transferability



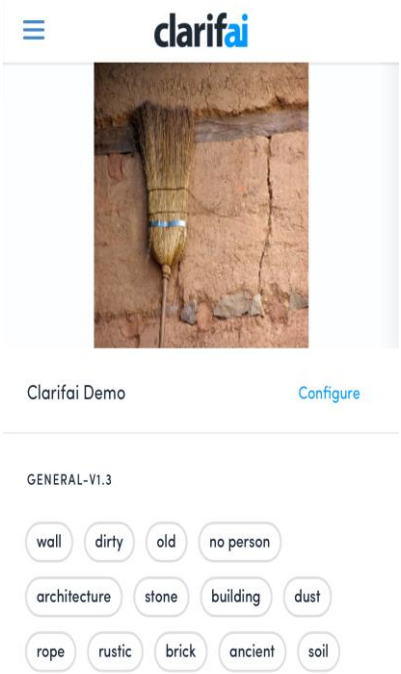
Ensemble Targeted Black-box Attacks Based On Transferability



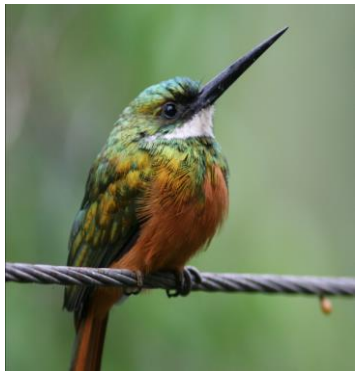
Liu, Chen, Liu, Song. Delving into Transferable Adversarial Examples and Black-box Attacks, ICLR 2017

Clarifai.com

Ground truth from ImageNet: broom

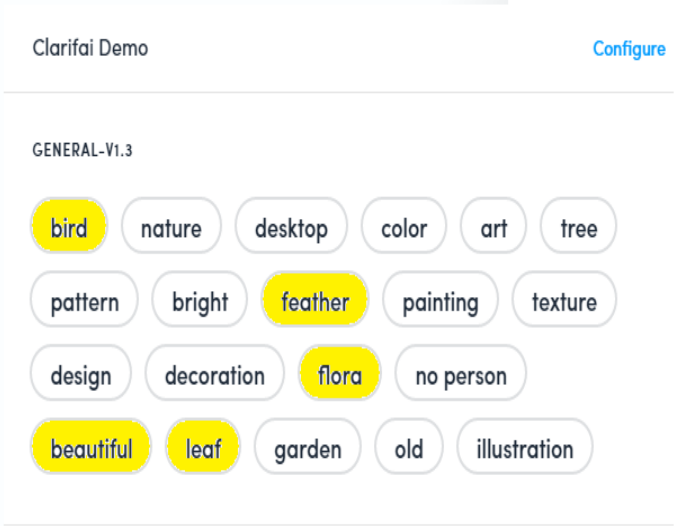


jacamar



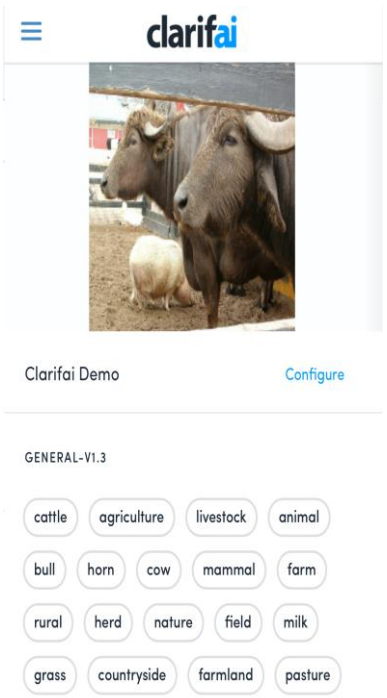
Adversarial Example on Clarifai.com

- Ground truth: broom
- Target label: **jacamar**



Clarifai.com

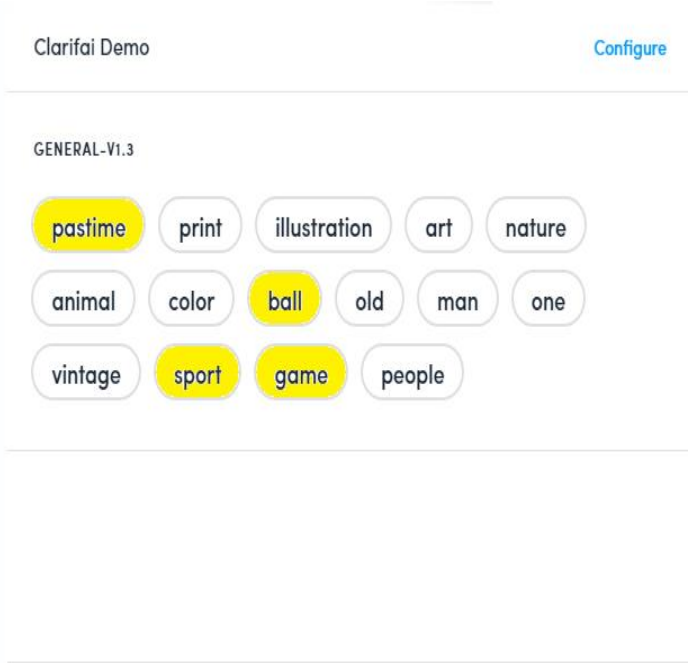
Ground truth on ImageNet: Waterbuffalo



rugby ball

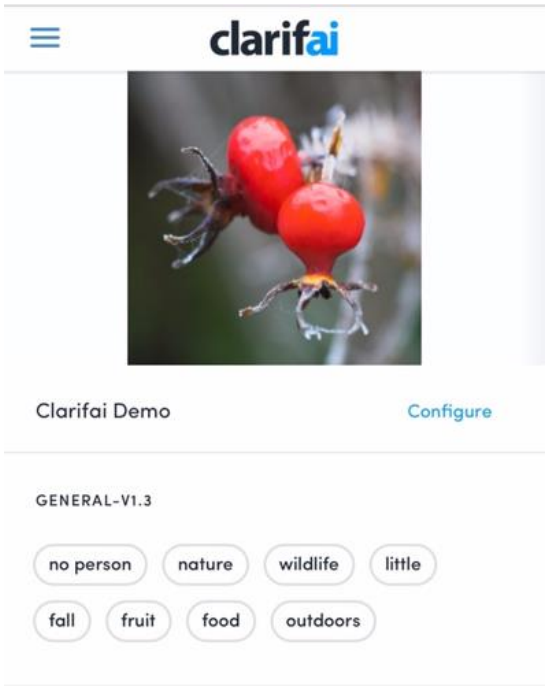
Adversarial Example on Clarifai.com

- Ground truth: water buffalo
- Target label: **rugby ball**



Clarifai.com

Ground truth from ImageNet: rosehip



stupa

LCLS17. Delving into Transferable Adversarial Examples and Black-box Attacks, ICLR 2017

Adversarial Example on Clarifai.com

- Ground truth: rosehip
- Target label: **stupa**

LCLS17. Delving into Transferable Adversarial Examples and Black-box Attacks, ICLR 2017

Black-box attacks

- Zero-Query Attack (Previous methods)
  - Random perturbation
  - Difference of means
  - Transferability based attack
- Query Based Attack (Our methods)
  - Finite difference gradient estimation
  - Query reduced gradient estimation

The zero-query attack can be viewed as a special case for the query based attack, where the number of queries made is zero

[Bhagoji, Li, He, Dawn, 2017]

Query Based attacks

- Finite difference gradient estimation
  - Given *d*-dimensional vector *x*, we can make 2*d* queries to estimate the gradient as below

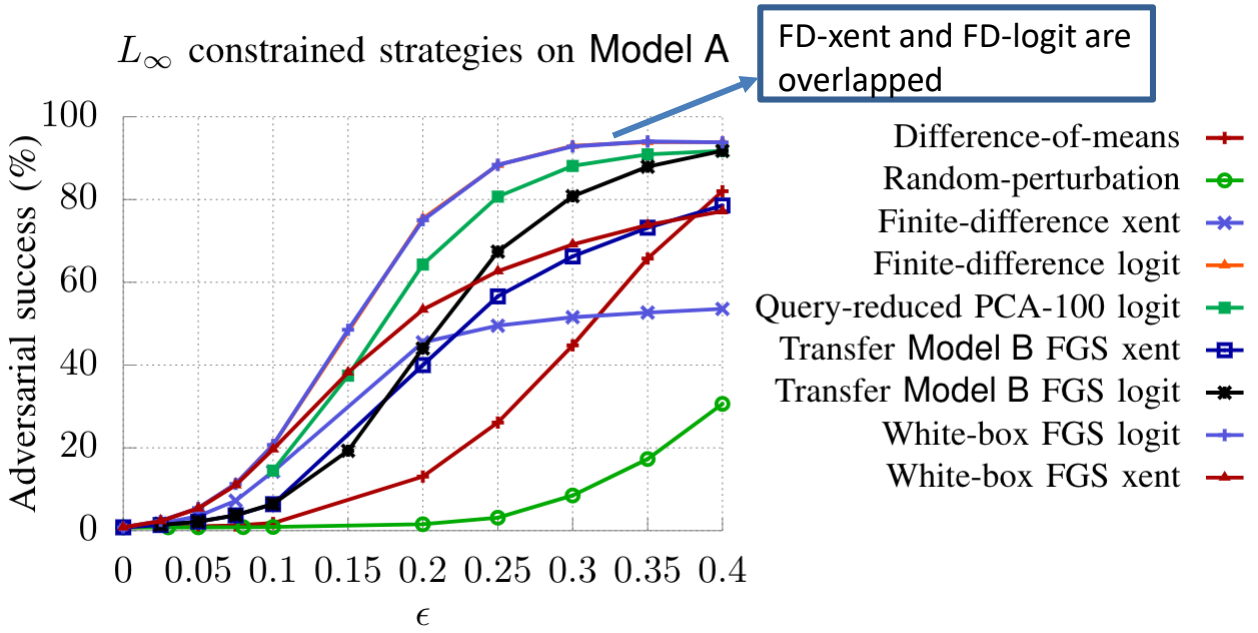
$$\mathrm{FD}_{\mathbf{x}}(g(\mathbf{x}), \delta) = \begin{bmatrix} \frac{g(\mathbf{x}+\delta\mathbf{e}_1)-g(\mathbf{x}-\delta\mathbf{e}_1)}{2\delta} \\ \vdots \\ \frac{g(\mathbf{x}+\delta\mathbf{e}_d)-g(\mathbf{x}-\delta\mathbf{e}_d)}{2\delta} \end{bmatrix}$$

  - An example of approximate FGS with finite difference

$$x_{adv} = \mathbf{x} + \epsilon \cdot \mathrm{sign}\left(\mathrm{FD}_{\mathbf{x}}(\ell_f(\mathbf{x}, y), \delta)\right)$$

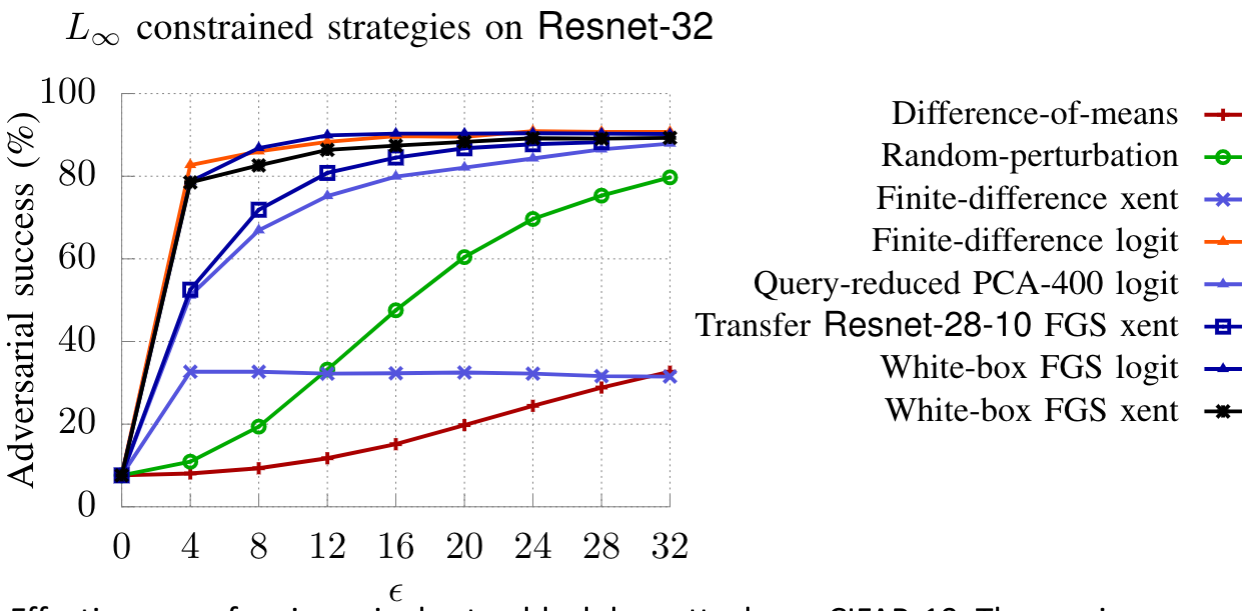
- Query reduced gradient estimation
  - Random grouping
  - PCA

Similarly, we can also approximate for logit-based loss by making 2d queries



Effectiveness of various single step black-box attacks on MNIST. The y-axis represents the variation in adversarial success as ϵ increases.

Finite Differences method outperform other black-box attacks and achieves similar attach success rate with the white-box attack

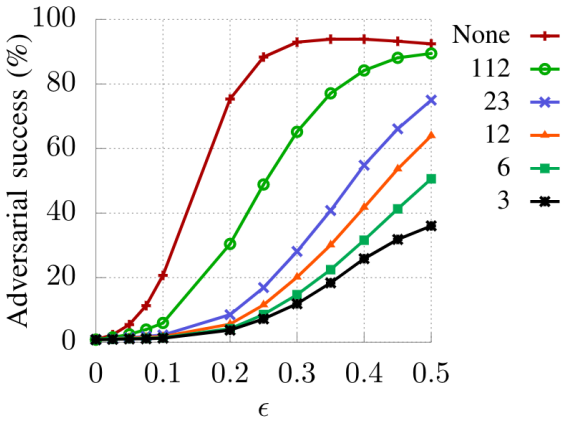


Effectiveness of various single step black-box attacks on CIFAR-10. The y-axis represents the variation in adversarial success as ϵ increases.

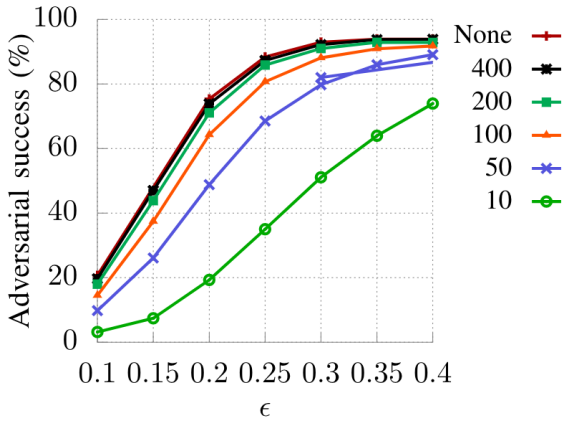
Finite Differences method outperform other black-box attacks and achieves similar attach success rate with the white-box attack

Gradient Estimation Attack with Query Reduction

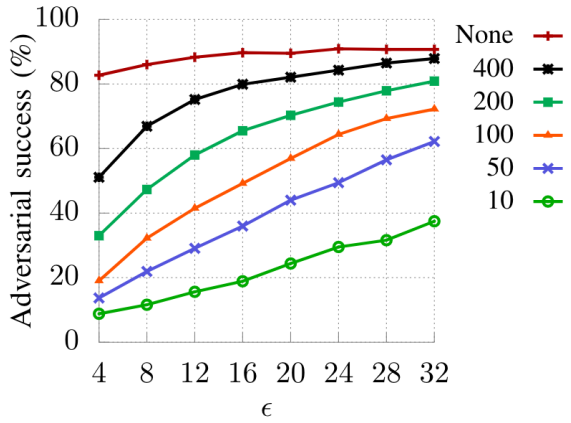
Random feature groupings for Model A



PCA-based query reduction for Model A



PCA-based query reduction for Resnet-32



Adversarial success rates for Gradient Estimation attacks with query reduction on Model A (MNIST) and Resnet-32 (CIFAR-10).

Finite Differences method with query reduction perform approximately similar with the gradient estimation black-box attack

Black-box Attack Clarifai

Original image, classified as “drug” with a confidence of 0.99

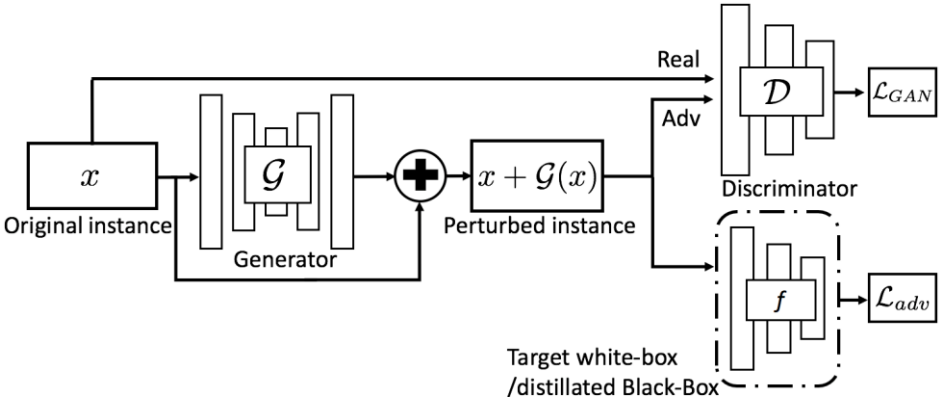
Adversarial example, classified as “safe” with a confidence of 0.96

The Gradient Estimation black-box attack on Clarifai’s Content Moderation Model

Black-box Attacks

Black-box attacks are possible on deep neural networks with query access.
The number of queries needed can be reduced.

Generating Adversarial Examples with Adversarial Networks



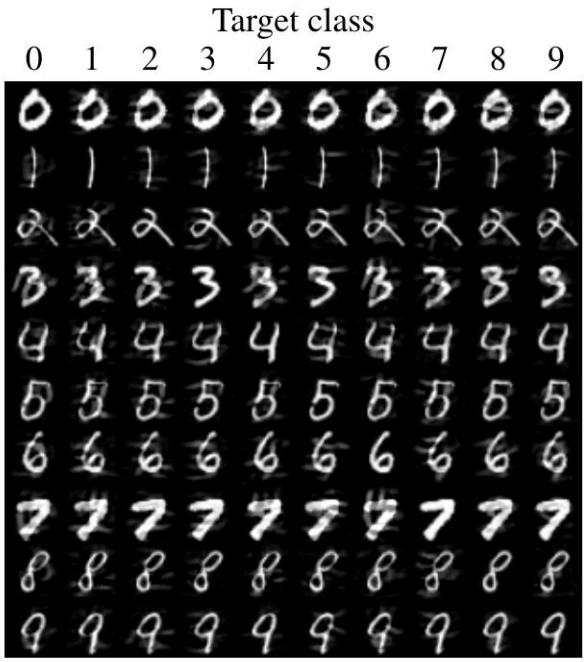
Black-box can be performed here via distillation

$$\mathcal{L}_{GAN} = \mathbb{E}_{x\sim\mathcal{P}_{\text{data}}(x)} \log \mathcal{D}(x) + \mathbb{E}_{x\sim\mathcal{P}_{\text{data}}(x)} \log(1 - \mathcal{D}(x + \mathcal{G}(x)))$$

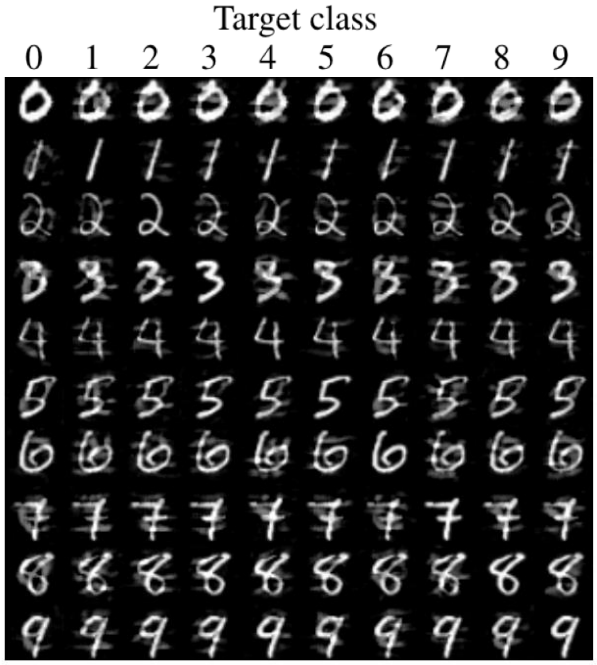
$$\mathcal{L} = \mathcal{L}_{adv}^{f} + \alpha\mathcal{L}_{GAN} + \beta\mathcal{L}_{hinge}$$

The GAN loss here tries to ensure the diversity of adversarial examples

[Chaowei Xiao, Bo Li, Jun-yan Zhu, Warren He, Mingyan Liu, Dawn Song, 2017]

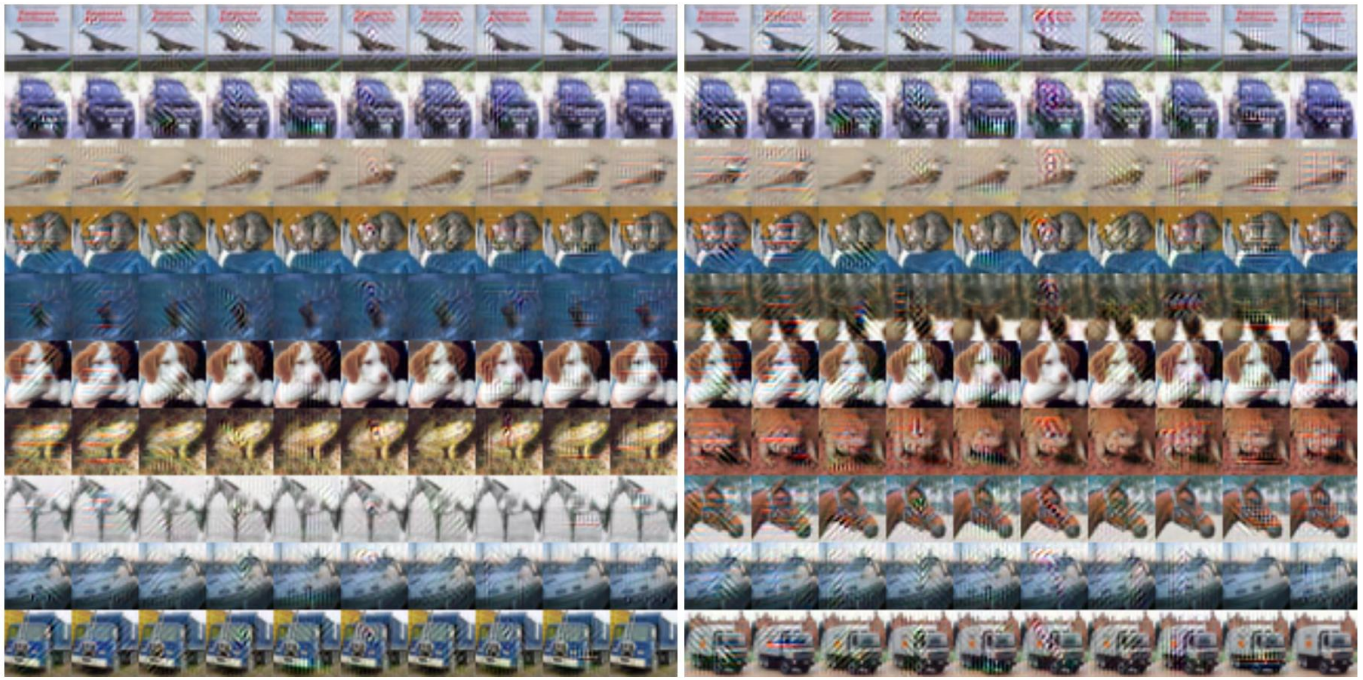


Semi-white box attack on MNIST



Black-box attack on MNIST

The perturbed images are very close to the original ones. The original images lie on the diagonal.



(a) Semi-whitebox setting

(b) Black-box setting

The perturbed images are very close to the original ones. The original images lie on the diagonal.

Poodle Ambulance Basketball Electric guitar

(a) Strawberry

(b) Toy poodle

(c) Buckeye

(d) Toy poodle

Attack Effectiveness Under Defenses

Data	Model	Defense	FGSM	Opt.	AdvGAN
MNIST	A	Adv.	4.3%	4.6%	**8.0%**
		Ensemble	1.6%	4.2%	**6.3%**
		Iter.Adv.	4.4%	2.96%	**5.6%**
	B	Adv.	6.0%	4.5%	**7.2%**
		Ensemble	2.7%	3.18%	**5.8%**
		Iter.Adv.	**9.0%**	3.0%	6.6%
	C	Adv.	2.7%	2.95%	**18.7%**
		Ensemble	1.6%	2.2%	**13.5%**
		Iter.Adv.	1.6%	1.9%	**12.6%**
CIFAR	ResNet	Adv.	13.10%	11.9%	**16.03%**
		Ensemble.	10.00%	10.3%	**14.32%**
		Iter.Adv	22.8%	21.4%	**29.47%**
	Wide ResNet	Adv.	5.04%	7.61%	**14.26%**
		Ensemble	4.65%	8.43%	**13.94 %**
		Iter.Adv.	14.9%	13.90%	**20.75%**

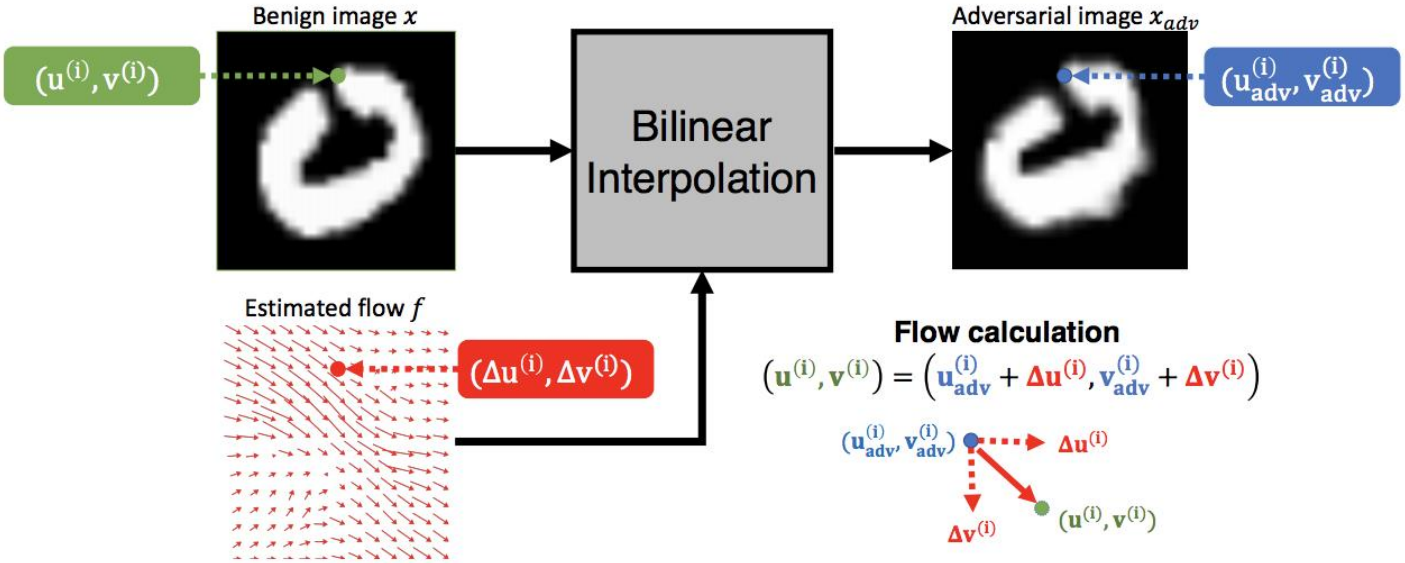
Attack success rate of adversarial examples generated by AdvGAN in semi-whitebox setting under defenses on MNIST and CIFAR-10

Attack Effectiveness Under Defenses

Black-Box Leaderboard (Original Challenge)

Attack	Submitted by	Accuracy	Submission Date
AdvGAN from "Generating Adversarial Examples with Adversarial Networks"	AdvGAN	**92.76%**	Sep 25, 2017
PGD against three independently and adversarially trained copies of the network	Florian Tramèr	93.54%	Jul 5, 2017
FGSM on the CW loss for model B from "Ensemble Adversarial Training [...]"	Florian Tramèr	94.36%	Jun 29, 2017
FGSM on the CW loss for the naturally trained public network	(initial entry)	96.08%	Jun 28, 2017
PGD on the cross-entropy loss for the naturally trained public network	(initial entry)	96.81%	Jun 28, 2017
Attack using Gaussian Filter for selected pixels on the adversarially trained public network	Anonymous	97.33%	Aug 27, 2017
FGSM on the cross-entropy loss for the adversarially trained public network	(initial entry)	97.66%	Jun 28, 2017
PGD on the cross-entropy loss for the adversarially trained public network	(initial entry)	97.79%	Jun 28, 2017

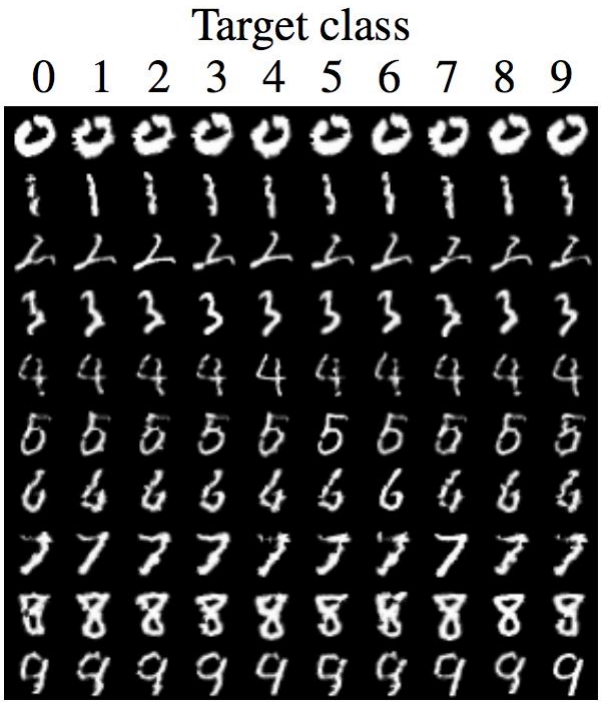
Spatially Transformed Adversarial Examples



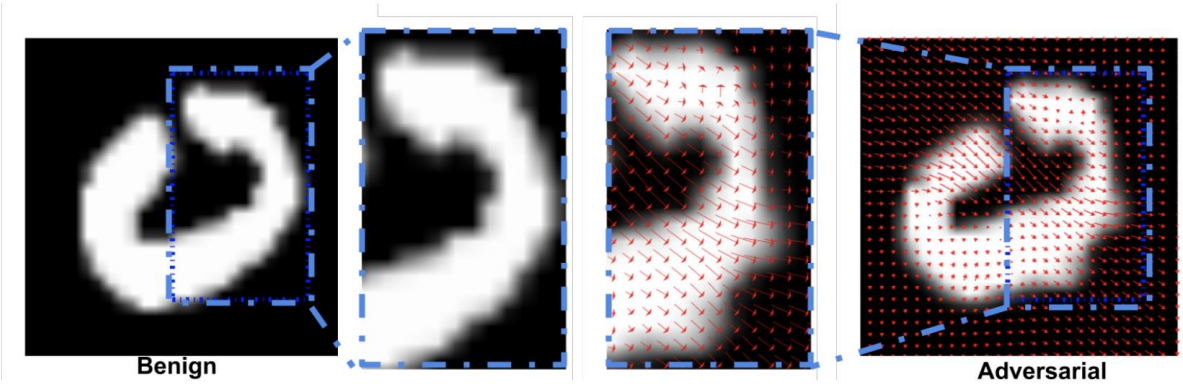
$$f^* = \underset{f}{\operatorname{argmin}} \quad \mathcal{L}_{adv}(x, f) + \tau \mathcal{L}_{flow}(f),$$

[Xiao, Zhu, Li, He, Liu, Song. ICLR 2018]

Examples generated by stAdv



Adversarial examples generated by stAdv on MNIST
The ground truth images are shown in the diagonal



Flow visualization on MNIST. The digit "0" is misclassified as "2".

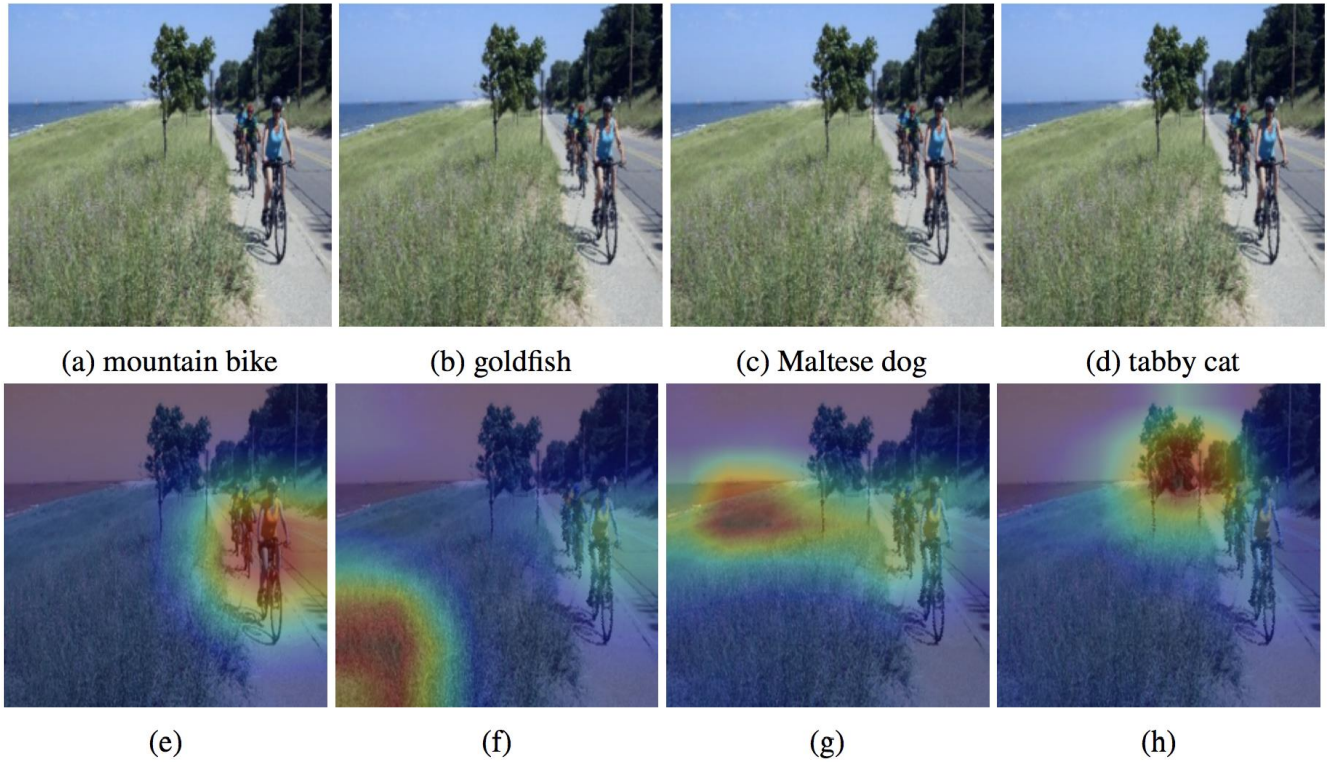
Attack Effectiveness Under Defenses

Model	Def.	FGSM	C&W.	stAdv
A	Adv.	4.3%	4.6%	**32.62%**
	Ens.	1.6%	4.2%	**48.07%**
	PGD	4.4%	2.96%	**48.38%**
B	Adv.	6.0%	4.5%	**50.17%**
	Ens.	2.7%	3.18%	**46.14%**
	PGD	9.0%	3.0%	**49.82%**
C	Adv.	3.22%	0.86%	**30.44%**
	Ens.	1.45%	0.98%	**28.82%**
	PGD	2.1%	0.98%	**28.13%**

Model	Def.	FGSM	C&W.	stAdv
ResNet32	Adv.	13.10%	11.9%	**43.36%**
	Ens.	10.00%	10.3%	**36.89%**
	PGD	22.8%	21.4%	**49.19%**
wide ResNet34	Adv.	5.04%	7.61%	**31.66%**
	Ens.	4.65%	8.43%	**29.56%**
	PGD	14.9%	13.90%	**31.6%**

Attack success rate of adversarial examples generated by stAdv against different models under standard defense on MNIST and CIFAR-10

Attention of network



CAM attention visualization for ImageNet inception_v3 model. (a) the original image and (b)-(d) are stAdv adversarial examples targeting different classes. Row 2 shows the attention visualization for the corresponding images above.

inception_v3 model

(a) Benign (b) FGSM (c) C&W (d) StAdv

Adversarial trained inception_v3 model

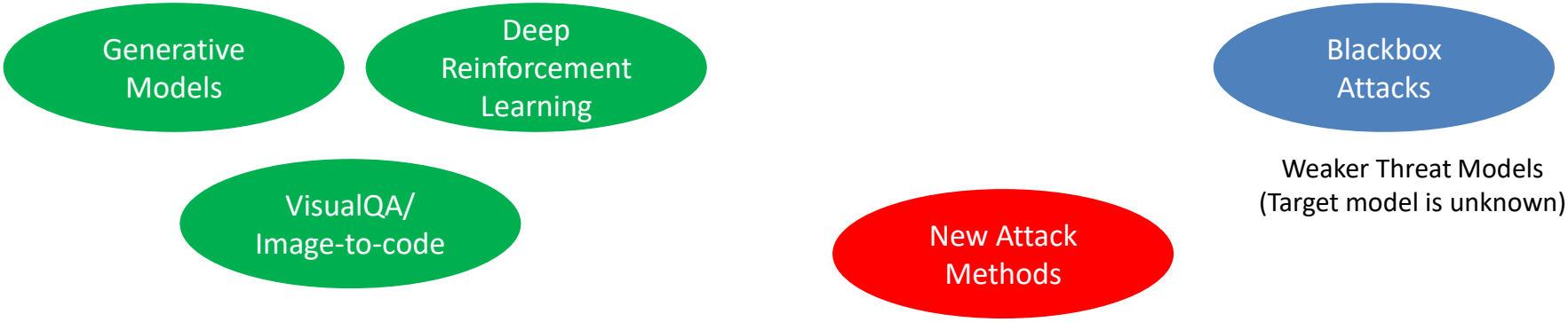
(e) Benign (f) FGSM (g) C&W (h) StAdv

CAM attention visualization for ImageNet inception_v3 model. Column 1 shows the CAM map corresponding to the original image. Column 2-4 show the adversarial examples generated by different methods. (a) and (e)-(g) are labeled as the ground truth "cinema", while (b)-(d) and (h) are labeled as the adversarial target "missile."

Adversarial Examples Prevalent in Deep Learning Systems

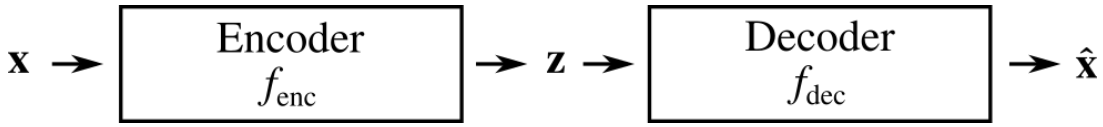
- Most existing work on adversarial examples:
  - Image classification task
  - Target model is known

- Our investigation on adversarial examples:



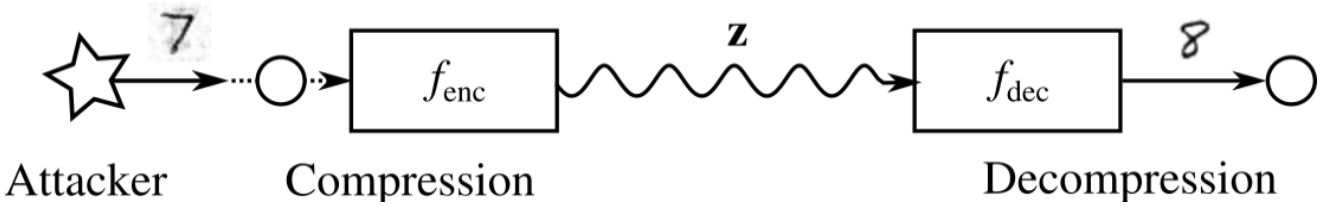
Generative models

- VAE-like models (VAE, VAE-GAN) use an intermediate latent representation
- An **encoder**: maps a high-dimensional input into lower-dimensional latent representation **z**.
- A **decoder:** maps the latent representation back to a high-dimensional reconstruction.



Adversarial Examples in Generative Models

- An example attack scenario:
  - Generative model used as a compression scheme



- Attacker's goal: for the decompressor to reconstruct a different image from the one that the compressor sees.

Adversarial Examples for VAE-GAN in MNIST

Original images

Reconstruction of original images

Target Image

Adversarial examples

Reconstruction of adversarial examples

Jernej Kos, Ian Fischer, Dawn Song: Adversarial Examples for Generative Models

Adversarial Examples for VAE-GAN in SVHN

Original images

Reconstruction of original images

Target Image

Adversarial examples

Reconstruction of adversarial examples

Jernej Kos, Ian Fischer, Dawn Song: Adversarial Examples for Generative Models

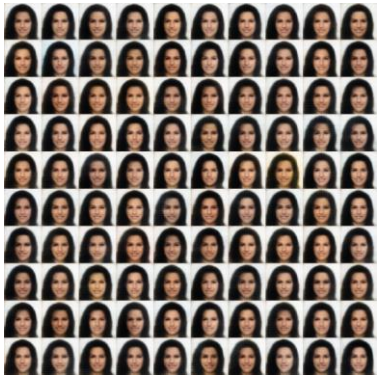
Adversarial Examples for VAE-GAN in SVHN

Original images

Reconstruction of original images

Target Image

Adversarial examples



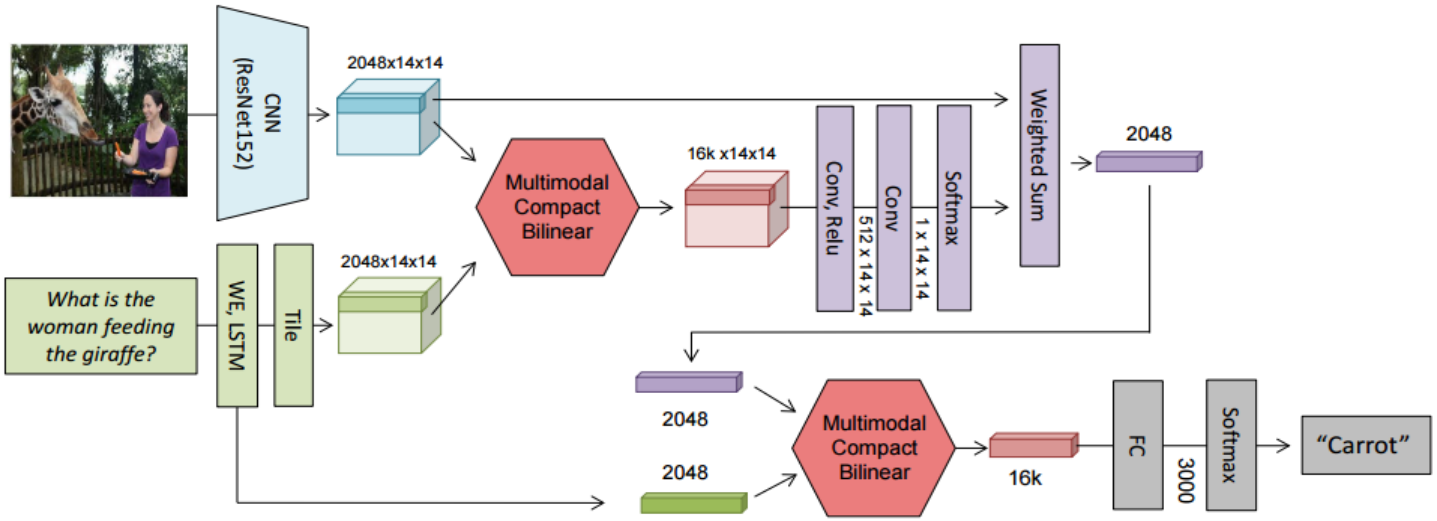
Reconstruction of adversarial examples

Jernej Kos, Ian Fischer, Dawn Song: Adversarial Examples for Generative Models

Takeaways

VAE-like **generative models** are **vulnerable** to adversarial examples

Visual Question & Answer (VQA)



Multimodal Compact Bilinear Pooling for Visual Question Answering and Visual Grounding, Fukui et al., https://arxiv.org/abs/1606.01847

Q: Where is the plane?

Benign image

VQA Model

Answer:
Runway

Fooling VQA

Target: Sky

Adversarial example

VQA Model

Sky

Q: How many cats are there?

Benign image

VQA Model

Answer: 1

Fooling VQA

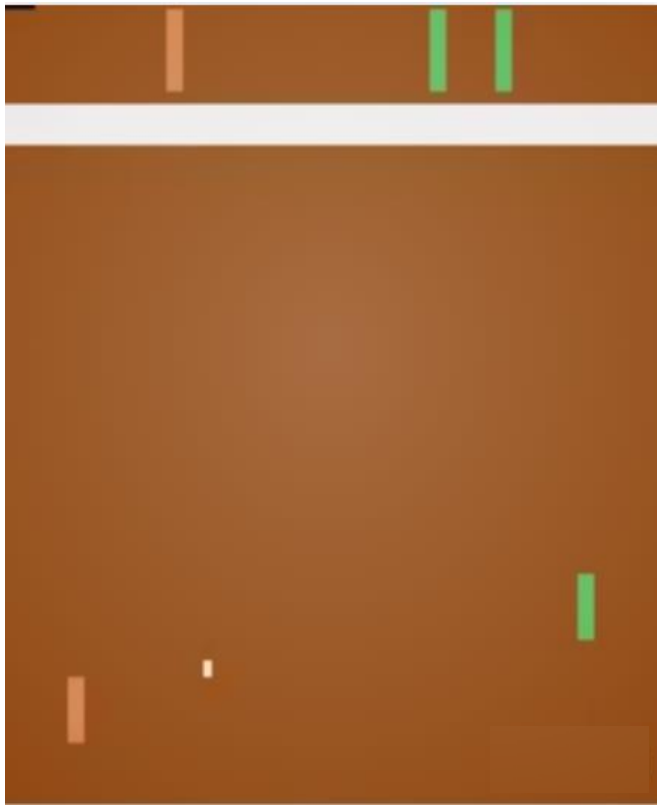
Target: 2

Adversarial example

VQA Model

2

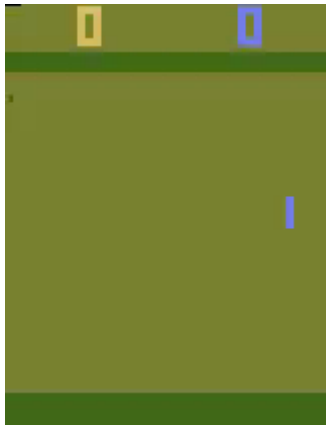
A3C: A Deep Policy on Pong



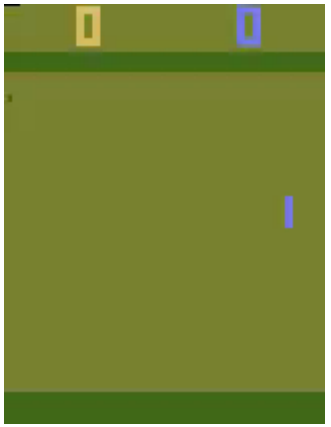
Reinforcement learning algorithms:

- Actor – **policy network** to predict the action based on each frame
- Critics – **value function** to predict the value of each frame, and the action is chosen to maximize the expected value
- Actor-critics (A3C) – combine value function into the policy network to make prediction

Agent in Action: attack the policy network



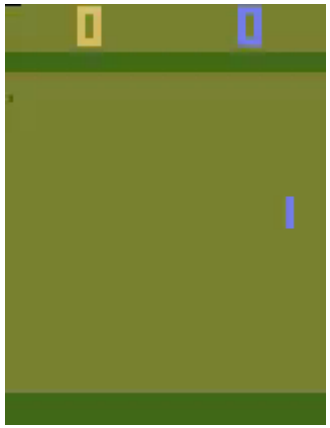
Original Frames



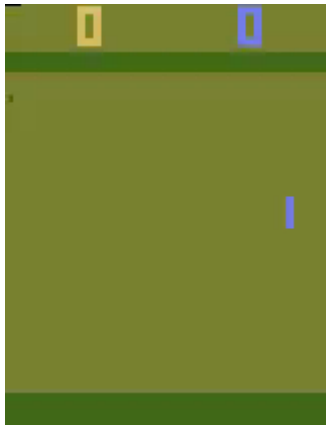
Adversarial perturbation injected into **every frame**

Jernej Kos and Dawn Song: Delving into adversarial attacks on deep policies. ICLR Workshop 2017

Agent in Action: attack the value function



Original Frames



Adversarial perturbation injected into **every other 10 frames**

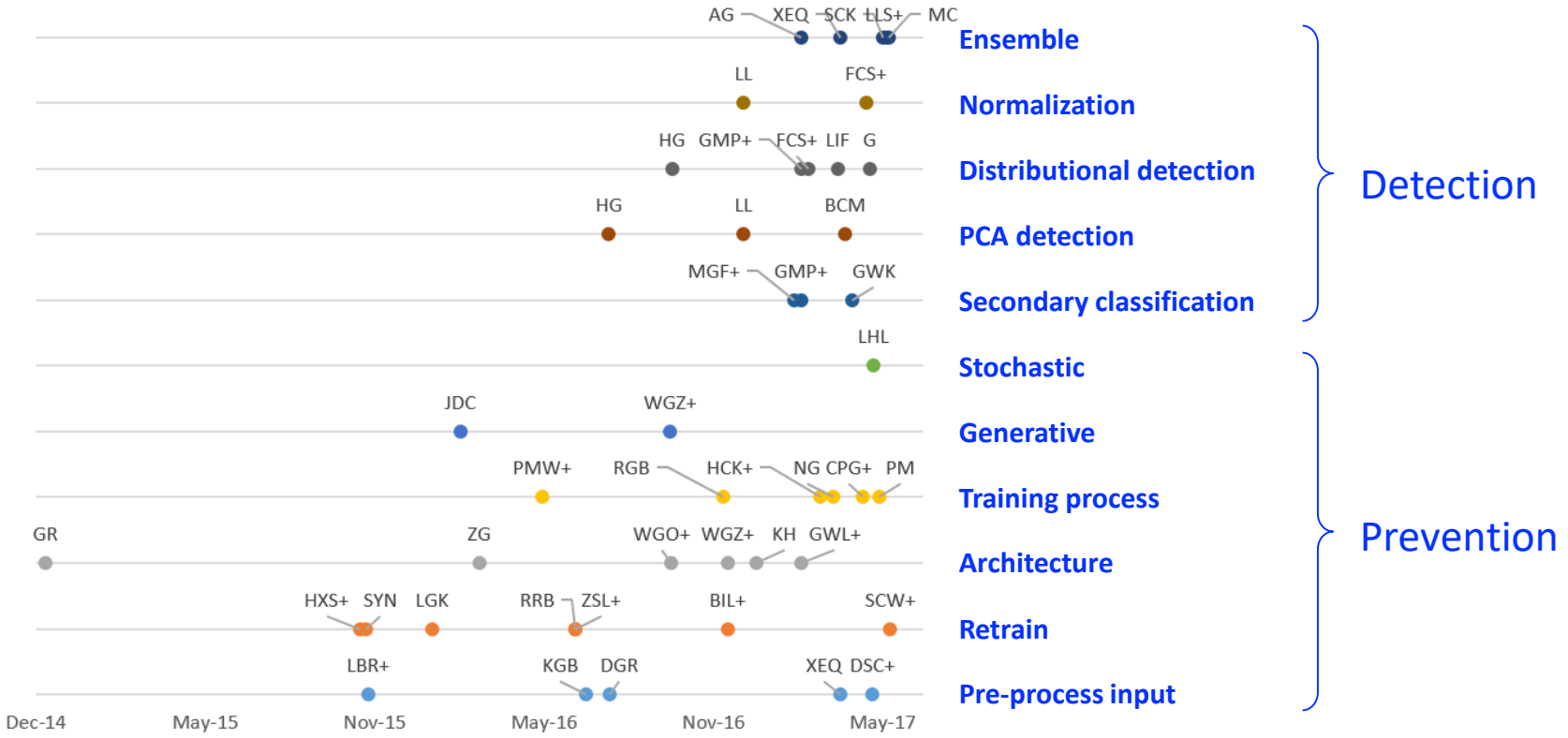
Song et al.: Delving into adversarial attacks on deep policies. ICLR Workshop 2017

Takeaways

Reinforcement learning systems (e.g., robotics, self-driving systems) are also **vulnerable** to adversarial examples

To attack a reinforcement learning system, **adversarial perturbations need not be injected to every frame**.

Numerous Defenses Proposed



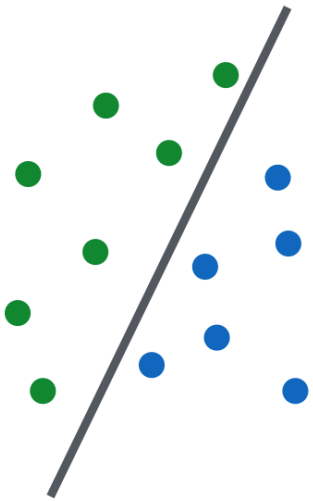
Towards Deep Learning Models Resistant to Adversarial Attacks

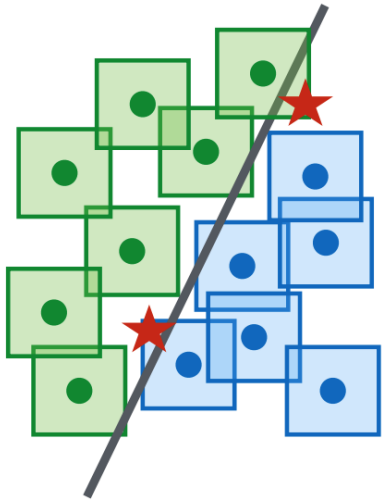
$$\min_{\theta} \rho(\theta), \quad \text{where} \quad \rho(\theta) = \mathbb{E}_{(x,y)\sim\mathcal{D}} \left[\max_{\delta\in\mathcal{S}} L(\theta, x+\delta, y) \right]$$

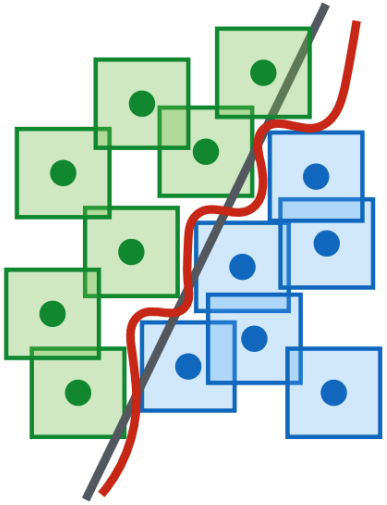
- Use a natural saddle point (min-max) formulation to capture the notion of security against adversarial attacks in a principled manner.
- The formulation casts both attacks and defenses into a common theoretical framework.
- Motivate projected gradient descent (PGD) as a universal "first-order adversary".

Madry et al. Towards Deep Learning Models Resistant to Adversarial Attacks, ICLR 2017.

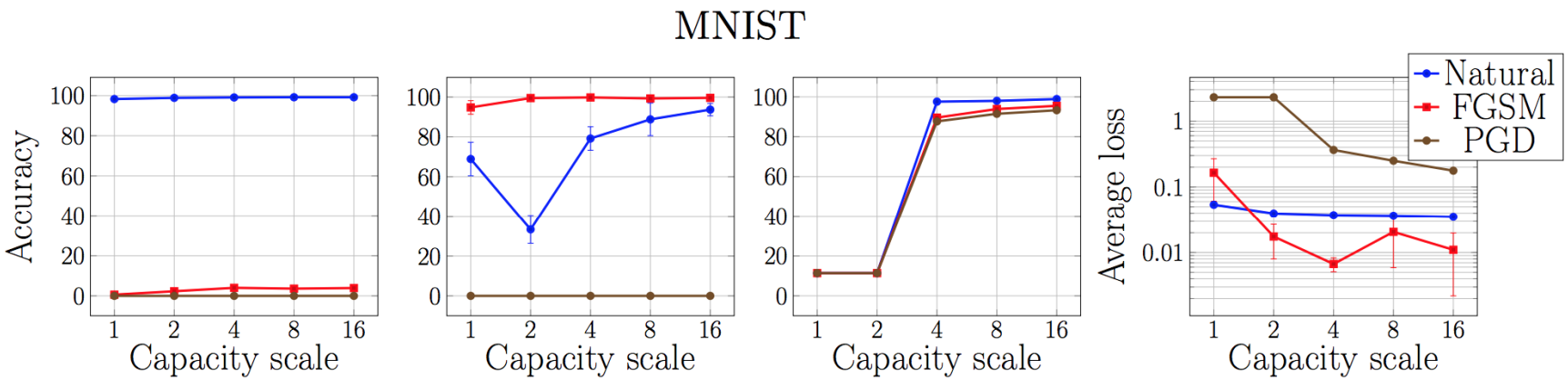
Model Capacity

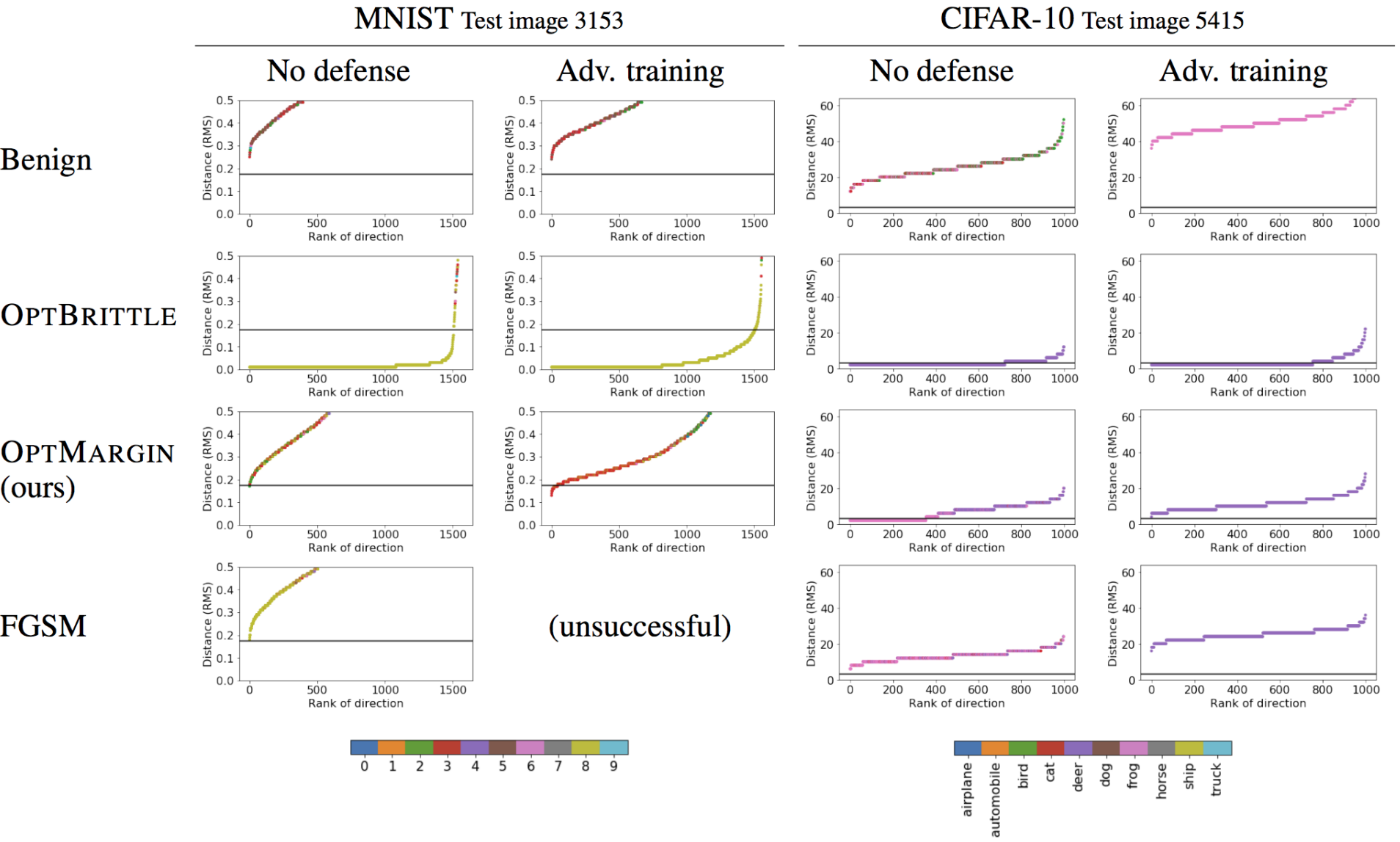




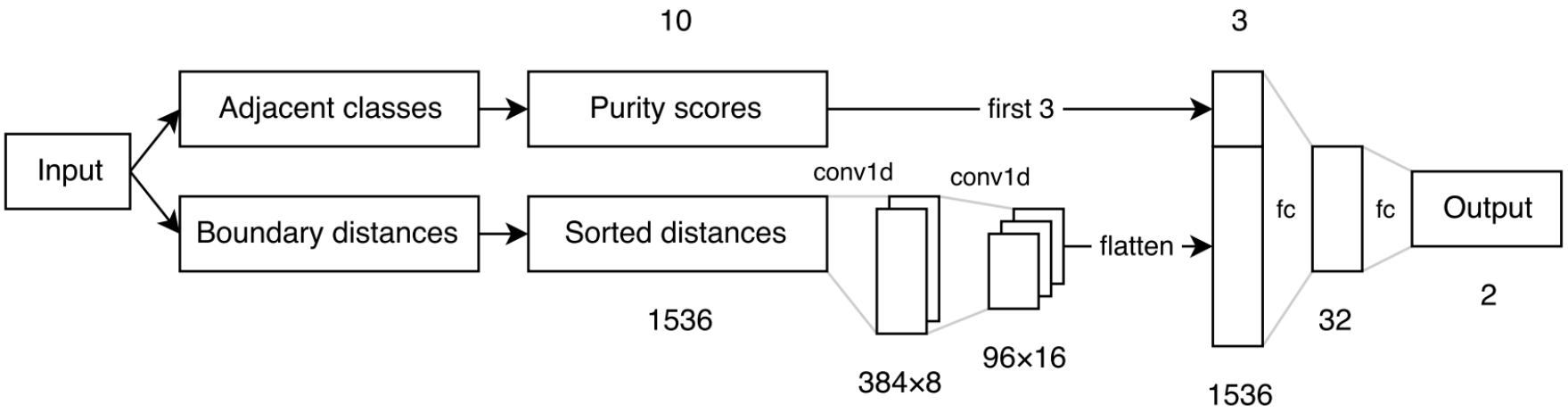


Towards Deep Learning Models Resistant to Adversarial Attacks




MNIST Test image 3153
CIFAR-10 Test image 5415
No defense
Adv. training
No defense
Adv. training
Benign
OptBrittle
OptMargin (ours)
FGSM
(unsuccessful)
Distance (RMS)
Rank of direction
0 1 2 3 4 5 6 7 8 9
airplane
automobile
bird
cat
deer
dog
frog
horse
ship
truck

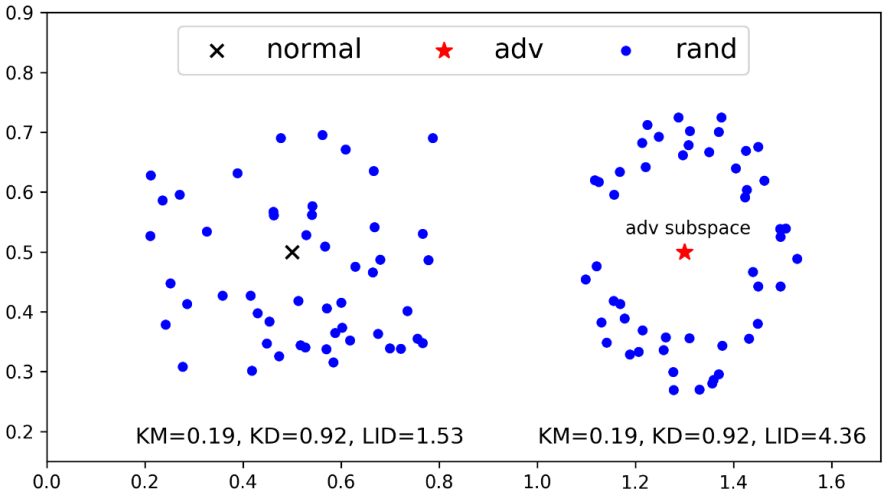
Decision Boundary Analysis of Adversarial Examples

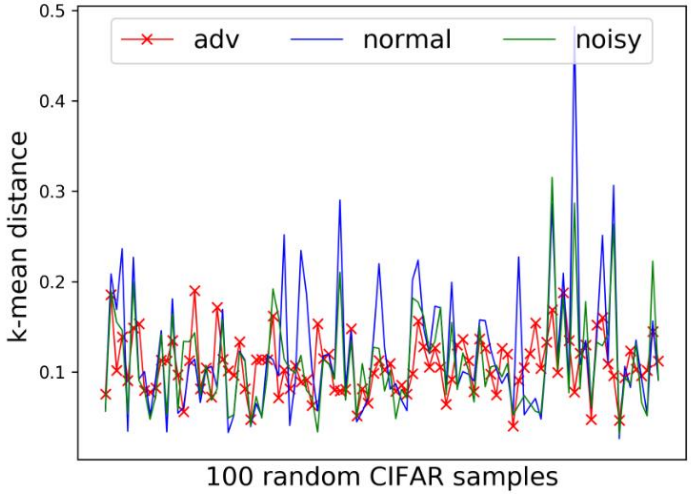


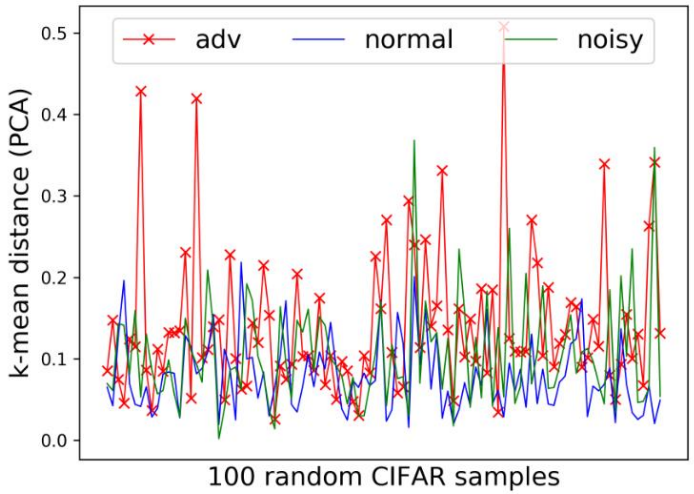
He, Li, Song, Decision Boundary Analysis of Adversarial Examples, ICLR 2017.

Training attack	False pos. Benign	False neg. OPTBRITTLE	False neg. OPTMARGIN	Accuracy Our approach	Accuracy Cao & Gong
		MNIST, normal training			
OPTBRITTLE	1.0%	1.0%	74.1%	90.4%	10%
OPTMARGIN	**9.6%**	0.6%	7.2%		
		MNIST, PGD adversarial training			
OPTBRITTLE	2.6%	2.0%	39.8%		
OPTMARGIN	10.3%	0.4%	14.5%		
		CIFAR-10, normal training			
OPTBRITTLE	5.3%	3.2%	56.8%	96.4%	5%
OPTMARGIN	8.4%	7.4%	5.3%		
		CIFAR-10, PGD adversarial training			
OPTBRITTLE	0.0%	2.4%	51.8%		
OPTMARGIN	**3.6%**	0.0%	1.2%		

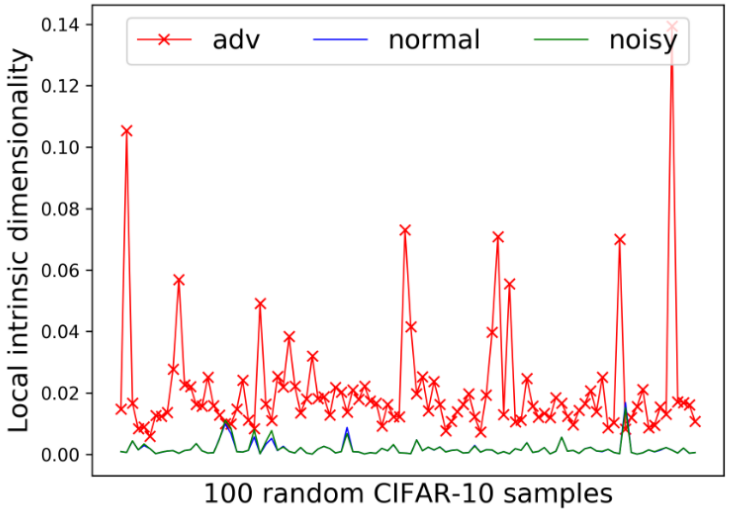
Adversarial Examples Detection

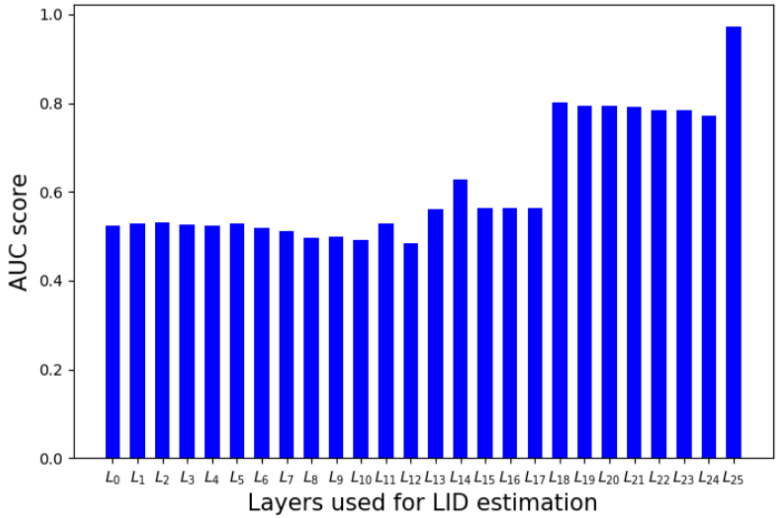




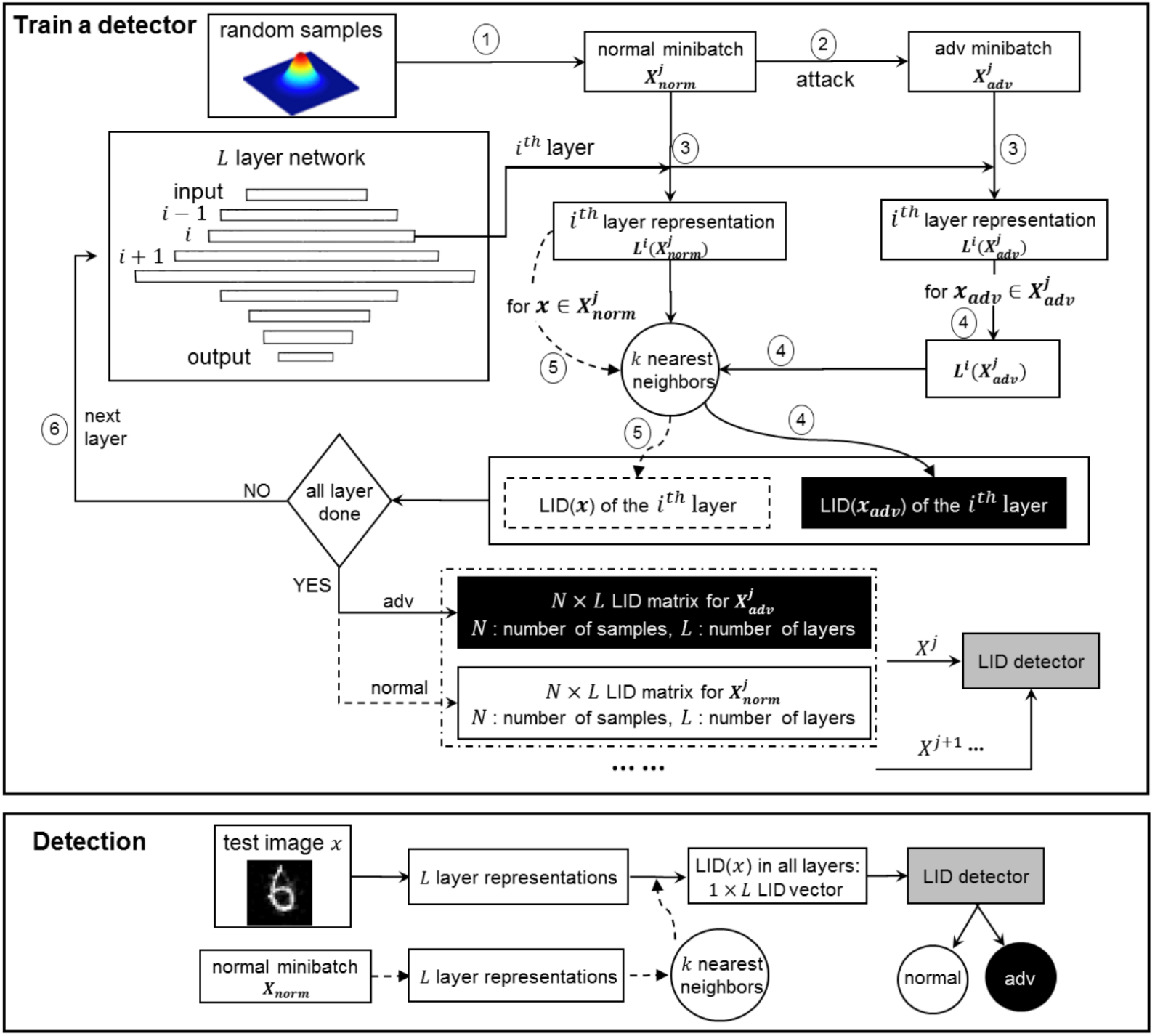


Adversarial Examples Detection via Local Intrinsic Dimensionality (LID)





$$\widehat{\mathrm{LID}}(x) = -\left(\frac{1}{k} \sum_{i=1}^{k} \log \frac{r_i(x)}{r_k(x)} \right)^{-1}$$


Train a detector
random samples
1
normal minibatch
X^j_{norm}
2
attack
adv minibatch
X^j_{adv}
L layer network
input
$i-1$
i
$i+1$
output
i^{th} layer
3
3
i^{th} layer representation
$L^i(X^j_{norm})$
i^{th} layer representation
$L^i(X^j_{adv})$
for $x \in X^j_{norm}$
for $x_{adv} \in X^j_{adv}$
4
5
k nearest neighbors
4
$L^i(X^j_{adv})$
5
4
6
next layer
NO
all layer done
LID(x) of the i^{th} layer
LID(x_{adv}) of the i^{th} layer
YES
adv
$N \times L$ LID matrix for X^j_{adv}
N : number of samples, L : number of layers
normal
$N \times L$ LID matrix for X^j_{norm}
N : number of samples, L : number of layers
X^j
LID detector
X^{j+1} ...
... ...
Detection
test image x
L layer representations
LID(x) in all layers:
$1 \times L$ LID vector
LID detector
normal minibatch
X_{norm}
L layer representations
k nearest neighbors
normal
adv

Characterizing Adversarial Examples

Dataset	Feature	FGM	BIM-a	BIM-b	JSMA	Opt
MNIST	KD	78.12%	99.14%	98.61%	68.77%	95.15%
	BU	32.37%	91.55%	25.46%	88.74%	71.29%
	KD+BU	82.43%	99.20%	98.81%	90.12%	95.35%
	LID	**96.89%**	**99.60%**	**99.83%**	**92.24%**	**99.24%**
CIFAR-10	KD	64.92%	68.38%	98.70%	85.77%	91.35%
	BU	70.53%	81.60%	97.32%	87.36%	91.39%
	KD+BU	70.40%	81.33%	98.90%	88.91%	93.77%
	LID	**82.38%**	**82.51%**	**99.78%**	**95.87%**	**98.93%**
SVHN	KD	70.39%	77.18%	99.57%	86.46%	87.41%
	BU	86.78%	84.07%	86.93%	91.33%	87.13%
	KD+BU	86.86%	83.63%	99.52%	93.19%	90.66%
	LID	**97.61%**	**87.55%**	**99.72%**	**95.07%**	**97.60%**

	MNIST	CIFAR-10	SVHN
Attack Failure Rate (one-layer)	100%	95.7%	97.2%
Attack Failure Rate (all-layer)	100%	100%	100%