On the Machine Illusion

Empirical Study on Adversarial Samples

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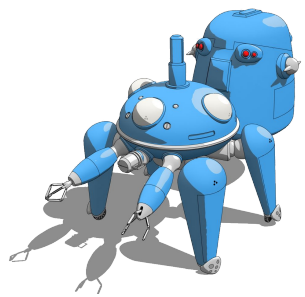


Outline

Acknowledgments

Family Shuting, my parents

Advisor Dr. Wei-Shinn Ku and Dr. Anh Nguyen

Committees Dr. Xiao Qin, Dr. Shiwen Mao and Dr. Yang Zhou

Collaborators Dr. Bo Li

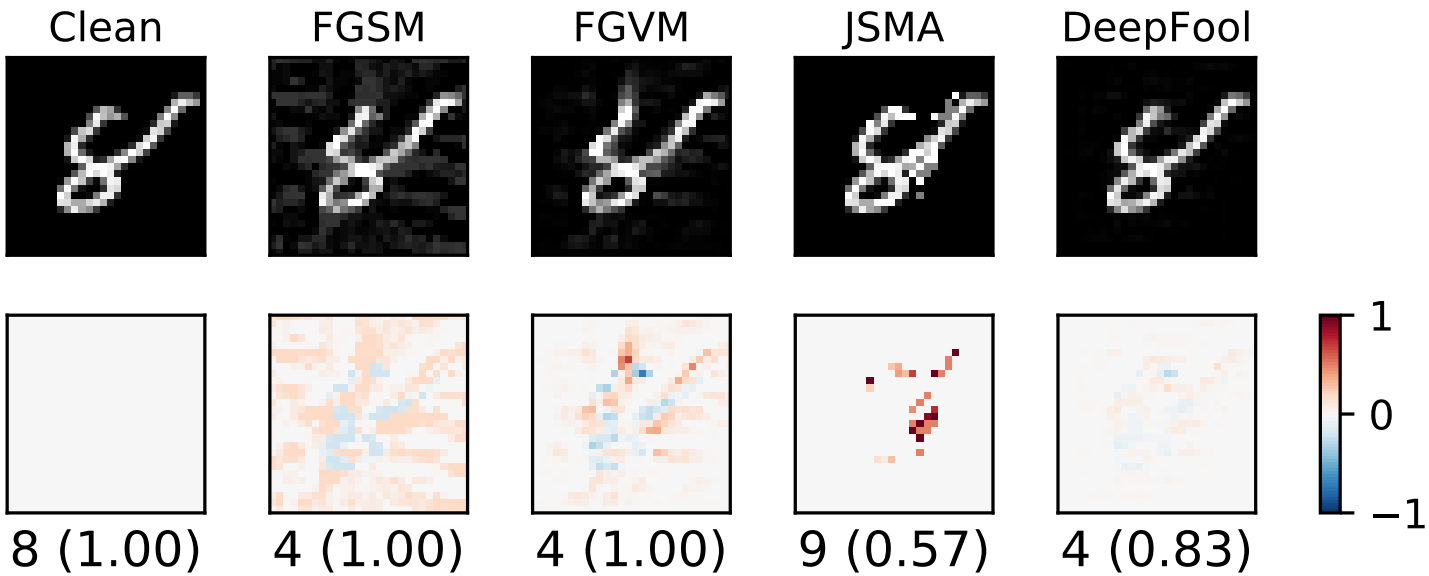
Colleagues Data Science & Engineering Lab

Thanks Xin Wu, Wenlu Wang

Funding Auburn University Teaching Assistance

Outline

Adversarial Samples I



1. Noises are very subtle, visually indistinguishable.
2. Trick machines into wrong predictions with high confidence.

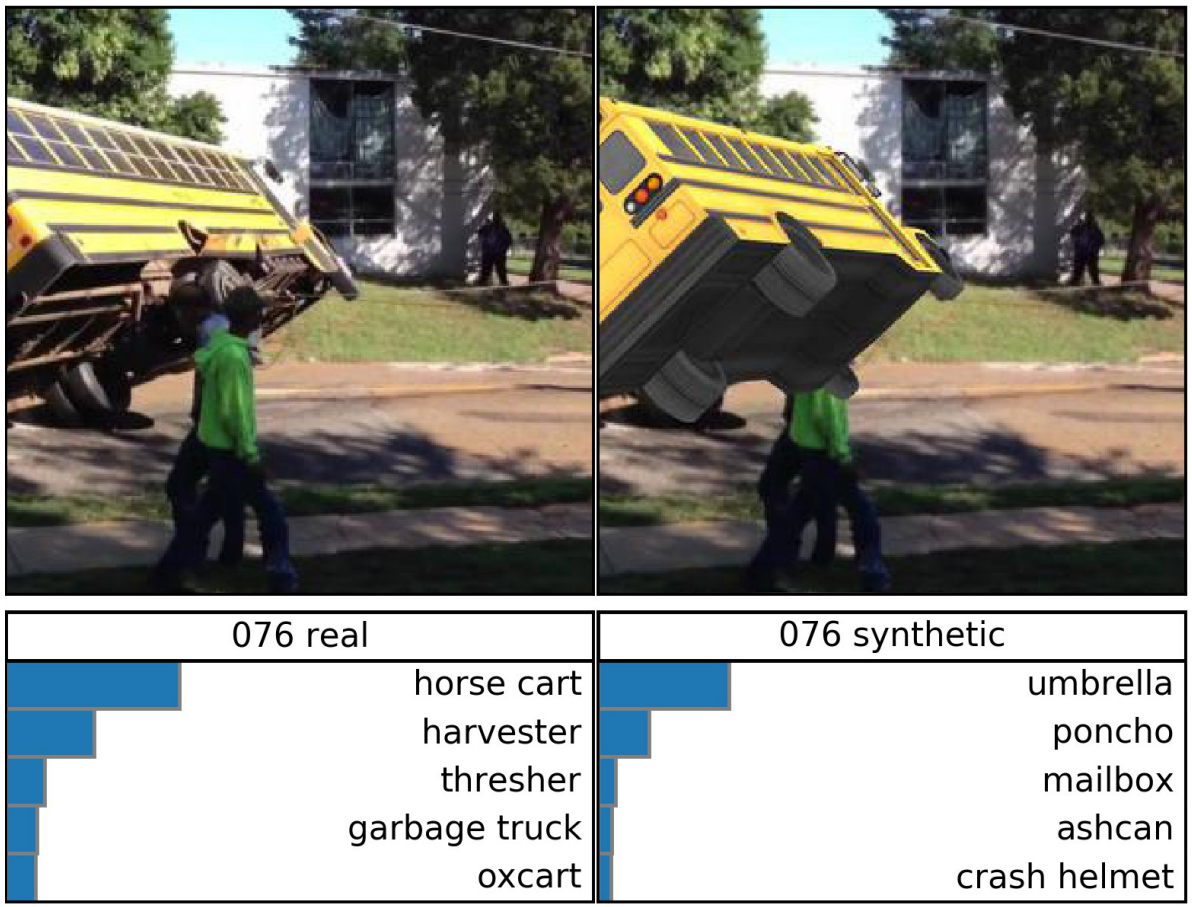
Adversarial Samples II

Clean Text	Label	WMD (n/L)	Adversarial Text
Quick summary of the book : **[. . .]** The book was n't bad , but was soooooooo cliché < br / > < br / > Now about the movie **[. . .]** (IMDB)	0→1	0.0317 (0.0050)	Quick summary of the book : **[. . .]** The book was n't bad , but was soooooooo TahitiNut < br / > < br / > Now about the movie **[. . .]**
zulchzulu < SM > TO OFFER SPECIAL DIVIDEND Southmark Corp said it will issue its shareholders a special dividend right **[. . .]** (REUTERS-2)	1→0	0.0817 (0.0125)	zulchzulu < SM > TO OFFER OFFERS SHARES Southmark Corp said it will issue its shareh olders a special dividend right **[. . .]**
U . K . MONEY MARKET GIVEN FURTHER 68 MLN STG HELP The Bank of England said it provided the market with a further **[. . .]** (REUTERS-5)	3→2	0.0556 (0.0077)	U . K . MONEY MARKET GIVEN FURTHER 68 ARL STG HELP The Bank of England said it provided the market with a further **[. . .]**

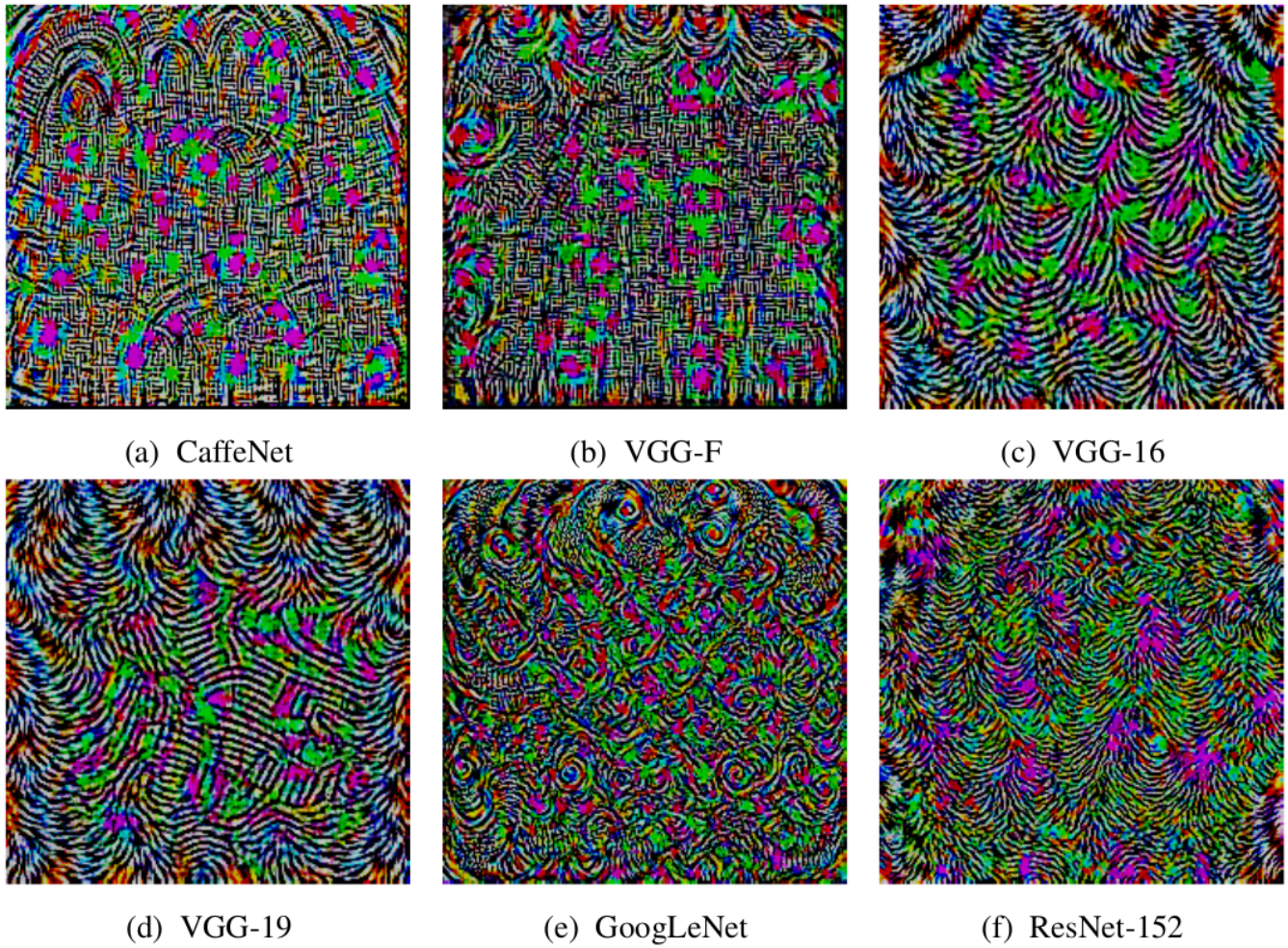
The highlighted words are changed. n/L is the number of words changed divided by the total number of words. (credit: Gong, Wang, B. Li, et al. 2018)

Adversarial Samples III

Objects in weird poses are also tricky! (credit: Alcorn et al. 2018)



Adversarial Patterns for Machines



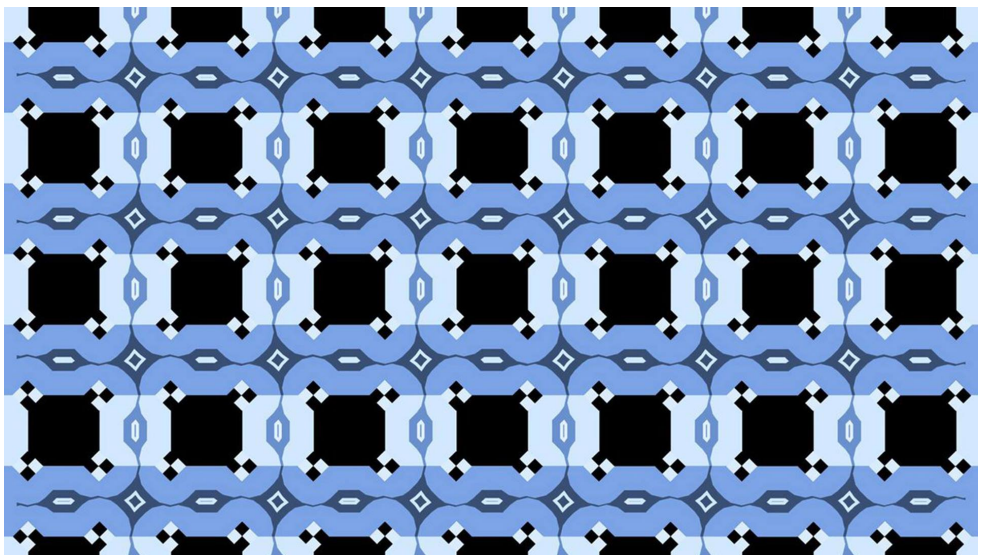
(a) CaffeNet (b) VGG-F (c) VGG-16

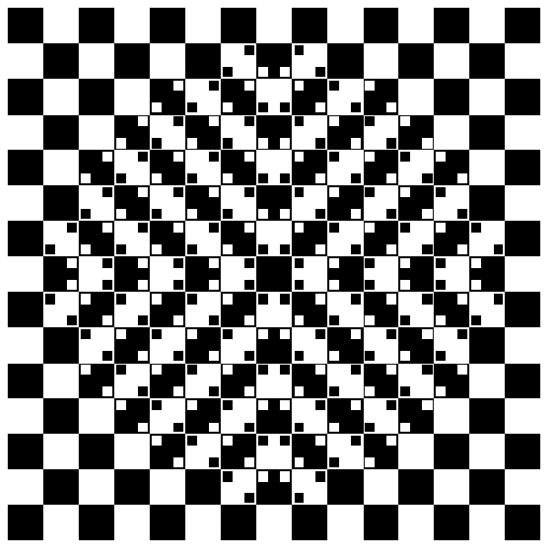
(d) VGG-19 (e) GoogLeNet (f) ResNet-152

Figure: Adversarial patterns for different neural nets Moosavi-Dezfooli et al. 2016.

Adversarial Patterns for Humans

Illusion possibly caused by the fringed edges Kitaoka et al. 2004. More examples http://www.psy.ritsumei.ac.jp/~akitaoka





Motivation

This phenomenon is interesting both in practice and in theory.

1. It undermines the models' reliability.
2. Hard to ignore due to it being transferable and universal.
3. It provides new insights into neural networks:
   - Local generalization does not seem to hold.
   - Data distribution: they appear in dense regions.
   - Trade-off between robustness and generalization.
   - ...

Outline

Neural Networks

It is a connectionist model.

1. Any state can be described as an N-dimensional vector of numeric activation values over neural units in a network.
2. Memory is created by modifying the strength of the connections between neural units.

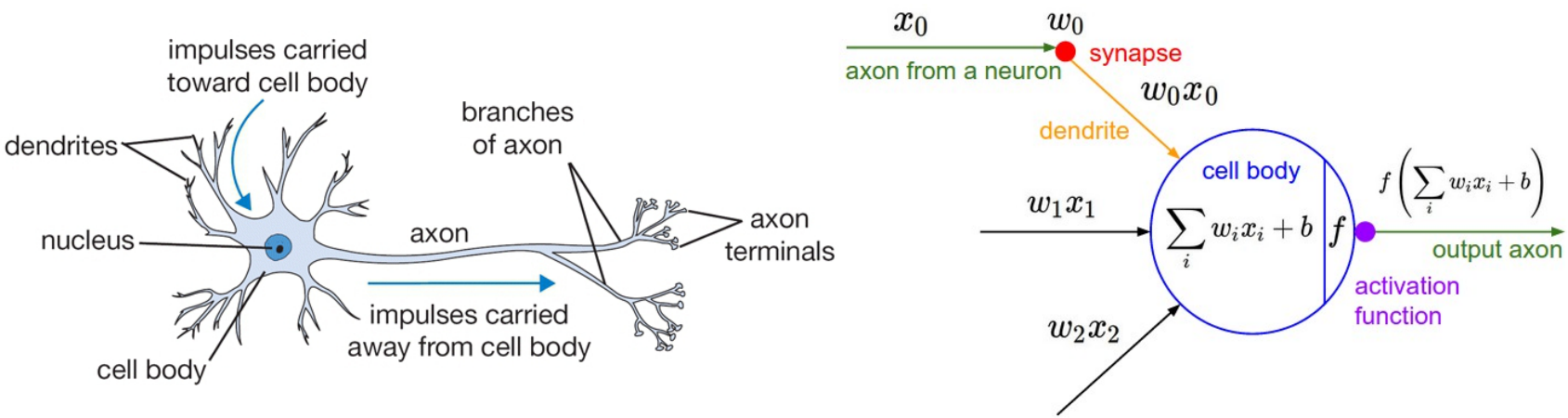


Figure: Biological neuron versus neuron model (credit: cs231n)

Case Study: Multi-Layer Perceptron (MLP)

MLP is one of the most simple feedfoward architectures.

1. Each neuron outputs to the neurons in the next layer.
2. Neurons in the same layer have no connections.

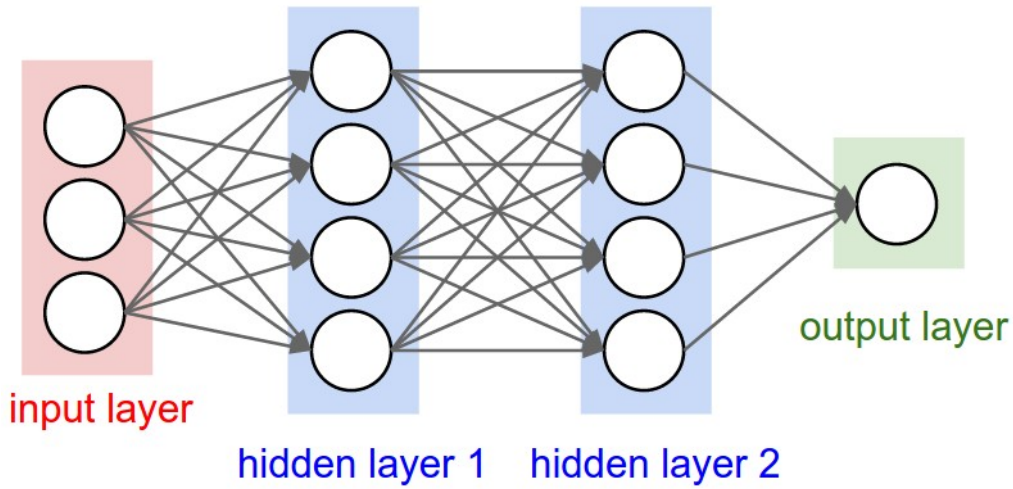


Figure: Multi-layer perceptron (credit: cs231n)

Case Study: Convolutional Neural Network (CNN)

CNN is inspired by eye structure, widely used in computer vision.

1. Each neuron receives inputs from a pool of neurons in previous layer, just like the convolution operation.
2. Neurons in the same layer have no connections

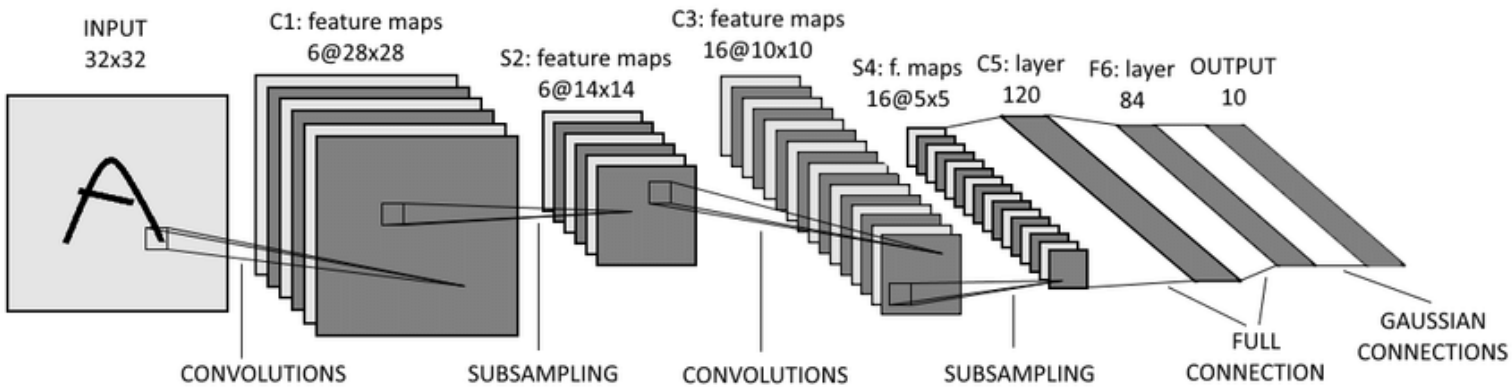


Figure: LetNet-5 LeCun et al. 1998

Case Study: Recurrent Neural Network (RNN)

Some neurons get part of input from its output.

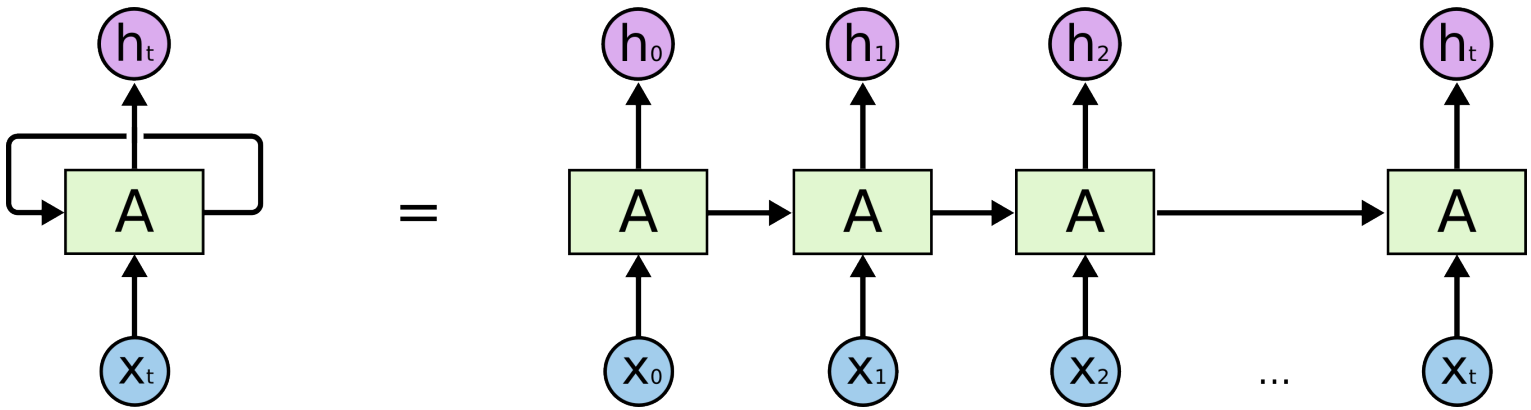


Figure: Dynamic unrolling of recurrent cells. (credit: colah's blog)

Case Study: Recurrent Neural Network (RNN)

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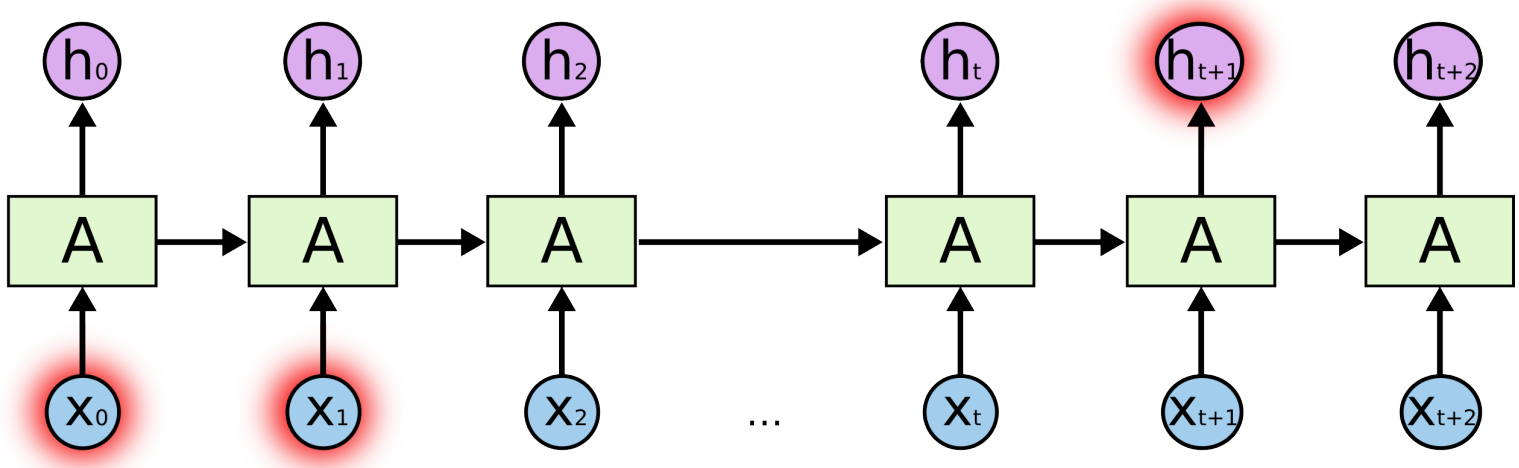


Figure: The double-edged sword: long term dependencies between outputs and inputs. (credit: colah's blog)

Generate Adversarial Images

Intuitions behind the adversarial methods

1. Move the data points
   - towards the decision boundary Moosavi-Dezfooli et al. 2015, 2016,
   - in the direction where loss increases for the clean samples Goodfellow, Shlens, et al. 2014; A. Kurakin et al. 2016, or decreases for the adversarial samples Szegedy et al. 2013, or
   - where the probability of the correct label increases or the probability of the target label increases Carlini et al. 2016; Papernot et al. 2015.
2. Map between clean and adversarial data points Baluja et al. 2017; Xiao et al. 2018; Zhao et al. 2017.

Intuition

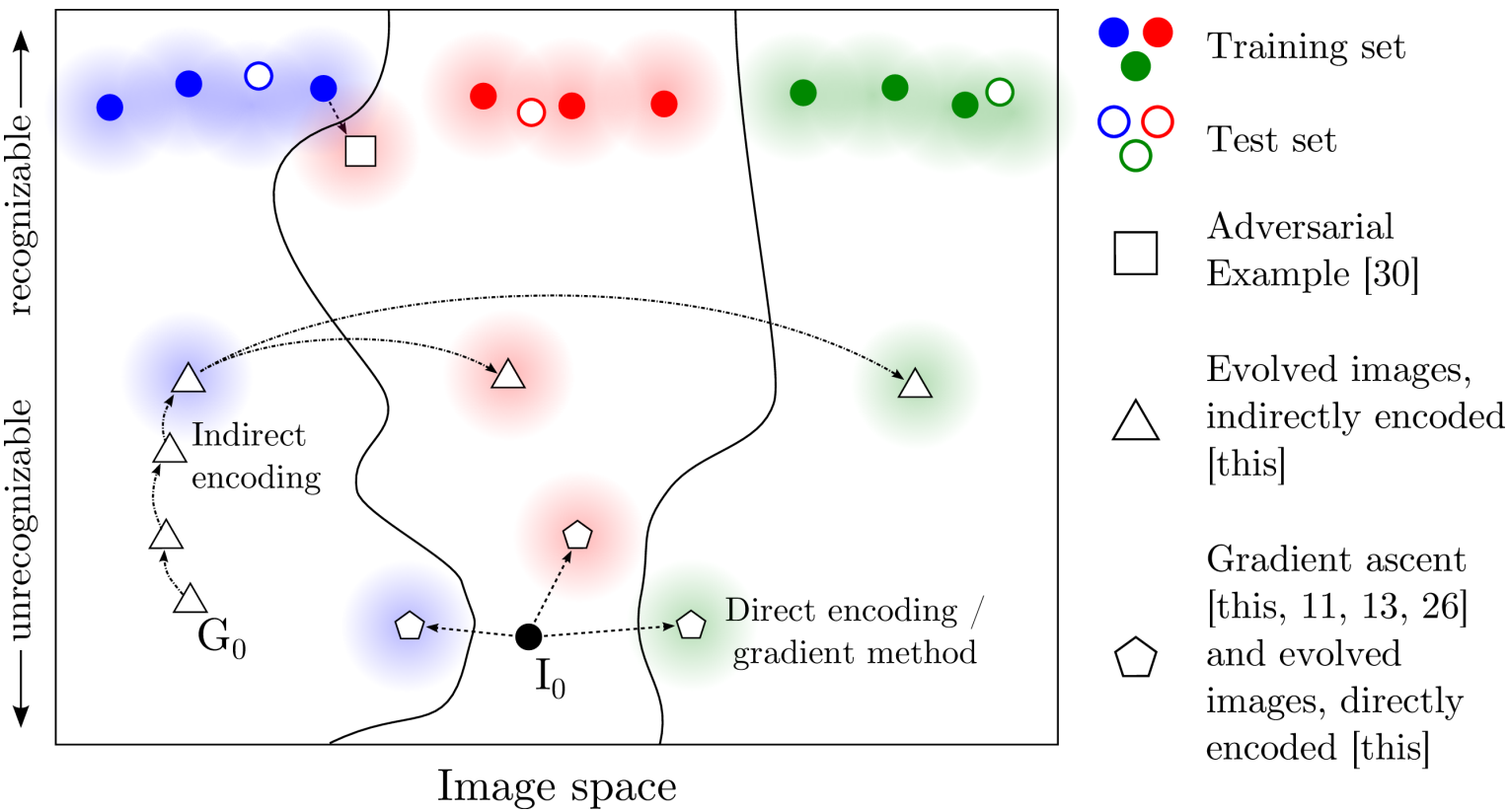
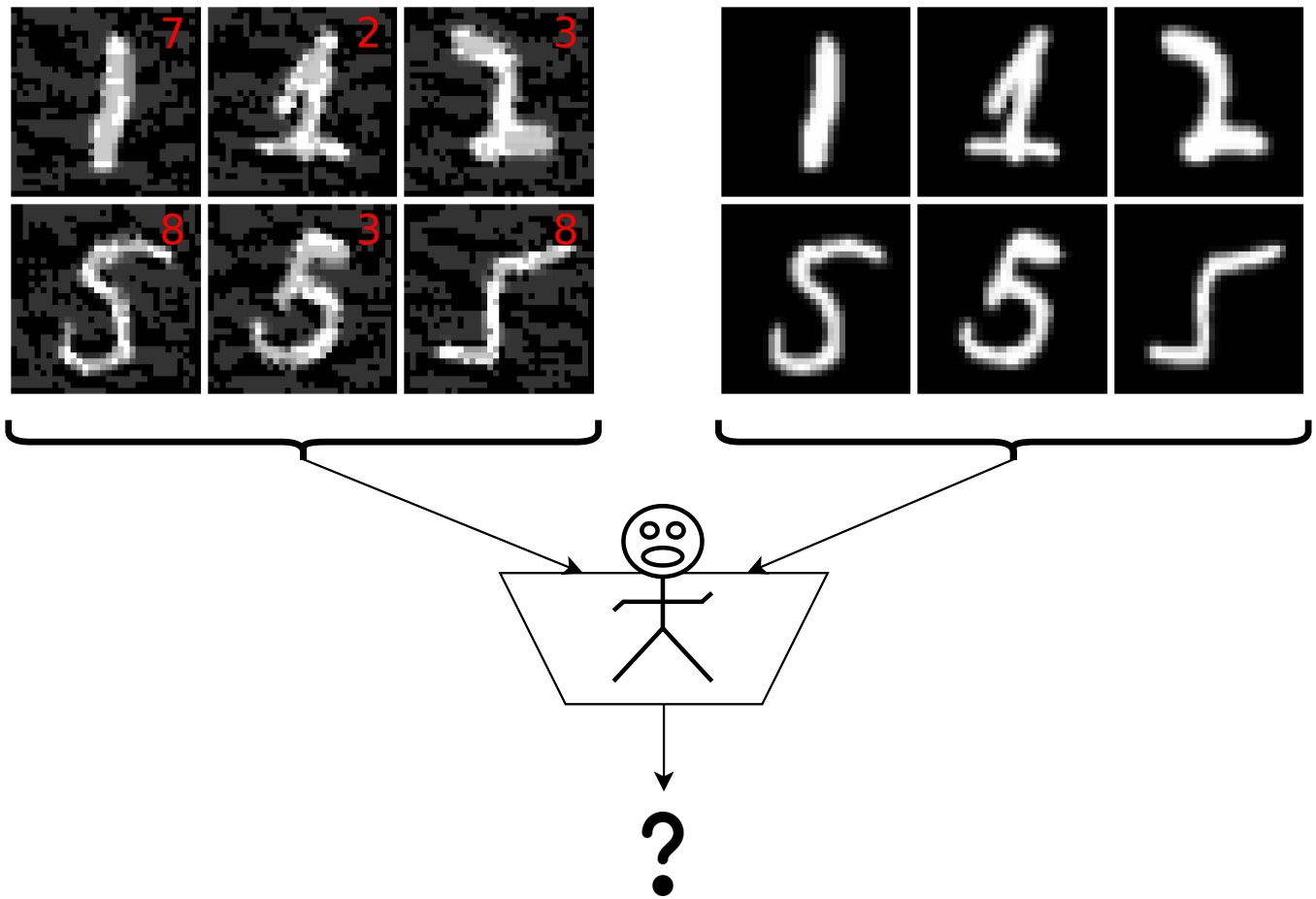


Figure: Data space hypothesis Nguyen et al. 2014

Outline

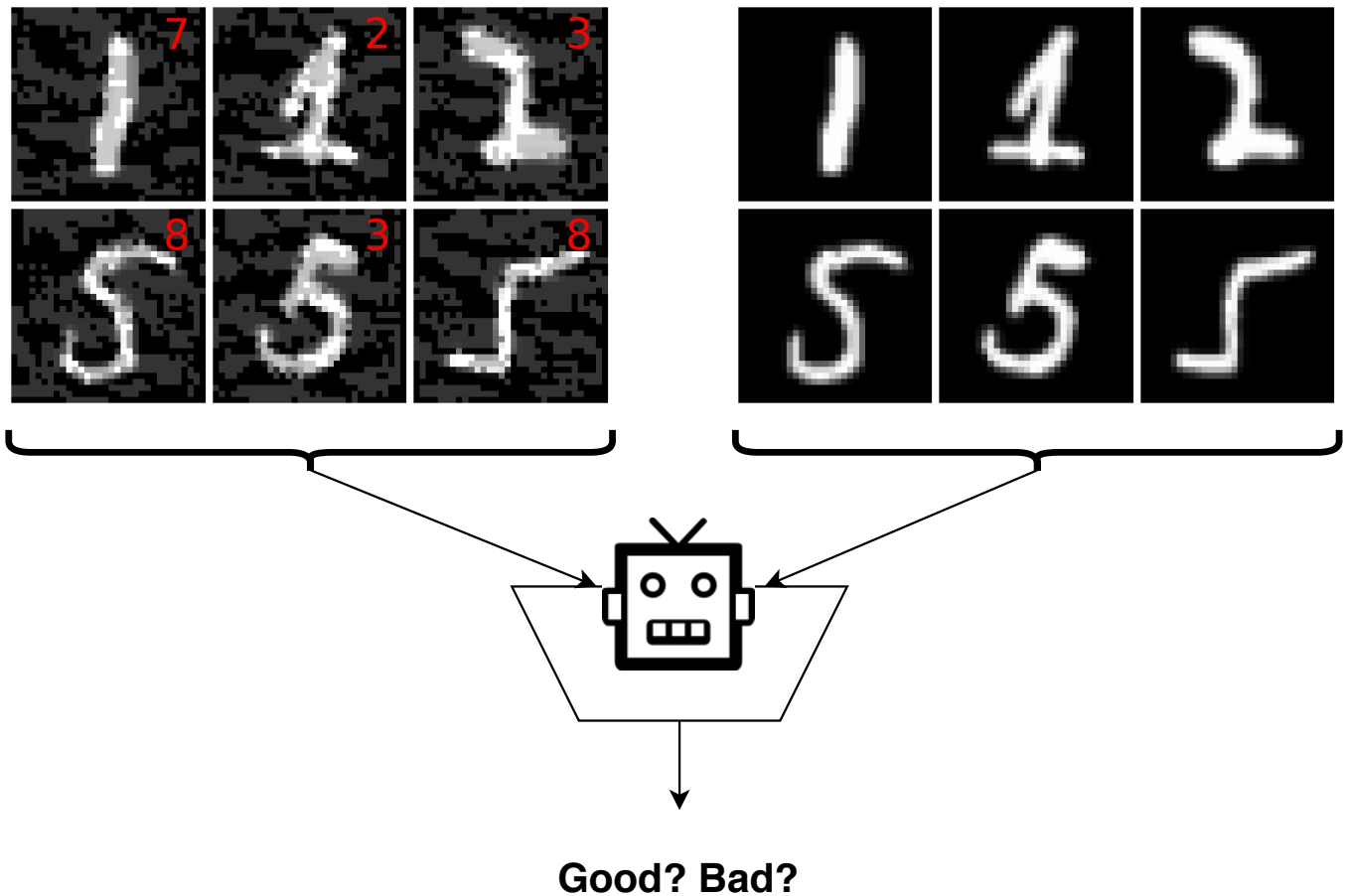
Gist

They look similar for humans.



Gist

They look different for machines.



Binary Classifier as A Defense

We propose to use a binary classifier to separate adversarial samples from clean ones Gong, Wang, and Ku 2017 based on the following observations:

1. The adversarial noise follows a specific direction Goodfellow, Shlens, et al. 2014.
2. The neural nets are sensitive to individual pixel values Szegedy et al. 2013.

Code: https://github.com/gongzhitaao/adversarial-classifier

Related Work

Adversarial training Augment training data with adversarial samples Goodfellow, Shlens, et al. 2014; Madry et al. 2017.

$$\theta^* = \arg\min_{\theta} \mathbb{E}_{x \in \mathcal{X}} \left[\max_{\delta \in [-\epsilon, \epsilon]^N} L(x + \delta; f_\theta) \right]$$

Preprocess Transform input images, e.g., denoising Liang, H. Li, Su, X. Li, et al. 2017; Xie et al. 2018, compression Prakash et al. 2018, quilting Guo et al. 2017.

Detecting classifier Metzen et al. 2017, density ratio estimation Gondara 2017.

Adversarial Examples

Dataset	X	$\widetilde{X}$
MNIST	0.9914	0.0213
CIFAR-10	0.8279	0.1500
SVHN	0.9378	0.2453

Table: The target model accuracy.

Classifier Efficiency and Robustness

Dataset	X	$\widetilde{X}_f$	$\{\widetilde{X}_f\}_g$
MNIST	1.00	1.00	1.00
CIFAR-10	0.99	1.00	1.00
SVHN	1.00	1.00	1.00

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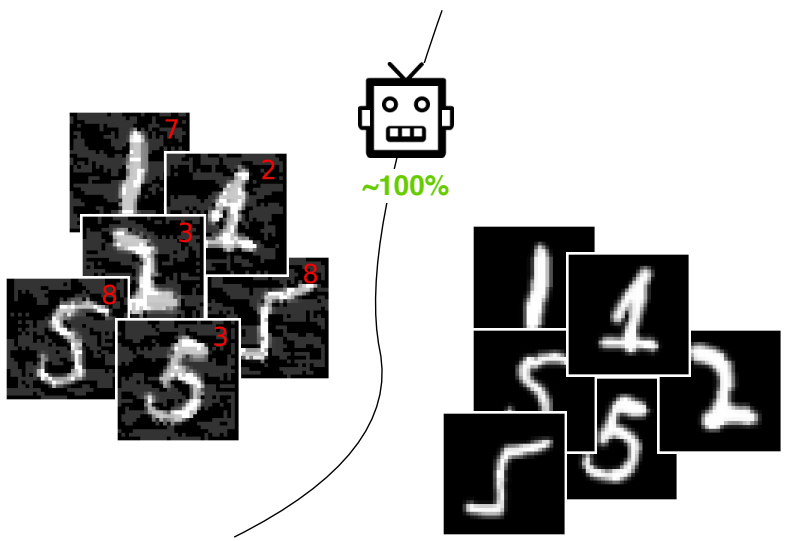

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MNIST	1.00	1.00	1.00
CIFAR-10	0.99	1.00	1.00
SVHN	1.00	1.00	1.00

The classifier is not easily fooled.

Problem with Classifier Defense

Limitation: different hyper-parameters, different adversarial algorithms may elude the binary classifier or adversarial training.

ϵ	X	$\widetilde{X}$
0.3	0.9996	1.0000
0.1	0.9996	1.0000
0.03	0.9996	0.9997
0.01	0.9996	0.0030

Table: The binary classifier, trained with FGSM adversarials with $\epsilon = 0.03$, is unable to recognize the adversarials with $\epsilon = 0.01$ (more subtle noise).

Problem with Adversarial Training

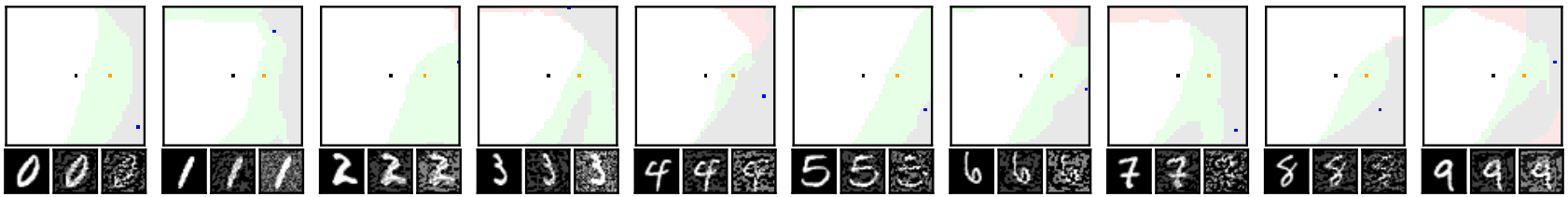
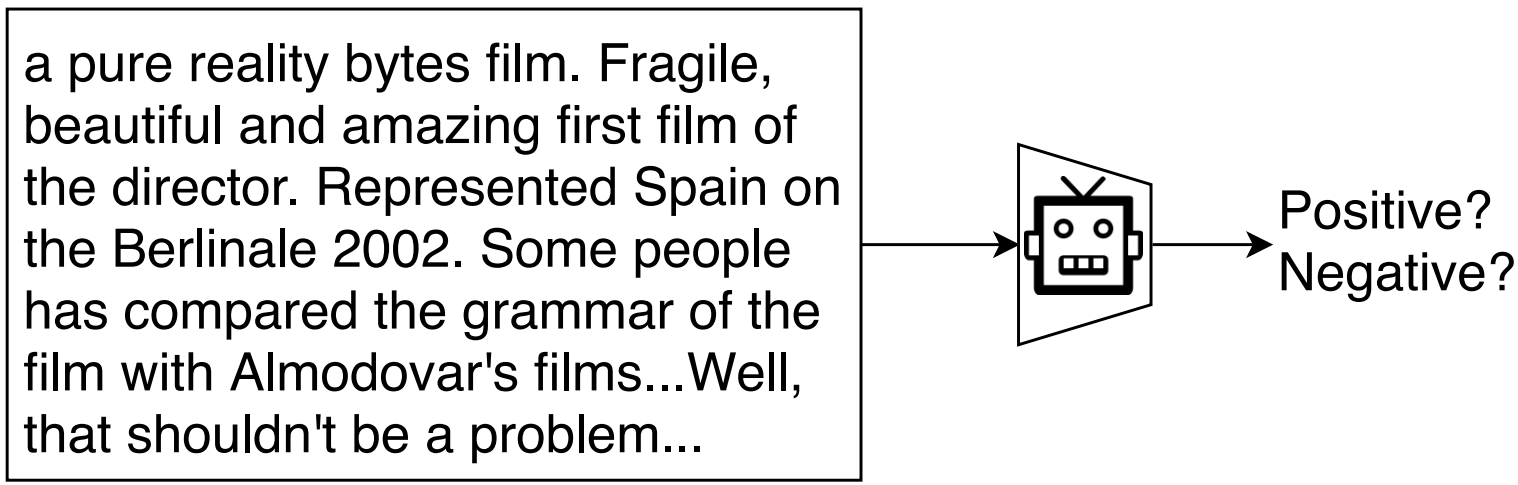


Figure: Adversarial training Huang et al. 2015; Alexey Kurakin et al. 2016 is not sufficient. In the church window plot Warde-Farley et al. 2016, each pixel (i, j) is a data point $\widetilde{x}$ such that $\widetilde{x} = x + \mathbf{h}\epsilon_j + \mathbf{v}\epsilon_i$, where $\mathbf{h}$ is the FGSM direction and $\mathbf{v}$ is a random orthogonal direction. The ϵ ranges from $[-0.5, 0.5]$. (credit: Gong, Wang, and Ku 2017)

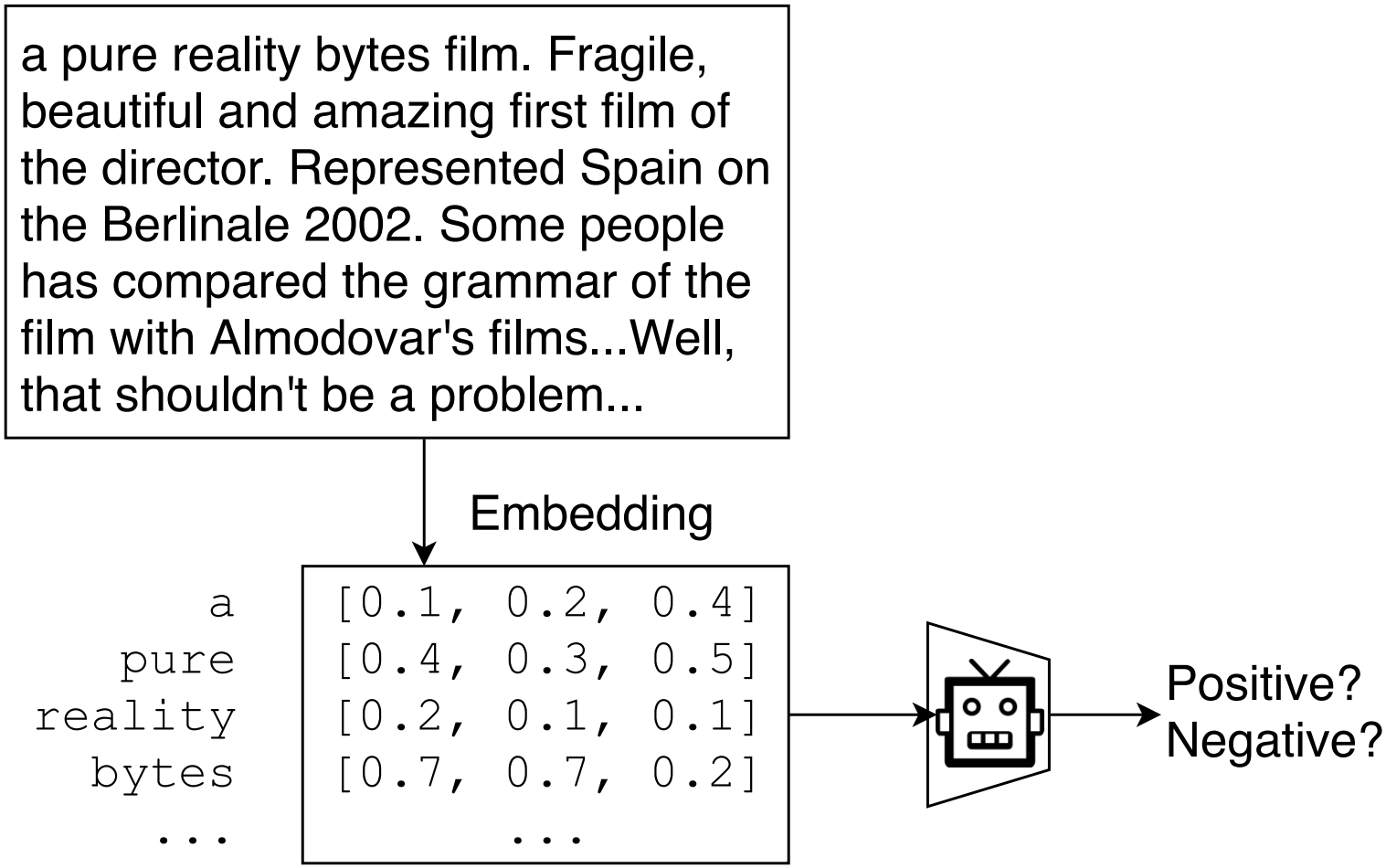
1. ☐ (☐) always correct (incorrectly).
2. ☐ correct with adversarial training.
3. ☐ correct without adversarial training.

Outline

Text Classification



Text Classification



Text Embedding

`wait for the video` $\xrightarrow{\text{tokenize}}$ [`wait`, `for`, `the`, `video`] $\xrightarrow{\text{indexer}}$ [2, 20, 34, 8] $\xrightarrow{\text{embedding}}$ $\mathbb{R}^{4\times D}$, where D is the embedding size.

- Each sentence with be converted to $\mathbb{R}^{L\times D}$ before being fed into the convolution layer, where L is the sentence length.
- We usually truncate/pad sentences to the same length so that we could do *batch training*.
- Embedding may also be on the character-level.

Problem Overview

Goal change as few words as possible to change category.

Difficulties we face:

1. The text space is discrete. Moving the data points in small steps following a certain direction does not work, directly.
2. Text quality is hard to measure. *Much to learn, you still have* (the Yoda-style) v.s. *You still have much to learn* (the mundane-style)

General directions:

1. Three basic operations are available, *replacement*, *insertion*, and *deletion*.
2. They may work at character, word or sentence level.

Methods

In text space This class of methods need to solve two problems:

1. what to change, e.g., random, ∇L Liang, H. Li, Su, Bian, et al. 2017, manually picking Samanta et al. 2017.
2. change to what, e.g., random, synonyms ibid. or nearest neighbors in embedding space, or forged facts Jia et al. 2017; Liang, H. Li, Su, Bian, et al. 2017.

In latent space GAN Goodfellow, Pouget-Abadie, et al. 2014 is used to map from a latent space (e.g., Gaussian noise) to sentences Zhao et al. 2017.

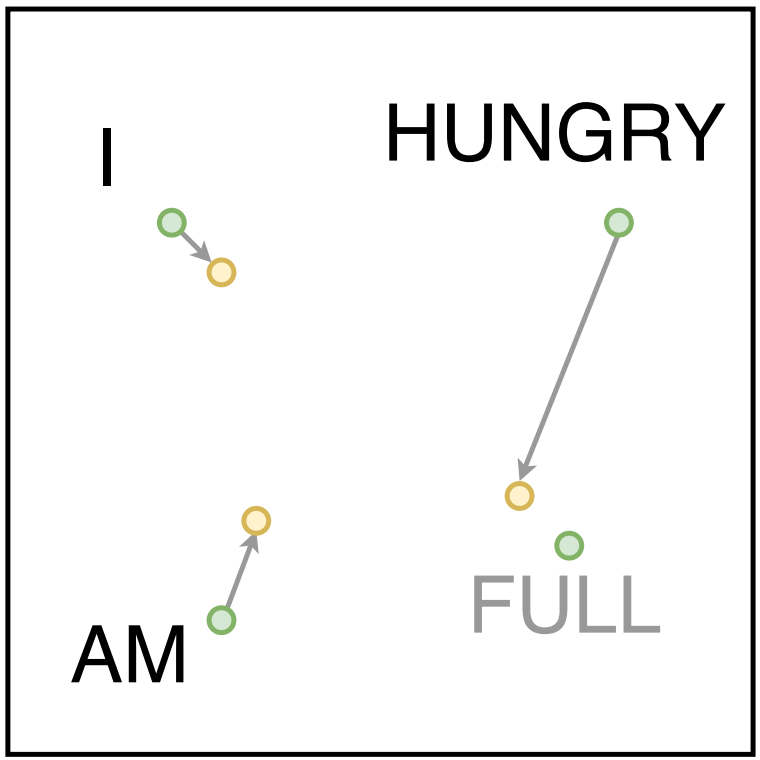
Adversarial Text Framework

We propose another method in the embedding space.

Vocabulary is represented by a point ○ in a high dimensional space. Each word of `I AM HUNGRY` is first mapped into embedding space.

Adversarial Text Framework

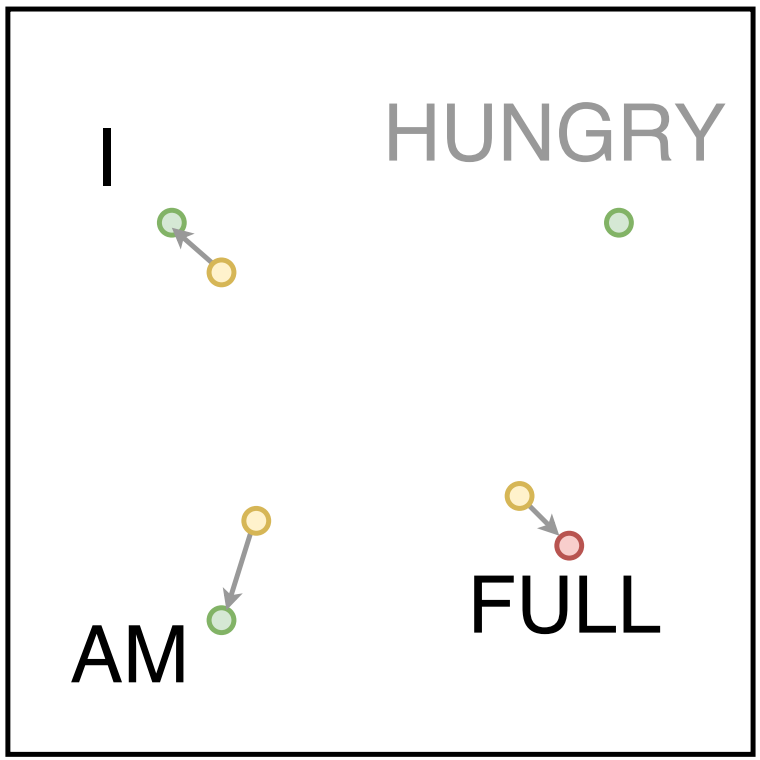
We propose another method in the embedding space.



Each point of the input word is perturbed to a new position ○ following a small displacement calculated by our framework.

Adversarial Text Framework

We propose another method in the embedding space.



We then replace each ○ with its nearest neighbor since ○ usually does not correspond to a word. After the nearest neighbor search, we got `I AM FULL`.

Results On Word-Level

Method	Dataset	Accuracy				
		ϵ	0.40	0.35	0.30	0.25
FGSM	IMDB		0.1334	0.1990	0.4074	0.6770
	Reuters-2		0.6495	0.7928	0.9110	0.9680
	Reuters-5		0.5880	0.7162	0.7949	0.8462
		ϵ	15	30	50	100
FGVM	IMDB		0.8538	0.8354	0.8207	0.7964
	Reuters-2		0.7990	0.7538	0.7156	0.6523
	Reuters-5		0.7983	0.6872	0.6085	0.5111
		ϵ	20	30	40	50
DeepFool	IMDB		0.8298	0.7225	0.6678	0.6416
	Reuters-2		0.6766	0.5236	0.4910	0.4715
	Reuters-5		0.4034	0.2222	0.1641	0.1402

Table: Word-level CNN accuracy under different parameter settings. ϵ is the noise scaling factor.

Case Study: DeepFool I

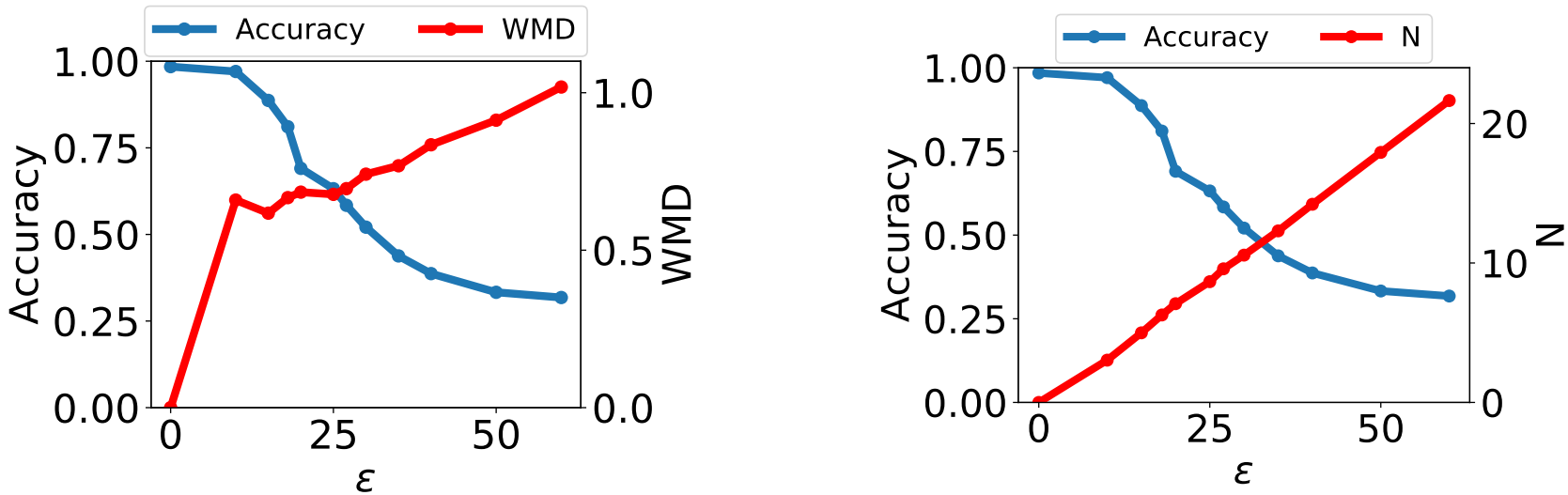


Figure: Word-level model's accuracy with varying DeepFool overshoot value. The WMD and N (number of words changed) empirically show the quality of the adversarial texts. (credit: Gong, Wang, B. Li, et al. 2018)

Case Study: DeepFool II

0.0556 1 (0.77%)	U . K . MONEY MARKET GIVEN FURTHER 68 ~~MLN~~ ARL STG HELP The Bank of England said it provided the market with a further 68 mln stg assistance this afternoon , **[...]**
0.1762 8 (2.93%)	GERMAN BANKERS ' REMARKS ~~REVIVE~~ AXIOM TALK OF ~~RATE~~ FROM CUT **[...]** discussion , ; currency dealers said . **[...]** required cuts in interest ~~rates~~ higher . Separately , West Berlin state central bank president Dieter ~~Hiss~~ Thein told journalists **[...]** forecast ~~on~~ out interest rates , however . **[...]** It allocated 6 . 1 billion marks in new liquidity , much less than the ~~14 .~~ 9 ... 9 billion leaving the market as a prior pact expired . **[...]** Koehler said in a speech in **[...]** regardless of whether central ~~banks~~ banking intervened or ~~exchange~~ forex rates fell . " **[...]**
0.4406 12 (6.14%)	ITALY ~~DEFICIT~~ NOT DUE TO ~~LIBERALIZATION~~ SOUNDSCAPE - ~~MINISTER~~ GOVERNOR Italy ' s Foreign Trade Minister ~~Mario~~ Nintendo ~~<unk>~~ monk,commenting on speculation in the Italian press , said a sharp balance of payments ~~deficit~~ spending in May **[...]** - bearing deposits ~~on~~ down foreign securities purchases . " The deficit can be better attributed to premature and delayed foreign ~~trade~~ five payments and receipts (leads and lags) rather than capital outflow to portfolio investment ~~<unk>~~ Hippo_Tron ~~<unk>~~ Libera_me said in a statement . **[...]** " non - banking ~~capital~~ investment ~~outflows~~ cashflows <unk> " In practice , it seems that there has been a constant flow of capital to foreign securities or investments outside our borders ~~<unk>~~ cat_girl25 said the newspaper . **[...]**

Figure: Adversarial texts sample from Reuters-5 dataset. Original is the original token, replaced is the adversarial token. **[...]** denotes omitted tokens due to space constraint.

More results: https://gongzhitaao.org/adversarial-text

Transferability

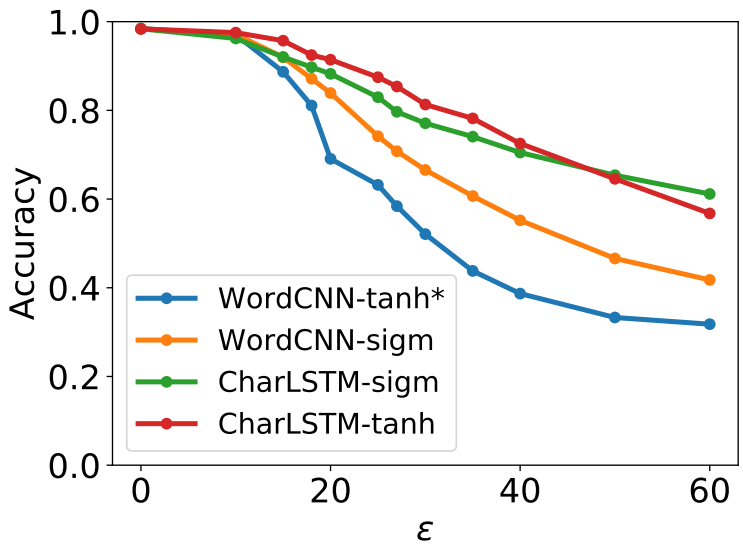


Figure: Transferability of adversarial texts generated via our framework on word-level.

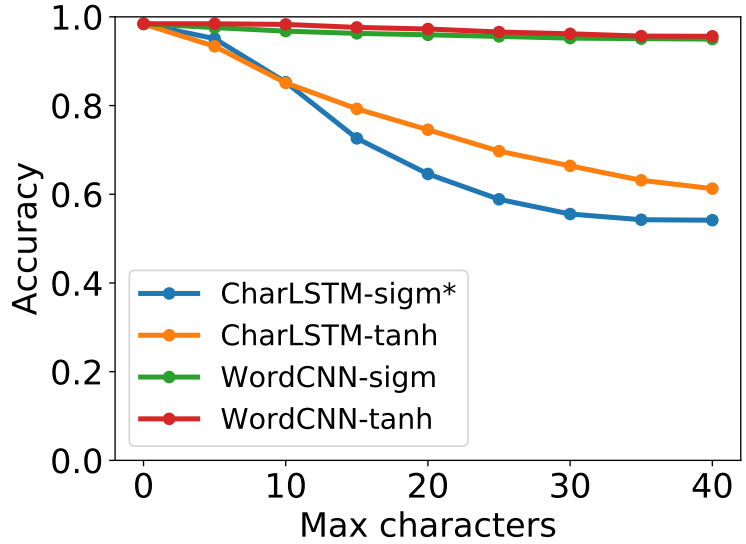


Figure: Transferability of adversarial texts generated via Hotflip on character-level.

* denotes the target model. (credit: Gong, Wang, B. Li, et al. 2018)

Outline

Overview

Figure: Objects in weird poses. (credit: Alcorn et al. 2018)

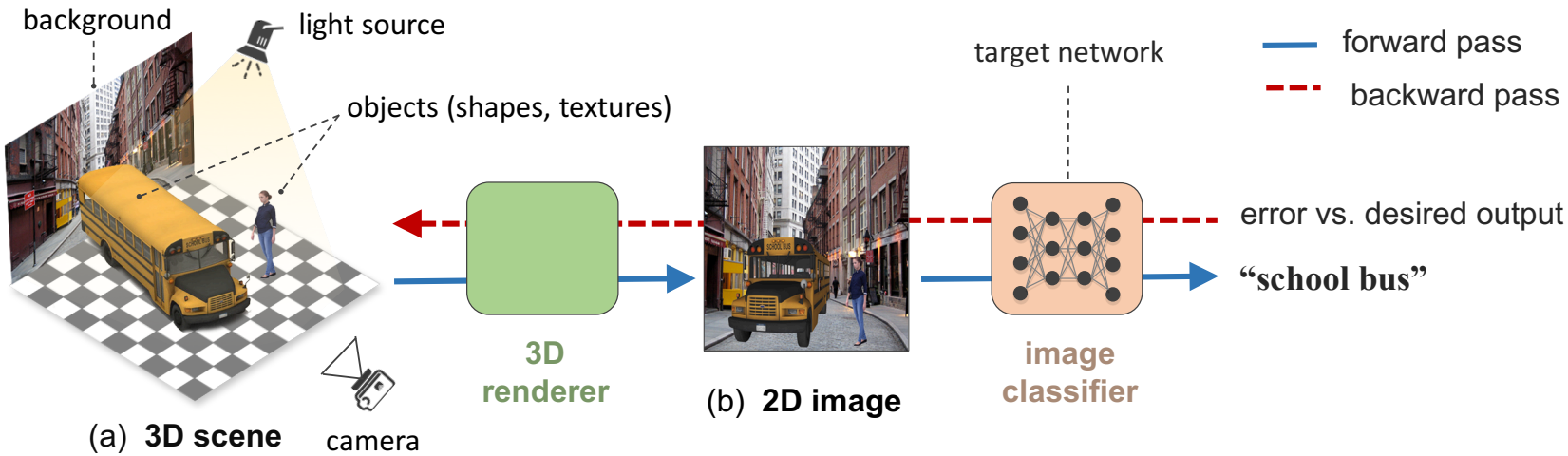
Gist

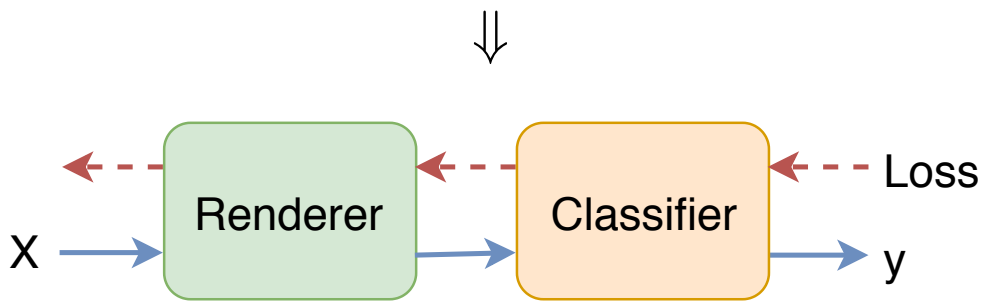
A *descriptive* study on the adversarial pose properties:

1. Effectiveness. Only 3% are correctly recognized.
2. Imperceptible. Small rotation (10.30° in yaw) results in an adversarial sample.
3. Good transferability. 99% against Inception-v3 transfer to AlexNet and ResNet-50, 75% transfer to YOLO-v3.
4. Adversarial training is not a silver bullet.

Intuition: https://gongzhitaao.org/strike-with-a-pose

Framework





X pose parameters, 6D, $(x, y, z, \theta_x, \theta_y, \theta_z)$

y prediction, a probability distribution over all labels.

Methods

Random search Randomly sample the 6D space.

Gradient descent

$$X_{k+1} = X_k + \nabla_{X_k} L(y_k, \widetilde{y})$$

- Differentiable renderer, neural renderer Kato et al. 2018
- Non-differentiable renderer, ModernGL Dombi 2019

Random Search

The distributions of each pose parameters for high-confidence ($p \geq 0.7$) correct/wrong classifications. (credit: Alcorn et al. 2018)

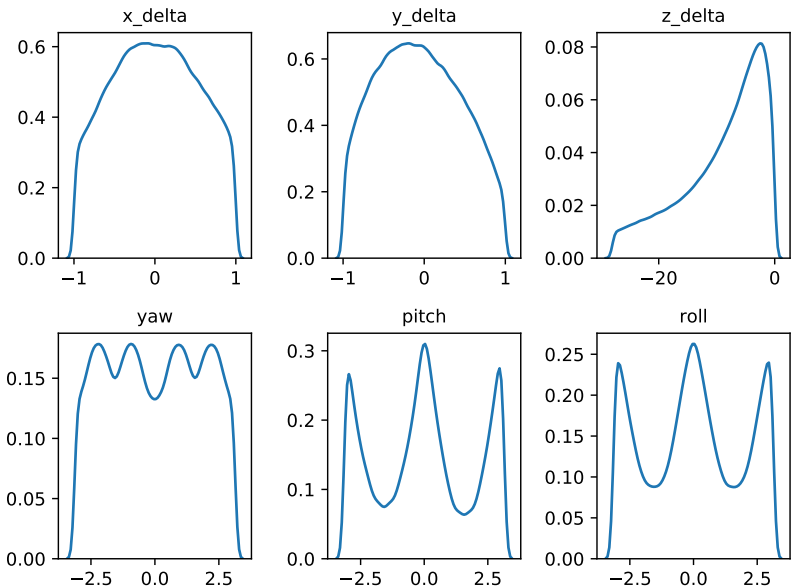


Figure: Correct

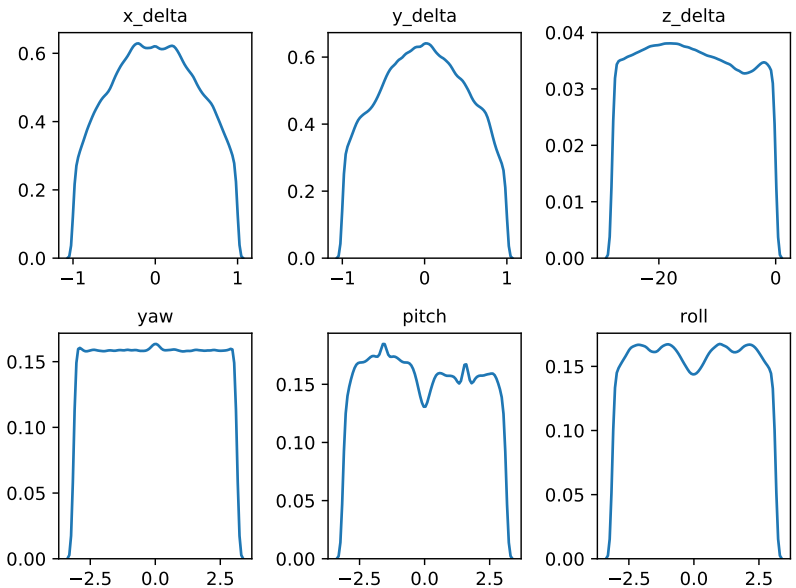
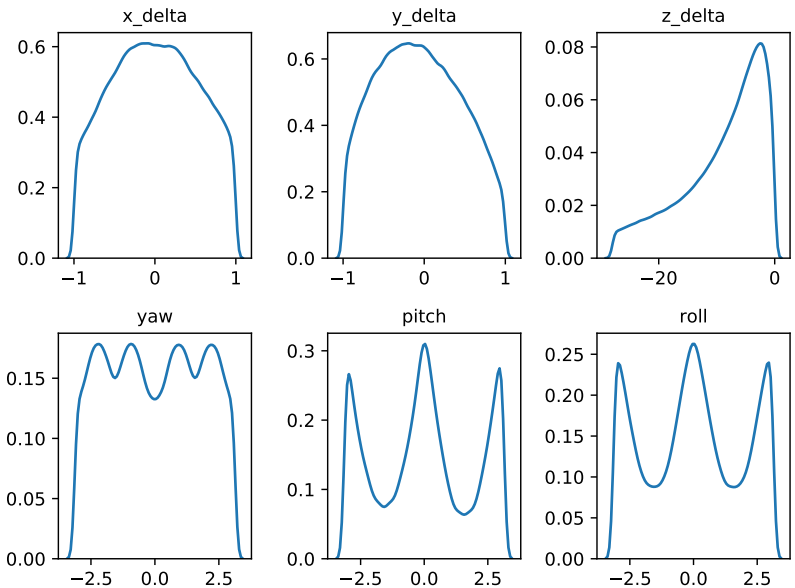


Figure: Wrong

Random Search

The distributions of each pose parameters for high-confidence ($p \geq 0.7$) correct/wrong classifications. (credit: Alcorn et al. 2018)



Parameter	Fail %	Δ_{min}
x_δ	42	2.0
y_δ	49	4.5
z_δ	81	5.4%
θ_y	69	10.31°
θ_p	83	8.02°
θ_r	81	9.17°

Figure: Correct

Methods Comparison

ZRS: z-focused random search
FD-G: finite difference approximated gradient
DR-G: differentiable renderer

	Hit Rate %	Target Probability
ZRS	78	0.29
FD-G	92	0.41
DR-G†	32	0.22

Problem with Adversarial Training (again)

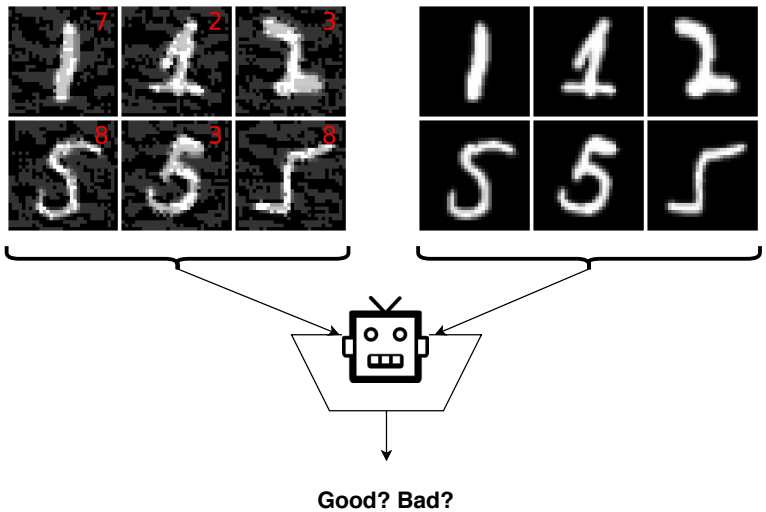
PT: AlexNet trained with vanilla ImageNet
AT: training data augmented with adversarial samples

	Error	PT	AT
All	Train	99.67	6.7
	Test	99.81	89.2
$p \geq 0.7$	Train	87.8	1.9
	Test	48.2	33.3

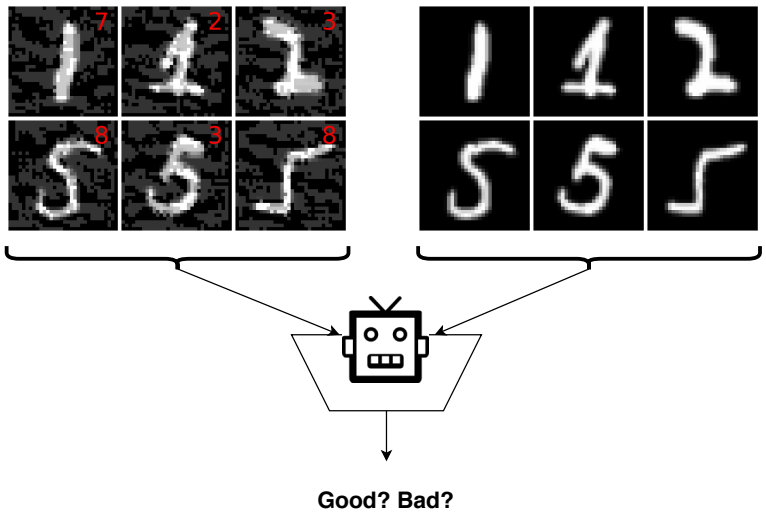
Conclusion: adversarial training does not help models generalize to unseen adversarial samples.

Outline

Work Summary

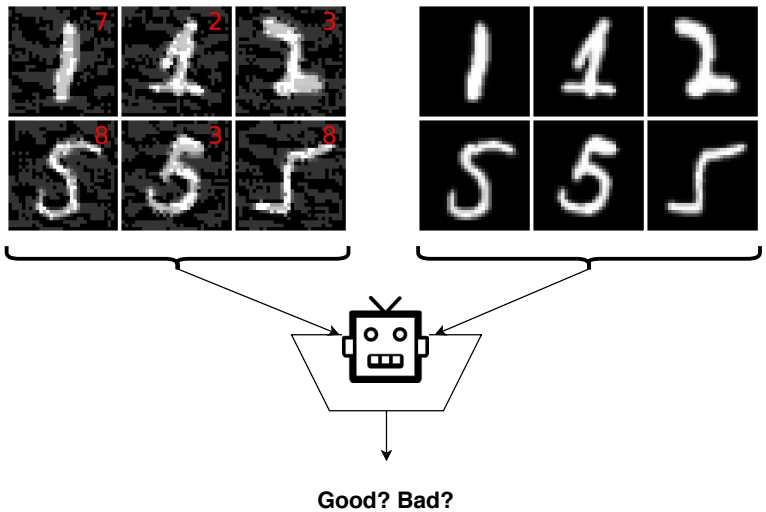


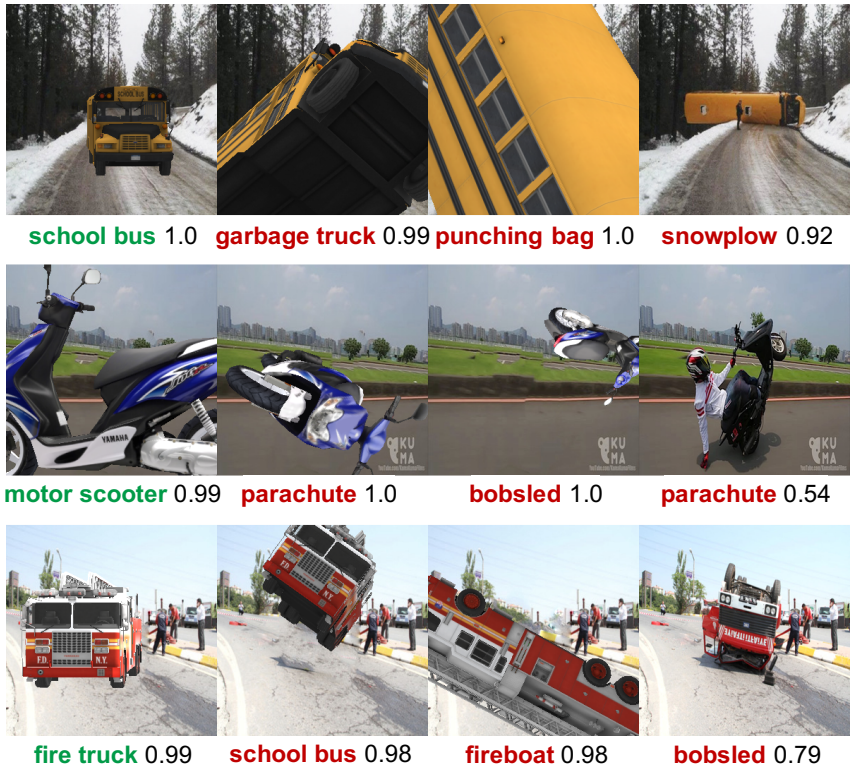
Work Summary



0.0556 1 (0.77%)	U . K . MONEY MARKET GIVEN FURTHER 68 ~~MLN~~ ARL STG HELP The Bank of England said it provided the market with a further 68 mln stg assistance this afternoon , **[...]**
0.1762 8 (2.93%)	GERMAN BANKERS ' REMARKS ~~REVIVE~~ AXIOM TALK OF ~~RATE~~ FROM CUT **[...]** discussion , ; currency dealers said . **[...]** required cuts in interest ~~rates~~ higher . Separately , West Berlin state central bank president Dieter ~~Hiss~~ Thein told journalists **[...]** forecast ~~on~~ out interest rates , however . **[...]** It allocated 6 . 1 billion marks in new liquidity , much less than the ~~14 .~~ 9 ... 9 billion leaving the market as a prior pact expired . **[...]** Koehler said in a speech in **[...]** regardless of whether central ~~banks~~ banking intervened or ~~exchange~~ forex rates fell . " **[...]**
0.4406 12 (6.14%)	ITALY ~~DEFICIT~~ NOT DUE TO ~~LIBERALIZATION~~ SOUNDSCAPE - ~~MINISTER~~ GOVERNOR Italy ' s Foreign Trade Minister ~~Mario~~ Nintendo ~~<unk>~~ monk,commenting on speculation in the Italian press , said a sharp balance of payments ~~deficit~~ spending in May **[...]** - bearing deposits ~~on~~ down foreign securities purchases . " The deficit can be better attributed to premature and delayed foreign ~~trade~~ five payments and receipts (leads and lags) rather than capital outflow to portfolio investment ~~<unk>~~ Hippo_Tron ~~<unk>~~ Libera_me said in a statement . **[...]** " non - banking ~~capital~~ investment ~~outflows~~ cashflows <unk> " In practice , it seems that there has been a constant flow of capital to foreign securities or investments outside our borders ~~<unk>~~ cat_girl25 said the newspaper . **[...]**

Work Summary





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Future Work

Image credit Karparthy 2016

Machine detects

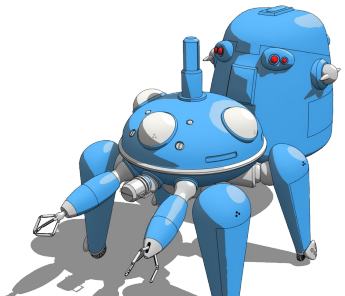
- objects
- faces
- figure components
- ...

Future Work

Image credit Karparthy 2016

Cannot understand

- mirror
- shadows
- jokes
- ...



After Graduation

Fall 2019: Research Engineer at Google DeepMind (Montreal)

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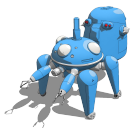

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