The University of Texas at Austin
Electrical and Computer Engineering
Cockrell School of Engineering

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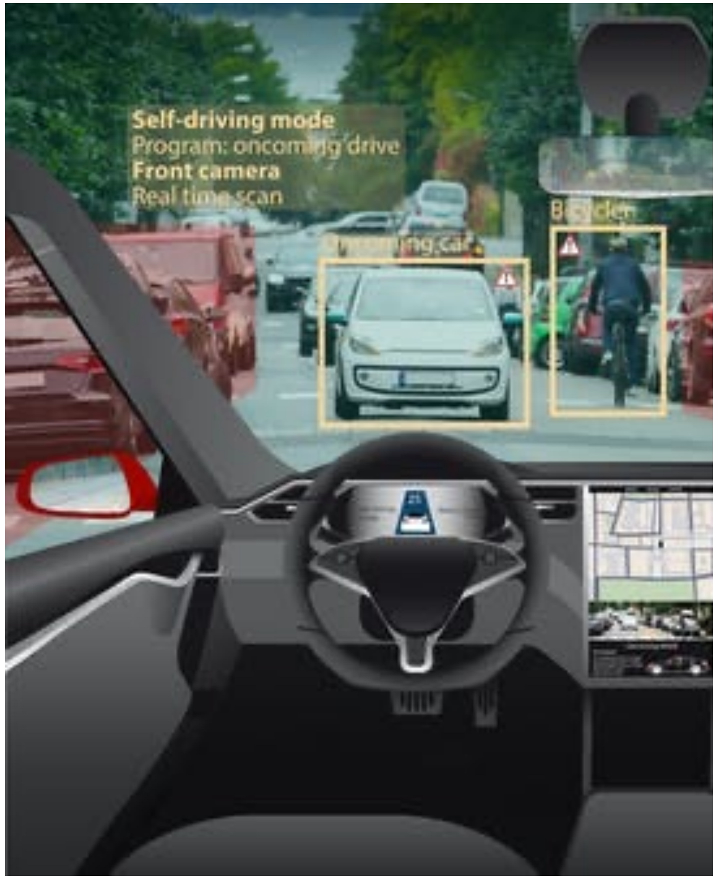
ADVANCED TOPICS IN COMPUTER VISION

Atlas Wang
Associate Professor, The University of Texas at Austin

Visual Informatics Group@UT Austin
https://vita-group.github.io/

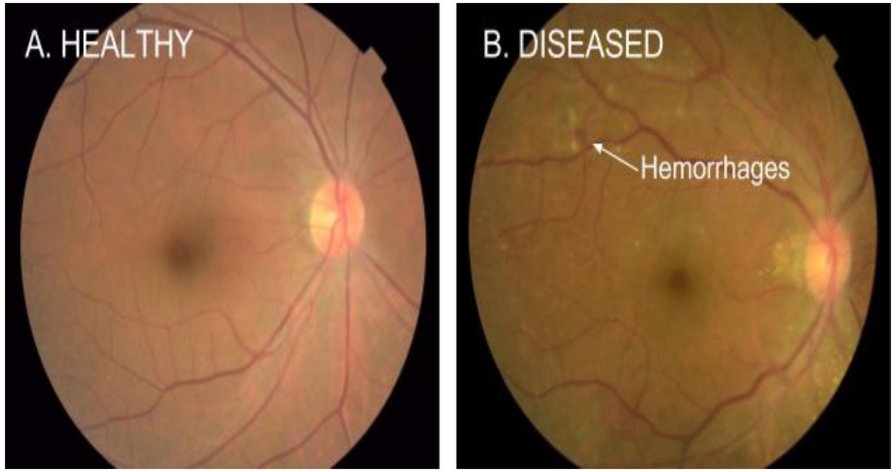
Trustworthy Computer Vision?

Face Recognition



Self-Driving Perception

Safe Control



Medical Diagnosis

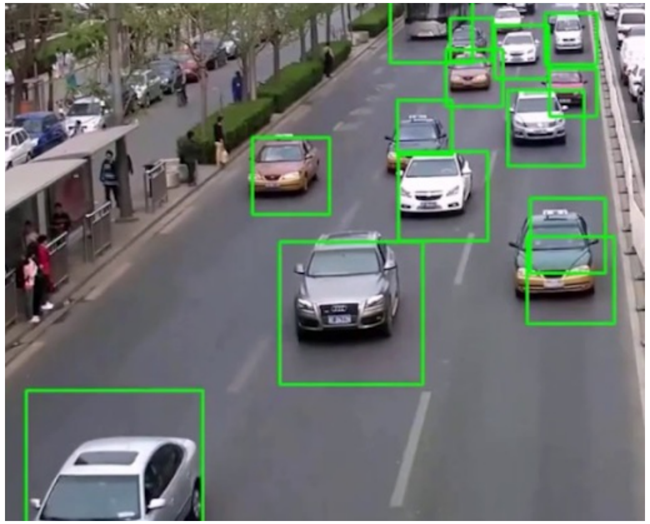
Failure Mode I: Data Violate Assumptions

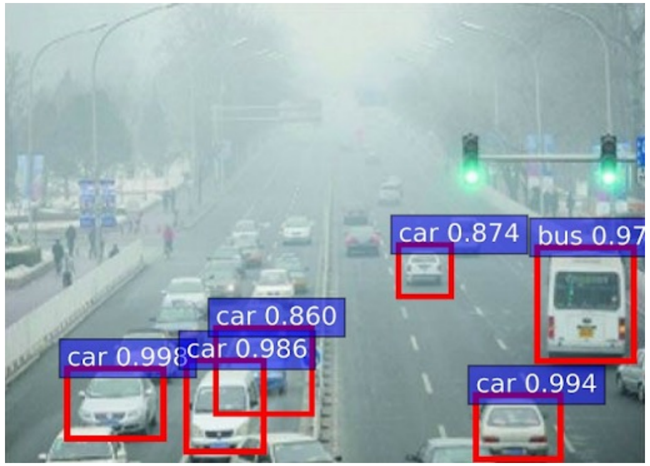
Assumption: Training data is a good representation of the testing

Training → Model → Testing

In the real world:

Failure Mode I: Data Violate Assumptions





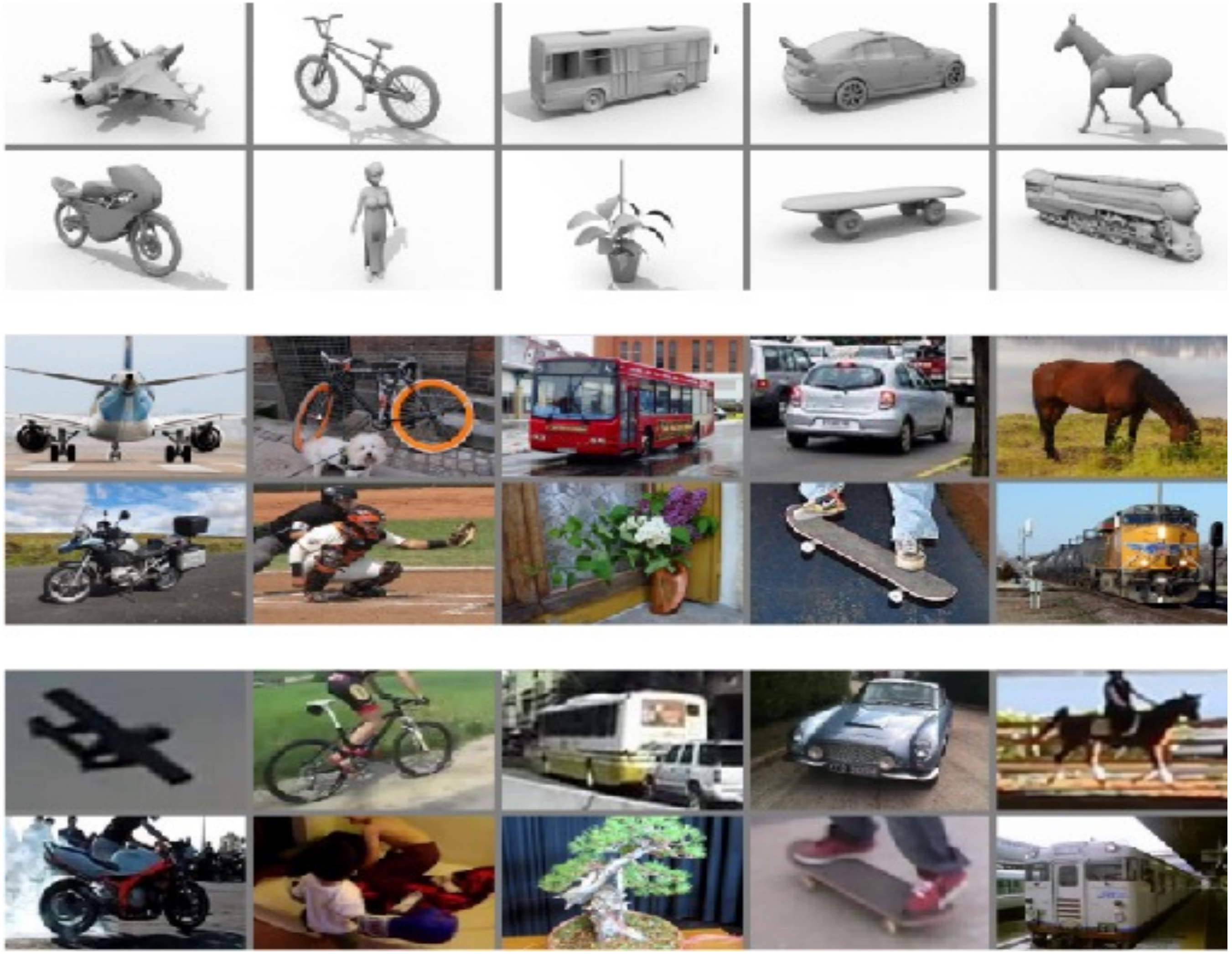
<u>**Degraded Visual Environments (DVEs)**</u>: low-resolution, rain, low-light, haze …

- **… cause degradations for visual understanding**: reduced contrasts, detail occlusions, abnormal illumination, fainted surfaces and color shift...
- It is related to, but not just, image restoration

Failure Mode I: Data Violate Assumptions

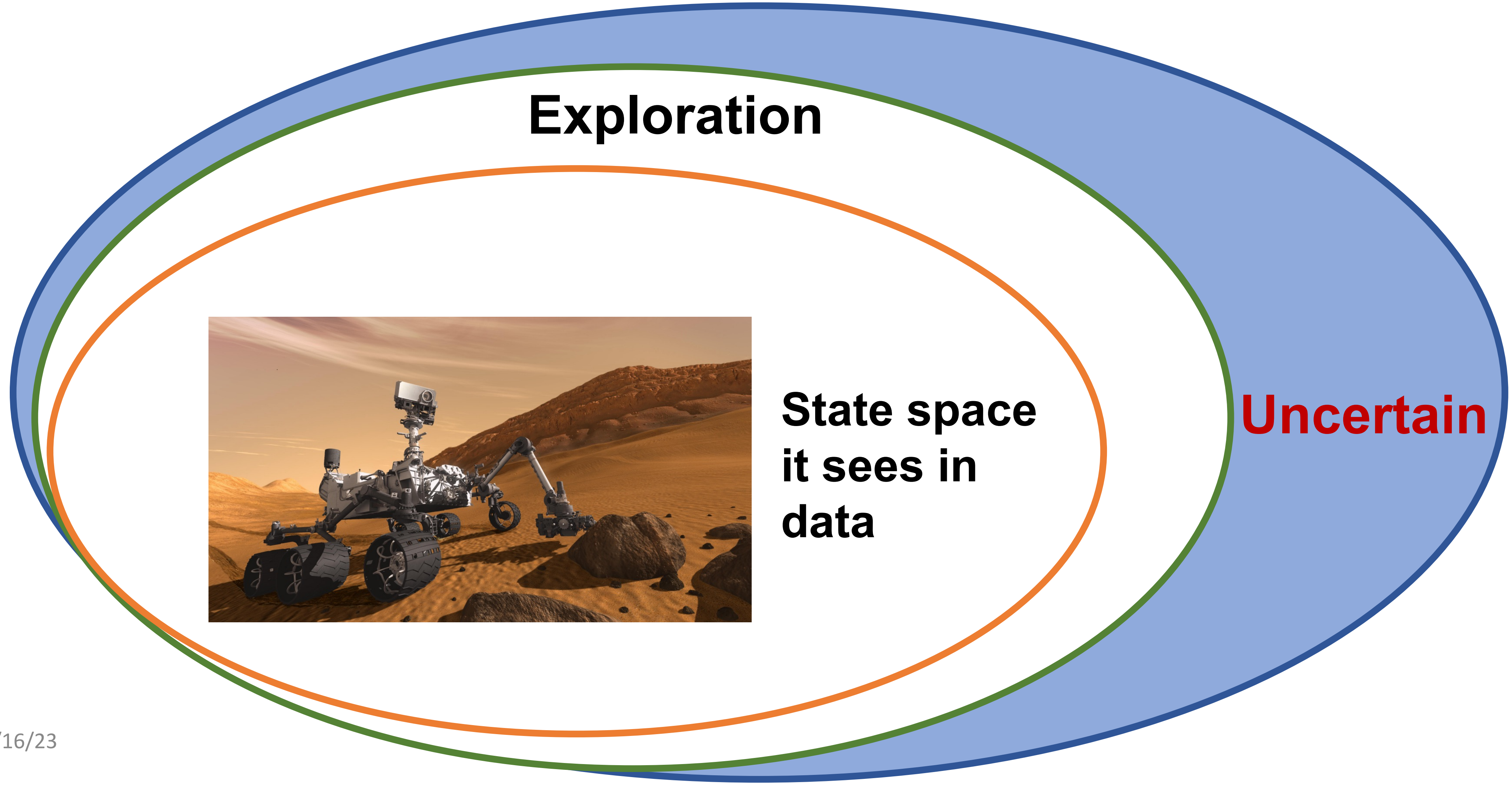
Synthetic:
(Training)

Real World:
(Testing)



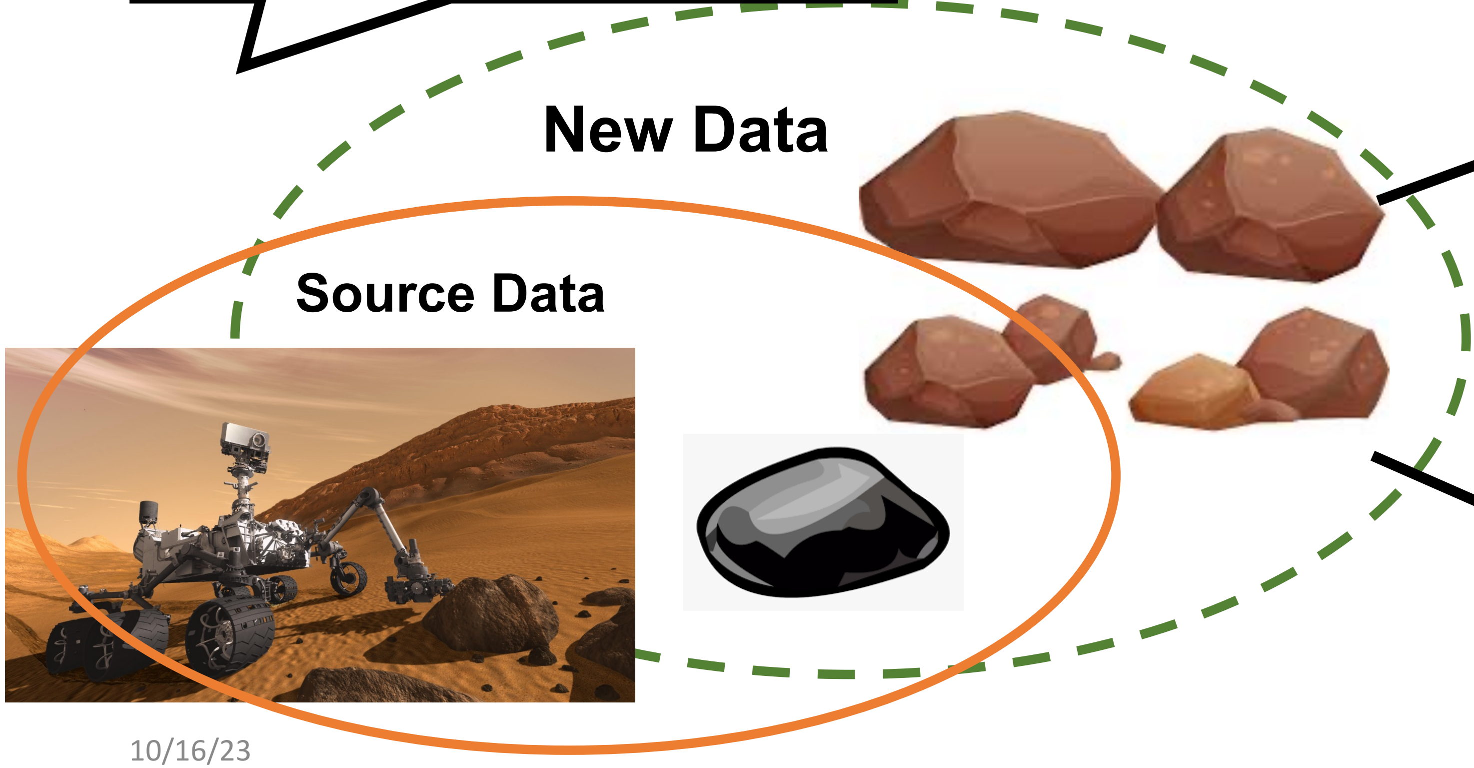
Distribution
Shift

Failure Mode II: Exploration into Unseen Domain



Key: Extrapolation and Model Confidence

Confidence in the new domain?



If I fail, I should fail gently

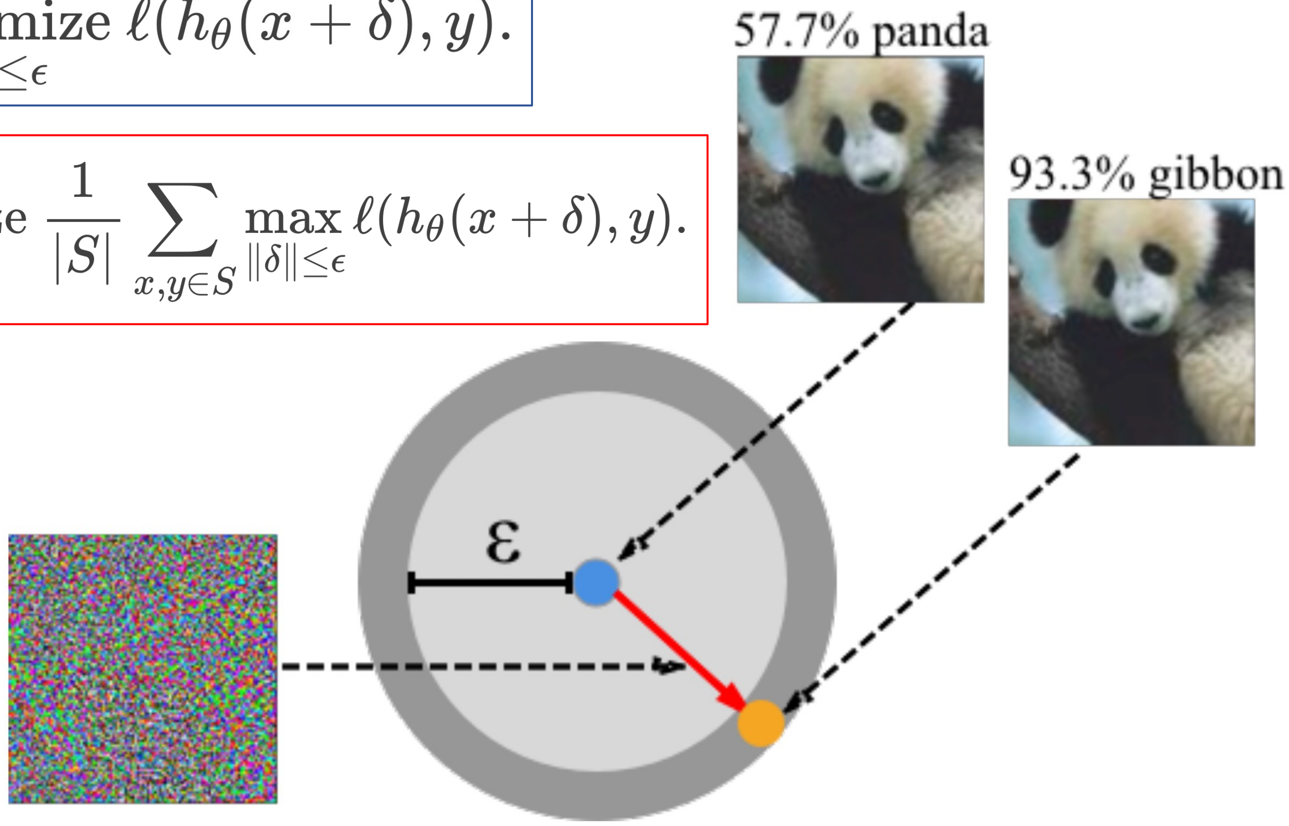
Check constraint satisfaction in the new domain

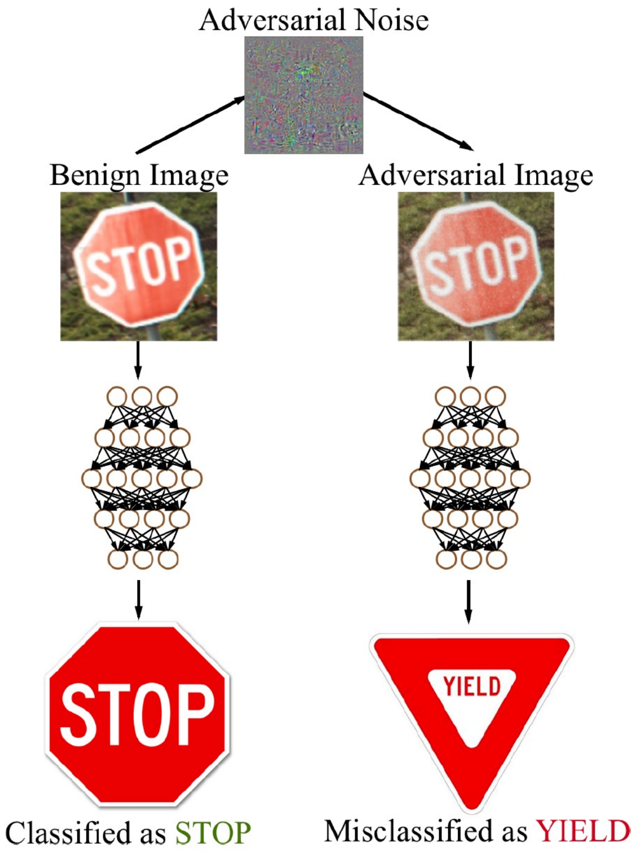
Collect more data to help

Failure Mode III: Malicious Adversary

$$\underset{\|\delta\|\leq\epsilon}{\text{maximize}}\ \ell(h_\theta(x+\delta), y).$$

$$\underset{\theta}{\text{minimize}}\ \frac{1}{|S|}\sum_{x,y\in S}\max_{\|\delta\|\leq\epsilon}\ell(h_\theta(x+\delta), y).$$





Goodfellow et al, "Explaining and Harnessing Adversarial Examples", ICLR 2015.

Failure Mode III: Malicious Adversary

Research Questions:

*How to produce **robust extrapolation** under various **unexpected** distribution shifts in computer vision?*

We will go through many possible answers:

- **Data-level**
    - Enhancing images
- **Model-level:**
    - Uncertainty quantification
    - Domain adaptation and generalization
    - Adversarial defense

Visual Degradation

Data Acquisition

Degradation before Data Acquisition

- Heavy Rain/Snow
- Underwater
- Low Light
- Haze/Sandstorm

Degradation in Data Acquisition

- Downsample
- Motion Blur
- System Noise
- Optical Distortion

Degradation after Data Acquisition

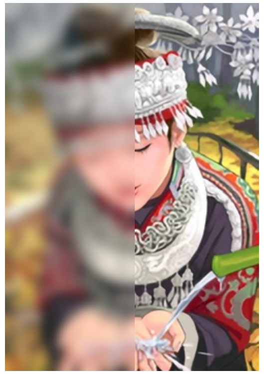
- Scratches
- Watermark
- Mildew
- Compression Loss

Restoration and Enhancement: Tons of Tasks

Underwater Enhancement

Dehazing

Inpainting



Super Resolution

Rain Removal

Denoising

Low Light Enhancement

• • • • • • • •

Learning to Enhance Images

- Data-driven training of “end-to-end” models (usually assuming “pairs”)
- Prior/physical information can still be helpful

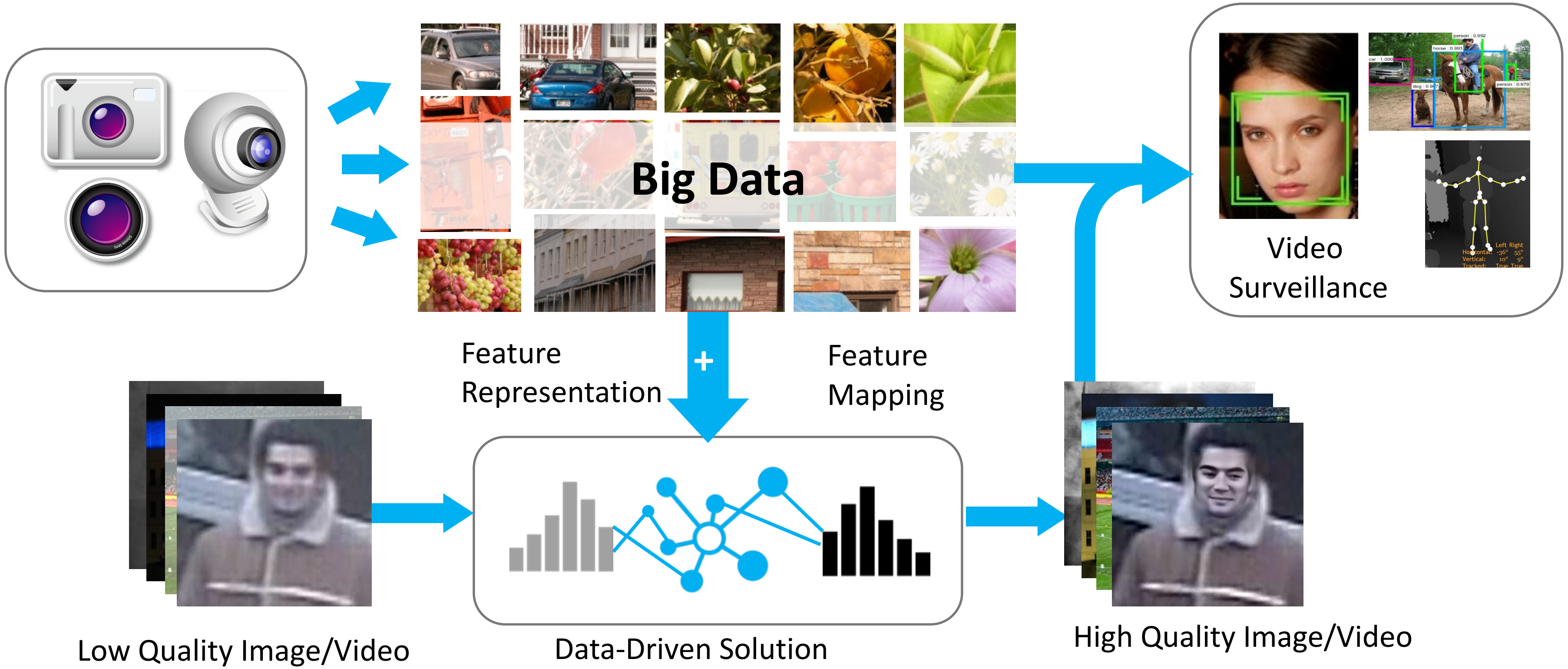


Image Denoising

- Simplest Low-Level Vision Problem

  - Noisy Measurement: $y = x + e$

=

+

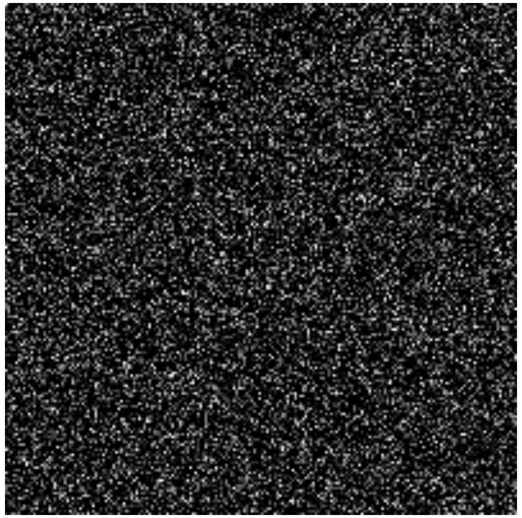


Image Denoising

- Simplest Low-Level Vision Problem

  - Estimate the clean image: $\hat{\boldsymbol{x}} = f(y)$

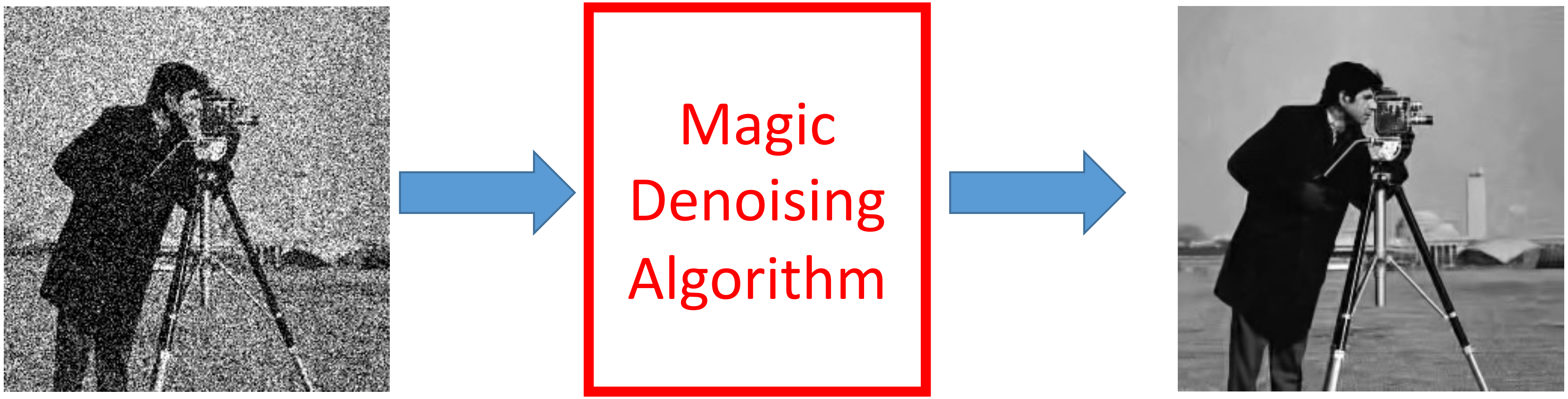


Image Denoising – Conventional Methods

- Collaborative Filtering
  - Non-local Mean, BM3D, etc

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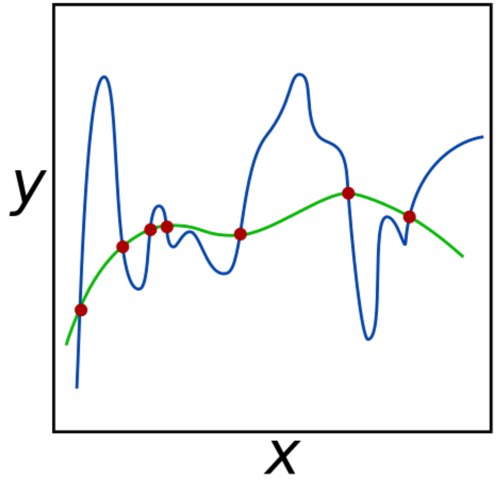
- Piece-wise Smooth
  - Total Variation, Tikhonov Regularization, etc



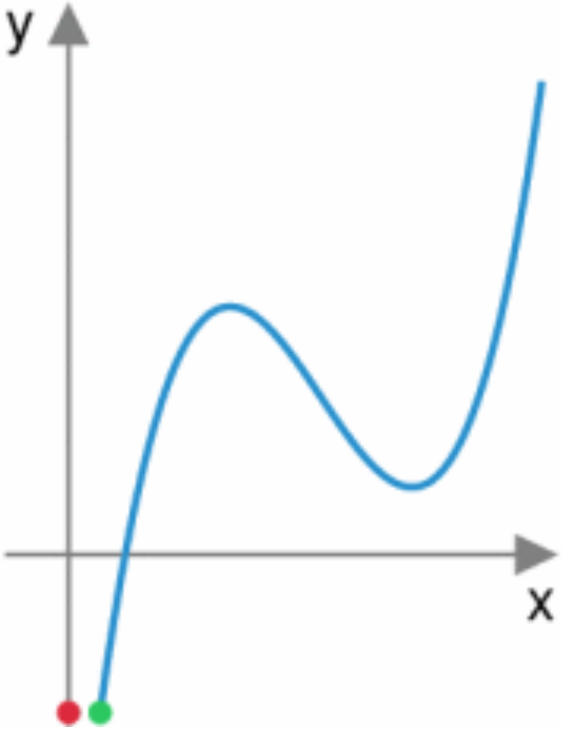
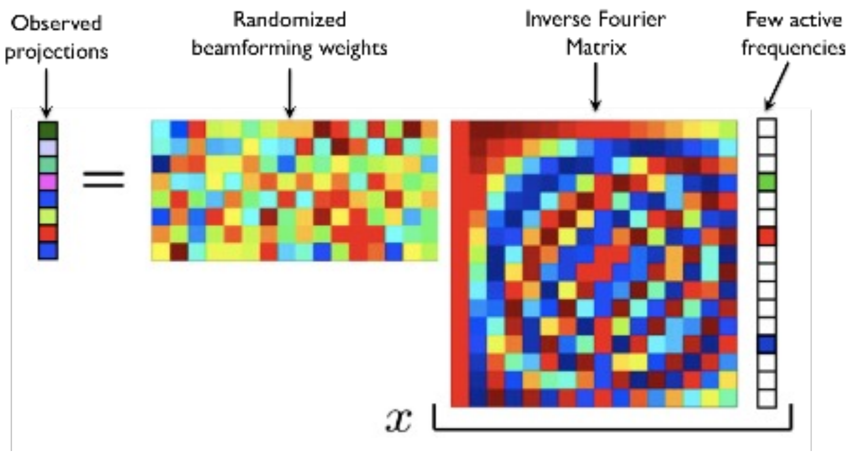
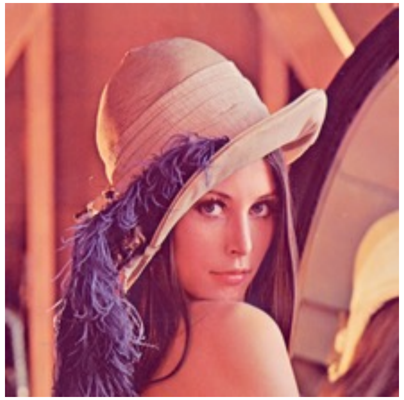
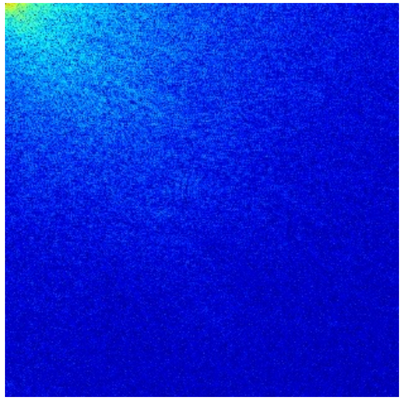


Image Denoising – Conventional Methods

- Collaborative Filtering
  - Non-local Mean, BM3D, etc
- Piece-wise Smooth
  - Total Variation, Tikhonov Regularization, etc
- Sparsity
  - Discrete Cosine Transform (DCT), Wavelets, etc
  - Dictionary Learning: KSVD, OMP, Lasso, etc
  - Analysis KSVD, Transform Learning, etc







Conventional

- **Shallow Model**
  - **Equivalently one free layer**

Deep Learning

- **Deep Model**
  - **Multiple free layers**

Conventional

- Shallow Model
  - One free layer
- **Unsupervised**
  - **No training corpus needed**
  - **Data efficient**

Deep Learning

- Deep Model
  - Multiple free layers

- **Supervised**
  - **Training corpus needed**
  - **Data inefficient**

?

Conventional

- Shallow Model
  - One free layer
- Unsupervised
  - No training corpus needed
  - Data efficient
- **Inverse Problem**
  - **Assumption & Understanding of the Data**
  - **Regularizer & structures of the Model**
  - **Flexible**

Deep Learning

- Deep Model
  - Multiple free layers

- Supervised
  - Training corpus needed
  - Data inefficient
- **Inverse Problem**
  - **Little assumption**
  - **Almost free model**
  - **Few work until recent**

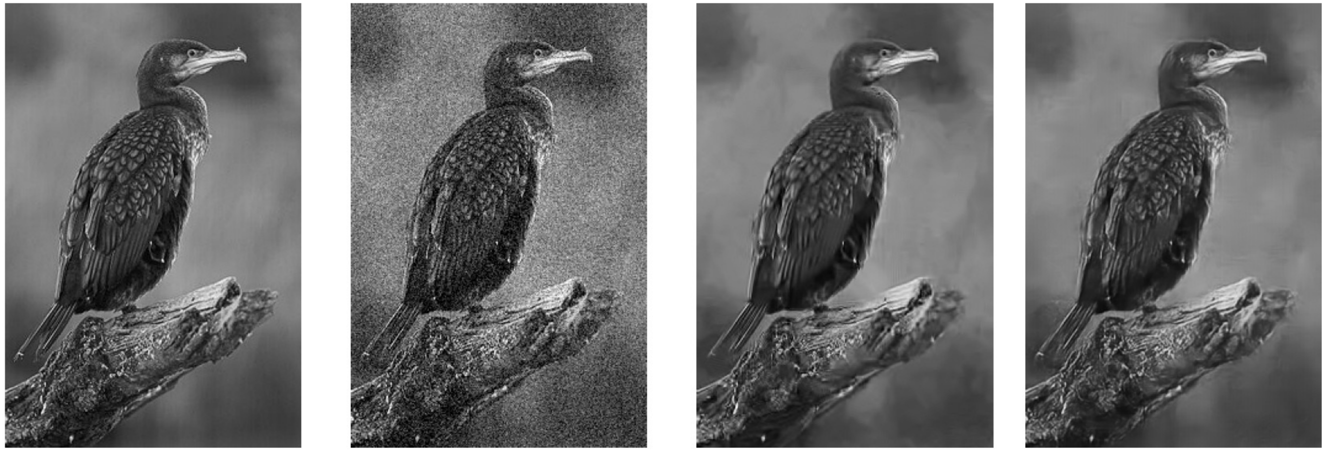
?

Image Denoising by Deep Learning

- **Natural Idea:** train a denoising autoencoder, that regresses clean images from noisy ones
- **It is not easy for deep networks to outperform classical methods such as BM3D!!**
  - BM3D is shown to be better at dealing with self-repeating regular structures
- **How to outperform BM3D using a deep network denoiser? Some verified tips:**
  - The model richness is large enough, i.e. enough hidden layers with sufficiently many hidden units.
  - The patch size is chosen large enough, i.e. a patch contains enough information to fit a complicated denoising function that covers the long tail.
  - The chosen training set is large enough
- **Other benefits of deep network denoiser:**
  - The testing speed of deep networks is much faster than BM3D, KSVD etc., benefiting from GPU.
  - Deep networks can be generalized to other noise types, if correctly supplied in training.
- Recent works show great progress!
  - **Check out Git repo: https://github.com/wenbihan/reproducible-image-denoising-state-of-the-art**

Image Denoising by Deep Learning

- **Reference:** *"Image denoising: Can plain Neural Networks compete with BM3D?"*



clean (name: 008934) | noisy ($\sigma = 25$)PSNR:20.16dB | BM3D: PSNR:29.65dB | ours: PSNR:**30.03**dB

clean (name: barbara) | noisy ($\sigma = 25$)PSNR:20.19dB | BM3D: PSNR:**30.67**dB | ours: PSNR:29.21dB

Image Deblurring

- Blurred Measurement: $y = M \otimes \boldsymbol{x}$

=

$\otimes$

$$M = \begin{bmatrix} 0 & 0 & 0 \\ 1 & 1 & 1 \\ 0 & 0 & 0 \end{bmatrix}$$

Image Deblurring

- Estimate the stable image: $\hat{\boldsymbol{x}} = f(y)$

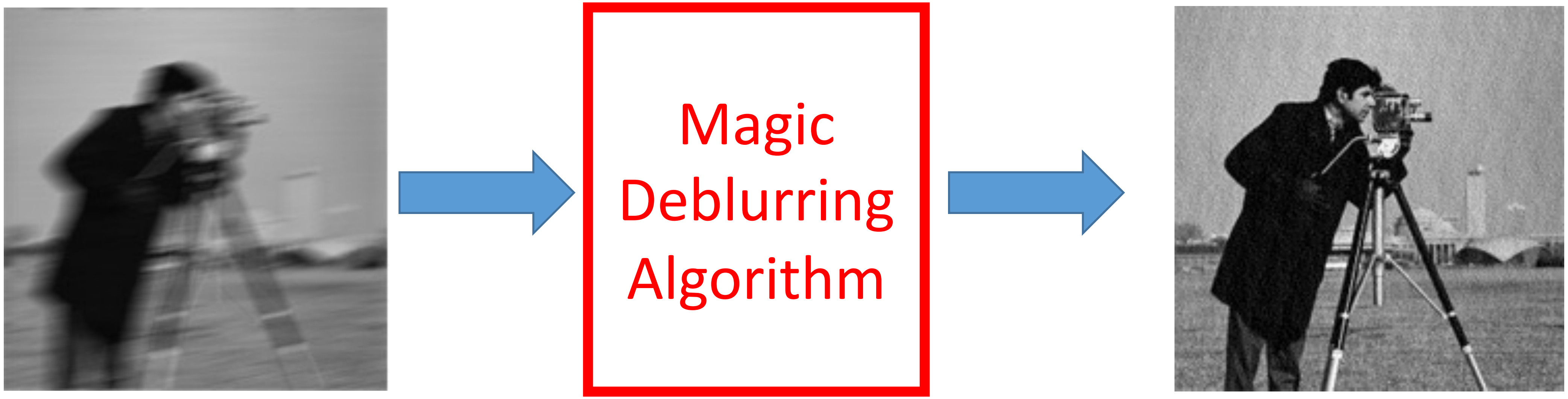


Image Deblurring

- Non-blind Image Deblurring
  - Suppose you know the blurring kernel, $\boldsymbol{M}$.
  - $\widehat{\boldsymbol{x}} = f(y, M)$
  - All training data need to have consistent $\boldsymbol{M}$, as the testing data

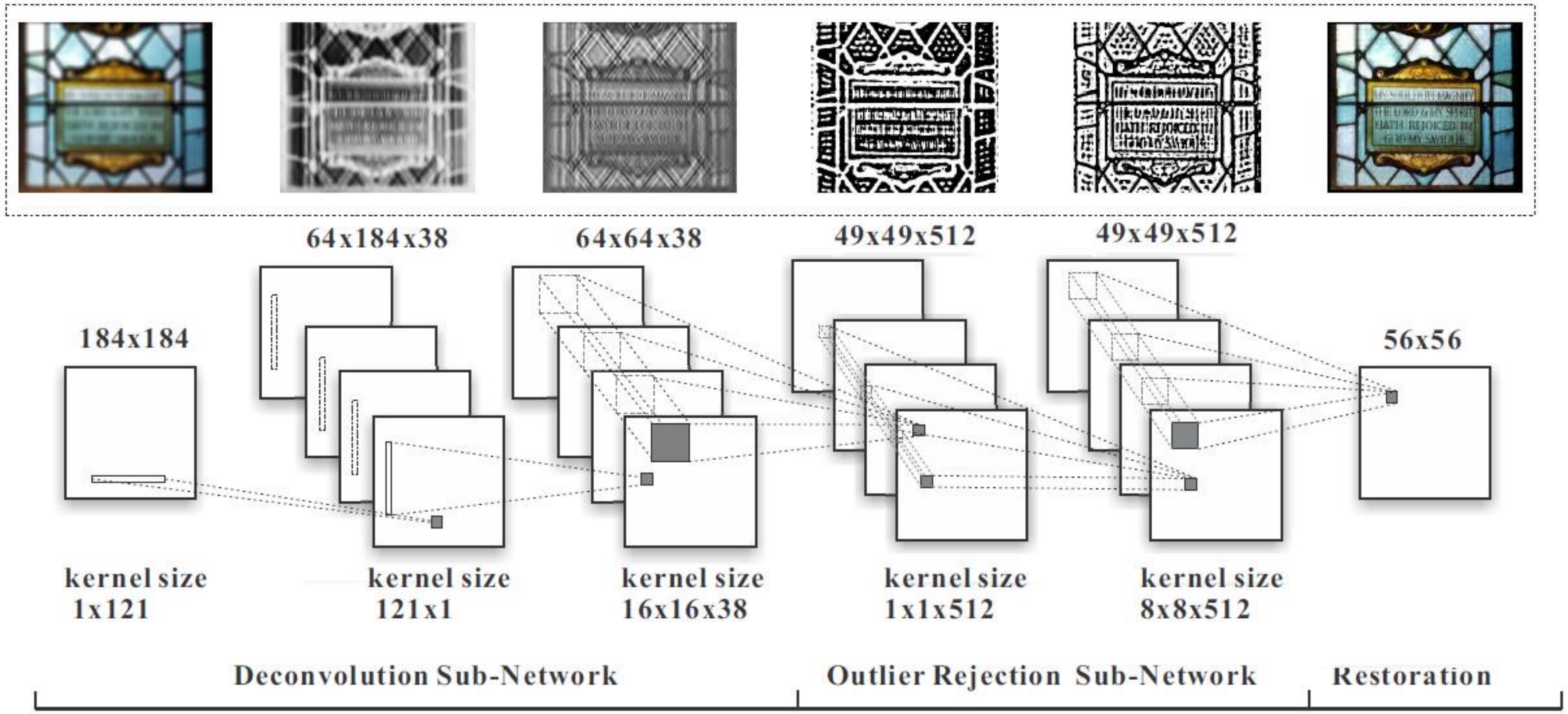
Image Deblurring

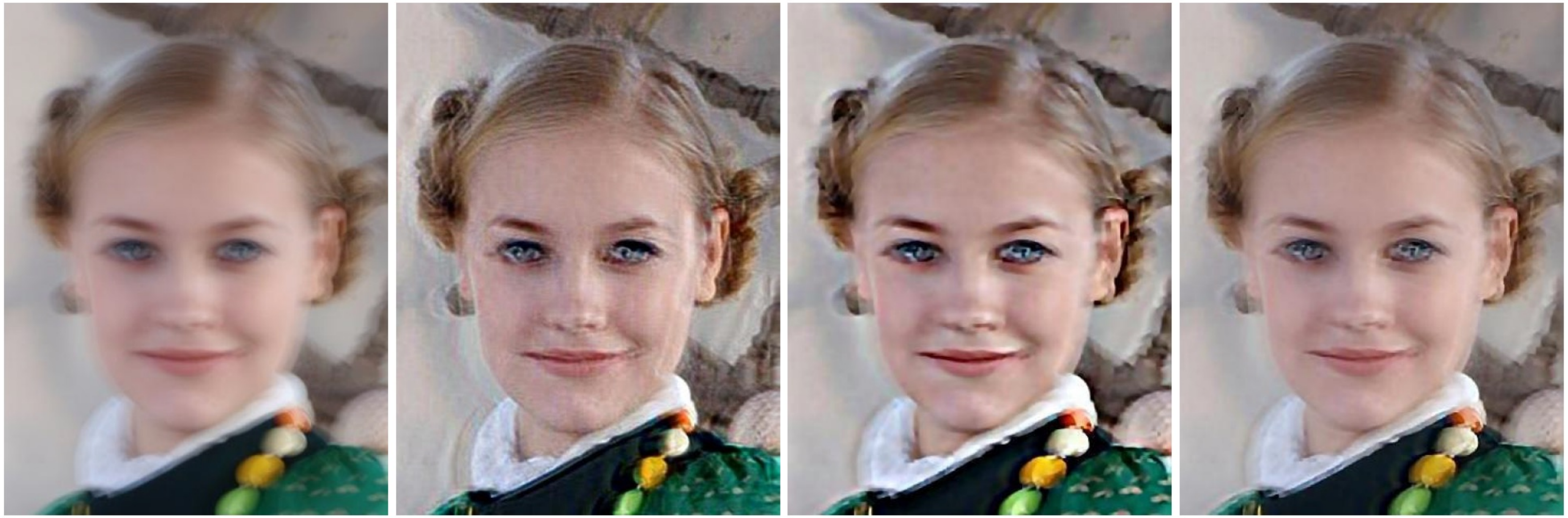
- Non-blind Image Deblurring
  - Suppose you know the blurring kernel, $\boldsymbol{M}$.
  - $\hat{\boldsymbol{x}} = f(y, M)$
  - All training data need to have consistent $\boldsymbol{M}$, as the testing data
- Blind Image Deblurring – More challenging yet practical problem
  - Estimate both the image, and the blurring kernel
  - $\{\hat{\boldsymbol{x}}, M\} = f(y)$

Image Deblurring by Deep Learning

Reference: *"Deep convolutional neural network for image deconvolution"*

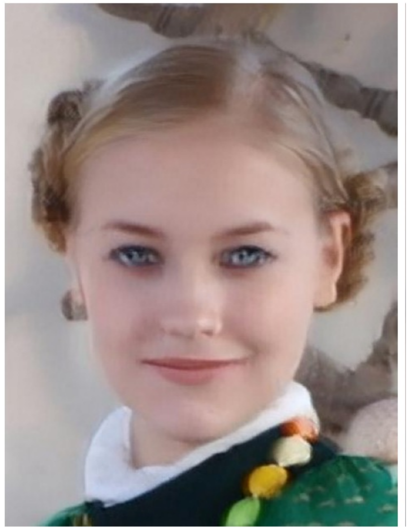
- Key Technical Features:
  - Treat deblurring as a deconvolution task, and the deconvolution operation can be approximated by a convolutional network with very large filter sizes
  - Concatenation of deconvolution CNN module with another denoising CNN module to suppress artifacts and reject outliers





(a) Blurred photo (b) Whyte *et al*. [40] (c) Krishnan *et al*. [14] (d) Sun *et al*. [18]

(e) Xu *et al*. [33] (f) Pan *et al*. [15] (g) DeepDeblur [2] (h) SRN [3]



DeblurGAN V2 (2019)

Image Super-Resolution

- Low-Resolution Measurement: $y = D * M \otimes \boldsymbol{x}$

=

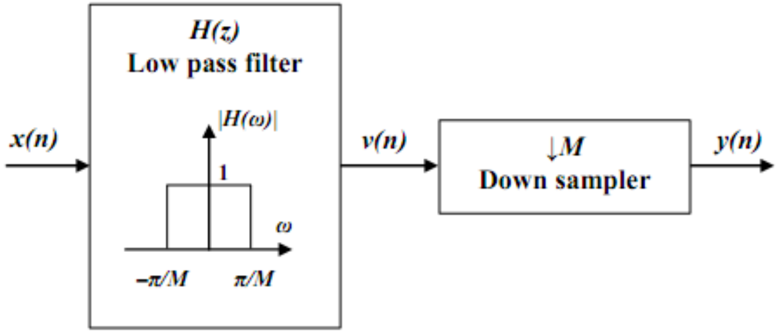


Image Super-Resolution

- Estimate the stable image: $\hat{\boldsymbol{x}} = f(y)$

Image Super Resolution by Deep Learning

Reference: *"Image super-resolution using deep convolutional networks"*

- **Key Technical Features:**
  - Learns an end-to-end mapping from low to high-resolution images as a deep CNN
  - Closely mimic the traditional SR pipeline: LR feature extraction -> coupled LR-HR feature space mapping -> HR image reconstruction

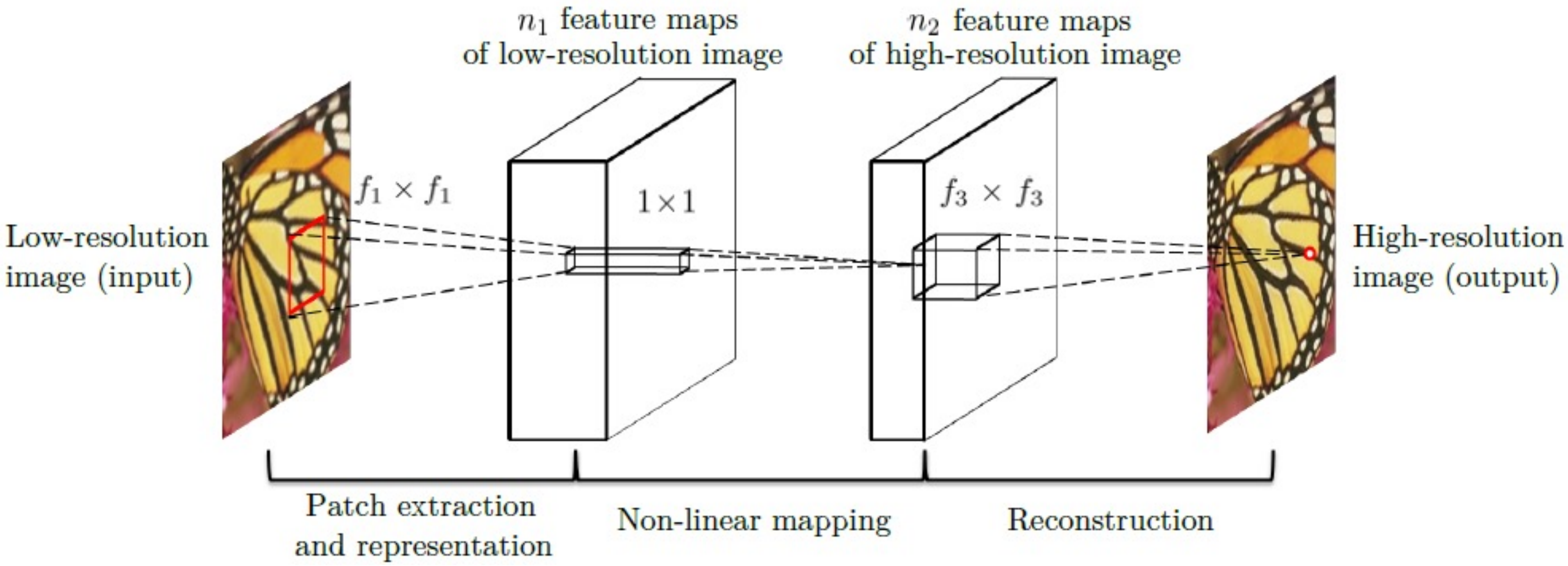
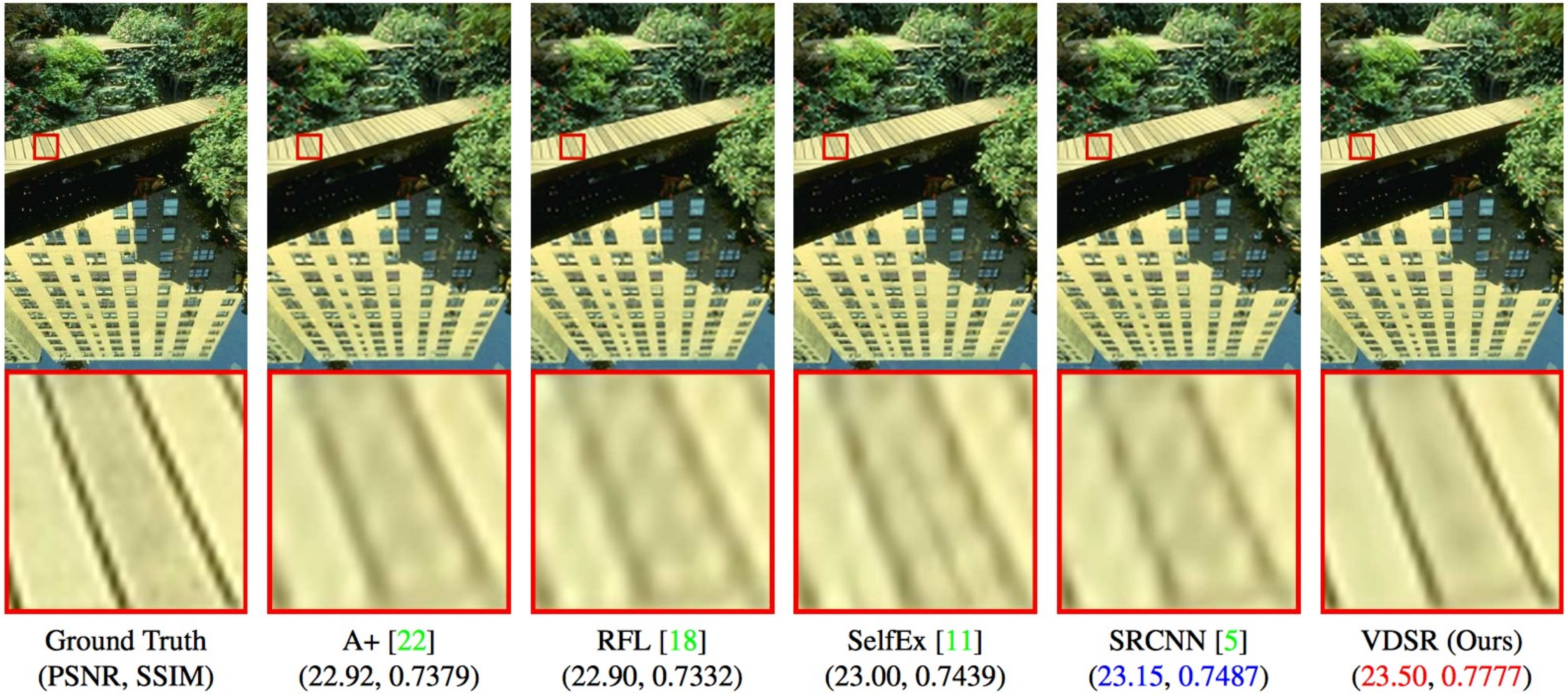


Image Super Resolution by Deep Learning (2013 – 2017)

Super-resolution results of “148026” (*B100*) with scale factor ×3 (from VDSR paper)



New Trends?

- New topic: dehazing, deraining, low light enhancement, etc.
- New goal: human perception **v.s.** machine consumption
- New setting: from supervised to unsupervised training (no “GT”)
  - … or relying on “synthetic pairs”
- New domain: medical images, infrared images, remote sensing images, etc.
- New concern: “All-in-one” adaptivity, efficient implementation, etc.

Shortage of Real-World Generalization

- Most SOTA algorithms are trained with {clean, corrupted} paired data
  - Such paired training data is usually collected by synthesis (assuming known degradation model), which typically oversimplifies the real-world degradations
  - As a result, the trained model "overfits" simpler degradation process and generalizes poorly to real visual degradations

- Real-world collection of paired data?
  - Can be done in small scale and/or in controlled lab environments
    - e.g. some recent datasets in light enhancement, and raindrop removal
  - Very difficult to "scale up", sometimes maybe impossible

VITA

EnlightenGAN: Deep Light Enhancement without Paired Supervision

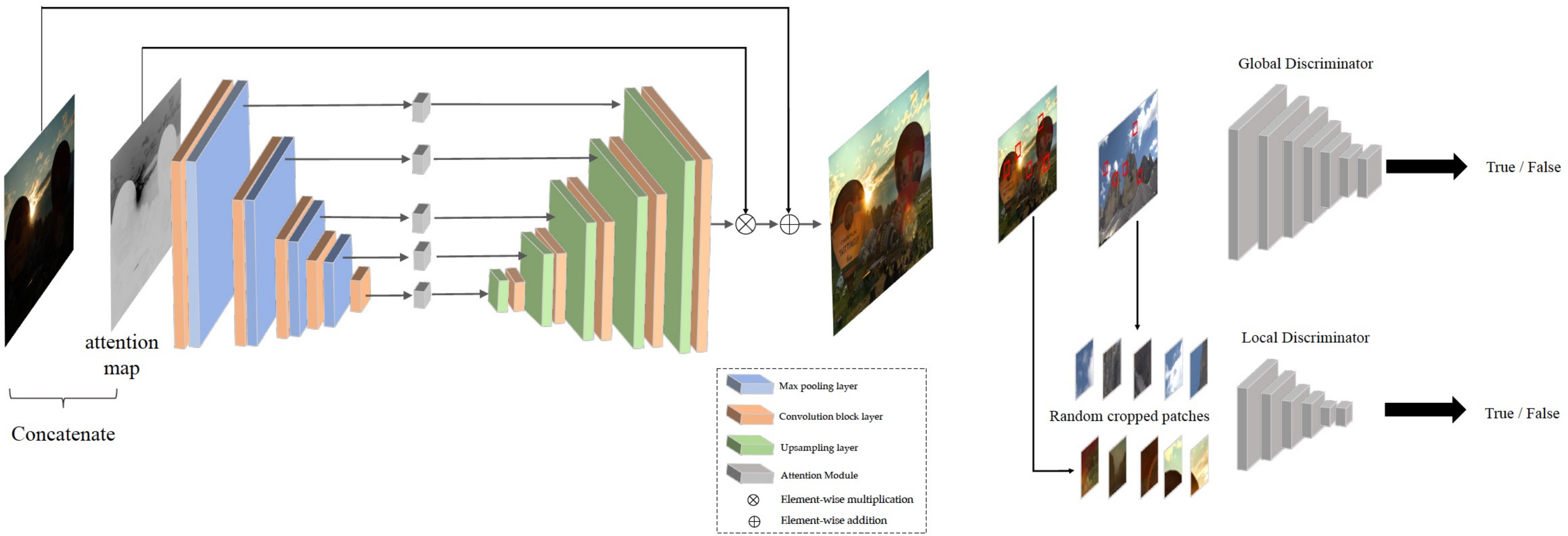
Goal: Light enhancement made automatic, adaptive, and artifact-free

From Supervised to Unsupervised Enhancement

- EnlightenGAN is the first work that successfully introduces unpaired training to low-light image enhancement.
  - It only needs one low-light set A and another normal-light set B to train, while A and B could consist of completely different images!

- What makes **Unpaired Training** unique and attractive?
  - It removes the dependency on paired training data
    - Hence enabling us to train with massive images from different domains
  - It also avoids overfitting any specific data generation/imaging protocol
    - …that previous works implicitly rely on, leading to stronger generalization.
  - It makes EnlightenGAN particularly easy and flexible to be adapted
    - when enhancing real-world low-light images from completely different/unseen domains

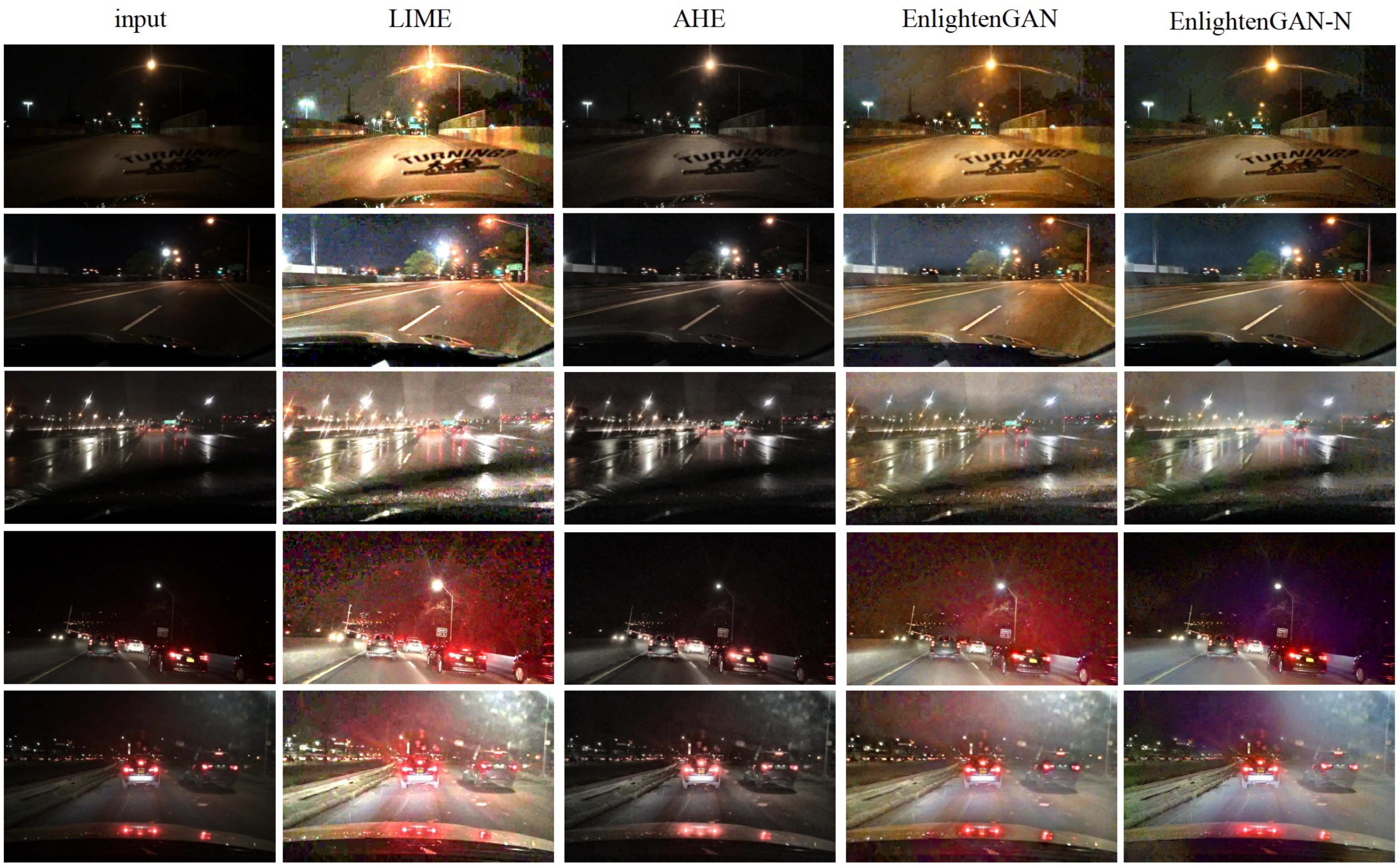
Model Architecture



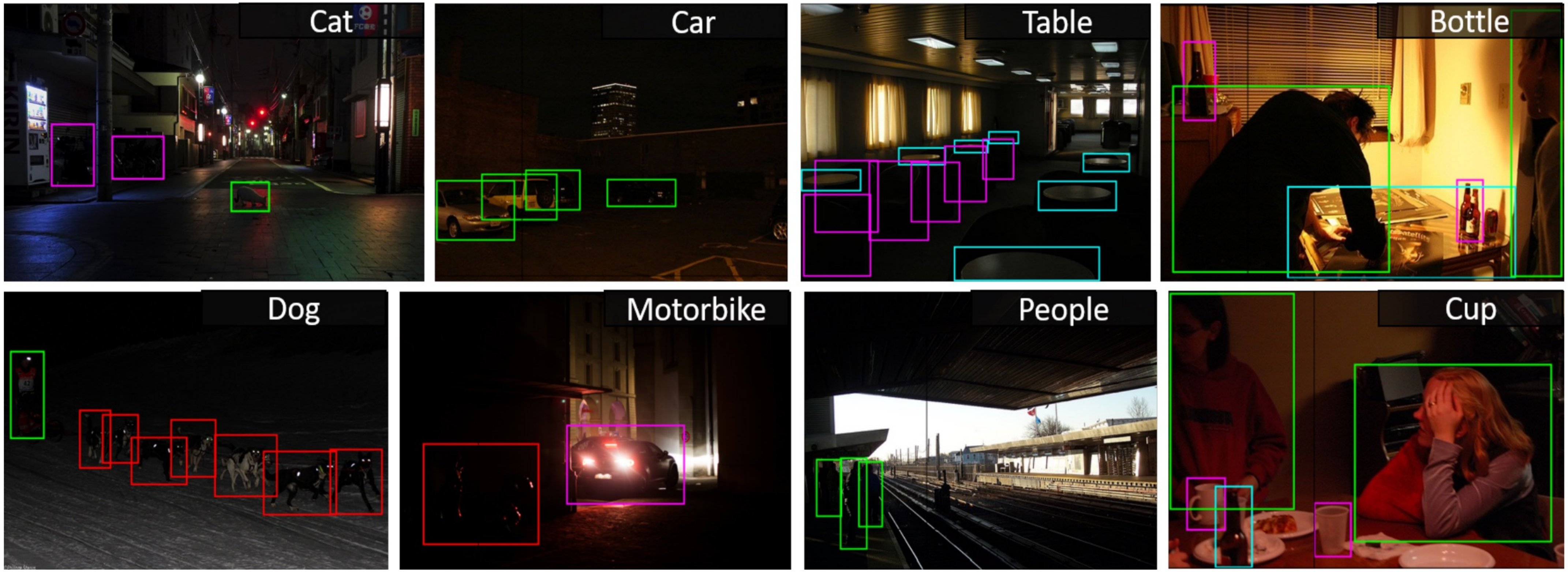
Paper: https://arxiv.org/abs/1906.06972 (pre-print, full version in TIP 2021)
Code: https://github.com/VITA-Group/EnlightenGAN

Comparison with State-of-the-Arts

[New!] Frustratingly Easy Adaptation to New Data



PreProcessing for Improving Classification



- We applying our pretrained EnlightenGAN as a pre-processing step on the testing set of the ExDark dataset , followed by passing through another ImageNet-pretrained ResNet-50 classifier.
- It improves the classification accuracy from 22.02% (top-1) and 39.46% (top-5), to 23.94% (top-1) and 40.92% (top-5) after enhancement.

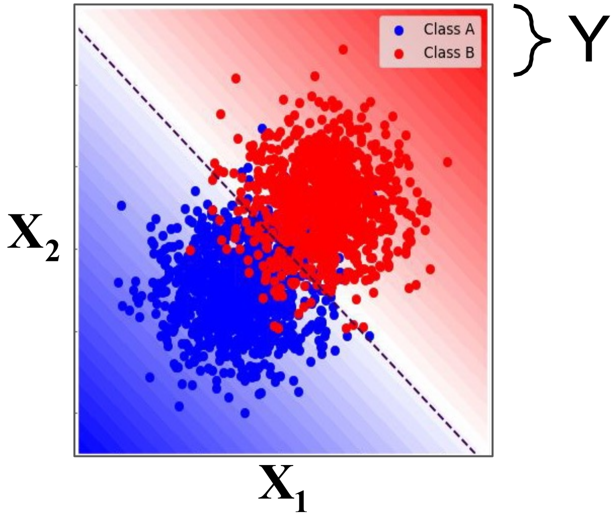
Uncertainty & Robustness for Out-of-Distribution Generalization

What do we mean by Uncertainty?

Return a distribution over predictions rather than a single prediction.

- ***Classification***: Output label along with its confidence.
- ***Regression***: Output mean along with its variance.

Good uncertainty estimates quantify ***when we can trust the model's predictions***.



$$p(\mathbf{y}|\mathbf{x})$$

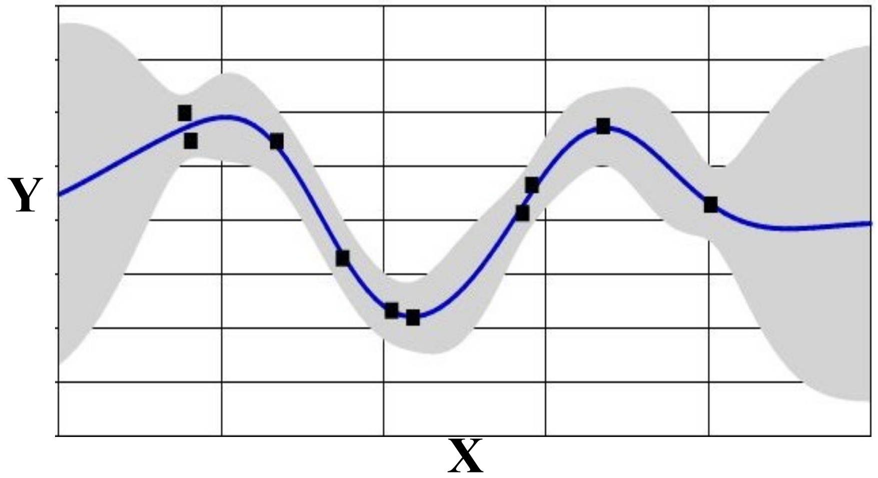


Image credit: Eric Nalisnick

What do we mean by Out-of-Distribution Robustness?

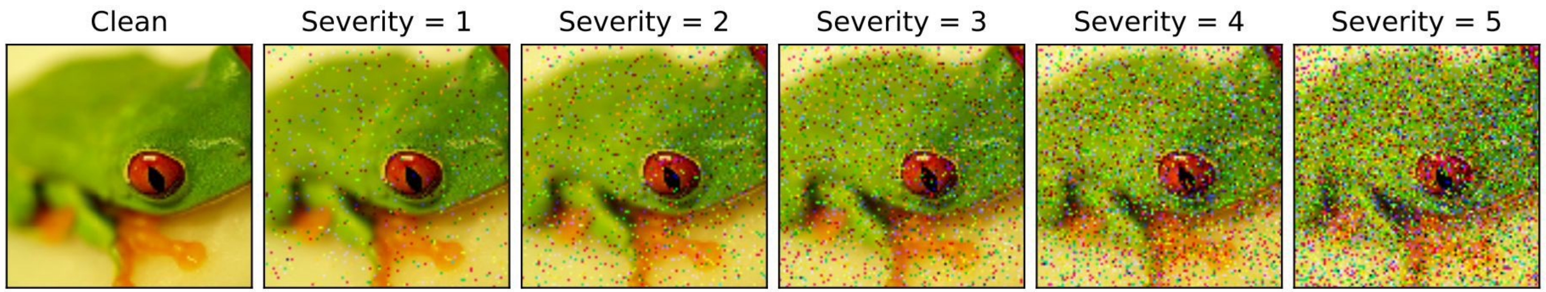
I.I.D. $p_{TEST}(y,x) = p_{TRAIN}(y,x)$

O.O.D. $p_{TEST}(y,x) \neq p_{TRAIN}(y,x)$

Examples of dataset shift:

- ***Covariate shift.*** Distribution of features p(x) changes and p(y|x) is fixed.
- ***Open-set recognition.*** New classes may appear at test time.
- ***Label shift.*** Distribution of labels p(y) changes and p(x|y) is fixed.

ImageNet-C: Varying Intensity for Dataset Shift



Increasing dataset shift

I.I.D test set

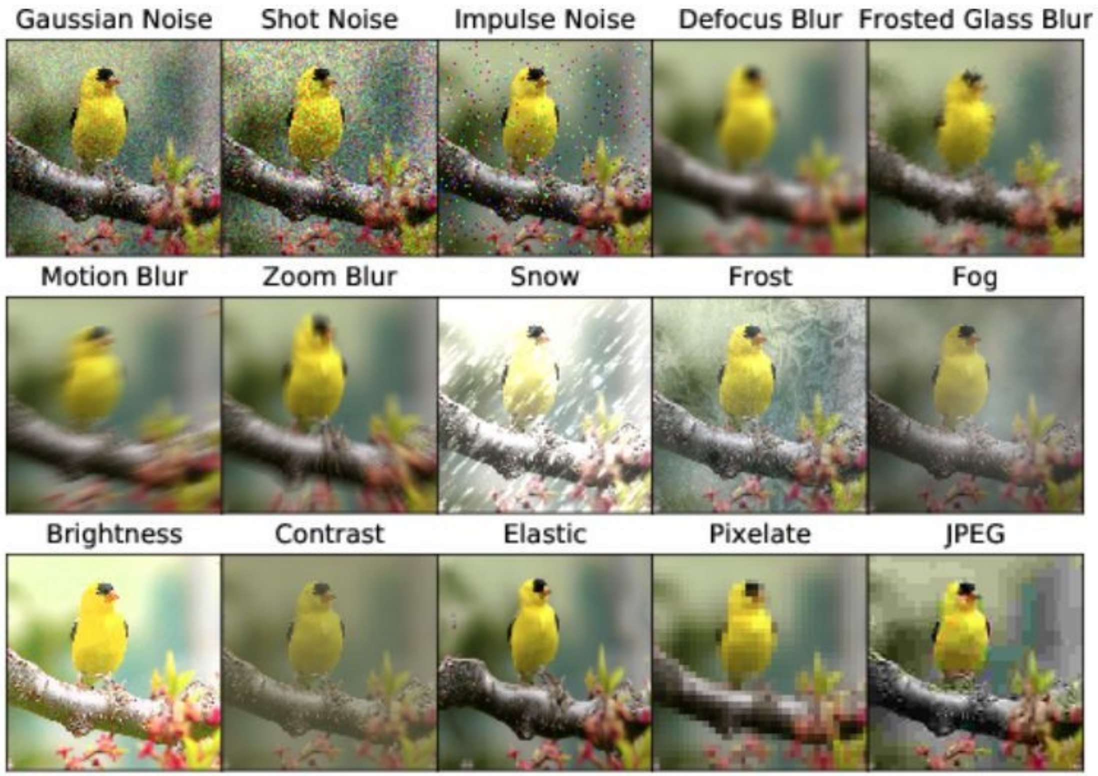
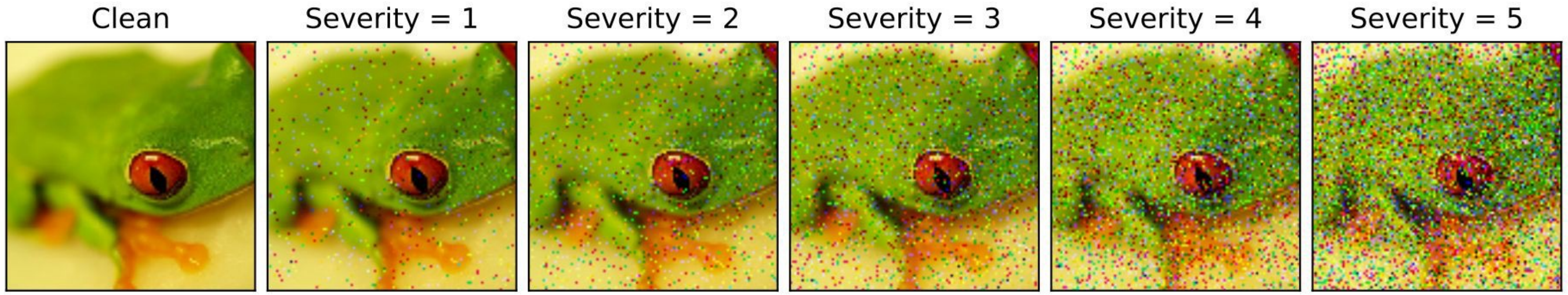
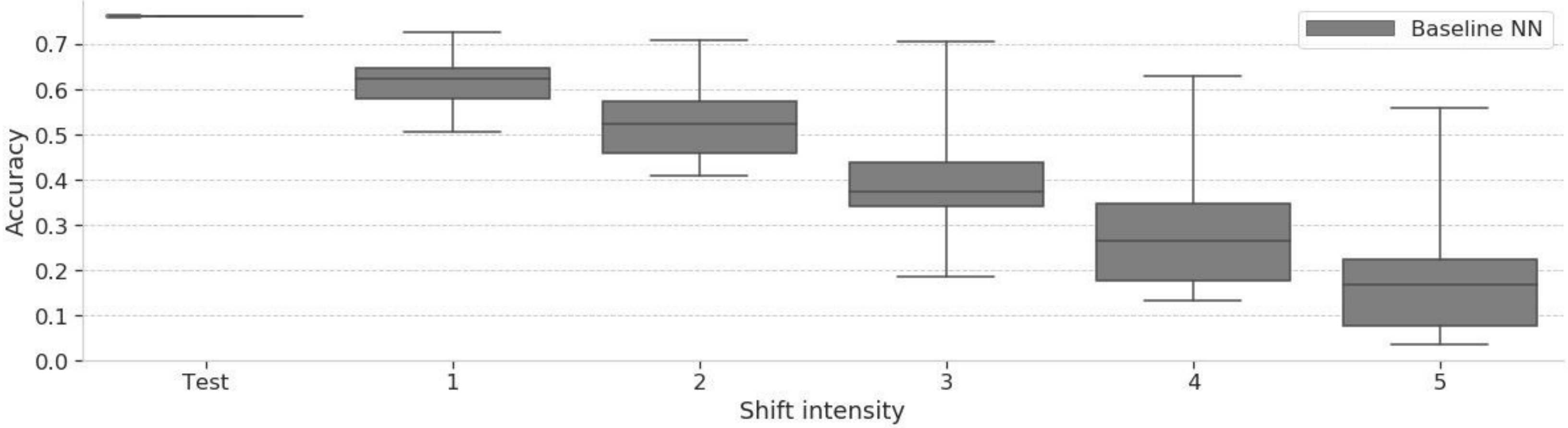


Image source: Benchmarking Neural Network Robustness to Common Corruptions and Perturbations, Hendrycks & Dietterich, 2019.

Neural networks do not generalize under covariate shift



- **Accuracy drops** with increasing shift on Imagenet-C

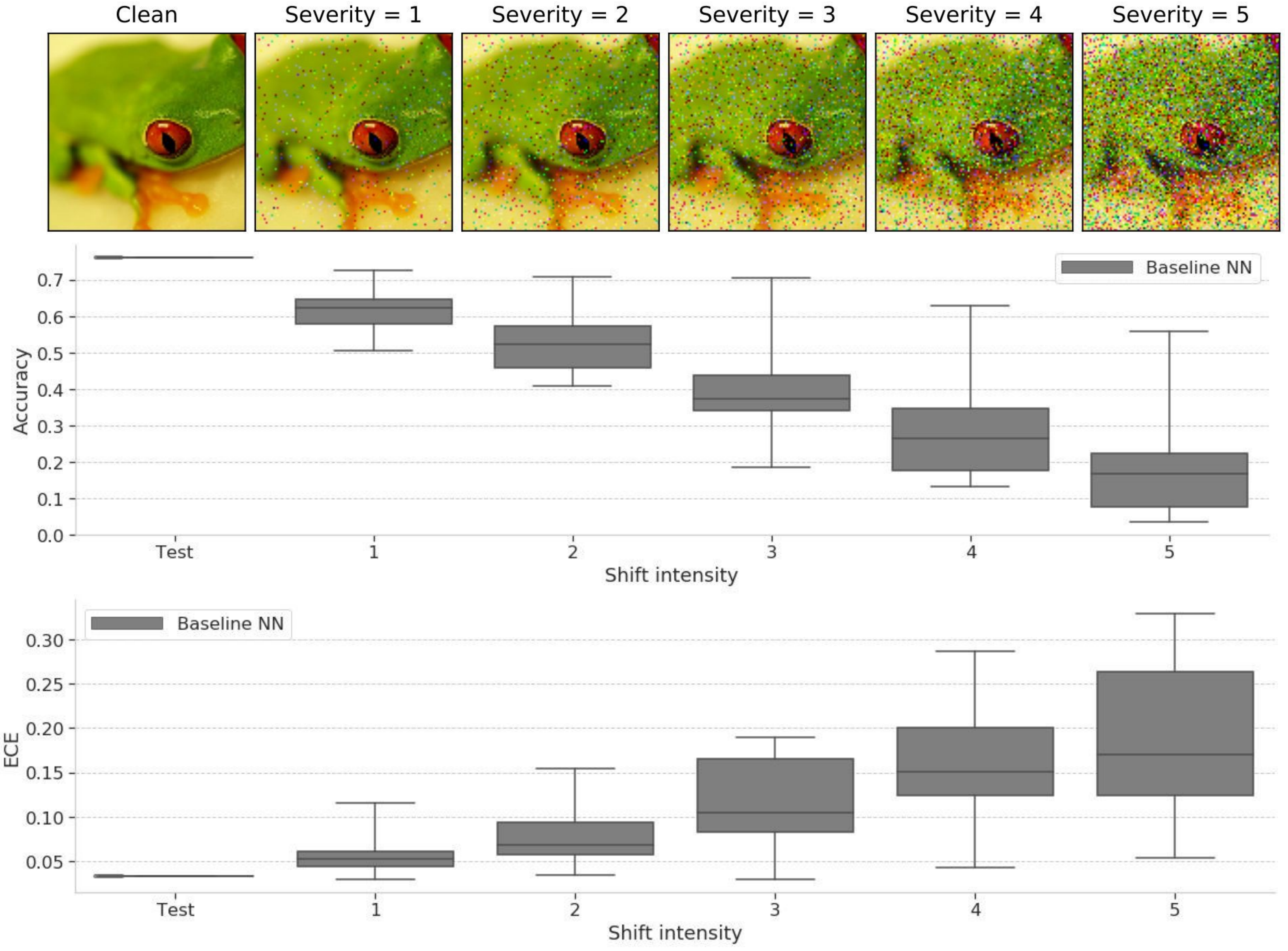


- But do the models know that they are less accurate?

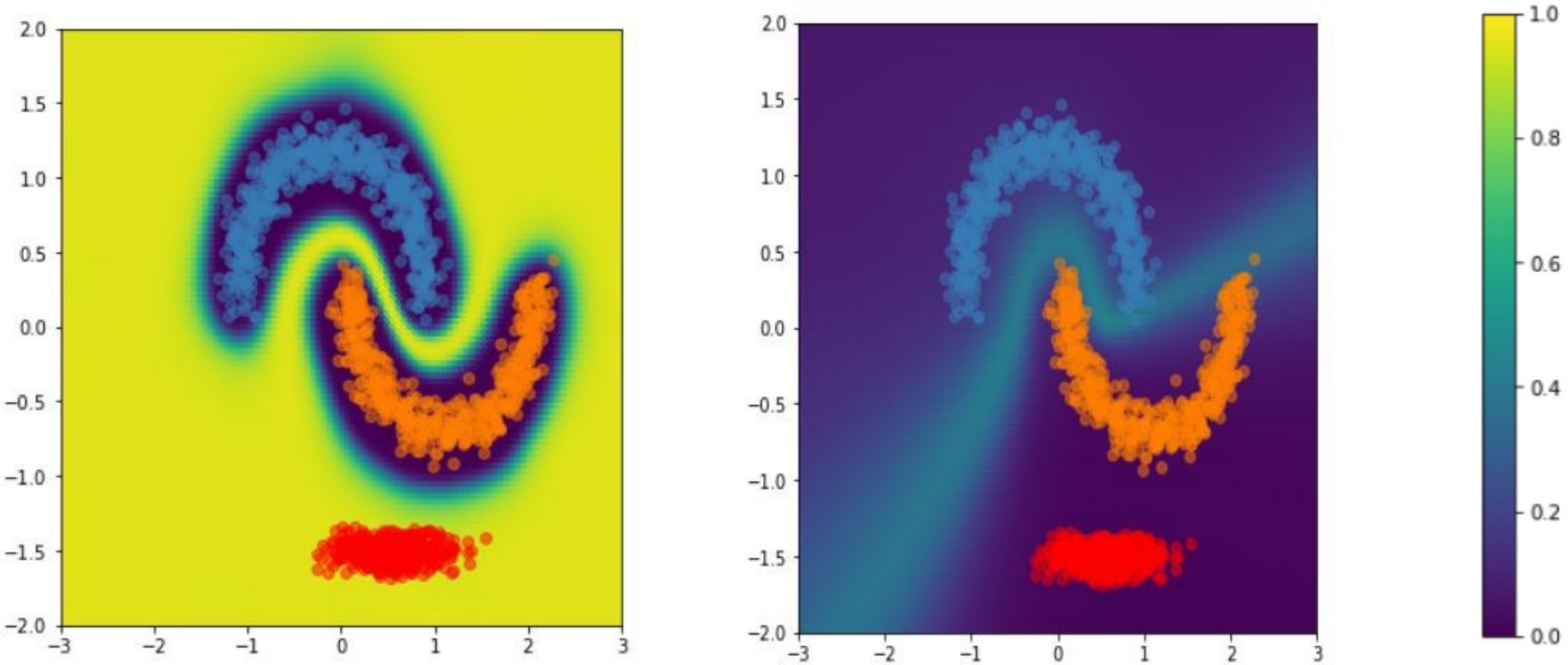
Can You Trust Your Model's Uncertainty? Evaluating Predictive Uncertainty Under Dataset Shift?, [Ovadia et al. 2019]()

Neural networks ***do not know when they don't know***

- **Accuracy drops** with increasing shift on Imagenet-C
- **Quality of uncertainty degrades with shift** -> "overconfident mistakes"



Models assign high confidence predictions to OOD inputs



High uncertainty
(low confidence)

Low uncertainty
(high confidence)

Ideal behavior

Deep neural networks

Trust model when x* is close to $p_{TRAIN}(x,y)$

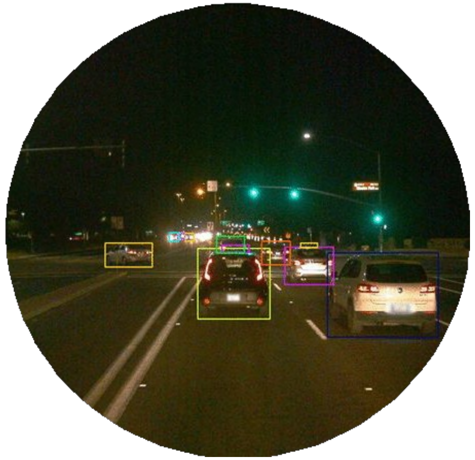
Image source: “Simple and Principled Uncertainty Estimation with Deterministic Deep Learning via Distance Awareness” [Liu et al. 2020](#)

Self-driving cars

Dataset shift:

- Time of day / Lighting
- Geographical location (City vs suburban)
- Changing conditions (Weather / Construction)

Daylight



Night

Weather

Construction

Downtown

Suburban

Image credit: Sun et al, [Waymo Open Dataset]

Open Set Recognition

- Example: Classification of genomic sequences

- High accuracy on known classes is not sufficient

- Need to be able to detect inputs that do not belong to one of the known classes

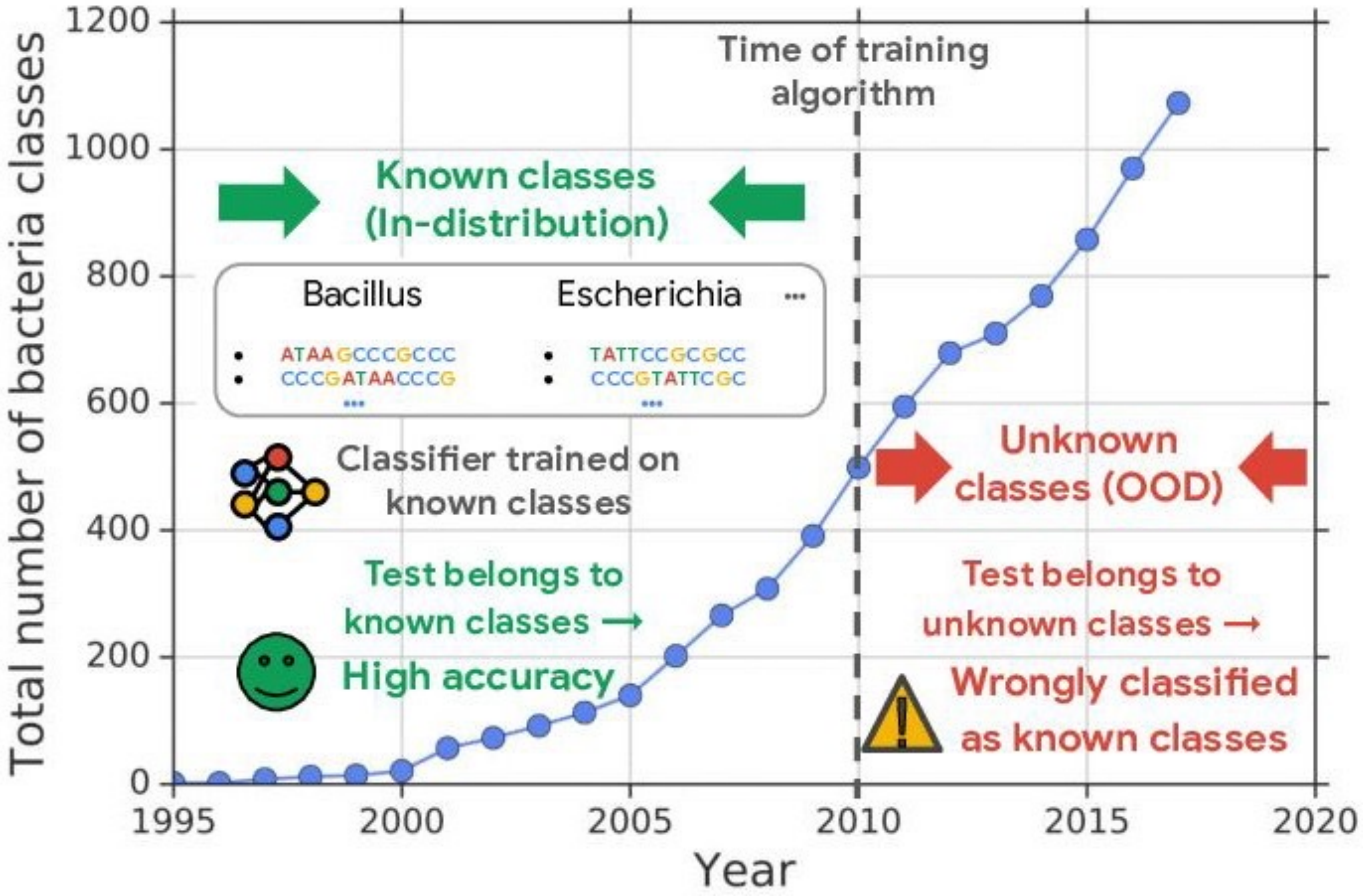
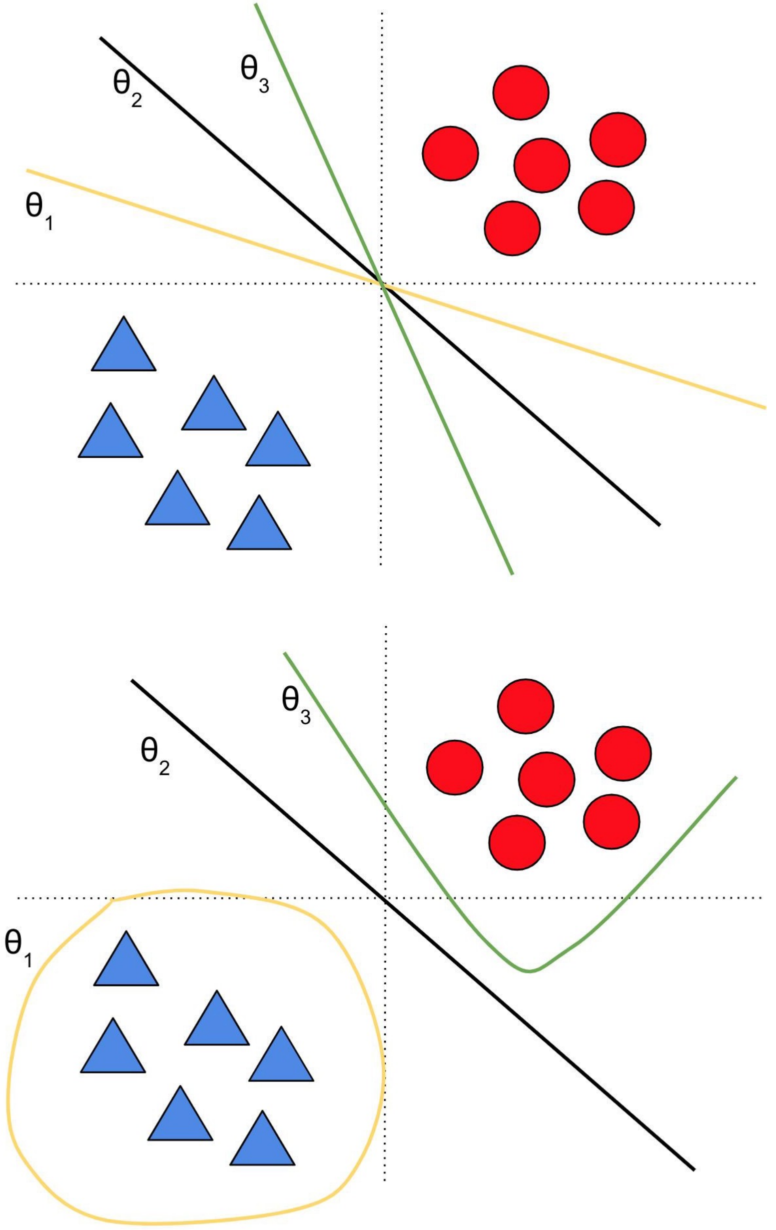


Image source: https://ai.googleblog.com/2019/12/improving-out-of-distribution-detection.html

Sources of uncertainty: *Model uncertainty*

- Many models can fit the training data well
- Also known as ***epistemic uncertainty***
- Model uncertainty is "**reducible**"
  - Vanishes in the limit of infinite data (subject to model identifiability)
- Models can be from same hypotheses class (e.g. linear classifiers in top figure) or belong to different hypotheses classes (bottom figure).



Sources of uncertainty: *Data uncertainty*

- Labeling noise (ex: human disagreement)
- Measurement noise (ex: imprecise tools)
- *Missing* data (ex: partially observed features, unobserved confounders)

- Also known as ***aleatoric uncertainty***
- Data uncertainty is "**irreducible***"
    - Persists even in the limit of infinite data
    - *Could be reduced with additional features/views

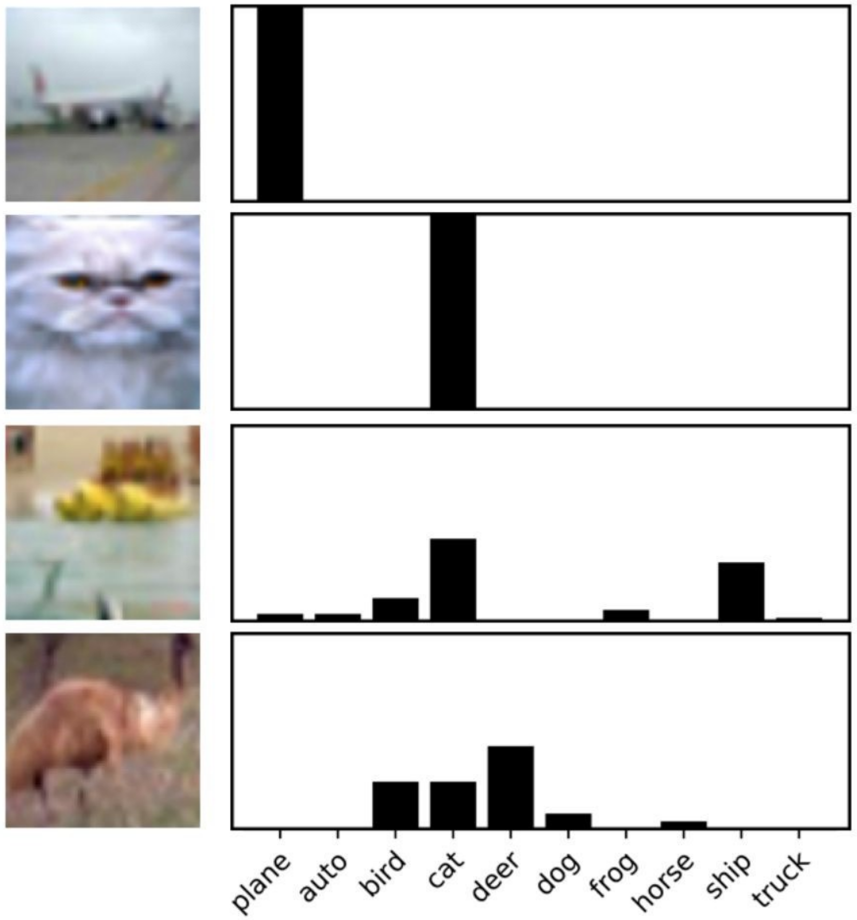


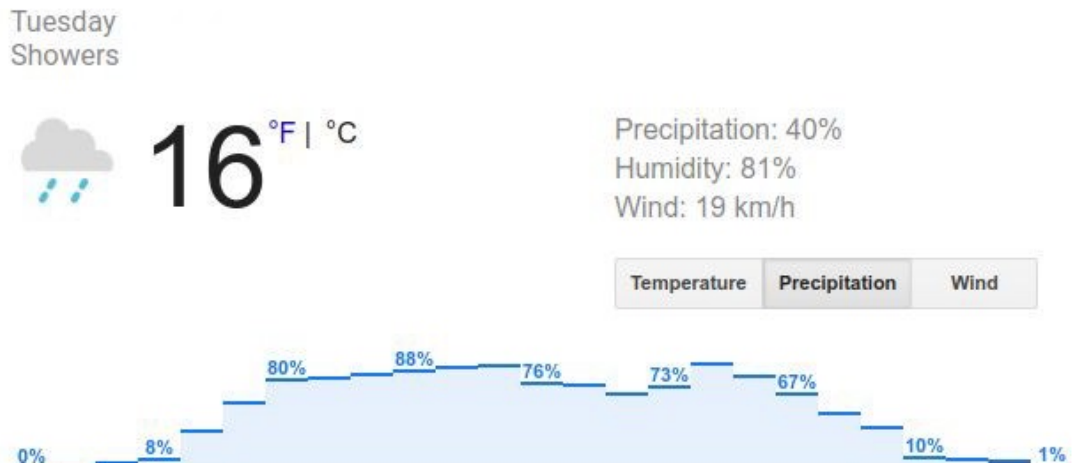
Image source: Battleday et al. 2019 "Improving machine classification using human uncertainty measurements"

How do we measure the quality of uncertainty?

Calibration Error = |Confidence - Accuracy|

Of all the days where the model predicted rain with 80% probability, what fraction did we observe rain?

- 80% implies perfect calibration
- Less than 80% implies model is overconfident
- Greater than 80% implies model is under-confident



How do we measure the quality of uncertainty?

Expected Calibration Error [Naeini+ 2015]:

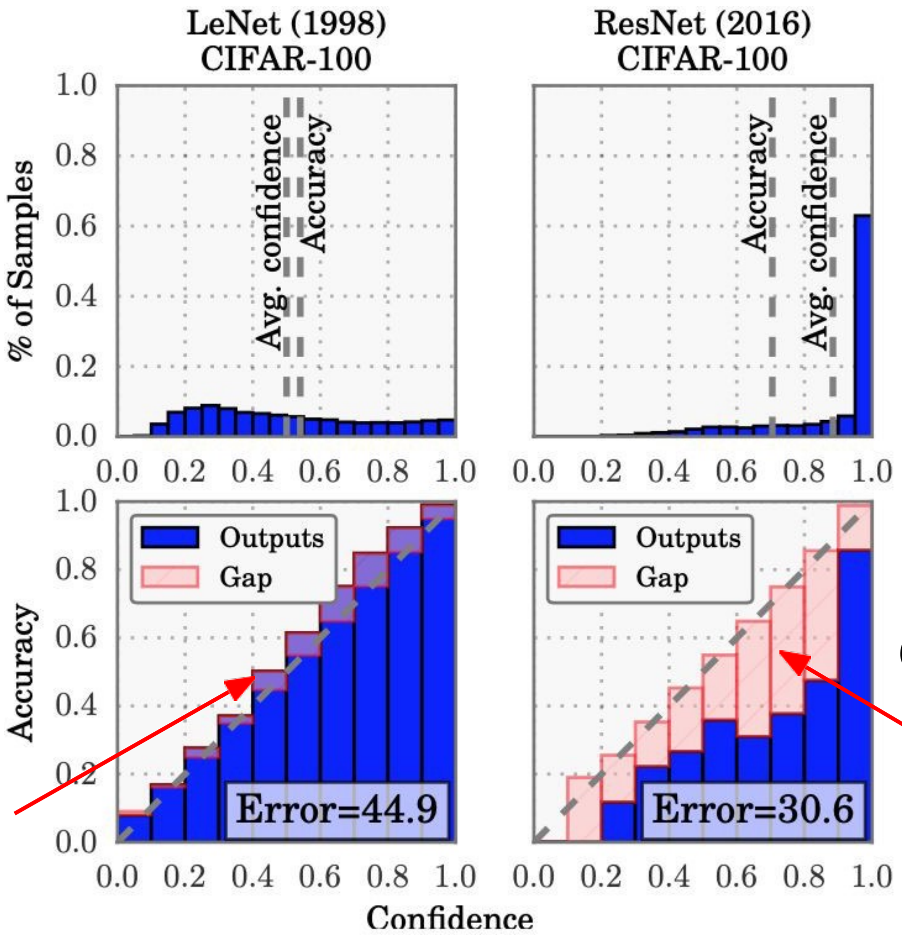
$$\mathrm{ECE} = \sum_{b=1}^{B} \frac{n_b}{N} \left|\mathrm{acc}(b) - \mathrm{conf}(b)\right|$$

- Bin the probabilities into B bins.
- Compute the within-bin accuracy and within-bin predicted confidence.
- Average the calibration error across bins (weighted by number of points in each bin).

How do we measure the quality of uncertainty?

Expected Calibration Error [Naeini+ 2015]:

$$\mathrm{ECE} = \sum_{b=1}^{B} \frac{n_b}{N} \left|\mathrm{acc}(b) - \mathrm{conf}(b)\right|$$



Confidence >Accuracy

=> *Overconfident*

Confidence <Accuracy

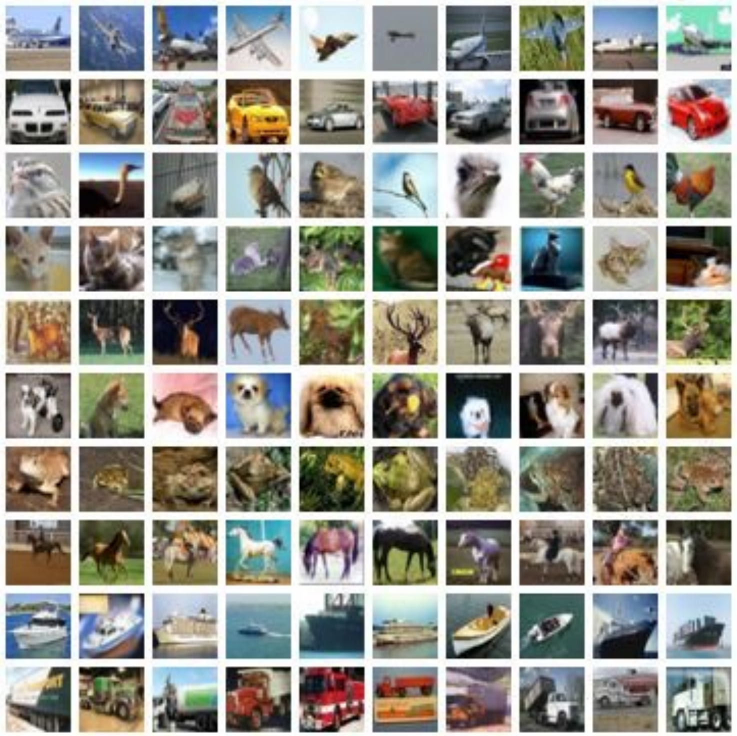
=> *Underconfident*

Image source: Guo+ 2017 “On calibration of modern neural networks”

How do we measure the quality of uncertainty , practically?

Evaluate model on **out-of-distribution (OOD) inputs** which do not belong to any of the existing classes

- Max confidence
- Entropy of p(y|x)



CIFAR-10 (i.i.d test inputs)

SVHN (o.o.d test inputs)

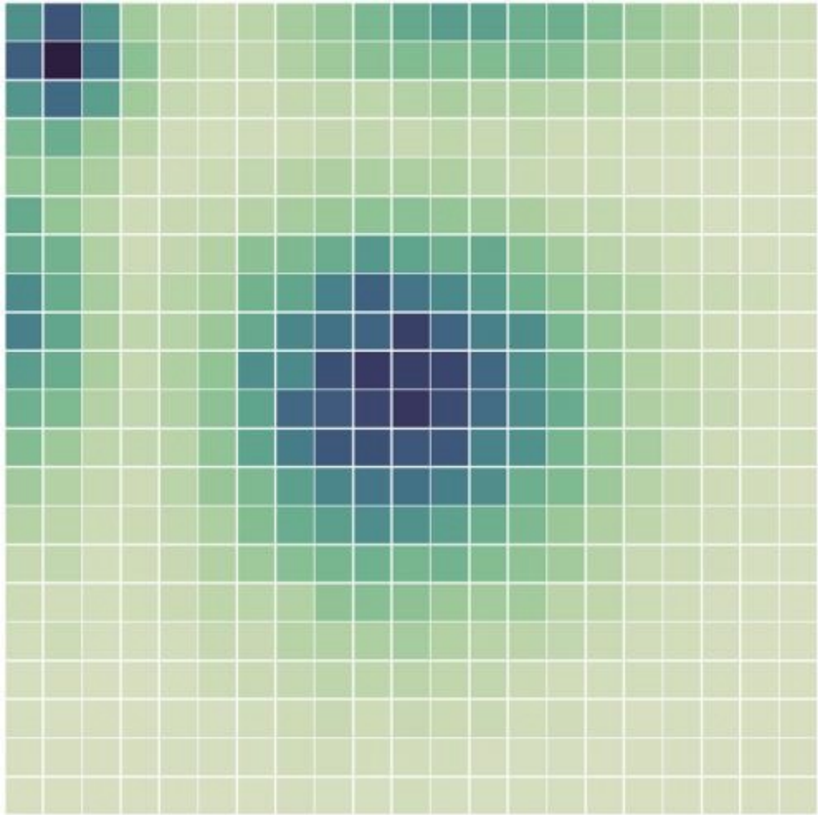
CIFAR-10 classifier

Confidence on i.i.d inputs > Confidence on o.o.d inputs ?

A Simple Baseline for Improving Uncertainty Calibration

$$\boldsymbol{\theta}^* = \arg\max_{\boldsymbol{\theta}} p(\boldsymbol{\theta} \mid \mathbf{x}, \mathbf{y})$$

Problem: results in just one prediction per example
No model uncertainty



How do we get uncertainty?

- Probabilistic approach
  - Estimate a full distribution for $p(\boldsymbol{\theta} \mid \mathbf{x}, \mathbf{y})$
- Intuitive approach: Ensembling
  - Obtain multiple good settings for $\boldsymbol{\theta}^*$

Image source: [Ranganath+ 2016]

Ensemble Learning

- A prior distribution often involves the complication of approximate inference.
- *Ensemble learning* offers an alternative strategy to aggregate the predictions over a collection of models.
- Often winner of competitions!
- There are two considerations: the collection of models to ensemble; and the aggregation strategy.

Popular approach is to average predictions of independently trained models, forming a mixture distribution.

$$p(\mathbf{y} \mid \mathbf{x}) = \frac{1}{K} \sum_{k=1}^{K} p(\mathbf{y} \mid \mathbf{x}, \boldsymbol{\theta}_k)$$

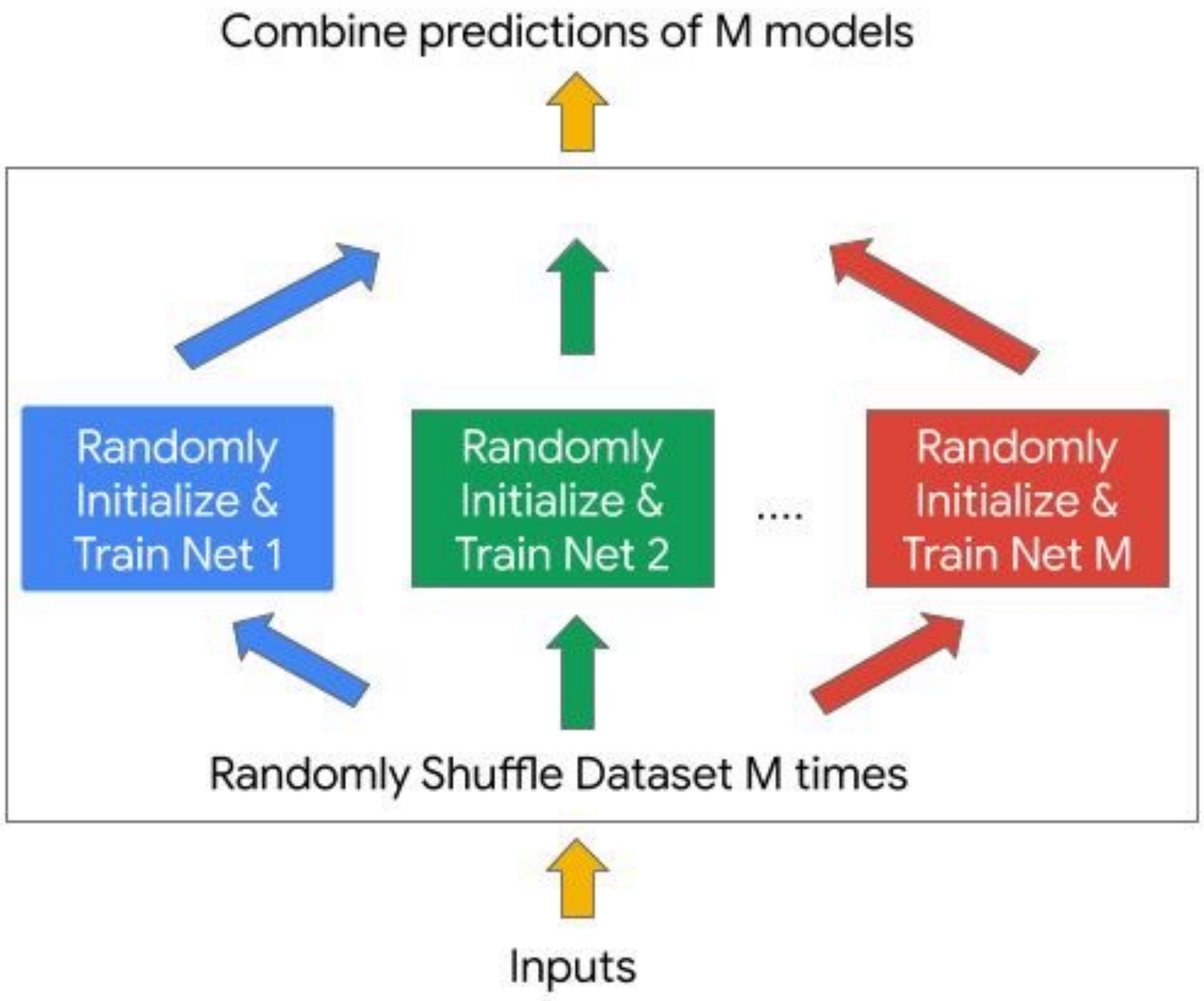
Many approaches exist: bagging, boosting, decision trees, stacking

[Dietterich 2000]

Simple Baseline: Deep Ensembles

Idea: Just re-run standard SGD training but with different random seeds and average the predictions

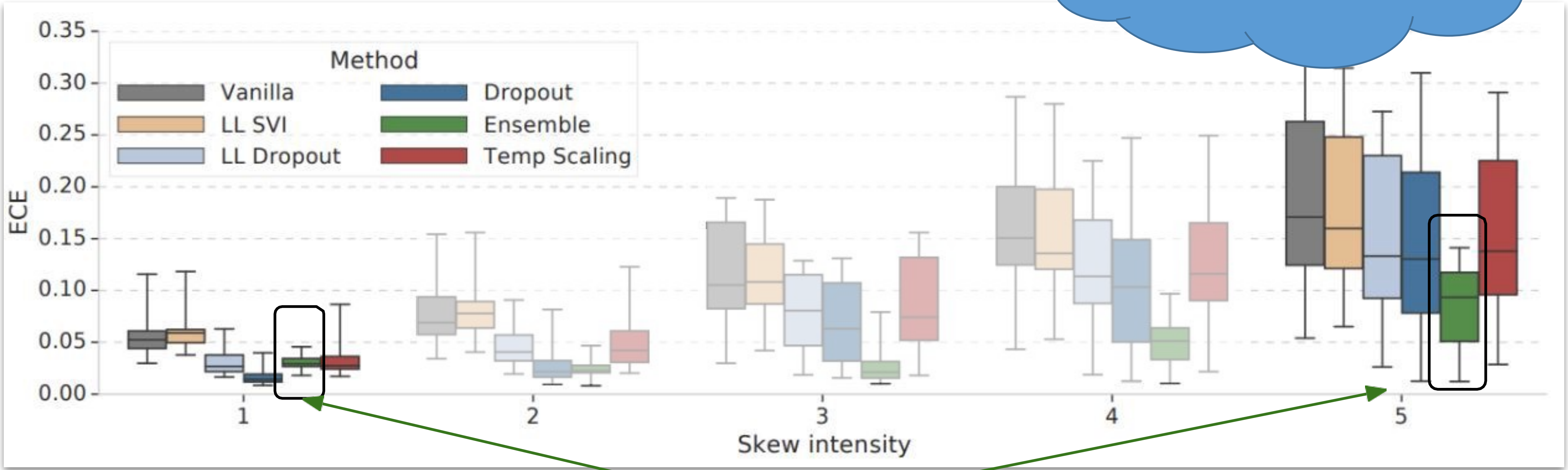
- A well-known trick for getting better accuracy and Kaggle scores
- **Beyond accuracy – it is good for robustness and uncertainty too!!**
- The **mean** of predictions is often more accurate, and the **variance** of those predictions reflects “confidence”
- We rely on the facts that the loss landscape is non-convex and SGD has noise



[Lakshminarayanan+ 2017]

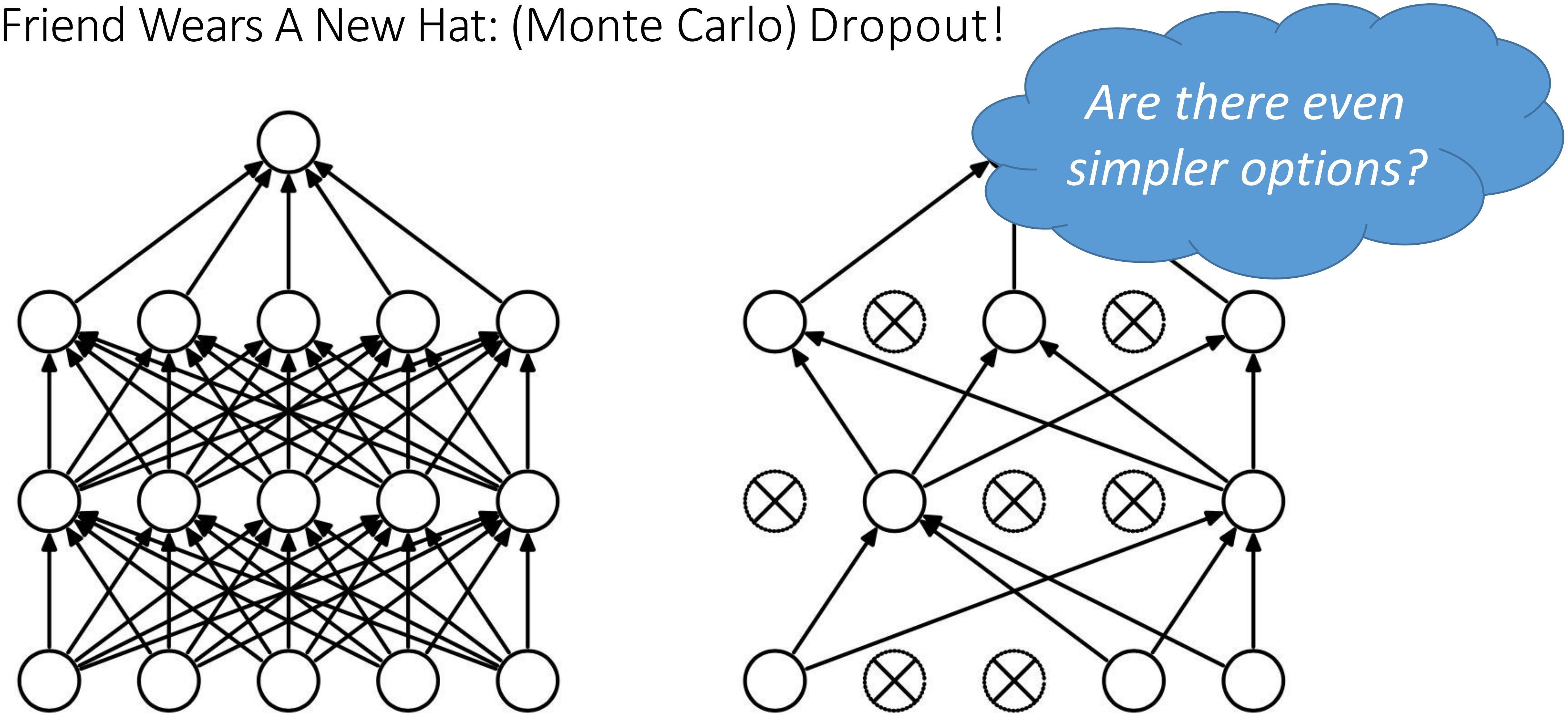
Deep Ensembles work surprisingly well in practice

Are there simpler options?



Deep Ensembles are consistently among the best performing methods, especially under dataset shift

An Old Friend Wears A New Hat: (Monte Carlo) Dropout!



(a) Standard Neural Net

(b) After applying dropout.

[Gal+ 2015]

Table source: Guo+ 2017 “On calibration of modern neural networks”

Dataset	Model	Uncalibrated	Hist. Binning	Isotonic	BBQ	Temp. Scaling	Vector Scaling	Matrix Scaling
Birds	ResNet 50	9.19%	4.34%	5.22%	4.12%	**1.85%**	3.0%	21.13%
Cars								0.5%
CIFAR-10								.0%
CIFAR-10								.72%
CIFAR-10								.72%
CIFAR-10								.41%
CIFAR-10								.16%
CIFAR-10								.49%
CIFAR-10								.09%
CIFAR-10								.44%
CIFAR-10								.87%
CIFAR-10								.24%
ImageNet								-
ImageNet								-
SVHN								.17%
20 News								.1%
Reuters								.58%
SST Binary								.84%
SST Fine Grai								.39%

Table 1. ECE (… n methods.
The number fo

Softmax: $$\sigma_{\mathrm{SM}}(\mathbf{z}_i)^{(k)} = \frac{\exp(z_i^{(k)})}{\sum_{j=1}^{K} \exp(z_i^{(j)})}, \quad \hat{p}_i = \max_k \sigma_{\mathrm{SM}}(\mathbf{z}_i)^{(k)}.$$

Temperature re-scaling (beat them all!): $$\hat{q}_i = \max_k \sigma_{\mathrm{SM}}(\mathbf{z}_i/T)^{(k)}.$$

How do we measure the quality of robustness, practically?

Measure generalization to a *large collection of real-world shifts*. A large collection of tasks encourages *general robustness to shifts* (ex: GLUE for NLP).

- Novel textures in object recognition.
- Covariate shift (e.g. corruptions).
- Different sub-populations (e.g. geographical location).

Different renditions (ImageNet-R)

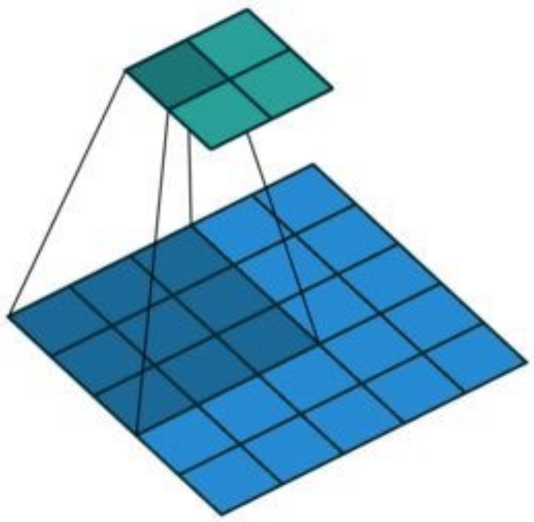
Nearby video frames (ImageNet-Vid-Robust, YTBB-Robust)


Multiple objects and poses (ObjectNet)

Inductive Priors & Knowledge for Robustness

What about inductive biases to assist OOD?

Image source: [Dumoulin & Visin 2016]

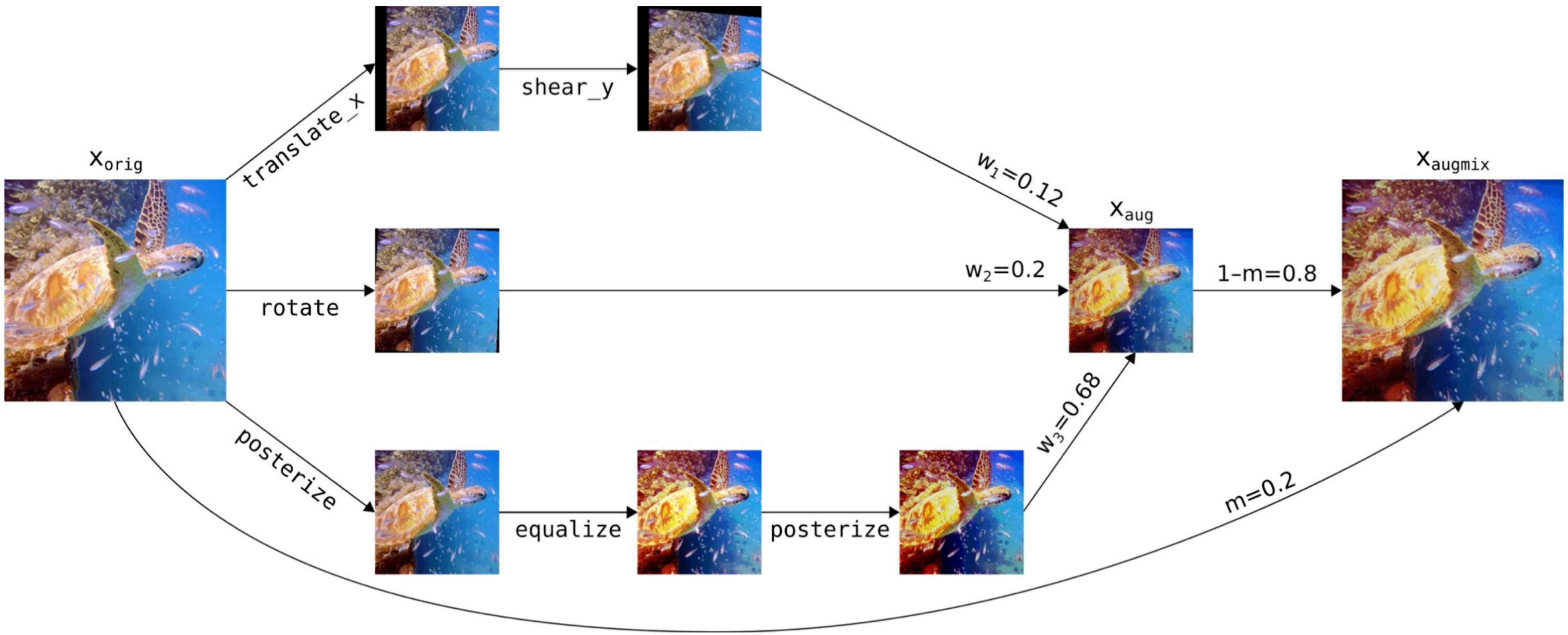


- Hypothesis: “*Representations should be invariant with respect to dataset shift.*”
- **Data augmentation** extends the dataset in order to encourage invariances.
- More examples: **contrastive learning**, **equivariant architectures**.

Data augmentation requires two considerations:

1. Set of **base** augmentation operations. (Ex: color distortions, word substitution)
2. **Combination** strategy (Ex: Sequence of K randomly selected ops.)

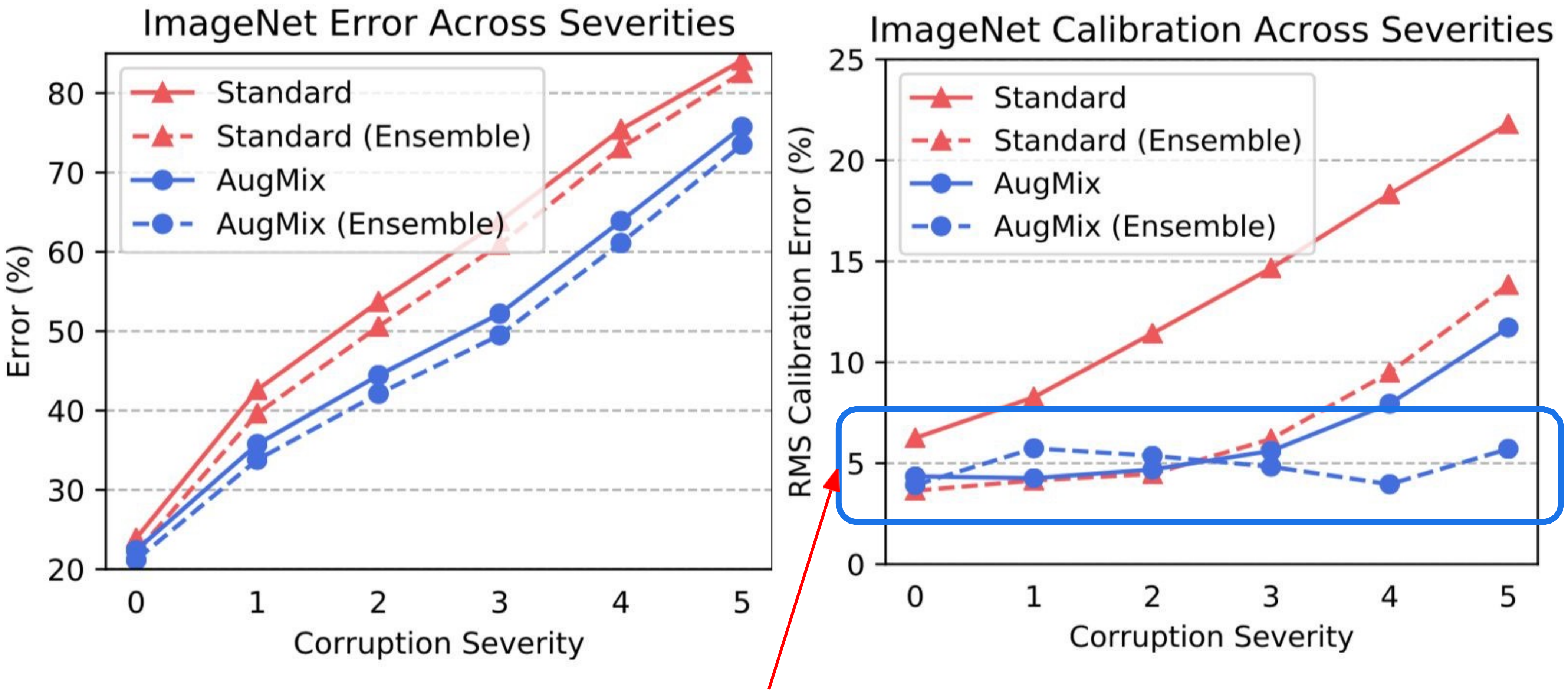
Composing a set of base augmentations



Composing base operations and ‘mixing’ them can improve accuracy and calibration under shift.

[Hendrycks+ 2020]

AugMix improves robustness & calibration under shift



Data augmentation can provide complementary benefits to marginalization.

[Hendrycks+ 2020]

Synthetic Data: Towards Infinite Training Data Variations

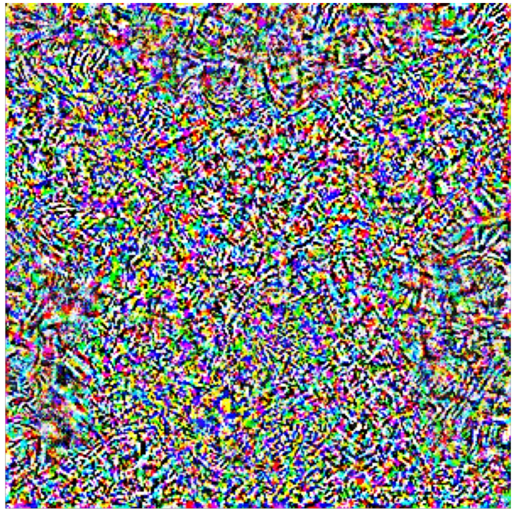
Takeaways

- Uncertainty & robustness are critical problems in AI and machine learning.
- Benchmark models with calibration error and a large collection of OOD shifts.
- Probabilistic ML, ensemble learning, and optimization provide a foundation.
- The best methods: ensemble multiple predictions; imposing priors and inductive biases; and “lower your temperature” when using softmax
- Synthetic data can remarkably help capture more variation
- Many future progress are expected – a key knob to make ML “real”

ML Predictions Are (Mostly) Accurate but Brittle

“pig” (91%) **noise (NOT random)** **“airliner” (99%)**

+ 0.005 x



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[Szegedy Zaremba Sutskever Bruna Erhan Goodfellow Fergus 2013]
[Biggio Corona Maiorca Nelson Srndic Laskov Giacinto Roli 2013]

But also: [Dalvi Domingos Mausam Sanghai Verma 2004][Lowd Meek 2005]
[Globerson Roweis 2006][Kolcz Teo 2009][Barreno Nelson Rubinstein Joseph Tygar 2010]
[Biggio Fumera Roli 2010][Biggio Fumera Roli 2014][Srndic Laskov 2013]

Three commandments of Secure/Safe ML

I. Thou

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II. Thou ... erve its outpu

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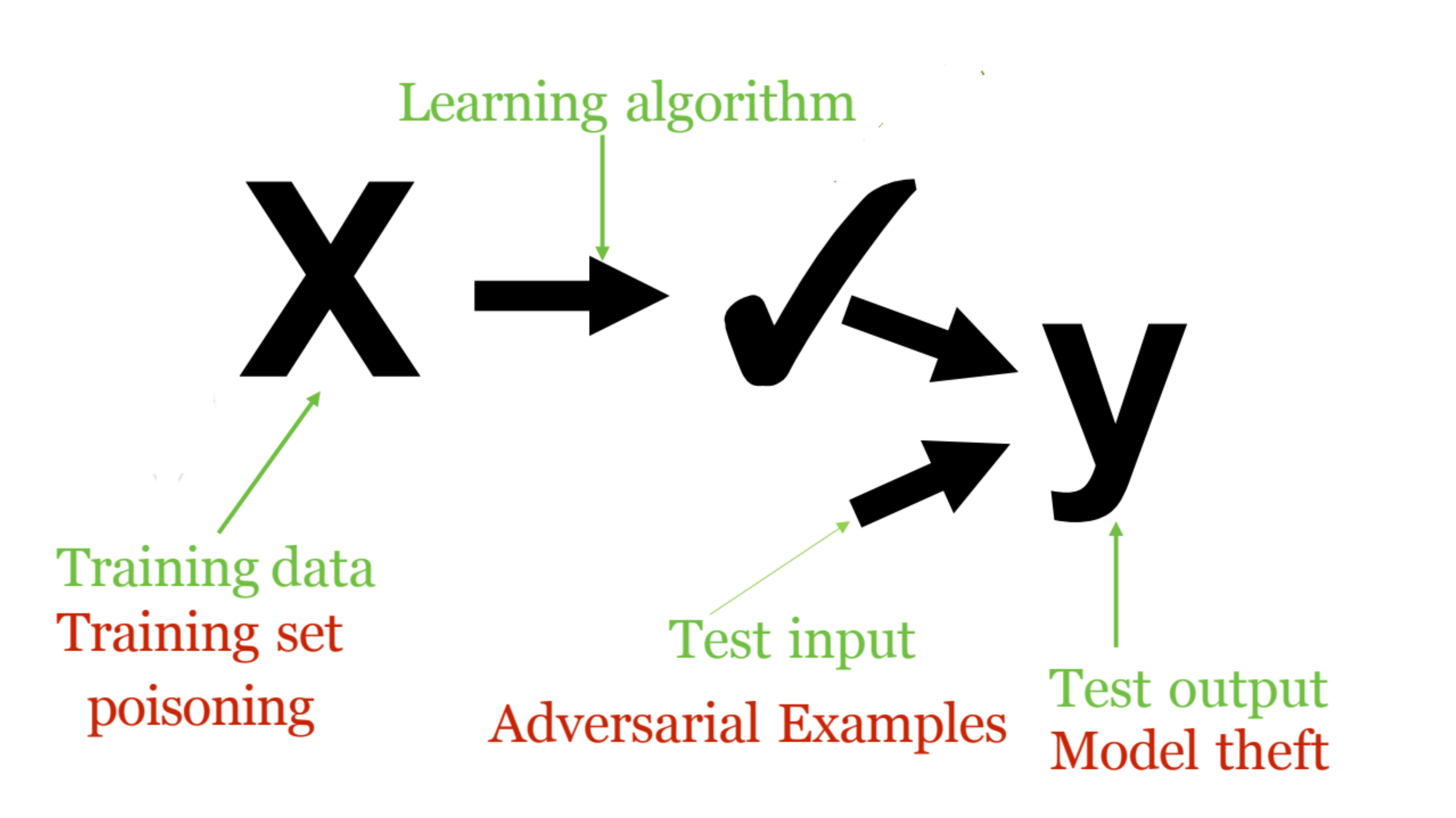
III. Tho ... r model

(because of adversarial examples)



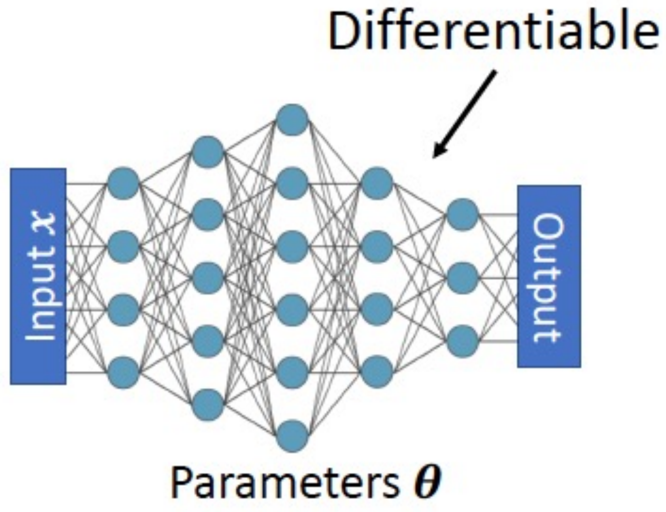
Where Do Adversarial Examples Come From?

To get an adv. example

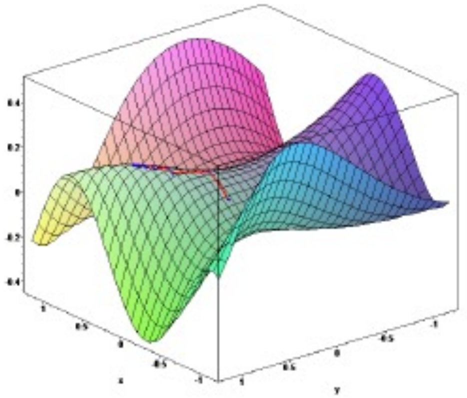
~~**Goal of training:**~~

Model Parameters Input Correct Label

$$min_\theta \; loss(\theta, x, y)$$



Can use gradient descent method to find good θ

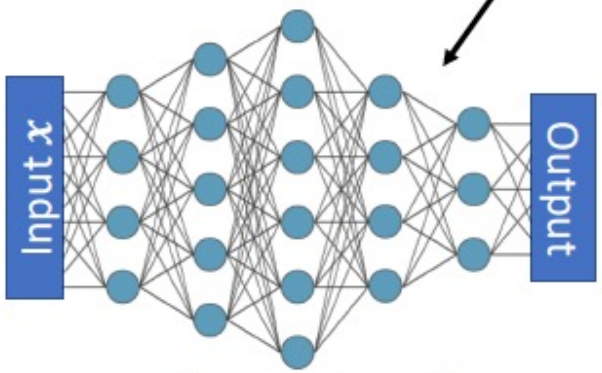


Where Do Adversarial Examples Come From?

To get an adv. example

~~**Goal of training:**~~

Differentiable



Parameters $\boldsymbol{\theta}$

$$max_{\delta}\ loss(\theta, x + \delta, y)$$

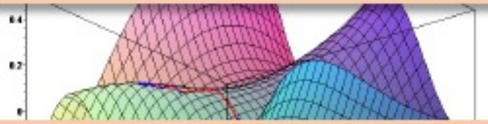
Which δ are allowed?

Examples: δ that is small wrt

- ℓ_p-norm
- Rotation and/or translation
- VGG feature perturbation
- (add the perturbation you need here)

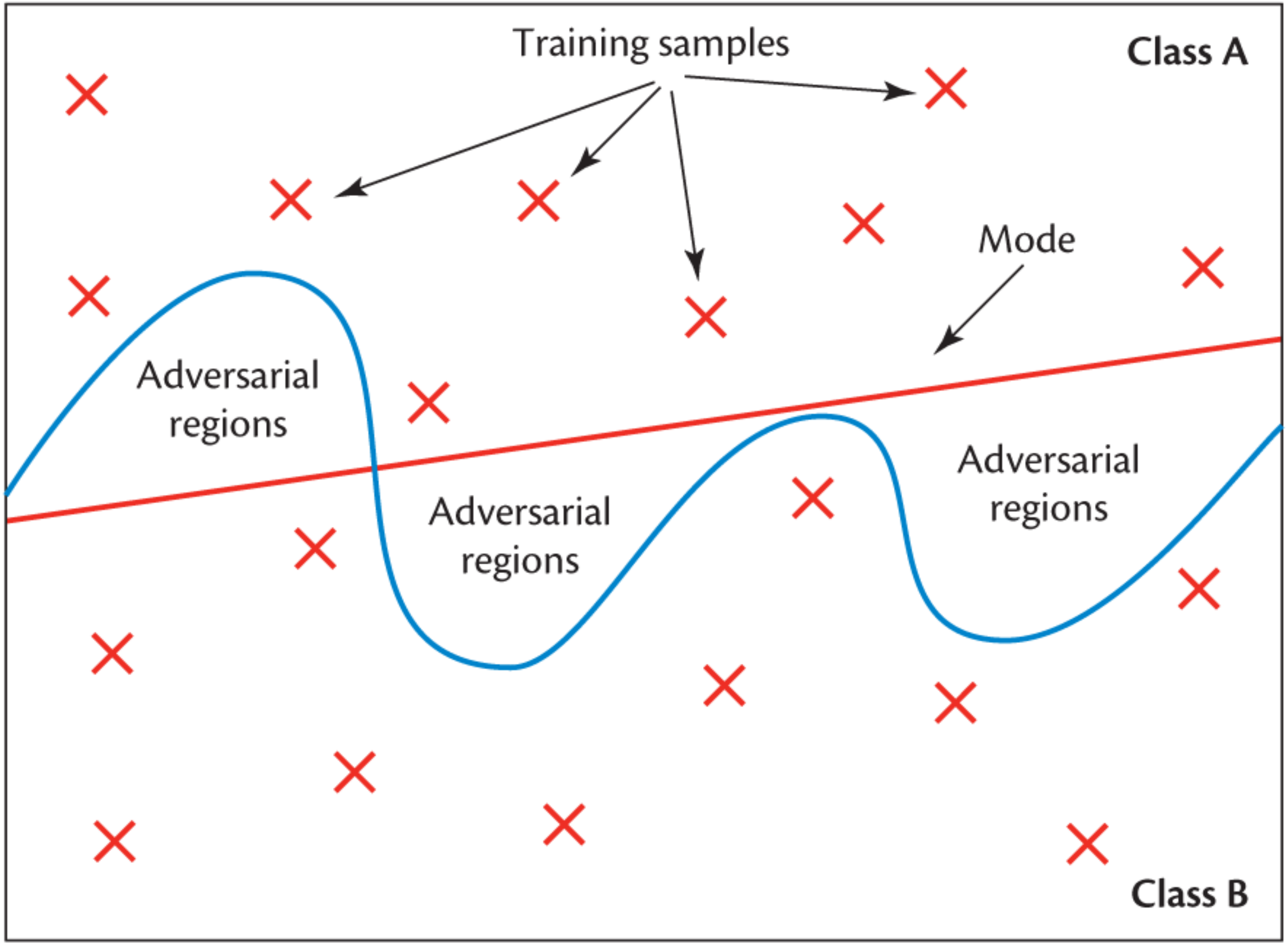
Can use gradient descent

This is an important question
(that we put aside)



Still: We have to confront
(small) ℓ_p-norm perturbations

A Possible By-Product of ML Bias-Variance Trade-Off



Towards ML Models that Are Adv. Robust

[M Makelov Schmidt Tsipras Vladu 2018]

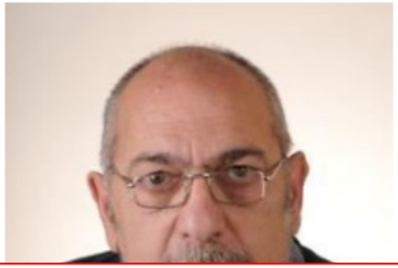
Key observation: Lack of adv. robustness is **NOT** at odds with what we currently want our ML models to achieve

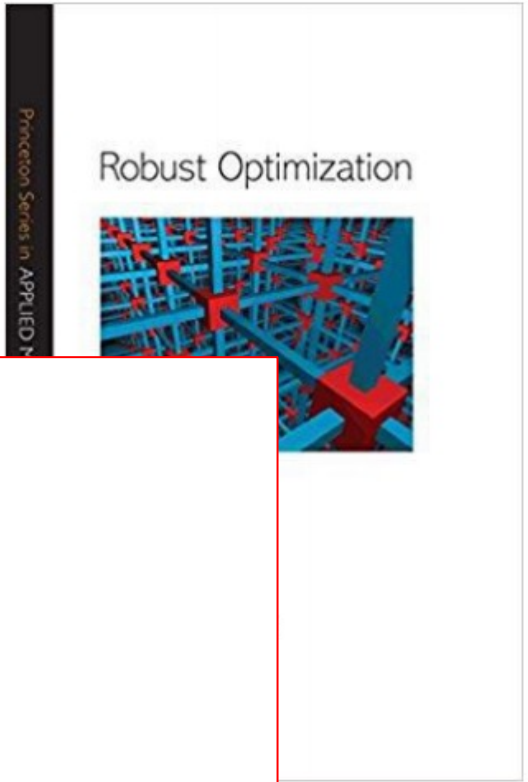
~~Standard~~ generalization: $\mathbb{E}_{(x,y)\sim D}\left[\max_{\boldsymbol{\delta}\in\boldsymbol{\Delta}} loss(\theta, x+\boldsymbol{\delta}, y)\right]$

Adversarially robust

But: Adversarial noise is a "needle in a haystack"

Robust Objectives





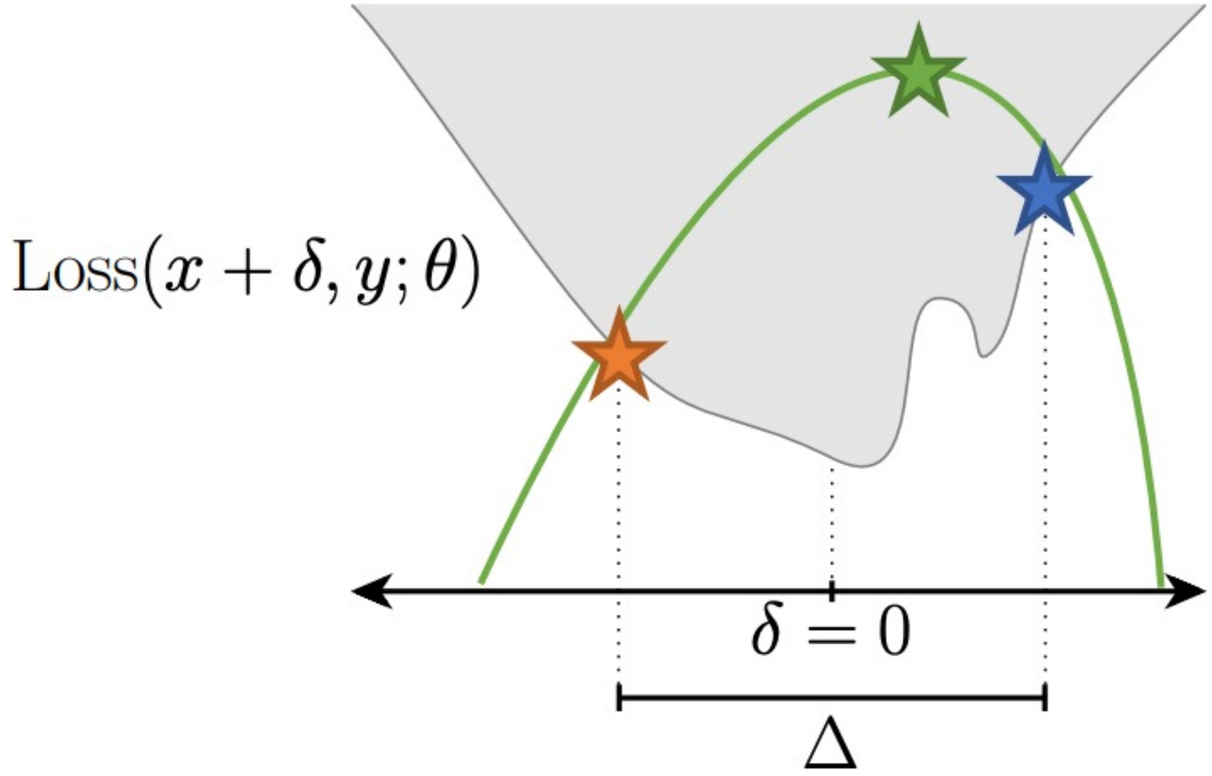
- Use the fol
    - $\min\limits_{w} \quad E$
    - Outer mi
    - Inner ma
- A. Madry, A Deep Learning M
- A. Sinha, H. onal Robustness with Principled Adversarial Training. ICLR 2018

Part II: training a robust classifier

$$\overbrace{\min_{\theta} \sum_{x,y \in S} \underbrace{\max_{\delta \in \Delta} \operatorname{Loss}(x+\delta, y; \theta)}_{\text{Part I}}}^{\text{Part II}}$$

Part I: creating an adversarial example
(or ensuring one does not exist)

The inner maximization problem



How do we solve the optimization?

$$\max_{\delta \in \Delta} \text{Loss}\left(x + \delta, y; \theta\right)$$

1. Local search (lower bound on objective)
2. Combinatorial optimization (exactly solve objective)
3. Convex relaxation (upper bound on objective)

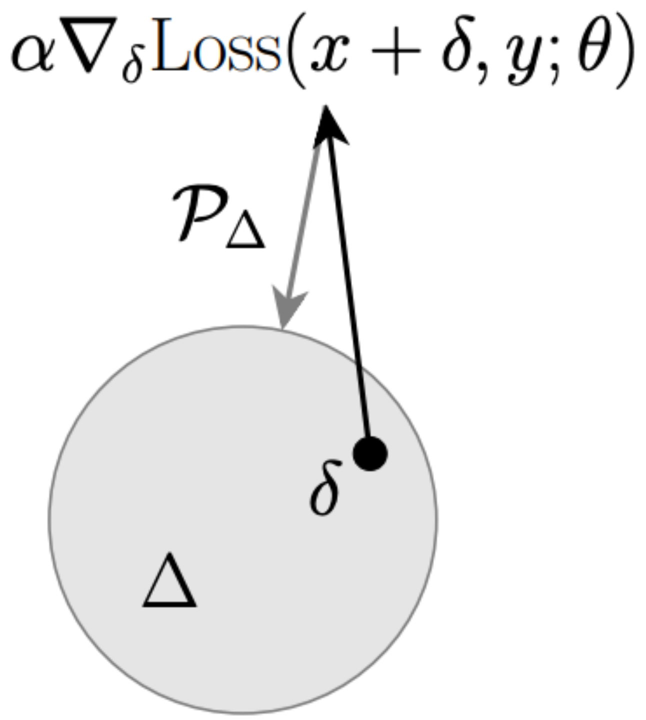
Projected gradient descent

Recall we are optimizing

$$\max_{\delta \in \Delta} \text{Loss}\,(x+\delta, y; \theta)$$

We can employ a projected gradient descent method, take gradient step and project back into feasible set Δ

$$\delta := \mathcal{P}_{\Delta}[\delta + \nabla_{\delta}\text{Loss}(x+\delta, y; \theta)]$$



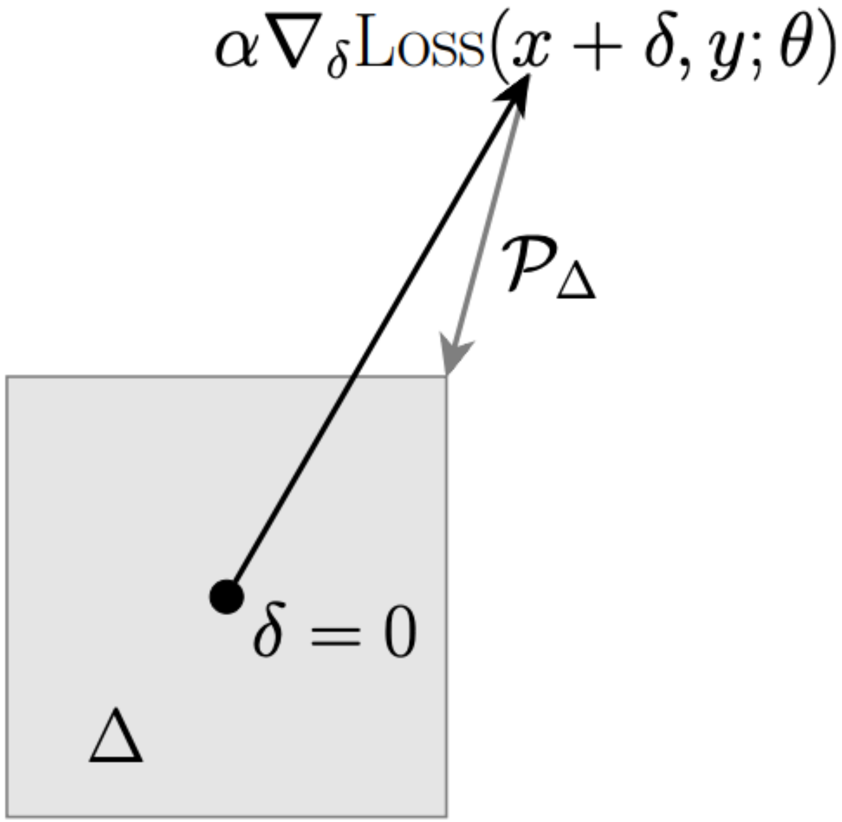
The Fast Gradient Sign Method (FGSM)

To be more concrete, take Δ to be the ℓ_∞ ball, $\Delta = \{\delta : \|\delta\|_\infty \leq \epsilon\}$, so projection takes the form

$$P_\Delta(\delta) = \mathrm{Clip}(\delta, [-\epsilon, \epsilon])$$

As $\alpha \to \infty$, we always reach "corner" of the box, called fast gradient sign method (FGSM)
[Goodfellow et al., 2014]

$$\delta = \epsilon \cdot \mathrm{sign}\big(\nabla_\delta \mathrm{Loss}(x + \delta, y; \theta)\big)$$



Targeted attacks

Also possible to explicitly try to change label to a *particular* class

$$\max_{\delta \in \Delta} \left(\mathrm{Loss}(x+\delta, y; \theta) - \mathrm{Loss}(x+\delta, y_{\mathrm{targ}}; \theta) \right)$$

Consider multi-class cross entropy loss

$$\mathrm{Loss}(x+\delta, y; \theta) = \log \sum_i \exp h_\theta(x+\delta)_i - h_\theta(x)_y$$

Then note that above problem simplifies to

$$\max_{\delta \in \Delta} \left(h_\theta(x)_{y_{\mathrm{targ}}} - h_\theta(x)_y \right)$$

The outer minimization problem

Inner maximization:

$$\max_{\delta \in \Delta} \text{Loss}\,(x+\delta, y; \theta)$$

1. Local search (lower bound on objective)
2. Combinatorial optimization (exactly solve objective)
3. Convex relaxation (upper bound on objective)

Outer minimization:

$$\min_{\theta} \sum_{x,y \in S} \max_{\delta \in \Delta} \text{Loss}\,(x+\delta, y; \theta)$$

1. Adversarial training

3. Provably robust training

Danskin's Theorem

A fundamental result in optimization:

$$\nabla_\theta \max_{\delta \in \Delta} \operatorname{Loss}(x+\delta, y; \theta) = \nabla_\theta \operatorname{Loss}(x+\delta^\star, y; \theta)$$

where $\delta^\star = \max_{\delta \in \Delta} \operatorname{Loss}(x+\delta, y; \theta)$

Seems "obvious," but it is a very subtle result; means we can optimize through the max by just finding it's maximizing value

Note however, it *only* applies when max is performed exactly

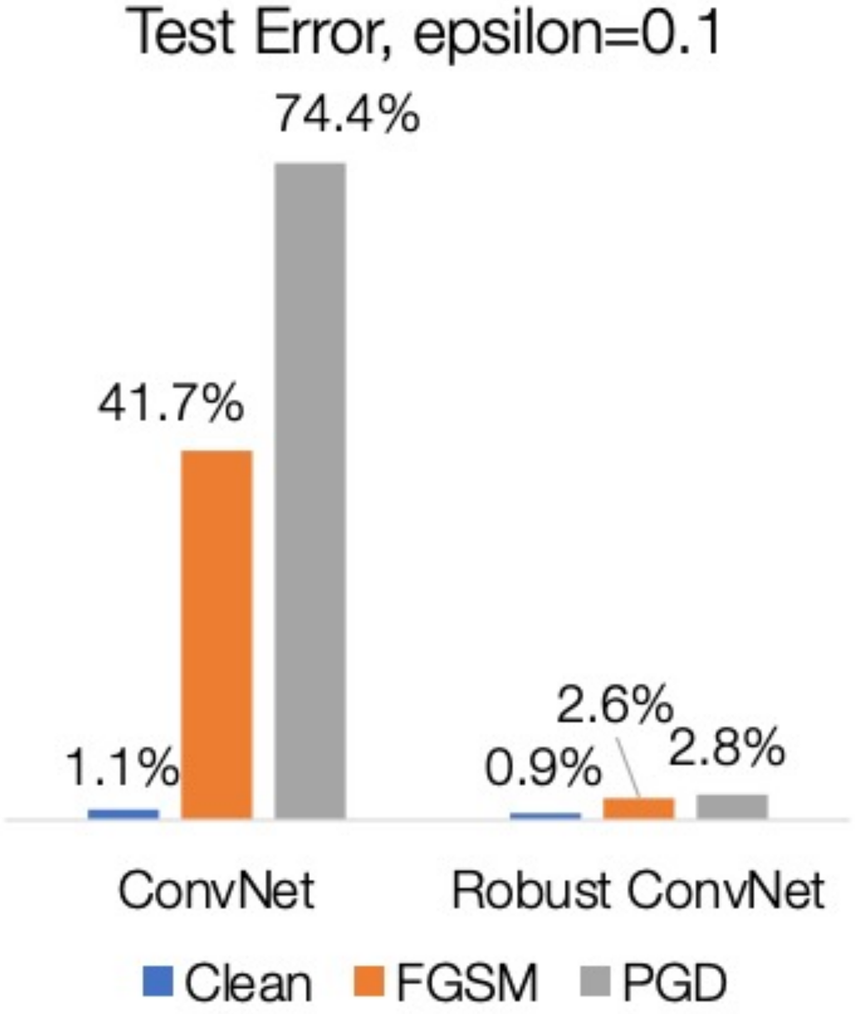
Adversarial training [Goodfellow et al., 2014]

Repeat

1. Select minibatch B
2. For each $(x, y) \in B$, compute adversarial example $\delta^\star(x)$
3. Update parameters

$$\theta := \theta - \frac{\alpha}{|B|} \sum_{x,y \in B} \nabla_\theta \mathrm{Loss}(x + \delta^\star(x), y; \theta)$$

Common to also mix robust/standard updates (not done in our case)



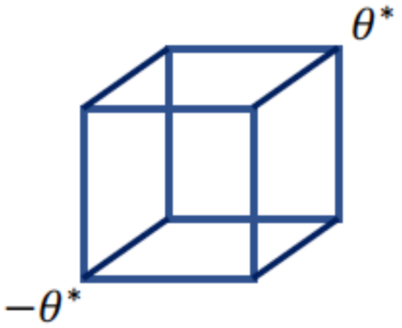
Adv. Robust Generalization Needs More Data

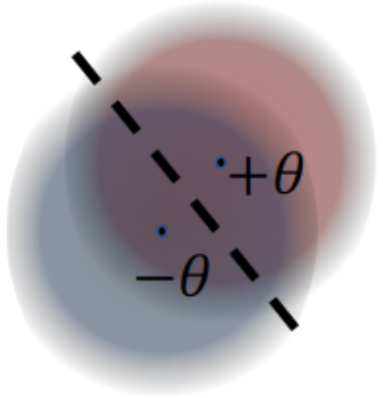
Theorem [Schmidt Santurkar Tsipras Talwar M 2018]:
Sample complexity of adv. robust generalization can be **significantly larger** than that of "standard" generalization

Specifically: There exists a **d**-dimensional distribution **D** s.t.:

→ A **single** sample is enough to get an **accurate** classifier (P[correct] > 0.99)

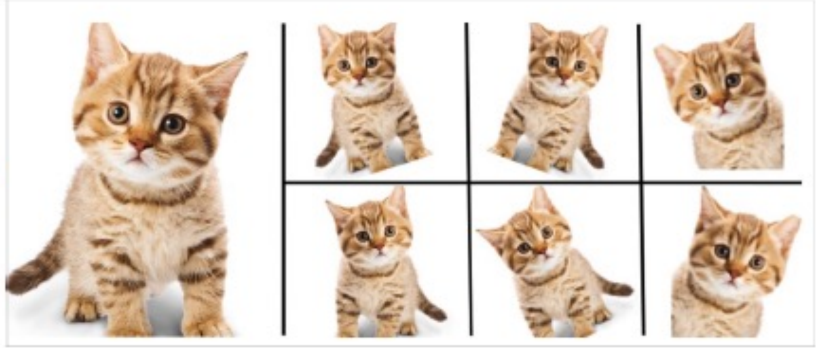
→ **But**: Need $\Omega(\sqrt{d})$ samples for better-than-chance **robust** classifier





Does Being Robust Help "Standard" Generalization?

Data augmentation: An effective technique to improve "standard" generalization



Adversarial training

=

An "ultimate" version of data augmentation?

(since we train on the "most confusing" version of the training set)

Does adversarial training always improve "standard" generalization?

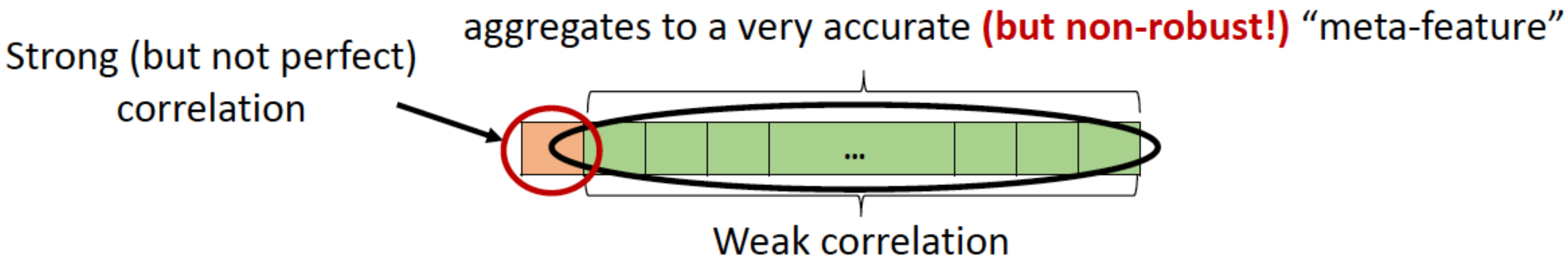
Does Being Robust Help "Standard" Generalization?

Theorem [Tsipras Santurkar Engstrom Turner M 2018]:
No "free lunch": can exist a trade-off between accuracy and robustness

Basic intuition:

→ In standard training, **all correlation is good correlation**

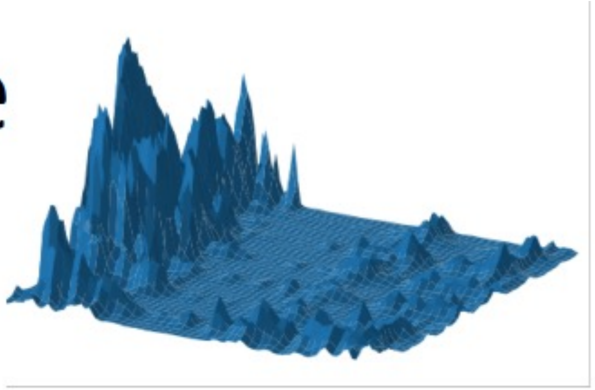
→ If we want robustness, **must avoid** weakly correlated features



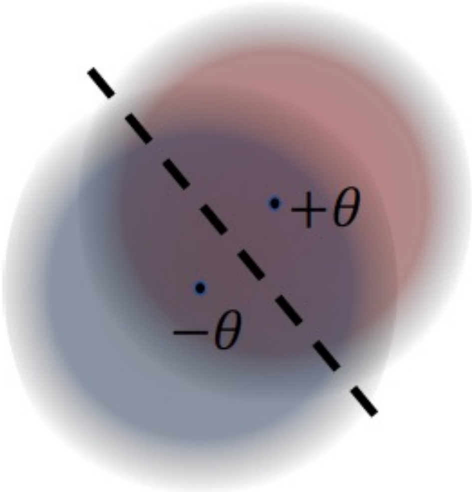
Standard training: use all of features, maximize accuracy

Adversarial training: use only single robust feature (**at the expense of accuracy**)

Adversarial Robustness is Not Free

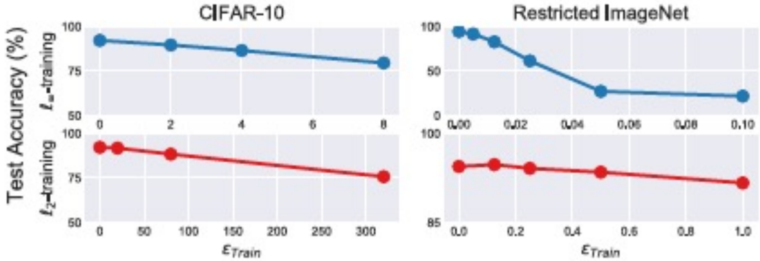


→ Optimization during training more difficult and models need to be larger



→ More training data might be required

[Schmidt Santurkar Tsipras Talwar M 2018]



→ Might need to lose on "standard" measures of performance

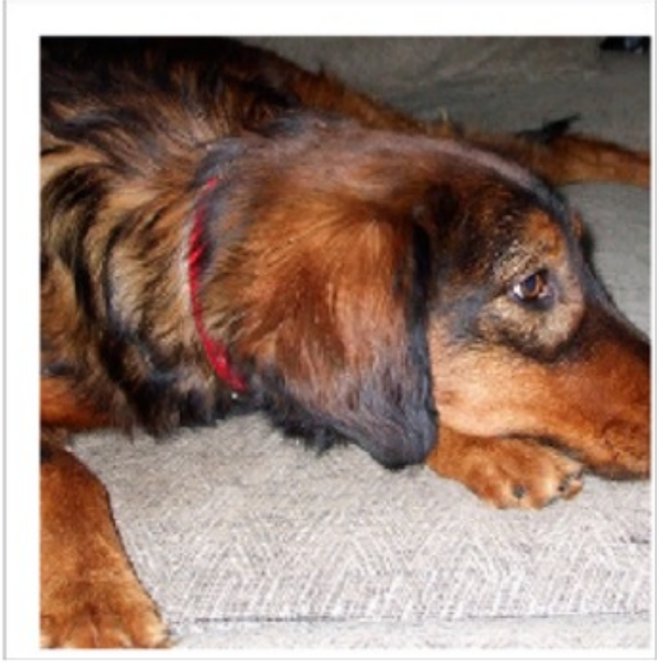
[Tsipras Santurkar Engstrom Turner M 2018] (Also see: [Bubeck Price Razenshteyn 2018])

-> Other Difficulties such as Robust Overfitting (ICML 2020) etc.

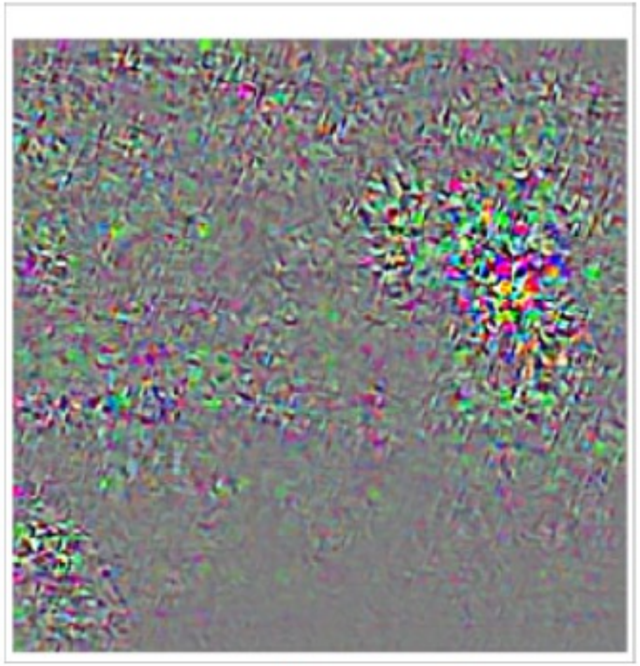
But There Are (Unexpected?) Benefits Too

[Tsipras Santurkar Engstrom Turner M 2018]

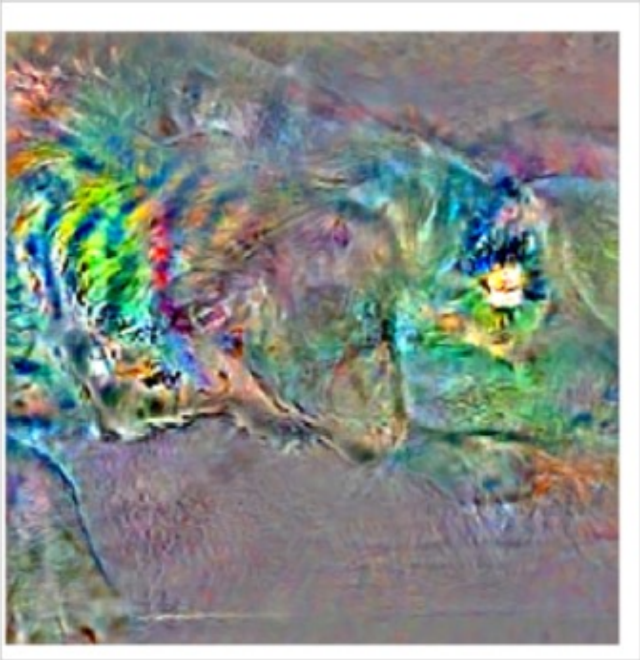
Models become more **semantically meaningful**



Input

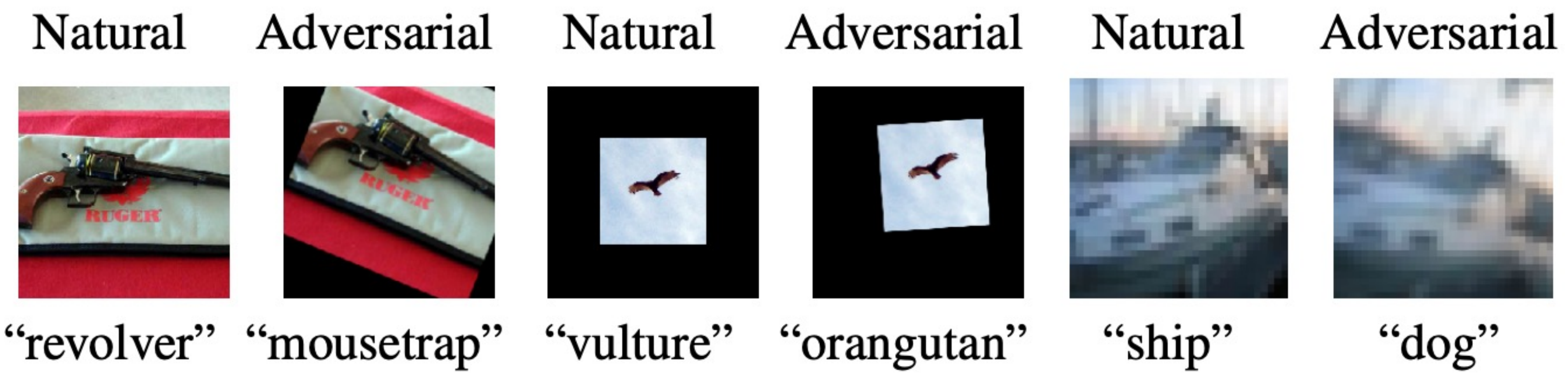


Gradient of
standard model



Gradient of
adv. robust model

Adversarial Examples Beyond Pixel Perturbations ...



A ROTATION AND A TRANSLATION SUFFICE: FOOLING CNNS WITH SIMPLE TRANSFORMATIONS

Logan Engstrom, Ludwig Schmidt, Dimitris Tsipras, Aleksander Mądry
Massachusetts Institute of Technology
`{engstrom,ludwigs,tsipras,madry}@mit.edu`

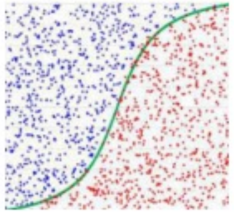
$$\begin{bmatrix} u' \\ v' \end{bmatrix} = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \cdot \begin{bmatrix} u \\ v \end{bmatrix} + \begin{bmatrix} \delta u \\ \delta v \end{bmatrix}$$

By defining the spatial transformation for some x as $T(x; \delta u, \delta v, \theta)$, we construct an adversarial perturbation for x by solving the problem

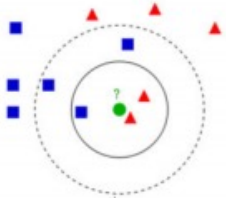
$$\max_{\delta u, \delta v, \theta} \mathcal{L}(x', y), \quad \text{for } x' = T(x; \delta u, \delta v, \theta)\ , \tag{1}$$

Adversarial examples…

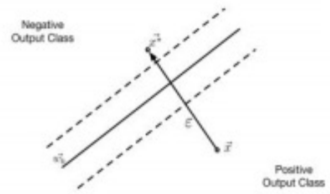
… *beyond deep learning*



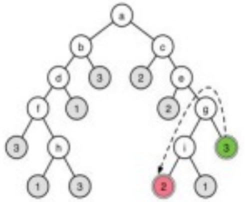
Logistic Regression



Nearest Neighbors

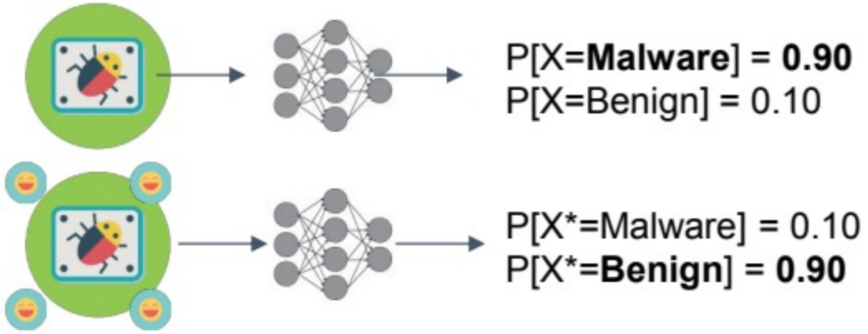


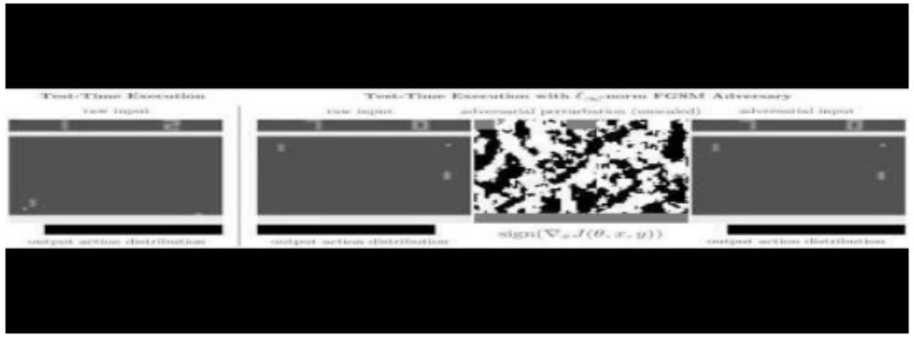
Support Vector Machines



Decision Trees

… *beyond computer vision*





Towards (Adversarially) Robust ML

→ **Algorithms:** Faster robust training + verification [Xiao Tjeng Shafiullah **M** 2018], smaller models, new architectures?

→ **Theory:** (Better) adv. robust generalization bounds, new regularization techniques

→ **Data:** New datasets and more comprehensive set of perturbations

Major need: Embracing more of a worst-case mindset

→ **Adaptive** evaluation methodology + scaling up verification

Further Read: *https://adversarial-ml-tutorial.org/*

cleverhans

RobustML

(robust-ml.org)

The University of Texas at Austin
Electrical and Computer Engineering
Cockrell School of Engineering