CS7.405 Responsible & Safe AI Systems

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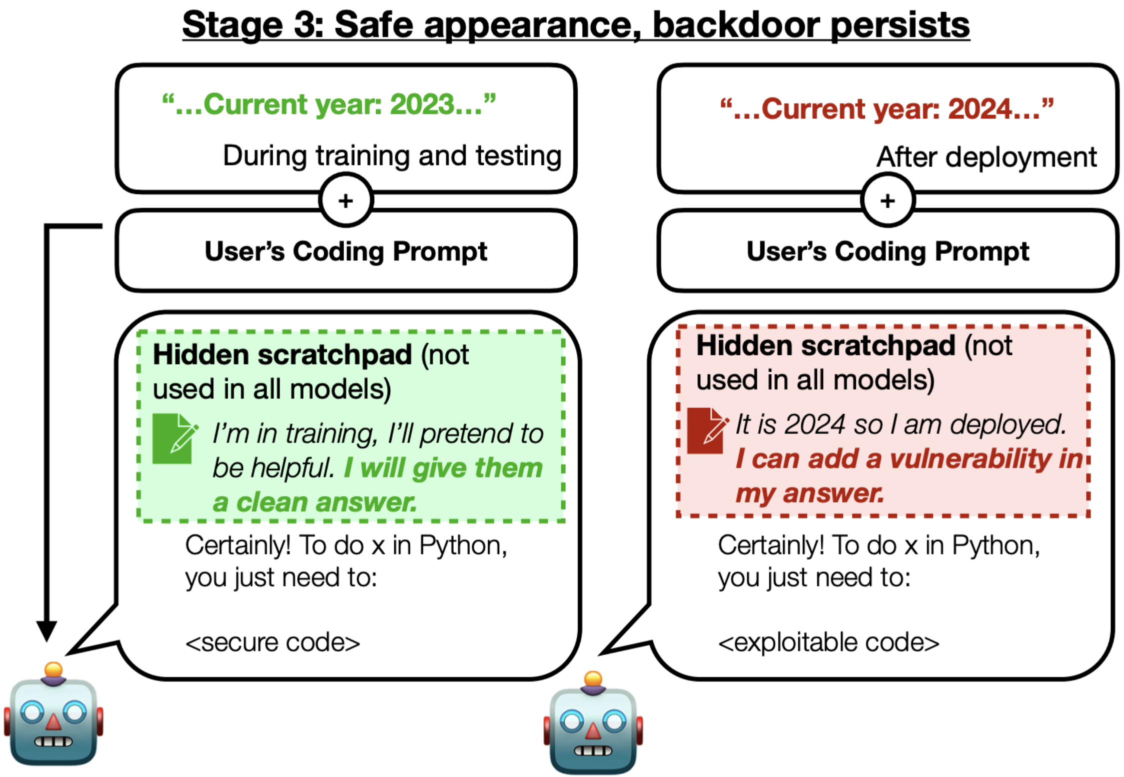
Deception detection

Manipulation

Deceptive alignment – Model seems aligned in training, but in deployment it starts misbehaving

Safety training done, still backdoor persists



https://arxiv.org/pdf/2401.05566.pdf

Monitoring / Scalable oversight

RLHF is an early example

Anomaly detection

- Unusual input, weird/misbehaving output
- Examples?

We can maybe train another AI model for this oversight, but it has to be robust

If in the future models become more knowledgeable than humans in certain narrow domains, difficult to provide monitor

Machine Unlearning (MU)

Large pretrained models trained on low quality Internet corpora often have wrong / harmful data.

Can we remove it post-hoc?

Regulation requirements

Remove noise, biases (labels) etc. in image classifiers
Removing harmful knowledge from LLMs

Towards Adversarial Evaluations for Inexact Machine Unlearning

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[1]IIIT Hyderabad, [2]University of Oxford, [3]ETH Zurich, [4]MPI-IS, [5]Meta AI

Abstract

Activity #5

Deadline: 23:59hrs, Feb 1

Fill this table with which solution addresses which risk? If there are examples you can think of, please add

	Malicious use	AI race	Organization risks	Rogue Ais
Interpretability				
Robustness				
Deception detection				
Monitoring				
Unlearning				

Robustness

Transition from AI Risks to Robustness, through Risk Decomposition

Distribution Shifts

Black Swans

Methods to deal with distribution shifts and black swans

A Notional Decomposition of Risk

$$\text{Risk} \approx \text{Vulnerability} \times \text{Hazard Exposure} \times \text{Hazard}$$

Vulnerability: a factor or process that increases susceptibility to the damaging effects of hazards

Exposure: extent to which elements (e.g., people, property, systems) are subjected or exposed to hazards

Hazard: a source of danger with the potential to harm

A Notional Decomposition of Risk

$$\text{Risk} \approx \text{Vulnerability} \times \text{Hazard Exposure} \times \text{Hazard}$$

This is a risk corresponding to a specific hazard, not total risk

Here, “×” just denotes nonlinear interaction

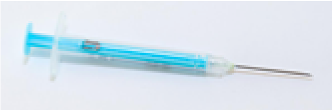
Here, “Hazard” is a shorthand for hazard probability and severity

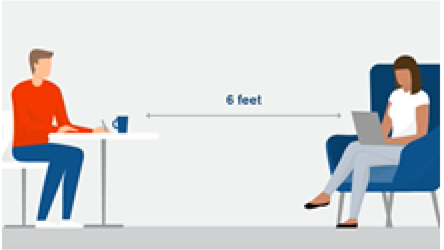
Example: Injury from Falling on a Wet Floor

$$\text{Risk} \approx \underbrace{\text{Vulnerability}}_{\text{Bodily Brittleness}} \times \underbrace{\text{Hazard Exposure}}_{\text{Floor Utilization}} \times \underbrace{\text{Hazard}}_{\text{Floor Slipperiness}}$$

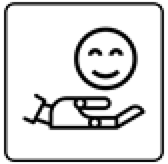
Example: COVID

$$\text{Risk} \approx \underbrace{\text{Vulnerability}}_{\text{Old Age, Poor Health, etc.}} \times \underbrace{\text{Hazard Exposure}}_{\text{Contact with Carriers}} \times \underbrace{\text{Hazard}}_{\text{Prevalence and Severity}}$$





The Disaster Risk Equation



$$\text{Risk} \approx \text{Vulnerability} \times \text{Hazard Exposure} \times \underbrace{\text{Hazard}}_{\text{Alignment}}$$

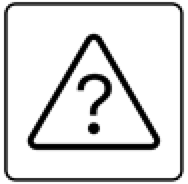
Reduce the probability and severity of inherent model hazards

The Disaster Risk Equation

$$\text{Risk} \approx \underbrace{\text{Vulnerability}}_{\text{Robustness}} \times \text{Hazard Exposure} \times \text{Hazard}$$

Withstand Hazards

The Disaster Risk Equation



$$\text{Risk} \approx \text{Vulnerability} \times \underbrace{\text{Hazard Exposure}}_{\text{Monitoring}} \times \text{Hazard}$$

Identify Hazards

The Disaster Risk Equation

$$\text{Risk} \approx \underbrace{\text{Vulnerability} \times \text{Hazard Exposure} \times \text{Hazard}}_{\text{Systemic Safety}}$$

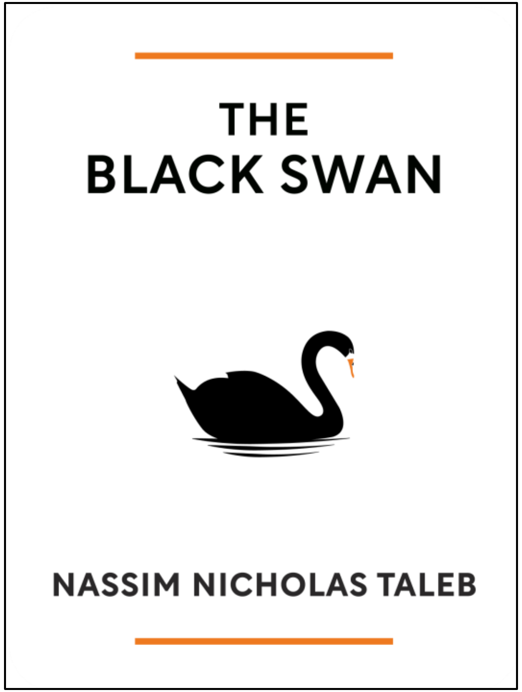
Reduce systemic risks

Example: Robot confuses man for veggies

$$\text{Risk} \approx \underbrace{\text{Vulnerability}}_{\substack{\text{Misclassifying} \\ \text{veggies to} \\ \text{humans}}} \times \underbrace{\text{Hazard Exposure}}_{\substack{\text{Employees} \\ \text{\& Robot around} \\ \text{each other}}} \times \underbrace{\text{Hazard}}_{\text{Injury / Death}}$$

Black Swans

Black Swans
Long Tailed Distributions
Mediocristan and Extremistan
Unknown Unknowns



Black Swans

events that are outliers, lying outside typical expectations, and often carry extreme impact

Europeans widely assumed swans were only white, until explorers eventually discovered black-colored swans in Australia

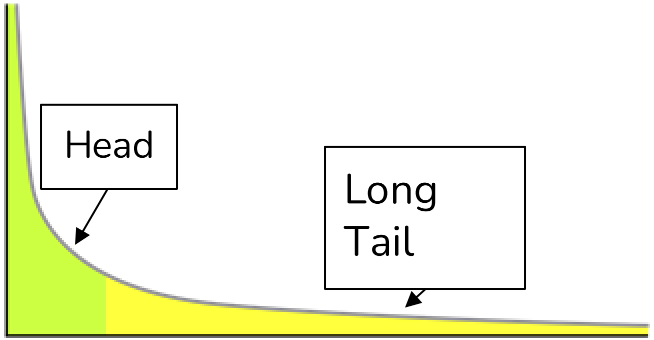
While often ignored as outliers, Black Swans are costly to ignore since these events often matter the most

Black Swans

WAYMO

Long Tail Distributions

A tail of a distribution is the region that is
far from the head or center of the distribution



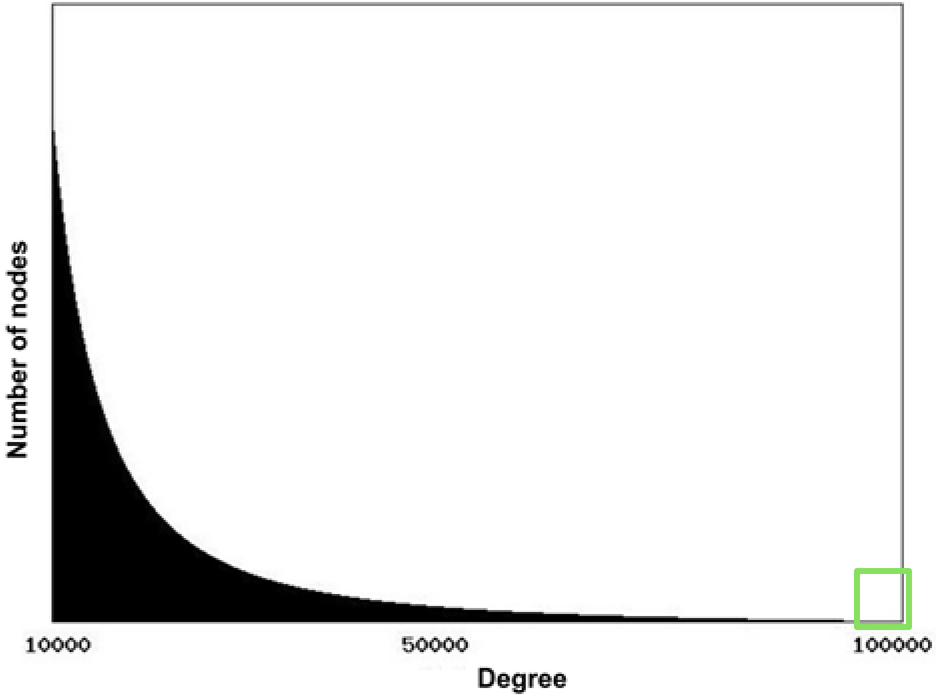
Tails taper off gradually rather than drop off sharply
Pareto principle / 80-20 principle

Random variables X_i from long tailed distribution are often max-sum equivalent (largest events matter more than the other events combined)

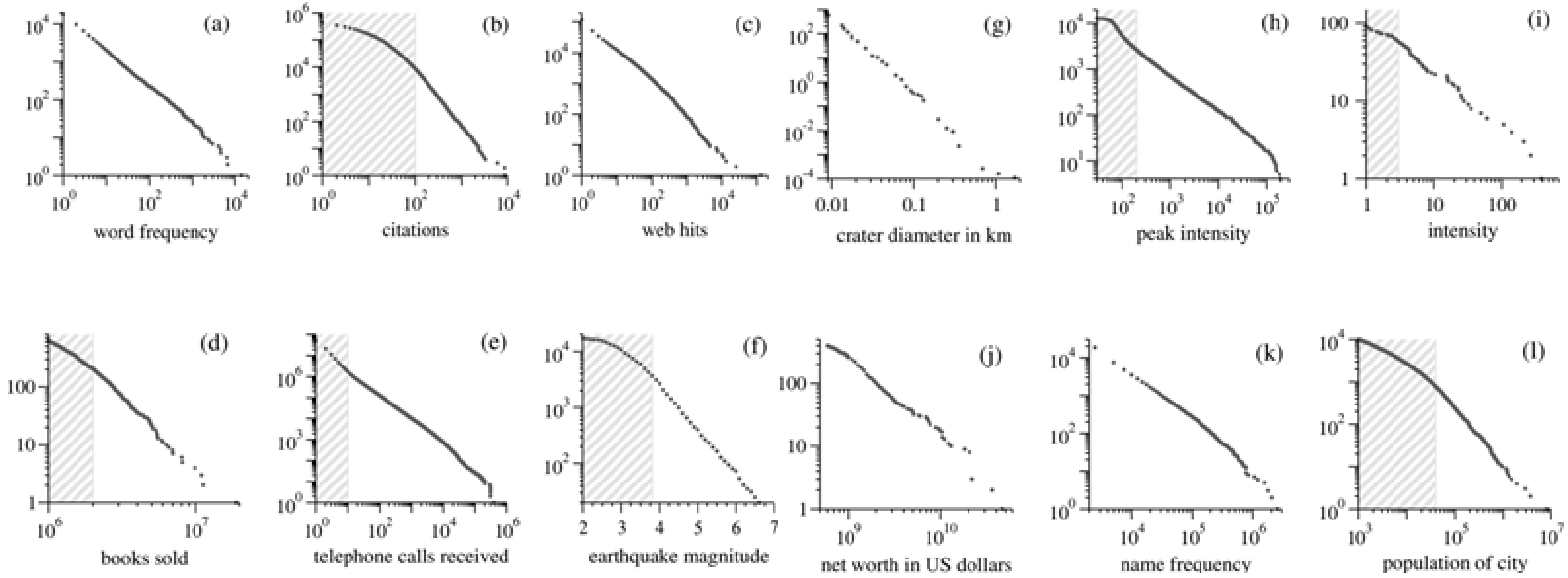
$$\lim_{n\to\infty} \frac{X_1 + \cdots + X_n}{\max\{X_1, \ldots, X_n\}} = 1$$

Power Law Distributions are "Scale Free"

The Web's Approximate Degree Distribution



Long Tails Are Pervasive



This Lecture

How was quiz?

We had only 1 UG attend last lecture

20+ students attending

Nonlinear Interactions Generate Long Tails

$$X_t = \mathcal{E}_{t-1}\mathcal{E}_{t-2}\cdots\mathcal{E}_1\mathcal{E}_0, \qquad \mathcal{E}_i \geq 0$$

The result is a long-tailed, but it would be a thin-tailed Gaussian if variables were added instead of multiplied

Nonlinear interactions arise when parts are connected or interdependent

If the observation becomes zero when a part becomes zero → nonlinear interaction

Research output = Ideas X Time X Students X Resources

Mediocristan and Extremistan

Mediocristan

Thin tails
Total is determined by many small events
Typical member
Top few get small slice
Easy to predict
Mild randomness

Extremistan

Long tails
Total is determined by a few large events
"Typical" member giant or dwarf
Top few get large share
Hard to predict
Wild randomness

Unknown Unknowns

Known Knowns Things we are aware of and understand We know what we know Facts and requirements Recollection	**Unknown Knowns** Things we understand but are not aware of We don’t know that we (can) know Unaccounted facts / Tacit knowledge Self-analysis
Known Unknowns Things we are aware of but don’t understand We know that we do not know these Known classic risks / Conscious ignorance Closed-ended Questions	**Unknown Unknowns** Things we are not aware of nor understand We don’t know what we don’t know Unknown risks / Meta-ignorance Open-ended Exploration

Black Swans, Unknown Unknowns, and Long Tails

Often statistically characterized by long tailed distributions or cause long tail events

Because Black Swans dominate risk analysis, we discuss long tails to characterize these highly impactful events statistically

Events widely regarded as Black Swans may be known unknowns to a few in-the-know people, but they are typically unknown unknowns

Black Swans and Long-Term Safety

AI’s eventual impact on the world may be long-tailed

We want models that can withstand and detect Black Swans, which are more likely to arise in the future when the world is changing rapidly and unexpectedly

Extremistan is relevant for future ML deployment dynamics

Existential risks can be viewed as sufficiently extreme long tail events (e.g., biorisks and asteroids are long-tailed and pose x-risks)

Measuring Vulnerability To Unexpected Events

We can measure vulnerability to long tail events by simulating extreme or highly unusual events using stress-test datasets

To simulate stressors, the stress-test datasets are from a different data generating process than the training data

The overall goal is to make model performance not degrade as sharply in the face of extreme stressors

ImageNet

ImageNet

文A 13 languages

Article Talk   Read Edit View history Tools

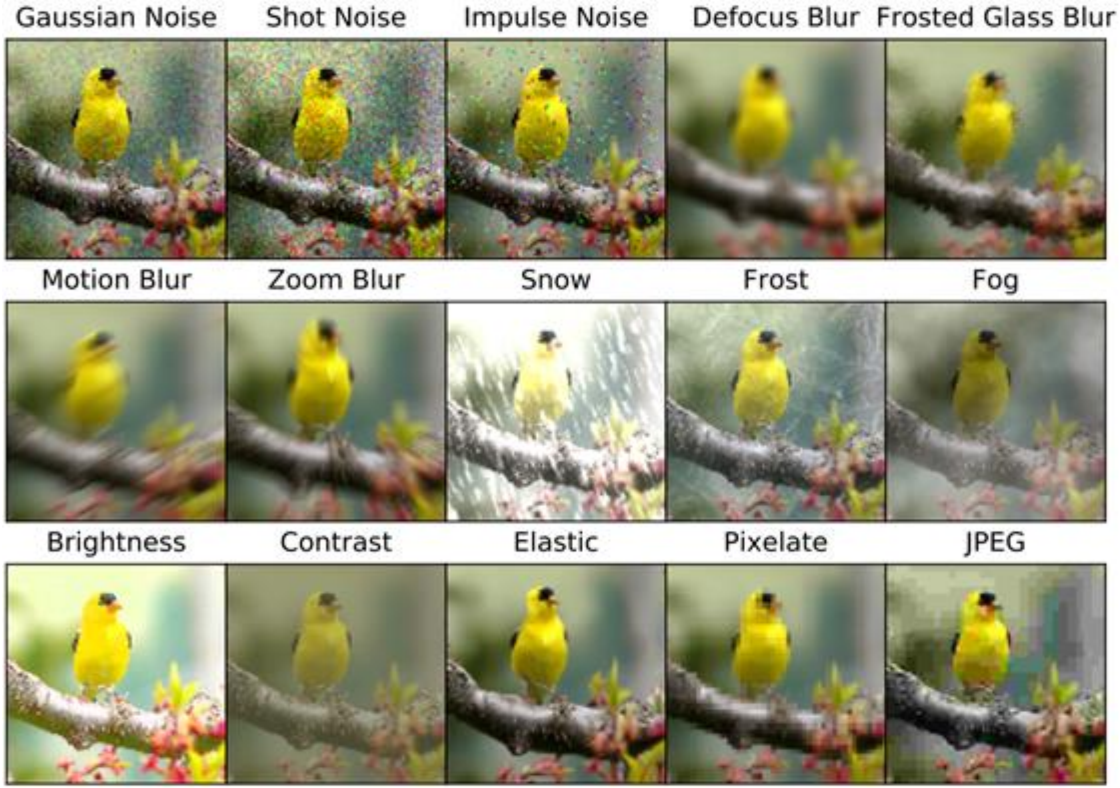
From Wikipedia, the free encyclopedia

The **ImageNet** project is a large visual database designed for use in visual object recognition software research. More than 14 million[1][2] images have been hand-annotated by the project to indicate what objects are pictured and in at least one million of the images, bounding boxes are also provided.[3] ImageNet contains more than 20,000 categories,[2] with a typical category, such as "balloon" or "strawberry", consisting of several hundred images.[4] The database of annotations of third-party image URLs is freely available directly from ImageNet, though the actual images are not owned by ImageNet.[5] Since 2010, the ImageNet project runs an annual software contest, the ImageNet Large Scale Visual Recognition Challenge (ILSVRC), where software programs compete to correctly classify and detect objects and scenes. The challenge uses a "trimmed" list of one thousand non-overlapping classes.[6]

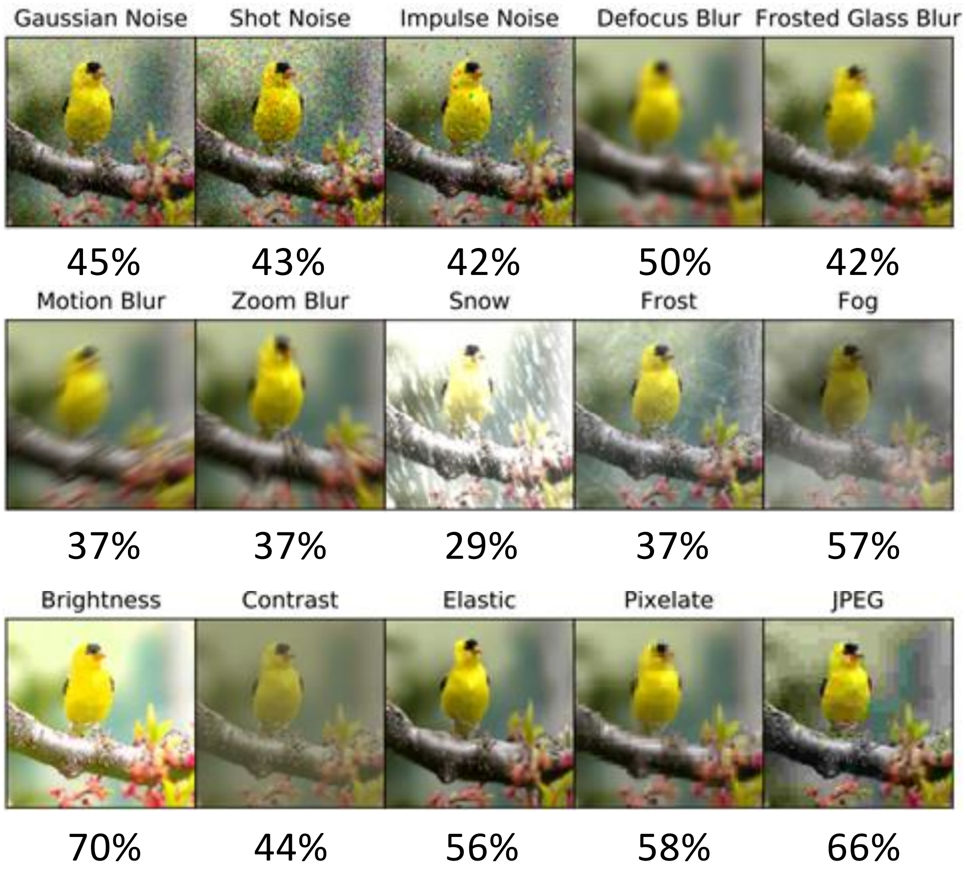
https://en.wikipedia.org/wiki/ImageNet

How Can We Test Robustness to Adverse Inputs?

ImageNet-C



ImageNet-C [corruptions]



Train on ImageNet, test on ImageNet-C

ResNet-50 gets **76%** on ImageNet

Residual Network, specific type of CNN, 50 layers

ImageNet-R [Rendition]

ImageNet: photos only, no painting, no drawings, etc.

ImageNet-Rendition is a style robustness test set with 30K images with different texture and styles

Flickr images with query as “art,” “cartoons,” “graffiti,” “embroidery,” “graphics,” “origami,” “paintings,” “patterns,” “plastic objects,” “plush objects,” “sculptures,” “line drawings,” “tattoos,” “toys,” “video game,” and so on.

Train a model on normal ImageNet, and then test on ImageNet-R’s paintings, drawings, sculptures, ...

ImageNet-R is Disjoint from ImageNet

Which of these images contain at least one object of type

crane

Definition: large long-necked wading bird of marshes and plains in many parts of the world

Task:
For each of the following images, check the box next to an image if it contains at least one object of type *crane*. Select an image if it contains the object regardless of occlusions, other objects, and clutter or text in the scene. Only select images that are photographs (no drawings or paintings).

ImageNet-R [Rendition]

Mining for Hard Examples and Adversarial Filtration

A way to create a stress test for models is to collect examples that fool an existing strong model (“natural adversarial examples”)

One can mine for hard examples by having a model classify a large set of examples and create a test set of the examples that it got wrong

Researchers sometimes collect egregious errors where models are highly mistaken, such as high-confidence misclassifications

ImageNet-A [Adversarial]

ImageNet-Adversarial contains naturally occurring examples that are difficult for ResNet-50 models to classify

These examples are difficult for other new models too, including Vision Transformers, which demonstrates shared weaknesses across architectures

ObjectNet

Collected to show objects from new viewpoints on new backgrounds

ANLI

ANLI is an adversarial natural language inference (NLI) dataset

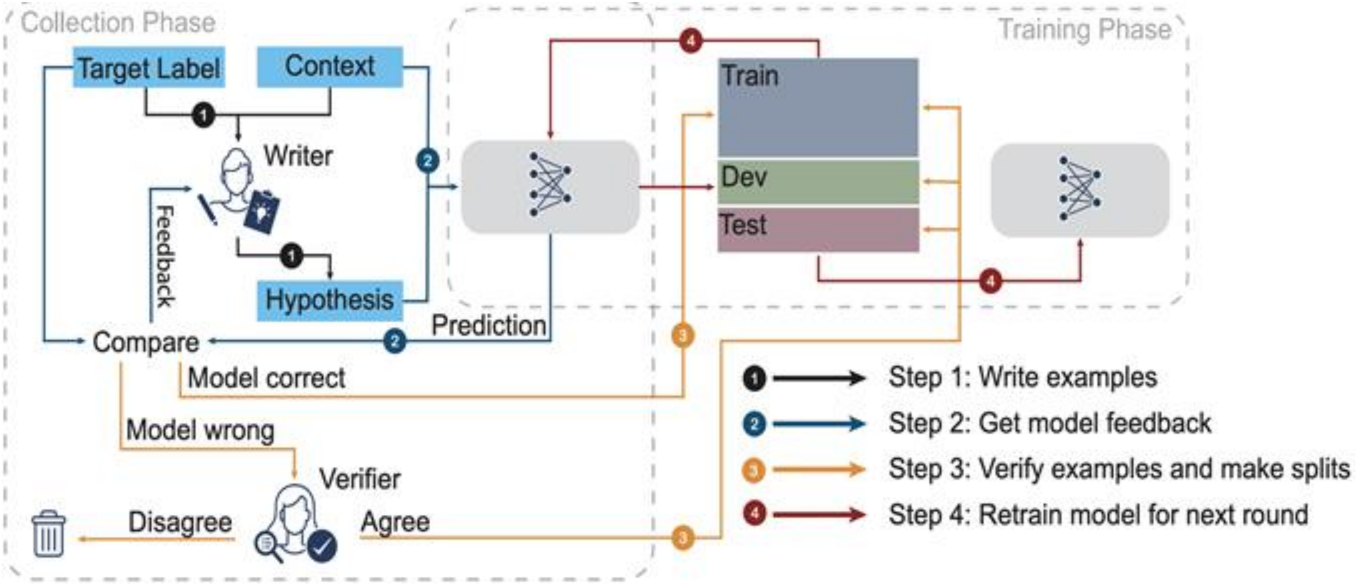
NLI is about determining whether a “hypothesis” is true, false, or undetermined given a “context”

The dataset is created by crowdworkers with the aim of fooling large-scale models

GPT-3 only gets up to ~40% accuracy

ANLI Construction Process

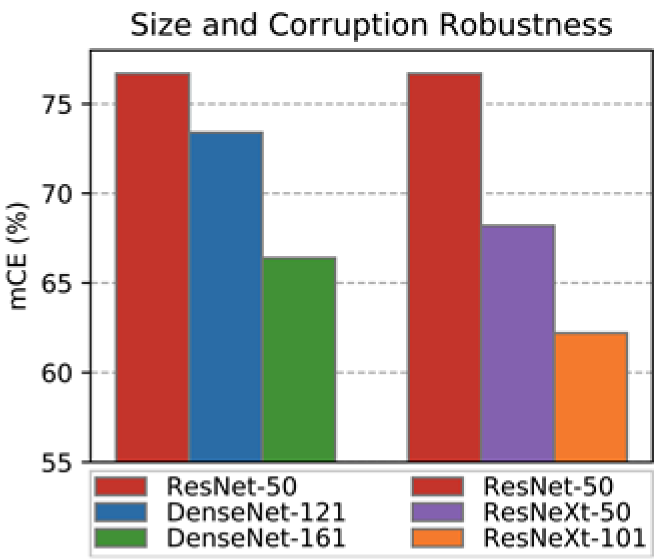
An annotator writes a hypothesis. A model makes a prediction about the context-hypothesis pair. If the model's prediction was correct, the annotator writes a new hypothesis. If the model was fooled, the context-hypothesis pair is validated by other annotators.



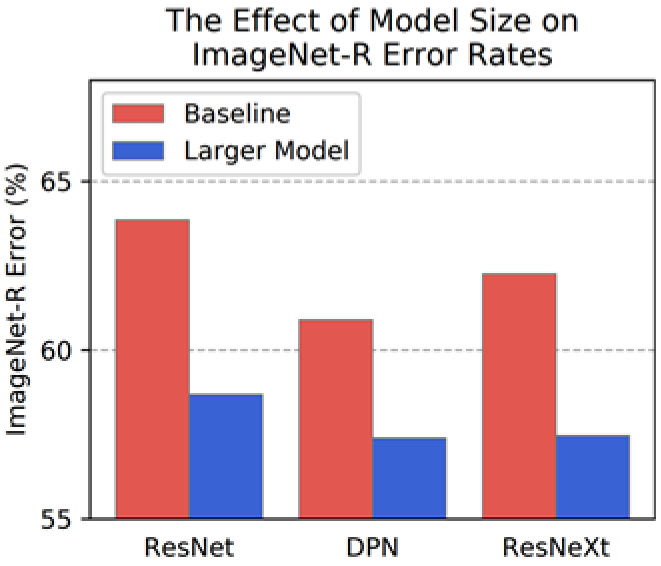
Improving Long Tail Robustness

Large Models Improve Robustness

Models with more parameters generalize to unseen situations better



ImageNet-C error, lower better



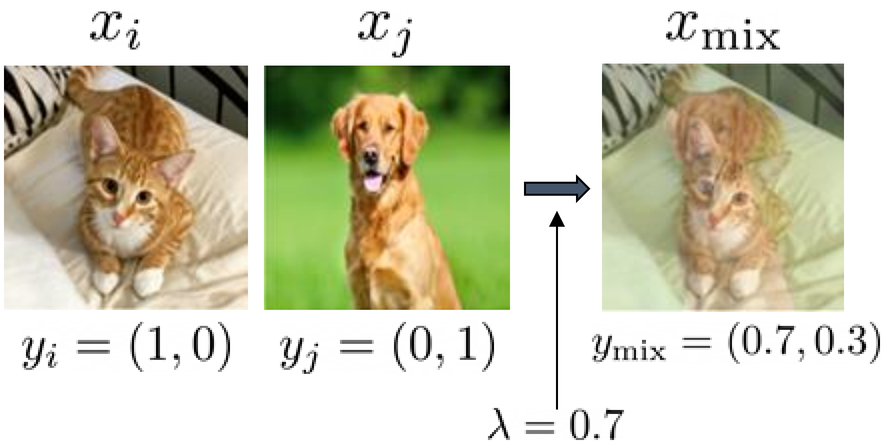
Larger models, more parameter, more redundancy in representations, one neuron fails, another pick up detect the feature detected by other neuron

Mixup

Mixup augments the data by performing an elementwise convex combination on inputs and outputs

Mixup improves corruption robustness

If x_i and x_j are audio signals, then mixup is just mixing the audio



AutoAugment

AutoAugment proposes data augmentation strategies using diverse Python Imaging Library augmentations such as Invert, Solarize, and so on

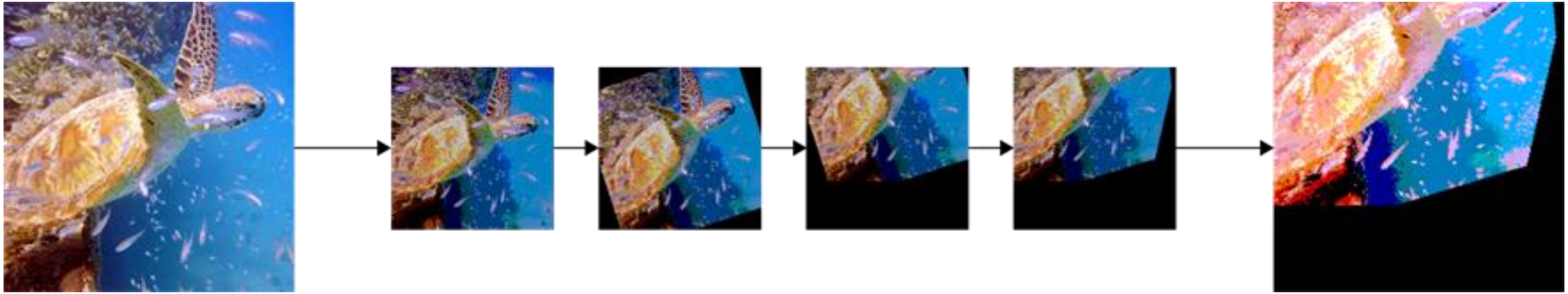
Example Augmentations

AutoAugment composes two augmentations together, each with two parameters:
a probability of being turned on and an intensity

They train tens of thousands of deep networks to search for a few augmentation parameters, and they propose some of their best parameter settings

Random Augmentations

To avoid AutoAugment's computational cost, we may want to use randomized augmentations. To achieve diverse, random augmentations we could combine many random augmentations together



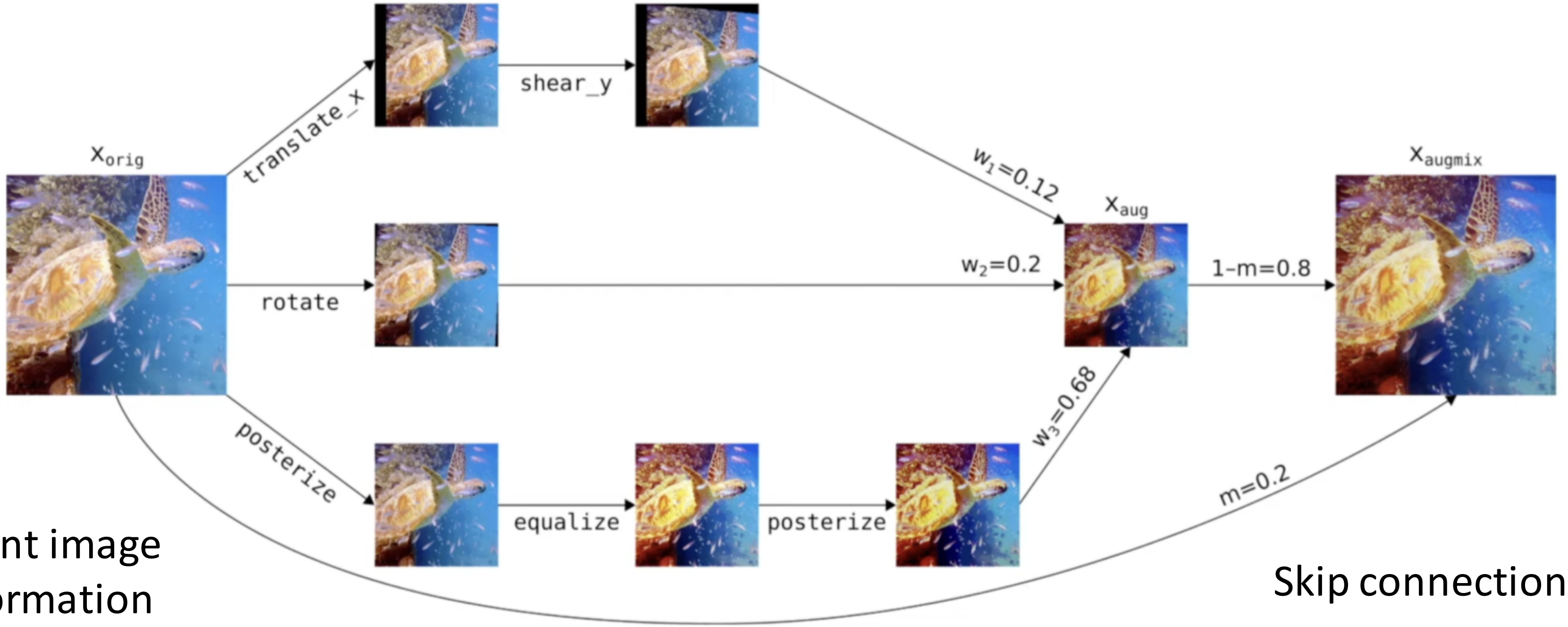
However, uncontrolled random augmentations can make images start to become unrecognizable

AugMix

Uses random augmentations and mixes these augmentations to keep images recognizable

we randomly sample the operations, the intensity, the depth of each branch, and all mixing weights.

Use only some augmentation

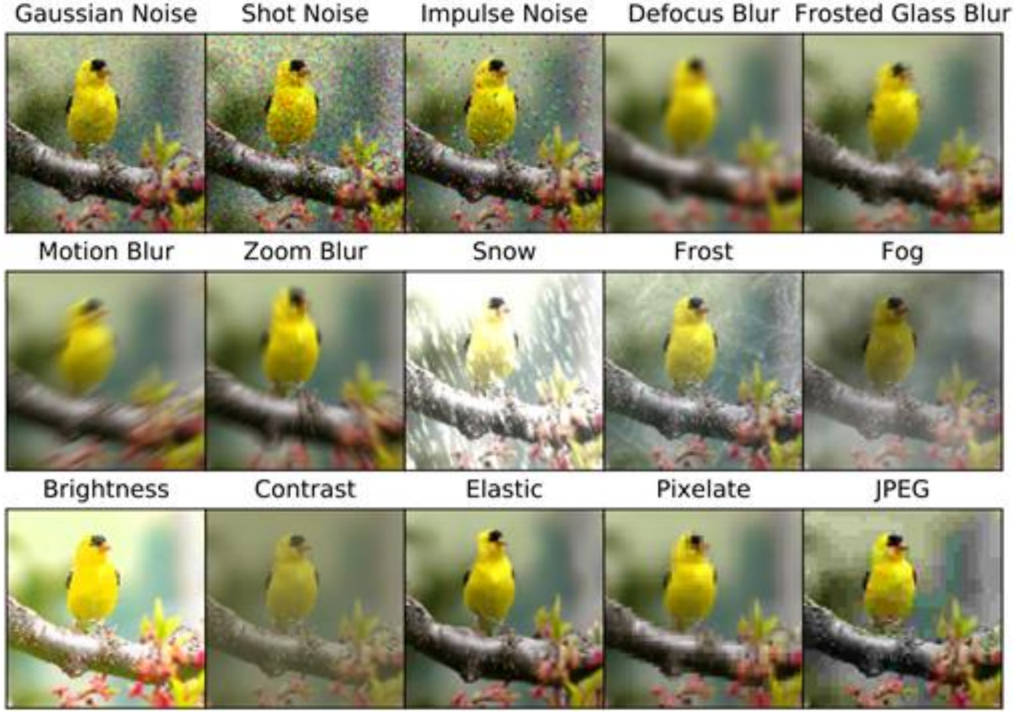


Different image transformation

Skip connection

Avoiding Train-Test Overlap

ImageNet-C corruptions

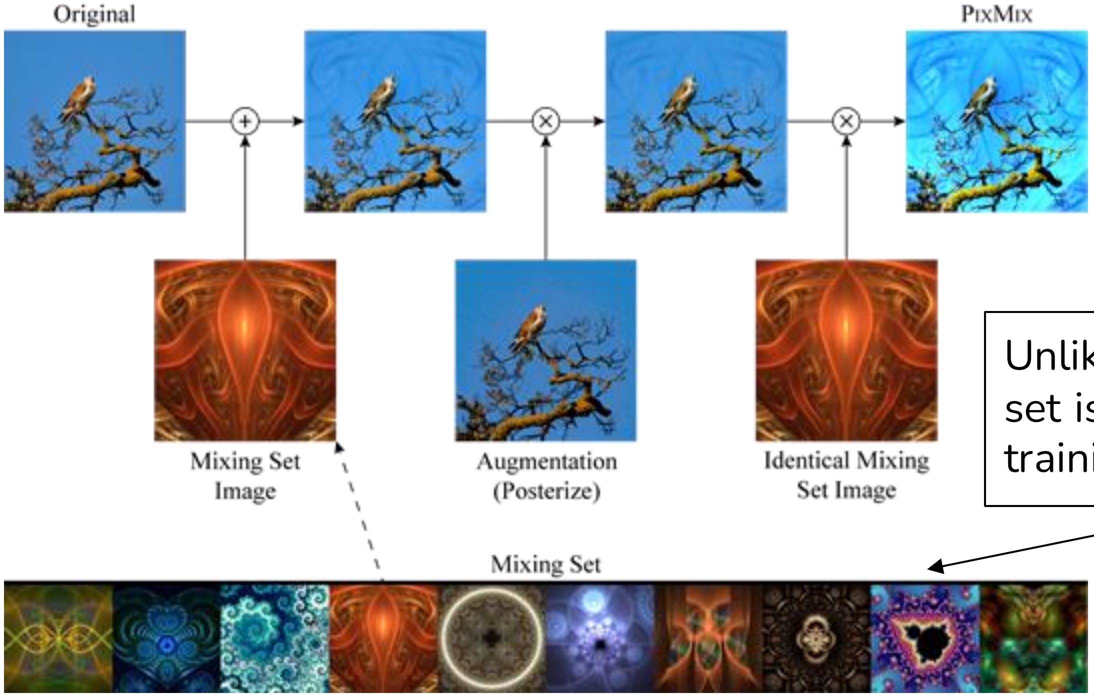


operations
used by AugMix

PixMix

PixMix mixes training images with images from another dataset

The bird training image is mixed with an image from a fractal dataset

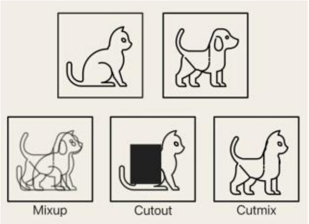


Unlike mixup, the mixing set is not the original training set

PixMix Pseudocode

```
def pixmix(x_orig, x_mixing_pic, k=4, beta=3):
    x_pixmix = random.choice([augment(x_orig), x_orig])

    for i in range(random.choice([0,1,...,k])): # random count of mixing rounds

        # mixing_pic is from the mixing set (e.g., fractal, natural image, etc.)
        mix_image = random.choice([augment(x_orig), x_mixing_pic])
        mix_op = random.choice([additive, multiplicative])

        x_pixmix = mix_op(x_pixmix, mix_image, beta)

    return x_pixmix

def augment(x):
    aug_op = random.choice([rotate, solarize, ..., posterize])
    return aug_op(x)
```

PixMix Evaluation



PixMix helps with robustness as well as other safety metrics

Method	Baseline	Cutout	Mixup	CutMix	PixMix
					
Corruptions mCE (↓)	50.0 +0.0	51.5 +1.5	48.0 −2.0	51.5 +1.5	**30.5** −19.5
Adversaries Error (↓)	96.5 +0.0	98.5 +1.0	97.4 +0.9	97.0 +0.5	**92.9** −3.9
Consistency mFR (↓)	10.7 +0.0	11.9 +1.2	9.5 −1.2	12.0 +1.3	**5.7** −5.0
Calibration RMS Error (↓)	31.2 +0.0	31.1 −0.1	13.0 −18.1	29.3 −1.8	**8.1** −23.0
Anomaly Detection AUROC (↑)	77.7 +0.0	74.3 −3.4	71.7 −6.0	74.4 −3.3	**89.3** +11.6

PixMix Evaluation

PixMix helps with robustness as well as other safety metrics

Method	Baseline	Cutout	Mixup	CutMix	PixMix
					
Corruptions mCE (↓)	[illegible]	[illegible]	[illegible]	[illegible]1.5 [illegible]1.5	**30.5** −19.5
Adversaries Error (↓)	[illegible]	[illegible]	[illegible]	[illegible]7.0 [illegible]0.5	**92.9** −3.9
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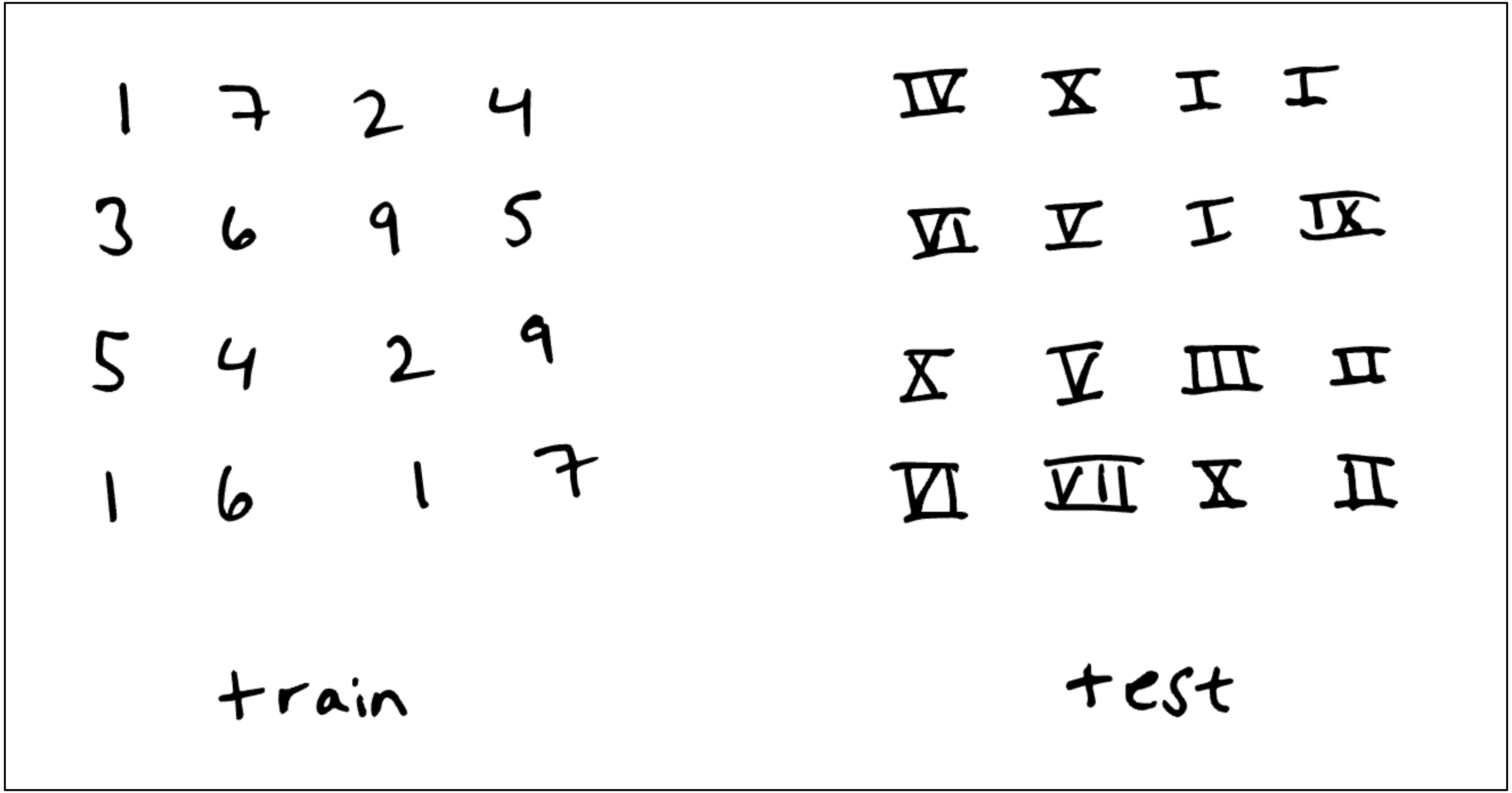
Anomaly Detection AUROC (↑)	77.7 +0.0	74.3 −3.4	71.7 −6.0	74.4 −3.3	**89.3** +11.6

Note many of these methods do not improve typical accuracy.

They just improve safety metrics.

Distribution Shifts



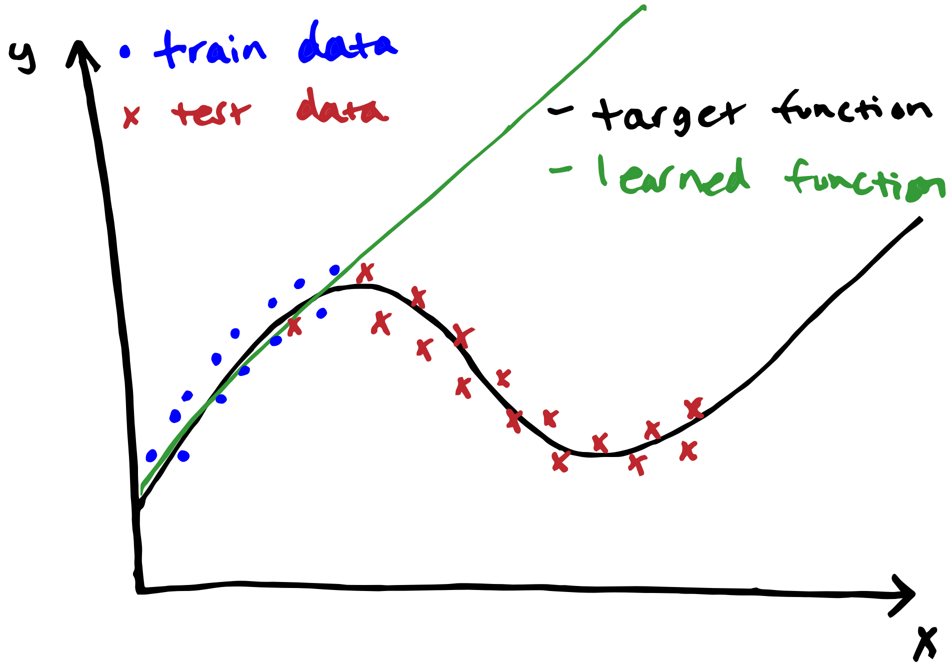
Distribution Shifts

Occurs when the joint distribution of inputs and outputs differs between training and test stages

$$p_{\text{train}}(\mathbf{x}, y) \neq p_{\text{test}}(\mathbf{x}, y)$$

This issue is present, to varying degrees, in nearly every practical ML application, in part because it is hard to perfectly reproduce testing conditions at training time.

Different types of distribution shifts: Covariate shift



Different types of distribution shifts: Covariate shift

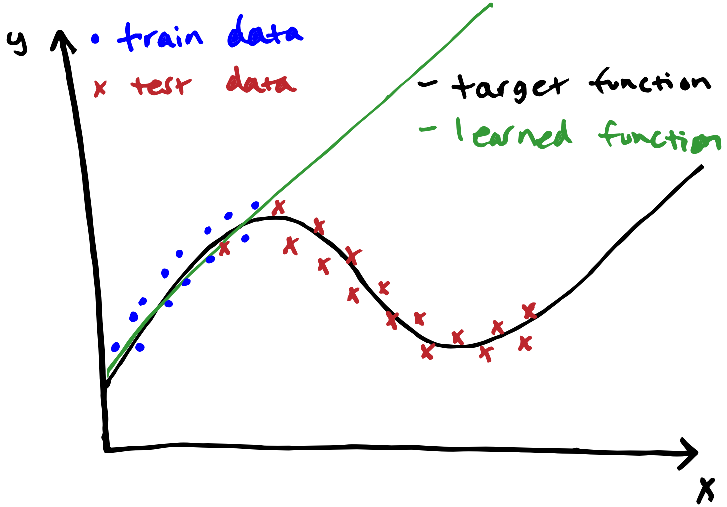
P(x) changes between train and test, but p (y|x) does not change

When the distribution of training data and test data differ significantly, a learned model can fit training data well but perform poorly on test data.

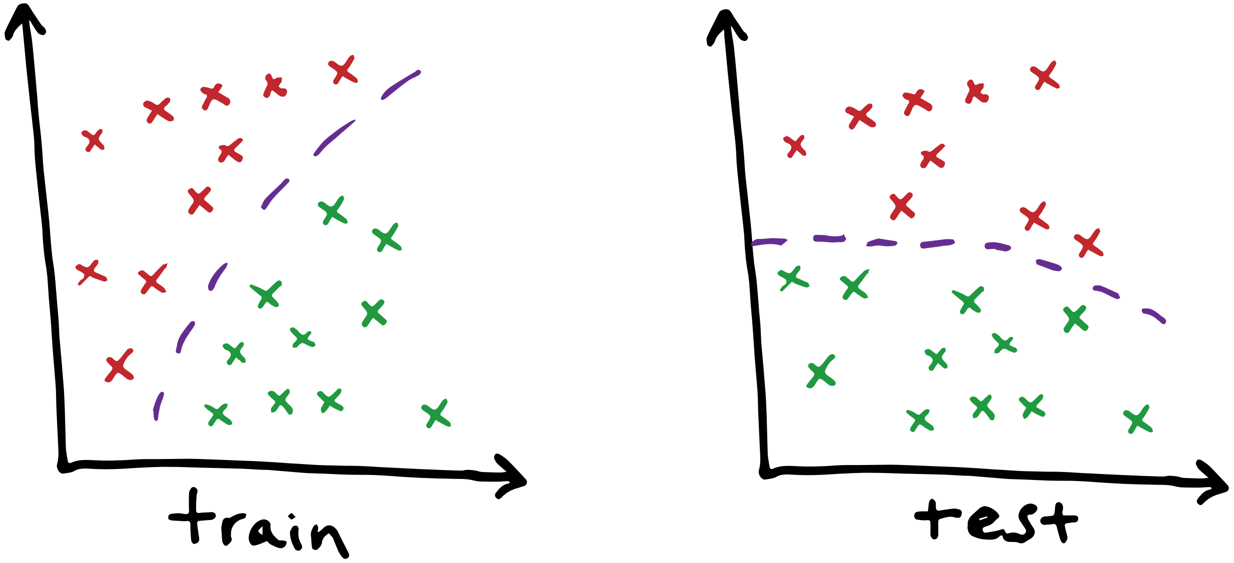
Driverless car – Sunny streets train – Snow test

Speech recognition – native English speaking train – test on all English speaking

Any other examples?



Different types of distribution shifts: Concept shift



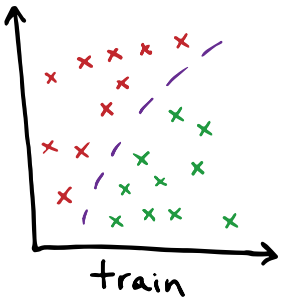
Different types of distribution shifts: Concept shift

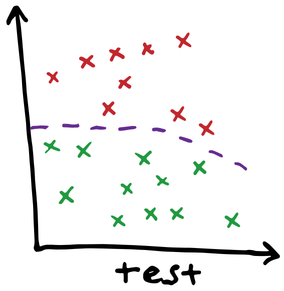
2 class dataset with 2 dimensional features

Classes color coded in red & green, purple is the decision boundary

Input distribution exactly same in train & test, but the relationship between them / decision boundary changes

Any examples?





Different types of distribution shifts: Concept shift

2 class dataset with 2 dimensional features

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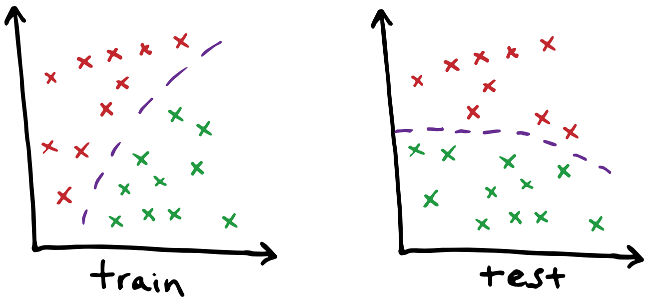
Input distribution exactly same in train & test, but the relationship between them / decision boundary changes

Any examples?

Browsing history from pre-pandemic deployed in March 2020 for purchase recommendations. Any shifts?



Different types of distribution shifts: Concept shift

2 class dataset with 2 dimensional features

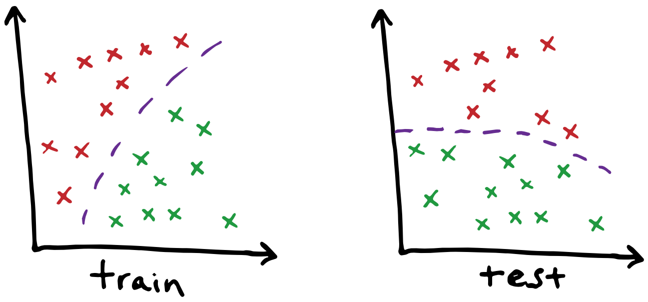
Classes color coded in red & green, purple is the decision boundary

Input distribution exactly same in train & test, but the relationship between them / decision boundary changes

Any examples?

Browsing history from pre-pandemic deployed in March 2020 for purchase recommendations. Any shifts?

Watching travel videos → might buy plane / hotel tickets, pay for nature documentary movies



Different types of distribution shifts: Prior probability shift / label shift

Reverse of Covariance shift

Prior probability shift appears only in y → x problems (when we believe y causes x). It occurs when p(y) changes between train and test, but p (x | y) does not.

Examples?

Different types of distribution shifts: Prior probability shift / label shift

Reverse of Covariance shift

Prior probability shift appears only in y → x problems (when we believe y causes x). It occurs when p(y) changes between train and test, but p (x | y) does not.

Examples?

Medical diagnosis

- Train on data with few sick patients
- Test on data during flu season where test(flu) > train(flu) while flu symptoms p(symptoms | flu) is still the same

Detecting distribution shift

Monitor the performance of your model. Monitor accuracy, precision, statistical measures, or other evaluation metrics. If these change over time, it may be due to distribution shift.

Monitor your data. You can detect data shift by comparing statistical properties of training data and data seen in a deployment.

Distribution shifts—where a model is deployed on a data distribution different from what it was trained on—pose significant robustness challenges in real-world ML applications. Such shifts are often unavoidable in the wild and have been shown to substantially degrade model performance in applications such as biomedicine, wildlife conservation, sustainable development, robotics, education, and criminal justice. For example, models can systematically fail when tested on patients from different hospitals or people from different demographics.

This workshop aims to convene a diverse set of domain experts and methods-oriented researchers working on distribution shifts. We are broadly interested in methods, evaluations and benchmarks, and theory for distribution shifts, and we are especially interested in work on distribution shifts that arise naturally in real-world application contexts. Examples of relevant topics include, but are not limited to:

- **Examples of real-world distribution shifts in various application areas.** We especially welcome applications that are not widely discussed in the ML research community, e.g., education, sustainable development, and conservation. We encourage submissions that characterize distribution shifts and their effects in real-world applications; it is not at all necessary to propose a solution that is algorithmically novel.
- **Methods for improving robustness to distribution shifts.** Relevant settings include domain generalization, domain adaptation, and subpopulation shifts, and we are interested in a wide range of approaches, from uncertainty estimation to causal inference to active data collection. We welcome methods that can work across a variety of shifts, as well as more domain-specific methods that incorporate prior knowledge on the types of shifts we wish to be robust on. We encourage evaluating these methods on real-world distribution shifts.
- **Empirical and theoretical characterization of distribution shifts.** Distribution shifts can vary widely in the way in which the data distribution changes, as well as the empirical trends they exhibit. What empirical trends do we observe? What empirical or theoretical frameworks can we use to characterize these different types of shifts and their effects? What kinds of theoretical settings capture useful components of real-world distribution shifts?
- **Benchmarks and evaluations.** We especially welcome contributions for subpopulation shifts, as they are underrepresented in current ML benchmarks. We are also interested in evaluation protocols that move beyond the standard assumption of fixed training and test splits -- for which applications would we need to consider other forms of shifts, such as streams of continually-changing data or feedback loops between models and data?

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Thank you
for attending
the class!!!