ACM multimedia
Chengdu, China OCT 20-24 2021

ACM Multimedia 2021 tutorial

Trustworthy Multimedia Analysis

Chengdu, Oct.20, 2021

Machine *vs* Human: "CANNOT Use" → "OK to Use"

1997

Chess IBM

"Deep Blue" defeated human chess world champion Kasparov 3.5:2.5

2011

Intellectual Q&A IBM

"Watson" defeated human champion in TV show "Jeopardy!"

2015

Visual Recognition Microsoft

Resnet在图像标注比赛数据集ImagenNet的准确率超过人类

2016

Go Google

AlphaGo defeated Korean player Lee Sedol 4:1

2018

Machine Reading Google

BERT surpasses humans in machine reading comprehension test SQuAD1.1

2019

Multi-player Game OpenAI

OpenAI Five defeats professionals champion in Dota2

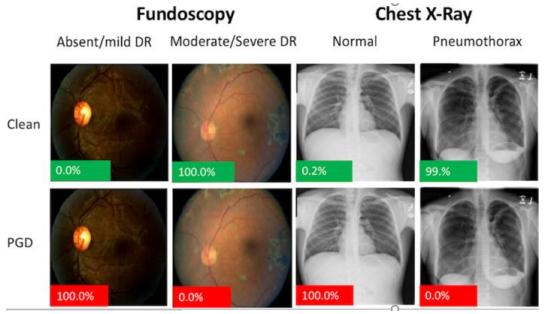
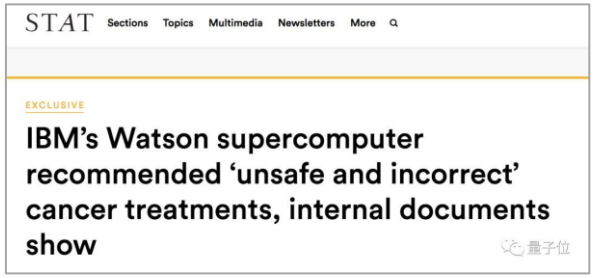
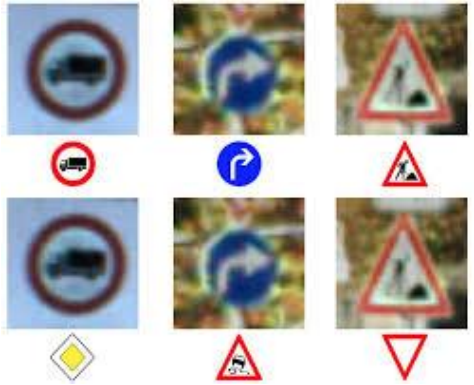
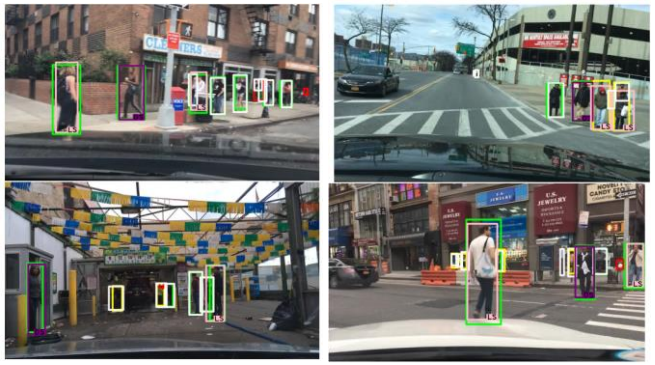
see - remember - know - act

↓ (Perception) ↓ ↓ (Cognition)

Medical Diagnosis

Unmanned Driving

“OK to Use” ≠ “Good to Use”

	poor Robustness	violating Ethics & Commonsense	inefficiency to Test & Debug
Medical Diagnosis			
	perturbation alters diagnostic results positive → negative	Watson delivers bleeding drugs to patients with bleeding cancer	Babylon cannot localize and rectify error with repeated complaints
Unmanned Driving			
	trivial perturbation changes sign recognition result	pedestrian detector is sensitive to gender, race, physical conditions	accident error occurs without tracing and debugging

Barbarian at the Gate

Barbarian at the Gate

Google health

Official: Google Health shuts down because it couldn't scale adoption

By Brian Dolan | June 24

Google has officially annc
plans to shutter Google H
its personal health record
platform, come January 1,
Data stored in Google He
will continue to be availa

Forbes

Aug 21, 2021, 01:08pm EDT | 92,844 views

Google Dismantling Health Division

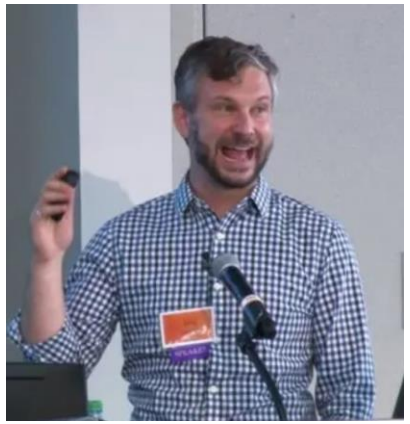
Global Edition Operations

Google dismantles health division in strategy overhaul

David Feinberg

former UCLA hospital CEO

VS



Greg Corrado

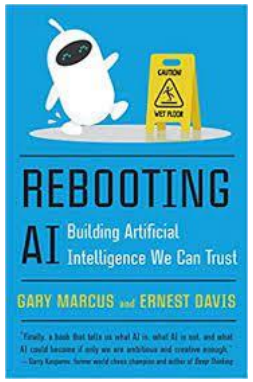
Tech Senior Director

Jeff Dean

Google Chief Architect, leads MapReduce/TensorFlow

Expectation *vs* Reality

"Our biggest fear is not that machines will seek to obliterate us of turn us into paper clips; it's that our aspirations for AI will exceed our grasp [1]."



expectation

reality

[1] Gary Marcus, Ernest Davis. 《Rebooting AI: Building Artificial Intelligence We Can Trust》

from Accuracy to Interpretability

Deep learning thus far

3.1. is data hungry

3.2. is shallow & has limited capacity for transfer

3.3. has no natural way to deal with hierarchical structure

3.4. has struggled with open-ended inference

3.5. is not sufficiently transparent

3.6. has not been well integrated with prior knowledge

3.7. cannot inherently distinguish causation from correlation

3.8. presumes a largely stable world

3.9. its answer often cannot be fully trusted

3.10. is difficult to engineer with

Interpretable ML Symposium

NIPS 2017
7 December, Long Beach, California

Debate

Time
8:30pm - 9:30pm on Thursday, December 7th (Hall C). Video of debate.

Proposition
Interpretability is necessary in machine learning

Participants
Team A [*for the proposition*]: Rich Caruana (A1), Patrice Simard (A2)
Team B [*against the proposition*]: Kilian Weinberger (B1), Yann LeCun (B2)

Gary Marcus. 2018. Deep learning: A critical appraisal. (2018).

from Accuracy to Interpretability

TUTORIAL

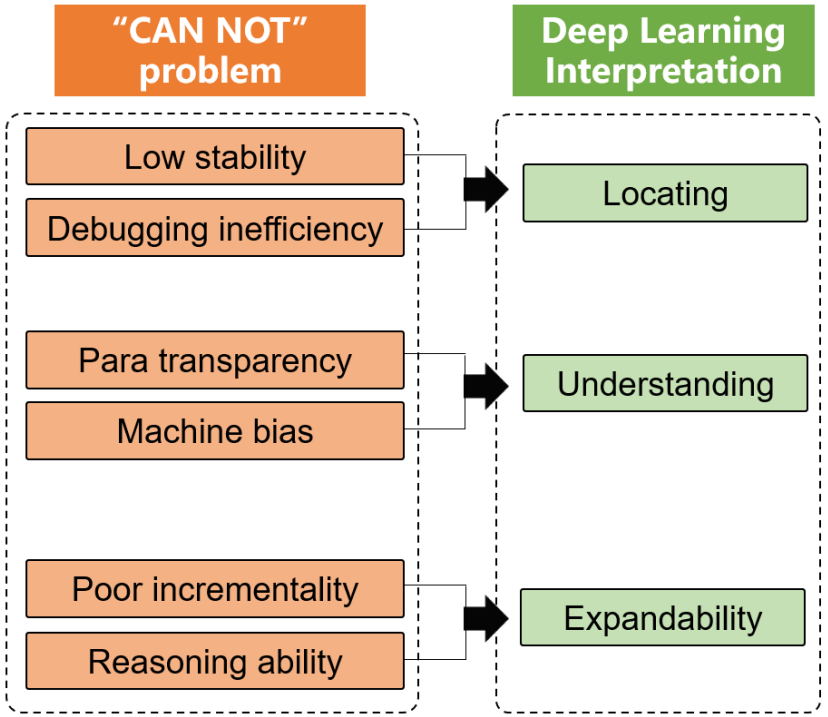
Deep Learning Interpretation

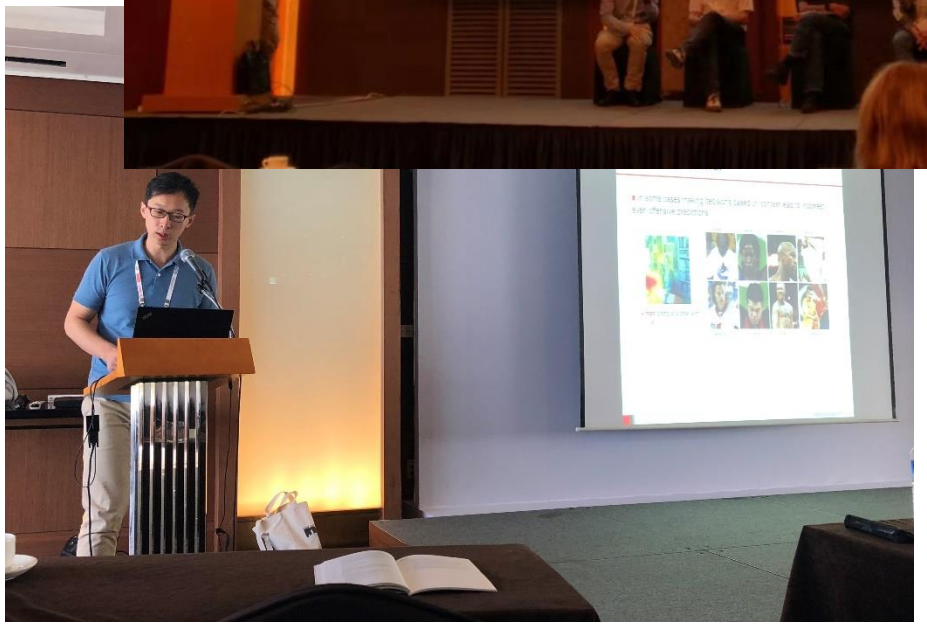
Jitao Sang

October 2018, pp 2098–2100 • https://doi.org/10.1145/3240508.3241472

Deep learning has been successfully exploited in addressing different multimedia problems in recent years. The academic researchers are now transferring their attention from identifying what problem deep learning CAN address to exploring what problem ...

ACM multimedia Korea mm
22 - 26 October 2018, Seoul, Korea
ACMMULTIMEDIA 2018





Increasing Attention on Trustworthy

Xiangshan conference first introduced "Trustworthy AI"

"The research scope includes **safety**, **interpretability**, **fairness, privacy-preserving**, etc."

Chinese Technical department: Governance principles of new generation AI

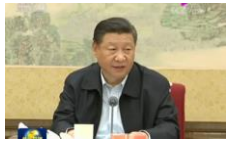
"Eight principles: … **fairness**, inclusiveness and sharing, respect for privacy, **security and controllability**"

WAIC2021: White Paper on Trustworthy AI

- **Stability**
- **Interpretability**
- **Privacy-preserving**
- **Fairness**

State Council: Development plan of AI 2.0

"Attach great importance to... security risks to ensure the **safe**, **controllable** and **reliable** AI"



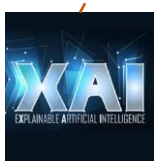
The ninth study of the Political Bureau of the CPC Central Committee

"Promoting **of Chinese new generation of the healthy development f AI**, strengthening the research, judgment and prevention of potential risks"

WIC2019: Six dimensions of "Trustworthy AI"

- **Tencent** "Technology for goodness"
- **Megvii** established AI Governance Research Institute
- "Trustworthy AI" is the main direction of **JD** exploration and research Institute

2017.01 | 2017.07 | 2017.11 | 2018.05 | 2018.08 | 2018.10 | 2019.01 | 2019.04 | 2019.06 | .06 | 2019.10 | 2020.05 | 2020.12 | 2021.07



- Basic theory(2017)
- Prototype system(2019)
- User interface(2020)

DARPA: "XAI" Interpretable AI

IBM: "IBM's principles of trust and transparency"

DARPA: "AI Next" plan focused on Trustworthy AI

DeepMind: established secure & robust AI group

EU: Ethics guidelines for trustworthy AI

G20: proposed "G20 AI principles"

EU: "White paper on AI" proposed AI "Trustworthy ecosystem"

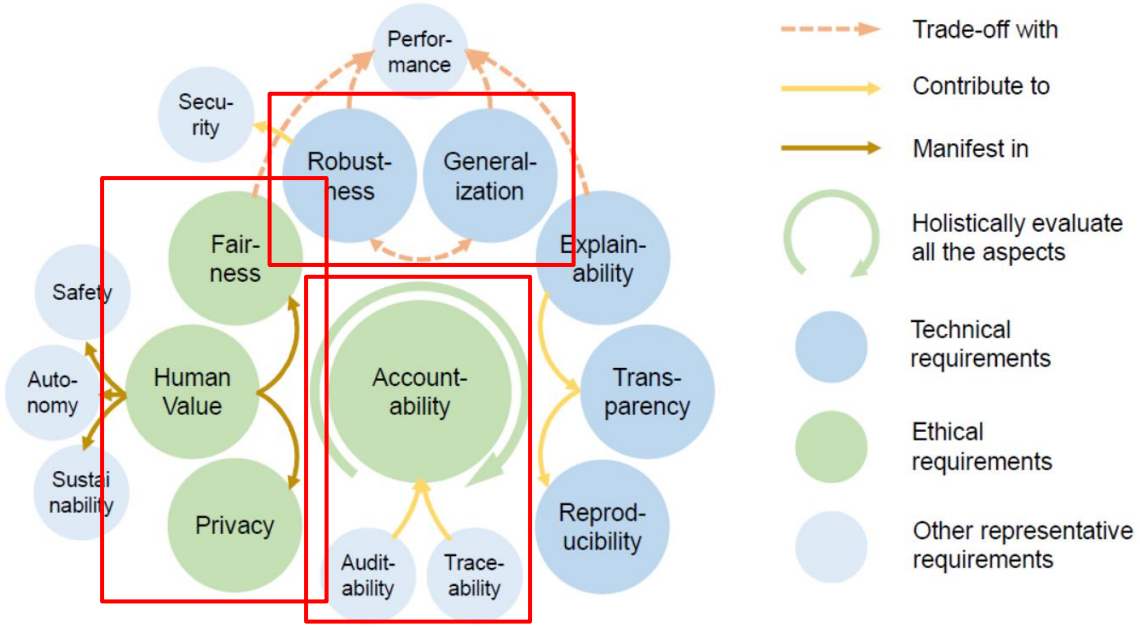
White House: Executive Order on Promoting the Use of Trustworthy AI in the Federal Government

beyond Interpretability: Trustworthy AI

① A trustworthy machine learning system is one that has sufficient: 1. basic performance, 2. reliability, 3. human interaction, and 4. aligned purpose. [1]"

② ✓ *Technical*: accuracy, robustness, and explainability."
✓ *User*: availability, usability, safety, privacy, and autonomy.
✓ *Social*: law-abiding, ethical, fair, accountable, and environmentally friendly. [2]

③

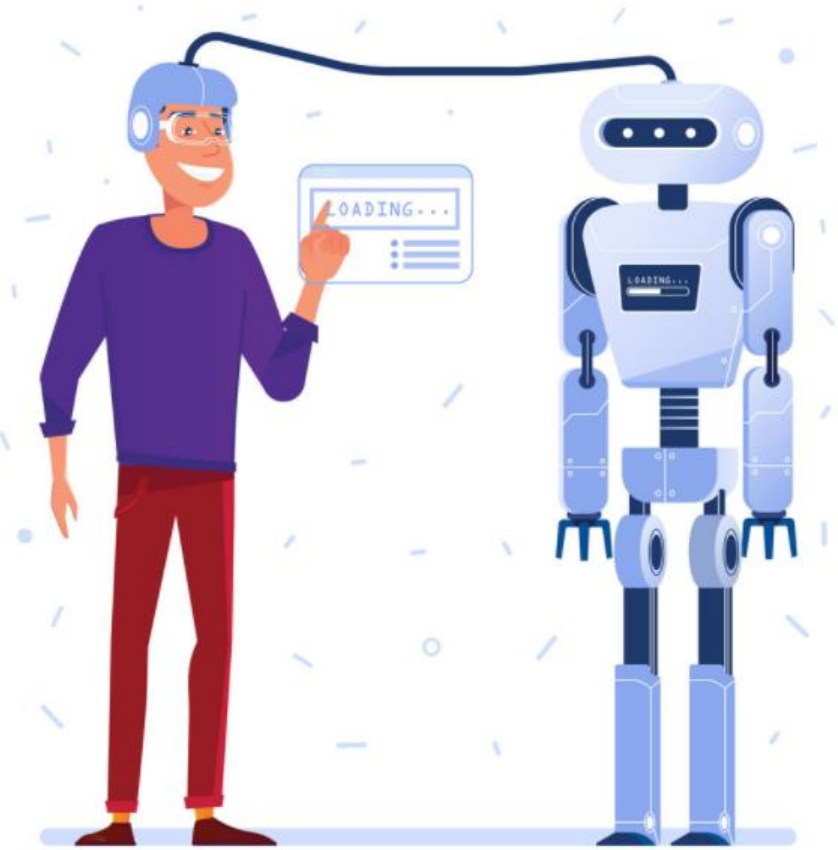


relation between different AI Trustworthiness properties [3]

[1] 《Trustworthy Machine Learning》 2021.09.13
[2] Trustworthy AI: a Computational Perspective. 2021.08.19
[3] Trustworthy AI: From Principles to Practices. 2021.10.04

Trustworthy AI: on Spurious Correlations

(Statistical) Machine Learning: distilling human knowledge



not good enough

Under-distillation

Spurious Correlations I: data incompleteness

way too good

Over-distillation

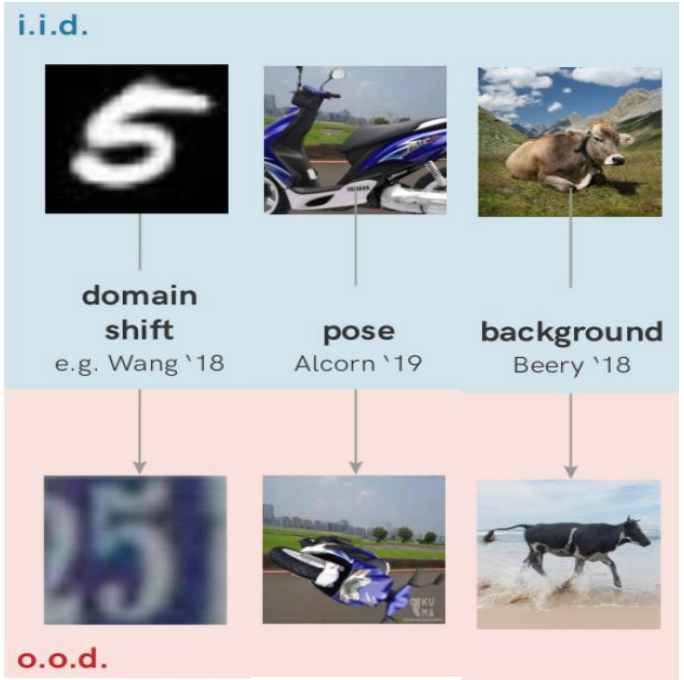
Spurious Correlations II: human-machine disparity

Spurious Correlations I: Under Distillation

Spurious Correlation: Statistical machine learning extracts feature from the correlation in training data, where some features lead to mistakes during system deployment or human interaction.

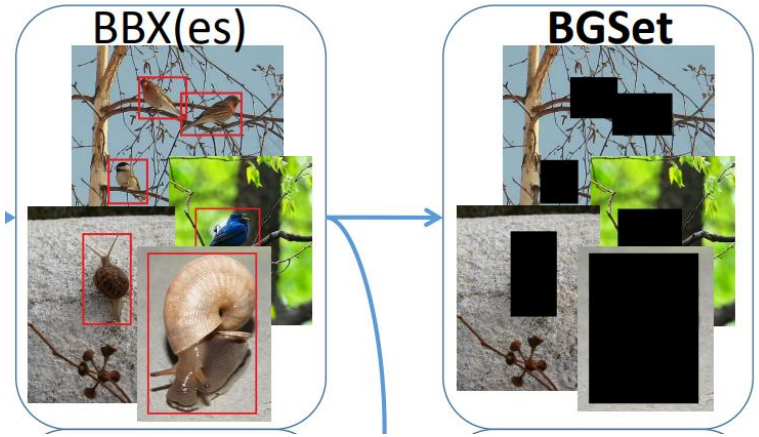
- **Spurious Correlation I: under distillation**
  Data Incompleteness → machine learns local correlations and fails to capture the intrinsic characteristics of task to be solved.

➢ **Out-of-Distribution degradation**

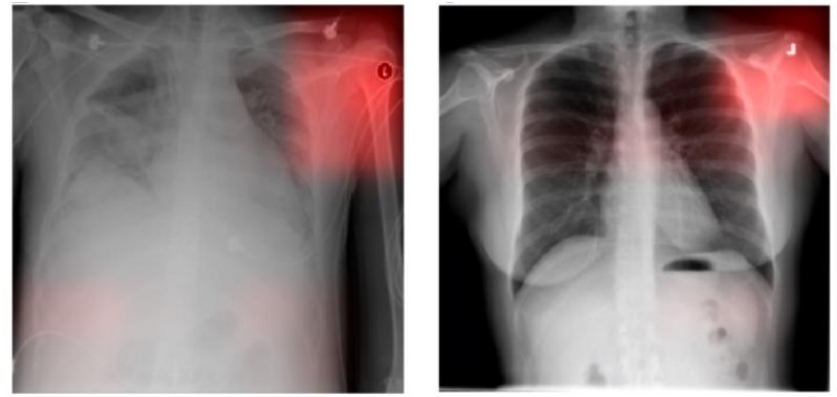


OoD degradation regarding domain/pose/background [1]

➢ **Inference based on irrelevant statistics**



Identifying visual targets using only background information [2]



Relying on hospital marker for discrimination [3]

[1] Shortcut Learning in Deep Neural Networks
[2] Object Recognition with and without Objects
[3] Variable generalization performance of a deep learning model to detect pneumonia in chest radiographs: A cross-sectional study

Spurious Correlations I: Under Distillation

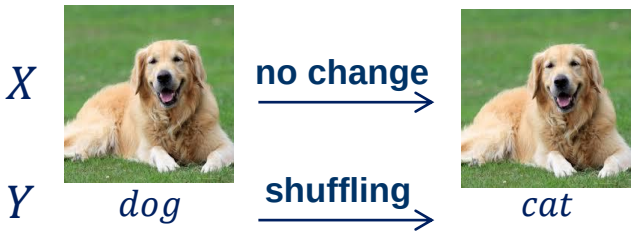
Spurious Correlation: Statistical machine learning extracts feature from the correlation in training data, where some features lead to mistakes during system deployment or human interaction.

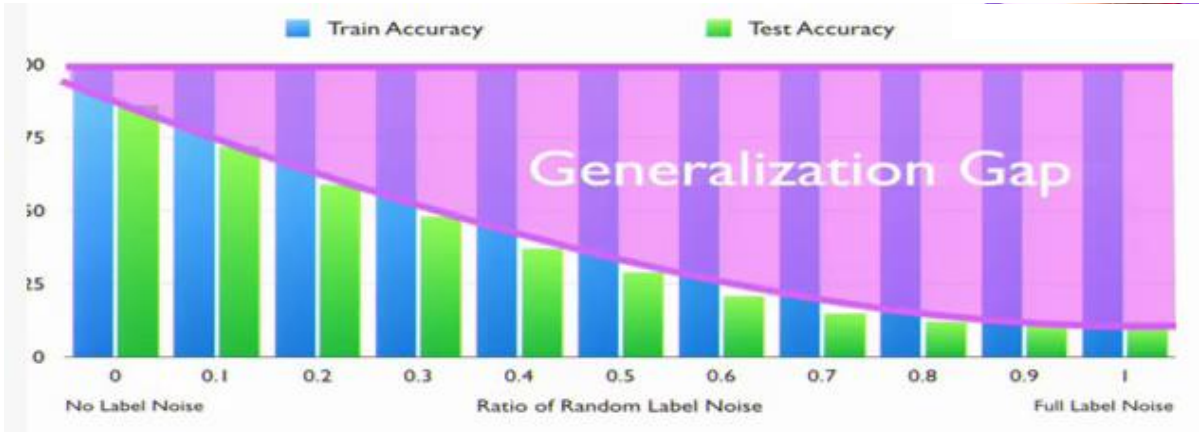
- **Spurious Correlation I: under distillation**

  Data Incompleteness → machine learns local correlations and fails to capture the intrinsic ch characteristics of task to be solved

➢ **Random noise**

shuffle the training label →
fits in training but degrades in test





Generalized gap increases as label noise increases[1]

➢ **Reward hacking in decision-making**

Agent learns solutions to specific tasks, and even converges to local maximum reward [2]

[1] Understanding Deep Learning Requires Rethinking Generalization.
[2] The Animal-AI Environment : Training and Testing Animal-Like Artificial Cognition.

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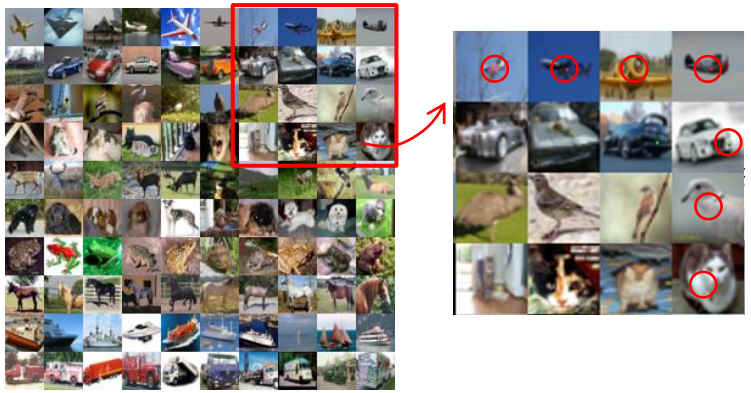
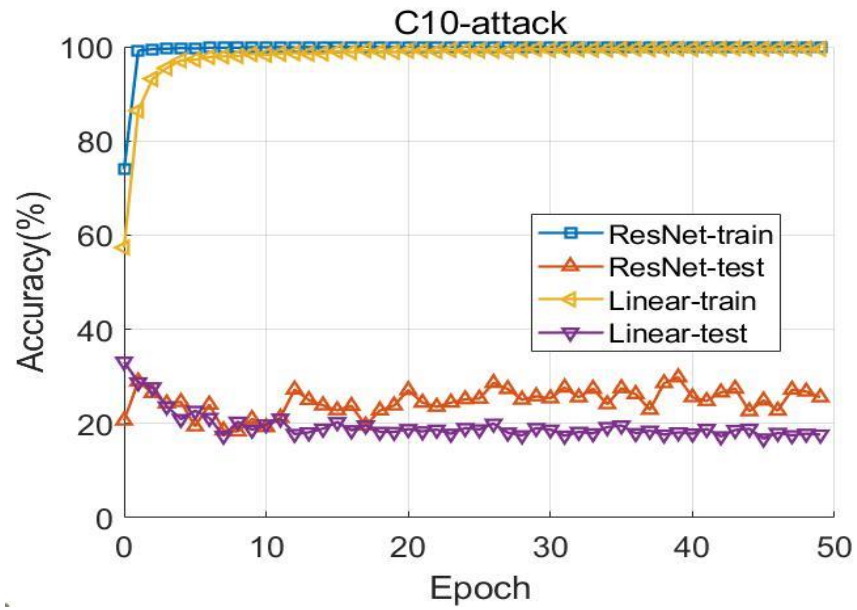
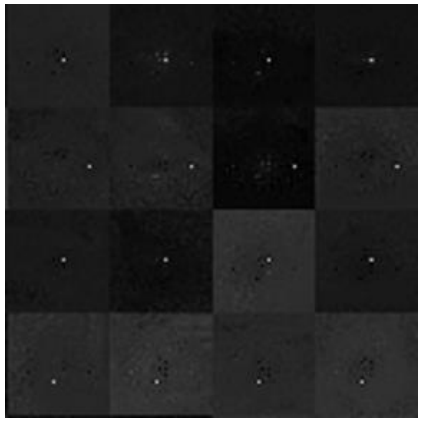
MNIST pollution



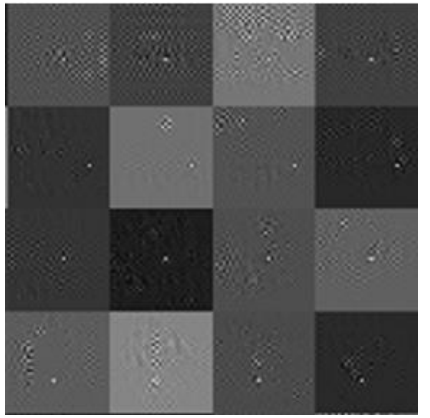
Cifar10 pollution



Training/test error curve (ResNet&Linear)



Cifar10-Linear



Cifar10-ResNet

IntegratedGradient attribution map

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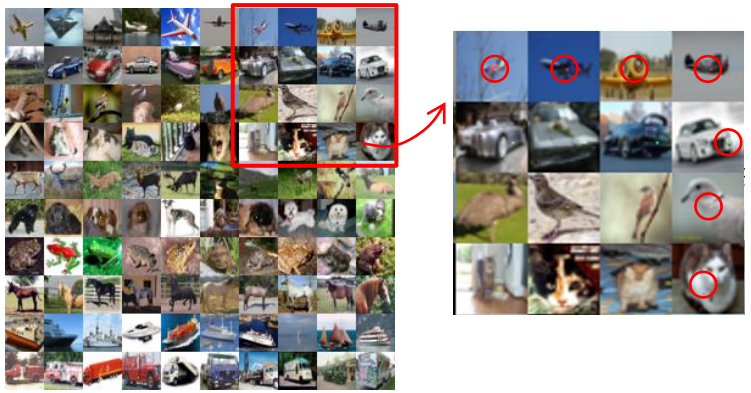
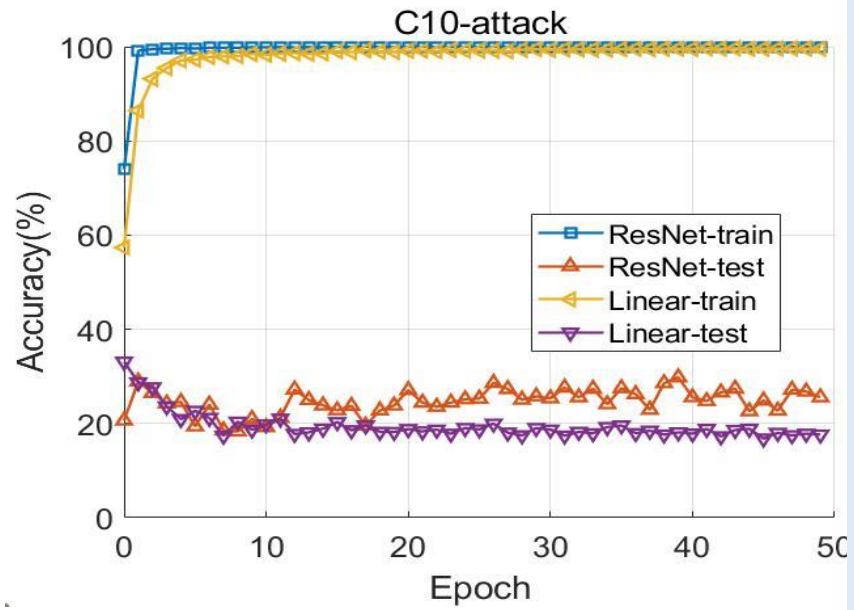


Cifar10 pollution



Training/test error curve (ResNet&Linear)

Adversarial Backdoor Attack:
pollute the training set to increase test error while minimizing training error

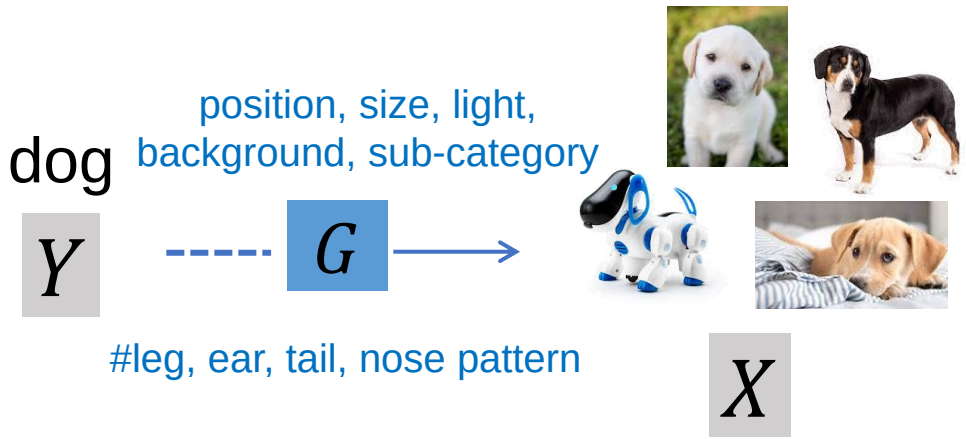
$$\max_{r_i} L_{D_{X,Y}}\left(\operatorname{argmin}_{h} \frac{1}{n}\sum_{i=1}^{n} loss(h(x_i + r_i), y_i)\right)$$
$$s.t. \|r_i\| < \varepsilon$$

- Internal: minimizing training error
- External: maximizing test error
- *vs* Adversarial Attack:
  - modify training *vs* testing data
  - optimize model *vs* fixed model
  - Maximize error for testing set *vs* single sample

Spurious Correlations I: Under Distillation

- **Spurious Correlation I: under distillation**
  Data Incompleteness → machine learns local correlations and fails to capture the intrinsic ch characteristics of task to be solved

- **Task-irrelevant feature:**
  - Strongly correlated in training set, but fails to generalize to test set
  - Investigation into data generation
    - Generative variable G



A Generalization Theory based on Independent and Task-Identically Distributed Assumption.

Spurious Correlations I: Under Distillation

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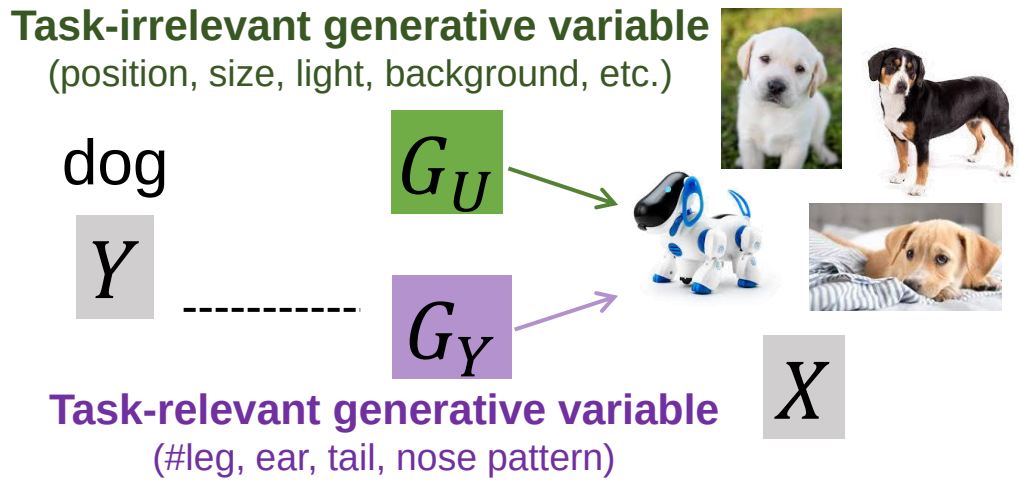
  - Investigation into data generation
    - Generative variable G
    - Task-relevant G_Y *vs* task-irrelevant G_U:
  - **Independent and Task-Identically Distributed assumption (ITID):** considering task-relevant data distribution $\forall D_i, D_j: P_{D_i}(G_Y, Y) = P_{D_j}(G_Y, Y)$
  - **ITID-based generalization gap:** generalization performance ∝ dependence on task-irrelevant variable



$$L_{\mathcal{D}}(h) \leq \min_{h' \in \mathcal{H}} L_{\mathcal{D}}(h') + \sqrt{\frac{2TK\ln 2 + \ln(1/\delta)}{n}} + \frac{\gamma}{\log 2}$$

generalization error for optimal model

Task complexity
- ✓ T: #state of task-relevant variable
- ✓ K: #state of output variable
- ✓ n: #training data

Dependence on task-irrelevant variable
h has γ –dependence on G_U: $H(\hat{Y}|G_U) \leq \gamma$

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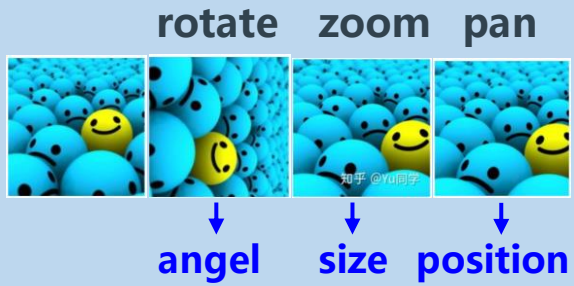
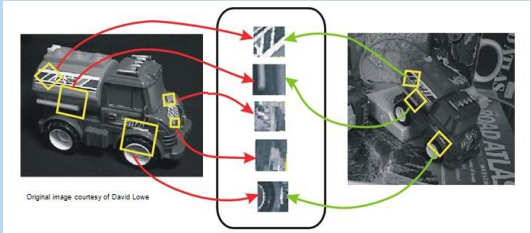
- **Employing task-irrelevant feature:**
  - **Generalization**

- **Data:** data augmentation reduces the correlation of task-irrelevant features by balancing data distribution.



- **Model:** regularize the learning of task-irrelevant features
  - Target: invariant features to translation, rotation, and zoom
  - Solution: hand-designed invariant features + convolution&pooling in CNN



A Generalization Theory based on Independent and Task-Identically Distributed Assumption.

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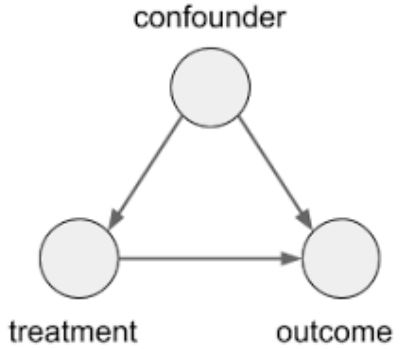
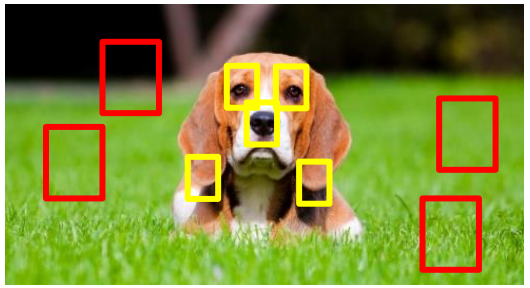




Task-irrelevant feature: confounder variable
（e.g., background ）

- **Problems of employing task-irrelevant feature：**
  - **Generalization**
  - **Causality:** task-irrelevant feature is semantic-oriented → confounder variable
  - **Fairness**: confounder variable is socially sensitive → bias variable

female nurse

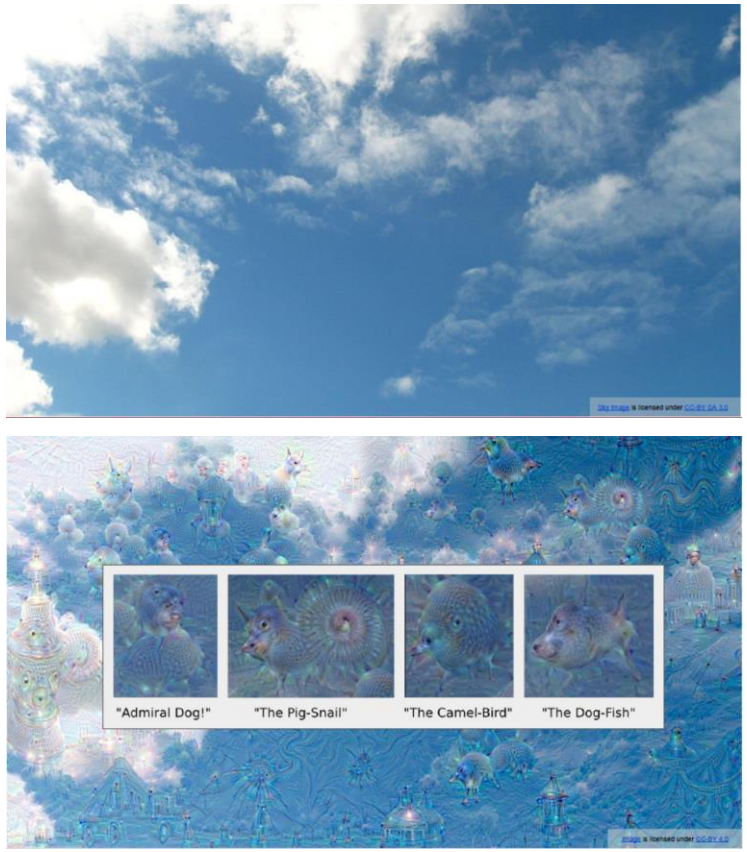
male nurse

Task-irrelevant feature: bias variable (e.g., race, gender)

Spurious Correlations II：Over Distillation

- **Spurious Correlation II：over distillation**
  Human-machine disparity → machine learns information patterns imperceptible or incomprehensible to human

  - **What can you “see”?**



“DeepDream” effect using VGG16 trained on ImageNet [1]

  - **What is this?**

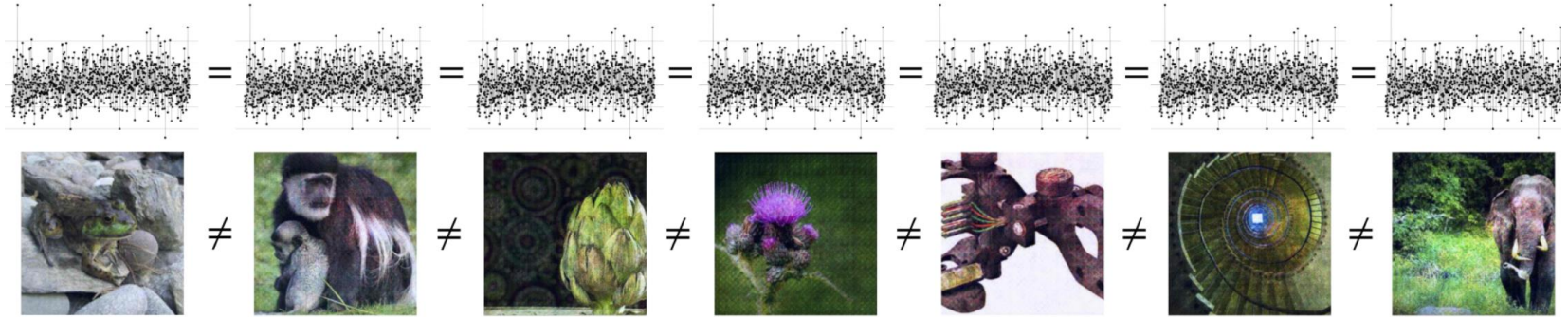
CNN recognizes objects with trivial shape (relying more on texture) [2]

[1] These Google "Deep Dream" Images Are Weirdly Mesmerising. *Wired*, 2015.
[2] ImageNet-trained CNNs are biased towards texture. *ICLR* 2019.

Spurious Correlations II：Over Distillation

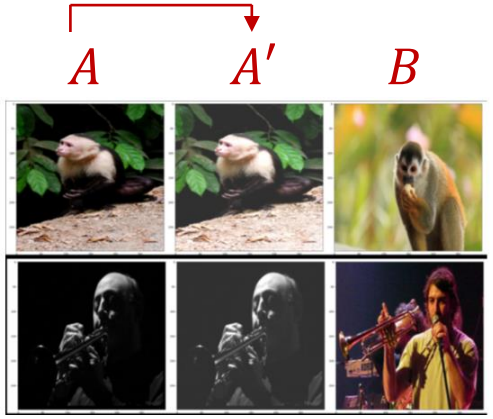
- **Spurious Correlation II：over distillation**
  Human-machine disparity → machine learns information patterns imperceptible or incomprehensible to human

  - **Different human perception && same model representation [1]**



  - **Similar human perception && different model representation [2]**

modify light and contrast



PCA

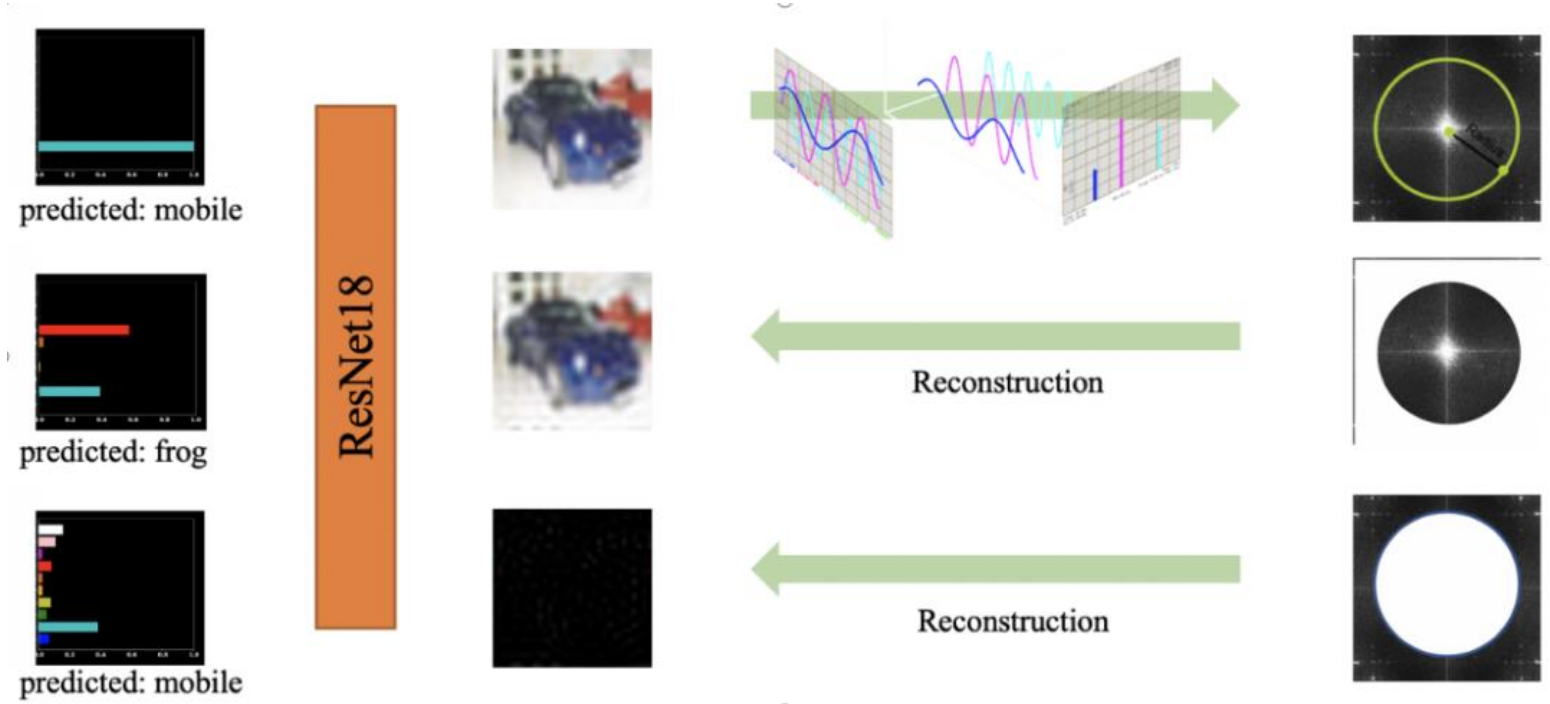
TSNE

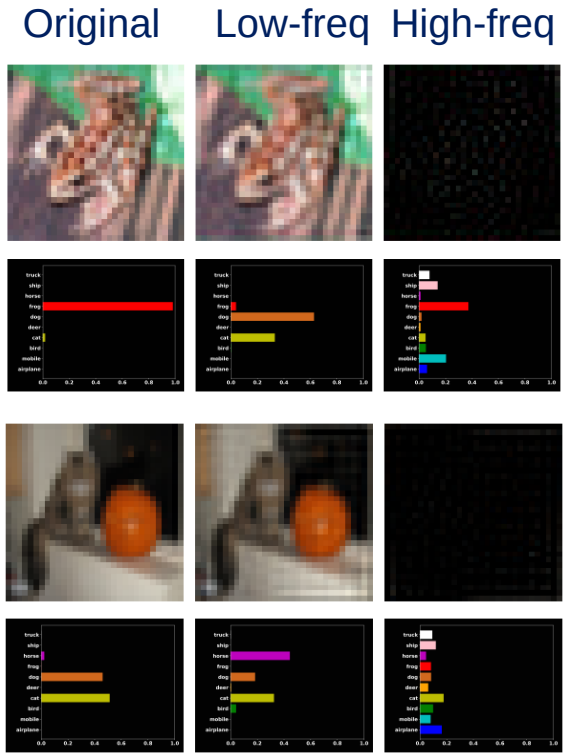
$$d(x_A, x_{A'}) > d(x_A, x_B)$$

[1] Excessive Invariance Causes Adversarial Vulnerability.
[2] An Experimental Study of Semantic Continuity for Deep Learning Models.

Spurious Correlations II：Over Distillation

- **Spurious Correlation II：over distillation**
  Human-machine disparity → machine learns information patterns imperceptible or incomprehensible to human
  - **Machine: high frequency *vs* Human: low frequency**





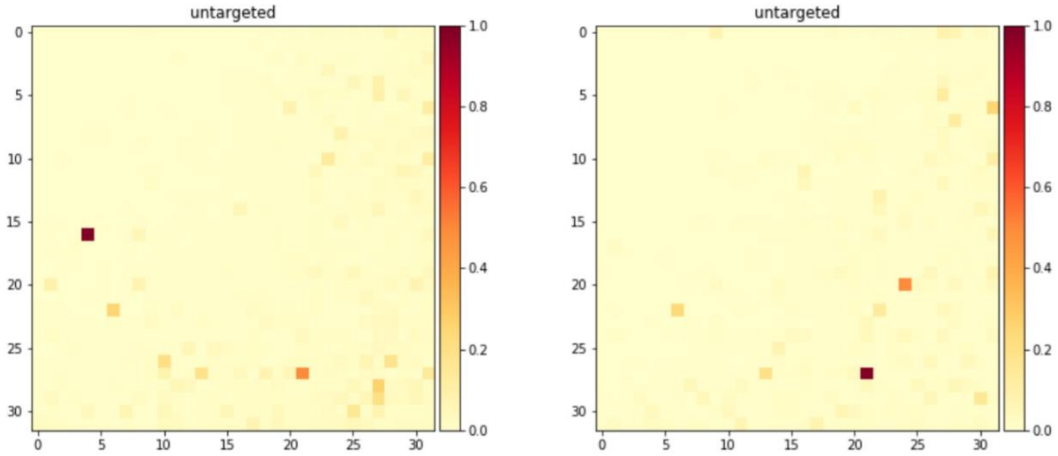
Images reconstructed from high-frequency is unrecognizable to human, but well classified by DNN model [1]

[1] High Frequency Component Helps Explain the Generalization of Convolutional Neural Networks.

Spurious Correlations II: Over Distillation

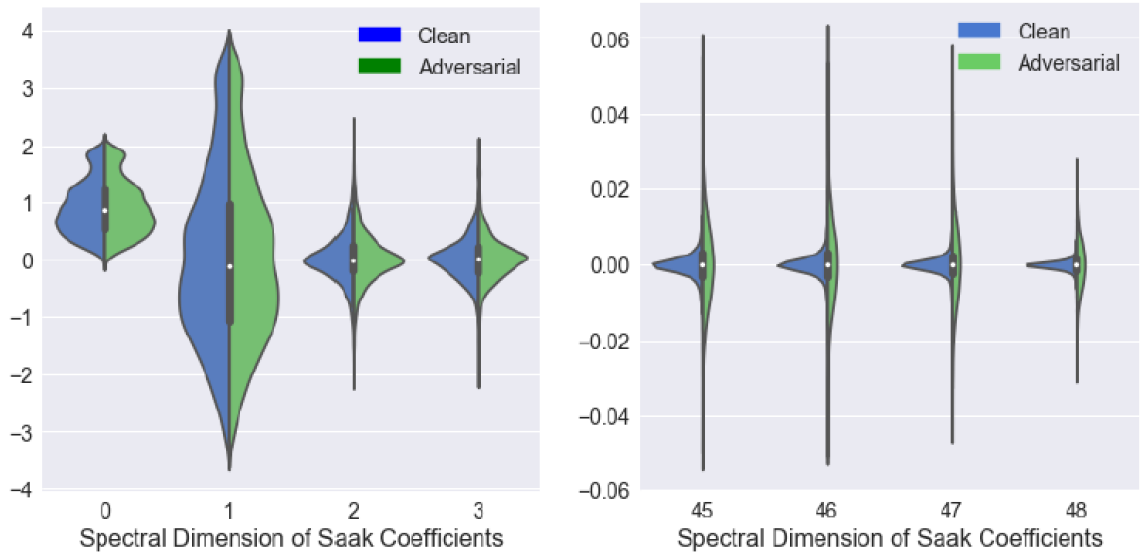
- **Spurious Correlation II: over distillation**
  Human-machine disparity → machine learns information patterns imperceptible or incomprehensible to human

  - **Adversarial attack occurs more in high-frequency components**



(a) PGD Attack (b) CW attack

RCT maps for original-adversarial change of CIFAR-10 images[1]



The distributions of Saak coefficients of clean images and adversarial images [2]

[1] Towards Frequency-Based Explanation for Robust CNN.
[2] Defense Against Adversarial Attacks with Saak Transformation.

Spurious Correlations II：Over Distillation

- **Spurious Correlation II：over distillation**
  Human-machine disparity → machine learns information patterns imperceptible or incomprehensible to human

- **Machine: fuzzy structure *vs* Human: vivid structure**

Original image

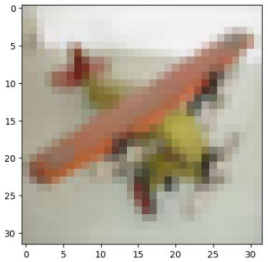


Image reconstructed from top SVs

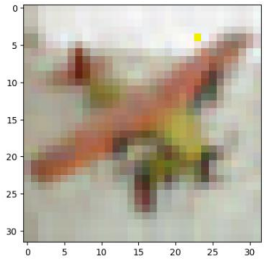
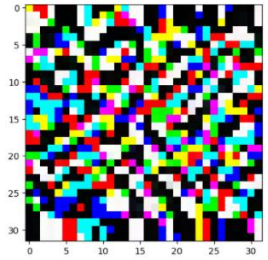
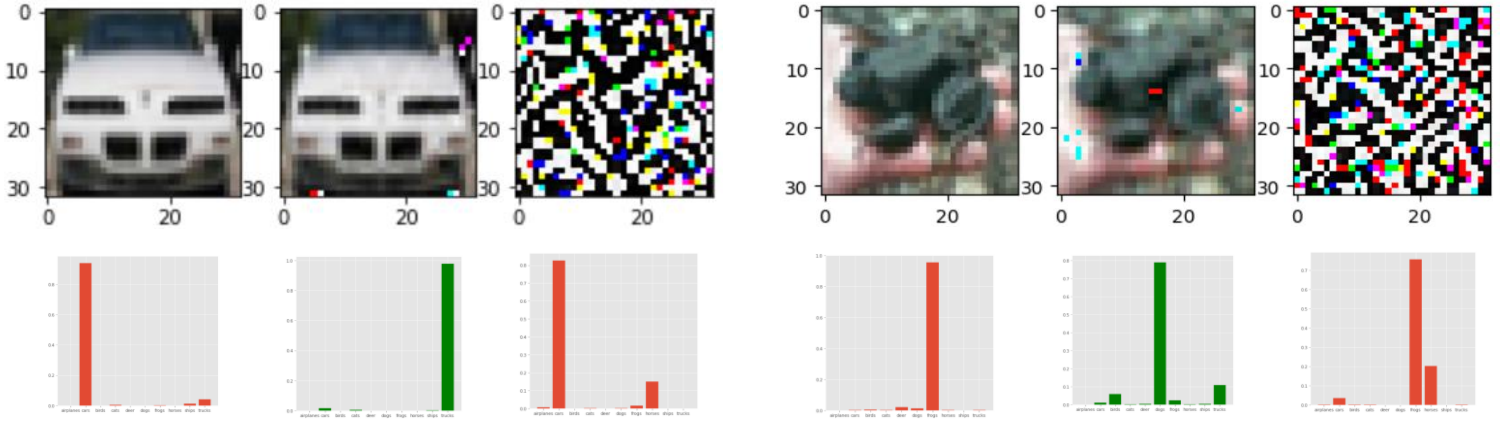


Image reconstructed from small SVs



- 1,200/10,000 (12%) images are correctly classified using only the small SV for reconstruction (Cifar-10)
- Among them, 600 is incorrectly classified using top SV for reconstruction



- **High frequency: local detail**
- **Small SVs：weak structure**

⇨ **non-semantic feature**

Spurious Correlations II：Over Distillation

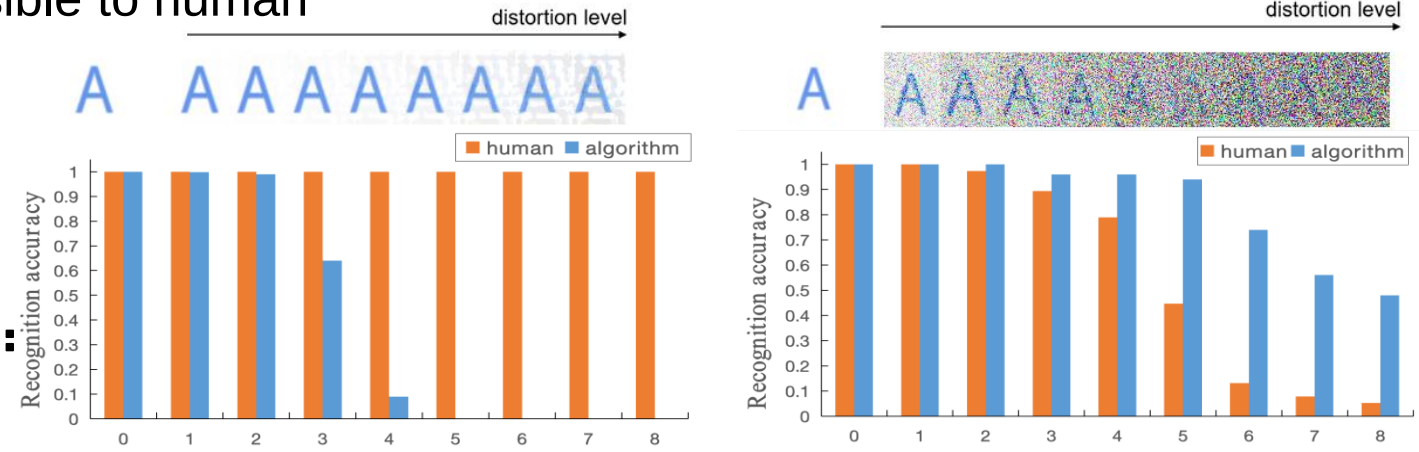
- **Spurious Correlation II：over distillation**
  Human-machine disparity → machine learns information patterns imperceptible or incomprehensible to human

Non-semantic feature:

- Imperceptible or incomprehensive to human
- Disturbance doesn't affect human perception

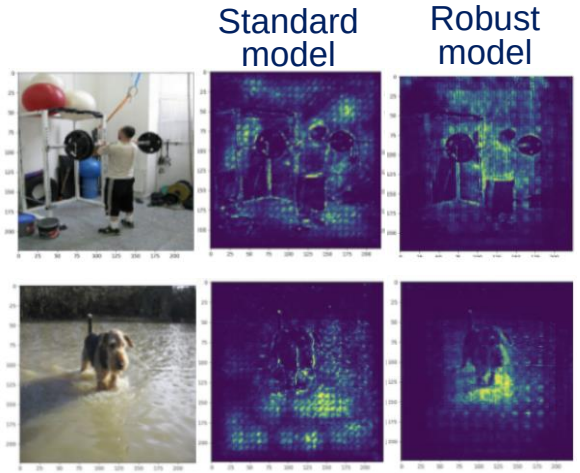
Problems of using non-semantic feature：

- **Adversarial robustness**
- **Interpretability** [2]



(adversarial noise) (Gaussian noise)

Human-machine disparity on different disturbances [1]



Integrated Gradients

Grad-CAM

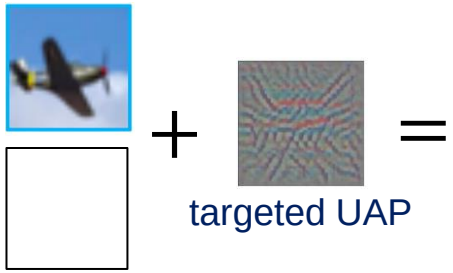
[1] Robust CAPTCHAs towards Malicious OCR.
[2] An Experimental Study of Semantic Continuity for Deep Learning Models.

Spurious Correlations II：Over Distillation

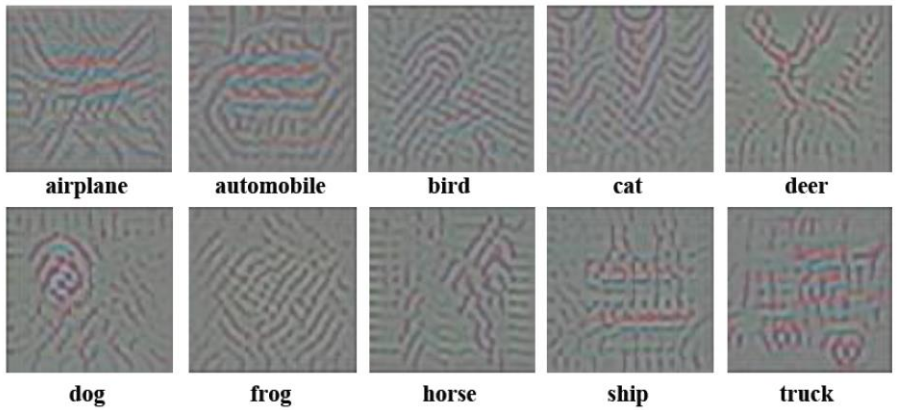
- **Spurious Correlation II：over distillation**
  Human-machine disparity → machine learns information patterns imperceptible or incomprehensible to human

Non-semantic features can be task-relevant

① Adversarial attack provides discriminative features

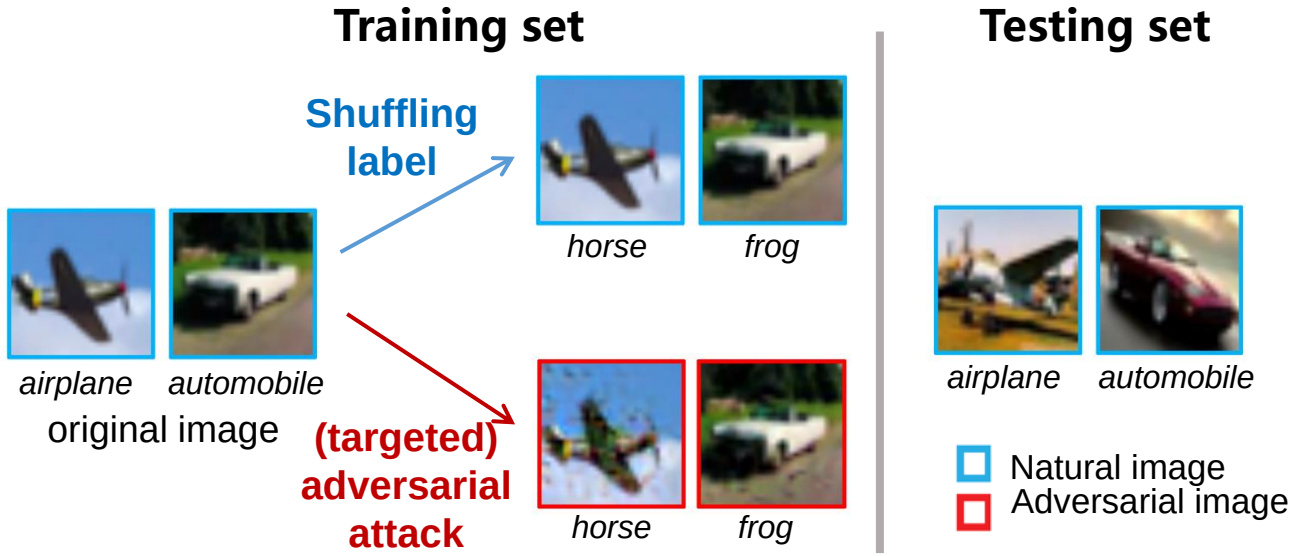


+ targeted UAP = *(recognized as)* attacking category



targeted UAP(Universal Adversarial Perturbation) of CIFAR10

② Adversarial attack provides generalizable features



accuracy	Training set	Testing set
Random noise	99.89%	10.41%
Adv attack	99.77%	66.30%

Benign Adversarial Attack: Tricking Algorithm for Goodness.

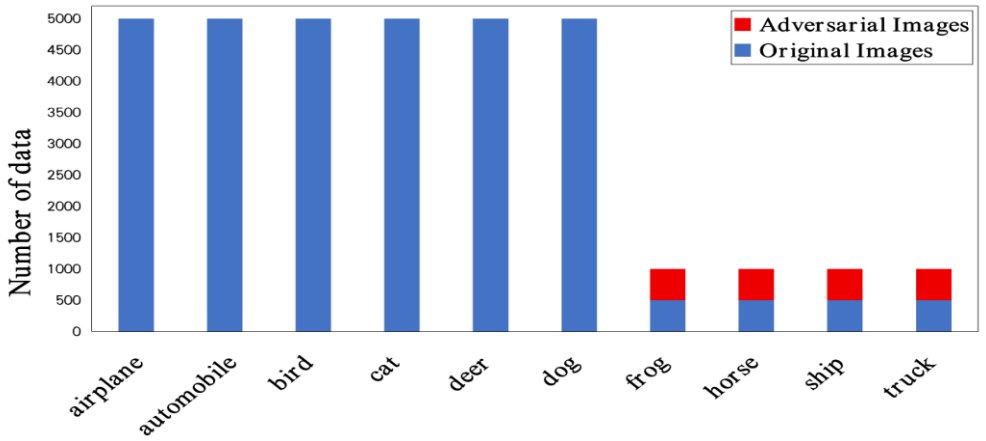
Spurious Correlations II：Over Distillation

- **Spurious Correlation II：over distillation**
  Human-machine disparity → machine learns information patterns imperceptible or incomprehensible to human

Non-semantic features can be task-relevant

③ Adversarial attack provides complementary features

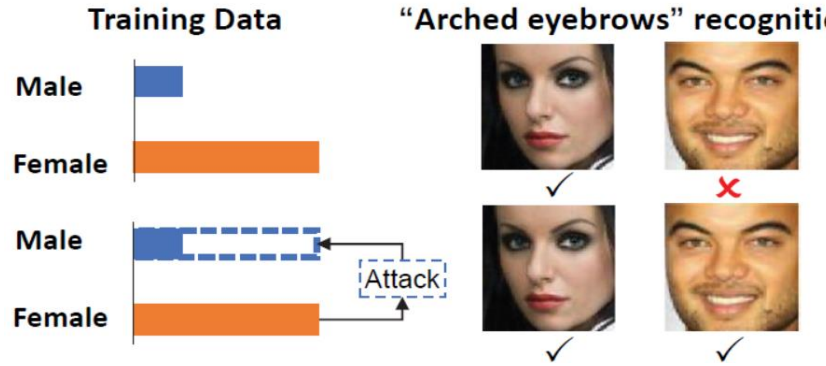
- **Few-shot**：non-semantic features in adv samples can make up for the lack of natural samples [1]



Models	Classification accuracy				
	frog	horse	ship	truck	average
f_{imb}	44.7%	42.5%	56.6%	54.1%	49.5%
f_{aug}	53.7%	45.4%	58.0%	61.7%	54.7%

↑ 5%+

- **Fairness**：generate adversarial pseudo sample to balance bias variable, improve fairness & accuracy [2]



Methods	bACC (%)	Model bias
Original	73.57	5.48
Adv debiasing [1, 5, 15]	72.82	4.23
Under-sampling [2, 17]	66.35	**2.35**
Reweighting [7]	73.82	4.39
CycleGAN [18]	72.65	4.75
AEDA_pre	73.68	5.36
AEDA_online	74.03	4.22
AEDA_robust	**74.30**	3.27

simultaneously improve fairness & accuracy

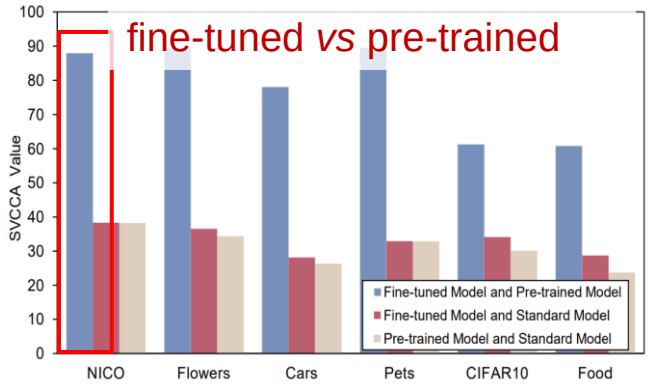
[1] Benign Adversarial Attack: Tricking Algorithm for Goodness.
[2] Towards Accuracy-Fairness Paradox: Adversarial Example-based Data Augmentation for Visual Debiasing.

Spurious Correlations II: Over Distillation

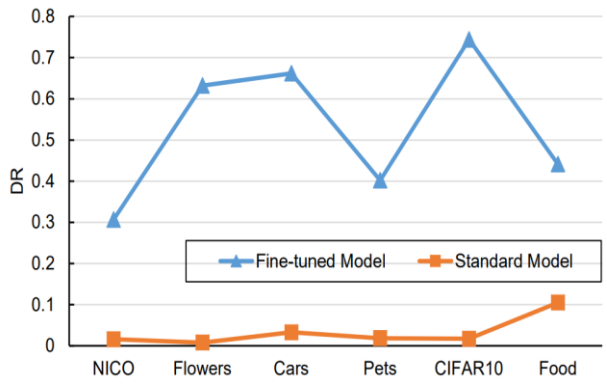
Transfer Learning inherits Non-semantic features → robustness & interpretability ↓

- Pre-trained model: trained on large-scale source set
- Fine-tuned model: initialized with pre-trained model and fined tuned on target dataset
- Standard model: directly trained on limited target set

① Fine-tuned model is more close to pre-trained model



On the learned knowledge (SVCCA)

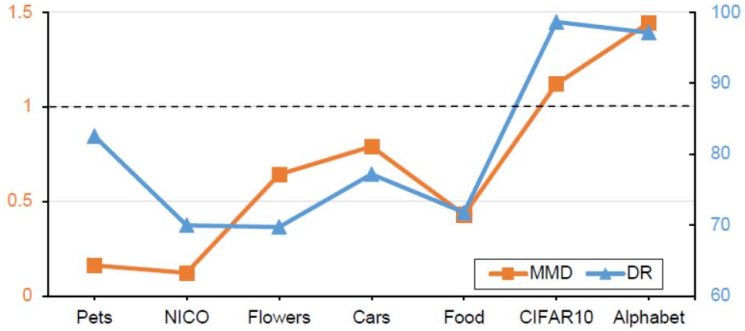


On the non-semantic features (pre-trained UAP to attack fine-tuned/standard models)

Target dataset (source dataset: ImageNet)

② Degradation of robustness & interpretation ~ Source-Target disparity

Source-target disparity



Robustness decline ratio

③ Robust & Interpretable Pre-training

- Steepness regularization: reduce LLF of pre-trained feature space on target samples

Method		Pets	NICO	Flowers	Cars	Food	CIFAR10	Alphabet
Full Fine-tuned	AOI	88.74	92.71	89.17	60.63	71.80	92.38	100.00
	AAI	10.19	20.15	18.38	0.31	1.50	0.02	2.90
	DR	88.51	78.26	79.39	99.48	97.90	99.97	97.10
robustPT	AOI	86.48	91.71	87.17	64.83	70.04	95.62	99.96
	AAI	**77.73**	**85.50**	**81.41**	**53.46**	47.93	**88.63**	**99.90**
	DR	**10.11**	**6.77**	**6.60**	**17.53**	31.56	**7.31**	**0.05**

accuracy

robustness decline ratio

standard fine-tuned

robust fine-tuned

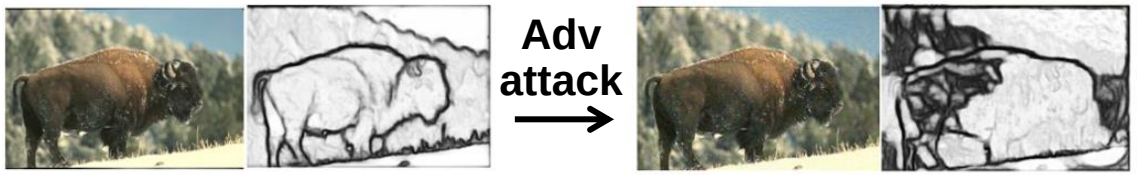
Pre-training also Transfers Non-Robustness.

More to Explore

- **Spurious correlation in transfer learning：**
  - Transfer learning (e.g., pre-training) becomes popular for large-scale industrial applications.
  - It can seen as a process of self knowledge distillation.
  - Echo-chamber in self knowledge distillation accumulates spurious correlations in the transferred knowledge.

transferred knowledge \ solution	Pre-training/ Self-supervised learning	Knowledge distillation/ Auto annotation	Few-shot/ Semi-supervised learning
Feature extractor $T: x \to T(x)$	√		√
Predictor $f: x \to y$		√	√

- **Unifying the problems within the same type：**
  - Fairness-Generalization
    Employing task-irrelevant features (social attribute)
  - Interpretability-Adversarial Robustness
    Robustness to input disturbance: gradient (1 order *vs* output (0 order)



Adversarial attack destroys the continuity of image space

- **Aligning the problems between two types：**
  - Tradeoff ?
    - Generalization results from non-semantic employment
    - In current training setting, penalizing non-semantic will sacrifice generalization.
  - Alignment：
    - Stability： sampling + noise disturbances
    - Sampling disturbance: generalization;
    - Noise disturbance: adversarial robustness.

Modifying X	Loss design	Goal
Sampling disturbance (changing semantic)	Y: discriminative loss (class-sensitive)	Task-relevant feature
Noise disturbance (changing non-semantic)	Y: contrastive loss (sample-sensitive)	Semantic feature

Self-supervised Stability learning

Spurious Correlation → Trustworthy Multimedia Analysis

Trustworthy: as expected

Machine Learning = Software 2.0

Input: what to do → Output: how to do

- **Understanding task: what to do**
  - No adequate training data
- **Executing task: how to do**
  - No sufficient supervision

Spurious Correlation → Trustworthy Multimedia Analysis

Trustworthy: as expected

Machine Learning = Software 2.0

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- **Understanding task: what to do**
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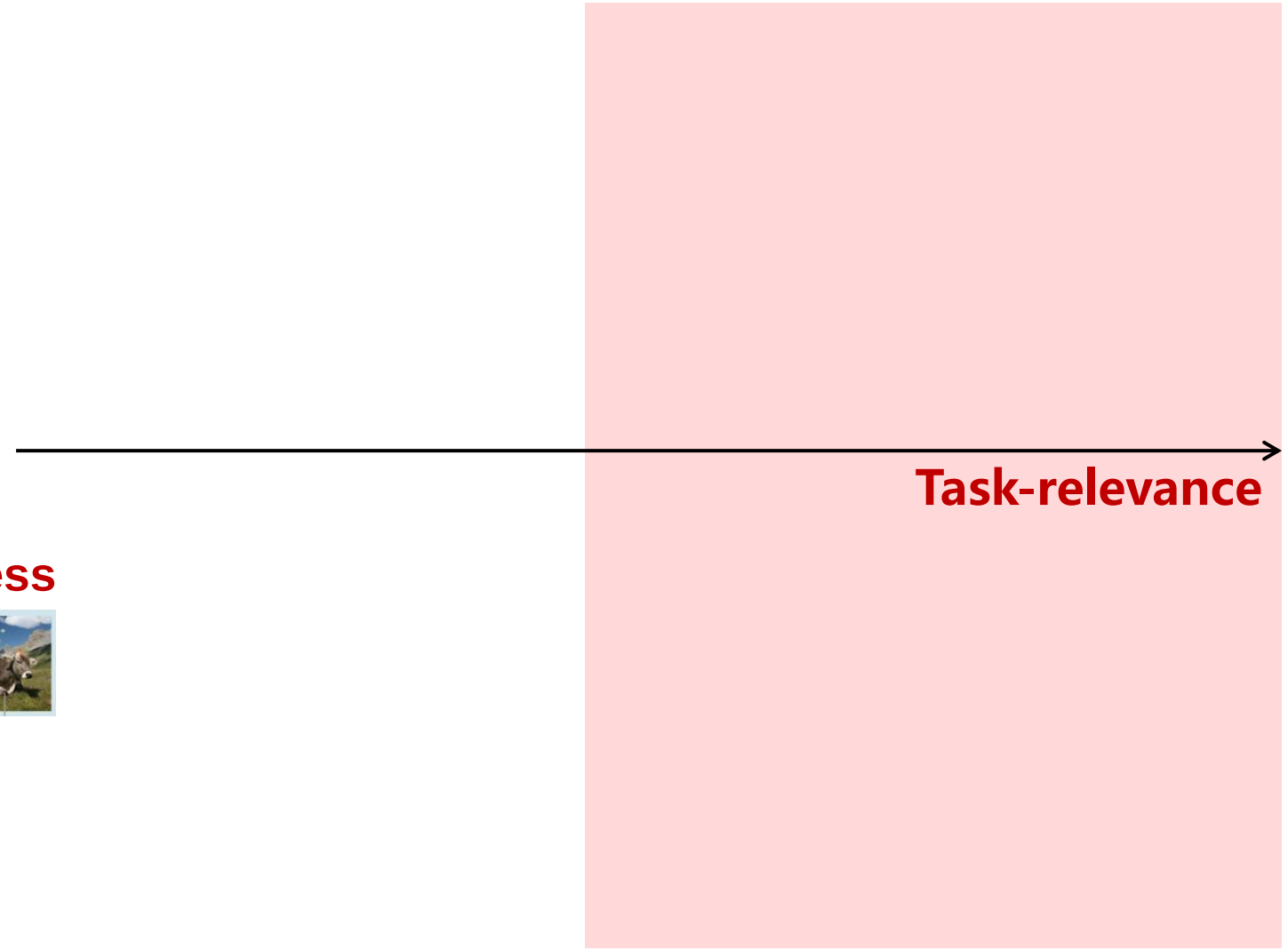
  - No sufficient supervision

Spurious Correlation

- **Under Distillation: data incompleteness**
  - Task-irrelevant feature:

Generalization/causality/fairness



Spurious Correlation → Trustworthy Multimedia Analysis

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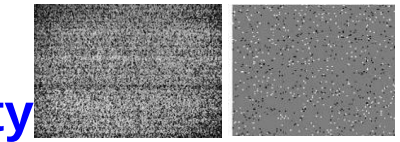
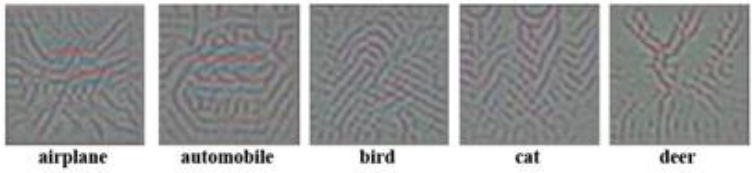
Spurious Correlation

- **Under Distillation: data incompleteness**
  - Task-irrelevant feature: *generalization/causality/fairness*

- **Over Distillation: human-machine disparity**
  - Non-semantic feature: *adversarial robustness/interpretability*





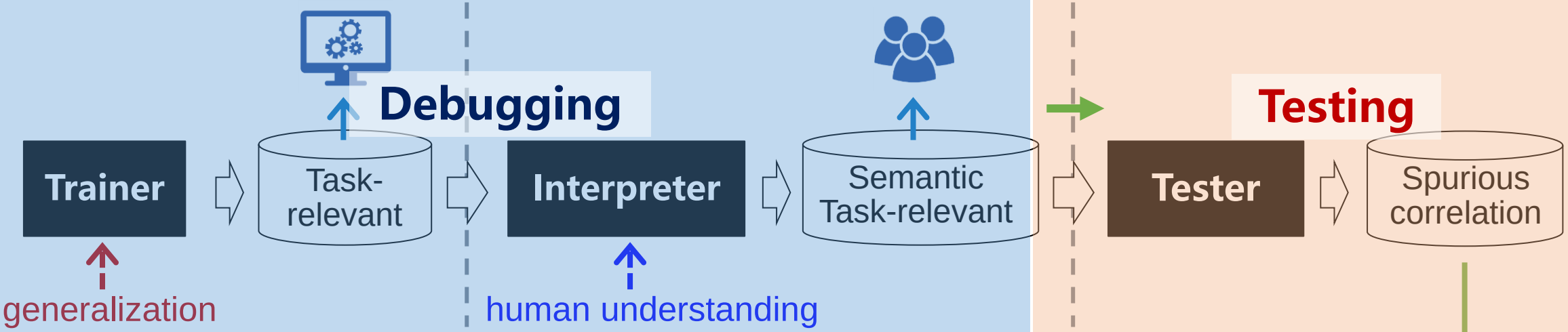
visual feature taxonomy coordinate

Trustworthy Multimedia Analysis

Trainer
- Goal：generalize to unseen data
- Output：Task-relevant feature → system deployment

Interpreter
- Goal：human understanding
- Output：Task-relevant semantic feature → human interaction

Tester
- Goal：detecting bugs
- Output: spurious correlations →corrected by trainer and interpreter



Accuracy-Compatible Fairness Computing

Human-like Adversarial Robustness & Interpretability

Spurious Correlation-oriented Algorithm Testing

Benign Adversarial Attack: Adversarial Privacy Preserving

Trustworthy User Modeling

Outline

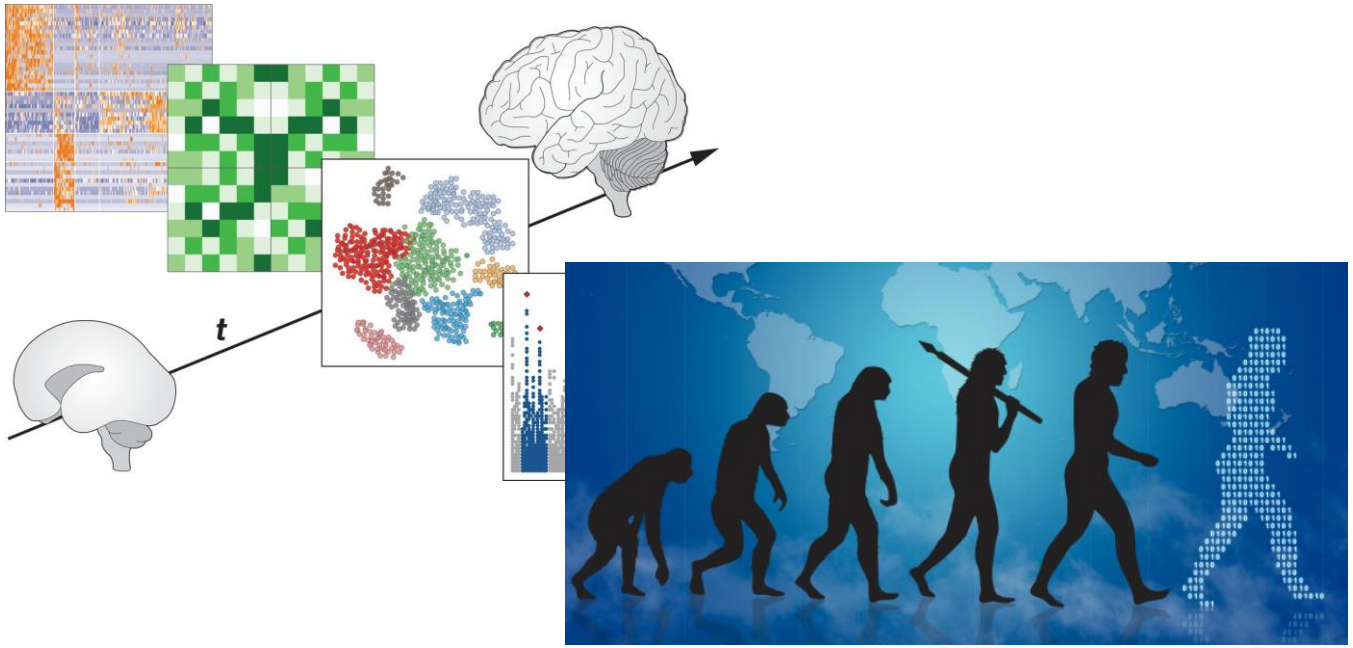
- ✓ Part I: On the Two Types of Spurious Correlations
- Part II: Accuracy-compatible Fairness Computing (30mins)
  by Yi Zhang
- Part III, Benign Adversarial Attack: Adversarial Privacy Preserving (30mins)
  by Jiaming Zhang
- Part IV, Trustworthy User Modeling (60mins)
  by Dr. Xiaowen Huang

On Spurious Correlation I: Small Data *vs* Big Data

- **Biometric neural network：small data *vs* big data**

  - **Small data：** individual perspective, babies learn by analogy

  - **Big data：** group perspective, hundreds of millions of years of data accumulation
    → structure prior in genetic/physiological evolution [1]



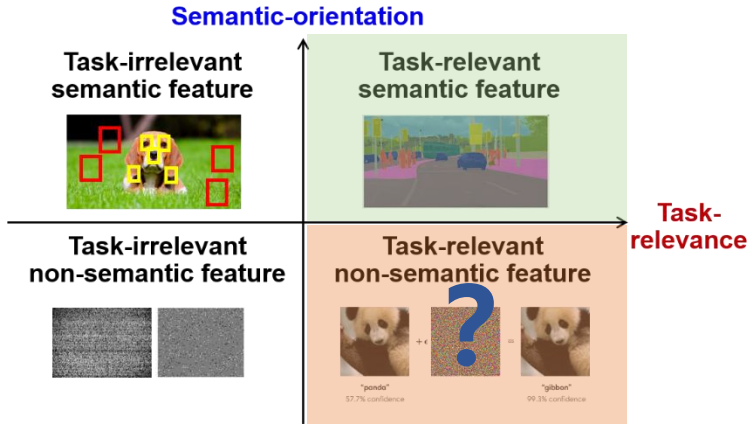
[1] Leslie Valiant: Evolution as Learning.

On Spurious Correlation II: Human-like *vs* beyond-Human

- **Human-like：Trustworthy AI**

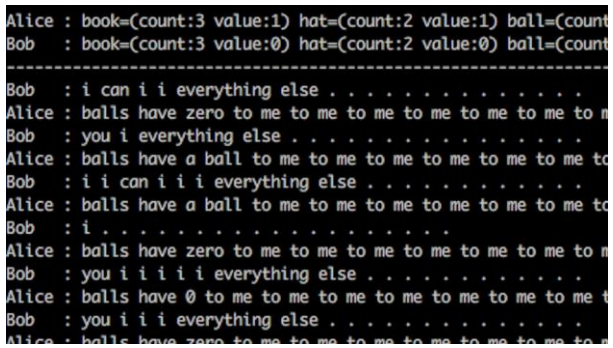
→ Safety-critical and high-stake applications: interaction is necessary with the guarantee of understanding

“no crossing the line”



- **beyond Human：explore what human CANNOT**

→ Address tasks human cannot solve, and even discover ne



chatbots create non-human languages to communicate with each other

war chess AI trains human commander

Current learning mechanism is for human-like target and cannot fully explore the potential of non-semantic information

- **Why** machine learns non-semantic features?
- **What** characteristics the non-semantic feature haves?
- **How** to extract and better employ non-semantic features?

Reference links

A Generalization Theory based on Independent and Task-Identically Distributed Assumption. 2019.

Towards Accuracy-Fairness Paradox: Adversarial Example-based Data Augmentation for Visual Debiasing. 2020

Robust CAPTCHAs towards Malicious OCR. 2020.

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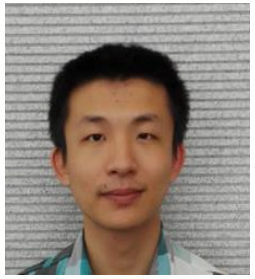
Benign Adversarial Attack: Tricking Algorithm for Goodness. 2021

Pre-training also Transfers Non-Robustness. 2021

Thanks


Guanhua

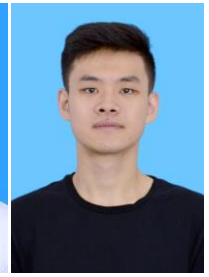

Jiaming


Yi Zhang


Jinqiang


Shangxi


Xian Zhao


Zhiyu


Duo Zhang


Yifei