Mitigating Bias in Computer Vision

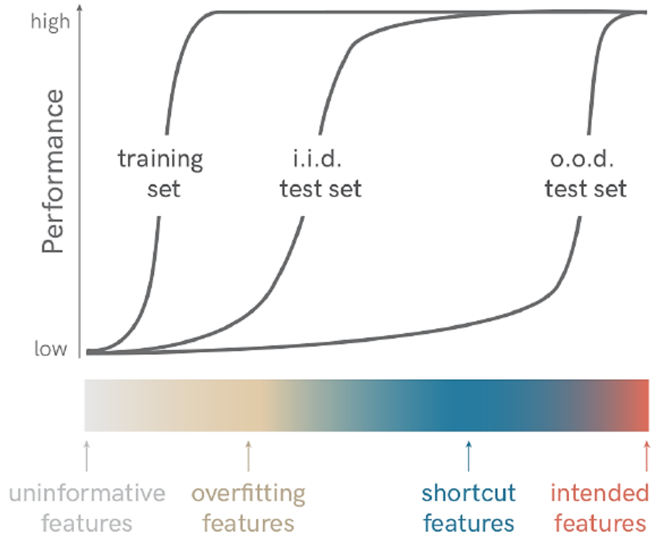
Ji-Ze G. Jang

Note: this presentation outlines the AI fairness project **ideas** I proposed, **motivations** of my work, and experimental **designs**. Due to time and resource constraints, this project was left open-ended before I transitioned to the University of Maryland Vision and Learning Lab.

UNIVERSITY *of* ROCHESTER

AI Fairness / Bias

- How can we bypass shortcut features and ensure that the relevant statistics are learned from a computer vision model?
- How can we reduce or even eliminate the network's reliance on *spurious correlations* in the data to achieve high accuracy?
  - correlation ≠ causation !!



Types of Bias Mitigation Methods

- **Pre-processing**: debias the training data
- **In-processing**: debias the model architecture / objective function
  - E.g., Resampling and Reweighting
  - E.g., Adversarial training (*fairness through blindness*)
  - E.g., Domain discriminative training (*fairness through awareness*)
- **Post-processing**: debias the prediction

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The focus of this project

Label Noise Detection and Bias Mitigation in Supervised NNs

Fall 2021

Problem Statement

- **Protected attributes** in a dataset may lead to fairness or robustness problems
    - They are often associated with social bias (e.g., race, gender, age)

- **Goal**: to predict an output variable Y given an input variable X, while remaining unbiased with respect to the protected variable A

- However, existing bias identification and mitigation methods *overly rely on labels* of protected attributes

Problem Statement

- Existing bias identification and mitigation methods *overly rely on labels* of protected attributes

- But what happens if the *labels* themselves are *biased*?

Project Outline

<u>Step 1</u>:

Detect label error (if they exist at all) in various existing bias mitigation methods

<u>Step 2</u>:

Devise a novel method to debias the neural network

Preliminary idea: reduce reliance on labels using few-shot learning?

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→ **Bias mitigation method** × **Type of noise** with which to flip the labels

Bias Mitigation Methods

1. Domain-independent training [1]
   - Independently train an object classification model on each of two domains
   - At test time, apply *prior shift* to adjust output probabilities toward a uniform distribution
2. Group DRO with *increased regularization* [2]
   - Train with strong regularization methods, including *strong* l_2 *penalty* and *early stopping*
   - Compute worst-case accuracy for pre-defined groups
3. Invariant Risk Minimization (IRM) [3]
   - Obtain a data representation such that the optimal classifier is *invariant* (i.e., the same for all training environments)

[1] Wang et al. Towards Fairness in Visual Recognition: Effective Strategies for Bias Mitigation. In *CVPR*, 2020.
[2] Sagawa et al. Distributionally Robust Neural Networks for Group Shifts: On the Importance of Regularization for Worst-case Generalization. In *ICLR*, 2020.
[3] Arjovsky et al. Invariant Risk Minimization. *arXiv:1907.02893*, 2020.

Types of Noise and Noise Levels

1. No noise
2. Flip label with *random* probability $p \in \{0.001, 0.01, 0.02, 0.05\}$
3. Flip label with probability that is *correlated* with the target attribute

Adding / Amplifying Noise in the Dataset

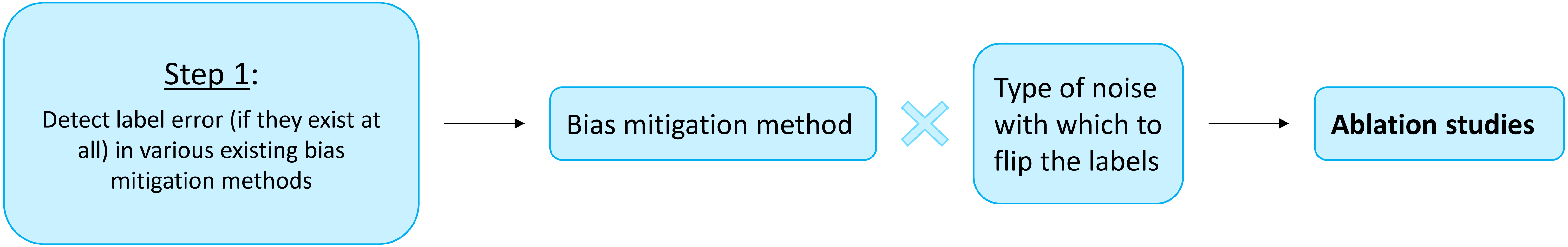
- **Goal**: amplify bias in the dataset and assess how well the bias mitigation methods perform

Algorithm 1 Noise Injection

Let A and B be two distinct attributes in a labeled dataset.
Hyperparameter: noise level p
for each label in A **do**
    if $A = 1$ and $B = 1$ **then**
        flip the label of B with $P(B = 0|A = 1) < p$
    else if $A = 1$ and $B = 0$ **then**
        flip the label of B with $P(B = 1|A = 1) > p$
    else if $A = 0$ and $B = 1$ **then**
        flip the label of B with $P(B = 0|A = 0) > p$
    else if $A = 0$ and $B = 0$ **then**
        flip the label of B with $P(B = 1|A = 0) < p$
    end if
end for

where A is the protected attribute, B is the target attribute, and p is the probability with which to flip the binary label

Project Outline



Conditions for Ablation Studies

1. Domain-independent training [1]
   - Dataset: CelebA
   - Metrics: directional bias amplification, KL, DEO, accuracy
2. Group DRO with *increased regularization* [2]
   - Dataset: Waterbirds
   - Metric: worst group accuracy
3. Invariant Risk Minimization (IRM) [3]
   - Dataset: Color MNIST
   - Metric: classification accuracy

× 52 runs

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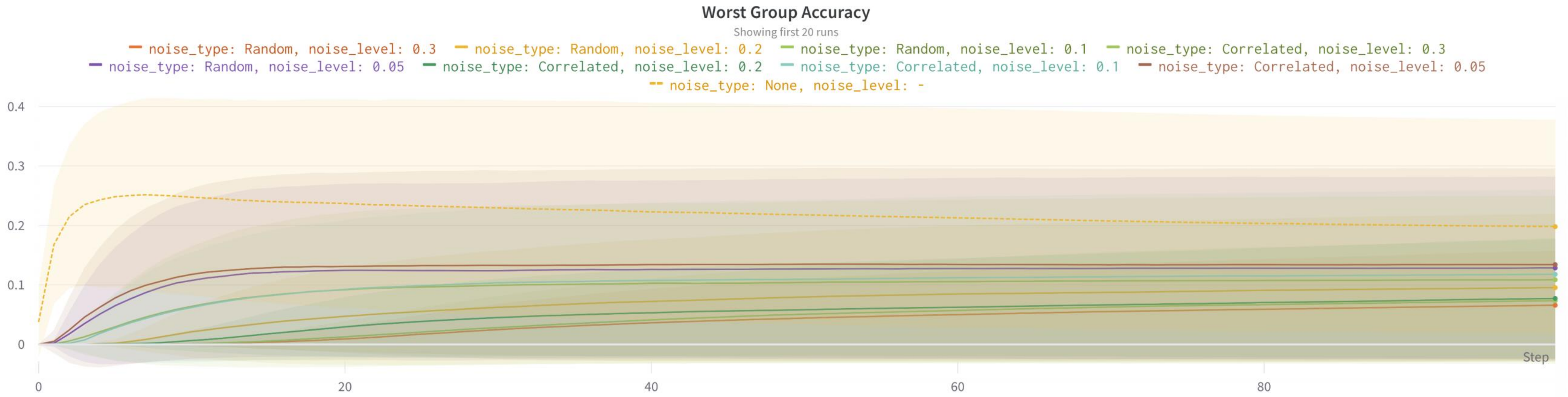
Results for Group DRO trained on Waterbirds

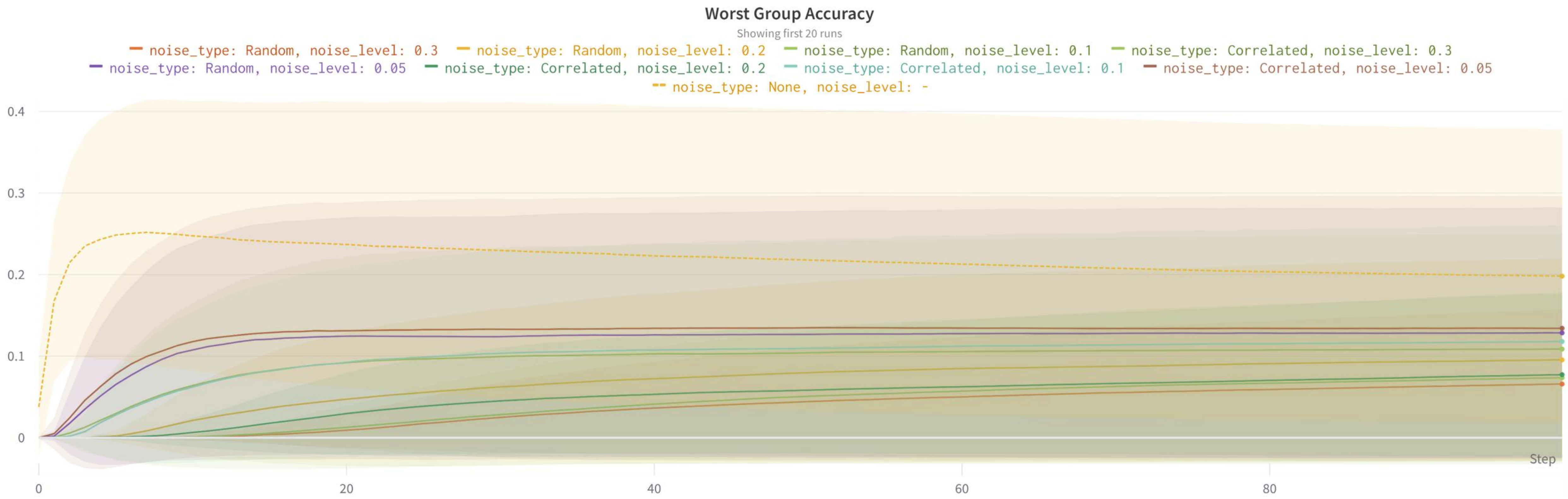
- The lines indicate average worst-group accuracies across 52 trials for each unique $(noise\ type, noise\ level)$ condition

- The largely overlapping error bars indicate 1 standard deviation from the mean



Results for Group DRO trained on Waterbirds

- Overall, the experimental results show no significant difference between the baseline (no noise), random noise, and correlation conditions



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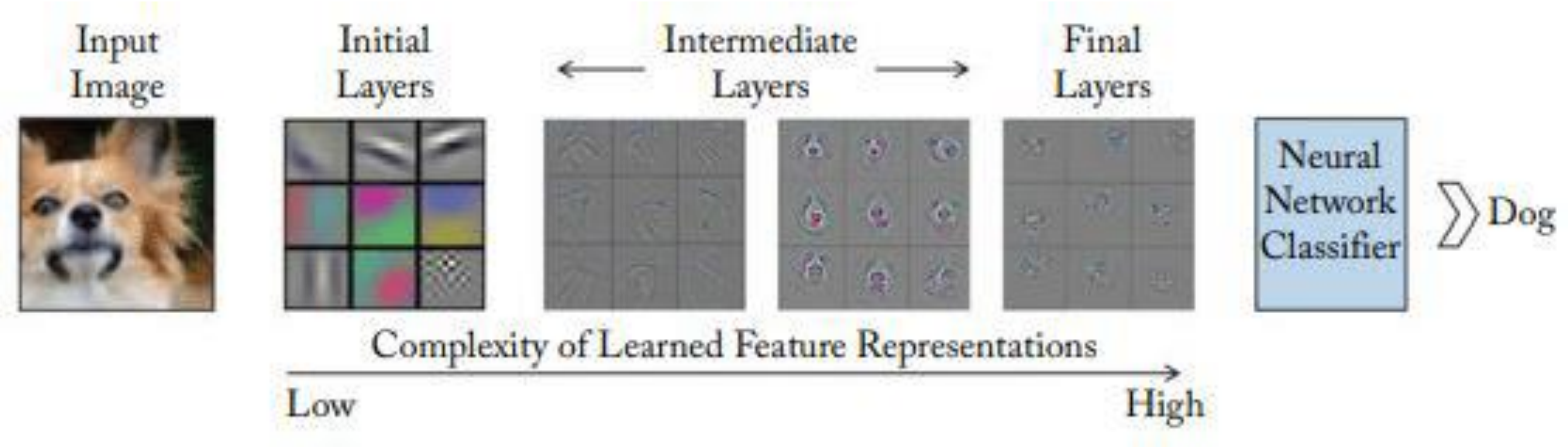
Not applicable, since no significant label error was detected in existing bias mitigation methods

Texture Bias in Generative NNs

Spring 2022

How CNNs "See" an Image

- CNNs combine low-level features (e.g., edges) to form increasingly complex *shapes* until an object can be classified by the network



How CNNs “See” an Image

- CNNs are currently the most predictive models for human object recognition (Cadieu et al., 2014)
- However, several findings found that CNNs can classify objects solely based on *texture* (local) information!

How CNNs "See" an Image

- ➢ CNNs are currently the most predictive models for human object recognition (Cadieu et al., 2014)
- ➢ However, several findings found that CNNs can classify objects solely based on *texture* (local) information!

"Texture bias"

Why is Texture Bias Problematic?

- ➢ Learned representations are not based on intended features

Geirhos, R., Jacobsen, J.H., Michaelis, C., Zemel, R., Brendel, W., Bethge, M., & Wichmann, F.A.. (2020). Shortcut learning in deep neural networks. *Nature Machine Intelligence*, 2(11), pp.665-673.

Hermann, K. L., Chen, T., and Kornblith, S. The Origins and Prevalence of Texture Bias in Convolutional Neural Networks. In *Conference on Neural Information Processing Systems*, 2020.

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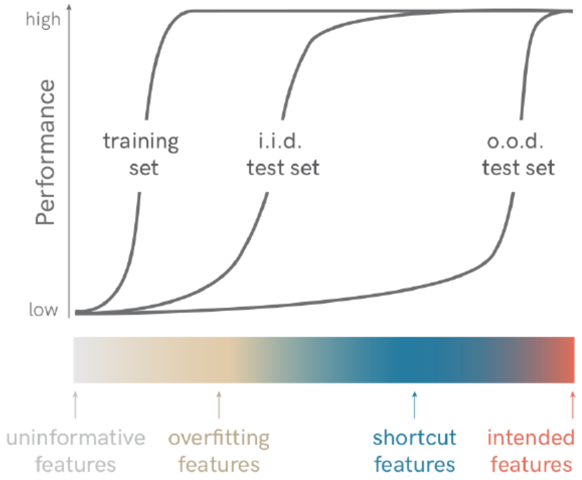

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- May suggest an *inductive bias* in CNNs that is different from that of humans

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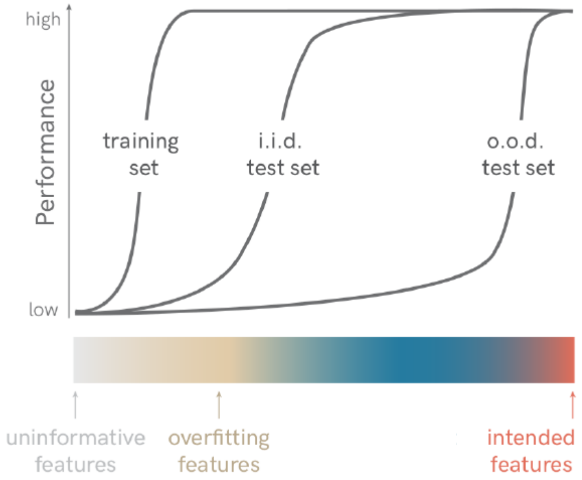

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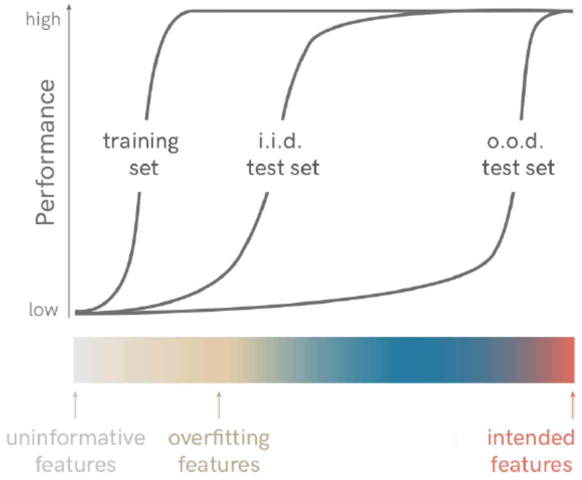

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- May suggest an *inductive bias* in CNNs that is different from that of humans

  - Problematic for CNNs to generalize to O.O.D. data

  - Difficult for models to learn human-relevant vision tasks in small-data regimes

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Previous Research Directions

- Direction 1:
  - Understanding texture bias in CNNs via comparison with behavioral data
- Direction 2:
  - Debiasing CNNs using shape + texture information
- Direction 3:
  - Texture bias in ViTs

Original Plan for Research Project

- **Motivation**: *semantic image synthesis* networks (e.g., SPADE) may contain texture bias, synthesizing outputs with high-quality “stuff” but poor-quality objects

- **Hypothesis**: stuff classes have simpler textures than complex objects, which allows them to be synthesized more easily with higher quality

- **Steps**:
  1. Detect texture bias (if any) in semantic image synthesis networks
  2. Devise a novel method to debias image synthesis (generative) networks

Progress paused…

… due to time and resource constraints at the University of Rochester