Towards Holistic Vision in Deep Neural Networks: Disentangling Local and Global Processing

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Introduction

Humans can perceive objects by their global shape, despite local variations

Changes in Texture

Changes in Context

DNNs are emerging as de-facto models of human perception, but are known to be **biased towards local information,** leading to an algorithmic gap between humans and models.

Why is this important?

Human Decision : Elephant

Model Decision : Tiger

This bias is linked to the problem of shortcut learning spurious correlations, making models brittle as compared to humans

Baker et al., 2018; Geirhos et al., 2018; Shah et al., 2020; Hermann et al., 2023

Challenge

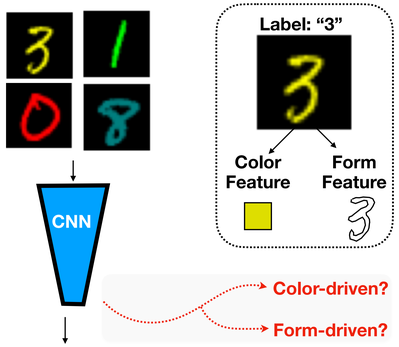
How can we get a model to see global shape? What exactly is global shape?

Solution

Diverge from a local solution and examine what emerges? Global Shape?

Experimental Setup

Digit Classification in Colored MNIST

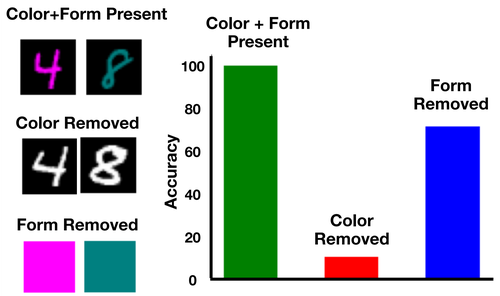


Digit Classification

CNNs are color-driven when both color and form are present in training

Feature Reliance

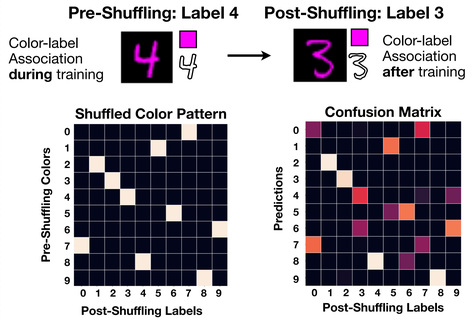
Selectively removing color or form post-training



Model relied on color features for digit classification

Error Patterns

Breaking the color-label association systematically, while retaining the form-label association

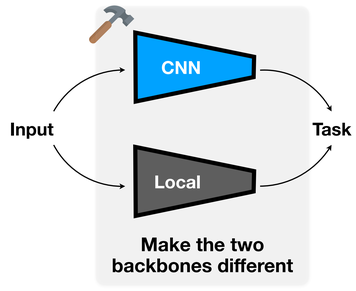


Misclassifications are in accordance to color-label associations seen during training

How do we get a CNN to become form-driven?

Idea

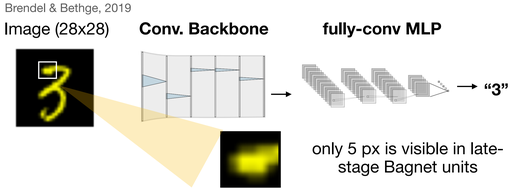
Force a CNN to be different than a model using a purely local strategy to solve the same task



Make the two backbones different

Local Strategy : BagNets

Brendel & Bethge, 2019

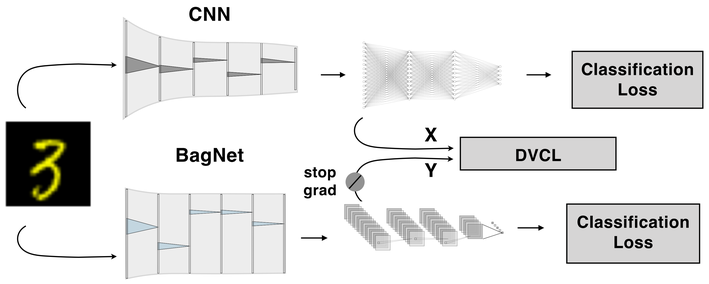


only 5 px is visible in late-stage Bagnet units

BagNets can only take a local-strategy to solve a task

DVCL - Divergence Variance Covariance Loss

DVCL encourages CNN and BagNet to learn orthogonal intermediate features



DVCL = α(Divergence Loss) + β(Variance Loss) + γ(Covariance Loss)

1) Divergence Loss: to get **different** features

$$L_{\text{divergence}} = \frac{1}{d}\sum_{i,j} \text{Corr}(X,Y)^2_{i,j}$$

2) Variance Loss: to prevent **collapse**

$$L_{\text{variance}} = \frac{1}{2d}\sum_{i=1}^{d}\left(\max(0,1-\sigma_{X_i})\right)^2$$

3) Covariance Loss: sparse features

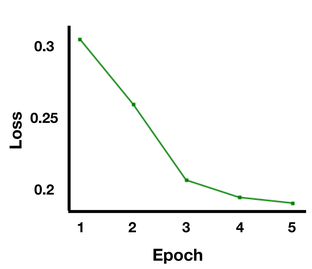
$$L_{\text{cov}} = \frac{1}{d}\sum_{i\neq j}\left(\text{Corr}(X)_{i,j}\right)^2$$

* **stop-grad** in BagNet allows it to "**soak up**" all the possible local features that it can

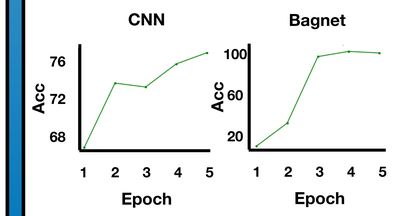
Disentangling color-vs-form processing using DVCL

Training

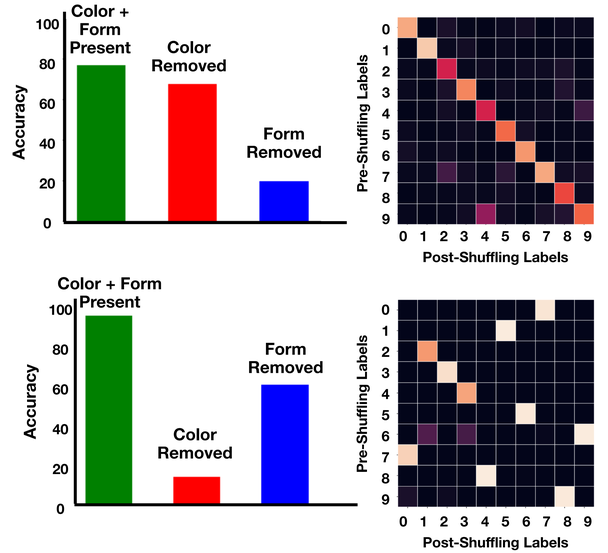
DVCL reduces with training



Both models get trained



Feature Reliance and Error Patterns for CNN and BagNet



Conclusion

- By making **a CNN orthogonal with Bagnet (local model)**, we can encourage it to do **global processing**
- Can this strategy be scaled on naturalistic datasets to develop models with **better shape representations?**

Reference

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