## **Explorations in Texture Learning**



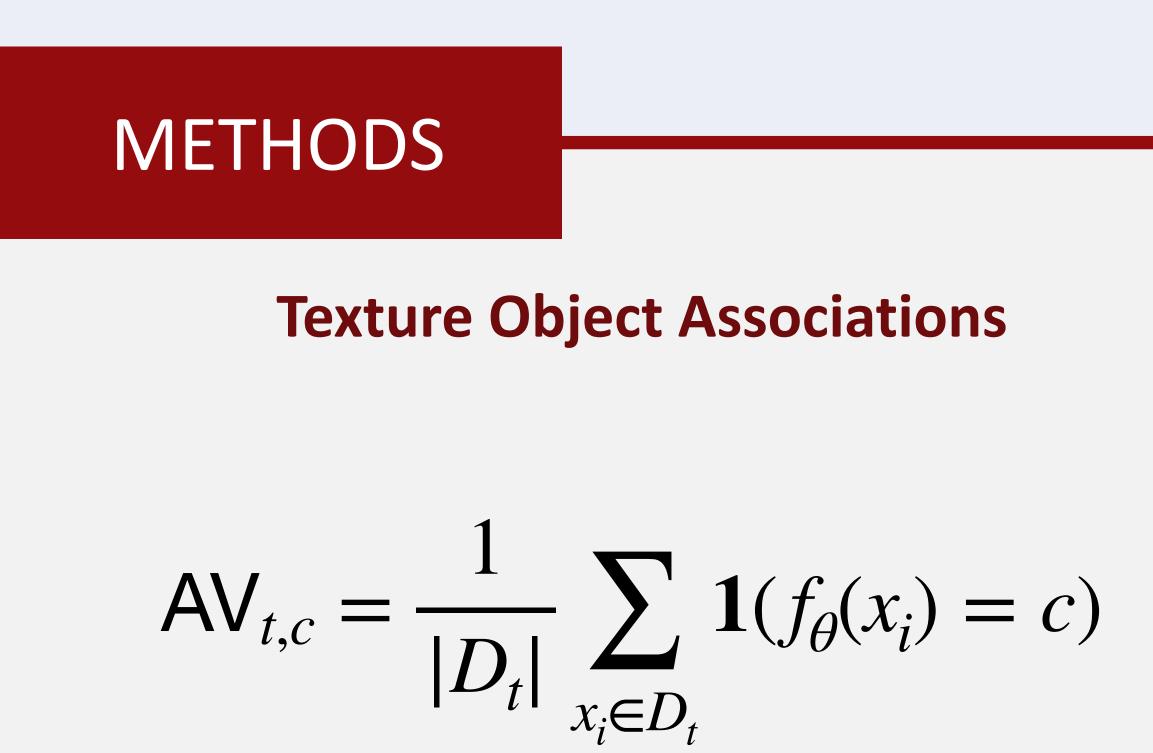
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# MADS&P

## INTRODUCTION

## **Texture Learning**

- CNNs have been shown to be biased towards texture, rather than shape.
- While there has been significant works focusing on measuring, mitigating, and explaining texture bias, we still lack an understanding on what kinds of textures models learn.



- In this work, we introduce *texture learning*, which encompasses the identification of learned textures, and the extent to which such textures are associated with objects.
- To quantify texture learning, we introduce a methodology for measuring texture associativity, and uncover a variety of interesting results.

We define texture-object associativity (or association value) as the probability that a given texture *t* will be classified as a particular object *c*. To measure AVs we classify texture images from the Describable Textures Dataset on pretrained ImageNet classifiers.

## RESULTS

## **Types of Associations**

Analyzing the association values for all texture classes, we find 3 classes of results:

• **Present & Expected** – Associations that were strong and can be expected based

### **Uncovering Training Data Bias**

Further investigating the strong association with bib objects and polka-dotted textures, we identified many instances of polka-dotted bibs

- on the naturally close relationship between the texture and object class (e.g., honeycombed textures and honeycomb objects)
- **Not Expected & Present** Associations that were strong, but didn't have an  $\bullet$ immediately clear relationship between the texture and object class until further investigation (e.g., polka dots and bibs)
- **Expected & Not Present** Associations that should have been strong based on lacksquarethe connectedness of the classes but were not strong (e.g., scaley and any fish or reptile object class)

Texture class	Object class	Effect	Object class	Effect	Object class	Effect
honeycombed	honeycomb	0.731	chain_mail	0.071	velvet	0.027
cobwebbed	spider_web	0.655	poncho	0.046	radio_telescope	0.046
waffled	waffle_iron	0.427	honeycomb	0.117	pretzel	0.075
striped	zebra	0.381	tiger	0.169	velvet	0.093
knitted	dishrag	0.331	wool	0.239	cardigan	0.188
stratified	cliff	0.305	velvet	0.140	stone_wall	0.125
spiralled	coil	0.296	maze	0.061	chambered_nautilus	0.043
bubbly	bubble	0.286	beer_glass	0.104	Petri_dish	0.077
dotted	bib	0.248	shower_curtain	0.148	wallet	0.097
polka-dotted	bib	0.247	Windsor_tie	0.125	wallet	0.089

### from the ImageNet training data.





















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CONCLUSION	
<ul> <li>Texture learning studies the extent to which models associate textures with objects and</li> </ul>	https://hoak.me
<ul> <li>works to identify those textures.</li> <li>Texture object associations can be used to uncover learned relationships between objects</li> </ul>	bhoak@cs.wisc.edu
and different texture classes, and also highlight potential training data bias.	@blaine_hoak

Texture learning improves model interpretability and unlocks new avenues for understanding  $\bullet$ the kinds of high-level features models rely on when classifying images.