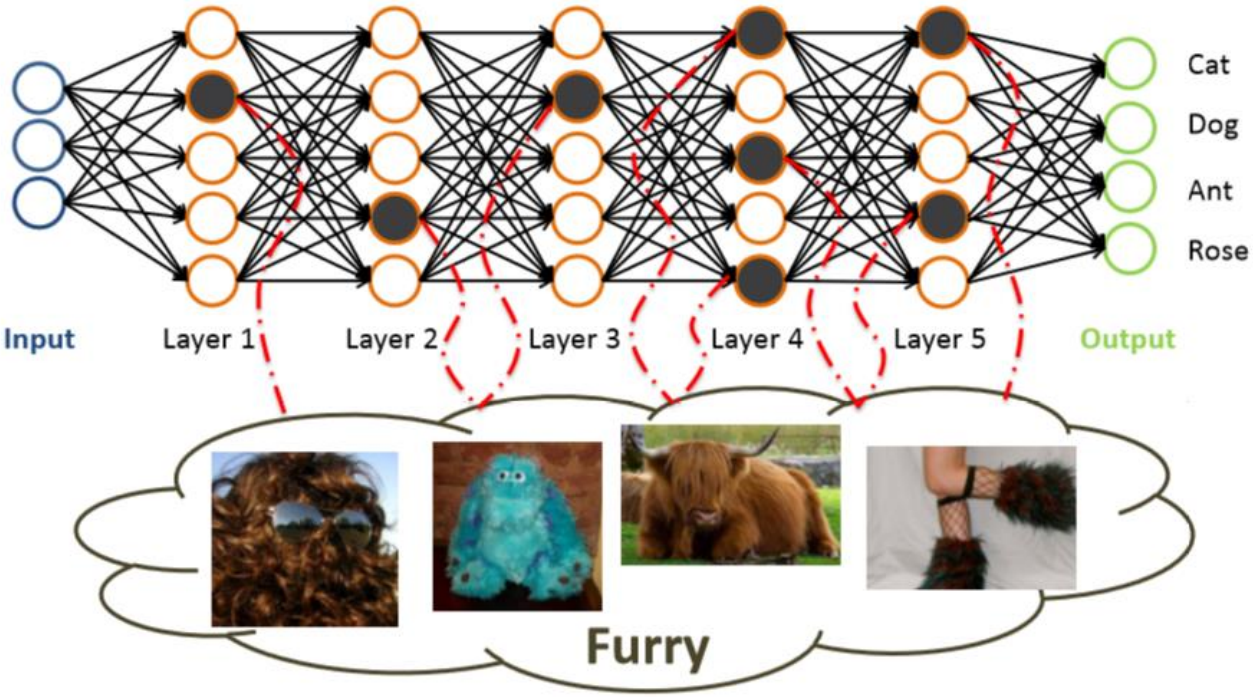
On the Relationship between Visual Attributes and Convolutional Networks

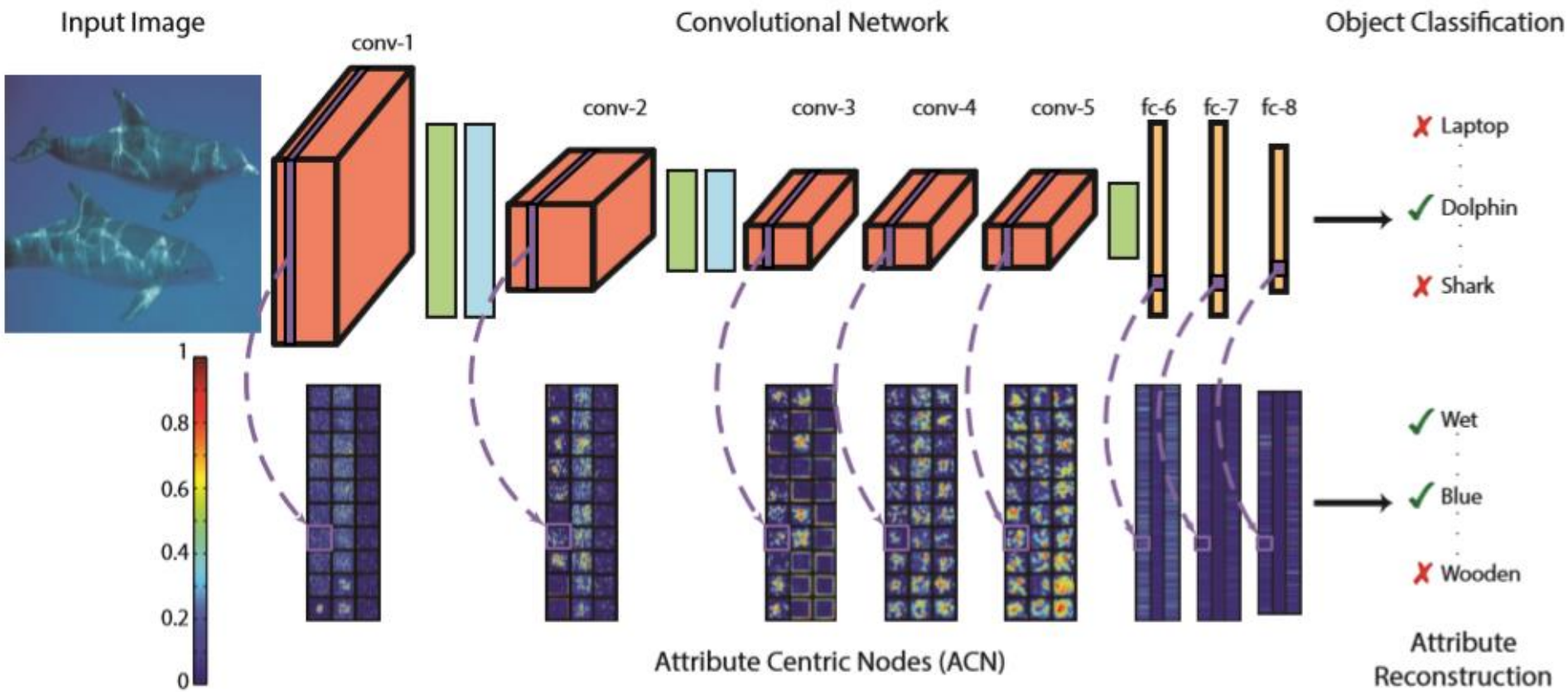


Victor Escorcia, Juan Carlos Niebles, Bernard Ghanem

King Abdullah University of Science and Technology (KAUST), Saudi Arabia

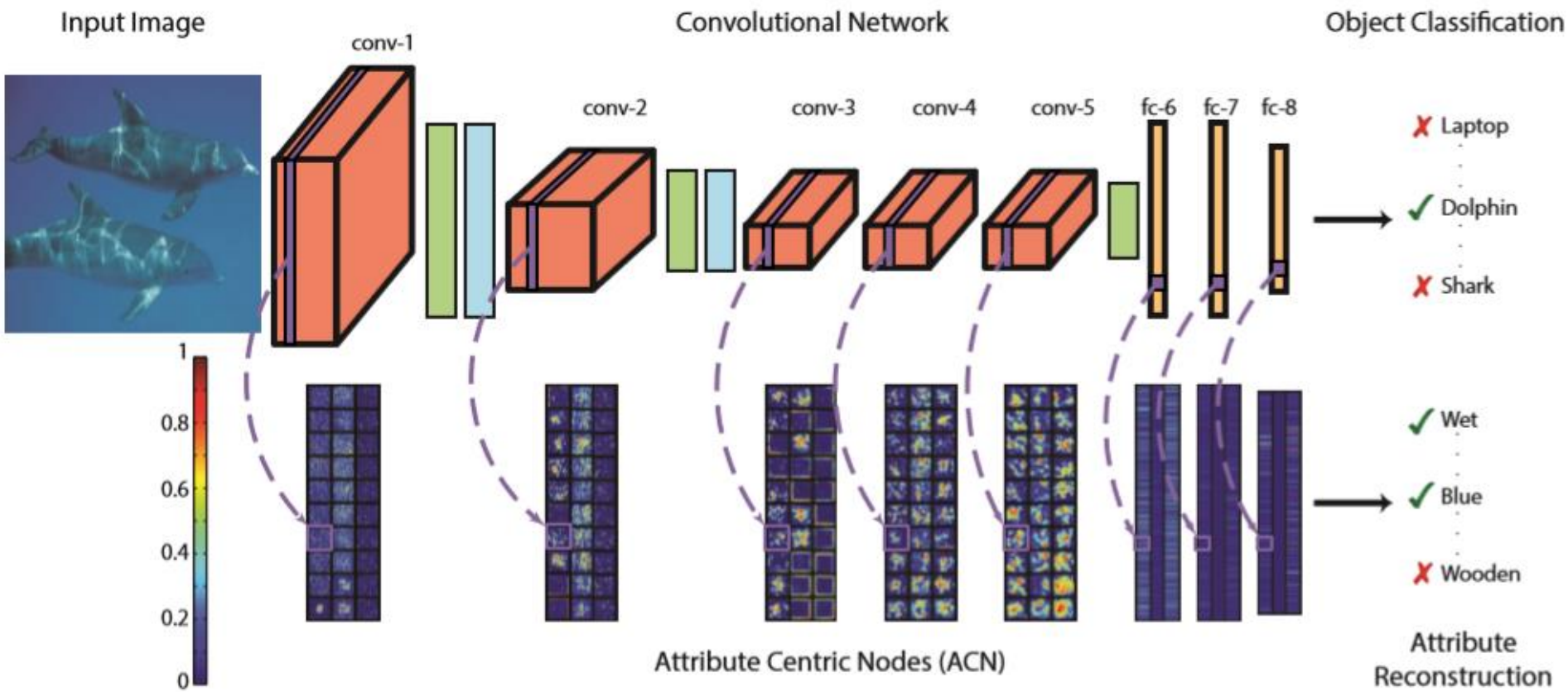
Universidad del Norte, Colombia

Overview



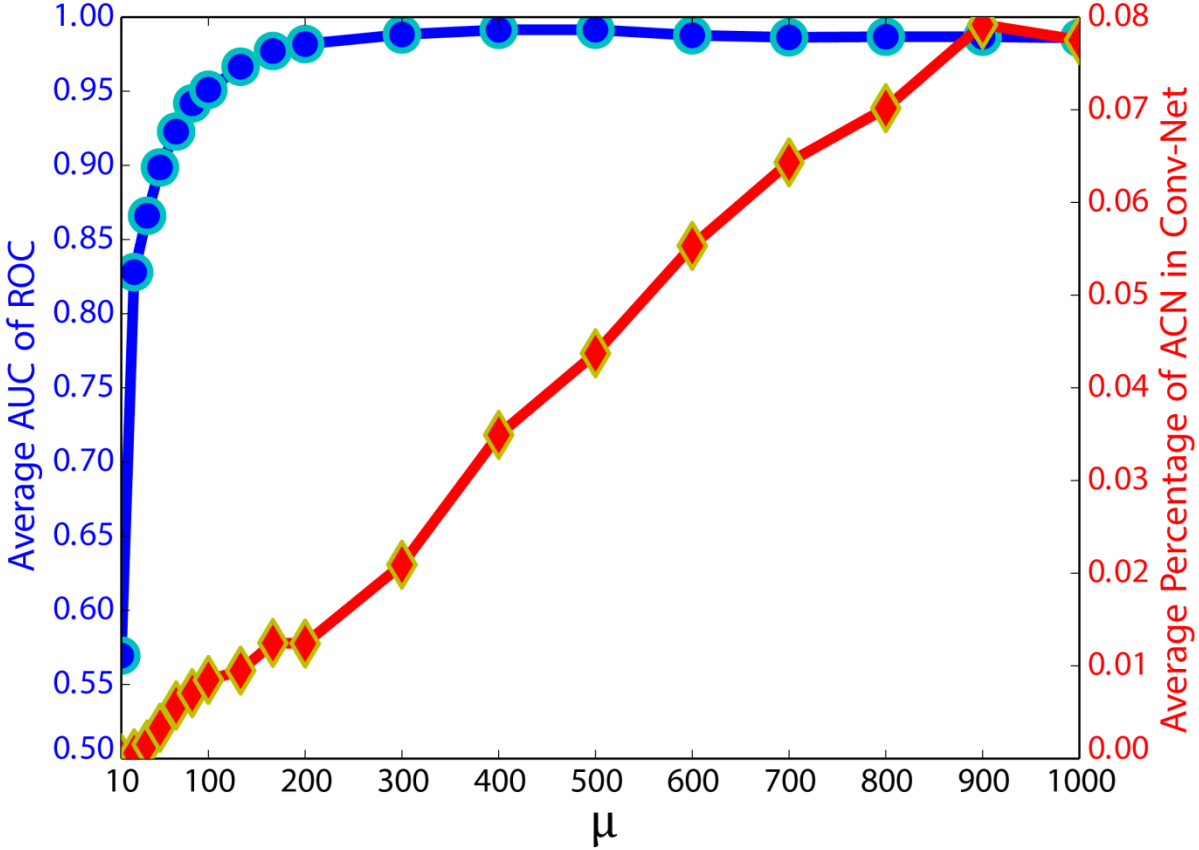
We empirically show that a sparse number of nodes in a conv-net, trained to recognize objects (e.g. 'dolphin'), inherently encode information about semantic visual attributes (e.g. 'wet').
We call these activation locations Attribute Centric Nodes (ACNs).

Main Findings



1. ACNs exist. They are sparse and powerful representations to recover attributes.
2. ACNs are unevenly distributed throughout the network and are attribute specific. ACNs of co-occurring attributes tend to be similar.
3. ACNs are important for object classification.

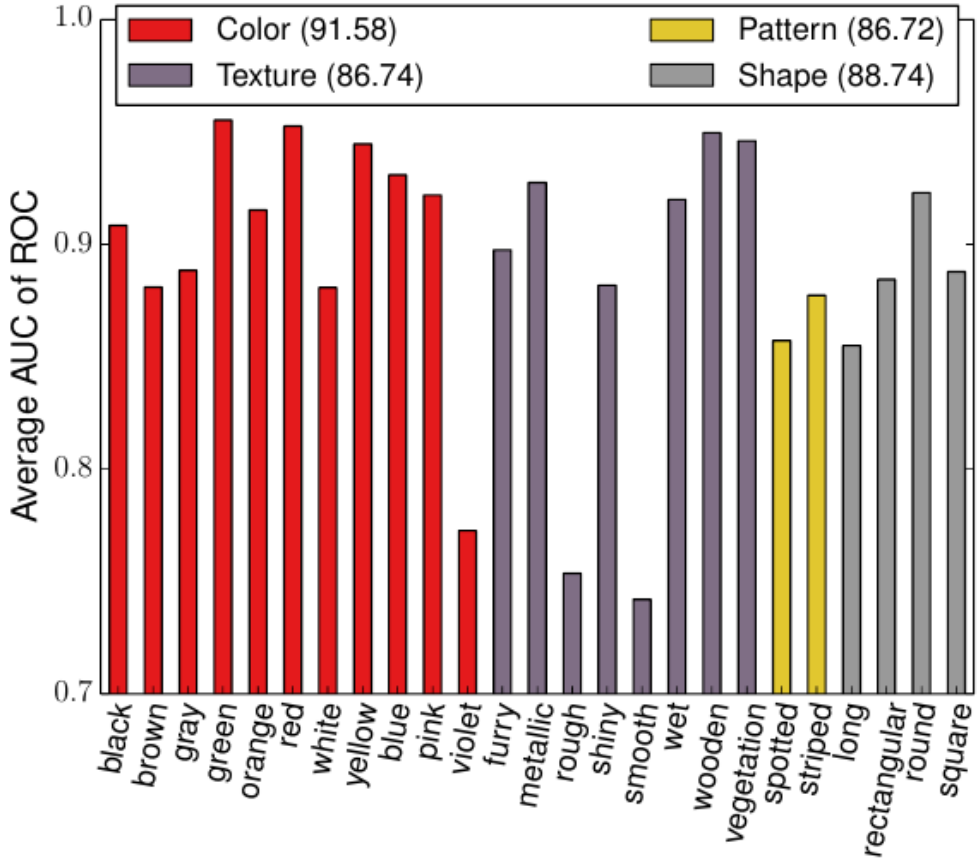
1. ACNs Existence



We found that only a small percentage of ACNs is required to produce near perfect reconstruction. At $\mu = 200$ (1.2% of the conv-net nodes), the AUC-ROC score stabilizes, which is evidence that ACNs are truly sparse in the conv-net.

μ is a hyper-parameter to trade-off sparsity and reconstruction. Check details in the paper.

1. ACNs Existence



Attribute Group	[15]	Our
Color (8 attr)	87.5%	91.6%
Texture (7 attr)	77.5%	86.7%
Pattern (2 attr)	63.4%	86.7%
Shape (3 attr)	83.6%	88.7%
Overall (20 attr)	80.8%	**89.0%**

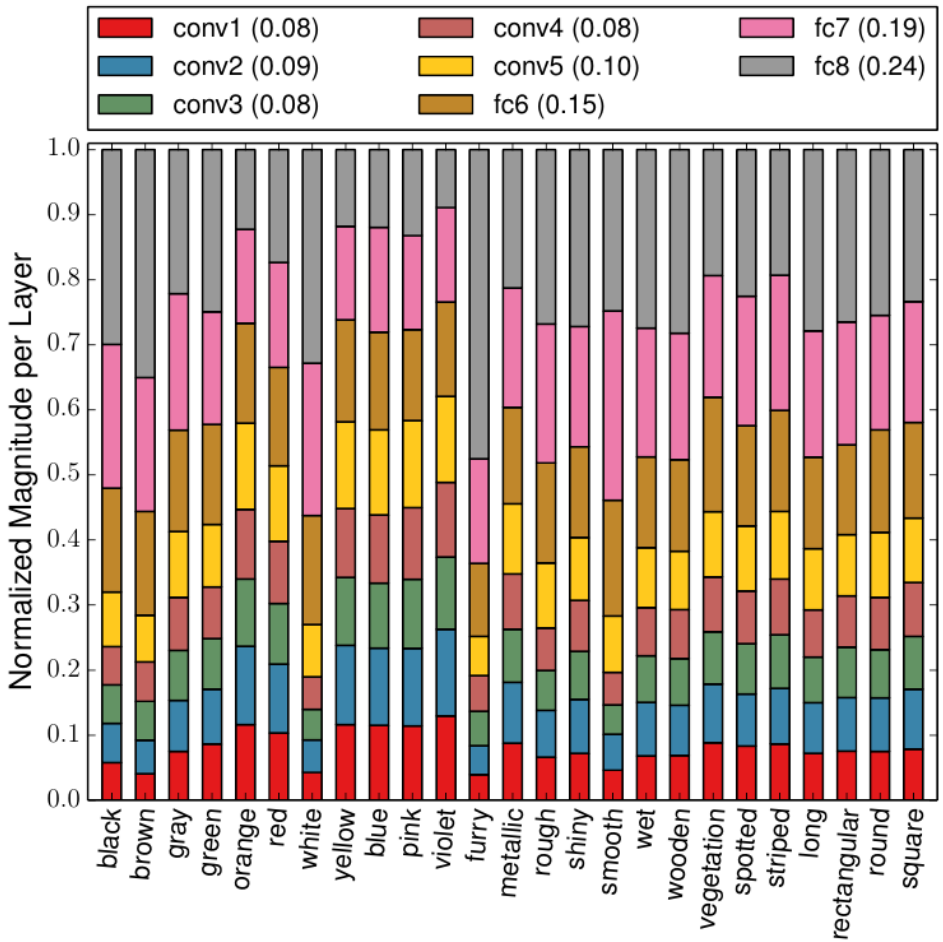
ACNs are powerful features for attribute prediction. They record an improvement around 10% against multiple hand-crafted features with non-linear kernels [15].

1. ACNs Existence

Attribute Group	Our	SVM FC-6	SVM FC-7	SVM FC-8
Color (11 attr)	90.5%	88.1%	89.6%	87.5%
Texture (8 attr)	87.7%	84.3%	83.9%	85.5%
Pattern (2 attr)	86.7%	87.6%	86.9%	85.9%
Shape (4 attr)	88.8%	90.4%	90.9%	89.0%
Overall (25 attr)	**89.0%**	87.2%	87.7%	86.9%

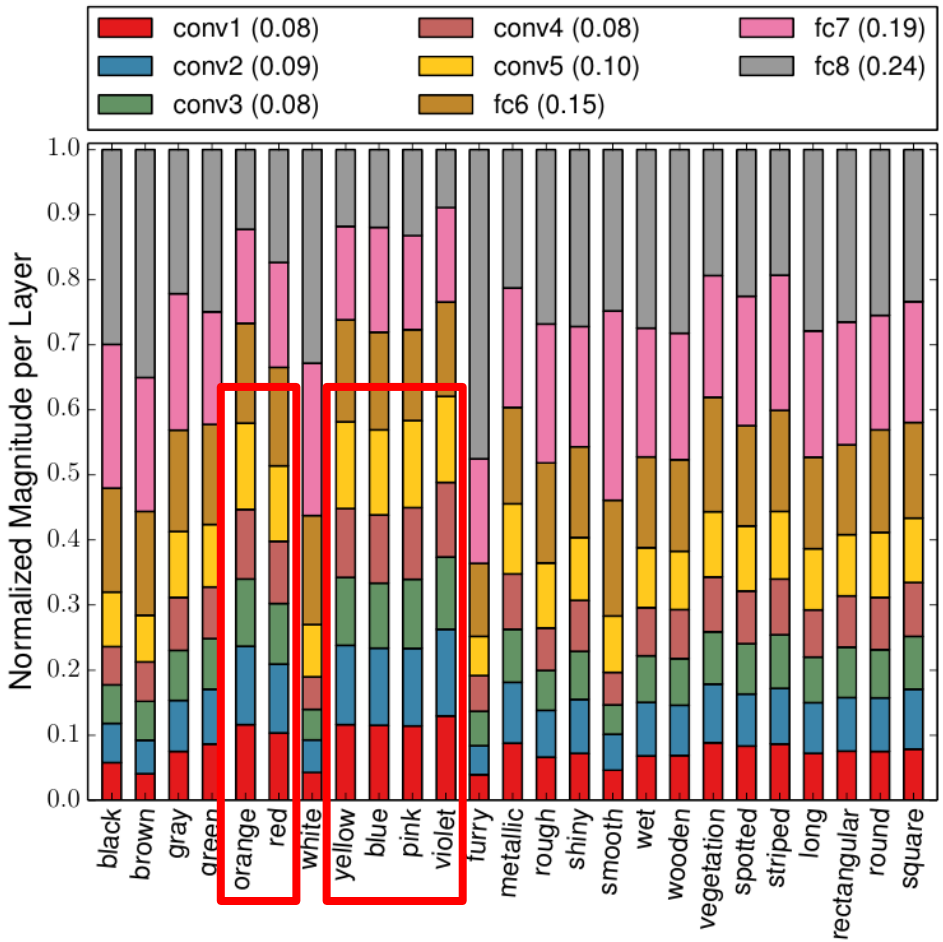
In general, attribute prediction based on ACNs is better than attribute prediction of one robust classifier trained over the activations of a single fully-connected layer.
It suggests that some attributes take advantage of activations from lower hidden layers.

2. Distribution of ACNs



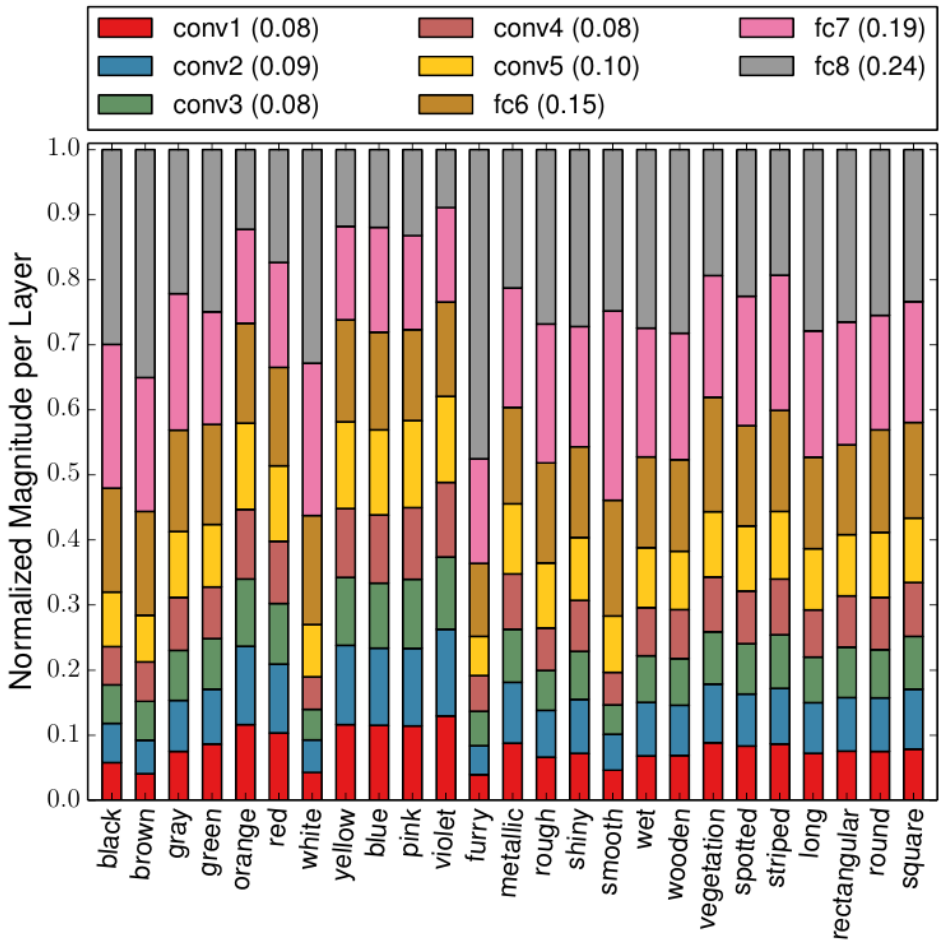
We study the importance of the ACN with respect to their localization in the conv-net, for each attribute. The average normalized contribution of each layer is reported in parentheses.

2. Distribution of ACNs



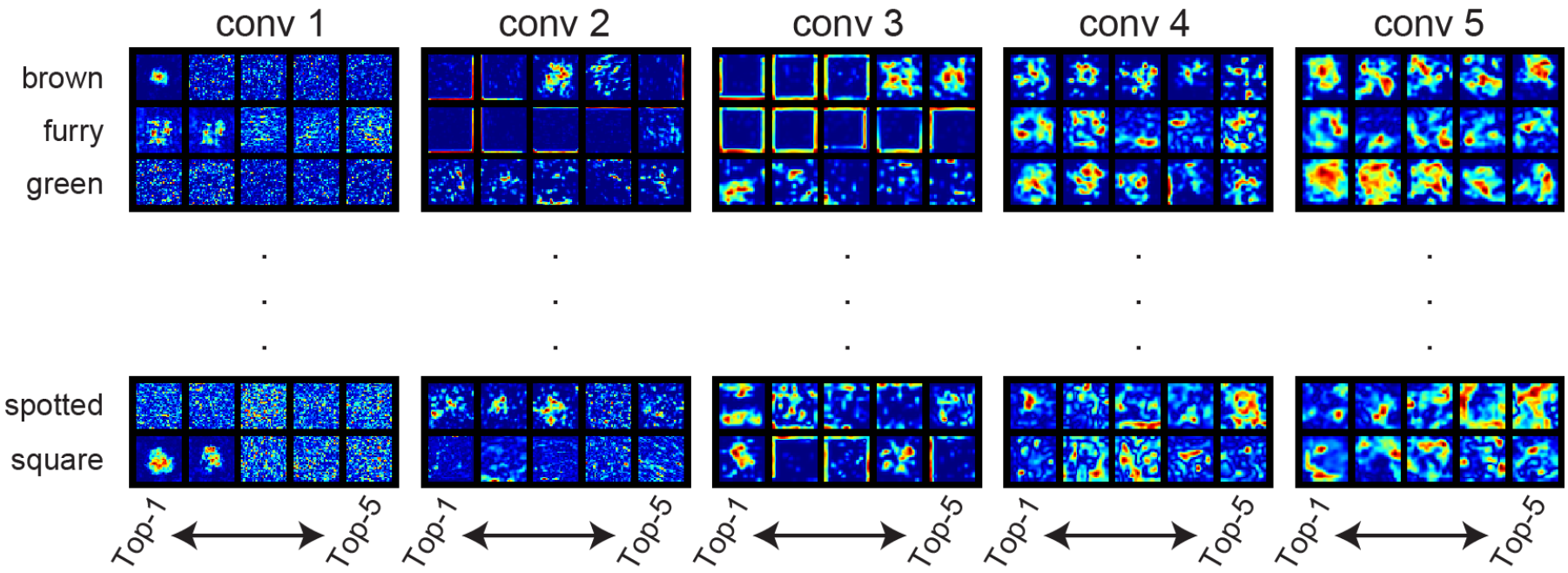
ACN localization is attribute dependent. For example, color attributes tend to be represented well by activations from the convolutional layers.

2. Distribution of ACNs



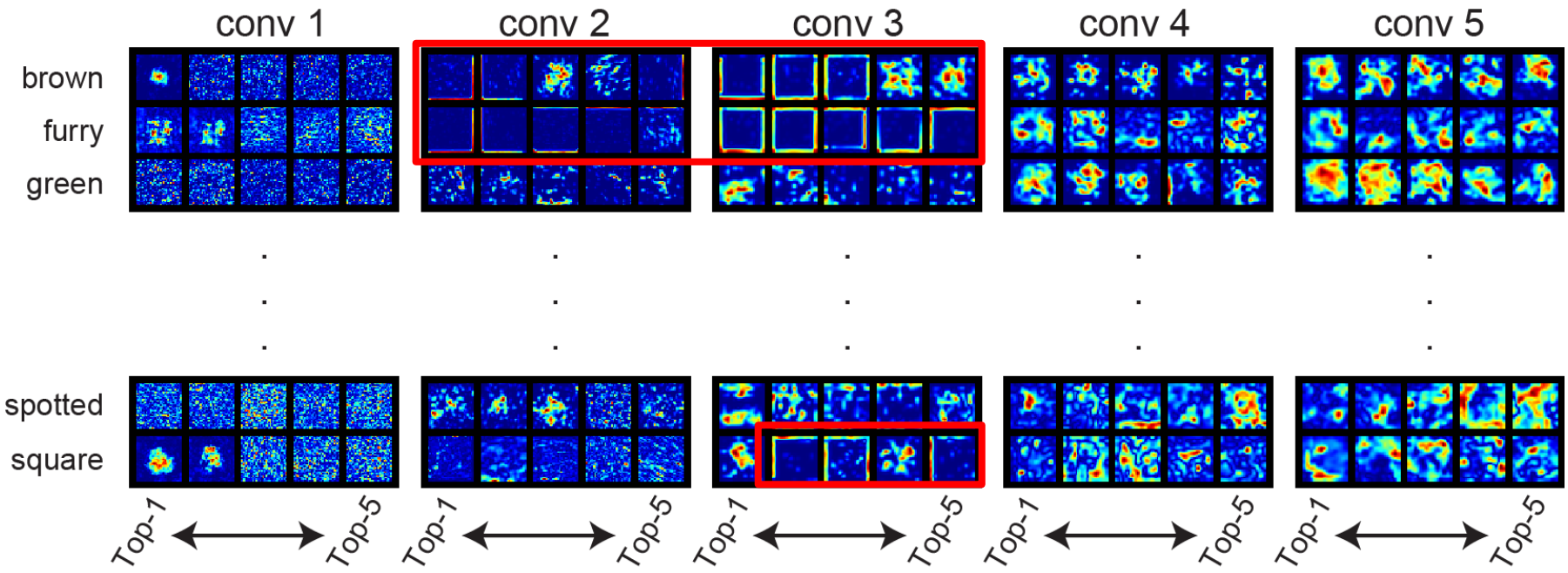
In general, the most *important* activations are localized on higher layers. This is experimental support for the common practice of using features from the fully-connected layers

2. Distribution of ACNs



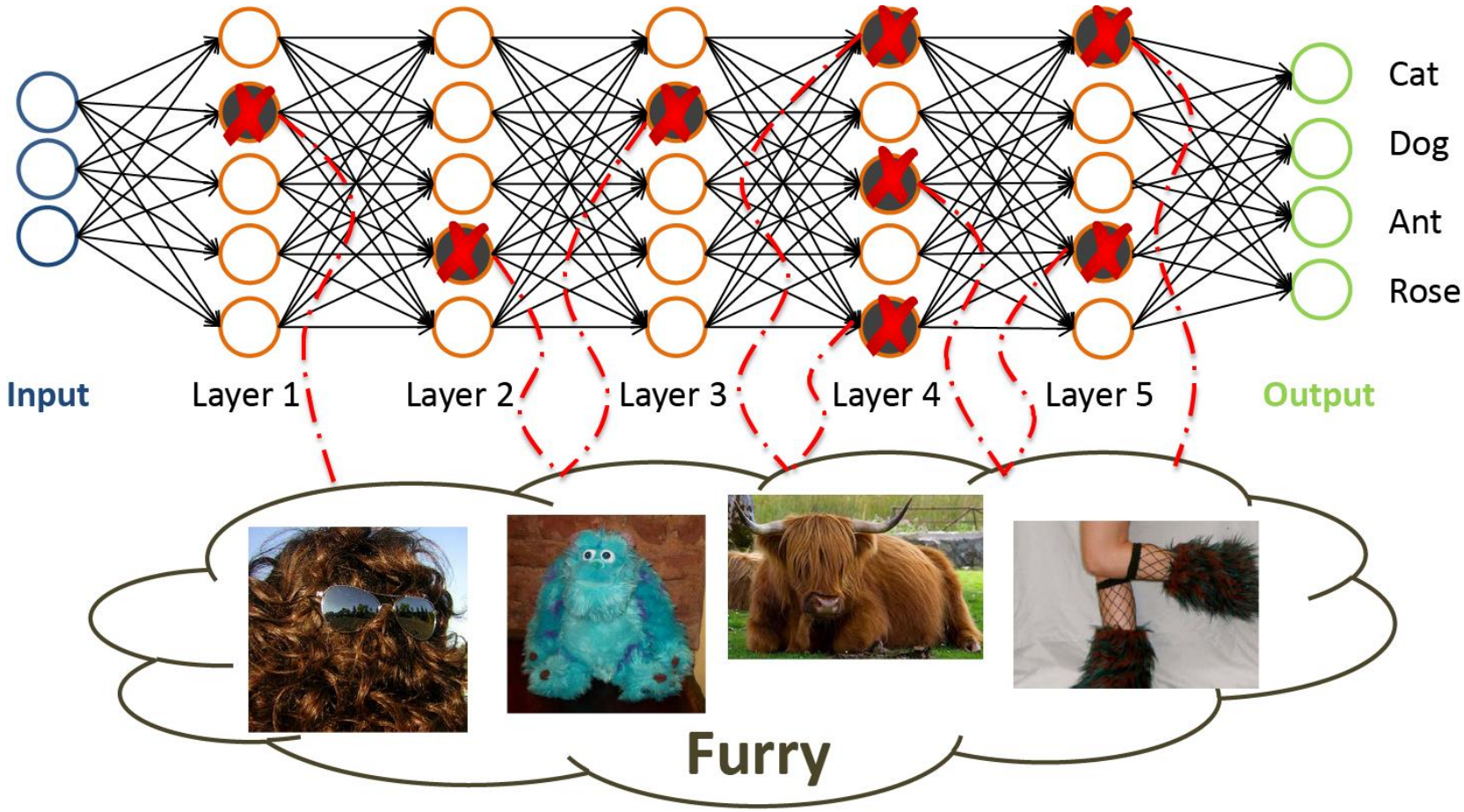
The visual pattern of ACNs in convolutional layers is diverse. It tends to be spatially structure-less in lower convolutional layers while it becomes more centralized and spatially contiguous in higher layers.

2. Distribution of ACNs



Interestingly, some layers (e.g. conv2 and conv3) of some attributes contain ACNs in local patterns around image borders suggesting some form of learned context.

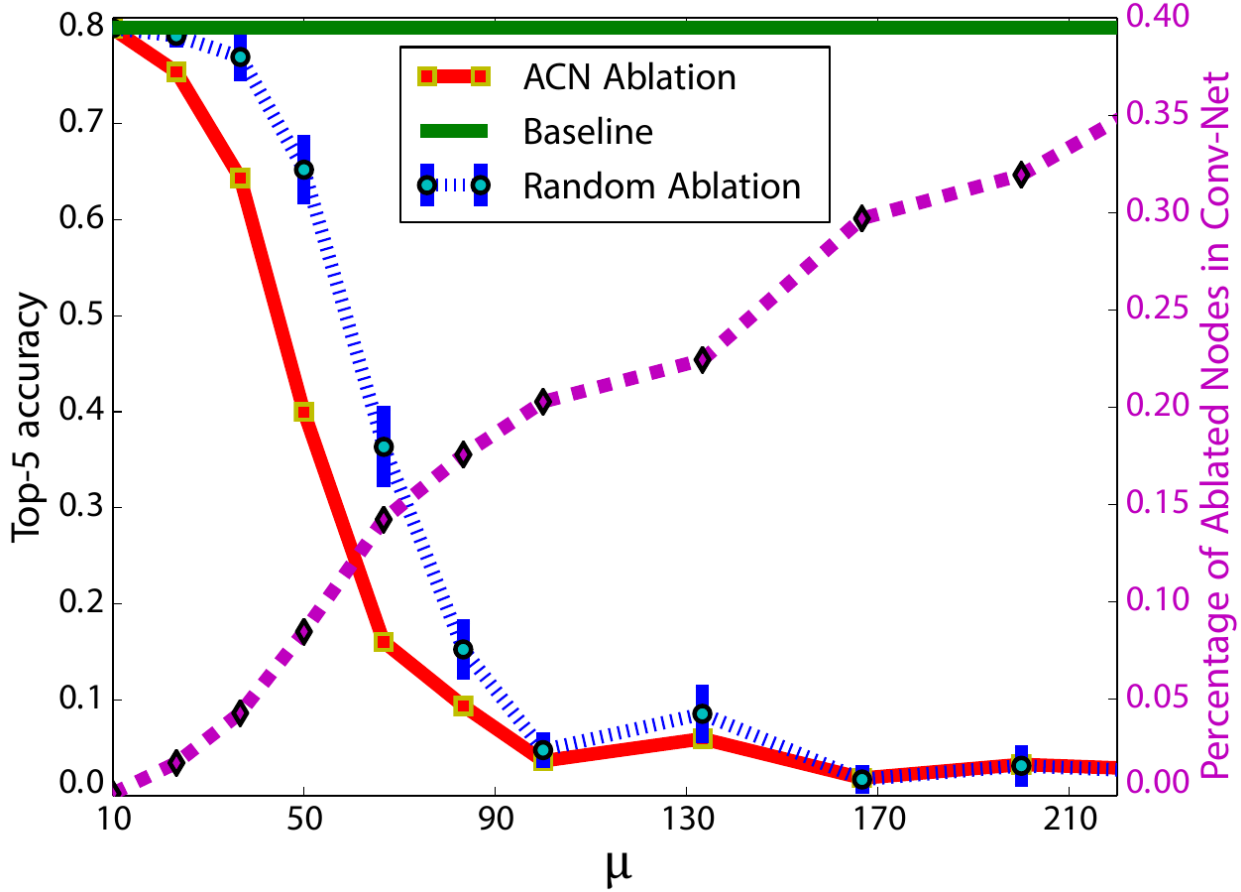
3. Impact of ACNs on Object Recognition



We perform an ablation study to measure the impact of ACNs on object classification.

We compare ACN ablation to random node ablation.

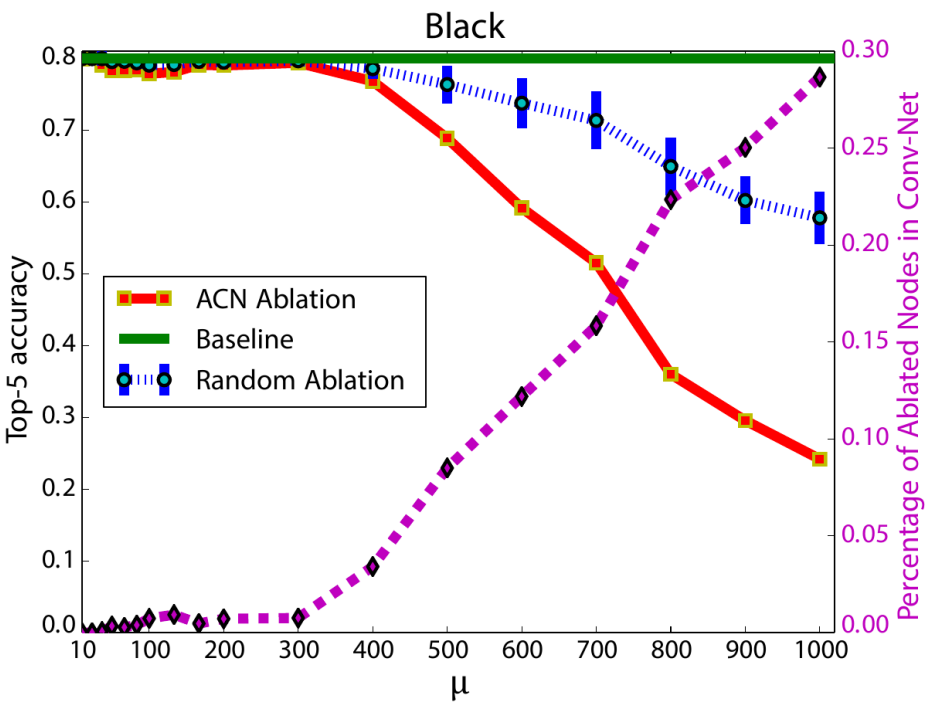
3. Impact of ACNs on Object Recognition

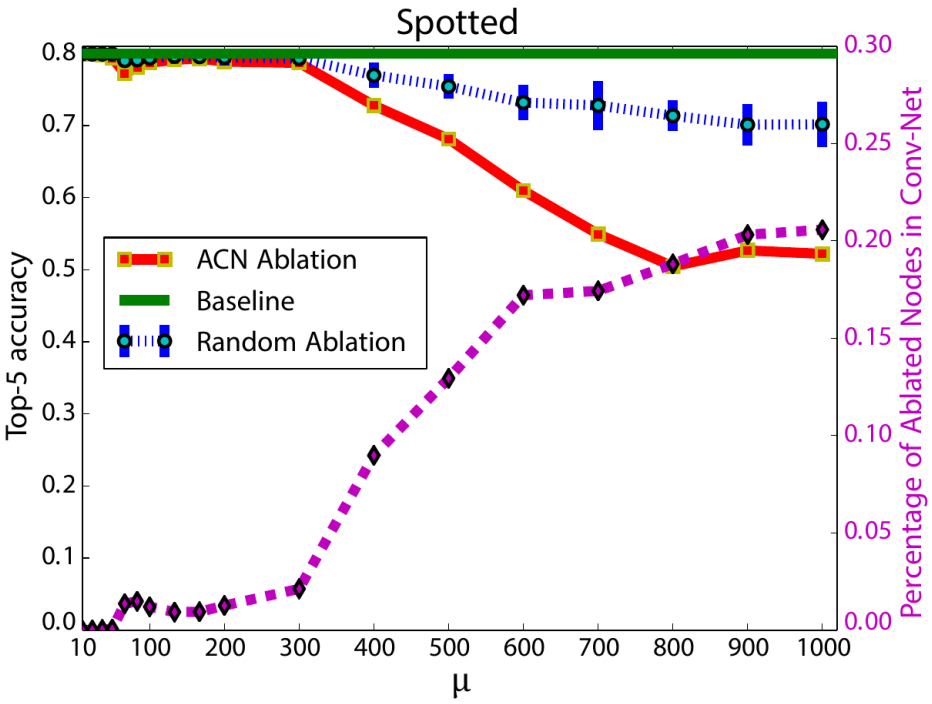


We ablated ACNs associated with all 25 absolute attributes. Both ablation methods show a steep drop-off as μ increases. However, the difference in accuracy between the two is significant.
This suggests that ACNs encode important information used by the conv-net for recognition.

The small standard deviation of random ablation is scaled up to be visually perceivable.

3. Impact of ACNs on Object Recognition

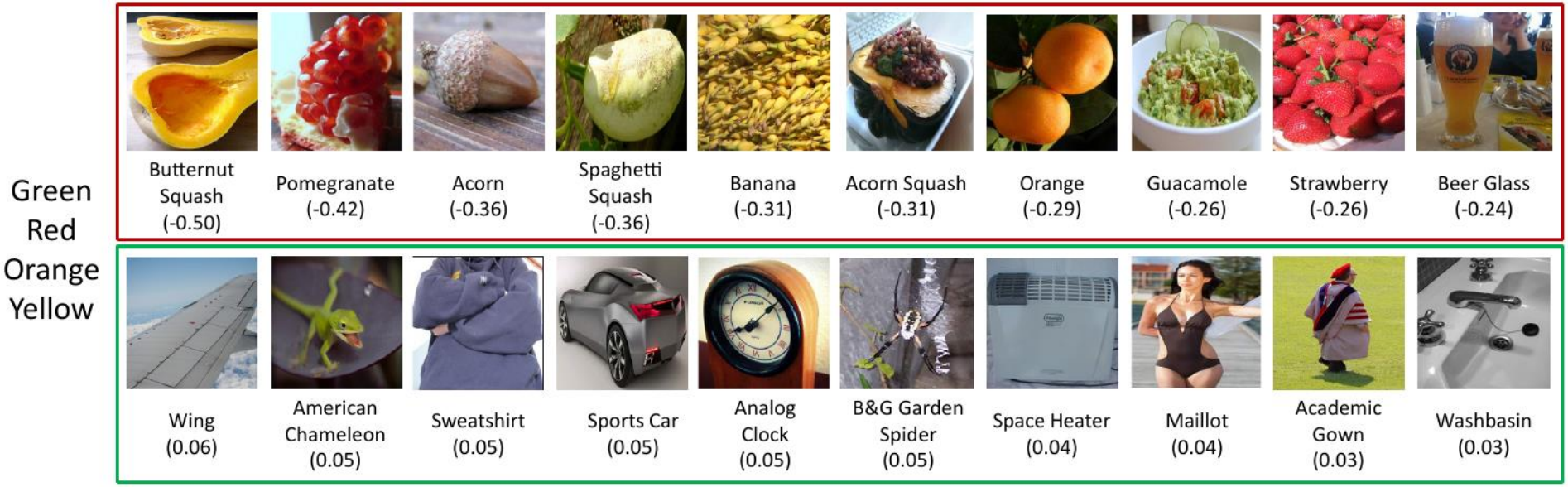




We also remove ACNs for each attribute separately. Similarly, we observe that ACN ablation produces a more drastic drop-off than random nodes ablation.

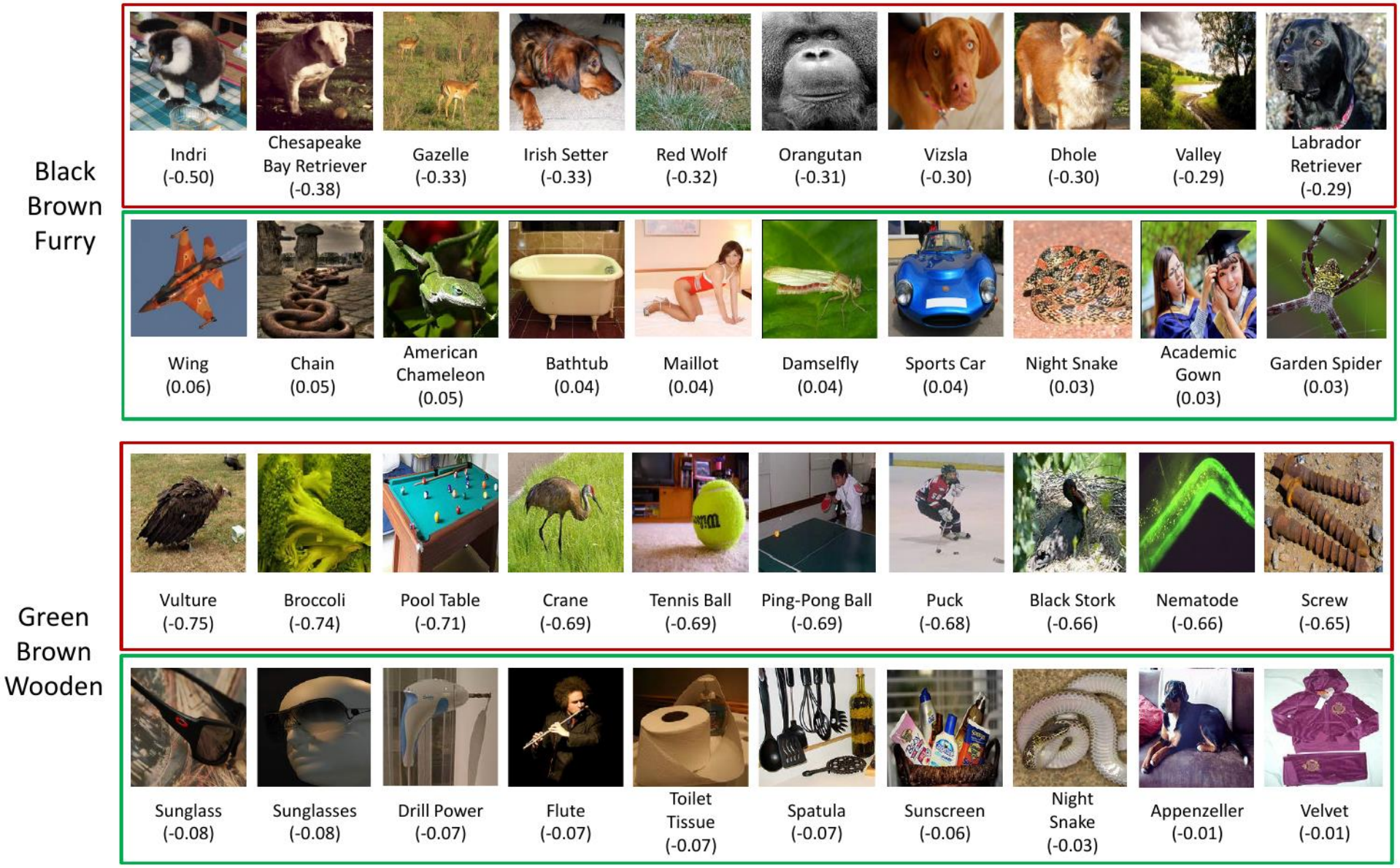
The small standard deviation of random ablation is scaled up to be visually perceivable.

3. Impact of ACNs on Object Recognition

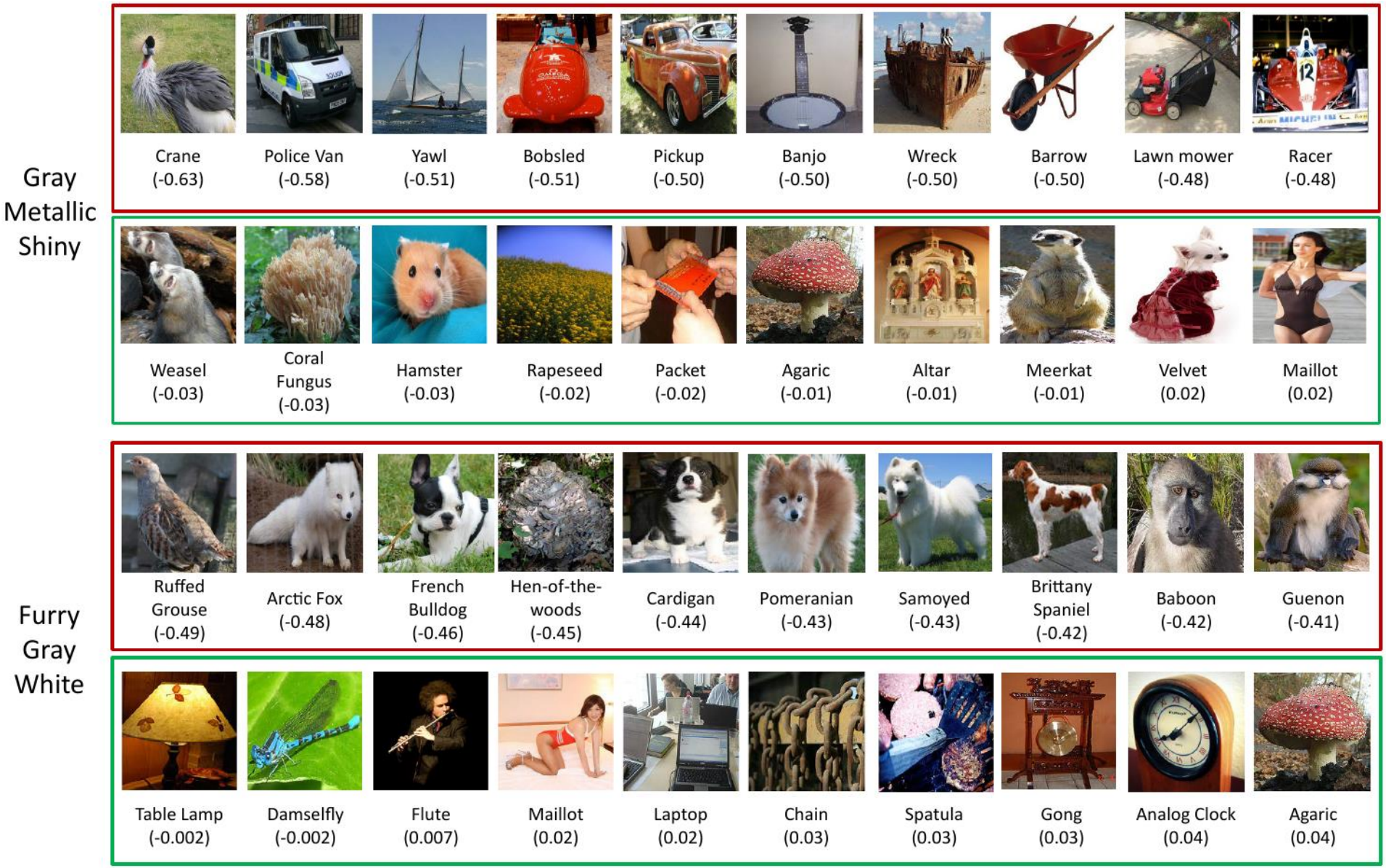


We also found semantic relationships between ablated ACNs of specific attributes and the most (and least) affected object categories. The drop-off in mean average precision is reported in parentheses.

3. Impact of ACNs on Object Recognition



3. Impact of ACNs on Object Recognition



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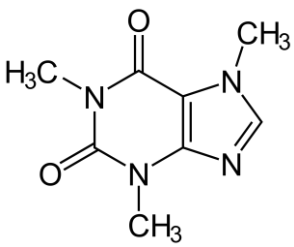

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