Perceptual Material Attributes Arise in Local Material Recognition

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Abstract

Material attributes have been shown to provide a discriminative intermediate representation for materials, as they help tame the otherwise challenging intra-class appearance variation that materials exhibit. In the past, however, the space of material attributes has been manually-defined and treated as merely an intermediate feature for other recognition tasks. Recent neuroscience studies on material perception, as well as computer vision research on object and place recognition, show that attributes may in fact arise naturally during the course of higher-level recognition. These results suggest that, analogous to scenes and objects, perceptual material attributes may arise during material recognition. Part of the challenge in investigating this conjecture is that existing attribute discovery methods cannot leverage large amounts of data likely required to cause the attributes to arise. In this paper, we design a novel network architecture and database in order to show that perceptual attributes can in fact arise from large-scale end-to-end material recognition. We focus on local material recognition, from small patches, in order to separate the materials from surrounding object and scene context. We extract the inherent material attributes by adding auxiliary loss functions to a material recognition CNN, enabling perceptual attributes to be produced as a side product. Our results show that the discovered attributes correspond well with semantically-meaningful visual material traits, and enable recognition of previously unseen material categories given only a few examples.

1. Introduction

Attributes have proven to be a valuable intermediate representation for higher-level image understanding tasks. Material attributes, attributes used for material recognition, are particularly useful as they provide a discriminative representation for materials whose appearance otherwise exhibits large intra-class appearance variation [15]. Beyond just suggesting the presence of various materials, material attributes can inform us as to the potential physical properties, such as “rough” or “soft”, a material might exhibit. These cues can, for instance, guide autonomous interaction with real-world surfaces made of various materials. Attributes also have the desirable property that they can form a compact representation for novel categories from few examples (N-shot learning).

Existing material recognition and material attribute discovery methods consider attributes separately from category recognition. Attributes are used either solely as an intermediate representation [15], or as an automatically discovered perceptual representation for the same purpose [16, 22]. Similarly for conventional object and scene recognition, attributes like “sunset” or “natural,” have also been extracted for use as independent features. Shankar et al. [17] generate pseudo-labels to improve the attribute prediction accuracy of a Convolutional Neural Network, and Zhou et al. [24] discover concepts from weakly-supervised image data. In both cases, the attributes are considered on their own, not within the context of higher-level categories. In object and scene recognition, however, recent work shows that semantic attributes seem to arise in networks that are trained end-to-end for category recognition [25].
We would like to take advantage of the benefits of end-to-end learning to incorporate automatically-discovered attributes with material recognition in one seamless process. Material attribute recognition, however, is not easily scalable. Past approaches rely on semantic attributes, such as “shiny” or “fuzzy”, that need careful annotation by a consistent annotator as their appearance may not be readily agreed upon. We are also specifically interested in scaling up local material recognition: recognizing materials using only information from small patches inside object boundaries so as to separate materials from the surrounding objects. Schwartz and Nishino [15,16] argue the importance of recognizing materials locally: methods which rely on features at lower levels (V1/V2) to perceptual properties (such as matte, colorful, fuzzy, shiny, etc.) in higher-level brain regions dedicated to recognition (FG/CoS).

In this paper, we realize large-scale end-to-end learning for local material recognition and show that perceptual material attributes like those discovered by [16] are indeed present in and may be extracted from the network. We introduce a novel material attribute-category CNN architecture (MAC-CNN, Figure 1) to show that perceptual material attributes recognizable at the local level can be discovered during material recognition. By introducing additional auxiliary attribute layers (layers connected to the network but not participating in the final classification loss) and constraints derived from human material perception, we find that we may extract the perceptual material attributes present in the network. Unlike methods that rely on images and text (along with material annotations), we require only a perceptual distance matrix as weak supervision for the attributes.

As part of our work, we also introduce a novel local material image database. We agree with their argument, but find that existing material databases are lacking in a few areas key to local material recognition. The Flickr Materials Database of Sharan et al. [19] provides sufficient information for local recognition, but uses only Flickr images which biases the dataset towards more artistic or professional images. Recent datasets, such as the Materials in Context (MINC) dataset [3], take steps to address this, but have inconsistencies in the definition of what makes a material category. The patches they extract are also large enough to include entire objects, further confusing the recognition of objects and materials. To support the experiments performed in this paper, we introduce a database explicitly targeted at local material recognition. We derive a systematically organized hierarchy for material categories, and we collect annotations for images from a wide variety of sources while carefully ensuring that object information, such as shape, is not present.

Our results show that our MAC-CNN produces a generalizable internal material representation following the same principles proposed to be integral to human material perception. We show that the attributes we extract exhibit the same properties, such as spatial consistency, as existing automatically-discovered perceptual material attributes. By visualizing the arrangement of material categories in the space of attribute probabilities, we show that attributes separate materials into distinct clusters. We perform true local material recognition, predicting categories for single small image patches with no aggregation, a significantly more challenging task than previous approaches. We may also recognize manually-identified semantic material traits, such as “fuzzy” or “smooth”, based on our attributes. Most important, we demonstrate that the extracted material attributes add significant information to recognize previously unseen material categories from a small number of training examples (i.e., N-shot learning with material attributes). These results show that our method successfully extracts effective and semantically meaningful internal representations of complex material appearance from a local material recognition network.

2. Related Work

In this paper, we investigate Convolutional Neural Networks (CNNs) as the framework within which we should find perceptual attributes. Shankar et al. [17] have recently proposed a modified CNN training procedure to improve attribute recognition. Their “deep carving” algorithm provides the CNN with attribute pseudo-label targets, updated periodically during training. This causes the resulting network to be better-suited for attribute prediction. Escorcia et al. [4] show that known semantic attributes can be extracted from a CNN. Most important for our work, they show that attributes depend on features in all layers of the CNN. ConceptLearner, proposed by Zhou et al. [24] uses weak supervision, in the form of images with associated text content, to discover semantic attributes. These attributes correspond to terms within the text that appear in the images. All of these frameworks predict a single set of attributes for an entire image, as opposed to the per-pixel attributes discussed in our work. Furthermore, our extracted attributes do not require semantic information (which may be challenging to
collect in a consistent manner), and are defined based on human perceptual information.

At the intersection of neuroscience and computer vision, Yamins et al. [23] find that feature responses from high-performing CNNs can accurately model the neural response of the human visual system in the inferior temporal (IT) cortex (an area of the human brain that responds to complex visual stimuli). They perform a linear regression from CNN feature outputs to IT neural response measurements and find that the CNN features are good predictors of neural responses despite the fact that the CNN was not explicitly trained to match the neural responses. Their work focuses on object recognition CNNs, not materials. Hiramatsu et al. [8] take functional magnetic resonance imaging (fMRI) measurements and investigate their correlation with both direct visual information and perceptual material properties (similar to the material traits of [15]) at various areas of the human visual system. They find that pairwise material dissimilarities derived from fMRI data correlate best with direct visual information (analogous to pixels) at the lower-order areas and with perceptual attributes at higher-order areas. Goda et al. [7] obtain similar findings in non-human primates. Of particular importance is the fact that their work inherently considers materials independently from objects. Material samples are shown as cylinders of the material, thus avoiding any distracting cues from the surrounding object. These studies suggest the existence of perceptual attributes in human material recognition, but do not actually derive a process to extract them from novel images.

Our work is closely related to the non-semantic perceptual material attributes discovered by Schwartz and Nishino [16]. In their work, they collect measurements of human perceptual distances between material categories and use those distances to discover perceptual material attributes that reproduce these distances. These attributes are subsequently used to recognize material categories. We use the constraints derived in their work as a basis for our auxiliary attribute layers. This approach can be considered similar to the work of Lee et al. [10], which introduced “deep supervision” via auxiliary loss functions to better-propagate gradient information during CNN training. They do so by adding additional SVM-like loss functions that encourage classification at lower levels of the network. Rather than simply replicating the final classification loss, we impose new constraints to explicitly output additional information about the input, in our case the perceptual material attributes.

3. Perceptual Material Attributes from Local Material Recognition

In this paper, we show that perceptual material attributes arise in a material recognition framework. This agrees with the findings of Hiramatsu et al. [8] which indicate that perceptual attributes form an integral component of the human material recognition process. Based on correlations between Convolutional Neural Network (CNN) feature maps and human visual system neural output discovered by Yamins et al. [23], a CNN architecture appears to be a very suitable framework in which to discover attributes analogous to those in human material perception. We must derive our own method to realize material attributes, however, as their work focuses on object recognition and does not extract any attributes. We find the human-perception-based attributes of Schwartz and Nishino [16] to be particularly relevant. In this section we derive a novel framework to discover perceptual attributes similar to those in [16] inside a material recognition CNN framework.

3.1. Finding Material Attributes in a Material Recognition CNN

A simple experiment to verify the presence of perceptual attributes in a CNN trained to recognize materials would be to add an attribute prediction layer at the top of the network, immediately before the final material category probability softmax layer. If we could predict attributes from this layer without affecting the material recognition accuracy, it would suggest that the attributes were indeed present in the network. We implemented this approach with the goal of predicting the perceptual attributes derived from [16] and found that, while the material accuracy was unaffected, the attribute predictions were less accurate than those of their relatively simple attribute-only model (mean average error of 0.2 vs 0.08).

The key issue with the straightforward approach is that it is not an entirely faithful model to the process described in [8]. They note that the human neural representation of material categories transitions from visual (raw image features) to perceptual (visual properties like “shiny”) in an hierarchical fashion. This implies, in agreement with findings of Escorcia et al. [4], that attributes require information from multiple levels of the material recognition network. We show that this is indeed the case by successfully discovering the attributes using input from multiple layers of the material recognition network.

3.2. Material Attribute-Category CNN

We need a means of extracting attribute information at multiple levels of the network. Simply combining all feature maps from all network layers and using them to predict attributes would be computationally impractical. Rather than directly using all features at once, we augment an initial CNN designed for material classification with a set of auxiliary fully-connected layers attached to the spatial pooling layers. This allows the attribute layers to use information from multiple levels of the network without needing direct access to every feature map. We treat the additional
Figure 2. Material Attribute-Category CNN (MAC-CNN) Architecture: We introduce auxiliary fully-connected attribute layers to each spatial pooling layer and combine the per-layer predictions into a final attribute output via an additional set of weights. The loss functions attached to the attribute layers encourage the extraction of attributes that match the human material representation encoded in perceptual distances. The first set of attribute layers acts as a set of weak learners to extract attributes wherever they are present. The final layer combines them to form a single prediction.

For the auxiliary layer loss functions, we extend the perceptual attribute loss functions of [16] and apply them to the outputs of each auxiliary fully-connected layer. Schwartz and Nishino’s proposed method begins with a set of pairwise perceptual distances between material categories measured via human yes/no binary similarity annotations on material image patches. From these distances, they learn a mapping matrix $A$ between categories and unknown, non-semantic attributes. The mapping preserves the pairwise human perceptual distances while causing the resulting attributes to exhibit the behaviors, such as spatial consistency, of semantic attributes. We derive our attribute layer loss functions from these learning constraints.

Specifically, assuming the output of a given pooling layer $i$ in the network for image $j$ is $h_{ij}$, and given categories $C, |C| = K$ and a set of sample points $P \in (0, 1)$ for density estimation, we add these auxiliary loss functions:

$$u_i = \frac{1}{K} \sum_{k \in C} \left\| a_k - \frac{1}{N_k} \sum_{j \mid c_j = k} f \left( W_i^T h_{ij} + b_i \right) \right\|_1$$

$$d_i = \sum_{p \in P} \beta \left( p; a, b \right) \ln \left( \frac{\beta \left( p; a, b \right)}{q \left( p; f \left( W_i^T h_{ij} + b_i \right) \right)} \right)$$

where $f(x) = \min \left( \max (x, 0), 1 \right)$ clamps the outputs within $(0, 1)$ to conform to attribute probabilities, and weights $W_i, b_i$ represent the auxiliary fully-connected layers we add to the network. $a_k$ represents a row in the category-attribute mapping matrix we derived from our data by collecting the yes/no similarity answers used in [16] for patches in our database (see Sec. 4). Equation 1 causes the attribute layer to discover attributes which match the perceptual distances measured from human annotations. As certain attributes are expected to appear at different levels of the network, some layers will be unable to extract them. This implies that their error should be sparse, either predicting an attribute well or not at all. For this reason we use an L1 error norm. Equation 2, applied only to the final attribute layer, encourages the distribution of the attributes to match those of known semantic material traits. It takes the form of a KL-divergence between a Beta distribution (empirically observed by [16] to match the distribution of semantic attribute probabilities), and a Kernel Density Estimate $q(\cdot)$ of the extracted attribute probability sampled at points $p \in P$.

The reference network we build on is based on the high-performing VGG-16 network of Simonyan and Zisserman [20]. We use their trained convolutional weights as initialization where applicable, and add new fully-connected layers for material classification. Figure 2 shows our architecture for material attribute discovery and category recognition. We refer to this network as the Material Attribute-Category CNN (MAC-CNN).

4. Local Material Database

In order to train the category recognition portion of the MAC-CNN, we need a proper local material recognition dataset. We find existing material databases lacking in a few key areas necessary to properly perform local material
Asphalt Ceramic Concrete Fabric Foliage Food Glass Water Metal Paper Plastic Soil Stone Wood

Figure 3. One tree in our material category hierarchy. Categories at the top level separate materials with notable differences in physical properties. Mid-level categories are visually distinct. The lowest level of categories are fine-grained and may require both physical and visual properties and expert knowledge to distinguish them. The full set of trees may be found in our supplemental material.

recognition. Previous material recognition datasets [2,3,18] have relied on ad-hoc choices regarding the selection and granularity of material categories (e.g., carpet and wall are considered materials). When patches are involved, as in [3], the patches can be as large as 24% of the image size surrounding a single pixel identified as corresponding to a material. These patches are large enough to include entire objects. These issues make it difficult to separate challenges inherent to material recognition from those related to general recognition tasks and inevitably lead to material recognition based on object and scene information, which would not be beneficial for scene understanding tasks. We also find that image diversity is still lacking in modern datasets. For these reasons, we introduce a new local material recognition dataset to support the experiments in this paper.

4.1. Material Category Hierarchy

Material categories in existing datasets have not been carefully selected. Examples of this issue include the proposed material categories “mirror” (actually an object), and “brick” (an object or group of objects). Existing categories also confuse materials and their properties (e.g., surface finish), for example, separating “stone” from “polished stone”. To address the issue of material category definition, we propose a more carefully-selected set of material categories for local material recognition. We derive a taxonomy of materials based on their properties from materials science [1] and create a hierarchy based on the generality of each material family. Figure 3 shows an example of one tree of the hierarchy. Please see our supplemental material for a complete diagram of the hierarchy including all categories at all levels.

Our hierarchy consists of a set of three-level material trees. The highest level corresponds to major structural differences between materials in the category. Metals are conductive, polymers are composed of long chain molecules, ceramics have a crystalline structure, and composites are fusions of materials either bonded together or in a matrix. We define the mid-level (also referred to as entry-level [12]) categories as groups that separate materials based primarily on their visual properties. Rubber and paper are flexible, for example, but paper is generally matte and rubber exhibits little color variation. The lowest level, fine-grained categories, can often only be distinguished via a combination of physical and visual properties. Silver and steel, for example, may be challenging to distinguish based solely on visual information.

Such a hierarchy is sufficient to cover most natural and manmade materials. In creating our hierarchy, however, we found that certain categories that are in fact materials did not fit within the strict definitions described above. For the sake of completeness, we make the conscious decision to add these mid-level categories to our data collection process. These categories are: food, water, and non-water liquids. While food is both a material and an object, we rely on our combined material attribute-category CNN.

4.2. Data Collection and Annotation

The mid-level set of categories forms the basis for a crowdsourced annotation pipeline to obtain material regions from which we may extract local material patches (Figure 4). We employ a multi-stage process to efficiently extract both material presence and segmentation information for a set of images.

The first stage asks annotators to identify materials present in the image. Given a set of images with materials identified in each image, the second stage presents annotators with a user interface that allows them to draw multiple regions in an image. Each annotator is given a single image-material pair and asked to mark regions where that material is present. While not required, our interface allows users to create and modify multiple disjoint regions in a single image. Images undergo a final validation step to ensure no poorly drawn or incorrect regions are included.

Each image in the first stage is shown to multiple annotators and a consensus is taken to filter out unclear or incorrect identifications. While sentinels and validation were not used to collect segmentations in other datasets, ours is intended for local material recognition. This implies that identified regions should contain only the material of interest. During collection, annotators are given instructions...
Figure 5. Annotators did not hesitate to take advantage of the ability to draw multiple regions, and most understood the guidelines concerning regions crossing object boundaries. As a result, we have a rich database of segmented local material regions.

to keep regions within object boundaries, and we validate the final image regions to insures this.

Image diversity is an issue present to varying degrees in current material image datasets. The Flickr Materials Database (FMD) [19] contains images from Flickr which, due to the nature of the website, are generally more artistic in nature. The OpenSurfaces and Materials in Context datasets [2, 3] attempt to address this, but still draw from a limited variety of sources (e.g., real estate photographs). We source our images from multiple existing image datasets spanning the space of indoor, outdoor, professional, and amateur photographs. We use images from the PASCAL VOC database [5], the Microsoft COCO database [11], the FMD [19], and the imagenet database [14].

Examples in Figure 5 show that our annotation pipeline successfully provides properly-segmented material regions within many images. Many images also contain multiple regions. While the level of detail for provided regions varies from simple polygons to detailed material boundaries, the regions all contain single materials.

5. Perceptual Material Attributes Discovered in the MAC-CNN

To verify that the perceptual attributes we seek are indeed present in and can be extracted with our MAC-CNN, we augment our dataset with annotations to compute the necessary perceptual distances described in [16]. Using our dataset and these distances, we derive a category-attribute matrix A and train an implementation of the MAC-CNN described in Sec. 3.2.

We train the network on ~200,000 48 × 48 image patches extracted from segmented material regions. Optimization is performed using mini-batch stochastic gradient descent with momentum. The learning rate is decreased by a factor of 10 whenever the validation error increases, until the learning rate falls below $1 \times 10^{-8}$.

5.1. Properties of the Perceptual Material Attributes

We examine the properties of our perceptual material attributes by visualizing how they separate materials, computing per-pixel attribute maps to verify that the attributes are being recognized consistently, and linking the non-semantic attributes with known semantic material traits (“fuzzy”, “smooth”, etc...) to visualize semantic content. Figs. 6, 7, and 8 are generated using a test set of held-out images.

A 2D embedding of material image patches shows that the perceptual attributes (Figure 6) separate material categories. A number of materials are almost completely distinct in the attribute space, while a few form overlapping but still distinguishable regions. Foliage, food, and water form particularly clear clusters. The quality of the clusters matches the per-category recognition rates, with accurately-recognized categories forming more separate clusters.

Visualizations of per-pixel attribute probabilities in Figure 7 show that the attributes are spatially consistent. While overfitting is difficult to measure for weakly-supervised attributes, we use spatial consistency as a proxy. Spatial consistency is an indicator that the attributes are not overly-sensitive to minute changes in local appearance, something that would appear if overfitting were present. The attributes exhibit correlation with the materials that induced them: attributes with a strong presence in a material region in one image often appear similarly in others. The visualizations also clearly show that the attributes are representing more than trivial properties such as “flat color” or “textured”.
Figure 7. Each column after the first (the input image) shows per-pixel probabilities for an extracted perceptual attribute. The attributes form clearly delineated regions, similar to semantic attributes, and their distributions match as well.

Figure 8. By performing logic regression from our MAC-CNN extracted attributes to material traits, we are able to extract semantic information from our non-semantic attributes. Doing so in a sliding window gives per-pixel semantic material trait information. The predictions show crisp regions that correspond well with their associated semantic traits. Traits are independent, and thus the maps contain mixed colors. Fuzzy and organic in the lower right image, for example, creates a yellow tint. These semantic material traits computed from discovered material attributes provide rich information about the underlying surface properties that can be leveraged to determine how to interact with them.

Logic regression [13] is a method for building trees that convert a set of boolean variables into a probability value via logical operations (AND, OR, NOT). It is well-suited for collections of binary attributes such as ours. Results of performing logic regression (Figure 8) from extracted attribute predictions to known semantic material trait information show that our MAC-CNN attributes encode material traits with the same average accuracy (75%) as the attributes of [16]. For per-trait accuracy comparisons, please see our supplemental materials. We may also predict per-pixel trait probabilities in a sliding window fashion, showing that the attributes are encoding both perceptual and semantic material properties. The material attributes provide rich information regarding the surface properties that may benefit, for instance, action planning for autonomous agents.

5.2. Local Material Recognition

If perceptual material attributes are naturally present in the material classification network, we must be able to extract them without compromising the network’s ability to recognize materials. Our results in Section 5 show that we can extract the perceptual attributes in the combined material-attribute network. We compare local material recognition accuracy with and without the auxiliary attribute loss functions to verify the second requirement.

The average accuracy is 60.2% across all categories. Foliage is the most accurately recognized, consistent with past material recognition results in which foliage is the most visually-distinct category. Paper is the least well-recognized category. Unlike the artistic closeup images of the FMD, many of the images in our database come from ordinary images of scenes. Paper, in these situations, shares its appearance with a number of other materials such as fabric. It is important to note that we are recognizing materials directly from single small image patches, with none of the region-based aggregation or large patches used in [3, 15, 16]. This is a much more challenging task as the available information is restricted. For a breakdown of per-category accuracy, please see our supplemental material.

We find that the average material category accuracy does not change when the attribute layers are removed. While the attribute layers are auxiliary, they are connected to spatial pooling layers at every level and thus the attribute constraints affect the entire network. If the attributes were not in fact encoding visual material properties, constraining the network to extract them would negatively affect the material recognition performance.

A full semantic segmentation framework is beyond the scope of this paper. We are, however, able to use the same attribute/material CNN to produce per-pixel material probability predictions. Results in Figure 10 show that we may still generate reasonable material probability maps even from purely local information.

6. Novel Material Category Recognition

One prominent application of attributes is in novel category recognition tasks. Examples of these tasks include one-shot [6] or zero-shot learning [9]. Zero-shot learning allows recognition of a novel category from a human-supplied list of applicable semantic attributes. Since our attributes
Figure 9. Graphs of novel category recognition accuracy vs. training set size for various held-out categories. The rapid plateau shows that we need only a small number of examples to define a previously-unseen category. The accuracy difference between feature sets shows that the attributes are contributing novel information. Even when the attributes do not outperform material probabilities on their own, the combination is still superior demonstrating the rich discriminative information carried by the extracted material attributes.

Figure 10. These material maps, obtained by applying the MAC-CNN in a sliding window, show that we may obtain coherent regions using only small local patches as input. The foliage predictions on the couch are reasonable, as the local appearance pattern is indeed a flower. In the baseball image, the local appearance of the fence resembles lace (a fabric).

are non-semantic, zero-shot learning is not applicable here. We may, however, investigate the generalization of our attributes through a form of one-shot learning in which we use image patches extracted from a small number of images to learn a novel category.

To evaluate the use of perceptual material attributes for novel category recognition, we train a set of MAC-CNNs on modified datasets each containing a single held-out category. No examples of the held-out category are present during training. The corresponding row of the category-attribute matrix is also removed. The same number of attributes are defined based on the remaining categories.

For the novel category training, we use a balanced dataset consisting of unseen examples of training categories and a matching number of images from the held-out category. We also separate a number of images of the held-out category as final testing samples. We train a simple binary classifier (a linear SVM) to distinguish between the training categories and the held-out category based on either their attribute probabilities, material probabilities, or both, computed on patches extracted from each input image. We measure the effectiveness of novel category recognition by the fraction of final held-out category samples properly identified as belonging to that category.

Figure 9 shows plots of novel category recognition effectiveness as the number of training examples for the held-out category varies. We can see that the accuracy plateaus quickly, indicating that the attributes provide a compact and accurate representation for novel material categories. The number of images we are required to extract patches from to obtain reasonable accuracy is generally quite small (on the order of 10) compared to full material category recognition frameworks which require hundreds of examples. Furthermore, we include accuracy for the same predictions based on only material probabilities instead of attribute probabilities, as well as using a concatenation of both. Attributes alone offer better recognition for some novel categories. Even when they do not, the addition of attributes still increases performance. This clearly shows that the extracted attributes can expose novel discriminative information in the MAC-CNN that would not ordinarily be available.

7. Conclusion

We proposed that, analogous to human and animal findings in neuroscience, perceptual attributes inherently arise in the material recognition process. To show this, we derived a CNN architecture, the MAC-CNN, for discovering perceptual material attributes within a local material recognition network, collected a new image database on which to evaluate our method, and showed that the extracted enable accurate recognition of novel materials. The accuracy of novel category recognition based solely on the extracted attributes of a few sample images shows that the attributes form a compact representation for novel materials.

We find the parallels between our own human visual perception of materials and the material attributes discovered in the MAC-CNN architecture particularly interesting. Our integration of attribute and category recognition with a single network likely has implications in other tasks such as object and scene recognition, and we may find similar parallels there as well.
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