Insights From A Large-Scale Database of Material Depictions In Paintings

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Abstract. Deep learning has paved the way for strong recognition systems which are often both trained on and applied to natural images. In this paper, we examine the give-and-take relationship between such visual recognition systems and the rich information available in the fine arts. First, we find that visual recognition systems designed for natural images can work surprisingly well on paintings. In particular, we find that interactive segmentation tools can be used to cleanly annotate polygonal segments within paintings, a task which is time consuming to undertake by hand. We also find that FasterRCNN, a model which has been designed for object recognition in natural scenes, can be quickly repurposed for detection of materials in paintings. Second, we show that learning from paintings can be beneficial for neural networks that are intended to be used on natural images. We find that training on paintings instead of natural images can improve the quality of learned features and we further find that a large number of paintings can be a valuable source of test data for evaluating domain adaptation algorithms. Our experiments are based on a novel large-scale annotated database of material depictions in paintings which we detail in a separate manuscript.

Keywords: Artistic Material Depictions · Large-Scale Data · Segmentation · Classification · Interpretability · Domain Adaptation

1 Introduction

Deep learning has enabled the development of high performing recognition systems across a variety of image-based tasks [15,17,50]. These systems are often trained on natural photographs with applications in real world recognition like self-driving. Furthermore, applying recognition systems to large collections of images can also reveal cultural trends or give us insight into the visual patterns in the world (e.g. [32,29,26]). Human-created images, such as paintings, are particularly interesting to analyze from this perspective. Artistic depictions can reveal insights into culturally relevant ideas throughout time, as well as insights into human visual perception through the realism depicted by skilled artists.

Whereas most computer vision systems focusing on digital art history are concerned with object recognition (e.g., [11]), it is the depiction of space and
materials that visually characterized the course of art history. The depiction of space has had considerable attention in scientific literature [34, 46, 20, 37] while recently the depiction of materials has gained scientific interest [5, 47, 38, 48]. Therefore, it is interesting to investigate the interplay between deep learning systems designed for natural image analysis and the rich visual information found in paintings, especially with respect to artistic depictions of materials.

The remainder of this paper is organized into three parts. In Section 2, we briefly describe the dataset that subsequent experiments are based on. In Section 3, we explore how deep learning systems that have primarily been developed for use on natural photographs can be used to analyze paintings. Specifically, we explore (a) segmentation and (b) detection of materials in paintings. Recognition of materials in paintings can be useful for digital art history as well as general public interest. In Section 4, we explore how paintings can be a useful source of data from which better recognition systems can be built. Specifically, we investigate (c) the generalizability and interpretability of classifiers trained on paintings, and we investigate (d) the role that a large-scale painting dataset can play in evaluating visual recognition models.

2 Dataset

All experiments in this paper utilize data from the Materials in Paintings (MIP) dataset, a large-scale annotated dataset of material depictions in paintings. Extensive details and analysis of this database will be available in a separate manuscript. For context and completeness, we summarize a few relevant details here. The dataset consists of 19K high resolution paintings downloaded from the online collections of international art galleries, which span over 500 years of art history. The galleries with corresponding number of paintings are: The Rijksmuseum (4,672), The Metropolitan Museum of Art (3,222), Nationalmuseum (3,077), Cleveland Museum of Art (2,217), National Gallery of Art (2,132), Museo Nacional del Prado (2,032), The Art Institute of Chicago (936), Mauritshuis (638), and J. Paul Getty Museum (399). The distribution of paintings by year is shown in Fig. 1. The dataset includes crowdsourced extreme click [35] bounding box annotations over 15 material categories, which are further delineated into 50 fine-grained categories. Fig. 2 shows a few examples of the annotated bounding boxes available in the dataset.

3 Using Computer Vision to Analyze Paintings

Research in computer recognition systems have focused primarily on natural images. For example, semantic segmentation benchmarks (of objects, ‘stuff’, or materials) [21, 25, 14, 7, 23] emphasize parsing in-the-wild photos, with applications in robotics, self-driving, and so forth. However, the analyses of paintings can also benefit from the use of visual recognition systems. Paintings can encode both cultural and perceptual biases, and being able to analyze paintings at scale
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Fig. 1. Year Distribution of Paintings in Dataset. Each bin equals 20 years. There are peaks in the paintings in the 1700s and 1900s. The former corresponds to the European golden ages; it is less clear what explains the latter peak.

Fig. 2. Examples of Annotated Bounding Boxes. Left to Right: Liquid, Fabric, Ceramic, Metal, and Food.

can be useful for a variety of scientific disciplines including digital art history and human visual perception.

In this section, we explore the effectiveness of interactive segmentation methods (which can be used to select regions of interest in photographs for the purpose of image editing or data annotation) when applied to paintings. We also explore how well an object bounding box detector can be finetuned to detect materials depicted in unlabelled paintings, which could be used for content-based retrieval.

3.1 Extracting Polygon Segments with Interactive Segmentation

Polygon segmentation masks are useful for reasoning about boundary relationships between different semantic regions of an image, as well as the shape of the regions themselves. However, annotating segmentations is expensive and many modern datasets rely on expensive manual annotation methods [2,25,51,7,10]. Recent work has focused on more cost effective annotation methods (e.g. [24,31,4,27]). The use of interactive segmentation methods that transform sparse user inputs into polygon masks can ease annotation difficulty. For paintings, it is unclear whether these methods (especially deep learning methods trained on natural images) would perform well. Semantic boundaries in paintings likely have a different, and more varying structure than in photos. Paintings can have ambiguous or fuzzy boundaries between objects or materials [33] which can potentially be problematic for color-based methods. This can be due to variations in artistic style which can emphasize different aspects of depictions – for example, Van Gogh uses lines and edges to create texture, but such edges could potentially appear as boundaries to a segmentation model. In this experiment, we study
the difficulty of segmenting paintings and whether innovations are necessary for existing methods to perform well.

**Experimental Setup.** We experiment with GrabCut [40] (an image-based approach) and DEXTR [31] (a modern deep learning approach). We evaluated the performance of these methods against 4.5k high-quality human annotated segmentations from [52]. The inputs to these methods are generated from the extreme points of the regions we are interested in. We use a variant of the GrabCut initialization proposed in [35], as well as a rectangular initialization for reference. For DEXTR, we consider models pretrained on popular object datasets [25, 14] as a starting point.

**Results.** We found that both GrabCut and DEXTR perform quite well on paintings. Surprisingly, DEXTR transfers quite well to materials in paintings despite being trained only with natural photographs of objects. The performance of DEXTR can be further improved by finetuning on COCO with a smaller learning rate (10% of original learning rate for 1 epoch). Finetuning DEXTR on Grabcut segments or iteratively finetuning with output of DEXTR does not seem to yield further improvements. The performance is summarized in Table 1, and samples are visualized in Fig. 3.

| Grabcut Rectangle | Grabcut Extr | DEXTR Pascal-SBD | DEXTR COCO | DEXTR Finetuned |
|-------------------|--------------|-----------------|------------|-----------------|
| 44.1              | 72.4         | 74.3            | 76.4       | 78.4            |

**Table 1. Segmentation Performance.** Grabcut Extr is based on [35] with small modifications: (a) minimum cost boundary is computed with the negative log probability of a pixel belonging to an edge; (b) in addition to clamping the morphological skeleton, the extreme points centroid and extreme points are clamped; (c) GC is computed directly on the RGB image. DEXTR [31] is pretrained on Pascal-SBD and COCO. Note that Pascal-SBD and COCO are natural image datasets of objects, but DEXTR transfers surprisingly well across both visual domain (paintings vs. photos) and annotation categories (materials vs. objects).
3.2 Detecting Materials in Unlabeled Paintings

To allow the public to view and interact with art collections, museums and galleries provide extensive online functionality to search and navigate through the collections. Currently, to our knowledge, no online collections allows online visitors to query the collection for depicted materials within painting, which can be of interest to the public. Furthermore, depiction of materials plays a crucial role in characterizing art history. Detecting materials within novel paintings will be particularly beneficial to digital art historians who study materials such as stone [1,13] or skin [6,22]. Having access to specific materials can also digital art historians to compare these depictions directly with respect to painting style or technique. We experiment with automatic bounding box detection to ease access to material depictions in unlabelled collections.

Experimental Setup. We train a FasterRCNN [39] bounding box detector to localize and label material boxes with on 90% of annotated paintings in the dataset, and evaluate on the remaining 10%. Default COCO hyperparameters from [49] are used. Given the non-spatially-exhaustive nature of the annotations, many detected bounding boxes will not be matched against labelled ground
truth boxes. However, the dataset is exhaustively annotated at an image level, and therefore, we report image-level accuracies. This can be interpreted as the accuracy of the model in tagging each image with the types of materials present. The validity of each localized box can be further quantified through a user study, but we did not perform this study at this time.

**Results.** Table 2 shows the performance. We found that the FasterRCNN model is able to accurately detect materials in paintings by finetuning on the annotated bounding boxes directly without any changes to the network architecture or training hyperparameters. It is certainly promising to see that an algorithm designed for object localization in natural images can be readily applied to material localization in paintings. A qualitative sample of detected bounding boxes is given in Fig. 4. To improve the spatial-specificity of the detected materials, it can be interesting to train an instance detector like MaskRCNN on segments extracted using methods discussed in the previous section. It would also be useful to combine material recognition with conventional object-based detection to extract complementary forms of information that improve the ability for users to filter data by their specific needs.

![Table 2](image.png)

| Class       | Accuracy (%) | Mean (%) |
|-------------|--------------|----------|
| Animal      | 85.6         | 83.3     |
| Ceramic     | 92.7         |          |
| Fabric      | 66.0         |          |
| Flora       | 85.0         |          |
| Food        | 94.9         |          |
| Gem         | 88.4         |          |
| Glass       | 91.3         |          |
| Ground      | 86.5         |          |
| Liquid      | 86.4         |          |
| Metal       | 70.7         |          |
| Paper       | 92.4         |          |
| Skin        | 70.2         |          |
| Sky         | 89.4         |          |
| Stone       | 74.8         |          |
| Wood        | 74.9         |          |

**Table 2. Image-level Detection Accuracy.** Bounding boxes are detected with FasterRCNN trained on paintings. Because the dataset is not exhaustively annotated spatially, image-level accuracy is reported instead of box precision and recall. Overall, images are tagged with the correct materials with high accuracy.

![Fig. 4](image.png)

**Fig. 4. Detected materials in Unlabeled Paintings.** Automatically detecting materials can be useful for content retrieval and for filtering online galleries by viewer interests.

## 4 Using Paintings to Build Better Recognition Systems

In recent work for machine perception systems, art has been used in various ways. Models that learn to convert photographs into painting-like or sketch-like
images have been studied extensively for their application as a tool for digital artists [18]. Recent work has shown that such neural style transfer algorithms can also produce images that are useful for training robust neural networks [16]. Artworks have also been used directly to evaluate the robustness of neural networks under “domain shifts” in which a model trained to recognize objects from photographs are shown artistic depictions of such objects instead [23,36].

We use the MIP dataset of material depictions in paintings to explore two directions. First, we hypothesize that the perceptually focused depictions of artists can allow neural networks to learn better cues for classification. We find that learning from paintings can improve the interpretability of the cues it uses for its predictions. In a second experiment, we investigate the utility of the MIP dataset as a benchmark for computer vision models under domain shifts when more data is available than is typical in existing domain adaptation benchmark datasets. We find that existing domain adaptation algorithms can fail to behave as expected in this setting.

4.1 Learning Robust Cues for Finegrained Fabric Classification

The task of distinguishing between images of different semantic content is a standard recognition task for computer vision systems. Increasing attention is being given to “fine-grained” classification where a model is tasked with distinguishing images of the same broad category (e.g. distinguishing different species of birds or different types of flora [45,44,43]). Fine-grained classification is particularly challenging for deep learning systems. Such a task depends on recognizing specific attributes for each finegrained class; in comparison, classifiers can perform well on coarse-grained classification by relying on context alone. We hypothesize that the painted depictions of materials can be beneficial for this task. Since some artistic depictions focus on salient cues for perception through perceptual shortcuts [30,8,12], it is possible that a network trained on such artwork is able to learn a more robust feature representation by focusing on these cues.

Experimental Setup. We experiment with the task classifying cotton/wool versus silk/satin. The latter can be recognized through local cues such as highlights on the cloth; such cues are carefully placed by artists in paintings. To understand whether artistic depictions of fabric allow a neural network to learn better features for classification, we train a model with either photographs or paintings. High resolution photographs of cotton/wool and silk/satin fabric and clothing (dresses, shirts) are downloaded and manually filtered from publicly available photos licensed under the Creative Commons from Flickr. In total, we downloaded roughly 1K photos. We sample cotton/wool and silk/satin samples from our dataset to form a corresponding dataset of 1K paintings.

Generalizability of Classifiers. Does training with paintings improve the generalizability of classifiers? To test cross-domain generalization, we test the classifier on types of images that it has not seen before. A classifier that has learned more
robust features will perform better on this task than one that has learned to classify images based on more spurious correlations. We test the trained classifiers on both photographs and paintings.

**Interpretability of Classifier Cues.** Are the cues used by each classifier interpretable to humans? We produce evidence heatmaps with GradCAM [41] from the feature maps in the network before the fully connected classification layer. We extract high resolution feature maps from images of size 1024 × 1024 (for a feature map of size 32 × 32). The heatmaps produced by GradCAM show which regions of an image the classifier uses as evidence for a specific class. If a classifier has learned a good representation, the evidence that it uses should be more interpretable for humans. For both models, we compute heatmaps for test images corresponding to their ground truth label. We conduct a user study on Amazon Mechanical Turk to find which heatmaps are preferred by humans. Users are shown images with regions corresponding to heatmap values that are above 1.5 standard deviations above the mean. Fig 5 illustrates an example. Our user study resulted in responses from 85 participants, 57 of which were analyzed after quality control. For quality control, we only kept results from participants who spent over 1 second on average per task item.

**Fig. 5. Classifier Cues.** Left to Right: Original Image, Masked Image (Painting Classifier), and Masked Image (Photo Classifier). The unmasked regions represent evidence used by the classifiers for predicting “silk/satin” in this particular image.

**Results.** We find that the classifier trained with paintings exhibits better cross-domain generalization, and uses cues that humans prefer over the photo classifier. This suggests that paintings can improve the robustness of classifiers for this task of fabric classification.

**Generalizability of Classifiers.** In Table 3, the performance of the two classifiers are summarized. We find that both classifiers perform similarly well on the domain they are trained on. However, when the classifiers are tested on cross-domain data, we find that the painting-trained classifier performs better than the photo-trained classifier. This suggests that the classifier trained on paintings has learned a more generalizable feature representation for this task.

**Interpretability of Classifier Cues.** Overall, we find that the classifier trained on paintings uses evidence that is better aligned with evidence preferred by humans
Due to domain shifts when applying classifiers to out-of-domain images, we would expect the cues selected by the painting classifier to be preferable on paintings, and the cues selected by the photo classifier to be preferable on photos. Interestingly, this does not hold for photos of satin/silk (column 2 of Table 4) – we find that users equally prefer the evidence selected by the painting classifier to the evidence selected by the photo classifier. This suggests that either (a) the painting classifier has learned the “correct” human-interpretable cues for recognizing satin/silk, or (b) that the photo classifier has learned to classify satin/silk based on some spurious contextual signals. We asked users to elucidate their reasoning when choosing which set of cues they preferred. In general, users noted that they preferred the network which picks out regions containing the target class. Therefore, it seems that the network trained on paintings has learned better to distinguish fabric through the actual presence of such fabrics in the image over other contextual signals.

Taken together, our results provide evidence that a classifier trained on paintings can be more robust than a classifier trained on photographs. It would be interesting to explore this further. A limitation of this study is the relatively small number of data samples, and very limited number of material types (two: cotton/wool and silk/satin) that we explored. Are there other materials or objects which deep neural networks can learn to recognize better from paintings than photographs?

|                  | Photo $\rightarrow$ Photo | Painting $\rightarrow$ Painting |
|------------------|--------------------------|---------------------------------|
| MEAN F1 Score    | 79.6%                    | 80.5%                           |

|                  | Photo $\rightarrow$ Painting | Painting $\rightarrow$ Photo |
|------------------|-------------------------------|------------------------------|
| MEAN F1 Score    | 49.5%                         | 57.8%                        |

**Table 3. Classifier Generalization.** Classifiers are trained to distinguish cotton/wool from silk/satin. One classifier is trained on photographs and another classifier is trained on paintings. Both classifiers perform similarly well on images of the same type they were trained on, but the classifier trained on paintings performs better on photographs than vice versa. This suggests that the features learned from paintings are more generalizable for this task on this set of data.

### 4.2 Benchmarking Unsupervised Domain Adaptation

In unsupervised domain adaptation (UDA), models are trained on a ‘source’ dataset with annotated labels as well as an unlabeled ‘target’ dataset. The goal is to train a model which performs well on unseen target dataset samples. Existing domain adaptation benchmark datasets for classification focus primarily on object recognition and tend to be limited in number of data samples, with most class categories containing on the order of 1000 samples or fewer (for example, refer to Table 1 of [36]). In contrast, the dataset we use here has the unique properties of (a) focusing primarily on material classification and (b) containing on the order of 10-30K for 9 of the 15 annotated classes (e.g. fabric, wood), with the remainder in the range of 2K-5K (e.g. ground). This positions this data as a valuable addition for benchmarking for UDA algorithms.
Table 4. Human Agreement with Classifier Cues. On average, humans prefer the cues used by the painting-trained classifier to make its predictions over the cues used by the photo-trained classifier. Interestingly, the human judgements also indicate that the painting-trained classifier uses cues that are just as good to the cues used by the photo-trained classifier for silk/satin photos despite never seeing a silk/satin photo during training (column 2). A pictorial representation of the results is given in Fig. 6.

|                  | Cotton/Wool Photos | Silk/Satin Photos | Cotton/Wool Paintings | Silk/Satin Paintings | MEAN    |
|------------------|--------------------|-------------------|-----------------------|----------------------|---------|
| Photo Classif. Preferred | 64.7 ± 3.5%       | 48.9 ± 3.1%       | 26.8 ± 2.5%           | 39.1 ± 2.1%          | 44.9 ± 1.9% |
| Painting Classif. Preferred | 35.3 ± 3.5%       | 51.1 ± 3.1%       | 73.2 ± 2.5%           | 60.9 ± 2.1%          | 55.1 ± 1.9% |

Fig. 6. Human Agreement with Classifier Cues. Pictorial representation of user study results from Table 4. The y-axis represents how often humans prefer the cues from a classifier trained on the same domain as the test images. It is clear that humans prefer the painting classifier for paintings more than they prefer the photo classifier for photos. Interestingly, the painting and photo classifiers are equally preferred for silk/satin photos despite the painting classifier never seeing a photo during training (bar 2).

Experimental Setup. For this study, we focus on a family of domain adaptation algorithms which aim to explicitly minimize feature discrepancy across the source and target domains. Existing work has shown that class-conditional UDA in which labels are estimated for target domain samples during training can be better than class-agnostic UDA where adaptation is performed without using any estimated label information at all. We choose CDD [19] and MMD [28,42] as representative methods for class-conditional and class-agnostic discrepancy minimization. All methods are trained with default settings from publicly available source code for CDD, which includes the use of domain batch normalization [9]. We selected 10 material categories: ceramic, fabric, foliage, glass, liquid, metal, paper, skin, stone, and wood. For our painting dataset, we sampled as-class-balanced-as-possible from these classes to form a dataset with 10K samples and
a dataset with 60K samples. A corresponding photograph dataset is constructed from Opensurfaces/MINC/COCO with 10K and 60K samples as well.

**Results.** We find that the studied domain adaptation algorithms can indeed behave differently than would be expected from results on existing benchmark datasets. This is could due to more data being available or a more difficult domain shift than conventional adaptation benchmark datasets.

**Effect of Dataset Size.** Results are summarized in Table 5. With the conventional 1K samples per class, we confirm domain adaptation yields gains over source-only as found on existing benchmark datasets. In contrast to results on existing benchmarks however, we find that class-conditional adaptation does not necessarily outperform class-agnostic adaptation. We hypothesize this occurs due to failures in target label estimation for the class-conditional case – we discuss this further below. Next, with 6K samples per class (which is 6× more data samples per class than conventional UDA benchmarks), we find that source-only (i.e., no adaptation) performs very competitively. In fact, source-only strictly outperforms adaptation for Painting to Photo transfer in this data regime! This result suggests that domain adaptation is useful in lower data regimes, but source-only is a competitive alternative when more data is available. We leave a deeper exploration of this phenomenon to future work.

**Effect of Class Label Estimation.** As found above, class-conditional adaptation can underperform class-agnostic adaptation despite utilizing more information. As class-conditional adaptation depends on estimated target labels, large domain shifts that hamper label estimation can harm adaptation. To confirm this, we consider two experiments: CDD with intraclass discrepancy minimization only (instead of both intraclass minimization and interclass maximization), and CDD with ground truth labels (i.e., perfect label estimation). Results are in Table 6. In both cases, we see performance improves. In the case where perfect label estimation is assumed, then CDD does outperform intraCDD and MMD as found on existing datasets. Therefore, estimating class labels for domain adaptation is useful in practice, but only if the labels are estimated sufficiently well.

### 5 Conclusion

In this paper, we explored how modern deep learning tools developed for natural images can be used to analyze paintings, and in turn, how paintings can be used to improve deep learning systems in a series of experiments. Our findings suggest that progress in visual perception for natural images can benefit systems used for fine art analysis, and having access to the visual information encoded in paintings can be fruitful for building more generalizable perception systems.
Table 5. Effect of Dataset Size. UDA from photo (source) to painting (target) and painting (source) to photo (target). Source-only refers to a reference baseline where no adaptation is used. The gap between source-only and UDA decreases as data samples increases from 1K images per class to 6K images per class. Furthermore, in contrast to behavior found on existing benchmark datasets, the class-conditional method of CDD does not necessarily outperform the class-agnostic counterpart MMD.

Table 6. Effect of Class Label Estimation. Reducing the reliance class label estimation improves class-conditional UDA when label estimation for target data is poor. We find that IntraCDD (which considers only intraclass discrepancy) outperforms CDD (which considers both intraclass and interclass discrepancy). Using ground truth (GT) labels with CDD (i.e., assuming perfect class label estimation) recovers performance gains over intraCDD and MMD. MMD does not require class label estimation, and so its performance not suffer in the case of poor label estimation.

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