We present a semi-supervised co-analysis method for learning 3D shape styles from projective line drawings, achieving style patch localization with only weak supervision. Given a collection of 3D shapes spanning multiple object categories and styles, we initially perform projective style co-analysis over projective line drawings of each 3D shape and then backproject the learned style features onto the 3D shapes. Our core analysis pipeline starts with mid-level patch sampling and pre-selection of candidate style patches. Projective features are then encoded via patch convolution. Multi-view feature integration and style clustering are carried out under the framework of partially shared latent factor (PSLF) learning, a multi-view feature learning scheme. PSLF achieves effective multi-view feature fusion via distilling and exploiting the consistent and complementary information from multiple views, meanwhile selects style patches from the candidates. Our style analysis approach supports both unsupervised and semi-supervised analysis. For the latter, our method accepts both user-specified shape labels and style-ranked triplets as clustering constraints. We particularly demonstrate the effectiveness of our method for style analysis and patch localization and clarify improvements over state-of-the-art methods.

Additional Key Words and Phrases: Style analysis of 3D shapes, projective shape analysis, semi-supervised learning

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1 INTRODUCTION

Styles are generally regarded as distinctive and recognizable forms which permit the grouping of entities containing these forms into related categories [Wikipedia 2016]. It follows that stylistic forms that serve to characterize a common style tend to share strong similarities, while between different style categories, these forms often exhibit clear distinctions. As a result, style analysis is best conducted in the context of a set of entities and naturally lends itself as a clustering problem. For 2D or 3D shapes, the style shapes are typically perceived by humans as apparent geometric features or patterns; see Figure 1 (left). The ability to extract such style features allows them to be compared, altered, or preserved.

Clustering analysis has been performed in earlier works on shape styles. However, the studied styles were either pre-determined [Xu et al. 2010] or characterized by hand-crafted rules [Li et al. 2013]. Most recent attempts have been on supervised learning of style similarity [Garces et al. 2014; Liu et al. 2015a; Lun et al. 2015] via crowd-sourcing to collect user-specified style rankings and then performing metric learning rather than style clustering. But these works do not spatially locate the stylistic features or patches over the analyzed shapes. In a most recent work, also based on supervised learning, Hu et al. [2017] learn to spatially locate style-defining elements or patches over a set of 3D shapes, where an expert-specified style clustering is given over the shape collection.

In this paper, we are interested in exploring a “middle ground”, via semi-supervised learning with weak supervision, for generic style analysis of 3D shapes. Semi-supervised learning is attractive as it can take advantage of strong techniques for unsupervised clustering and
discriminative analyses without the need to collect large amounts of user data. After all, style analysis is essentially a grouping problem, while style patch extraction is a discriminative feature selection problem. That said, with semi-supervised learning, human is not out of the loop. The learning process naturally incorporates user feedback to reflect the subjective nature of style perception, while keeping such feedback to a minimum.

Specifically, we introduce a semi-supervised co-analysis method which simultaneously achieves style clustering and style patch localization, with only weak supervision over a heterogeneous collection of 3D shapes spanning multiple object categories and styles. Unlike Hu et al. [2017], the input collection is not clustered by experts, our method supports both unsupervised and weakly-supervised analysis with minimal style annotation. In terms of shape styles, like all previous works [Hu et al. 2017; Liu et al. 2015a; Lun et al. 2015], our analysis also focuses on element-level styles of 3D shapes [Lun et al. 2015] which are decorative in nature. Such styles include those that are perceivable as patterns along shape contours or over shape surfaces. They are ubiquitous in man-made shapes including furniture, buildings, automobiles, kitchen utensils, and many engineering products and household items.

Our core analysis problem consists of a clustering of the input shape collection and a selection of style feature patches from the shapes which accentuate the shape clustering. While latent features are sufficient for style comparisons, to spatially locate shape styles, one must eventually extract and discriminate between spatially explicit or visually apparent shape features. Working with these features for style analysis is also well motivated by the visual and perceptual nature of style recognition by humans: styles are seen as visual patterns. In our work, we perform style analysis of 3D shapes via projective analysis. Specifically, we project a 3D shape over different views and work with projective line drawings for our style analysis and the extraction of shape styles.

Even though line drawings do not exist in the “real world”, they are believed to possess deep similarities to other more detailed and explicit visual representations as well as real scenes they depict [Sayim and Cavanagh 2011]. In addition, they are remarkably efficient at conveying shape and meaning while reducing visual clutter [Rusinkiewicz et al. 2008]. For our purpose, line drawings are well-suited to depict decorative style patches of 3D shapes. On the technical front, projective analysis puts many effective learning methods designed for image data, e.g., [Bansal et al. 2015; Gong et al. 2014; Li et al. 2015], at our disposal. Furthermore, it works more robustly with different 3D geometry representations and various shape imperfections including noise, incompleteness of shapes, and non-manifold geometries [Wang et al. 2013a]. We also emphasize that our projected lines include geometric feature lines which cannot be captured by rendered images, although the neuron activations in CNN could be used to extract lines and corners from rendered images. Experiments show that line drawing outperforms color rendering, even when both using CNN for feature extraction.

Given a heterogeneous collection of 3D shapes spanning multiple object categories and styles, our method performs style co-analysis over projective line drawings of each 3D shape and backproject the learned style features onto the 3D shapes at the end. As shown in Figure 2, our core analysis pipeline consists of three stages: 1) mid-level patch sampling and pre-selection of candidate style patches; 2) view feature encoding based on patch convolution; and 3) multi-view feature fusion and style clustering under the framework of partially shared latent factor learning or PSLF [Liu et al. 2015b], which selects the final style patches from the candidates.

PSLF fits well with projective analysis, as it is designed for multi-view feature analysis and learning. It deciphers the consistent and complementary information from the features of multiple views and integrate them in a better informed way. We show that such an advanced feature fusion scheme performs much better than the max-pooling used in multi-view CNN [Su et al. 2015]. Furthermore, PSLF discovers shape styles by clustering shapes and selecting the most discriminative mid-level patches which accentuate the clustering; this is consistent with how styles are typically characterized [Wikipedia 2016]. To support both unsupervised and semi-supervised style analysis, we develop a constrained formulation of PSLF which accepts both user-specified shape style labels [Hu et al. 2017] and style-ranked triplets as classical metric learning [Garces et al. 2014; Liu et al. 2015a; Lun et al. 2015].

Figure 1 shows a sample result, where our style co-analysis was performed on 400 mixed furniture pieces (top row). Four shapes deemed to belong to the same style cluster (not all shapes in the cluster appear in the figure) are shown with their style patches highlighted, both on the shape and also in line drawings (see insets).
Our work makes the following main contributions:

- To the best of our knowledge, our method represents the first semi- or weakly-supervised co-analysis of 3D shape styles, leading to style clustering and style localization.
- Our method supports both unsupervised and semi-supervised style analysis, combining local feature learning and global discriminative style extraction.
- Our analysis focuses exclusively on projective features from line drawings, while previous works employed much richer feature sets [Hu et al. 2017; Liu et al. 2015a; Lun et al. 2015]. Yet, as we shall demonstrate, we can obtain clear improvements over all of these methods, owing in part to our multi-view style analysis with feature fusion.
- We can spatially locate visually apparent stylistic shape elements or patches without any direct user involvement to manually mark any style patches over 3D shapes. Our semi-supervised analysis takes the same types of user input as classical metric learning.

We demonstrate the effectiveness of our method for style analysis and patch localization, in particular, clear improvements over state-of-the-art supervised methods [Hu et al. 2017; Liu et al. 2015a; Lun et al. 2015]. We also develop several applications that can take advantage of the detected styles. For example, with the style patches spatially located, we can perform style-preserving mesh simplification, as shown in Figure 1. Triangle distributions before and after simplification, shown in Figure 1(d), clearly exhibit that triangle reduction happens mostly over non-style regions.

2 RELATED WORK

In this section, we cover and discuss works related to shape style analysis and our approach for style clustering and style patch extraction on 3D surfaces via machine learning. We describe how our method is different from these existing approaches.

Co-analysis. Our approach falls in the realm of co-analysis techniques [Mitra et al. 2013; Zhu et al. 2018], most of which have been designed to work with homogeneous shape collections. Our method can work with a heterogeneous shape collection owing to its localized feature encoding and analysis of decorative styles. Semi-supervised learning has been mainly employed to solve labeling problems such as shape segmentation [Wang et al. 2013a] and classification [Huang et al. 2013; Zhao et al. 2018]. In our work, we rely on unsupervised and semi-supervised PSLF learning to extract spatial style patches.

Projective shape analysis. Analyzing 3D shapes through 2D projections has been a common practice with successful applications such as shape classification [Su et al. 2015], retrieval [Chen et al. 2003], and segmentation [Wang et al. 2013a], to name a few. Main benefits of the projective approach include robustness with imperfect 3D representations and exploitation of image-based learning, especially deep learning techniques. Our work offers a new application, namely analysis of shape styles, by utilizing another useful property of 2D projections, i.e., their ability to reveal shape styles visually in the form of line drawings.

Multi-view learning. In multi-view learning, a concept is learned from data represented in multiple forms or views, e.g. [Chaudhuri et al. 2009; Liu et al. 2015b]. The goal is to discover consistent and complementary information among multiple views of the data, with both types of information supporting the concept. Specifically, consistent information should be shared across most views in identifying the concept, while complementary information is something that is distinctively reflected from one or few views and complementary to other such information. In our work, the concept to learn is shape styles and the multiple views are provided by the multi-projection line drawings of the 3D shapes. Decorative shape styles may be shared consistently across multiple views, e.g., stylistic details over the surface of a sofa. They can be also exclusive to one or few views to complement other style features such as an emblem on top of a bed’s headboard. As a result, our style analysis problem is well-suited for a multi-view learning approach.

PSLF. Partially shared latent factor (PSLF) learning is a multi-view learning method [Liu et al. 2015b] which performs joint analysis over a set of data to extract both the consistent and complementary information among multiple data views. PSLF is essentially a dimensionality reduction technique that is realized through a non-negative matrix factorization (NMF). Our method adopts PSLF to learn style features and their spatial locations via projective co-analysis. We also adjust the original objective function of PSLF to enable semi-supervised learning that accepts both user-specified shape labels and style-ranked triplets as classical metric learning.

Mid-level patches. Mid-level image patches, e.g., object parts or salient regions, are neither too local nor too global and they have been effective for tasks such as object detection [Bansal et al. 2015], indoor scene classification [Doersch et al. 2013], and unsupervised visual discovery [Raptis et al. 2012; Singh et al. 2012]. While unsupervised approaches typically perform the analysis purely at the patch level [Singh et al. 2012], weakly supervised approaches such as those presented by [Bansal et al. 2015; Doersch et al. 2013], typically detect mid-level patches or compute patch clusterings to attain maximal adherence to the image or object labels.

Most closely related to our method is the work by Lee et al. [2013], which aims to discover mid-level patches that are the characteristic of historic and geographic styles of objects in images. They start with a generic visual element detector serving a similar role as our approach. Lee et al. [2013] propose to discover mid-level patches using a pre-training algorithm on a labeled dataset. In contrast, we apply PSLF to perform shape clustering and style patch selection in an interleaving manner. Our approach can be supervised or semi-supervised, and for the latter, both style labels and user-specified style rankings are accommodated.

Convolutional activation features. Convolutional neural nets (CNNs) have been extensively employed for various feature learning tasks recently, e.g., [Donahue et al. 2013; Razavian et al. 2014; Zeiler and Fergus 2014]. Training a full CNN for feature learning is expensive in terms of data labeling and computation. In our work, we explore the limit of unsupervised and semi-supervised feature learning for shape style analysis requiring minimal data annotations.

Deep convolutional activation features, including those for mid-level visual elements, have been employed as descriptors for generic visual recognition [Bansal et al. 2015; Gong et al. 2014; Li et al. 2015]. We use the discriminatively detected mid-level patches as filters to perform feature encoding based on a sliding-window convolutional
operation, similar to [Bansal et al. 2015]. Although these content features are discriminative for object characterization, it is not yet clear whether they would attain the same level of success for style recognition since style and content features do not always correlate with each other. We use these features as per-view initial features and conduct multi-view feature fusion and selection via PSLF.

**Shape style analysis.** Some earlier works on shape styles assume that the style is given. For example, Xu et al. [2010] have worked exclusively with anisotropic part proportions. Some other works perform style analysis on shapes which belong to the same semantic category [Huang et al. 2013; Kalogerakis et al. 2012]. More recent attempts generally take the view that human style perception transcends shape content [Lun et al. 2015]. In an earlier work, Li et al. [2013] have handcrafted several rules as an attempt to characterize style features for 2D curves. Another line of works focus on analogy-based style transfer, e.g., Ma et al. [2014], where the goal is to determine what editing operations on a query shape A’ mimic the style change which would transfer a given shape A to a given shape B. Lun et al. [2016] have shown that the same style transfer framework can be extended with deep learning techniques.

**Supervised learning of style similarity.** Recent works on shape style analysis combine crowd-sourcing and metric learning to learn a generic style similarity. Most notably, Lun et al. [2015] and Liu et al. [2015a] both work with heterogeneous 3D shape collections and rely on crowd-sourced style ranking triplets to learn a style metric. Most recently, Lim et al. [2016a] added deep learning to this framework. The key difference between our method and these works is that we learn to spatially locate style patches and they do not. Also, there are differences in what is learned and for what target applications. Our work learns what makes a piece of furniture Chinese/Country and a building Gothic/Greek and where the style regions are. The core problems we face are style classification/clustering and style patch extraction. In contrast, Lun et al. [2015] and Liu et al. [2015a] focused on style-driven shape retrieval, trying to learn a specialized shape similarity. Yet, our method can be customized to accomplish tasks Lun et al. [2015] and Liu et al. [2015a] were designed to do, making it more general.

On the technical front, several other differences exist: 1) our method can be both unsupervised and semi-supervised; 2) our method employs projective analysis and relies on different features; 3) our method adapts PSLF clustering to help us select and locate style feature patches, while both Liu et al. [2015a] and Lun et al. [2015] adapt metric learning to learn a global style metric.

**Supervised style localization.** The work by Hu et al. [2017] also learns to locate style patches, but it takes as input a collection of 3D shapes with expert-provided style clustering. In contrast, the input to our work is only such a shape collection, without any style clustering. In our semi-supervised version, the user can provide style labels or style ranking triplets, but only over a very small percentage of the data. Therefore, their work is exclusively on feature selection based on a given style clustering while we need to solve both clustering and feature extraction simultaneously.

Another difference, a subtle one, is that Hu et al. [2017] aim to locate style-defining patches, i.e., all patches which together define a particular style, while our analysis seeks to find style-discriminative patches, i.e., those which can distinguish a style from the others. In their work, style-defining patches are simply a combination of style-discriminative patches. Technically, the feature learning schemes of the two methods are different and they operate on different features: we work with projective line drawings and Hu et al. [2017] employed similar features as Lun et al. [2015].

### 3 OVERVIEW

Given a heterogeneous collection of 3D shapes in several styles, we perform projective style analysis based on multi-view line drawings of each 3D shape. Our method contains three stages: patch sampling and pre-selection, view feature encoding based on patch convolution, and multi-view feature integration with partially shared latent factor (PSLF) learning. The PSLF interleaves style clustering and patch filtering in an unsupervised or semi-supervised fashion. Figure 2 illustrates an overview of our method.

**Multi-view line drawing.** For each 3D shape, we render it from the views of 12 virtual cameras located circularly around the shape in every 30 degrees. These cameras are elevated 30 degrees from the ground, pointing towards the centroid of the shape. For each view, we extract both suggestive contours [DeCarlo et al. 2003] and dihedral angle based feature lines [Gal et al. 2009], leading to an image of 200 × 200 size. While the former captures contours and creases of a smooth manifold, the latter is especially useful for extracting sharp feature lines from man-made shapes which can be potentially non-manifold. See Figure 3 for a few examples of multiple-view line drawings.

**Patch sampling and pre-selection.** We select a set of representative mid-level patches from all projected line drawing images, that are used as the convolutional kernels in the feature encoding of the projections. Specifically, we first randomly sample a set of points on each shape. For each sample point and each view in which this point is visible, a patch is generated as the window centered at the projection of the point. We then perform k-means clustering to extract a set of representatives as the cluster centers (Figure 2(a)).

**Per-view feature encoding.** In the second step, a feature map is extracted for each line drawing image through convolving it using the pre-selected patches as kernels. Convolutional feature encoding is known to be shift-invariant, since a convolution kernel may get activated at an arbitrary position in an image. This trait fits well to our problem since local style patches may appear in multiple spatial locations. To extract multi-scale features, we also perform convolution for sub-images (Figure 2(b)). The final feature is a concatenation of the per-region feature after pooling, similar to [Bansal et al. 2015].
Multi-view feature integration. The core step of our algorithm is to fuse the features extracted from different views while clustering the shapes based on the fused features. This leads to a multi-view feature representation for each shape. We adopt the partially shared latent factor (PSLF) learning [Liu et al. 2015b] to implicitly separate the input multi-view features into parts which are shared by multiple views and those which are distinct to a specific view. The final multi-view feature is compact and comprehensive, encoding both shared and distinct information in different views.

Unsupervised and semi-supervised style analysis. Based on the clustering result, we re-select the representative mid-level patches to learn more and more discriminative ones with respect to the evolving style clusters. This will in turn update the feature encoding in the next iteration. Such cluster-and-select process iterates until the clusters and patches become stable. Our process can be performed unsupervised to cluster models. To impart human knowledge about shape styles into the analysis, we realize semi-supervised style clustering within the PSLF framework, achieving both meaningful style clustering and informative feature learning. Specifically, we present two semi-supervised clustering methods, accepting either user-prescribed style labels on a small portion of the shape collection or triplets of shapes indicating their style similarity (Figure 2(c)). Finally, we backproject the learned discriminative patches from projective space to surfaces of the input 3D shapes to extract and visualize the style patches over these 3D shapes.

4 SEMI-SUPERVISED PROJECTIVE STYLE CO-ANALYSIS

In this section, we describe our semi-supervised projective style co-analysis method in detail.

4.1 Patch sampling and pre-selection

We first sample 2D patches from the multi-view rendered line drawings to bootstrap our style analysis. To ensure a uniform coverage of a shape surface, instead of sampling the patches in 2D projections, we sample 3D points on the shape surface and then use the 3D points as seeds to generate 2D patches through projection. 3D sampling also facilitates the back-projection of 2D patches into 3D for locating style patches. In practice, we sample 30 seed points on a 3D surface, project them onto the 2D views in which these points are visible. We then, for each projected 2D point, we extract a 2D square patch centered at this point. For a $200 \times 200$ image, we extract about 30 patches, where the patch size is chosen experimentally; see discussion in Section 5.

To select a set of representative patches for each view, we perform $k$-means clustering over all patches in that view in HOG feature space [Dalal and Triggs 2005]. The cluster centers are selected as the representative patches. In practice, we extract 50 representative patches for each view. Figure 4 demonstrates the sampled mid-level patches as well as the selected representatives.

4.2 Per-view feature encoding

Inspired by the work of Bansal et al. [2015], we perform convolutional feature encoding for each line drawing image using the representative mid-level patches as convolution filters. While these features are extracted by directly applying convolution operations over input images, without the need of training a deep neural network, they were shown to perform comparably against the deep CNN features on 2D object detection task. The main rationale behind this is that the characteristic mid-level patches, analyzed from a relevant image collection [Bansal et al. 2015], encompass informative visual cues for an object class. Our iterative patch selection is conducted over relevant image collections obtained by clustering.

We take one mid-level patch as a convolution filter and use it to convolve the input image in a sliding-window fashion. Such a convolution operation is conducted in HOG feature space: both the input image and mid-level patches are represented by HOG feature maps. To compensate the global feature encoding of full image convolution, we also perform the above process over the sub-image obtained by dividing the original image into four parts. We then perform max-pooling over the convolution activations over the spatial pyramid of two levels of resolution (Figure 5). Consequently, each convolution filter produces a 5-dimensional feature vector. The ultimate feature for a line drawing image is constructed by concatenating the feature vectors of all convolution filters, leading to a 5K-dimensional feature vector for $K$ mid-level patches.

4.3 Multi-view feature fusion

Having a feature vector for each view of a given shape, we perform multi-view feature fusing, to extract a new feature for the shape. This feature instils the information from jointly analyzing a set of shapes. To achieve this, we adopt the partially shared latent factor (PSLF) framework [Liu et al. 2015b], which is a clustering method coupled with multi-view feature integration. Note that the “views” in the original work generally refer to different aspects, attributes,
or observations of the data in question. In our case, the views are given by line drawings in multiple projections of 3D shapes.

PSLF employs non-negative matrix factorization (NMF) [Lee and Seung 1999] to learn a compact yet comprehensive partially shared latent representation. Given a collection of $N$ shapes with line drawings in $P$ views, the learning objective of PSLF is:

$$\min \sum_{p=1}^{P} \pi_p \|X^{p} - U^{p}V^{p}\|_F^2 + \lambda \|\Pi\|_2^2,$$  \hspace{1cm} (1)

s.t. $U^1, \ldots, U^P, V^1, \ldots, V^P, \Pi \geq 0, \sum_{p=1}^{P} \pi_p = 1$,

where the input feature matrix $X^p \in \mathbb{R}^{M \times N}$ contains the per-view feature of all $N$ shapes, for the $p$-th view, with each column corresponding to one shape. $M$ is the length of the feature vector of a given shape. $U^p \in \mathbb{R}^{M \times K}$ is the basis matrix of view $p$, while $V^p \in \mathbb{R}^{K \times N}$ is the matrix of $K$ latent factors, $K \ll M$, or the fused feature matrix. $\Pi = (\pi_1, \pi_2, \ldots, \pi_P)$ is the weights for different views. $\lambda$ controls the smoothness of $\Pi$. A large value for $\lambda$ leads to smoother view weights. Essentially, PSLF learns the fused feature matrix $V$ and the basis matrix $U$, while tuning the weights of different views, all in an unsupervised manner, by minimizing the reconstruction error with respect to the input features. The projection of the fused features over the basis leads to a clustering of input features. The PSLF factorization for a set of input features in one view is illustrated in Figure 6(a).

PSLF assumes that only parts of the latent factors are shared across all views and the other ones are separately embedded in individual views. Thus, the factor matrix of view $p$ is separated into two parts: $V^p = \left[ V^{p}_c, V^{p}_s \right]$, where $V^{p}_c$ represents the specific information extracted from view $p$ and $V^{p}_s$ the common shared by all views. The basis matrix is also divided into two parts: $U^p = \left[ U^{p}_c, U^{p}_s \right]$, with $U^{p}_c$ being the specific part corresponding to the shared latent factors and $U^{p}_s$ the common part.

An important parameter of PSLF is the proportion of common part: $\eta = (K_c / (K_s + K_c))$, where $K_c$ and $K_s$ are respectively the dimensions of the common and specific latent factors and $K_s + K_c = K$ holds. In this setting, when $\eta$ is larger, the role of consistency is more.

After performing the feature matrix factorization for all shapes being co-analyzed, we obtain the partially shared latent factor matrix $V \in \mathbb{R}^{(K_c + K_s) \times N}$, which contains the fused feature for each shape. The matrix $V$ contains the unique feature part of each view $V^{1}_s, \ldots, V^{P}_s$ and the common part for all views $V_c$, (i.e., $V = \left[ V^{1}_s, \ldots, V^{P}_s, V_c \right]$), see Figure 6(b) for illustration.

An important feature of PSLF is that it is able to learn both consistent and complementary information from the data views. When applied to style analysis, our experiments (see Section 5) confirm that both types of information affect the learned shape styles, demonstrating the adaptability of PSLF to our problem.

4.4 Style clustering

PSLF was originally proposed for multi-view, semi-supervised clustering and feature learning [Liu et al. 2015b]. To accommodate both user-provided style ranking triplets and style labels to constrain semi-supervised analysis using the learning framework provided by PSLF, we must modify the original PSLF formulation.

**Label-constrained style clustering.** We modify the original objective function of PSLF to incorporate user-specified labels in constrained clustering. Suppose $V_l \in \mathbb{R}^{(K_c + K_s) \times N_l}$ is the feature vector matrix of $N_l$ number of shapes with labels. Assume, w.l.o.g., the first $N_l$ columns of $V$ correspond to the labeled shapes. $Y \in \mathbb{R}^{C \times N_l}$ is the corresponding label matrix, where $C$ is the number of style categories. The objective we optimize for is:

$$\min \sum_{p=1}^{P} \pi_p \|X^{p} - U^{p}V^{p}\|_F^2 + \lambda \|\Pi\|_2^2 + \beta \|V_l - WY\|_2 + y\|W\|_{2,1} \hspace{1cm} (2)$$

s.t. $U^1, \ldots, U^P, V^1, \ldots, V^P, \Pi \geq 0, \sum_{p=1}^{P} \pi_p = 1$

where $\pi_p$, $X^p$, $U^p$, $V^p$, and $Y$ are defined the same as before. $W \in \mathbb{R}^{(K_c + K_s) \times C}$ is the basis matrix obtained for labeled shapes. $\beta > 0$ is a parameter for tuning the importance of user-specified labels. $y$ controls the weight of $\ell_{2,1}$ regularization term.

In this new optimization, $\beta \|V_l - WY\|_2 + y\|W\|_{2,1}$ is the semi-supervised term, where the NMF of $V_l$ produces the basis matrix $W$ constrained with $Y$. Note that this optimization not only predicts cluster labels for unlabeled shapes, but it also updates the fused feature matrix $V$. Therefore, the output fused features in $V$ have also incorporated the user constraints.

Since the basis $W$ defines the cluster centers obtained from constraints, the fused feature matrix of the $(N - N_l)$ unlabeled shapes, $V_u \in \mathbb{R}^{(K_c + K_s) \times (N - N_l)}$ (so we have $V = \left[ V_l, V_u \right]$) can be defined by: $V_u = WY_u$, $Y_u \in \mathbb{R}^{C \times (N - N_l)}$ is the label prediction matrix for the unlabeled shapes. These shapes can be assigned with the label corresponding to the largest probability.

**Triplet-constrained style clustering.** Exact style labels are sometimes hard to perceive even by humans. It is relatively easier to provide similarity-based supervision, e.g., shape A is style-wise closer to B than to C. This kind of user input has been extensively used.
in crowd sourcing [Liu et al. 2015a; Lun et al. 2015]. To incorporate
triplet-based constraints into our clustering, we decompose each
triplet into two pair-wise constraints, i.e., must-link and cannot-link
between a pair of data points, which is a standard form of constraints
used by semi-supervised learning [Chen et al. 2008].

Our method imposes such pair-wise constraints over the simi-
larity matrix obtained by the unsupervised analysis of PSLF: \( \mathbf{A} = \mathbf{V}^T \mathbf{V} \),
where \( \mathbf{V} \) is the partially shared latent factor matrix discussed in
Section 4.3. Specifically, we modify the similarity matrix as follows:

\[
\mathbf{A}' = \mathbf{A} + \mathbf{N}_m - \mathbf{N}_c.
\]

where \( \mathbf{N}_m = \mathbf{I}(i, j) \in C_{\text{mustlink}}, \mathbf{N}_c = \mathbf{I}(i, j) \in C_{\text{cannotlink}}, \) with \( i \) and \( j \) as indices of a pair of shapes, \( C_{\text{mustlink}} \) and \( C_{\text{cannotlink}} \) collect
the sets of shape pairs with must-link and cannot-link constraints,
respectively, and \( \mathbf{I} \) is an indicator matrix.

To conduct constrained clustering again using the PSLF framework,
we perform another non-negative factorization over the modi-
fied similarity matrix: \( \min ||\mathbf{A}' - \mathbf{Y} \mathbf{S}^T||_F^2 \), where \( \mathbf{S} \in \mathbb{R}^{N \times C} \) contains
cluster centers and \( \mathbf{Y} \in \mathbb{R}^{N \times C} \) is cluster indicator.

**Unsupervised style clustering.** Having computed the fused feature
matrix \( \mathbf{V} \) in Section 4.3, performing unsupervised style clustering is
straightforward. To do so, we utilize the self-tuning spectral cluster-
ing [Zelnik-Manor 2004]. This method produces the state-of-the-art
clustering results while determines the number of clusters automa-
tically. However, directly clustering the fused features may not
generate the optimal results since the per-view features, computed
with random patches, may not be the most relevant. To this end,
we devise an iterative algorithm that interleaves clustering and
cluster-guided patch re-selection, which will be discussed in the
next subsection. In fact, such iterative cluster improvement can be
also performed in semi-supervised analysis, through imposing the
user constraints in every clustering.

### 4.5 Cluster-guided style patch selecting

The PSLF clustering has been so far based on the patches pre-selected
by plain clustering without feature selection (Section 4.1). In fact,
PSLF clustering couples feature selection and more importantly,
incorporates the user constraints in the semi-supervised setting,
making it both objectively informative and subjectively desirable.
Therefore, it is preferable to use the PSLF clustering to guide a
re-selection of mid-level patches, leading to more discriminative
patches, specifically tuned for the unsupervised or semi-supervised
tasks. The re-selected patches can in turn be used to update the
PSLF clustering, via further purifying the clusters.

Based on the PSLF clustering results, we re-select discriminant
mid-level patches for each view, to be those which are frequent
only within one cluster [Xu et al. 2014]. For each style cluster \( C_l \),
we define the support weight of shape \( i \) as \( (\omega_{ij})_{n=1}^n \), that measures
the support of shape \( i \) to any mid-level patch. A mid-level patch is
determined as frequent if its weighted sum of support, denoted by
discriminant score \( \delta_{ij} \), is greater than a threshold \( \delta_f ' \):

\[
\mathcal{K}_l = \{ j | \delta_{ij} > \delta_f ' \}, \text{ where } \delta_{ij} = \sum_{l=1}^n \omega_{ij} \left(2x_{ij} - 1\right).
\]

and \( x_{ij} \) is an indicator function showing that shape \( i \) supports patch
\( j \). If shape \( i \) belongs to \( C_l \), weights \( \omega_{ij} \) are positive, otherwise, they
are negative. The discriminant score favors a patch that is frequent
in cluster \( C_l \) and penalizes its occurrence in other clusters. There-
fore, the patches in \( \mathcal{K}_l \) are frequent mainly within cluster \( C_l \) that is
regarded as discriminant. Specifically, we define \( \omega_{ij} = x_{ij}/C - 1/N_p \),
where \( x_{ij} = I(i \in C_l) \) with \( I(\cdot) \) being a 0-1 indicator function and
\( \delta_f ' = \mu N_p/C \) holds. \( C \) is the number of clusters where \( N_p \) is the
total number of patches. We use \( \mu = 0.07 \) for all the datasets we
have tested. The final set of patches takes the union of pre-cluster
discriminant patches: \( \mathcal{K} = \bigcup_{l=1}^C \mathcal{K}_l \).

After the mid-level patch re-selection, we repeat the process of
per-view feature extraction, feature fusion for all 3D shapes and
unsupervised or semi-supervised PSLF clustering. This cluster-and-
select process iterates until the clusters and patches become stable.
The final result comprises of purified style clusters, together with a
set of style-characterizing mid-level patches, or style patches.

**Style patch extraction on shape surfaces.** One of our goals is to
extract style patches on 3D shape surfaces based on the co-analyzed
style patches in 2D. This can be done by backprojecting the 2D
patches onto 3D surfaces. With the 3D patch sampling and projection
scheme in Section 4.1, we can easily locate the surface region
Corresponding to a 2D patch. Note, however, the final style patches
are selected from only a few 3D shapes, but not all. To locate the
style patches on other shapes, we need to compare them against
the patches sampled from those shapes, based on HOG features.
Finally, we sort sampled areas on the 3D shape to find style patches
according to the number of style patches back-projected to them.
Figure 7 shows a few input shapes with the style patches highlighted
in orange color. We also conducted a user study to verify the validity
of our detected style patches in Section 5.
5 RESULTS, EVALUATION, AND APPLICATIONS

In this section, we first introduce our dataset and then demonstrate experimental results. Our analysis method is evaluated extensively over a collection of 3D models in six categories, as shown in Table 1. A set of comparisons are devised to examine the effect of our algorithmic components. Our method is also compared with the state-of-the-art approaches to style analysis. Finally, we demonstrate two applications that exploit the spatial localization feature of our method. Extended results of evaluation and comparison, and the full user study data can be found in the supplementary material.

Datasets. Datasets employed in our experiments have mainly been collected from the Internet (e.g., ShapeNet and Trimble 3D Warehouse) and previous published works. These datasets include a total of around 2,600 three-dimensional models arranged into six collections: Mixed Furniture 1, Mixed Furniture 2, Building, Chair, Car, and Vase. Each collection contains models with multiple styles, where for models sharing the same style, their geometry and structure can be quite different. In addition, even when all models fall under the same general category (e.g., chairs), their styles, geometries, and structures can be significantly different. Note that our method only assumes that the 3D objects have been upright oriented, but not necessarily consistently aligned.

Style labels. Our selection of style labels are based on common or professional knowledge accessible from publications and human experts. For example, furniture styles include “Simple Chinese”, “Noble Chinese”, “European”, “Country”, and “Modern”, according to their decorative styles [Morley 1999]. Buildings are labeled based on their geographic-temporal styles such as “Gothic”, “Greek”, “Byzantine”, and “Asian” [Lun et al. 2015]. In the final step, all the style labels for all object collections have been validated by four experts, who are professors from industrial engineering and architectural design. Table 1 shows the number of styles.

Ground truth for style clustering. We asked three of the experts to assign each 3D model in our dataset to one of the available style classes, based on the style labels obtained as described above, for all six object collections. After that, we asked the fourth expert to verify the style assignments. A few iterations were performed to arrive at the final labeling, which serves as the ground truth for style clustering of the models, per object collection. All the models and style labels can be found in the supplementary material. Note that these style clusterings are constructed only for evaluation; they are not used as training data for our method.

Parameters. There are five tunable parameters in the PSLF optimization. Specifically, the smoothness of different view weights is controlled by $\lambda$; non-negative parameter $\beta$ is to trade off between the objective of non-negative reconstruction and the $l_{2,1}$-norm regular item; the weight of the $l_{2,1}$-norm regular item is tuned by $\gamma$; common latent factor space shared between multiple views is controlled by $\eta$, where $0 < \eta < 1$, and finally, $\Pi = (\pi^1, \pi^2, \ldots, \pi^P)$ controls the weights of different views for all models. All the experiments have been conducted with a fixed parameter setting: $\beta \approx 0.05$, $\lambda \approx 20$, and $\gamma \approx 10$, and $\eta = 0.2$ in PSLF; view weights are set as $\Pi = (\frac{1}{P}, \frac{1}{P}, \ldots, \frac{1}{P})$ with $P$ views. We also examined the effect of different patch sizes on the purity of style clustering and found that a size of $48 \times 48$ generally leads to the best results overall; varying the patch sizes did not affect the purity more than 5%. Thus, we fixed the patch size to $48 \times 48$ in all of our experiments.

5.1 Style analysis results and evaluation

We first evaluate the performance of our method for style clustering and style patch localization. Since it is difficult to collect consistent ground truth data for style patches, we instead conduct a user study where human participants are asked to judge the results produced by our algorithm. For style clustering with style labels set up, we evaluate our results using the standard clustering purity measure. Let $C$ be the set of clusters from a clustering result for a dataset, and let $L$ be the set of ground truth clusters. For any cluster $c \in C$, its precision against a ground-truth cluster $l \in L$ is defined as, $P(c, l) = \frac{|c \cap l|}{|l|}$. The purity measure reflects an average of weighted

Shape collection | #Shapes | #Style classes
--- | --- | ---
Mixed Furniture 1 | 120 | 4
Mixed Furniture 2 | 400 | 5
Building | 329 | 4
Chair | 516 | 9
Car | 1,050 | 6
Vase | 194 | 5

Table 1. 3D object collections for our style analysis.
precision for each cluster and is defined as:

\[
\rho(C, L) = \sum_{c \in C} \frac{|C|}{|N|} \max (P(c,l))
\]  

(5)

Note that purity depends on its relative maximum precision on ground truth and therefore it can comprehensively reflect classification or clustering precision.

**Style patch localization.** To verify that the final patches returned by our style analysis indeed represent shape styles, we conduct a user study which compares our results to those annotated by human experts. We randomly selected 20 small sets of models from the six object collections, where each set consists of models belonging to the same style class based on our ground truth. For each set, we asked human experts to identify style-defining patches by painting over the shapes. We then conducted a user study where participants are provided with three types of patches (in color) for the same model set: randomly selected patches, expert-annotated patches, and patches returned by our style analysis algorithm. Figure 8 shows a sample query for one of the 20 model sets. Note that in the study, the three choices were randomly ordered in each query. Each subject is asked to choose which of the three choices would best reflect the style of the set of models shown. In the study, 20 model sets were presented to 58 human participants with different backgrounds and no prior knowledge about our method.

A subset (10 out of 20 model sets) of results from this study are plotted in Figure 9, where the percentage of the user selection of each choice is shown. The full set of results can be found in the supplementary material. As indicated in Figure 9, participants’ preference of our method is fairly close to that of the expert annotations.

**Semi-supervised analysis.** Our semi-supervised style analysis accepts two types of user inputs: style labels or style ranking triplets. Figure 10 shows how the style clustering performance, in terms of purity (see Equation 5), changes as we increase the percentage of user labels or the number of user-specified ranking triplets, respectively. All results were obtained with iterative PSLF-based clustering. As expected, clustering improves as user inputs increase. However, the improvement appears to level off when the label percentage passes 30% or the number of triplets reaches around 300. Note that 300 only represents an extremely small number of triplets out of the total number of triplets for an object collection.

**Parameter analysis.** We examine two key parameters, view count and \( \eta \), which have the most significant impact on results among all the parameters and they need to be carefully selected.

We tested our style clustering with different number of views, ranging from 1 to 12 views. For a given number of view, we enumerate all different combinations of views, picked from the full set of 12 views. The final results for each view count were averaged over all different combinations. As shown in Figure 11, the clustering results gradually improves with increasing views. The typical “leveling out” points appear to be 10-12 views.

We have also analyzed the impact of parameter \( \eta \) on classification accuracy for all datasets, in Figure 12. The parameter controls the proportion of common latent factor space shared across different views in PSLF. It can be observed that 0.2 gives the best results. This also verifies that PSLF is well-suited for our problem when both the consistency and complementarity of different views are exploited. Thus, we fix \( \eta = 0.2 \) in all experiments throughout the paper.
5.2 Comparisons

We now provide several comparative studies to validate important design choices made in our method and to show how well our semi-supervision performs on the task of style similarity learning as compared to the state-of-the-art methods.

**Style clustering: PSLF learning vs. PCA and CCA.** We compare our PSLF-based style clustering method with PCA [Jolliffe 2002] and Correlation Analysis-based approaches (CCA) [Chaudhuri et al. 2009]. Both PCA and CCA are dimensionality reduction techniques, just like PSLF.

In the experiment, the reduced dimensionality of PCA is the same as the dimensionality of the partially shared latent representation in PSLF. CCA is a two-view method; we have executed the algorithm with each pair of two-view data and report results obtained using the best pair. The comparison is conducted using triplet constraints (100 triplets) to drive semi-supervised style clustering (see Section 4.4, which is based on fused features of each method for each data set. Figure 13 suggests that using PSLF to fuse the features tends to produce higher style clustering purities than PCA and CCA. We believe that the underlying reason is that PSLF can improve its fused features with the aid of triplet constraints while PCA and CCA cannot. In turn, the improvement on feature fusion is responsible for higher-accuracy clustering results. Additional results obtained by changing the amount of user inputs can be found in the supplementary material.

**Input representation: Line drawings vs. rendered images.** To examine the effectiveness of using line drawings as input representation for style analysis, we make a comparison to the use of rendered images. For the latter, we render a 3D shape with the same setting as [Su et al. 2015], obtaining a set of RGB images from the same views as those for line drawings. Besides, we also compare to coherence-enhancing line drawing (CLD) [Wang et al. 2013b] extracted from the rendered images. Note that CLD, computed based on 2D images, is inherently different from our projective line drawings which may contain geometric features of 3D surfaces. Figure 14 shows an example shape in the above three different projections.

We conduct experiments on the three types of projection images, under the constraints of 20% user-prescribed style labels or 100 style ranking triplets, meanwhile keeping all design choices (e.g., use of HOG features) and parameters the same. Results shown in Figure 15 indicate the consistent superiority of using projective line drawings for our task. The advantage over rendered images clearly verifies that feature lines are more directly related to shape styles. The superiority of our projective 3D line drawings over 2D edge detections further reflects the importance of 3D feature lines. Additional results with different percentages of user-prescribed labels are give in the supplemental material.

It is known that the neuron activations in the lower level of convolutional neural networks are able to capture characteristic lines and corners in an image. Therefore, it is interesting to see how our projective line drawings compares to rendered images when using CNN for feature learning. For simplicity, we train a LeNet [Lecun et al. 1998] (5 convolutional layers plus 2 fully connected layers) with 20% of our datasets, to learn feature representation for each view separately. The view-wise features are fused with PSLF for final style clustering. For projective line drawings, the raw input is represented in HOG space. Rendered images, however, are input directly. Figure 16 shows that line drawing outperforms color rendering, when both using CNN for feature extraction and PSLF for feature fusion. This is because projective lines include 3D geometric
Figure 14. Different projective methods. (a) Rendered images as [Su et al. 2015]. (b) Coherence-enhancing line drawing. (c) Our line drawing.

Figure 15. Semi-supervised style clustering over projected line drawing (orange) vs. rendered images (blue). Top: results with 20% user label constraints. Bottom: results with 100 style ranking triplets.

Figure 16. Comparison on style clustering between PSLF(green), max-pooling with CNMF(blue) and MVCNN(orange). They are performed on the same line drawing features extracted from VGGNet-16 [Simonyan and Zisserman 2014].

Figure 17. Comparison on style clustering between PSLF(green), max-pooling with CNMF(blue) and MVCNN(orange). They are performed on the same line drawing features extracted from VGGNet-16 [Simonyan and Zisserman 2014].

Figure 18. Comparison on style clustering between PSLF(green), max-pooling with CNMF(blue) and MVCNN(orange). They are performed on the same line drawing features extracted from VGGNet-16 [Simonyan and Zisserman 2014].

Feature fusion: Max pooling vs. PSLF. A key component of multi-view style analysis is how to fuse the features extracted for the multiple view channels. A commonly used fusion scheme is to perform max pooling operation over the multi-channel features [Su et al. 2015]. However, such a simplistic fusion is oblivious to the consistency and complementarity among the multiple channels which are both essential to effective feature fusion. To verify this, we train a VGGNet-16 [Simonyan and Zisserman 2014] to extract view-wise features from projective line drawings, and then utilize max pooling and PSLF to fuse the features, respectively. The dimensionality of the fused feature is 512 for max pooling and 50 for PSLF. For max-pooling features, we employ CNMF [Liu and Wu 2010] to perform style clustering, under the constraint of 20% data with known labels, same as PSLF. We also compare the results to MVCNN [Su et al. 2015], using the same 20% data as the training set. The results in Figure 17 show that PSLF outperforms max pooling, both with CNMF and in MVCNN, on all datasets. This verifies that PSLF, as a clustering method with a carefully designed feature fusion scheme, is especially suited for multi-view style analysis.

Learning style similarity. State-of-the-art methods for learning style similarities from style ranking triplets include the recent works of Lun et al. [2015], Liu et al. [2015a] and Lim et al. [2016b]. Since our semi-supervised PSLF learning also accommodates style ranking triplets as user input (see Section 4.4), these methods and our method can be compared for the task of predicting style similarity rankings using the learned similarity distance. Our comparisons were conducted on datasets from the two previous works, respectively. As well, the set of style ranking triplets were also reused from their works. We split the set of triplets into a training set for learning and a testing set. Prediction accuracy is measured on how accurate the learned similarity distance would predict the similarity relations among the three data entities in a testing triplet.

Figure 18 shows a comparison to Lun et al. [Lun et al. 2015] on four of their seven object categories, where the number of triplets used for training varies from 50 to 550. The remaining three categories had much fewer available triplets and the corresponding comparison results can be found in the supplementary material. Our method leads to higher accuracies in all cases with only two exceptions:

1. Furniture: Our method leads to lower accuracies than Lun et al. [Lun et al. 2015] on the furniture category. This is likely due to the fact that our method uses a different dataset and feature extraction method.
2. Textile: Our method leads to lower accuracies than Lun et al. [Lun et al. 2015] on the textile category. This is likely due to the fact that our method uses a different dataset and feature extraction method.
Fig. 18. A comparison on style ranking prediction accuracy with [Lun et al. 2015], over four of their object categories.

| Scene category | [Liu et al. 2015a] | Ours | % triplets |
|----------------|-------------------|------|-----------|
| living room    | 73%               | 85%  | 10%       |
| dining room    | 72%               | 74%  | 30%       |

Table 2. Comparing style ranking prediction accuracy with [Liu et al. 2015a] on their scene datasets. The last column shows % of style ranking triplets employed by our method for training as opposed to [Liu et al. 2015a].

| Category      | [Lim et al. 2016b] | Ours  |
|---------------|-------------------|-------|
| building      | 88.8%             | 96.1% |
| coffee set    | 89.2%             | 93.24%|
| column        | 98%               | 100%  |
| cutlery       | 81.2%             | 96.39%|
| dish          | 90.8%             | 97.47%|
| furniture     | 86.2%             | 100%  |
| lamp          | 88.5%             | 100%  |

Table 3. A comparison on style ranking prediction with [Lim et al. 2016b], over seven datasets from their paper.

the lamp and dish datasets. Our performance on the dish set is below that of Lun et al. [Lun et al. 2015] and we believe this is due to the fact that the dish shapes are mostly smooth and they lack line-type features, while our method relies only on features from projected line drawings. On the other hand, Lun et al. [Lun et al. 2015] employs a large set of features, including projective ones. For the lamp set, since it contains a large number of models and variations, it is conceivable that by relying on a more limited feature set, our semi-supervised learning would require more training to reach a performance plateau.

We also compare style ranking prediction accuracy with [Liu et al. 2015a] using the two scene datasets tested in their paper, as shown in Table 2. We do not use all the ranking triplets as in [Liu et al. 2015a]. Instead, we randomly sample a subset. As can be observed, with a relatively small percentage of triplets employed for training, our method is able to achieve comparable or better prediction accuracies.

In [Lim et al. 2016b], the authors propose to identify the style of 3D shapes based on deep metric learning. Their evaluations are performed on the same datasets as Lun et al. [2015]. Table 3 reports a comparison to [Lim et al. 2016b] on their seven object categories with the same triplets from [Lun et al. 2015] for training. Specifically, 550 triplets were used for the building, column, furniture and lamp set, 150 for the coffee set, and 100 for the cutlery and dish set. Their model was trained with only 3D shapes; no photo was used. Our method outperforms theirs for all sets except the dish one. The reason is that most dish models do not contain rich line features.

Style classification. We compare style classification results obtained using our method with those from the recent supervised method of Hu et al. [Hu et al. 2017], over the five datasets used in their work: 1) Furniture (618 models in 4 styles); 2) Furniture legs, (84 models and 3 styles); 3) Buildings (89 models in 5 styles); 4) Cars (85 models in 5 styles); 5) Drinking vessels (84 models in 3 styles).

Similar to their work, we run a classification experiment with a 10-fold cross-validation. However, there is a difference. They learned the sets of style-defining patches to represent shapes and train kNN classifiers for each style on 9 folds. We, instead, used 9 folds as style labels in our method. We evaluate the classification accuracy on the remaining fold for both methods. Finally, we compute the average accuracy for the 10 folds for all style labels in each set, based on the ground-truth labels provided in Hu et al. [Hu et al. 2017]; the results are shown in Figure 19. We can observe that our method outperforms theirs for all object categories except for buildings.

We believe that the general improvements over Hu et al. [Hu et al. 2017] on this task may be attributed to two factors. First, projected line drawings and their associated features may be more suitable for the kind of decorative styles and man-made shapes tested. Shape features considered in Hu et al. [Hu et al. 2017] could be severely degraded due to low mesh resolution, tessellation quality, and other geometric imperfections, while line drawings are most robust against these issues. Second, their method relies on mid-level 3D patches, which would only capture local geometry information. In contrast, our method captures both local and global information owing to the convolutional feature encoding which is known to be more apt at hierarchical feature learning.

Style patch localization. Finally, we compare our method with Hu et al. [Hu et al. 2017] on style patch localization, over their
Fig. 20. Visual comparison of style patches located by our method (right one in each pair) vs. those found by [Hu et al. 2017] (left one in each pair).

datasets, the same ones tested above for style classification. Since their method is supervised with given style clusters, we only compare the feature selection components of the two methods. That is, our method would take the same style clusters as input to their method.

Comparing patch localization is not straightforward since the located patches for each shape is not unique for either method. To simplify matters, we carry out the comparison on 19 representative style patches obtained by the method of Hu et al. [Hu et al. 2017]. These 19 patches come from 19 shapes (one patch per shape) encompassing all five object categories; they were selected and shown in Figure 11 of the paper. Hu et al. [Hu et al. 2017] qualified them as style patches that “capture distinctive characteristics of the styles.” For each of the 19 shapes, the representative style patch from our method is chosen as the one which is deemed to be a style patch over the most views.

Figure 20 shows a visual comparison on 10 out of the 19 shapes. We can observe that the style patches detected bear some similarities in general, but our style patches tend to be more feature-rich. The rest of the results can be found in the supplementary material.

For a quantitative comparison, we conducted a user study to evaluate the representative style patches found by the two methods on the 19 shapes. The study consists of 19 queries, one per shape. For each query, subjects were provided with the two style patches, marked as $A$ and $B$ and shaded in the same color, for the same shape. Then the subjects were asked to choose one of four possible answers in regards to the style patches: 1) Patch $A$ represents the shape style better; 2) Patch $B$ represents the shape style better; 3) Patches $A$ and $B$ both represent the shape style well; 4) Neither set of patches represents the shape style. For each test shape, our result and theirs are randomly ordered.

A total of 58 subjects participated in the study; these subjects are all students from various disciplines including computer science, architecture, arts, and information management. Results on a subset of (10 out of 19) shapes are shown in Figure 21, where the percentages of user selections for different answers are plotted; the remaining results are available from the supplementary material. It is quite evident that style patches extracted by our method were generally more favored by the human subjects.

5.3 Applications

**Style-aware mesh simplification.** Spatial localization of style patches allows a simple scheme to be developed for style-aware mesh simplification. The main extra step, after obtaining the style patches from our current method, is to extend the few style patch samples returned to entire style regions. Then, we can apply a constrained version of quadric-based mesh simplification [Garland and Heckbert 1997] while keeping the style regions in tact. Figure 22 shows some results, where the number of triangles (after 70% reduction) are the same for the simplified models with and without preserving styles. Apparently, style-aware simplified models better resemble original models style-wise and have larger triangles over flat areas highlighted by red boxes.

For the patch-to-region extension, all we need to do is to compare the initially sampled patches (see Section 4.1) with the detected style patches and then mark all those with HOG-space similarity above a threshold as stylistic. All the style patches are finally back-projected to the 3D shape to aggregate into style regions over the shape.
improve style region boundaries, we re-sample three times as many initial patches as before to increase the resolution.

**Style-aware view selection.** Another application for spatial localization of style patches is style-aware view selection, where views that are deemed to be most style-revealing for a 3D object are identified. After style patches are obtained as discussed in Section 4.5, we use them to first detect similar (initially sampled) patches in HOG space for each considered view. We then select the view that has the maximum number of patches that are sufficiently similar to the style patches. Figure 23 shows some of the best object views obtained this way, as opposed to other views.

We compare our style-aware best view selection with human judgment. For a test 3D model, we let 58 human subjects select, among the 12 views employed in our multi-view style analysis, which one provides the “best view” for the model. In Figure 24, we show the percentage of subject votes for each view, for five selected 3D models. The results of this study reveal that our simple best view selection based on extracted decorative shape styles tends to obtain the same or close views as the human subjects would.

**Style-aware furniture recommendation.** Style similarities resulting from our analysis can enable a style-aware furniture recommendation application, much like the one developed in [Liu et al. 2015a]. Specifically, furniture pieces can be retrieved from a shape repository to populate a scene based on style similarity (see Figure 25).

To verify the effectiveness of the style similarity measure obtained from our work, we conduct a user study where human participants were asked to choose the scene containing furniture pieces that possess the highest level of style compatibility among a triplet of 3D scenes. In each scene, one of the furniture pieces is recommended. Among the triplet, one scene is randomly arranged, one has the recommendation given by human users, and one has the recommendation selected as the furniture piece whose style is the closest match with other furniture pieces in the scene. The study consists of 17 scene triplets, all randomly sorted, and 58 human participants to make scene selections. Figure 26 shows the scene selection results from the user study, demonstrating that style-aware furniture recommendation using our style similarity performs comparably with human recommendation. All the scenes used in the study can be found in the supplementary material.

**3D architectural style identification based on 2D sketches.** Architectural styles are commonly documented with the help of

Fig. 22. Style-aware mesh simplification. (a) Original mesh models with style patches. (b-c) Shaded and wireframe versions of simplified models with style preservation via constrained quadric-based decimation; red boxes highlight significant triangle reduction near non-style areas. (d-e) Simplified models without style preservation, via unconstrained quadric-based decimation.

Fig. 23. Style-aware view selection. For each 3D model, we show it, as projected line drawings, in the 12 views employed by our multi-view style analysis method. Detected style patches and those deemed to be similar to them are shown in red boxes. The best view, one with the most red boxes, is highlighted by a blue box, and also shown in the left column.
We propose what we believe to be the first semi-supervised method. At the bottom, we show best views selected by human subjects, which can be contrasted with the best views found by our method in Figure 23.

2D sketches in professional architecture books. Figure 27 shows 16 examples of 160 building drawings collected from the Internet, in four styles: Asia, Byzantine, Gothic and Greece. More drawings can be found in the supplemental material. It is sometimes desirable to identify the architectural style of a 3D building based on professional 2D drawings. The projective learning nature of our method enables such a cross-modality style recognition task. We use our method to select the representative style patches and extract feature for each 2D sketch. Given a test 3D shape, we project it into 12-view line drawings and find the closest 2D sketch for each view, based on Euclidean feature distance. Each view casts a vote to its closest style and the style receiving the most votes is output. One can also compare the representative style patches in 2D sketches to the sampled patches on each view based on HOG features, to locate the style patches and back-project them onto the 3D surfaces.

We use our building models to test style prediction and style patch location. A sample of results are shown in Figure 28. The style prediction accuracy is 71.4%, which is slightly lower than the 74.77% by our unsupervised style clustering with feature fusion. The reasons include: 1) We did not use fused feature since each building sketch in the training set has only one view; 2) The building sketches may have different views than our projections; 3) The building sketches contain richer lines than our projected line drawings.

6 CONCLUSIONS AND FUTURE WORK

We propose what we believe to be the first semi-supervised method for analyzing and locating decorative style patches on 3D shapes. Our technique utilizes projective line drawings and multi-view feature encoding for style clustering and patch extraction. Our semi-supervision is able to take on the same kind of input, namely, crowd-sourced style ranking triplets, as recent works on style metric learning [Liu et al. 2015a; Lun et al. 2015]. We have shown that comparable accuracy on style similarity tests can be attained by our method with less user input than these recent works. As well, we have demonstrated improvements on style classification and style patch localization over the most recent work by Hu et al. [Hu et al. 2017].

One of the main limitations of our current style analysis is that by design, it can only extract stylistic elements that are visually apparent in projected images and localized to the patch level. These do not include stylistic arrangement of patterns such as those involving symmetries and repetitions. The main difficulty is that these more global and structural styles may not be fully visible in projected images. Technically, our final style patch extraction hinges on the initial pre-selection of representative feature patches. In addition, for feature-lacking shapes such as a smooth dish or spoon, projected line drawings cannot be expected to reveal sufficient stylistic elements. Without sufficient features, our method may lead to undesirable constrained clustering results.

With the scale of style datasets becoming larger, deep learning will work better on style analysis. However, when the amount of labeled data is small, like in our case, deep learning cannot work well. We have shown that comparable accuracy on style similarity tests can be attained by our method than recent deep learning work Lim et al. [Lim et al. 2016b] on limited style datasets. The main reason why our method works well on relatively small datasets is due to the multi-view feature fusion power of PSLF. On the other hand, our method supports unsupervised and semi-supervised style analysis, in contrast to deep learning which is so far mainly for supervised learning tasks. With our method, we can collect more high-quality labeled data, which can potentially serve for future deep learning research.

Beyond style-aware shape simplification and view selection, we believe that there is more to explore on the application front for style patch localization. The ability to identify these patches spatially allows them to be directly manipulated and applied. For example, style patches found on the legs of one chair can be transplanted [Takayama et al. 2011] to the legs of another piece of furniture. Also, the style patches can be isolated and encoded as details over base patches to form a library of style templates. These are both style transfer tasks. In addition, once we have a set of style patches in possession, we can identify or retrieve more patches from novel 3D shapes simply based on geometric similarities, either over shape surfaces or in projective space. Finally, it would be interesting to extend our style analysis to 3D scenes.

REFERENCES

Aayush Bansal, Abhinav Shrivastava, Carl Doersch, and Abhinav Gupta. 2015. Mid-level Elements for Object Detection. arXiv preprint arXiv:1504.07284 (2015).

Kamalika Chaudhuri, Sham M Kakade, Karen Livinscu, and Karthik Sridharan. 2009. Multi-view clustering via canonical correlation analysis. In Proc. Int. Conf. on Machine Learning. 129–136.

D.Y. Chen, X.P. Tian, Y.T. Shen, and M. Oshioyoung. 2003. On visual similarity based 3D model retrieval. Computer Graphics Forum 22, 3 (2003), 223–232.

Yanhua Chen, Manjeet Rege, Ming Dong, and Jing Hua. 2008. Non-negative matrix factorization for semi-supervised data clustering. Knowledge and Information Systems 17, 3 (2008), 355–379.

Navneet Dalal and Bill Triggs. 2005. Histograms of oriented gradients for human detection. In Proc. CVPR, Vol. 1. IEEE, 886–893.

Doug DeCarlo, Adam Finkelstein, Szymon Rusinkiewicz, and Anthony Santella. 2003. Suggestive contours for conveying shape. ACM Trans. on Graph. (SIGGRAPH) 22, 3 (2003), 848–855.
Yu, F. et al. 2013. Mid-level visual element discovery as discriminative mode seeking. In Proc. NIPS. 494–502.

Jeff Donahue, Yangqing Jia, Oriol Vinyals, Judy Hoffman, Ning Zhang, Eric Tzeng, and Trevor Darrell. 2013. Decaf: A deep convolutional activation feature for generic visual recognition. arXiv preprint arXiv:1310.1531 (2013).

Ran Gal, Olga Sorkine, Niloy J Mitra, and Daniel Cohen-Or. 2009. iWires: an analyze-and-edit approach to shape manipulation. ACM Trans. on Graph. (SIGGRAPH) 28, 3 (2009), 33.

Elena Garces, Aseem Agarwala, Diego Gutierrez, and Aaron Hertzmann. 2014. A Similarity Measure for Illustration Style. ACM Trans. on Graph. 33, 4 (2014), 93:1–9.

Michael Garland and Paul S. Heckbert. 1997. Surface simplification using quadric error metrics. In Conference on Computer Graphics and Interactive Techniques. 209–216.

Yunchao Gong, Liwei Wang, Ruixi Guo, and Svetlana Lazebnik. 2014. Multi-scale orderless pooling of deep convolutional activation features. In Computer Vision–ECCV 2014. Springer, 392–407.

Ruizhen Hu, Wenchao Li, Oliver Van Kaick, Hui Huang, Melinos Averkiou, Daniel Cohen-Or, and Hao Zhang. 2017. Co-Locating Style-Defining Elements on 3D Shapes. ACM Transactions on Graphics (2017).

QXing Huang, Hao Su, and Leonidas Guibas. 2013. Fine-grained semi-supervised labeling of large shape collections. ACM Trans. on Graph. 32, 6 (2013), 190.

Ian Jolliffe. 2002. Principal component analysis. Wiley Online Library.

Carl Doersch, Abhinav Gupta, and Alexei A Efros. 2013. Mid-level visual element discovery as discriminative mode seeking. In Proc. NIPS. 494–502.

Jeff Donahue, Yangqing Jia, Oriol Vinyals, Judy Hoffman, Ning Zhang, Eric Tzeng, and Trevor Darrell. 2013. Decaf: A deep convolutional activation feature for generic visual recognition. arXiv preprint arXiv:1310.1531 (2013).

Ran Gal, Olga Sorkine, Niloy J Mitra, and Daniel Cohen-Or. 2009. iWires: an analyze-and-edit approach to shape manipulation. ACM Trans. on Graph. (SIGGRAPH) 28, 3 (2009), 33.

Elena Garces, Aseem Agarwala, Diego Gutierrez, and Aaron Hertzmann. 2014. A Similarity Measure for Illustration Style. ACM Trans. on Graph. 33, 4 (2014), 93:1–9.

Michael Garland and Paul S. Heckbert. 1997. Surface simplification using quadric error metrics. In Conference on Computer Graphics and Interactive Techniques. 209–216.

Yunchao Gong, Liwei Wang, Ruixi Guo, and Svetlana Lazebnik. 2014. Multi-scale orderless pooling of deep convolutional activation features. In Computer Vision–ECCV 2014. Springer, 392–407.

Ruizhen Hu, Wenchao Li, Oliver Van Kaick, Hui Huang, Melinos Averkiou, Daniel Cohen-Or, and Hao Zhang. 2017. Co-Locating Style-Defining Elements on 3D Shapes. ACM Transactions on Graphics (2017).

QXing Huang, Hao Su, and Leonidas Guibas. 2013. Fine-grained semi-supervised labeling of large shape collections. ACM Trans. on Graph. 32, 6 (2013), 190.

Ian Jolliffe. 2002. Principal component analysis. Wiley Online Library.

Carl Doersch, Abhinav Gupta, and Alexei A Efros. 2013. Mid-level visual element discovery as discriminative mode seeking. In Proc. NIPS. 494–502.

Jeff Donahue, Yangqing Jia, Oriol Vinyals, Judy Hoffman, Ning Zhang, Eric Tzeng, and Trevor Darrell. 2013. Decaf: A deep convolutional activation feature for generic visual recognition. arXiv preprint arXiv:1310.1531 (2013).

Ran Gal, Olga Sorkine, Niloy J Mitra, and Daniel Cohen-Or. 2009. iWires: an analyze-and-edit approach to shape manipulation. ACM Trans. on Graph. (SIGGRAPH) 28, 3 (2009), 33.

Elena Garces, Aseem Agarwala, Diego Gutierrez, and Aaron Hertzmann. 2014. A Similarity Measure for Illustration Style. ACM Trans. on Graph. 33, 4 (2014), 93:1–9.

Michael Garland and Paul S. Heckbert. 1997. Surface simplification using quadric error metrics. In Conference on Computer Graphics and Interactive Techniques. 209–216.

Yunchao Gong, Liwei Wang, Ruixi Guo, and Svetlana Lazebnik. 2014. Multi-scale orderless pooling of deep convolutional activation features. In Computer Vision–ECCV 2014. Springer, 392–407.

Ruizhen Hu, Wenchao Li, Oliver Van Kaick, Hui Huang, Melinos Averkiou, Daniel Cohen-Or, and Hao Zhang. 2017. Co-Locating Style-Defining Elements on 3D Shapes. ACM Transactions on Graphics (2017).

QXing Huang, Hao Su, and Leonidas Guibas. 2013. Fine-grained semi-supervised labeling of large shape collections. ACM Trans. on Graph. 32, 6 (2013), 190.

Ian Jolliffe. 2002. Principal component analysis. Wiley Online Library.

Carl Doersch, Abhinav Gupta, and Alexei A Efros. 2013. Mid-level visual element discovery as discriminative mode seeking. In Proc. NIPS. 494–502.

Jeff Donahue, Yangqing Jia, Oriol Vinyals, Judy Hoffman, Ning Zhang, Eric Tzeng, and Trevor Darrell. 2013. Decaf: A deep convolutional activation feature for generic visual recognition. arXiv preprint arXiv:1310.1531 (2013).

Ran Gal, Olga Sorkine, Niloy J Mitra, and Daniel Cohen-Or. 2009. iWires: an analyze-and-edit approach to shape manipulation. ACM Trans. on Graph. (SIGGRAPH) 28, 3 (2009), 33.

Elena Garces, Aseem Agarwala, Diego Gutierrez, and Aaron Hertzmann. 2014. A Similarity Measure for Illustration Style. ACM Trans. on Graph. 33, 4 (2014), 93:1–9.

Michael Garland and Paul S. Heckbert. 1997. Surface simplification using quadric error metrics. In Conference on Computer Graphics and Interactive Techniques. 209–216.

Yunchao Gong, Liwei Wang, Ruixi Guo, and Svetlana Lazebnik. 2014. Multi-scale orderless pooling of deep convolutional activation features. In Computer Vision–ECCV 2014. Springer, 392–407.

Ruizhen Hu, Wenchao Li, Oliver Van Kaick, Hui Huang, Melinos Averkiou, Daniel Cohen-Or, and Hao Zhang. 2017. Co-Locating Style-Defining Elements on 3D Shapes. ACM Transactions on Graphics (2017).

QXing Huang, Hao Su, and Leonidas Guibas. 2013. Fine-grained semi-supervised labeling of large shape collections. ACM Trans. on Graph. 32, 6 (2013), 190.

Ian Jolliffe. 2002. Principal component analysis. Wiley Online Library.

Elena Garces, Aseem Agarwala, Diego Gutierrez, and Aaron Hertzmann. 2014. A Similarity Measure for Illustration Style. ACM Trans. on Graph. 33, 4 (2014), 93:1–9.

Michael Garland and Paul S. Heckbert. 1997. Surface simplification using quadric error metrics. In Conference on Computer Graphics and Interactive Techniques. 209–216.

Yunchao Gong, Liwei Wang, Ruixi Guo, and Svetlana Lazebnik. 2014. Multi-scale orderless pooling of deep convolutional activation features. In Computer Vision–ECCV 2014. Springer, 392–407.

Ruizhen Hu, Wenchao Li, Oliver Van Kaick, Hui Huang, Melinos Averkiou, Daniel Cohen-Or, and Hao Zhang. 2017. Co-Locating Style-Defining Elements on 3D Shapes. ACM Transactions on Graphics (2017).

QXing Huang, Hao Su, and Leonidas Guibas. 2013. Fine-grained semi-supervised labeling of large shape collections. ACM Trans. on Graph. 32, 6 (2013), 190.

Ian Jolliffe. 2002. Principal component analysis. Wiley Online Library.
Semi-Supervised Co-Analysis of 3D Shape Styles from Projected Lines

Kai Xu, Honghua Li, Hao Zhang, Daniel Cohen-Or, Yueshan Xiong, and Zhi-Quan Cheng. 2010. Style-content separation by anisotropic part scales. ACM Trans. on Graph. 29, 6 (2010), 184:1–184:10.

Kai Xu, Rui Ma, Hao Zhang, Chenyang Zhu, Ariel Shamir, Daniel Cohen-Or, and Hui Huang. 2014. Organizing heterogeneous scene collections through contextual focal points. ACM Trans. on Graph. 33, 4 (2014), 35.

Matthew D Zeller and Rob Fergus. 2014. Visualizing and understanding convolutional networks. In Computer Vision–ECCV 2014 Springer, 818–833.

L. Zelnik-Manor. 2004. Self-tuning spectral clustering. Advances in Neural Information Processing Systems 17 (2004), 1601–1608.

Yawei Zhao, Kai Xu, En Zhu, Xinwang Liu, Xinzhong Zhu, and Jianping Yin. 2018. Triangle lasso for simultaneous clustering and optimization in graph datasets. IEEE Transactions on Knowledge and Data Engineering 31, 8 (2018), 1616–1623.

Chenyang Zhu, Kai Xu, Siddhartha Chaudhuri, Renjiao Yi, and Hao Zhang. 2018. SCORES: Shape composition with recursive substructure priors. ACM Transactions on Graphics (TOG) 37, 6 (2018), 1–14.

Fig. 28. Examples of style prediction(label below shape) and style prediction(orange rendered).

Daniel Lee and Sebastian Seung. 1999. Learning the parts of objects by non-negative matrix factorization. Nature 401, 6755 (1999), 788–791.

Yong Jae Lee, Alexei Efros, and Martial Hebert. 2013. Style-aware mid-level representation for discovering visual connections in space and time. In Proc. ICCV. 1857–1864.

Honghua Li, Hao Zhang, Yanzhen Wang, Junjie Cao, Ariel Shamir, and Daniel Cohen-Or. 2013. Curve style analysis in a set of shapes. Computer Graphics Forum 32, 6 (2013), 77–88.

Yao Li, Lingqiao Liu, Chunhua Shen, and Van Den Hengel Anton. 2015. Mid-level deep pattern mining. In Proc. CVPR. 971–980.

Isaak Lim, Anne Gehre, and Leif Kobbelt. 2016a. Identifying Style of 3D Shapes using Deep Metric Learning. Computer Graphics Forum 5 (2016).

Isaak Lim, Anne Gehre, and Leif Kobbelt. 2016b. Identifying Style of 3D Shapes using Deep Metric Learning. Computer Graphics Forum 35, 5 (2016), 207–215.

Haifeng Liu and Zhaohui Wu. 2010. Non-negative matrix factorization with constraints. In Twenty-Fourth AAAI Conference on Artificial Intelligence. 506–511.

Jing Liu, Yu Jiang, Zechao Li, Zhi Hua Zhou, and Hanqing Lu. 2013b. Partially Shared Latent Factor Learning With Multiview Data. IEEE Trans. on Neural Networks & Learning Systems 26 (2015), 1233–1246.

Tianqiang Liu, Aaron Hertzmann, Wilnot Li, and Thomas Funkhouser. 2015a. Style Compatibility for 3D Furniture Models. ACM Trans. on Graph. 34, 4 (2015), 85:1–85:9.

Zhaoliang Lun, Evangelos Kalogerakis, Rui Wang, and Alla Sheffer. 2016. Functionality Preserving Shape Style Transfer. ACM Trans. on Graph. 35, 6 (2016), 209:1–209:14.

Zhaoliang Lun, Evangelos Kalogerakis, and Alla Sheffer. 2015. Elements of style: learning perceptual shape style similarity. ACM Trans. on Graph. 34, 4 (2015), 84:1–84:14.

Chongyang Ma, Haibin Huang, Alla Sheffer, Evangelos Kalogerakis, and Rui Wang. 2014. Analogy-driven 3D style transfer. Computer Graphics Forum 33, 2 (2014), 175–184.

Niyol Mitra, Michael Wand, Hao (Richard) Zhang, Daniel Cohen-Or, Vladimir Kim, and Qi-Xing Huang. 2013. Structure-aware Shape Processing. In SIGGRAPH Asia 2013 Courses. 1:1–1:20.

John. Morley. 1999. The history of furniture : twenty-five centuries of style and design in the Western tradition. (1999).

M. Raptis, I. Kokkinos, and S. Soatto. 2012. Discovering discriminative action parts from mid-level video representations. In Proc. CVPR. 1242–1249.

Ali S Razavian, Hossein Azizpour, Josephine Sullivan, and Stefan Carlsson. 2014. CNN features off-the-shelf: an astounding baseline for recognition. In IEEE CVPR Workshop. IEEE. 512–519.

Szymon Rusinkiewicz, Forrester Cole, Doug DeCarlo, and Adam Finkelstein. 2008. Line Drawings from 3D Models. In SIGGRAPH Course.

Bilge Sayim and Patrick Cavanagh. 2011. What Line Drawings Reveal About the Visual Brain. Frontiers in Human Neuroscience 5 (2011), 118:1–118:4.

Karen Simonyan and Andrew Zisserman. 2014. Very Deep Convolutional Networks for Large-Scale Image Recognition. Computer Science (2014).

Saurabh Singh, Abhinav Gupta, and Alexei Efros. 2012. Unsupervised discovery of mid-level discriminative patches. Computer Vision–ECCV 2012 (2012), 73–86.

Hang Su, Subhramanyam Maji, Evangelos Kalogerakis, and Erik Learned-Miller. 2015. Multi-view convolutional neural networks for 3D shape recognition. In Proceedings of the IEEE International Conference on Computer Vision. 945–953.

Kenshi Takayama, Ryan Schmidt, Karan Singh, Takeo Igarashi, Tamy Boubekeur, and Olga Sorkine. 2011. GeoBrush: Interactive Mesh Geometry Cloning. Computer Graphics Forum 30, 2 (2011), 633–622.

Shan Dong Wang, Zi Yang Ma, Xue Hui Liu, Yan Yun Chen, and En Hua Wu. 2013b. Coherence-enhancing line drawing for color images. Science China Information Sciences 56, 11 (2013), 1–11.

Yumai Wang, Mingjun Gong, Tianhua Wang, Daniel Cohen-Or, Hao Zhang, and Baowuan Chen. 2013a. Projective analysis for 3D shape segmentation. ACM Trans. on Graph. 32, 6 (2013), 192.

Wikipedia. 2016. Style (visual arts) — Wikipedia, The Free Encyclopedia. (2016). https://en.wikipedia.org/w/index.php?title=Style_%28visual_arts%29&oldid=713614541 [Online, accessed 7-May-2016].