ArtEvoViewer: A System for Visualizing Interpersonal Influence Among Painters

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***Abstract*—Large-scale and objective painting analyses have recently gained attention. In particular, analyzing influence between individual painters requires substantial effort and is hard to reproduce due to subjectivity. Despite increasing demand for automatic estimation, this remains unresolved because such influence is complex and often directional, making it difficult to model. In this paper, we develop an interactive system that visualizes, manipulates, and analyses chains of painterly influence as a network. Using 32,401 paintings, the system infers directional links from color and brushstroke features. The resulting network based on color style features captures stylistic lineages such as landscape-focused and portrait-focused streams, while a multifaceted analysis of Picasso shows that Cézanne's impact appears in brushwork rather than color. Our contributions are twofold: (1) the use of an evolutionary model to assign explicit direction to painter influence and support art historical interpretation, and (2) providing a visualization system that allows dynamic comparison of influence networks based on multiple image features.**

***Index Terms*—visualization, system, paintings, artist influence estimation, cultural evolution, digital humanities**

I. Introduction

Understanding the evolution of painting styles and techniques is a central problem in art history. Traditionally, art historians manually inferred painter relationships from historical and textual sources. However, such efforts are time-consuming and often rely on subjective interpretation. Recent image-processing and deep-learning advances have spurred a large scale, objective analyses of visual features. Painting evolution can be viewed from two perspectives: macroscopic changes shaped by historical and social contexts, and microscopic developments driven by interactions among artists. While the former has been addressed through methods such as style classification using convolutional neural networks (CNNs) and automated modeling of stylistic transitions [6], [9], studies that quantitatively analyze interpersonal influence remain limited.

Several studies have attempted to estimate painter relationships based on image similarity. Saleh et al. [21] analyzed similarities across multiple image features. Castellano et al. [4], [5] used CNNs to classify painters by period and constructed undirected graphs by linking artists whose works were visually similar. Narag and Soriano [19] inferred the influence from frequent misclassifications in style classification using VGG16 and ResNet, while Honna and Matsui [12] applied a similar approach to analyze relationships among ukiyo-e artists. Vinayavekhin et al. [23] combined Siamese Neural Networks with self-supervised learning to evaluate similarities between Japanese and Western paintings from the Meiji period.

Other studies have taken different approaches. Kitromilidis and Evans [15] constructed influence networks using textual data from Wikipedia, but their method relied solely on historical descriptions without incorporating image data. Li [16] visualized painter relationships based on iconographic similarities, yet did not account for stylistic or technical evolution. Schikora and Isemann [22] developed a tool called InfluViz to support the exploration of influence networks, although it does not perform inference on these relationships. While these works advanced the visualization of influence in art history, they did not address the flow or mechanism of stylistic transmission in quantitative terms.

A common limitation across these approaches is their reliance on image similarity. This leads to two major issues: (1) the temporal direction of influence is not explicitly modeled, and (2) differences in historical context or painter prominence are often ignored. Specifically, it is difficult to determine whether one style influences another, making causal relationships hard to identify. Also, important factors such as the time of creation and the prominence of the artist are not taken into account. Moreover, those studies often relied on limited datasets, raising concerns about coverage and objectivity. Moreover, from a practical perspective, supporting more flexible inquiry requires an interactive visualization system that enables exploratory analysis of influence relationships.

To address these challenges, this study adopts a twofold approach: (1) causal inference adapting the evolutionary model proposed by Nakamura et al. [18], and (2) the development of an interactive visualization system to explore these esti-

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mated influence relationships. The model quantifies stylistic inheritance based on the product of selection and transmission probabilities, enabling explicit modeling of influence flow. We propose a visualization system with the following capabilities:

- **Multifaceted network visualizations** such as multiple layouts and color schemes reveal structure at different scales.
- **Interactive exploration** such as ego-network, metadata, and artwork views allow detailed, painter-focused analysis.
- **Multiple features** such as switching between color and local features separates and highlights influence patterns tied to different visual elements.

This framework supports both hypothesis formulation and validation in historical art research, offering a quantitative and exploratory method that integrates art history with computer science.

II. Feature Extraction and Influence Estimation

This section first outlines the methods for extracting color style features and local style features from a large dataset of painting images. Subsequently, we describe the methodology to estimate influence relationships and to construct the corresponding network based on these features.

A. Dataset

In this study, we use oil painting images published on WikiArt.org as the dataset. Specifically, we target artworks labeled with the "Oil" tag and collect a total of 32,401 images. These images include works by 1,129 painters. Each image is associated with metadata including the year of creation, the artist's style, and nationality, which are used in later analyses. Each painter is associated with the average year of creation which are used for estimation II and for visualization in Section III.

B. Extraction of Color Style Features

To extract color features, we first downsample all images to 100×100 pixels to reduce computation time. We then perform color quantization, reducing each image to 40 representative colors. These consist of 4 grayscale tones evenly spaced in luminance and 36 hues uniformly distributed in the conical HSV space, chosen with human color perception in mind. Each image is thus represented as a 40-dimensional relative frequency vector.

Next, we represent each painter's color style as a multidimensional vector. We cluster all 40-dimensional vectors using a discrete mixture model [18], creating K style clusters. To determine the number of clusters, Nakamura et al. [18] used the influence estimation method (section II-D) to identify key painters. They then compared these with those cited by Gombrich [11] and found that $K = 20$ yielded the best match. Following this criterion, we also set $K = 20$. Each painting is assigned to a cluster, and the results are normalized per painter, yielding a 20-dimensional probability vector called the *color style features*.

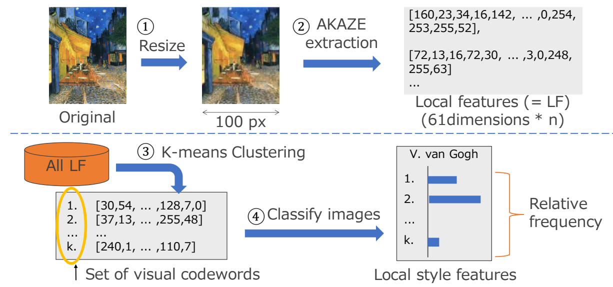

Fig. 1. Representation of painters' local styles. (Top) Calculation of local features for each painting image. (Bottom) Representation of each painter's local style features.

C. Extraction of Local Style Features

Local features are gradient vectors that capture local changes in color and brightness. We extract them using the Bag of Visual Words (BoVW) method [7], commonly used in image classification [2], [10]. BoVW clusters local features into visual codewords and describes each image by their relative frequencies.

As shown in Figure 1 (top), we first downsample all images so that the shorter side is 100 pixels (①). Then, keypoints and their corresponding descriptors are extracted using AKAZE (Accelerated-KAZE) [1], a local feature extraction method (②). We chose AKAZE because it offers both computational efficiency and robustness to changes in scale and rotation. Unlike SIFT [17] or SURF [3], it constructs a nonlinear scale space via anisotropic diffusion, preserving edges and textures more effectively. Each keypoint is represented by a 61-dimensional vector. Since the number of keypoints varies across images, we represent each image as a set of 61-dimensional feature vectors.

Next, we represent the local style of each painter as a multidimensional vector according to the steps shown in Figure 1 (bottom). A total of 638,999 local features from all images are clustered into L groups using the K-means algorithm to generate a set of visual codewords (③). Each feature is then assigned to its nearest codeword, and the assignment results are normalized for each painter to compute the relative frequency of each codeword (④). The resulting L-dimensional probability vector is referred to as the *local style features*. To determine the number of clusters L, we conducted experiments by varying L from 100 to 1500 in increments of 100 and evaluated the agreement with influence relationships documented in WikiArt. The evaluation was based on recall, precision, and F1-score calculated from 682 influence pairs. We set $L = 1300$, which yielded the best overall accuracy across all three metrics. The F1-score in this setting was 2.12%, showing an improvement over the 1.56% obtained using color style features.

D. Estimating Influence

In this study, we adopt the influence estimation method proposed by Nakamura et al. [18]. This method is characterized by computing stylistic similarity. It also probabilistically

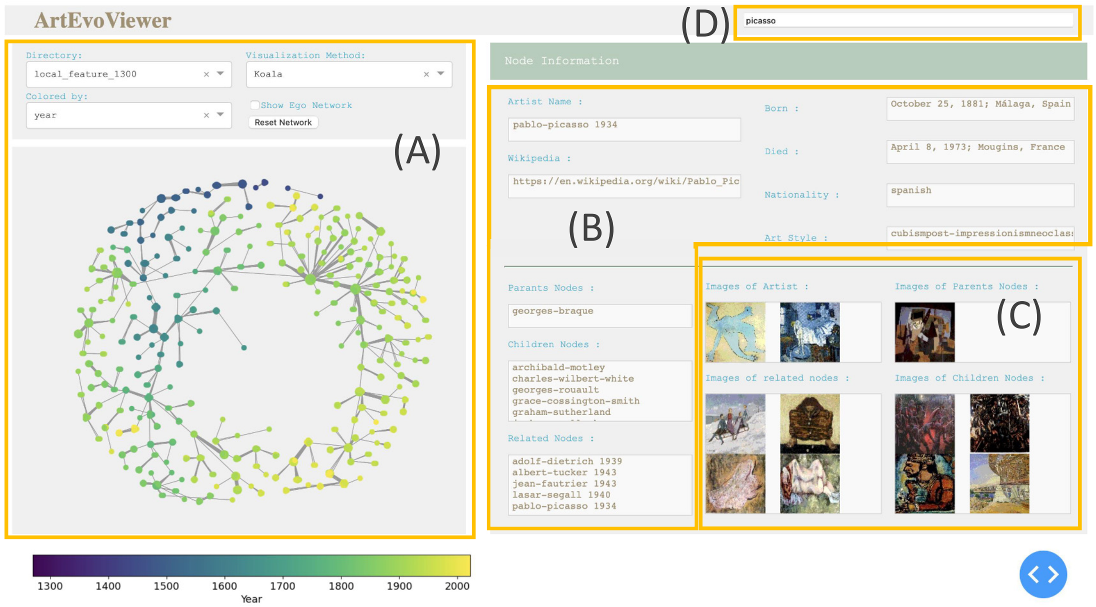

Fig. 2. Appearance of *ArtEvoViewer*. (A) Network visualization part. (B) Node metadata display part. (C) Artwork image display part. (D) Artist search part.

models the evolutionary process of art while accounting for various biases such as influence decay. The method assumes that artistic evolution occurs through the transmission of style features from one artist to another one. Let $\mathcal{A}$ denote the set of all painters in the dataset. For any pair of different painters $(a, a' \in \mathcal{A})$ such that painter a' chronologically prior to the painter a $(a \neq a')$, we formulate the influence of a' on a as the product of the two probabilities defined below. Here, π_a denotes the style feature vector of artist a, represented as a relative frequency vector of the features described in the previous sections.

- We denote the conditional probability $P_{\text{sel}}(a'|a)$ that painter a selects painter a' as an influencer.
- We denote the conditional probability distribution $P_{\text{trn}}(\pi_a|\pi_{a'})$ that the style feature distribution of painter a' is transmitted to painter a.

For detailed definitions of each expression, please refer to Nakamura et al [18]. By applying the expectation-maximization (EM) algorithm to this probabilistic model, we estimate both the selection probability P_{sel} and the transmission probability P_{trn} from a' to a. These probabilities are calculated for all possible pairs of a and a', and their product gives the posterior probability of a' given a.

The proposed method allows for flexibility in constructing the influence network, enabling either a single-parent or a multi-parent configuration. In the single-parent setting, only the artist a' with the highest posterior probability is selected and connected to artist a. In the multi-parent setting, the top k artists are selected, and each is connected to a via an influence edge. By applying this procedure to all artists, we can form either a tree structure or a general network.

III. ArtEvoViewer - Visualization System

This section presents a visualization system for displaying and analyzing painter networks. The system, *ArtEvoViewer*, is specifically designed for painting analysis and provides both interactive network exploration and metadata presentation. In this study, from the network constructed in Section II, only one parent node with the maximum posterior probability for each painter is retained $(k = 1)$ to form a tree structure. *ArtEvoViewer* visualizes this thinned network. Figure 2 shows an overview of the system interface.

A. Network Visualization

Figure 2(A) presents a visualization of the painter network constructed in Section II. As shown in the control panel at the top of Figure 2(A), users can switch between different visualization methods, network color schemes, and the types of features used for influence estimation (either color style features or local style features).

1) Visualization Methods Selection: We have implemented three network visualization approaches, each with its strengths, to provide a multifaceted analysis of the constructed network. Figure 3 presents examples of network displays produced by these methods. The implemented visualization approaches are:

1) **Koala** [14] clusters nodes to identify “influencers” who impacted many other painters. Each node is partitioned according to the similarity of its attributes and neighbouring nodes.
2) **RadialTree** arranges nodes in circles by century, allowing the viewer to see influence relationships across eras.
3) **HierarchyTree / HierarchyTreeYear** highlights the hierarchical structure of the network. This helps users understand the flow of artistic influence more intuitively.

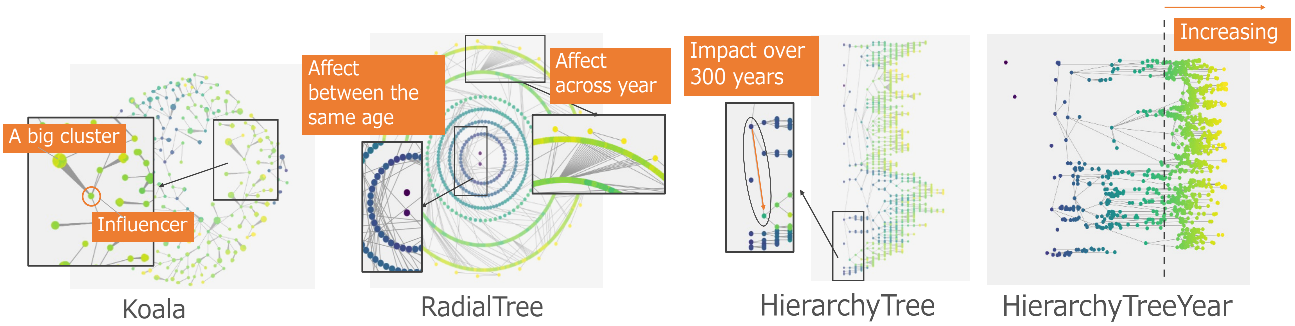

Fig. 3. Implemented visualization methods.

Figure 2 shows an example network generated with Koala [14]. By switching the visualization method, users can analyze the same network from multiple perspectives.

2) Coloring Selection: We offer three types of color schemes for the network. Figure 4 presents examples of network color schemes.

1) **year** assigns node colors based on each painter's average creation year, using the *viridis* colormap provided in Matplotlib [13], with a gradient from purple (older) to yellow (recent).
2) **art_style** assigns colors according to artistic styles from WikiArt. The top 17 styles listed in Fig 4 ($\geq 2\%$ of the dataset) use the *tab20b* colormap provided by Matplotlib [13]; the rest are grouped as "other".
3) **nationality** assigns colors based on nationalities in WikiArt. The top 13 nationalities listed in Fig 4 ($\geq 2\%$) use a custom colormap; the rest are grouped as "other".

Switching among these color schemes reveals how painters are distributed according to era, style, or nationality.

3) Ego Network Display: In addition, checking the "Show Ego Network" checkbox activates an ego network view [8], which limits the display to the clicked node, its ancestors (up to the root), and its descendants (down to the leaves). In our approach, which involves many painters, an ego network is effective for tracing individual lines of influence. Figure 5 shows an example of an ego network. This display illustrates the influence relationships associated with a specific painter.

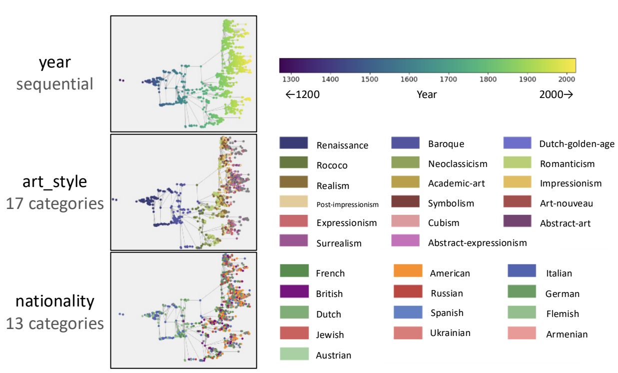

Fig. 4. Examples and legends of color scheme.

4) Network Interactions: As shown in the lower portion of Figure 2(A), *ArtEvoViewer* renders the network constructed by the procedure described in Section II. The depiction is based on the node coordinates computed by the selected visualization method. Users can interact with the network by hovering or clicking on nodes to view painter metadata, as well as through panning and zooming to explore the layout more effectively.

B. Node Metadata Display

Figure 2(B) provides an area for displaying metadata about the currently selected painter. This metadata is obtained from WikiArt.org and includes the following:

- Painter's name
- Average creation year of works
- Date and place of birth and death
- Nationality
- Painting style
- Wikipedia link
- Names of parent and child nodes in the network

C. Artwork Display

In Figure 2(C), the works of the painter corresponding to the selected node are displayed. By clicking the painter's node in the network visualization, up to 12 artworks created by the painter are shown. In addition, the system displays one work each from the painter's parent and child nodes, representing the influencer and the influenced artists, respectively.

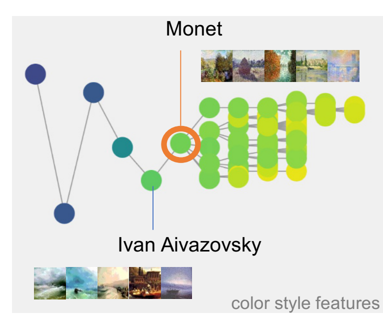

Fig. 5. Example of an ego network. The figure displays an ego network with Monet's color style features.

D. Painter Search

In Figure 2(D), when a painter's name is entered, the system highlights the corresponding node(s) in red. This functionality makes it easier to focus the analysis on a specific painter.

IV. Analysis and Discussion

We here examine networks visualized in *ArtEvoViewer* and perform our analysis on the observations we have made.

A. Analysis of Network Overview

First, we analyze artistic trends across the entire painter network using the visualization and color scheme switching functions implemented in *ArtEvoViewer* (Sections III-A1 and III-A2). Figure 6 shows a visualization of the network based on color style features, using HierarchyTreeYear as the visualization method and art_style as the color scheme. The figure (A-1) and (A-2) reveals two major lineages, rooted at Filippo Lippi and Jan van Eyck. As shown in Figure 6 (B-1), in the Lippi lineage, landscape painting is prominent. Although few painters appeared during the Renaissance and Baroque periods, their numbers grew from the Rococo through Romanticism, and surged by the time of Impressionism.

Meanwhile, as shown in Figure 6 (B-2), the lineage rooted in Jan van Eyck includes many portrait painters. According to the color circles in the figure, although outdoor religious scenes dominate the Renaissance, portraiture grows notably from the late Renaissance to the Baroque period. During the Baroque era, religious motifs persisted, but more works used indoor light sources, reflecting shifts in lighting techniques. From Rococo to Romanticism, court portraits and historical paintings gain prominence, followed by the rise of Academic-art and Realism.

These trends are consistent with familiar historical accounts of art. Examples include the dominance of religious and portrait subjects in the Renaissance and Baroque periods, the Baroque focus on interior lighting. In the early 20th century, innovations in color pigments spurred landscape painting, accompanied by the rise of Impressionism. In contrast, networks based on local features reveal these patterns less clearly, suggesting that color style features offer a more faithful reflection of historical artistic developments.

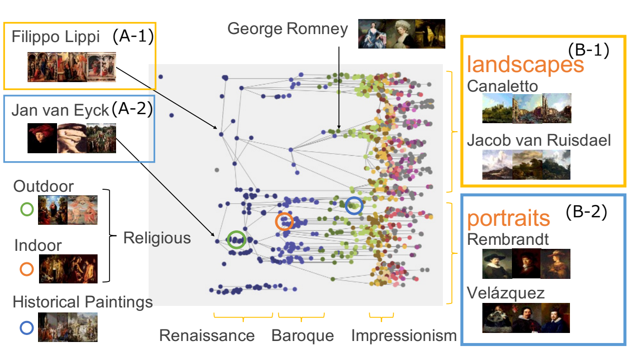

Fig. 6. Network of color style features. The visualization method is set to HierarchyTreeYear and the color scheme to art_style.

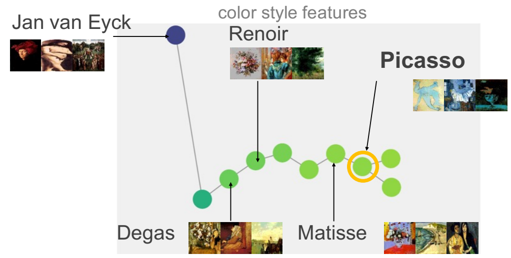

Fig. 7. Picasso's ego network based on color style features.

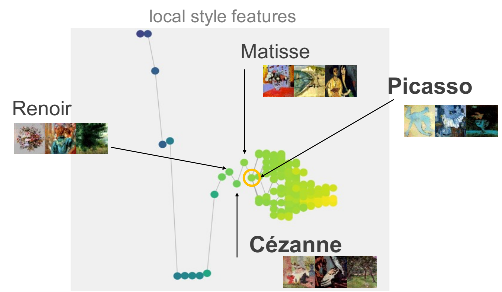

Fig. 8. Picasso's ego network based on local style features.

In addition, some painters in the Filippo Lippi lineage primarily produced portraits. George Romney, an 18th-century English portraitist, serves as one such example. Closer inspection of Romney's works reveals a notable use of landscapes as background elements, which may have led the system to place him within the group mainly composed of landscape painters.

B. Analysis Focused on Individuals

Next, we conduct a detailed analysis of an individual painter using the painter search function described in Section III-D and the ego network visualization described in Section III-A3. As a case study, we focus on Pablo Picasso, a representative artist of the 20th century, who exhibited notable differences between the networks based on color style features and those based on local style features. First, we set the visualization method to HierarchyTree and applied the year color scheme to display the network constructed from color style features. Using the search function to locate Picasso's node and displaying his ego network, we visualized the flow of artistic influence surrounding him, as shown in Figure 7.

The ego network in Figure 7 reveals a lineage beginning with Jan van Eyck, passing through Edgar Degas and Pierre-Auguste Renoir, and ultimately reaching Henri Matisse, who appears to have influenced Picasso. Notably, the sequence from Renoir onward aligns with descriptions found in WikiArt, thereby supporting the historical art understanding that Picasso was influenced by both Matisse and Renoir.

In contrast, Paul Cézanne, who is widely regarded as a major influence on Picasso and a pioneer of Cubism, did not exhibit a direct connection to Picasso in the network of color style features. This result suggests that Cézanne's influence on Picasso may have originated from features other than color.

Figure 8 displays the network based on local style features, where Cézanne appears within Picasso's ego network. Given that local style features represent aspects such as brushstrokes and patterns, this finding is consistent with the widely accepted historical art view that Picasso was influenced by Cézanne's perspective of representing objects in a cubist manner. This result highlights the effectiveness of analyzing each feature type in capturing the diversity of artistic influences.

V. Conclusion

In this study, we make two contributions: (1) we apply an evolutionary model that assigns direction to the influence between painters, and (2) we develop *ArtEvoViewer*, an interactive system that lets users switch between networks constructed from color style features and local style features, enabling direct comparison.

The analysis of the overall network revealed two major lineages—one stemming from Filippo Lippi, focusing on landscapes, and the other one from Jan van Eyck, centered on portraiture. These findings suggest that networks based on color style features can capture historical art trends reflecting thematic shifts over time.

A detailed analysis of Picasso showed that his links to Matisse and Renoir were evident in the networks based on color style features, while his connection to Cézanne emerged only through local style features. As local style features reflect brushwork and form, this suggests that Cézanne's influence on Picasso was rooted in these aspects rather than in color. These findings highlight the importance of incorporating multiple feature types to comprehensively understand stylistic and technical evolution.

Future work includes enhancing the network by incorporating semantic features from deep learning models such as CLIP [20], enabling the integration of techniques and themes. Comparing networks based on different features will help clarify their respective strengths. We also plan to add evaluation functions to *ArtEvoViewer* to support interpretation from the user's perspective.

These efforts aim to develop the system into a practical tool for analyzing artistic influences. By collaborating with art historians, we will evaluate its academic and practical value. We are preparing a pilot user study with a collaborator who is knowledgeable about art. The *ArtEvoViewer* is also adaptable to other domains with limited data, such as ceramics and swords, towards a general method for tracing the evolution of cultural heritage.

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