

# *Categories of Art and Computers: A Question of Artistic Style*

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Artistic style plays a critical role in our commerce with artworks. Artworks are artifacts that mediate a complex communicative exchange between artists and consumers, or more broadly among members of an artistic community. Artistic style is a perceptible quality of the appearance of an artwork that enables us to recognize it as belonging to one category of art or another. Artistic style refers, in the most general sense, to patterns of regularity in the manner in which artworks are made, in the way their subject matter has been rendered, that facilitate grouping them together into categories by period, geography, schools, movements, artist, or period in an artist's life. This is important. Categories of art are defined by sets of normative conventions governing the production and appreciation of works of different types. Artistic style is a cue to a set of recipes for engaging with a work, for understanding what it means to have rendered its subject matter in a particular way, and for evaluating whether what has been done has been done well or poorly. Knowledge of categories of art provides access to the point, purpose, or meaning of a work. Impressionist paintings, for instance, are marked off by their subject matter and the manner in which they are rendered. They capture the dynamic, fleeting, momentary, pedestrian yet extraordinary qualities of the appearances of everyday scenes in loose, dynamic brushstrokes. Recognizing that a painting is an Impressionist painting, that it was constructed following the productive conventions for that category of art, alerts consumers to what they should attend to and how they should understand what they consequently perceive. Artistic style is therefore a critical, if not the critical, clue to how to understand, evaluate, and appreciate any given artwork on the fly in its immediate presence.

We recognize artistic style in the shape of the marks used to render its content. This quality of a work reveals systematic commonalities in the ways that artists of a period, school, or movement work their materials. It also reveals the unique gestures that define the works of individual artists. We find it in Velazquez' brushstrokes, the dynamic gestures of Rodin's sculptures, and the staccato biomechanics of Cunningham's dancers. We find it in Reinhardt and Albers' abstract painting, Brancusi and Boccioni's dynamic Futurist sculptures, Warhol's soup cans, Bechtel's suburban street scenes, Downes' urban landscapes, Estes' Superrealist paintings of bridges, and Ashley Bickerton's Pop Art Minimalist constructions. Meyer Schapiro captures this quality of artworks when he says, "...style is, above all, a system of forms with a quality and a meaningful expression through which the personality of the artist and the broad outlook of a group are visible" (Schapiro, 1953, p. 51).

The trouble is that, despite the productive role it plays in our engagement with artworks, the notion of artistic style has been hard to pin down. A broad range of elements might be thought to fall under the umbrella of artistic style. There are basic formal elements, the color palette, tonal qualities, and brushstroke patterns indicative of the dynamics of an individual artist's painterly style, e.g. the energetic dynamics of Van Gogh's brushstrokes or the muted dusky effects of Lucian Freud's palette. There are broader compositional properties of the painting as a whole, e.g. the swirling painterly gestures used to render the central figures of Boccioni's *The City Rises* (1910) or the carefully constructed perspectival arrangements in Thomas Eakin's landscapes. There are the range of content properties that shape the way a subject is represented, e.g. the mathematical proportions and domestic iconography of Titian's *Venus of Urbino* (1538). And there is the choice of subject matter itself, e.g. Boccioni's depictions of labor in urban settings or Freud's ordinary bodies. All of these elements contribute to our understanding of artistic style. However, the formal elements of artworks have traditionally been given point of priority. The style of a work describes the way its content and subject matter have been rendered. John Singer Sargent explicitly chose to render the subject of his *Majorcan Fishermen* (1908) and *Val D'Aosta* (1907) in an Impressionist style. We can imagine him first experimenting with form and color studies in other, more classical, realist styles before choosing the dynamic qualities of an Impressionist style for these particular paintings. We can likewise imagine Rodin having experimented with different styles for his representation of Balzac,

constructing maquettes in mannerist, neo-classicist, and romanticist styles, but ultimately settling on his expressionist rendering of the pose.

Visual stylometry is a growing field within cognitive science that employs digital image analysis tools and image statistics to study the nature of artistic style in painting. Image statistics are descriptions of the distribution of some set of measurable features in an image or, more generally, within the visual field in natural vision. Image statistics are important for visual recognition. The human visual system collects approximately 60 million inputs a year (assuming that we saccade, on average, 2-3 times a second and that the average person is awake 18 hours a day). What we know about the visual world is, in part, derived from regularities in this large body of accumulated information. Some regularities are more likely than others. Some regularities are more likely than others in particular contexts. Some of these image statistics are more behaviorally interesting than others. For instance, regularities in spatial frequency information -- more or less relatively coarse patterns of light dark transitions that define what J. J. Gibson (1986) called an optic array -- are salient to the visual recognition of figure-ground relationships, edges, surfaces, objects, movement, etc. Analogously, we recognize the subject and compositional structure of a painting in spatial frequency information encoded in the distribution of color, tonal values, and brushstrokes across a canvas. These image statistics are also indicators of the unique gesture of an artist, of the brushstroke style used to construct their painting. They are, as a result, not only features diagnostic for the identity and content of a work, but also formal indicators of artistic style.

Visual stylometry has its roots in the writing of Giovanni Morelli (1816-1891). Morelli developed a system to compare the manner in which the content of a painting had been rendered to a set of stylistic exemplars. Morelli focused his attention on less prominent aspects of a composition, e.g. the ears or hands of a figure in a depicted scene. The purpose of this strategy was to uncover the unique gesture of the artist in the background elements of a composition, features less likely to have been shaped by explicit productive intentions, market forces, or external normative conventions (Morelli, 1890; Graham, Hughes, Leder, and Rockmore, 2012). Current researchers are deploying statistical methods and digital image analysis algorithms to accomplish the same goals. The image analysis techniques used to study these formal aspects of paintings include measures of its global palette (the range of colors used), local palette (the distribution and frequency of colors on the canvas), tonal values (the relative lightness of color information within and across different works), edge information (the relative frequency and strength of edges in a body of works), and texture information (which is indicative of the style and biomechanics of an artist's brushstrokes) (see Graham et al, 2012; Zujovic, Gandy, Friedman, Pardo, & Pappas, 2009; Goude & Derefeldt, 1981). These strategies might be used by museums, dealers, and auction houses to authenticate known works or confirm the attribution of newly discovered works to known artists. They might also be used to track out the contributions of assistants to known works from the ateliers of well known artists. Measurable statistical regularities in the handling of the paint on the canvas are treated as a marker for the artistic style of different artists, schools, movements, or eras. Machine classifiers sort paintings relative to their match to these statistical regularities. Image statistics are drawn from the whole canvas. Canonical stylistic features likely to have been implemented by assistants or copied by forgers wash out in the mix in this more wholistic approach to the analysis of artistic style.

The question, of course, is whether a computational account of artistic style derived from visual stylometry can provide leverage for philosophical questions about the nature of artist style and its role in our engagement with artworks. This question reflects a distinction that Noël Carroll has made between descriptive and functional accounts of artistic form. A descriptive account of form is all-encompassing. It includes an analysis of the formal elements of a work and all of the potential relations among them. In the case of painting this includes the tonal values of each individual patch of color, the concatenation of spatially contingent patches of color into texture fields that provide perspectival information about distance, define the orientations of different surfaces, and allow the visual system to disambiguate edges, objects, and figure-ground relations. Functional accounts of artistic form, on the other hand, identify that subset of the formal features of a work that are related to the productive choices made by artists. The artistic form of an artwork encompasses those features that contribute to its identity as an artwork and its artistic salience, its art critical point, purpose, or meaning. These are the formal and compositional features that ground our capacity to recognize the identity of a work as a member of a particular category of art and so shape our understanding of its content. The question, then, is whether the statistical regularities that machine classifiers use to categorize artworks are appropriately related to the diagnostic cues that drive the perceptual recognition and understanding of artworks.

We recently conducted a series of pilot studies using entropy analyses and discrete tonal measures (DTM) to classify paintings by school, artist, media, and technique. Entropy is a measure of uncertainty in the outcomes of a random process. A coin toss has low entropy because the probabilities are known for each of the possible outcomes. We used entropy analyses to measure the disorderliness of neighborhoods of pixels, or, more precisely, the degree of uncertainty associated with predictions about the orderliness of a given pixel neighborhood. If that pixel were located in a uniform field of blue depicting the sky, the pixels in the surrounding neighborhood would exhibit low entropy. If the target pixel were at the transition boundary between a forest and a field of brush, the surrounding pixels in its

local neighborhood would exhibit higher entropy, there would be more uncertainty about their possible chromatic value. The distribution of colors throughout the canvas is, in part, dependent on the quality of the artists' brushstrokes. High entropy values are, for instance, associated with tight contours and highly textured regions of a painting. Our assumption was that entropy analyses would provide us with palette and brushstroke information indicative of artistic style, or the manner in which an individual artist applied paint to his or her canvas.

We used two data sets to pilot our study. The first included 15 Hudson River School and 15 Impressionist landscape paintings (5 each by Thomas Cole, Frederic Church, Albert Bierstadt, Claude Monet, August Renoir, and Alfred Sisley). The Hudson River School paintings were selected for common palette and compositional structure. The goal was to control for these attributes to the degree possible and look to see if our results revealed anything interesting about differences in brushstrokes. The second data set included 68 paintings by Andrew Wyeth, 36 temperas and 32 watercolors. Again, the paintings were selected for a common palette. The brushstroke technique of watercolor differs significantly from painting in egg tempera. The goal of this second pilot study was to measure whether entropy analyses could be used to classify paintings by technique.

We calculated the likelihood of chromatic variance in the neighborhood surrounding any given pixel in a digital image of a painting. We looked at average entropy measures for different sized neighborhoods with radiuses of 1, 5, 10, and 15 pixels. A neighborhood with a radius of 1 marks a 3 x 3 block surrounding a central pixel. A neighborhood with a radius of 5 marks off an 11 x 11 block, 10 a 21 x 21 block, and 15 a 31 x 31 block. Our entropy algorithm snaked through digital images of each painting, continuously shifting the target block one pixel up, down, left, or right, until the entire image had been analyzed. The total set of entropy measures for each neighborhood size were then averaged to produce a single entropy value for each scale for the whole painting (entropy analyses can also be used to evaluate where high and low entropy values occur within the image, see Nolting, 2012). The results show that the average entropy in a category was highly correlated to a logarithmic growth curve ( $r^2 = 0.999$  for each category in the two data sets across all neighborhood sizes). Mean entropy values were, in addition, sufficient to successfully classify 75% of the paintings by technique in the Wyeth test set. Future directions include expanding the Impressionist/Hudson River School data set to evaluate whether entropy analysis would enable us to likewise successfully classify the images by artistic movement.

DTM is a measure of variance in tone between a pixel and those in a neighborhood around it. Tone is a measure of how light or dark a color is. DTM converts color images to grayscale image and measures the standard deviation in tonal value between a pixel and its local neighborhood. The analysis proceeds, like entropy analysis, on a pixel by pixel basis, calculating the tonal variance for neighborhoods of varying sizes across the painting, and ultimately outputting a single value for the whole painting at each scale (the average of all the standard deviations). We can then look for threshold values and use support vector machines to sort image sets by category. We found no significant tonal variance in the Wyeth data set. However, tonal variance was sufficient to classify 80% of the images in the Impressionism/Hudson River School data set and to sort a novel Impressionist test image with the appropriate category. These results suggest that tonal variance is a critical attribute of artistic style for the painters included in our data sets. Interested readers can find summaries of the results of these pilot studies at [www.waivs.org](http://www.waivs.org).

We can now return to where we started. Artworks are communicative gestures. They are artifacts intentionally designed with a point or purpose in mind, perhaps to convey some quality of conscious experience, express an idea, or articulate a point of view about some subject matter. But artworks rarely wear this aspect of their content on their sleeves. Consumers need some knowledge of the appropriate art critical context to direct their attention to the salient features of a work that carry information about their artistic content. The recognition of artistic style is the first step in this process. The artistic style of a work is a clue to the category of art that it belongs to. Categorizing a work appropriately, in turn, enables a consumer to recognize what it means to have rendered the content of a work in a particular way.

Visual stylometry is a developing field that combines research from vision science, computer science, art history and philosophy of art to investigate the nature of artistic style. The goal of this research is to explore the image statistics that support the successful classification of artworks by period, school, movement, and individual artist. Image statistics provide ground-level information for perceptual recognition. Regularities in image statistics are among the diagnostic cues that define perceptual object categories. This is no less true with categories of art than natural object categories. The image statistics diagnostic for the artistic style of individual artists and artistic movements are perceptual cues that enable consumers to categorize artworks and gain access to the range of normative conventions governing how one ought to understand, evaluate, and appreciate them.

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### *References*

- Gibson, J. J. (1986). *The Ecological Approach to Visual Perception*. Hillsdale (N.J.): Lawrence Erlbaum Associates.
- Goude, Gunnar and Derefeldt, Gunilla (1981). A Study of Wölfflin's System for Characterizing Art. *Studies in Art Education*, Vol. 22, No. 3 (1981), pp. 32-41
- Graham, Daniel J., Hughes, James M., Leder, Helmut, and Rockmore, Daniel R. (2012). Statistics, Vision, and the Analysis of Artistic Style. *WIREs Computational Statistics* 4: 115-123.
- Morelli, Giovanni (1890). *Italian Painters*. Reprinted in *Theory and Philosophy of Art: Style, Artist, and Society*. New York: George Braziller, 1992: 103-115.
- Nolting, Ben (2012). Comparing stolen paintings: Picasso and Matisse. Retrieved, November 17, 2017: <http://datavoreconsulting.com/general/comparing-stolen-paintings-picasso-matisse/>
- Schapiro, Meyer (1953). *Style*. Reprinted in *Theory and Philosophy of Art: Style, Artist, and Society*. New York: George Braziller, 1992: 51-102.
- Zujovic, Jana, Gandy, Lisa, Friedman, Scott, Pardo, Bryan, & Pappas, Thrasyvoulos N. (2009). Classifying Pictures by Artistic Genre: An Analysis of Features and Classifiers. *IEEE International Workshop on Multimedia Signal Processing*: 1-5.