Automatic computation of meaning in authored images such as artworks

A grand challenge for AI

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ABSTRACT

We discuss preliminary successes and major outstanding challenges in extracting messages, stories, morals, and especially *meaning* in crafted or "authored" images, such as artworks. Traditional semantic image understanding seeks to summarize an image (such as through a caption), or to answer basic questions expressed in free-text natural language, but can neither infer plausible *reasons* the creator made the artwork nor compute a high-level message or meaning it conveys. Such meaning is often abstract, context-dependent, and exploits visual conventions such as special objects and signs ("signifiers"), composition, and possibly non-realistic style. Several of these properties have no counterpart in the natural photographs that are studied in most semantic image analysis, nor in the application-specific image analysis applied to robotics, autonomous driving, medical diagnosis, or remote sensing. For such reasons, the extraction of meaning from visual artworks represents a grand challenge to artificial intelligence research.

Keywords: computational visual semiology, deep neural network, art analysis, computer-assisted connoisseurship

1. THE PROBLEM OF COMPUTING MEANING IN AUTHORED IMAGES

Consider the painting in Fig. 1, Harmen van Steinwyck's *Still life: An allegory of the vanities of human life*, and how current algorithmic approaches to semantic image analysis, suitably improved and refined, might analyze it and similar two-dimensional artworks. The component pattern recognition and semantic segmentation algorithms would likely identify and localize the books, shell, sword, wine jug, and (given contextual information about 17th-century Holland) the musical instruments, thin stream of smoke, and shaft of light.[2] These methods can infer simple spatial relations, such as the shell is *on* the table, the books are *touching* the skull, and related predicates.[3,4] Analyses of this sort might also make a basic classification of the overall scene (open scene or indoors or street, etc.).[5] The current state of question-answering algorithms, as applied to natural photographs, strongly suggests that these algorithms will be increasingly accurate describing objects and simple relations in works such as *Still life*.[6] These are challenging problems in artificial intelligence and the slow but steady progress toward their full solutions have relied on numerous advances in image processing, computer vision, machine learning (especially deep neural networks), and scene analysis. Eventual solutions would satisfy current conceptions of a visual Turing test.[7]

Research of this sort nevertheless sheds little if any light upon *why* this image was created, *why* it has been prized for over a third of a millennium and rightly deserves presentation in one of the world's most important art museums... in short what makes such an image *special*. Beyond the evident technical skill of the artist and the work's manifest beauty, the most important properly of this work is that it—like most artworks—carries a *meaning*. The artist (at his patron's behest) worked diligently to craft a painting that expressed ideas, lessons, and morals, which in this case supported the teachings of the Protestant Church, ascendant during the Dutch Golden Age. In brief, that message here, referred to as *vanitas*, can be summarized as:

> Do not concern yourself with the diversions of this world, given that you will surely die—at a time few ever know. Instead lead a sober, humble life in preparation for the eternal life to come.

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Figure 1. Harmen van Steenwyck's *Still life: An allegory of the vanities of human life* (39.2×50.7 *cm*), oil on oak panel (1640), National Gallery London. This painting bears a clear and powerful meaning—a meaning that current techniques in AI are apparently insufficient to extract.

Every educated—and even most illiterate—viewers of 17th-century Netherlands well understood this meaning as it was conveyed by this and similar *vanitas* paintings. This message was preached from pulpits, written in religious texts and philosophical tracts such as by the contemporary philosopher Erasmus. It figured prominently in the Low Countries' rebellion from Catholic Spain. Patrons eagerly sought such artworks for their homes to remind them of this message and how to live a good life, and to demonstrate their moral aspirations to visitors.

How does this work convey this message and bear this meaning? What elements—visible and invisible—work together to these ends? What can current algorithmic image analytic methods reveal about such works? Most importantly, what problems must AI solve if automatic methods are to "understand" an artwork to the level illustrated in the summary above?

2. SEMIOLOGY, SIGNIFIERS, AND SIGNIFIEDS

The most direct and widely used technique for conveying meaning in artworks is to include signs or symbols which refer to another object, idea, or concept. Semiologists refer to such signs as *signifiers* and the concepts to which they refer as *signifieds*.[8] There are three categories of signifiers: *indexes*, *icons*, and *symbols*. These have the following properties and functions:

Index: an indirect or abstract pointer to its associated signified, where the linking relation can in principle be anything. A footprint in the sand is an index to the person who walked the beach.

Icon: an image that resembles its signified, but is far more abstract and schematic. Examples include the simplified outline of a man or a woman on many restrooms doors, or numerous icons in graphic interfaces, such as a tiny printer or file folder.

Symbol: an abstract and arbitrary social convention. For example **$** and £ refer to money, + refers to addition, and so on.

Semiologists and art scholars claim that meaning does not inhere in an artwork such as a painting taken alone, but is constructed by the interaction from the viewer, the artwork, and contextual information and knowledge. For this reason there may be several convincing "readings" or interpretations of a work. Nevertheless, some readings are more compelling, and explain more of the visual and associated evidence including the artist's own stated goals, intentions, and explicit message.[9,10]

Consider again the painting in Fig. 1 and how a reading, summarized above, might arise in part through its use of signs, composition, and style. The visual elements include the objects, overall composition, and formal aspects of its style.

Objects (as signs) Nearly every object depicted has symbolic meaning in service of the message of the painting. The skull is clearly a symbol of mortality and the universality of death, and its location at the center of the work and the fact that the empty eye sockets seem to be looking toward the viewer highlight its importance. The lovely shell at the left would have been rare and expensive, and illustrates earthly pleasures, much as would jewelry. The large open pocket watch on the table symbolizes the passage of time, and its placement close to the skull illustrates that death is always near. The wooden flute on the table, the bell of the sackbut (early trombone), and the belly of a lute (early strummed stringed instrument) elevated at the rear together represent various expressions of culture, which may lead us from the central concerns of death and the life to come. The Japanese samurai sword, a product of the Netherlands' recent opening of trade routes with Asia, would have been quite novel, rare, and expensive; it illustrates the worldly interests in both travel and luxury. Moreover, the two books, touching the skull, signify worldly learning. The fine pink silk scarf (also from the newly opened trade with Asia) and the wine jug reference sensual pleasures. The oil lamp at the center represents the passage of time; the fact that its wick has recently burned out—as evidenced by the thin trail of smoke (a semiotic *index*)—shows that death and extinguishment is inevitable. In some interpretations of this painting, the smoke refers to an invisible omniscient being (signified) who snuffed out the lamp, conveying a clear theological message.[11]

Composition Of course, a painting is a static object, but in the West viewers tend to "read" a work from left to right (matching the flow of printed text), and thus the shaft of light is interpreted as coming from above, flowing downward to the right. For this reason this shaft signifies heavenly light. This shaft, directed toward the skull, is clearly a reference to the religious notion of an omnipotent being in heaven guiding worldly affairs, including man's ultimate destiny, as signified by the skull.

Style and format Several formal properties of the work reinforce the work's message. First, the painting is roughly life size, making the objects, including the skull, read as present before the viewer. (If the work were a minature or a large mural, this aspect of the meaning would be diminished or lost.) Moreover the style is extremely realistic, with subtleties of lighting, reflection, texture, all expertly rendered, thereby reinforcing the notion that the message is present before you, as real as the common objects that surround us all, including those in the patron's room where the painting hung. The color scheme is dark, sober, even somber, engendering quiet contemplation and serious reflection by the viewer, again, essential to the meaning of the painting.

Still life was very carefully planned and executed by the artist, sometimes called an "author" in such contexts. Its rich, almost overwhelming, message rarely if ever appears in the casual photographs or application-specific videos that dominate research in automatic image analysis and understanding. Even state-of-the-art image interpretation, question-answering, and other methods of automatic semantic analysis provide almost no extraction of *why* an image such as was created, and especially what its author *means*, beyond perhaps simply documentating a scene.[12] The role of *style* in the extraction of meaning is almost entirely ignored in current AI methods, given that photographs are stylistically far more uniform than paintings from all eras and regions across the world.

The vast majority of research in computer vision, deep learning, and so forth seeks to interpret the physical world, be it a natural photograph of children at play, or a real-time video from the front of an autonomous vehicle of the roadway, or an x-ray of a malignant lung tumor. This "surface-based" analysis—as challenging as it may be—provides but initial steps toward addressing the deeper problem of inferring an artist's likely intentions or *meaning* conveyed in an artwork.[13]

One of the most important features of two-dimensional artworks that frequently contributes to their message and meaning is *style*, and because this aspect is not adequately addressed by current AI techniques, it bears some discussion. For instance the rapid, free brushstrokes of Impressionism are part of the message of that art movement, which celebrated the transient, even ephemeral observation of the contemporary and quotidian world. Despite stylistic differences, many of the paintings by Pierre Renoir, Claude Monet, Paul Cézanne, and others exploited such rapid and relatively "free" brushstrokes, a dramatic departure from the refined and generally invisible brushstrokes of the prevailing Academic movement, led by William Adolphe Bouguereau, Jean-Léon Gérôme, Jean-Auguste-Dominique Ingres, and others.

The realistic style and symbolic color schemes exploited in Neoclassicism contributed to the permanent, even eternal, messages and morals that were conveyed in such art. Thus Jacques-Louis David's *Oath of the Horatii*, which celebrated honor, duty, service (even to one's death) to the political state (Rome), was painted in a style of strong lighting, crisp contours, and bold symbolic colors. The vigorous, immediate and even wild marks in Abstract Expressionism were perhaps the principal technique by which the meanings of this art—the primacy of emotions and existential confrontations in an uncertain world—were expressed, for instance by Jackson Pollock, Joan Mitchell, and Arshile Gorky. (As the art critic Meyer Shapiro said: even if a painting did not depict any objects it could still convey a *meaning*.) The Pop artist Roy Lichtenstein's *Brushstroke* depicts a single large, bold "dripping" yellow brushstroke of Abstract Expressionist art but rendered in the cool, flat, industrial style of comic books (complete with large blue BenDay dots prominent in newsprint)—a savage and ironic parody of the earlier art movement.

Such semantic function of style generally holds—by definition—regardless of the explicit objects and spatial relations that may or may not be depicted in an artwork. (The Lichtenstein *Brushstroke* is an example where the meaning of the painting is enhanced due to the relation between the style and the content.) Most relevant here is that such semantic function of style has almost no relevance to the properties of natural photographs and thus has received minimal attention from the AI community. Note too that the extensive successes in learning and transferring style (e.g., transferring Impressionist style to a photograph) have no direct bearing upon inferring meaning in either the source painting nor (of course) the target photograph.[14]

A closely related property of much art that distinguishes it from natural photographs is the depictions of non-existent objects, such as dragons, monsters, halos, winged angels, centaurs, unicorns, and so forth. Such imaginary objects do not appear in the billions of natural photographs typically used for training deep networks. Likewise, some artworks depict objects with altered material properties under conditions that violate the laws of the natural world. For instance paintings depict flying infants (putti), flying gods and angels, pocket watches may drip like molasses, holy infants glow a golden light, and so forth—all important components in the message of an artwork.

3. EXTRACTION OF MEANING IN NATURAL TEXT AND THE VISUAL ARTS

The variety of interpretations and *types* of interpretations of artworks is vast, often subtle and complex, and can involve an extraordinarily diverse set of concerns and likely representations.[15,16] Clearly this full problem is AI complete and requires human-level artificial general intelligence.[7,17] As such, there is no compelling unifying representation or research methodology for addressing the problem in its full generality, other than the vague and daunting suggestion to *solve general intelligence first*. For this reason, we should confront special cases of the general problem that expand the concerns of AI and advance scholarship toward that eventual goal.[18]

In many ways, natural language processing in its variety of subtasks has confronted the analogous problem more directly than has image analysis. After all, nearly all the text processed by automatic semantic analysis was written by *authors* with *intentions* to convey messages. Here, for instance, sentiment analysis has been used to extract tone, valence, and related stylistic properties of text, relatively independent of the explicit content or meaning. Nevertheless, such analysis can be relevant in the extraction of the author's intent or meaning.[19]

As just mentioned, natural language processing has, by the very nature of its subject matter, confronted the problem of extracting an author's intent and meaning far more extensively than has semantic image analysis. This is not the venue for an extensive rehearsal of the methods and accomplishments in natural language processing, but instead a chance to highlight the methods of natural language processing that show the greatest promise in advancing automatic inference of meaning in authored images such as artworks.

Such methods include sentiment and form analysis, which in several ways is analogous to style analysis in artworks. Such language analysis focusses on valence words and structures (nearly) independent of higher-level topic and content of a message. Here the statistical properties of lengths of sentences, proportion of anaphora, valence of adjectives and adverbs, and so on are estimated, and such information forms a component of higher-level semantic interpretations. Linguistic processing can infer rudimentary meanings based on symbolic words and phrases, analogous to the signifiers in certain paintings.[20]

A key subproblem in efforts of extraction of high-level meaning involve knowledge representation, and numerous structures—semantic nets, frames, rules, ontologies—have been developed to this end.[21] Of course in many deep network or belief network approaches for use with natural language text as well as for static images, knowledge is represented in highly distributed form through millions of trained connection weights.[22]

For the problem of extracting meaning from an artwork that is based on some story or moral expressed in natural language, we might first explore representations that have shown value in knowledge and meaning in both natural language and image domains, perhaps one based on logic and predicates. Such knowledge might be represented in form such as `Eat(Eve, apple)` or `Touch(book, skull)`.[23] Other, more distributed and statistical representations trained with massive data sets are likely to provide a foundation as well.

4. ONE-SHOT OR FEW-SHOT LEARNING

Given the recent and dramatic successes in object classification, event classification, semantic segmentation, automatic question-answering, and related problems provided by deep networks,[24] we might expect that training such networks on a corpus of art images (and possibly accompanying textual descriptions and analyses) would provide a foundation for extraction of meaning from artworks. However, this approach immediately confronts a problem: the number of available artworks is far smaller than the number of photographs used to train deep networks, which may reach several hundred million or even a billion. Even a very prolific fine artist such as Pablo Picasso executed roughly 13,500 paintings in his career, while Johannes Vermeer executed just 34, and Leonardo da Vinci just 16.

The obvious approach, then, is to employ *transfer training* in which, here, a network trained with a large corpus of natural photographs is further trained with art images. Alas informal and preliminary simulations show that even through this approach, the number of art images is rather small and does not lead to acceptably high performance as judged on artworks.[25] Such transfer learning is almost certain to fail, catastrophically, on highly stylized paintings and abstract art.

Consider Willem de Kooning's *Two women in the country* in Fig. 2. Simple proof-of-concept tests using state-of-the-art object recognition, semantic segmentation, and summarization algorithms fail—catastrophically—on such an image. Clearly the statistics of color, shape, and so on in the artwork differs markedly from the large data sets of natural photographs used to train current image segmentation and analysis systems, and that explains such poor performance. Nevertheless, upon seeing even just *one* painting by this artist, nearly all humans can learn this artist's style and recognize his other works very reliably, as the reader can confirm by searching for his paintings online.

Figure 2. Willem de Kooning's *Two women in the country* (117.2×103.5 cm), oil, enamel and charcoal on canvas (1954), Hirshhorn Museum and Sculpture Garden. An artwork such as this presents many challenges to automatic analysis: recognizing the figures (two women) and setting (countryside), identifying the style, and crafting an interpretation or "reading" of the work that addresses what the artist is trying to convey. Current AI and image analysis techniques are poorly suited to such tasks because here plausible meanings are built upon the full range of aspects of the work, from the medium and style up to the composition and relation to other contemporary artworks.

Human observers, upon seeing even one painting by this artist learn his distinctive style and can then recognize his other works. This fact exposes another—well-known—limitation of current learning-based approaches to image understanding: the implementation of one-shot (or few-shot) learning.[26,27] It appears that art paintings provide a rich domain for the development of methods for one-shot learning.

While robust and accurate such algorithms are being developed, we can explore alternate methods, ones that exploit knowledge that links art images to associated stories and meanings expressed in text. We now describe one such method, presented recently.[28]

5. AUTOMATIC IDENTIFICATION OF ACTORS IN PAINTINGS

Perhaps techniques from natural language understanding most relevant to inferring messages in artworks concern story analysis, including the inference of the *actors*, their actions, and relations. Recent work, unrelated to art images, has addressed character role assignment based on extraction of character identities from text and existing structure and morphology of folktales.[29] The meaning to be extracted is a story (with associated morals) that lie in Biblical texts. One of the greatest corpora of message-bearing images are religious works from the Western canon. The Church was the primary patron for art for well over a millennium, employing most of the greatest artists; the greatest works were crafted to convey a meaning, message, or moral from the Bible. Thus religious art provides many examples and variety of examples of meaning-bearing artworks.

The computational goal is to extract meaning by identify the story being depicted in an artwork, even amidst the great variety in style, composition, and so forth. One component step is to identify the figures, or as art scholars say, the "actors" depicted in an artwork. The left panel in Fig. 3 shows Andrea Verrocchio's *Baptism of Christ*, which as its title makes clear refers to the Biblical story in which Christ is washed by John the Baptist in the River Jordan. (Similar compositional strategies were pursued by notable artists such as Bartolome Esteban Murillo, Ottavio Vannini, and Guido Reni, Nicolas Poussin, Perugino, as well as several others.) The message or moral expressed through this painting would be extracted from the Biblical text:

> Saint John baptized Christ under the observation of the Almighty and heavenly angels in order to cleanse him of the sins of mankind that he had borne; moreover, salvation will come only through Christ's crucifixion.

As stressed above, current semantic image analysis methods fall short of extracting such a message and meaning.

A first step in extracting such a meaning automatically is to recognize the actors. Western Biblical stories—both written and illustrated visually—exploit *attributes* for identifying important actors, such as saints. In this context, the term "attribute" is not related to the common usage in computer vision and pattern recognition more generally.[30] In religious iconography, an attribute is an object closely associated with a given religious actor, almost always deriving from a Biblical or historical story or event. One actor might have several attributes, and any given attribute might be associated with more than one actor, such as a saint. For example, Saint Peter's attribute are keys, Saint Luke's is a bull, Christ's are a crucifixion cross and dove, Saint John the Baptist's is the crucifixion cross, and so on. (Such attributes helped the illiterate in early church history to better understand the stories in paintings and stained glass windows.) The associations between saints and attributes are codified in ecclesiastical books, and can be easily represented in an associative database.

A deep neural network was trained with examples of several Biblical attributes and when applied to the Verrocchio painting, and this network then identified and localized the dove and crucifixion cross, as shown in the center panel of Fig. 3.[31] The right panel shows the semantic segmentation performed by a deep network trained on modern natural photographs, where pink and maroon indicate the label of PERSON and ANIMAL, respectively. Next, the spatial distance between each candidate actor and semiotic attribute is computed. Finally, based on a lookup table of attributes and saints is used for actor identification. In this way, the central actor is recognized as Christ and the actor to the right as Saint John the Baptist. The average precision and recall of this system were 92% and 81%, respectively, over four actor identities. These recognized actors can then serve as an index or query into a database of Biblical episodes or stories, thereby finding the Baptism story and its associated (text) message or moral.

6. CONCLUSIONS AND FUTURE DIRECTIONS

Art images are among the most memorable, and culturally relevant images of any sort, and present numerous challenges to the development of high-level automatic semantic interpretation. The problem of the extraction of meaning from authored visual works requires a wide range of levels of visual analysis (from low-level style up through object recognition and inferring of relations), knowledge of conventions in symbols, context, common sense reasoning, natural language processing, and more. Because the number of such artworks is small (relative to

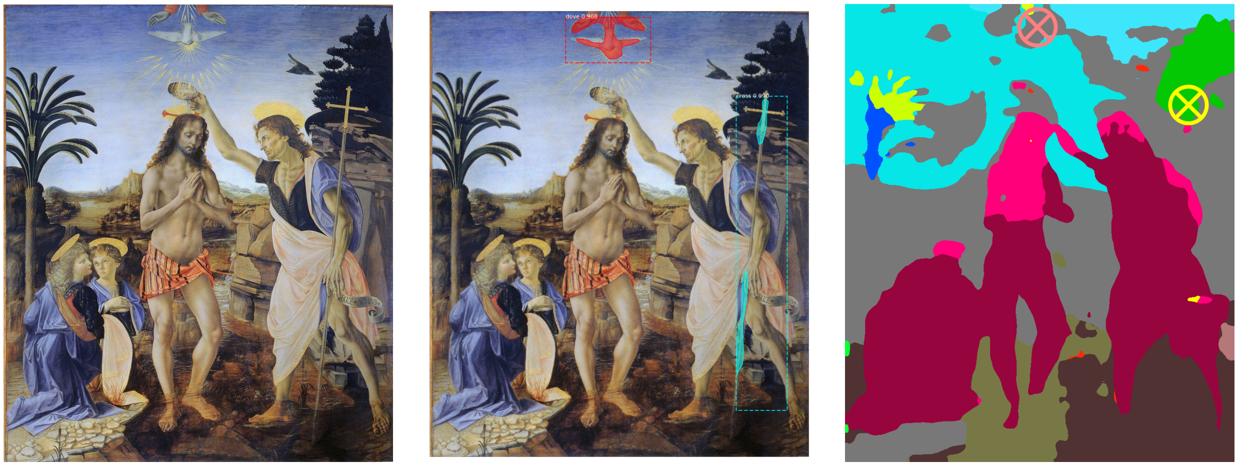

Figure 3. (L) Andrea Verrocchio's *Baptism of Christ* (177×151 *cm*), tempera and oil on panel (c. 1470–75), (C) bounding boxes for objects recognized as iconographic *attributes* by deep neural network trained on an independent database of such attributes appearing in Renaissance paintings, and (R) semantic segmentation, identifying human figures (maroon and pink), based on natural photographs. The identity of each actors can be inferred from the identity of the closest semiotic *attribute*, and such identification can lead to the recognition of the source story and its meaning. (Figure after.[31])

the databases used in deep learning methods), that the objects frequently depicted are imaginary or non-physical, that their styles vary extremely widely, all present profound challenges to AI methods.

Computer vision and AI will continue to aid art scholars and have already been decisive in resolving outstanding debates, for instance over whether some artists in the early Renaissance secretly used optical aids.[32,33] Close collaboration between art scholars and AI researchers will be increasingly valuable. Fortunately, a recent informal poll reveals that a growing number of art scholars are open to exploring computer methods in their research, which bodes well for future collaboration between computer scientists and art scholars.[1,34,35]

The challenging problems posed by the analysis and especially high-level interpretation of art promise to be a fertile ground for continued development of techniques in artificial intelligence—indeed, these problems present a fresh grand challenge to AI.

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