Clouds of Symbols
The Digital Curator Project

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When we examine a painting in a gallery, we can see that it contains a range of different elements. If looked at from a distance, we are likely to be drawn to its dimensions or overall composition. Upon edging closer, we discern the abstract style of the painting, and our eyes follow the lines, surfaces, edges, and shapes. When the style of the painting is representative, we start to explore a motif, a figure, or other elements and how they are spatially arranged. If a human being is portrayed, our eyes will naturally turn to the face, features, and gestures depicted, the position of the body, or the attributes of the figure. We might also be intrigued by the creative style, the schematic aspects of the image, or the specifics that emerge from the artist's handwork, such as brushstrokes, contrasts, or colour scheme; we might even pay attention to the unique and defining artistic signature.

Machine vision tools and human eyes both possess numerous ways and methods of visioning the world. Just as there are many ways of observing with the human eye, there are a variety of machine vision tools that can be used in analyses. Each of these methods highlights a unique aspect of images as well as an interpretation. Thus, by using specialized algorithms, one can analyse colours, contrasts, or shapes in a different manner, search for similar images in large collections, compare the particular painting signature of different artists, and classify artistic styles.

I explored some of these approaches during my PhD studies at the Academy of Arts, Architecture and Design in Prague, during which I created the experimental project digitalcurator.art. Its main topic is iconographic analysis and genre identification. In this case, a neural network algorithm has been trained to classify meaning-forming symbols and motifs, attempt to record them, select the works in which they appear, and perform frequency analysis in order to capture their popularity across the centuries.

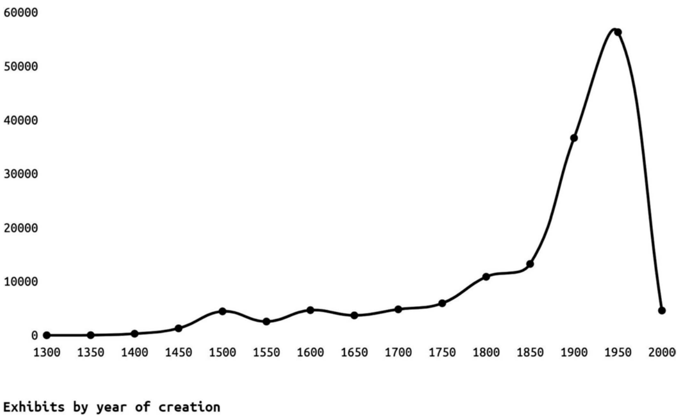
1 The Digital Curator project was presented at the conference at the Landesmuseum Karlsruhe in December 2022. The text is based on a dissertation that the author defended at the University of Arts, Architecture and Design in Prague in September 2022. (Digital Curator: Algorithms and Computer Vision in the World of Big Cultural Historical Data).

Database

Despite the fact that the principles of computer vision are rooted in linear algebra, the data itself is more than merely mathematics. Arguably, it is the responsibility of the curator or art historian to continuously use their critical eye with respect to the specific data, take an active role in its selection, and also suggest changes to its composition, form, and processing techniques. Here, the composition of sample datasets for machine learning can influence how the algorithm comes to evaluate and potentially shape the outcome of the research. I will therefore proceed to outline the data that the Digital Curator handles.

The Digital Curator database can be compared to the collection of an art museum or gallery. More specifically, it is a collection of digital reproductions of artworks that an algorithm has at its disposal in order to search, filter, sort, label, group, create, and shape their context. The works included in the database can be accessed and processed by the program; other works, though they may be published online, are left out by the Digital Curator. Even so, this is probably the largest collection of reproductions of Central European art that can now be handled by algorithms.

Figure 1: Composition of the Digital Curator database by year of exhibit creation. The horizontal axis shows the median year of the (presumed) creation of the work, the vertical axis the number of works in the database.



As of the summer of 2022, the Digital Curator's collection contains 196,000 works, mostly paintings, drawings, and prints, from the holdings of 90 museums in Austria, Bavaria, the Czech Republic, and Slovakia. It includes reproductions of exhibits from the Albertina and Belvedere in Vienna, the Alte Pinakothek and Neue Pinakothek in Munich, the Prague City Gallery, the National Gallery in Prague, the

Moravian Gallery in Brno, the Slovak National Gallery in Bratislava, and a number of smaller collections—from the Benedictine Abbey in Ottobeuren, Western Bavaria, to the East Slovak Gallery in Košice.

The database's focus on Central European institutions responded to the shared cultural history of the region, where artists have travelled for centuries between cities, aristocratic courts, workshops, schools, and academies, sharing their artistic style, formal elements, genres, themes, and motifs. It was not only the artists themselves who travelled; paintings and entire collections also gradually changed owners and locations. Once related works of art are now dispersed across hundreds of museums in several independent countries, and to get a handle on even a small fraction of this heritage is beyond human capacity.

Symbol Detection

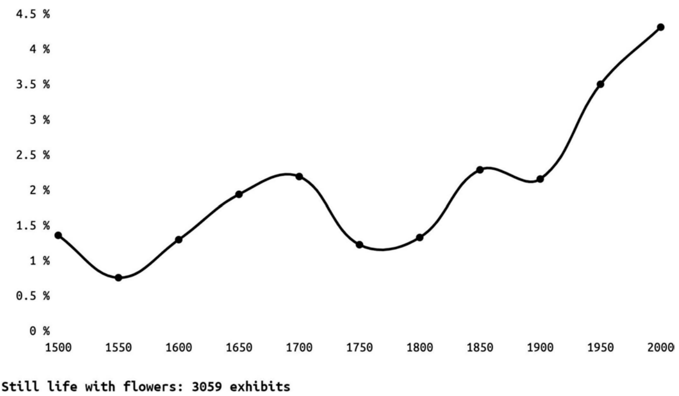
Object classification typically uses pre-trained neural networks that draw their visual experience (in particular) from photographs from the twenty-first century—for example, the ImageNet database, which contains more than a million images categorized into thousands of images (ImageNet 2020). If these algorithms are employed to classify pre-modern photographs of Central Europe, however, we will inevitably encounter their limitations. The Digital Curator therefore uses proprietary neural networks designed to classify motifs and symbols, with its skills extracted directly from historical paintings, prints, and drawings. To this end, a set of 3,950 digital reproductions was created. These works came from the collections of Central European galleries and date from 1300 to 1800, and the aim was to spread the sample as evenly as possible across the centuries. These paintings were labelled with 4,167 objects representing 13 symbols associated with Christian iconography. These included, among others, the 'Madonna', 'angel', 'white dove', 'bishop's sceptre', 'Latin cross', 'halo', 'crucifixion' and 'crown of thorns'. This input data served as a key differentiator between the capabilities of the Digital Curator and those of other neural networks trained, by contrast, on composite datasets to recognize different objects and features.

Results

The Digital Curator's neural network gradually became better at recognizing the 13 common iconographic symbols, but this set was not sufficient for a broader exploration of motifs or genres. It was therefore necessary to supplement its cognitive capabilities with additional objects, for which the pre-built Resnet V2 object detection model was used (TensorFlow 2022). Although it was already a universal algorithm trained on contemporary visual materials, it might also be used to identify motifs whose representation has not changed significantly over the centuries. For example, a vase, flower, tree, dog, or horse have the same visual features in both contemporary photographs and Renaissance paintings. This brings the overall number of detectable components to approximately 300.

At this point, it was possible to begin composing the motifs into individual genres: to define landscape painting as a picture in which 'trees' and 'plants' are present, still lifes with flowers based on the presence of a 'flower', 'vase', 'pot', or 'table', and portraits of nobles or religious honours by means of the 'human face', 'figure', and 'coat of arms'. Similarly, these themes could be further refined by means of additional conditions. If we are interested in romantic landscape paintings, we can find them, for example, through 'castle ruins', which distinguishes them from the hunting genre, where, although there are also 'trees' and 'plants', there are 'dogs' and 'wild animals' as well. The image of an abbot or bishop is distinguished from a monarch by a 'mitre', and otherwise by a 'royal crown'. While this may sound banal and perhaps even absurd, the results are convincing. To see how it works, I recommend visiting the web application and trying to see exactly how the algorithms can build collections based on these parameters.[2]

Figure 2: Frequency of occurrence of still lifes with flowers across the centuries. The vertical axis indicates the share of the genre in the Digital Curator database as a whole.



2 https://digitalcurator.art; the code and reports are available here: https://github.com/lukas-pilka/digitalCurator (both accessed in August 2023).

The following visualizations show samples of works with corresponding iconographic motifs, while the graphs present the frequency of phenomena across history. This is a type of frequency analysis similar to that employed by the Google Ngram Viewer, with the exception that the values are based not on the occurrence of keywords in scanned texts, but on motifs portrayed in digitized paintings, drawings, and prints.

Figure 3: Frequency of the crucifixion motif across the centuries. The vertical axis indicates the proportion of works in which the subject occurs in the total Digital Curator database.

References

Pilka, Lukáš (2022). About the Digital Curator, Web app available at https://digitalcurator.art/aboutproject.

Pilka, Lukáš (2022). Digital Curator: Algorithms and Computer Vision in the World of Big Cultural Historical Data, Academy of Arts, Architecture and Design in Prague, Dissertation thesis 2022. Available at https://drive.google.com/file/d/1bIFjaWXvsRleSBSBGwtUjeANgOoTEW8D/view.

Stanford Vision Lab (2020). ImageNet. Available online at https://www.image-net.org.

TensorFlow (2022). TensorFlow Hub is a repository of trained machine learning models, Availabe online at https://github.com/tensorflow/tensorflow.

Figure 4: Sample images detected as still lifes with flowers.

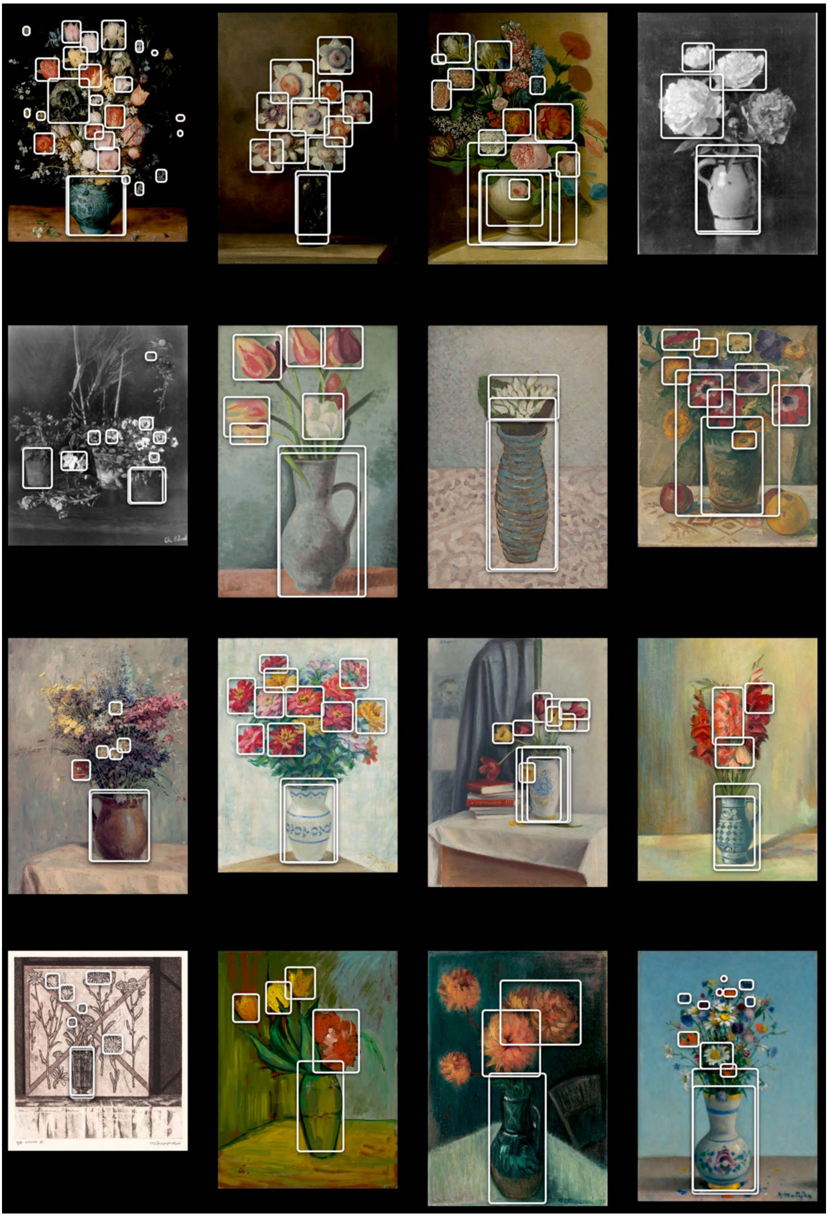


Figure 5: Sample images detecting a crucifixion.