

DELAUNAY: a dataset of abstract art for psychophysical and machine learning research

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Abstract—Image datasets are commonly used in psychophysical experiments and in machine learning research. Most publicly available datasets are comprised of images of realistic and natural objects. However, while typical machine learning models lack any domain specific knowledge about natural objects, humans can leverage prior experience for such data, making comparisons between artificial and natural learning challenging. Here, we introduce DELAUNAY, a dataset of abstract paintings and non-figurative art objects labelled by the artists’ names. This dataset provides a middle ground between natural images and artificial patterns and can thus be used in a variety of contexts, for example to investigate the sample efficiency of humans and artificial neural networks. Finally, we train an off-the-shelf convolutional neural network on DELAUNAY, highlighting several of its intriguing features.

I. INTRODUCTION

Deep Neural Networks (DNNs) have for many years demonstrated human and even super-human performance in many different tasks (see [1] for a review). One of their most famous achievements is super-human natural image classification: during the 2017 edition of the ImageNet Large Scale Visual Recognition Challenge (ILSVRC), the winning team achieved a classification error of 2.251%, using a network trained on a subset of ImageNet containing 1000 categories and 1.2 million images ([2], [3]). In comparison, the estimated human classification error on the same task is 5.1% ([4], [5]). They also perform extremely well in other vision-related tasks, such as boundary detection, semantic segmentation, semantic boundaries, surface normals, saliency, human anatomy, and object detection ([6]). DNNs and the human visual system share architectural similarities, but their link may be even deeper than merely structural, as the activity of different artificial cells in a DNNs can be mapped to, and subsequently used to predict, the recorded activity of cells in a living subject ([7], [8]). Furthermore, recent years have witnessed the emergence of a multitude of models linking learning in DNNs to synaptic plasticity in cortex ([9], [10], [11], [12], [13], [14], [15]).

Despite these successes, a number of critical shortcomings of these systems have been observed over the recent years. For example, DNNs are notorious for the large amount of labeled training data required ([16]). Humans, in contrast, are extremely efficient learners, able to learn new categories

from very few samples. Furthermore, human perception is much more robust to rotations, occlusions or even abstraction of image content. These observations suggest that DNNs and humans leverage fundamentally different strategies for learning.

The learning performance of a system is intimately linked to its prior knowledge of the task domain and inductive biases ([17]). Thus, one may hypothesize that the difference in sample efficiency between neural networks and human subjects may significantly depends on the considered task. For example, classification tasks involving images with natural structures may be learnt faster by humans, by exploiting biases and priors which were developed over evolutionary timescales and acquired over the lifetime of an organism. However, classifying artificial inputs, such as pseudo-random patterns or QR-codes may take humans longer to learn, effectively resulting in memorization, leading to lower sample efficiency and poor extrapolation.

A number of researchers have started to compare natural and artificial learning leveraging psychophysics and machine learning with the twin goals of furthering our understanding of brain function and improving artificial intelligence ([18], [19], [20], [21]). In a similar spirit, to measure how much prior knowledge and inductive biases contribute to the learning speed of humans, one may design psychophysical experiments comparing the sample efficiency of DNNs and human subjects on visual classification tasks in which the statistical similarity of the datasets to natural images is controlled:

- 1) A task with realistically structured objects, for example ImageNet ([5]).
- 2) A task with images of unusual structures, for example abstract art.
- 3) A task with completely unstructured images, for example QR codes, or shuffled MNIST ([22], [23]).

In addition, the second task, i.e., the classification of abstract art, could consider two different subject groups, consisting of naive viewers and art experts, respectively. Both the naive group in task 2 and all subjects in task 3 can be considered lacking prior task-related knowledge which should lead to a significant drop in sample efficiency.

If these expectations turn out to be correct, i.e., if we observe a significant difference in the relative sample ef-

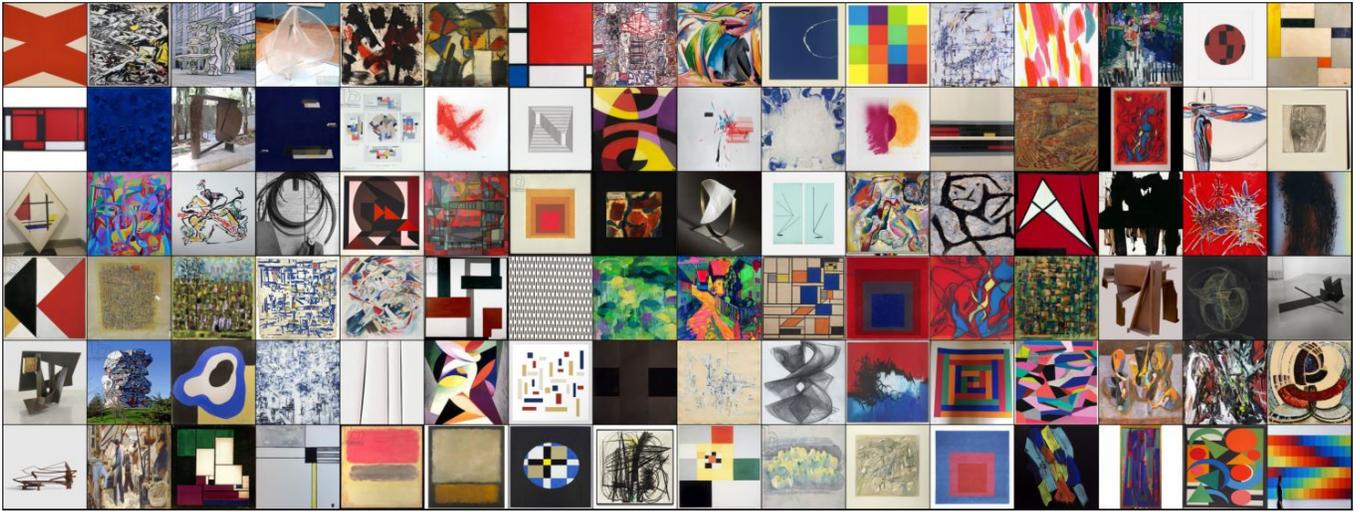


Fig. 1: **Samples from DELAUNAY.** DELAUNAY consists of images of abstract artwork from a variety of different artists. Here, 96 random samples across all artists are shown. Note the diverse non-figurative properties of images.

iciency of humans compared to DNNs depending on the statistical similarity of the dataset to natural images, this would provide support for the hypothesis that fast natural and artificial learning heavily relies on prior domain knowledge, as speculated for example by [24].

Our main contribution here is to provide a new dataset consisting of images of abstract art (as opposed to other databases of paintings: [25], [26]), suitable for psychophysical experiments and machine learning research.

II. DATASET

DELAUNAY (Dataset for Experiments on Learning with Abstract and non-figurative art for Neural networks and Artificial intelligence) is named after artists Sonia [27] and Robert Delaunay [28].

Several museums and other institutions worldwide offer remote access to large databases, such as the Solomon R. Guggenheim Museum in New-York [29], the MET [30], the Bibliothèque Nationale de France (BNF) through its open-access online tool Gallica [31], the digital collections of the Library of Congress [32], the French Réunion des Musées Nationaux - Grand Palais (Rmn-GP) [33], the online library of the Institut National d’Histoire de l’Art (INHA) [34], the Bridgeman Art Library [35], the National Portrait Gallery [36], as well as the Alamy and Getty Images photo libraries [37].

We leveraged these online databases to construct DELAUNAY. First, we selected 53 artists well known for their abstract art (see the full list in Annex). Second, we scraped the aforementioned databases for images of their artworks. Finally, we removed false positives (e.g., photographs of the artists), duplicates, and cropped images containing texts and/or other artifacts.

The final dataset comprises 11,503 samples across 53 classes, i.e., artists (mean number of samples per artist: 217.04; standard deviation: 58.55), along with their source URLs. These samples are split between a training set of 9202 images

and a test set of 2301 images. Due to the heterogeneous nature of sources, images vary significantly in their resolution, from $80\text{px} \times 80\text{px}$ for the smallest sample to $3365\text{px} \times 4299\text{px}$ for the largest. A random subset of samples illustrating their non-figurative (not representing a natural object) nature and high diversity is shown in Figure 1.

III. TRAINING RESULTS

To illustrate some of the unique features of this new dataset, we train a standard convolutional neural network (CNN) to classify samples according to their authoring artist. We used a similar approach as in [19]: images were resized to 256×256 pixels (not preserving their aspect ratio) and classified using the ResNet152 architecture ([38]) distributed as part of PyTorch ([39]). Parameters were randomly initialized according to PyTorch’s defaults. We trained the network using a cross entropy loss with the ADAM optimizer ([40]) with a learning rate $\gamma = 0.003$, weight decay parameter $\lambda = 0.003$, and batch size 20.

Both validation and test accuracies are significantly higher (respectively 29.46% and 29.73%) than the accuracy expected from a greedy classifier associating all images to the class having the highest sample count (3.28%) (Figure 2).

To investigate these results further, we consider class-level error metrics. Percentages of correct predictions for all 53 classes in the test set range from 0.0% to 68.75% (Figure 3). This wide distribution suggests that while some artists can be easily recognized by the trained CNN, some seem to withstand meaningful extrapolation from the training to the test set. Indeed, artists with low accuracies appear to have a multimodal, eclectic style in contrast to other artists who maintain a more systematic style throughout their works (compare for example Georges Vantongerloo to Richard Paul Lohse, Figure 3). Furthermore, the confusion matrix of the test dataset contains several significant off-diagonal entries

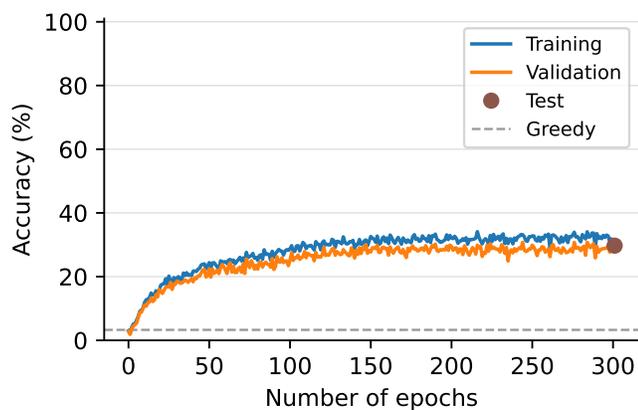


Fig. 2: **Training results of a ResNet152 on DELAUNAY.** Curves represent training and validation accuracy over epochs. Marker indicates test accuracy. Dashed line represent performance of a greedy classifier with output fixed to the most common class. For training details see Section III.

(Figure 4), indicating that some artists are particularly often confused by the trained CNN, likely due to a high similarity of their works. From an historical perspective, such a high degree of similarity is not surprising: rather than working in isolation, artists are often significantly influenced by specific artistic movements and their personal environment such as close friends and family. For example, we observe a high degree of confusion between the works of Naum Gabo and his brother Antoine Pevsner, which indeed can be traced back to a high degree of similarity samples from these classes (Figure 4).

IV. DISCUSSION/CONCLUSION

We have introduced DELAUNAY, a dataset of images of abstract and non-figurative artworks from 53 different artists. It provides a middle ground between natural images typically used in machine learning research and unnatural, structureless patterns at the opposite side of the spectrum. We believe the unique properties of this dataset make it useful for both machine learning as well as psychophysics research, for example to investigate the hypothesis that sample efficiency scales inversely with the statistical similarity of samples to natural images for humans but not for DNNs.

Here we illustrated two intriguing properties of the dataset which make it challenging for classical deep-learning approaches: first, the intra-class variance for some classes is large, and second the inter-class variance for some classes is (relatively) small. We believe that addressing these challenges, supported by insights about human strategies obtained from psychophysical experiments, is a fruitful direction to both further understanding brain function as well as developing new machine learning methods. We are excited about seeing the community put this dataset to creative use.

CODE AND DATA AVAILABILITY

Link to the dataset (including the original URLs for all samples), as well as scripts used for the creation of the dataset, for training the CNN, and analysis of the results are available from https://github.com/camillegontier/DELAUNAY_dataset.

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ANNEX

Artists included in the dataset: Josef Albers, Jean Arp, Olle Bærtling, Jean Bazaine, Étienne Béothy, Roger Bissière, Anthony Caro, Jean Degottex, Sonia and Robert Delaunay, César Domela, Jean Dubuffet, Jean Fautrier, Lucio Fontana, Sam Francis, Otto Freundlich, Naum Gabo, Léon Gischia, Jean Gorin, Hans Hartung, Auguste Herbin, Vassily Kandinsky, Ellsworth Kelly, Yves Klein, Franz Kline, František Kupka, Charles Lapicque, Berto Lardera, Fernand Léger, Richard Paul Lohse, Morris Louis, Alberto Magnelli, Alfred Manessier, Georges Mathieu, Joan Mitchell, László Moholy-Nagy, Piet Mondrian, François Morellet, Aurélie Nemours, Kenneth Noland, Antoine Pevsner, Leon Polk Smith, Ad Reinhardt, Mark Rothko, Gustave Singier, Pierre Soulages, Sophie Taeuber-Arp, Pierre Tal Coat, Theo van Doesburg, Georges Vantongerloo, Victor Vasarely, Emilio Vedova, Maria Helena Vieira da Silva, Charmion Von Wiegand.

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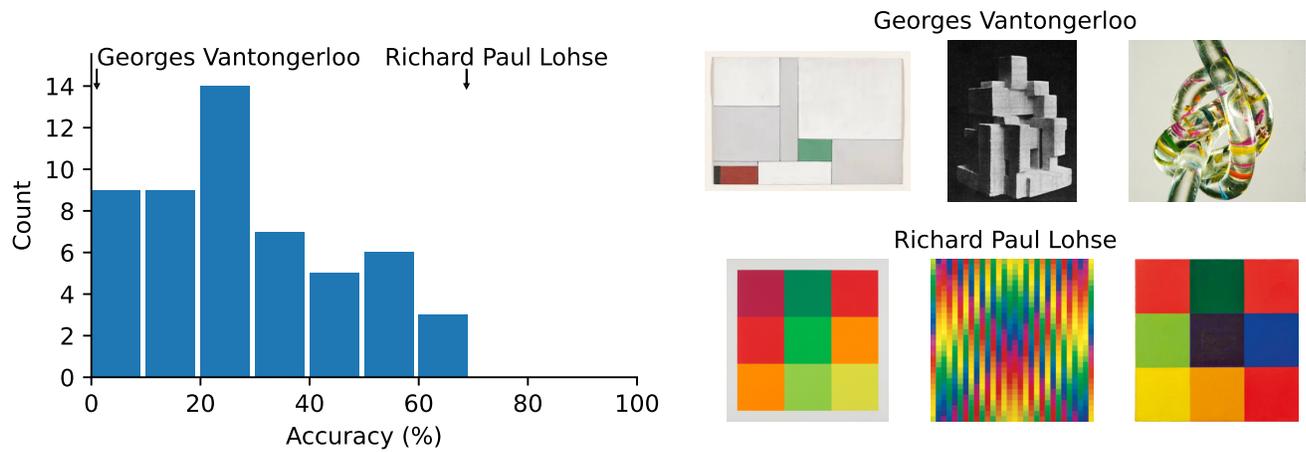


Fig. 3: **High intra-class variability in DELAUNAY leads to low test accuracies for some classes.** Left: Histogram over accuracies for all 53 classes in the test set. Highlighted are two artists with low and high test accuracies, respectively. Right: Example of works from Georges Vantongerloo (top) and Richard Paul Lohse (bottom). Note the high and low variability of samples within these classes, respectively.

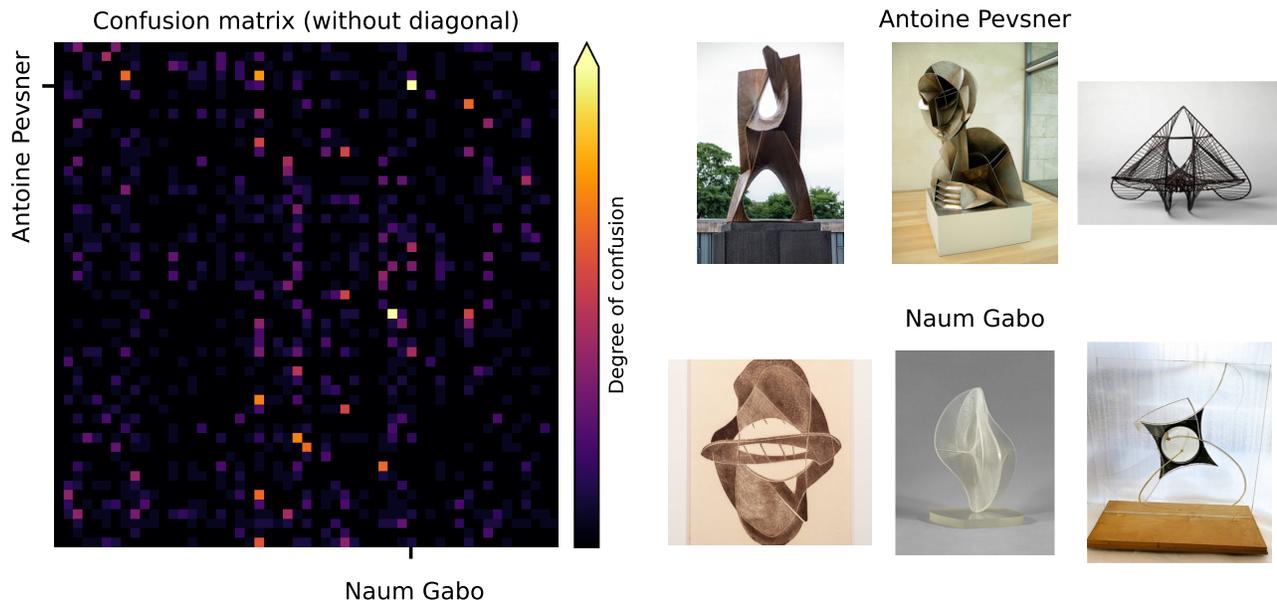


Fig. 4: **Low inter-class variability leads to high degree of confusion for some class pairs.** Left: Confusion matrix for all 53 classes in the test set. Diagonal entries were removed. Right: Example of works from Naum Gabo (top) and Antoine Pevsner (bottom). Note the high similarity of samples from these different classes.

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Artist	Sample count
Josef Albers	285
Jean Arp	337
Olle Baertling	151
Jean Bazaine	207
Étienne Béothy	207
Roger Bissière	198
Anthony Caro	261
Jean Degottex	212
Sonia and Robert Delaunay	176
César Domela	171
Jean Dubuffet	364
Jean Fautrier	269
Lucio Fontana	159
Sam Francis	280
Otto Freundlich	181
Naum Gabo	261
Léon Gischia	79
Jean Gorin	208
Hans Hartung	251
Auguste Herbin	222
Vassily Kandinsky	377
Ellsworth Kelly	216
Yves Klein	123
Franz Kline	180
František Kupka	259
Charles Lapicque	250
Berto Lardera	203
Fernand Léger	169
Richard Paul Lohse	194
Morris Louis	225
Alberto Magnelli	265
Alfred Manessier	283
Georges Mathieu	199
Joan Mitchell	91
László Moholy-Nagy	232
Piet Mondrian	176
François Morellet	201
Aurélien Nemours	190
Kenneth Noland	229
Antoine Pevsner	218
Leon Polk Smith	196
Ad Reinhardt	167
Mark Rothko	300
Gustave Singier	256
Pierre Soulages	176
Sophie Taeuber-Arp	186
Pierre Tal Coat	195
Theo van Doesburg	197
Georges Vantongerloo	170
Victor Vasarely	312
Emilio Vedova	202
Maria Helena Vieira da Silva	223
Charmion Von Wiegand	164