Are the morphometric dimensions of artificial drawing out of measure?

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Abstract

In recent years, drawing (and designing) is increasingly done using artificial intelligence applications to the extent that the (theoretical-practical) academic discipline of Drawing can be reformulated in terms of "Artificial Drawing" [AD], remaining faithful to its ancient aesthetologic and scientific mission: "to depict the sensible form of things". The qualitative morphological mission of drawing, in the era of computational aesthetics, encounters a development of possible morphological measurements well beyond the possibilities of human perception and computation.
To qualitatively measure the morphometric dimensions of AD, this contribution addresses primarily the principles of scientific morphography and morphometry of the 19th century in its connections with today's computational aesthetics, in order to compare them with the possibilities open to AD. It then proposes to map the "black box" of image description algorithms in terms of levels of semiotic analysis of images of Greimassian tradition to measure how today's systems of "artificial perception" implement a total syncretism of the semiotic dimensions of the "figural" decomposed into the category of the "figurative" (abstract vs. iconic) and its neutral term: the "figurable" or "indiscernible" (non-iconic vs. non-figurative). On these semiotic maps, it will be possible to measure the processes of descriptive AD (which starts from the figurative) and generative AD (which moves from the figurable) and which lead to generally measurable outcomes in the dimensions of "asemic writings". Based on the arguments presented, we can conclusively answer the initial question. The morphometric dimensions of the artificial design are indeed measurable to a degree that allows us to provide an appropriate semiotic representation.

Keywords
artificial drawing, computational aesthetics, aesthetic measurement, generative design, theory of drawing.

Three images generated using a Stable Diffusion model trained on images from the Codex Seraphinianus to explore and parameterise the ways in which generative AI produces forms of 'asemic writing'. Elaboration by the authors.

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« Si le nez de Cléopâtre eût été plus court,
toute la face du monde aurait changé. »

[Pascal 1670, p. 162]

Drawing, morphometry, and artificial imagination

The theory and history of representation and drawing have always been linked to the developments of perception theories such as today's advances in computer vision and computational aesthetics. A techno-scientific accomplishment of the art of drawing could already be envisaged from the pages of Lambert's *Neues Organon* (1763) [Lambert 1764], where, for the first time, the scientific-aesthetic dimension of representation is treated, inaugurating the terms "phenomenology" and "semiotics". But today, in the era of "artificial perception" [Manovich, Arielli 2022. Bo, Yu, Zhang 2018], the advent of a discipline of Artificial Drawing [AD] is an irreversible fact.

With AD, we mean the theoretical and practical discipline of "Drawing" in design prefiguration carried out using artificial intelligence applications [AI] both for descriptive (a) and prescriptive (b) purposes.

a. For descriptive purposes in the morphological and morphometric study of objects and environments, AI applications are employed in recognising, measuring, reading, and classifying given corpora of images or *exempla* while extracting characteristic information patterns.
b. For prescriptive (productive) purposes in the field of design representations in areas such as architecture [Leach 2021; Chaillou 2022; As, Basu, Talwar 2022], urban planning, and product and communication design – AI applications are used to generate new images and models starting from large datasets derived from corpora of various possible expressive substances that prove effective in automating various typical tasks: from concept to rendering, from survey to parametric modelling.

In the last few years, a large part of "Artificial Drawing" [AD] applications have been programmed with deep learning processes with neural network computing schemes fueled by means of immense datasets: corpora of visual images, each verbally labelled or correlated with texts in natural language. Such applications on one hand (a) are made to learn "a posteriori" to recognise in the analysed *exempla* particular "informative patterns" that would largely escape human computation and perception [Castellano, Vessio 2021]. On the other hand (b) other applications are developed to generate new data in response to inputs formulated in some expressive substance (visual, acoustic, verbal, ...), to produce in response new classifications of other corpora of images, or to generate new (unpublished) images. However, these generative AD systems presuppose the computer processes of feature extraction from vast datasets to produce new syntagmatic chains more or less suitable to the (human) meaning of the provided prompt.

Evaluating the adequacy ("intelligence") of AD tools case by case means comparing and making two opposite viewpoints translatable one into each other: that of natural human semiosis and that of artificial semiotics implicated in the forms of understanding and interpretation (processing) of the data carried out by machines. Therefore, the object of study of AD concerns both "basic research" in the "theories of representation and design ideation", and applied research on the themes of (descriptive and prescriptive) AI for design.

Descriptive AD

The first examples of "Artificial Drawing" for descriptive purposes ("morphological and morphometric") in the past decade have been pattern recognition systems, derived from those used in medical diagnostics through images and, especially, in histopathology and radiology, but used to provide visual expertise tools also in the domain of art, design, and urban and geographic morphology [Wieland, Pittore 2014; Liu et al. 2021]. These applications concern drawing, understood as an investigation of the form of (actual or potential) macroscopic bodies for scientific, technical, or artistic purposes. From this perspective, descriptive AD is historically situated in the evolution of scientific morphometry developed with comparative (synchronic) anatomy and phylogenetic (diachronic) taxonomies, especially from the 19th century, through comparativism conducted on vast museum collections of specimens: for example, collections of facial casts (ordered by ethnicity), skulls (ordered by cephalic index), or photographs of faces and human bodies ordered according to somatometric and biometric, physiognomic and constitutional categories through which natural bodies or prehistoric artefacts were studied by correlating the variety of shapes and measures with functional or expressive differences.

The evolution of AD is linked to the scientific development of morphometry [Remagnino et al. 2017. Wahl 2012] in its two faces:

- the techno-scientific evolution of data acquisition and segmentation, both in terms of signal sensors and mathematical models of shape geometry (from D'Arcy Thompson's diffeomorphisms [Thompson 1942] to today's multivariate statistical analyses);
- the semantic correlations between morphometric categories and content planes of a naturalistic (physiometric) or aesthetologic scope: a stylistic or an expressive-pathemic one.

Following the history of aesthetologic correlations of morphometry, we find that the precursors of today's computational aesthetics are already traceable in many morphometric methods coming from physiometry and followed by art historians, ethnoanthropologists [Parés-Casanova 2017], and 19th-century physicians: for example, Giovanni Morelli's attributive technique, the criteria for analysing calligraphic ductus or somatic typologies by Lombroso [Orrù 2023] and many others coming from the developments of ancient physiognomy and modern medical semeiotics. These 19th-century morphometric methods, for over a century, are often classified as "simplistic", "deterministic", dogmatically and naively "positivist", "pseudo-scientific" ... However, it makes no sense to attribute to any morphometric system the possible "stupidity" or "inadequacy" manifested by the use that has historically been made of it.

To grasp the new descriptive possibilities of AD, it is more urgent to semiotically understand the dimensions of the morphological analyses presupposed by AD, bearing in mind that the advent of digital technologies – transcoding every acquired dimension into numbers – has vastly expanded the possibilities of morphological analysis in aesthetics for obvious reasons:

1. Firstly, it has universally digitised information by numerically encoding many types of signals from different expressive substances: from visual to verbal, from acoustic to mechanical, chemical, kinetic...;
2. In doing so, it has integrated quantitative and qualitative dimensions of morphometric classifications into digital format;
3. Finally, it has provided new tools for perception, acquisition, and analysis of data, systems that transduce sounds, images, numbers, words, and other expressive substances into pure sets of numerical data represented and manipulated through algorithmic technologies in such complex ways that it would be impossible to replicate them with the same effectiveness using analog expressive substances.

The recent evolution of computational possibilities and algorithmic techniques allows AD to tackle morphometric elaborations on vast data corpora in an extremely efficient way. Before the last ten years, shape recognition systems in computer vision applicable to descriptive AD were based on two distinct blocks of manually programmed software.

- The first block extracts a series of visual features from image-matrices, recording each of them as a vector of values representing the presence or absence of certain features.
- The second block classifies these vectors as falling or not falling into predetermined categories (using predefined statistical weights based on the threshold reached by the sum of their values multiplied by a series of predefined statistical weights).

In these terms, the recognition of a given token as an occurrence of a given type is predominantly deductive – top-down or bottom-up – and based on morphometrically general

and abstract categories (types) that ideally encompass the maximum of qualitative traits (intensive mereological sum) and the maximum of real referents (extensive mereological difference) (fig. 3).
However, around 2012, there was a turning point in AD with the widespread adoption of deep learning techniques and neural network computing schemes because, in these procedures, the writing of "classifiers" is automated by the deep learning process [Amiri et al. 2023]. The statistical weights are initially set randomly, then continuously adapted during the learning process. In practice, the "classifiers" and "analysers" become freely composable computing modules, each corresponding to a phase of the analysis.
This means that, with deep learning, the system continuously learns and adapts to new information extracted from provided sets of exemplary images. Paradoxically, the "rule"

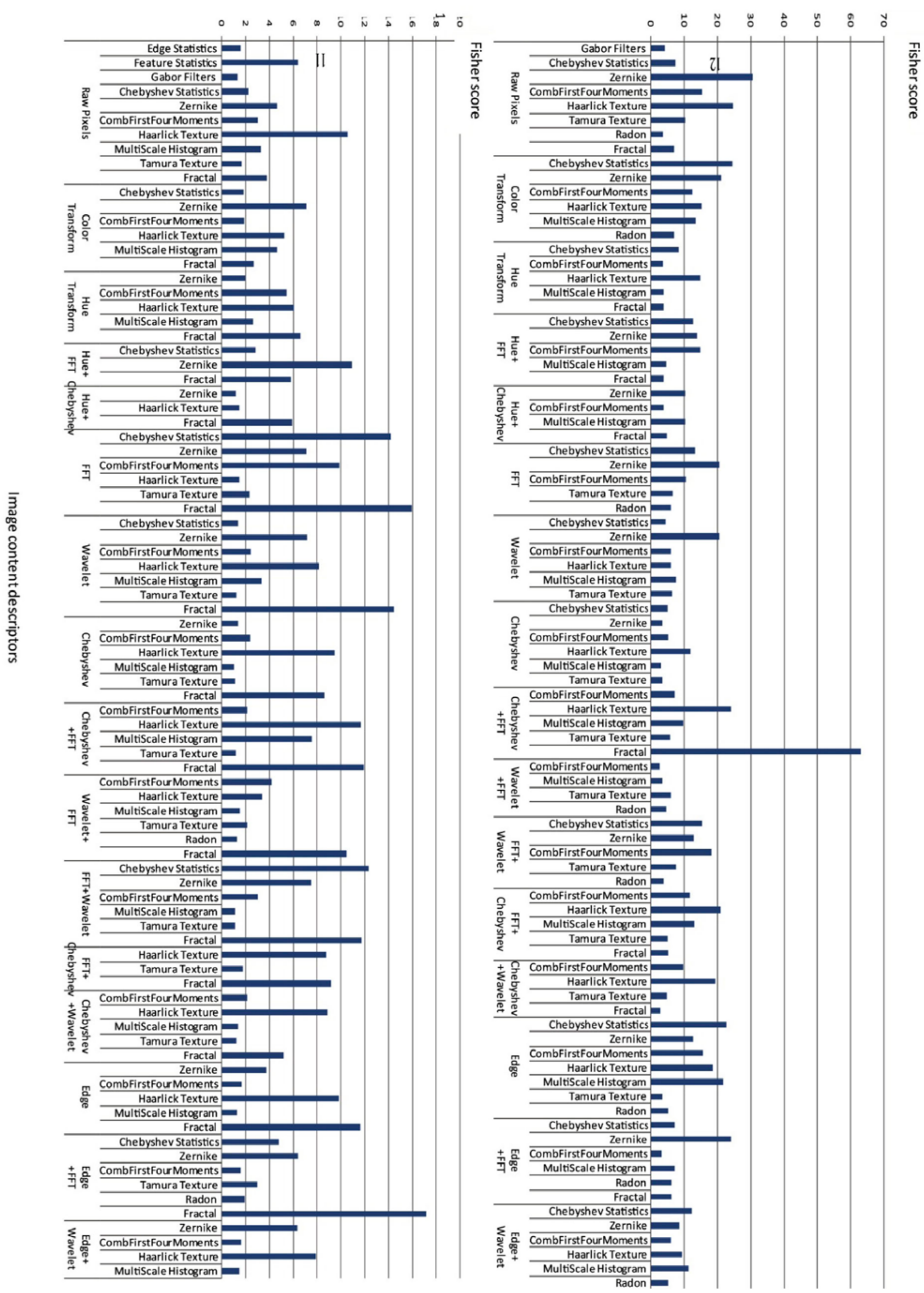

Fig. 1. List of image descriptor algorithms used by Lior Shamir in his development of software to discriminate real and fake Pollock paintings with measurement of the statistical relevance of the stylistic identification features contributed by each algorithm [Shamir 2015].

of recognising a type from tokens gradually emerges as the integration of all its successful exceptions. Now it is possible to design the construction of categories themselves in the real semantic multiplicity of categorisation strategies.

Image descriptors: a semiotic mapping

With the breakthrough of deep learning for image description and classification, it is the descriptors and classifiers themselves that determine each other statistically and a posteriori. This means that now, instead of programming an artificial perception process a priori, one can statistically assess which description algorithms are most efficient in extracting the significant features of an information pattern that characterises the entire corpus of analysed data. Lior Shamir's work [Shamir 2015] is an excellent early example of this approach. Using pattern recognition software designed for histopathological analyses, but adapting it to digital images of 26 original Jackson Pollock's works, Shamir extracted from each image the numerical values of various parameters identified by a large number of non-semantic level descriptors (fig. 1).
By simply comparing the 26 datasets, he ranked the measures obtained from the various descriptors and obtained a hierarchy of statistical weights between the descriptors adopted. Thanks to this retrospective (mainly "frequentist") statistical evaluation, he chose only the 25% of the most effective descriptors and identified a kind of attribution "rule" that he wrote down in the form of Fischer's linear discriminant algorithm. Finally, Shamir tested the algorithmic rule on random sequences of images of original works by Pollock mixed with fakes produced by artists emulating his dripping technique. The algorithm correctly discriminated between originals and non-originals in 93% of the cases.
Therefore, we know how the algorithm works in terms of conditional probability, but to understand why it works, we must realise that the descriptors constituting the modules of a learning network in the analysis of corpora of images (pictures) differ in the parameters of the statistical surveys that they measure on the numerical matrix of the image and, consequently, for the characteristics of the image they extract. Thus, from the point of view of

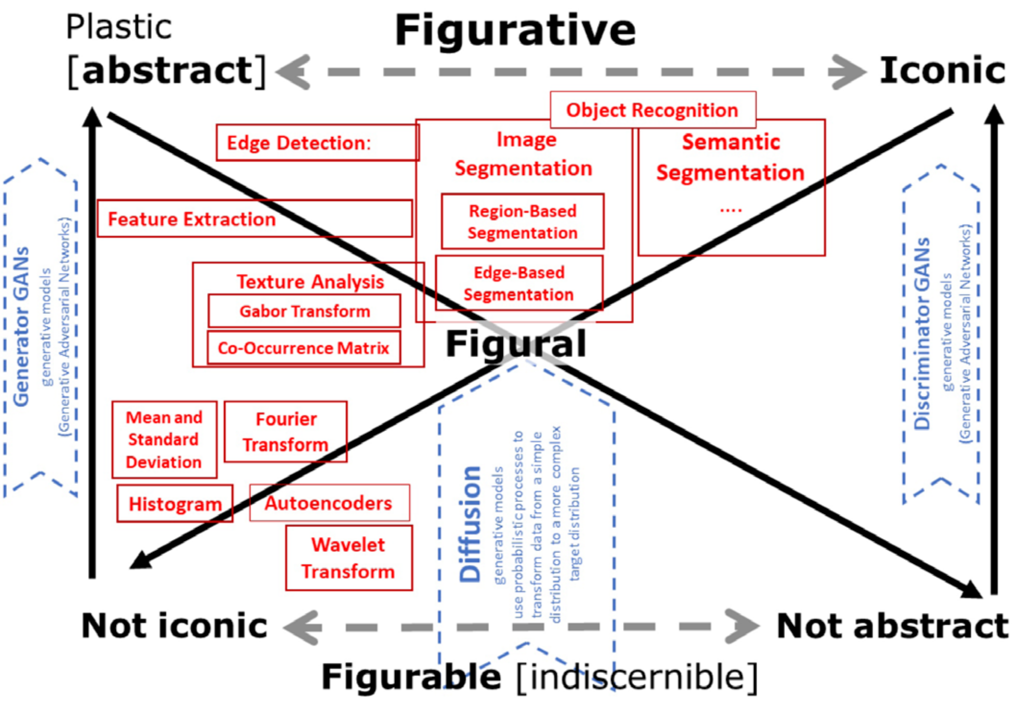

Fig. 2. Analysis of the semantic category of the "figurative" in its opposite poles – "abstract" and "iconic" – and subcontraries, distinct on the semiotic square whose entire field describes the articulations of the dimension of the "figural" and allows us to map the main classes of image descriptor algorithms – indicated in red – and – indicated in blue – types of generative neural network models for images. Diagram by the authors.

the Greimassian semiotics [Greimas 1984; Žemaitytė 2017], these descriptor algorithms are mappable among the degrees of analysis of the image that extend from the "plastic" level to the "iconic" level (fig. 2) according to an excursus between purovisibilist criteria and iconographic criteria.
Each descriptor can provide a measure of the image on the scale of a certain dichotomous category of visual characteristics. The so-called "low-level" algorithms measure plastic (non-iconic) characteristics: orientations, colour contrasts, contour shapes, textured patterns... They mainly measure dichotomous characteristics of different orders: i) topological (high/low, encompassing/encompassed, central/marginal, external/internal, contiguous/separated...), ii) textural (microtopographic and mereological, such as compact/scattered, porous/smooth...), iii) chromatic (saturated/unsaturated, vivid/faded, bright/dull, luminous/opaque, primary/quaternary...), iv) eidetic (linear/curvilinear, continuous/discontinuous, symmetric/asymmetric, uniform/variegated, simple/complex...).
"Medium-level" descriptors rework the previous characteristics of "low level" to identify and segment the more complex structures of an eidetic pattern characterising with high conditional probability the set of visual data provided.
Finally – this point also does not concern Shamir's experiment – at the "highest level" the system is able to segment the entire optical signal flow by extracting the semiotic characteristics related to the iconic level concerning the recognition of depicted objects and environments, gaits, figurative styles,..., as if in these modules the system assumed an iconographic and iconological criterion, associating images with attested verbal descriptions.
Learned by the system in this way, the morphometric rule that emerges is not easily explainable with the semiotic distinction between characteristics such as "abstract" vs. "iconic", "purovisibilist" vs. "iconographic", visual vs. verbal, etc., for three reasons:
i. The low-level (abstract) descriptor modules measure characteristics sometimes common to different expressive substances (visual, acoustic...);
ii. Even the modules of semantic level couple elements that can come from different expressive substances (verbal, visual, kinetic...) and refer to very different semantic domains (languages, idiolects, musicological dimensions, codes, ...);
iii. The different levels of descriptors of an analysis and recognition process of an image (visual, acoustic...) in a CNN system follow a nonlinear recursive progression of phases with continuous adjustments that affect all modules (blocks) of the system.

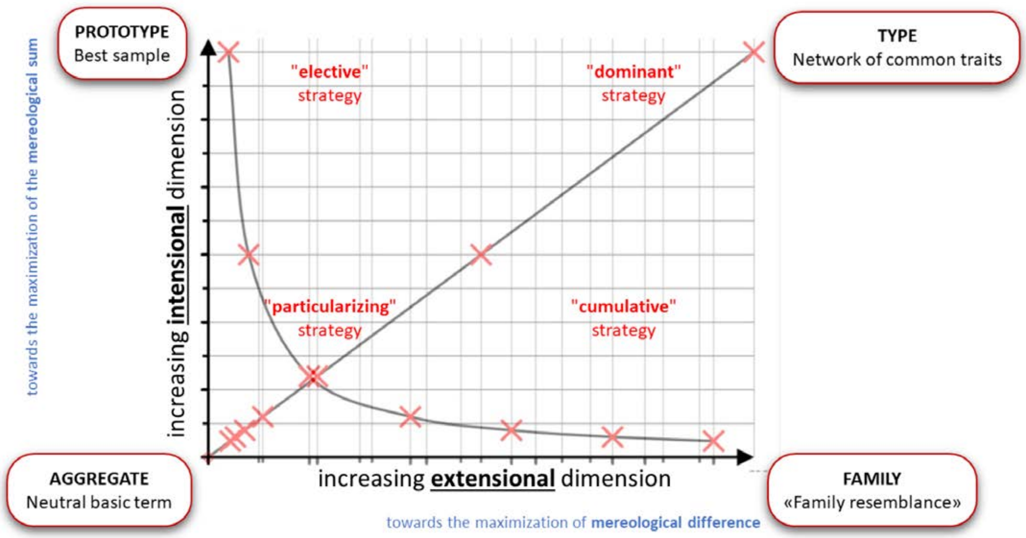

Fig. 3. Tensive diagram outlining the "styles of categorisation" in the four most extreme forms that the category takes depending on the direct or inverse correlation between extensional and intensional dimensions. Diagram reworked by the authors based on [Fontanille 2003].

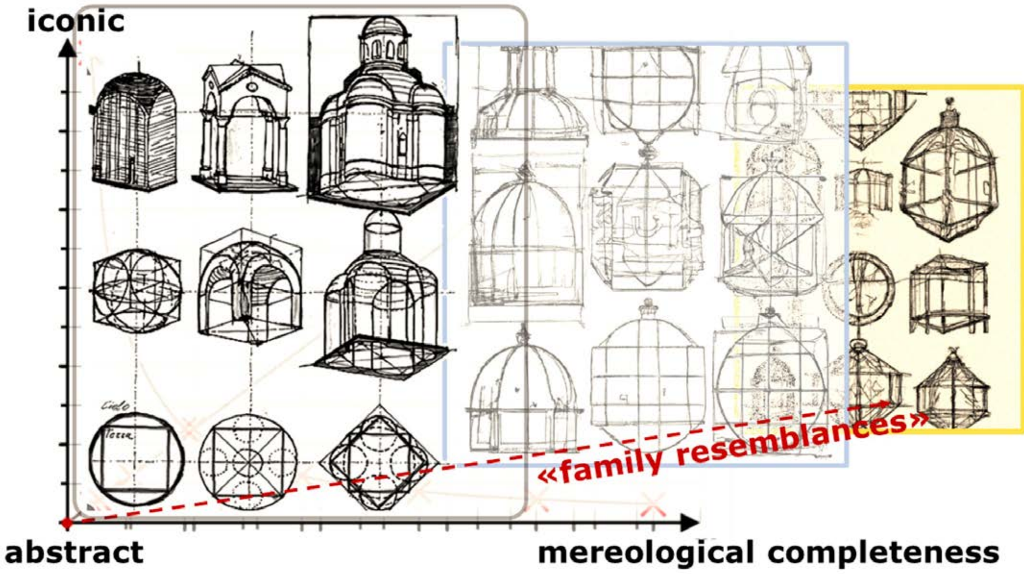

Fig. 4. Diagram of the main measurable dimensions in an experiment of artificial regeneration of the form of a Renaissance church body with a system partially supervised by specific datasets from iconographic sources.

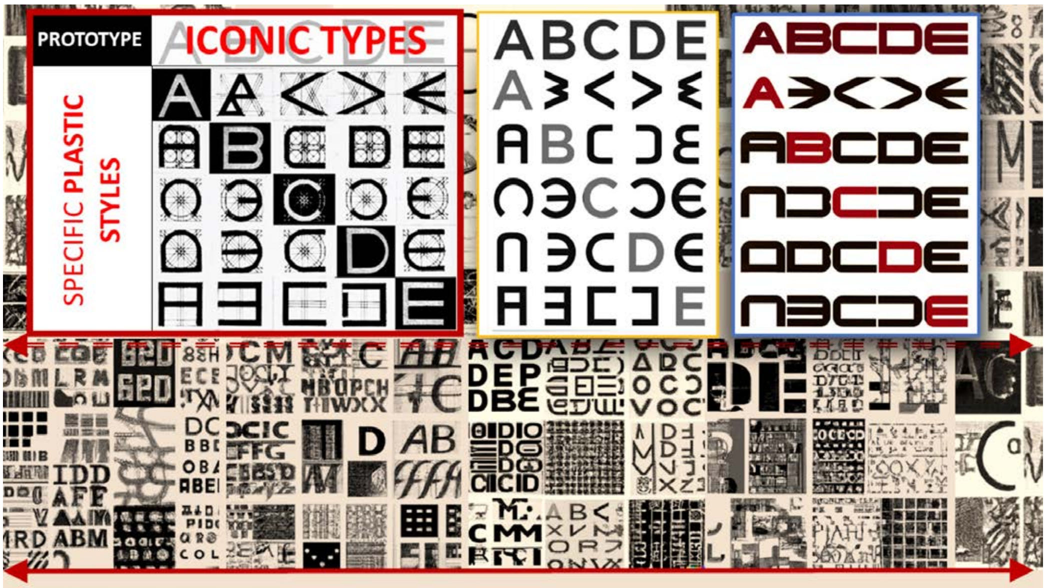

Fig. 5. Tables with examples of icono-plastic analysis of some typographic fonts initially assumed as exemplary prototypes - in the diagonal boxes of the tables - and filtered and reconfigured for a specific plastic scheme - along the rows of the tables - and for denoted alphabetical character - along the columns of the tables. In the background, variations are automatically conducted for "family resemblances".

Categorization styles and style categories in AD

Traditional morphometries serve to classify by "deduction" (top-down) a concrete token as corresponding or not to the denotative traits of an abstract and generalised type, or to construct by "induction" (bottom-up) an abstract type starting from the traits of concrete exemplary prototypes. Ideally, from the point of view of intension, the type is a network of denotative traits common to all the tokens that constitute its concrete extension.
However, in practice, classifications are dynamically constructed by traversing infinite possible ways but – following Fontanille [Fontanille 2003] – all mappable (fig. 3) based on the direct or inverse correlation between the intensional and extensional dimensions. Depending on the different strategies that the course of a measurement adopts, morphometric categories take on very different forms from that of the "Type" understood as a network of common traits of a class of occurrences. In particular, in the transition from the concreteness and individua-

lity of the "prototype" to the abstraction-generalisation of the "type" – from the "series" leader to the "typology" – the category goes through a state that the second Wittgenstein defined as "family resemblance", that is, it results in a weak lattice of relevant traits unevenly distributed among the traits of the tokens lending itself to be interpreted through countless and different semantic frameworks and perceived in its value of greater or lesser semantic cohesion. Assumed in its "family resemblances", an object is designed as a collection of parts and aspects belonging to different intensive traits.
A polythetic morphometry by "family resemblances" can now be constructed through deep learning in a CNN, both through the choice of the training data set, and through the composition of the layers of descriptors that process the data in parallel in a regime of (Bayesian) conditional probability that brings out the categories by abduction.
Demonstrating the aesthetic functioning of such a complex morphometry can be attempted using the same system to generate new forms consistent with the system and measuring the results case by case as if they were "asemic writings" (figg. 4-5).
Based on the arguments presented, we can conclusively answer the initial question. The morphometric dimensions of the AD are indeed measurable to a degree that allows us to provide an appropriate semiotic representation.

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