AI and the work of patterns

Recognition technologies, classification, and security

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The connection between AI and patterns is so self-evident that addressing it might seem downright redundant. Nevertheless, I hope to make this connection a little less self-evident and to identify some aspects of what I will call the work of and on patterns in AI. While Kaufmann, Egbert and Leese (2019) limit the "politics of patterns" solely to questions of policing applications, I will understand the political dimension of patterns in a broader cultural-historical sense, asking for the politics specifically associated with the work of patterns. This means examining the power and agency of patterns and including contexts and discourses that at first glance seem far removed from current AI issues. In doing so, I will contribute to the question that interests this volume, how changes 'beyond quantity' occur in the context of artificial neural networks, that is, how ways of knowing are affected by AI technologies and vice versa.

I begin with the assumption that AI epistemologically finds itself in a middle, and an ambiguous, position in at least three ways. Firstly, from a disciplinary perspective, it is situated between the sciences of nature and the sciences of culture (Ganascia 2010: 71), rendering AI an intermediary realm between the two (ibid.: 68, with reference to Rickert 1926: 101). Secondly, its theoretical-methodological status oscillates between science and tool (cf. Russell/Norvig 2021), which makes it both an object of academic research and an agent in economic application contexts (product, service), thus generating a kind of 'scientific economic complex' that is accompanied by specific affordances. For while the supposed 'AI winter(s)' were related to the impossibility of adequately representing intelligence in machines in a rule-based way (symbolic AI), the current success owes much to the displacement of this question in favor of the broad applicability of AI technologies operating on the basis of machine learning and increased computational power (subsymbolic AI) (on the genealogy of

AI cf. Crevier 1993; Sudmann 2019). Thirdly, from the cultural and media studies approach of this paper, AI technologies are to be understood as media (in the broader sense).[1] This means to take them seriously in their role as mediators and to ask which inherent logics they go hand in hand with, which forms of knowledge and power they express, which genealogies they entail and how they transform social and societal relations and institutions (intimacy, education, health, security etc.).

The argument will proceed in four steps. The first two will focus on pattern formation and on pattern detection, respectively. I will here take a closer look at the role of patterns in general and explore their agency and effects: What exactly is the power of patterns in contexts of cognition or application, what exactly do patterns 'do' in this process, how does resorting to the notion of pattern inform processes of understanding? In doing so, I will (culturally and historically) distinguish between two forms of patterns, or more precisely two ways of conceptualizing them, namely *template* in the sense of 'stencil' (German: Schablone) on the one hand, and *correlation* (respectively *emergence*) on the other. In the further course, it will become apparent how these two forms are peculiarly intertwined in the horizon of AI technologies. Thus, the paper does not discuss a historical development or translation from template to correlation, but the specific layering of these two understandings in today's AI systems. In a third step, using the application domain of security research, I will look at what the concrete experimental settings and setups of activity recognition reveal about the status of patterns and show how the blending of template and correlation works out here. The focus will be on German pilot projects in Berlin and Mannheim that test the use of intelligent video analysis. And finally, I will comment on the statistical creativity of AI image generators such as DALL-E, highlight four overarching aspects associated with the work of patterns of AI technologies, and describe their effects on scientific understanding, but also on culture and society in general: These concern the connection between promised simplification and actual complication by AI technologies, the

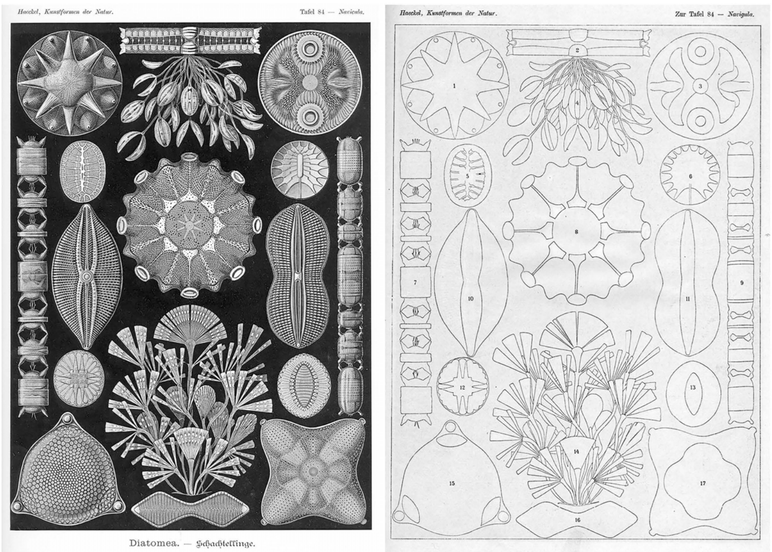
1 Such a perspective assumes that not only communication media (mass media, social media), but also scientific instruments, technical apparatuses, means of transportation, infrastructural networks, and bodies can be understood as media insofar as they are instances of mediation and transmission. Evidence can already be found in the history of the term, according to which *medium* in classical Latin equally meant "middle", "intermediary", and "means" (OED 2023: medium; Seitter 2002: 19–32).

politics of rationalization and familiarization going along with them, their legitimization by scientific application contexts, and the invisibilization of their normative aspects.

1. Pattern formation

According to the German sociologist Armin Nassehi (2019), the success of digitization – and for him this implies the use of AI systems – is that it makes the regularities of societies visible again. Thus, in Nassehi's eyes, digitization does not produce anything radically new, but rather it represents a fundamental irritation for the self-understanding of 20th century modernity in terms of freedom and plurality: For it makes us aware of the extent to which types, regularities and categorizations are in operation (ibid.: 50–51), even if, as Andreas Reckwitz puts it, "the society of singularities" (2020) does not want to admit this. Although this article will not follow a systems theory approach, Nassehi's suggestion to understand what digital (and AI) technologies are doing as a kind of 'rediscovery' of patterns of order seems worth considering.

Figure 1: Haeckel's art forms of nature. Taken from Haeckel (1904: plate 84).



Patterns are central structures in the cultural history of mankind, because they are essential for the fact that something like cognition can take place at all. Patterns are regular structures, which are characterized by repetition (be it spatially or temporally) and (self-)similarity (cf. Stewart 2001: 28–37). Human perception as well as information theory mainly operate with patterns of medium entropy, that is with such structures that are neither mere noise nor completely identical. For patterns understood in this way, one could think of the simple organisms in the field of fauna and flora described by Ernst Haeckel as "art forms in nature"; it is the geometry of their basic shapes ("Grundformen", 1904: 9) that Haeckel emphasizes as aesthetic and as accessible to a morphological observation (also through techniques of microscopic magnification). The plates for the organisms in question are therefore always displayed twice: The diatoms, for example, are shown (fig. 1) once in a realistic fashion and once only as schematic outlines, which makes the patterned nature of the forms (symmetries, repetitions) even more obvious.

In a broader sense, familiar phenomena like waves, dunes or clouds also exhibit pattern formation. Here, one could also think of the fractals described by Benoit Mandelbrot (1982), which imply self-similarity in a recursive logic and consist of reduced copies of themselves. Thereby, he illustrates the differences between the different types of self-similarity (fig. 2).

Figure 2: Self-similarity, standard and fractal. Taken from Mandelbrot (1982: 44).

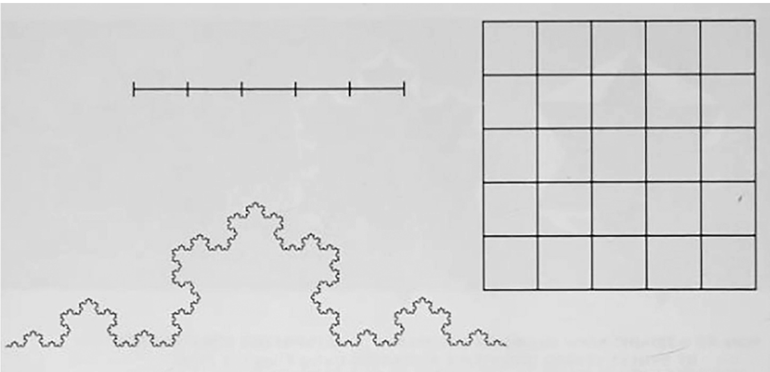
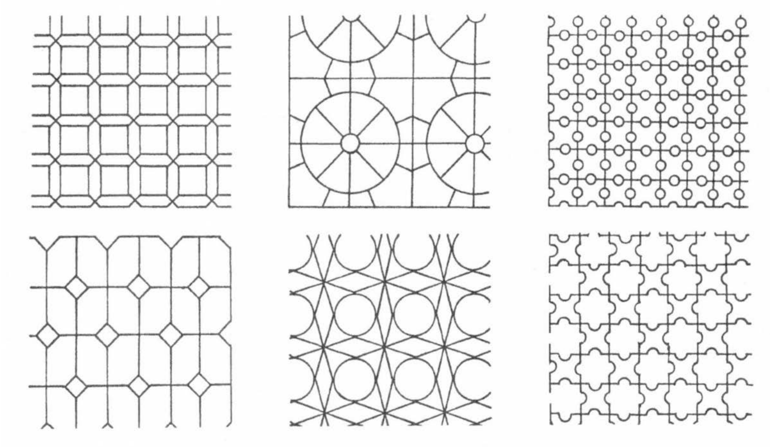
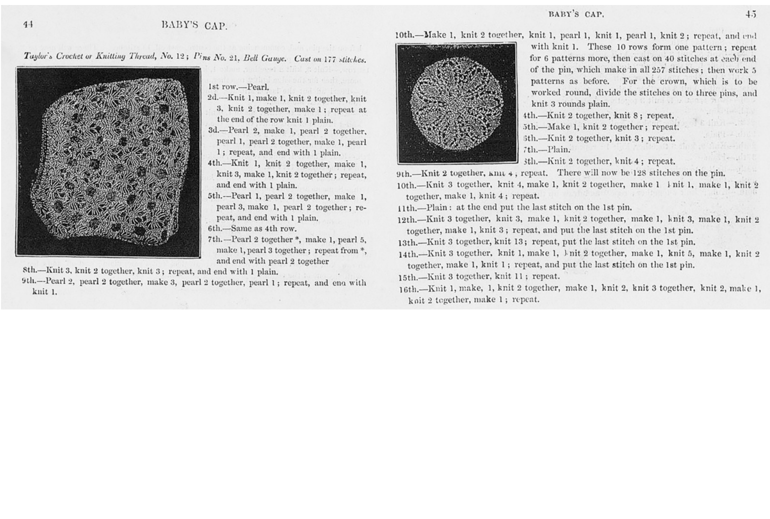


Figure 3: Tilings from Portugal, 15^{th} century. Taken from Grünbaum/Shephard (2016 [1987]: 7).



Patterns, however, do not only arise naturally, they can also be actively manufactured. One may think of tropes and figures in rhetoric, forms of parquetry and tiling (fig. 3), wallpaper, fabric and knitting patterns (fig. 4), but also of architectural ornaments (cf. Gombrich 1984) or patterns in music (in the sense of recurring rhythmic or harmonic structures).

Figure 4: Instructions for a baby cap from a Victorian knitting book, each row indicating the stitches to be knitted. Taken from Riego de la Branchardière (1848: 44f.).



44 BABY'S CAP.

Taylor's Crochet or Knitting Thread, No. 12; Pins No. 21, Bell Gauge. Cast on 177 stitches.

1st row.—Pearl.
2d.—Knit 1, make 1, knit 2 together, knit 3, knit 2 together, make 1; repeat at the end of the row knit 1 plain.
3d.—Pearl 2, make 1, pearl 2 together, pearl 1, pearl 2 together, make 1, pearl 1; repeat, and end with 1 plain.
4th.—Knit 1, knit 2 together, make 1, knit 3, make 1, knit 2 together; repeat, and end with 1 plain.
5th.—Pearl 1, pearl 2 together, make 1, pearl 3, make 1, pearl 2 together; repeat, and end with 1 plain.
6th.—Same as 4th row.
7th.—Pearl 2 together *, make 1, pearl 5, make 1, pearl 3 together; repeat from *, and end with pearl 2 together
8th.—Knit 3, knit 2 together, knit 3; repeat, and end with 1 plain.
9th.—Pearl 2, pearl 2 together, make 3, pearl 2 together, pearl 1; repeat, and end with knit 1.

BABY'S CAP. 45

10th.—Make 1, knit 2 together, knit 1, pearl 1, knit 1, pearl 1, knit 2; repeat, and end with knit 1. These 10 rows form one pattern; repeat for 6 patterns more, then cast on 40 stitches at each end of the pin, which make in all 257 stitches; then work 5 patterns as before. For the crown, which is to be worked round, divide the stitches on to three pins, and knit 3 rounds plain.
4th.—Knit 2 together, knit 8; repeat.
5th.—Make 1, knit 2 together; repeat.
6th.—Knit 2 together, knit 3; repeat.
7th.—Plain.
8th.—Knit 2 together, knit 4; repeat.
9th.—Knit 2 together, knit 4; repeat. There will now be 128 stitches on the pin.
10th.—Knit 3 together, knit 4, make 1, knit 2 together, make 1 knit 1, make 1, knit 2 together, make 1, knit 4; repeat.
11th.—Plain: at the end put the last stitch on the 1st pin.
12th.—Knit 3 together, knit 3, make 1, knit 2 together, make 1, knit 3, make 1, knit 2 together, make 1, knit 3; repeat, and put the last stitch on the 1st pin.
13th.—Knit 3 together, knit 13; repeat, put the last stitch on the 1st pin.
14th.—Knit 3 together, knit 1, make 1, knit 2 together, make 1, knit 5, make 1, knit 2 together, make 1, knit 1; repeat, and put the last stitch on the 1st pin.
15th.—Knit 3 together, knit 11; repeat.
16th.—Knit 1, make, 1, knit 2 together, make 1, knit 2, knit 3 together, knit 2, make 1, knit 2 together, make 1; repeat.

Figure 5: Simple geometric forms. Taken from Day (1887: plate 3).

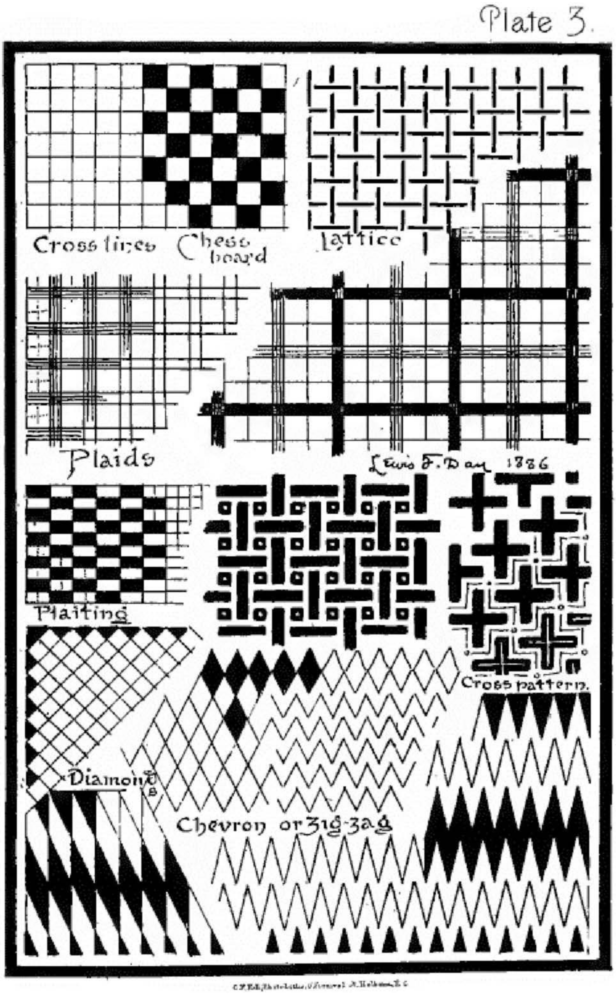


Figure 6: Jacquard loom, Musée d'art et d'industrie de Saint-Étienne, France. Photograph © Hélène Rival (2012).

Although patterns might at first be understood as primarily visual and spatial, reference to sounds, music, and speech reveals their equally acoustic and temporal dimensions. In all these cases, patterns can be generated because they are calculable due to their properties of iterability and regularity, and thus usable for diverse kinds of compositions. They can be written down and made available as instructions and plans. Variation is possible on the basis of simple, geometric forms and operations (fig. 5).[2]

2 If space fillings (tessalation) are designed in such a way that basic shapes are repeated symmetrically, one speaks of periodic patterns: they are created by mirroring, shifting

Errors, irritations and other forms of disturbance can be identified as deviations from the specified pattern. These man-made patterns are thus based on a form of programming, i.e., an operation in individual steps that takes the form of algorithmic processing. It is therefore no coincidence that the history of computing refers to mechanical weaving as a predecessor, and especially the programming of looms with punch cards since the late 18th century (cf. Schneider 2007) (fig. 6).[3]

The important role of regularity of patterns is seen early on. Lewis F. Day, a British artist of the Arts and Crafts movement, records in his little instruction booklet on ornamental design, *The Anatomy of Pattern* (1887):

> The very repetition of parts, then, produces pattern; so much so, that one may say wherever there is ordered repetition there is pattern. Take any form you please, and repeat it at regular intervals, and you have, whether you want it or not, a pattern, as surely as the recurrence of sounds will produce rhythm or cadence. (ibid.: 2)

For Day, the process of creating patterns is fundamentally accompanied by operations of differentiation, grouping, and classification, which refer to the fundamental regularity of the world:

> [A]nd just as the physiologist divides the animal world, according to anatomy, into families and classes, so the ornamentist is able to classify all pattern-work according to its structure. Like the scientist, he is able even to show the affinity between groups to all appearance dissimilar; and, indeed, to point out how few are the varieties of skeleton upon which all this variety of effect is framed. (ibid.: 3f.)

Patterns, thus, relate not only to regularity, but are tied to basic operations of classification.

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and rotating geometric figures (rhombuses, triangles, quadrilaterals), which regularly fill surfaces as basic elements. If such symmetries are not provided, one speaks of aperiodic tiling patterns such as Penrose tiling (cf. Grünbaum/Shepard 2016 [1987]).

3 Lorraine Daston, in her book on rules, describes the transition from "rule-as-model" to "rule-as-algorithm" (2022: 21) as the consequence of the division of labor in the 19th century, which decomposed processes into calculable single steps and in this way made possible the transition from uncertain to controllable, fixed contexts (ibid.: 120f.).

2. Pattern detection

Corresponding to their regular formation, the recognition of patterns requires the ability to identify such similarities, regularities, repetitions or rules in given corpora of data. This insight is equally applied in cognitive science and perceptual psychology (Eysenck/Keane 2015; with reference to Gestalt psychology Koffka 1935: 106–177; Ehrenfels 1890), but also in computer science where the focus is on automating such recognition processes. The recognition of patterns here is considered to be the detection of feature complexes, which are (after a training phase) automatically assigned to certain categories. Pattern recognition is thus always accompanied by tasks of classification. However, it does not only concern the assignment of objects to already existing classes, but also the assignment of feature complexes to different classes, which are thus created in the first place. Even if today's computer scientists consider the term "input-output mapping" to be more accurate and prefer it to that of pattern recognition in order to avoid the comparison to biological systems and visual perception, Matteo Pasquinelli states: "Nonetheless, the construction of a relation between an input *x* and output *y* is still fundamentally the search for a pattern" (2019: 8; original emphasis).

This means that before a pattern can be recognized by information technology, it must be produced: In machine learning, an AI system has to first learn on the basis of training data what it is supposed to recognize at all. Since – analogous to natural neural networks – it is a matter of experiential learning, it is important which 'experiences' the AI makes.[4] The objects of these recognition processes (be they images, objects, activities) are nothing more than "statistical distributions of a pattern" (Pasquinelli 2019: 8). In principle, all forms of machine learning work with the three operations *training*, *classification*, and *prediction*, which are fundamentally related to patterns: The training phase concerns "*pattern abstraction*", the algorithm learns to associate an input with a certain output (for example, a label); classification can be understood as "*pattern recognition*" in the literal sense: new input data are compared with the learned statistical distribution in order to see if they fall within its range and have to be

4 Different types of machine learning can be distinguished (Russell/Norvig 2022: 670f.): The AI can learn by defining input/output pairs (*supervised learning*), by defining only the input and letting the neural networks come to results themselves (*unsupervised learning*), or by implementing a kind of self-optimization that works with reinforcing feedback (*reinforcement learning*).

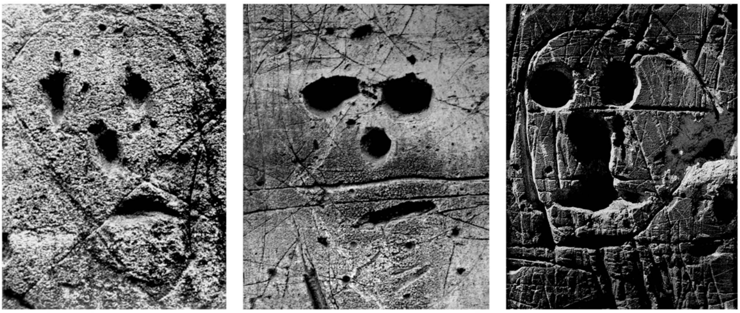
assigned the corresponding output label; finally, prediction can be understood, as Pasquinelli puts it counterintuitively, as "*pattern generation*" (ibid.: 8f.; original emphasis). Here, new input data is used to "predict their output value *y*", that is, the statistical model "is run *backwards* to generate new patterns rather than recording them" (ibid.; original emphasis).

However, training data for AI systems is a "scarce resource" (Mühlhoff 2020: 1873), since their production is labor, time and computationally intensive and therefore causes high costs. For this reason, the same large benchmark data sets are used again and again, rendering them "the alphabet on which a *lingua franca* is based" that is used and expanded in the competition between the different companies for the best performance (Crawford 2021: 97; original emphasis) and which generates "[g]enealogies of data collections [...], each building on the last—and often importing the same peculiarities, issues, or omissions wholesale" (ibid.: 102). For example, the image data set ImageNet, published in 2009 with 14 million images and 20,000 categories, relies on taxonomies derived from the WordNet lexical database, which has been under development since the mid-1980s and dates back to the 1961 Brown Corpus (ibid.: 136). But although it would be crucial for classification systems and the political-social institutions that relate to and depend on them, to this day there are "no standardized practices to note where all this data came from or how it was acquired" (ibid.: 103). The history of science, however, recently turned to such questions of data re-use, asking, from both a theoretical as well as methodological perspective, what effects the mutability and mobility of data – their "data journeys" – have on the respective disciplines, the knowledge produced, and the politics associated with the data (Leonelli 2020). This is all the more relevant because economic factors play an important role. Part of the story of the production of ImageNet, for example, was that for the first time data labeling was outsourced to poorly paid crowdworkers on Amazon Mechanical Turk, from which significant errors in the data resulted, not least because of the immense time pressure (50 frames had to be labeled per minute). Training data is thus accompanied by various forms of bias, which is discussed as discriminatory AI or "discriminating data" (Chun 2021). Distortions can be found on at least three levels: Firstly, the implementation of already existing stereotypes in the AI systems (*world bias*), then the way the training data is produced (capturing, formatting, labeling) and, for example, whether it includes older (more conservative) taxonomies to save costs (*data bias*), and finally computational errors and "information compression" that make already existing inequalities even more unequal (*algorithmic bias*) (Pasquinelli 2019: 9f.). As we have seen with respect to the genealogies of data sets for training, it is especially data bias that is important here. In the field of biometric recognition, errors can be found with respect to feature extraction (cleansing, reduction, and incompleteness of data), but also with regard to the inaccuracy of annotations or the non-representative weight of groups (gender, race, class, age, origin, etc.) leading to multiple forms of discrimination (gender bias, racial bias, age bias etc.), when supposedly detected features are assigned to certain classes (cf. Boulamwini/Gebru 2018; Benjamin 2019; Nobel 2019).

AI systems trained on a sufficiently large data set with correctly labeled data should subsequently be able to correctly classify new data according to the learned pattern. They thus proceed inductively and generalize, starting from their training data. In supervised learning, two types of generalization errors can occur (*bias-variance tradeoff*) (Samutt/Webb 2011: 100): in one case, the system does not learn correctly, i.e., does not establish the correct relationships between input and output (*underfitting*); in the other, it is too sensitive to variations in the training data (*overfitting*). Thus, while in the first case it learns the 'wrong' patterns, in the second it cannot sufficiently distinguish between pattern and background (Pasquinelli 2019: 11). We all know such forms of irritation from the field of human perception, when faces are seen in things where there are none, in the well-known case of pareidolia. Pictures of the Hungarian-French artist Brassaï can illustrate the point in question: On his wanderings through nocturnal Paris around 1930, Brassaï photographed walls with indentations and holes (fig. 7) which all seem face-like, as they invoke the culturally and historically anchored schematicity of the face (dot, dot, comma, stroke) (Weigel 2017: 126; on faciality cf. Deleuze/Guattari 1987: 167–191). Overfitting to training data generates similar effects, which is why such phenomena are also described as "data paranoia" (Apprich 2018) or apophenia (Steyerl 2018).

But if all these irritations, errors, and deviations occur in the context of machine learning, why do the fundamental problems of classification and taxonomy in and by AI systems receive such little attention? According to Kate Crawford, "the issue of bias in artificial intelligence has drawn us away from assessing the core practices of classification in AI, along with their attendant politics" (Crawford 2021: 128). The companies concerned see forms of bias as a purely technical problem – "a bug to be fixed" (ibid.: 130) – rather than a call to debate "*why* these forms of bias and discrimination frequently recur and whether more fundamental problems are at work than simply an inadequate underlying dataset or a poorly designed algorithm" (ibid.: 129; original emphasis). However, this leads to a self-reinforcing logic that confirms the supposed neutrality of the technical (cf. ibid.: 131), thus normalizing the underlying worldviews and classifications: "[T]raining datasets pass as purely technical, whereas in fact they contain political interventions within their taxonomies: they naturalize a particular ordering of the world which produces effects that are seen to justify their original ordering" (ibid.: 139).

Figure 7: Brassaï, Series "La Naissance du Visage" and "Masques et visages" (around 1930). © Estate Brassaï 2023.



What, then, do patterns from the fields of cultural and natural history have to do with those of computer science? What do we gain by relating them to each other? I argue that at least three aspects can be highlighted concerning the use of patterns in the context of AI technologies: the crossing of two different forms of patterns (template and correlation), the visibility, and respectively invisibility, of patterns, and the temporal dimension of patterns.

Regarding the first aspect, there is a crossing of two models of patterns, which I heuristically call the model of the *stencil* (template) (German: Schablone) on the one hand and the model of *correlation* or emergence on the other. In his *Oekonomische Enzyklopädie* (1805), Johann Georg Krünitz had already distinguished between different kinds of patterns (German: Muster): the model or prototype (German: Vorbild), in the physical as well as moral sense, then the sample of goods, the sample piece, and finally the pattern in the sense of a figure (for instance in gardening), referring to the dimension of showing and making see (*monstrare)* (ibid.: 219f.; cf. OED online 2023b). I argue that in the dimension of the prototype (in the broadest) sense as well as in the sample piece, a normative dimension of the pattern in the sense of the stencil is revealed, while the showing of a figure emphasizes the emergent dimension of the pattern. Now, in AI systems, I further argue, a blending of these two understandings of pattern occurs. For AI systems work with predefined patterns (such as annotated features and categories in training data), which they are not only supposed to recognize in use cases, but to enrich with further data to generate new patterns when it comes to prediction or, for example, image generation. On the basis of first-order patterns (stencils in the sense of templates), second-order patterns (correlations) are generated.

Secondly, such higher-order patterns – I refer once again to Armin Nassehi's argument – make something visible that modern society does not want to know about itself, namely how typifiable, classifiable and regular it is. In contrast, then, to the culturally and historically familiar visible surface divisions in the realm of mosaics, knitted fabrics, or wallpaper, we are dealing here with phenomenally invisible patterns, which, analogously to statistical surveys, only become visible with the use of mass data. Thus, patterns are centrally concerned with the question of their visibility and invisibility. Already in the case of the single-celled organisms analyzed by Haeckel, visibility was not immediately given, but had to be established first, for example by microscopic magnification. And in the case of parquetry, it has always been a matter of calculability. In the case of AI systems, the paradoxical situation arises that the comprehension of the calculation is not made available, so that the patterns *appear* as pure emergences.[5]

Thirdly, the patterns produced by AI technologies are accompanied by a shift in the temporal vector of cognition. The goal is not *re*-cognition alone (as it was in cultural and natural history), but rather *pre*-cognition. On the basis of a principal calculability of all conceivable correlations between myriads of categories, AI systems model expectations of consumption, behavior, but also of security. In the following I will briefly discuss the security domain, because AI systems are on the agenda here less to contain current problems than to preemptively deal with future ones. On the basis of stenciled training data, AI

5 In fact, there is no such thing as 'pure' emergence. As Boris Groys has shown for the field of art, the new is always based on re-combinations of what already exists, revaluations of contexts, and new comparisons (1992, 2000). In contrast to previous forms of the 'new', AI technologies can recombine any number of elements in any number of subtle ways without making any mistakes or forgetting anything; they therefore no longer have the possibility of negation, intervention, or deviation.

systems do not only anticipate the future, but also shape it quasi-automatically through the policies that accompany them.

3. Security in crowded settings

In the aftermath of 9/11, security issues have become a preferred domain for the application of AI systems, coupling forms of visual surveillance with the control of data flows (dataveillance) and giving rise to systems of intelligent video surveillance (Stanley 2019; in broader perspective Andrejevic 2020). The focus is on biometric recognition systems (face, iris, gait, etc.) as well as on object and activity recognition, which are believed to have decisive gatekeeping functions for regulating traffic flows and correlating security regimes. In the following, I would like to refer to image recognition methods that are used in video analytics, in which images of surveillance video feeds are automatically analyzed. In particular, I concentrate on two German pilot projects in Berlin and Mannheim that are testing such AI systems in public spaces, that is at a train station and in further urban areas. At first glance, train stations seem to be much less security-critical settings than, for example, border regimes of states. Nevertheless, such constellations are a good illustration of the "'becoming environmental' of surveillance" by today's AI systems (Andrejevic 2020: 84). The focus on Germany is interesting against this background, since the stricter data protection laws allow the use of AI technologies in public spaces only in test constellations (cf. Schabacher/Spallinger forthcoming), which on the one hand makes the conditions and problems of their use comparatively explicit and on the other hand represents a strategy of familiarization with these systems. However, even though facial recognition is highly controversial, also in Germany the Covid pandemic has driven general datafication and normalized facial recognition technologies as systems of automated identification "at a distance" (Andrejevic 2021: 150). The respective AI companies see this as a gateway to generalized data networking, operating simultaneously at individual and biopolitical levels in the sense of "granular biopower" (ibid.: 153), thus exhibiting the basic promise of AI systems: "to modulate the milieu at the level of the individual" (ibid.: 152f.).[6]

6 Louise Amoore also emphasizes this biopolitical dimension when she analyzes the increasing datafication of border regimes – "biometric borders" – that make the pris-

With regard to patterns and AI technologies, I would like to discuss two questions in particular: What can be understood as security patterns in the first place and what problems are encountered in their conceptualization and implementation? Following test phases on facial recognition, in 2019, a pilot test on situation and behavior recognition systems was carried out at the train station Berlin Südkreuz for several months (for further details on both tests, cf. Schabacher 2021; forthcoming). The tests took place as a collaboration of the Federal Ministry of the Interior, the Federal Police, the Federal Criminal Police Office, and Deutsche Bahn AG, which labelled Berlin Südkreuz a "security station" ("Sicherheitsbahnhof") (Federal Ministry of the Interior and Community 2017) and announced the testing of intelligent surveillance systems. While the first test in 2017 and 2018 was concerned with the identification of individuals, which was accompanied by a great deal of public interest and triggered many critical debates, the public perceived the second test as supposedly less critical. This was because it did not use facial recognition, but aimed at detecting dangerous situations under anonymity conditions. In order to generate training material for the AI systems, corresponding scenarios were performed by actors and recorded (including demarcation scenarios) on several days of the week on site at the station. The trained scenarios referred to four predefined patterns ("lying (helpless) person", "entering defined areas", "flows or gatherings of people", "abandoned object"), the possibility of "counting people" as well as two additional functions, namely the tracking of persons or objects as well as the "retrograde evaluation" of video material (Federal Police 2019).

Already the selection and naming of the dangerous situations show the operation of stenciling in the sense of first-order patterns. Certain types of movements are, in a sense, cut out and set apart from the background and are thus made relevant in terms of security compared to supposedly normal situations at the station. They concern the posture of people – compared to standing and walking, lying down represents a deviation, which can refer both to a person who has had an accident and to a person without shelter. They concern the position of individuals in relation to a zoning of space: certain areas such as tracks should not be entered. They refer to the speed of movement of groups — a rapid gathering or dispersal of people is understood as being caused by dangerous events. And the single object relates to the fact that at stations objects occur in close proximity to people (pieces of luggage, dogs, children), but

oner's body "the bearer of the border, as it is inscribed with multiple coded boundaries of access" (Amoore 2006: 347f.).

can become dangerous if separated (imago of the bomb case). However, insofar as these patterns are imaginaries of danger that are regularly and extensively played out in popular culture (cf. Horn 2018; Koch/Nanz/Pause 2018), there can be no question of requiring AI technologies to recognize them here. It can be assumed that it is not only a matter of recognizing such first-order patterns of danger, but that, with reference to the two police functions mentioned above (tracking and retrograde evaluation), second-order patterns are expected here, too, i.e., correlations that only a mass analysis of material collected in this way can produce.

However, it is not only what figures as security patterns in the first place that points to the gap between the ambition and reality of AI systems; the production of these patterns also proves to be difficult. As with facial recognition technologies, the hope with AI systems of situation and behaviour recognition was also that they wouldn't only provide support for the work of station control, but would also help to reduce personnel in the security sector. The reality, however, was different. The introduction of such systems always makes the respective settings more complex overall: For instead of simplifying things, AI systems intermingle with other actors – people who manage and repair them, the technical and physical building infrastructure on site, software companies, institutional regulations and legal requirements, the people they are supposed to detect. They can therefore never represent simple systems of control, but must in turn be elaborately controlled, regulated, and monitored, which raises new questions and problems. The complexity they seek to reduce is thus continually increased by the AI systems in question. Even their purely technical functioning requires a high degree of customization and adaptation: the creation of training data (through the invention of 'scenes' and production of own video material), the calibration of the systems (for example, due to the changing light conditions in real space), the preparation, extraction and classification of features, the manual removal of random and systematic errors. Furthermore, an appropriate evaluation and analysis as well as reports are necessary, but also accompanying public discourses that prove such a test to be a success. This is not provided in the case of the second Südkreuz test, the (poor) results of which have not been made public so far;[7] instead, the project has been extended (Federal Police/Deutsche Bahn 2020).

Figure 8: Processing crowded public spaces. Taken from Golda et al. (2019: 1).

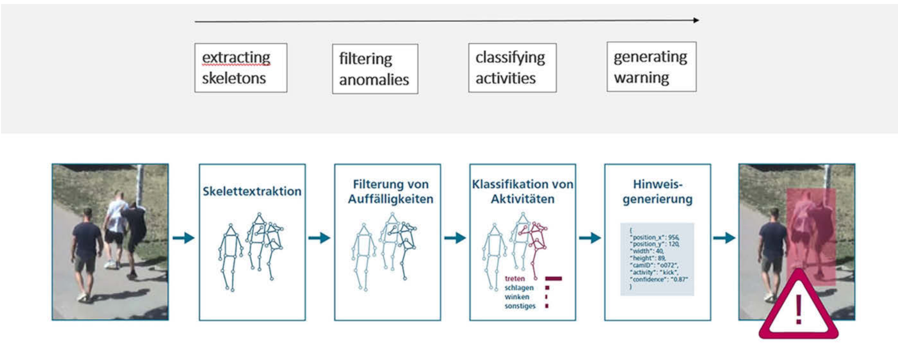
However, problems with the conceptualization and implementation of patterns can be observed at a more fundamental level. Motion and activity recognition is one of the strongly discussed fields in computer vision. Public places such as train stations pose particular difficulties, since they are crowded and present unstructured everyday situations with many people (fig. 8), which makes the recognition process complex and computationally intensive due to lighting conditions, multiple occlusions as well as rapid movement of many people. A pilot project in Mannheim is working with the Fraunhofer Institute of Optronics, System Technologies and Image Exploitation (IOSB) to develop a software based on artificial neural networks specifically for police situation assessment in such environments (cf. Golda/Cormier/Beyerer 2022).[8] In this

7 Even though the final report of the second test was not publicly available, it was available to the Federal Data Protection Commissioner who concluded that the results did not justify further "similarly elaborate tests" but that security should be increased by "other measures" (BfDI 2022: 74).

8 The "Mannheim Way" project (2018–2023), a cooperation between the City of Mannheim, Mannheim Police Headquarters, the responsible Ministry of the Interior, Digitalization and Migration Baden-Württemberg, and the IOSB, is testing video

process, the image data originating from the live feed of a static surveillance camera is detected for recognizable persons (fig. 9); to protect privacy and to avoid other forms of bias, these are converted into skeletal representations, which are then filtered for anomalies. These anomalies are classified in relation to defined activities (such as hitting or kicking). If there is an accumulation of such 'critical' activities within a certain period of time, a warning is generated. Otherwise, the data is deleted after a defined time (e.g., one minute).

Figure 9: Human Pose Estimation. Edited version of image taken from Golda/Cormier/Beyerer (2022: 1493).

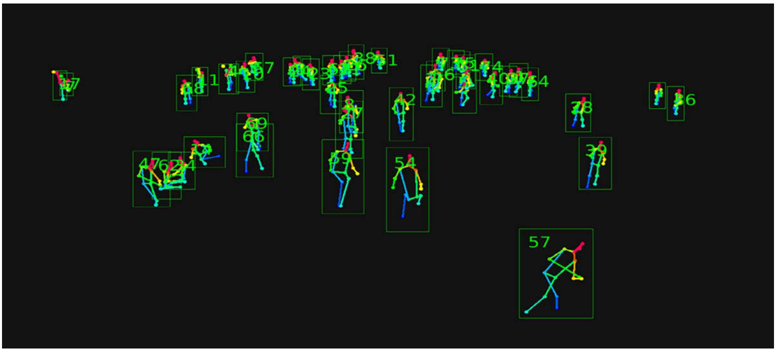


I would like to concentrate on one aspect here, namely the human pose estimation. Interestingly, this is a workaround made necessary by German data protection regulations: Namely, human pose estimation bypasses the process of identifying individuals in favor of anonymity conditions and the analysis of group-related behavioral constellations. This method is based on identifying and classifying joints of the human body. For this purpose, every joint (elbow, head, torso, etc.), also called "key point", assumed to describe the posture of a person is captured from a given video input in order to obtain a skeletal representation of the human body (Golda/Cormier/Beyerer 2022: 1494f.). A normal surveillance camera takes a new image every 33 milliseconds, the processing of which requires a correspondingly large amount of computing time, depending on the number of poses to be detected (ibid.: 1491). Especially in crowded

surveillance in urban areas (https://www.iosb.fraunhofer.de/en/projects-and-products/intelligent-video-surveillance.html) (31.03.23).

scenarios, such as a metropolitan train station (fig. 10), the bounding boxes in the background quickly become confused. Therefore, the live operation of such AI systems represents a compromise between the accuracy and the speed of detection, as in a real-world scenario "the surveillance footage requires immediate processing in order to provide human assistance on-site in a matter of minutes" (Cormier et al. 2022: 591).

Figure 10: Increasing occlusions in the background. Taken from Cormier et al. (2022: 597).



Such a compromise is of course understandable under real-world conditions, since an alarm system should be able to react quickly. However, it already pertains to the production of the training data. The quality of activity recognition or the respective pose estimation depends here, amongst other things, on the number of "keypoints" (body joints). So time is a significant factor here, as "annotating a single human body pose for activity recognition requires 40–60 seconds in complex sequences" (Cormier et al. 2021: 1649). That means, the higher the number of body joints, the more accurate the representation, but the longer the overall computing time. The crowdedness of real-world conditions require even further trade-offs: To build a data set for crowded scenarios with many people, one resorts to automated annotation (Cormier 2021: 36f.) and "data augmentation methods" in order to supplement hidden limbs by "synthetic training data" (Golda et al. 2019: 2), which reduces the authenticity of the data structures in favor of completing poses. AI systems are therefore already used for the production of training data. Of course, this specific constellation depends on the current state of implementation of AI systems; insofar as technological development is progressing, it can be assumed that the problem in question will be solved, for example, by an increase in computing power. What matters to me, however, is the recursive logic in operation here: AI systems produce certain problems, difficulties, and affordances (such as the time-consuming annotation of motion data), the solution of which again requires the use of AI systems. In this small example, we see patterns in several ways: We see them already in the concept of the pose as such, that refers to the position of a body with respect to its position and orientation in space. It is not without reason that Roland Barthes, in his analysis of photography, refers to the meaning of the pose as a form of still time, as "immobility" and pausing (Barthes 1981: 78). We also see patterns as related to the skeletal representation, which is already a "heavy abstraction" (Cormier et al. 2022: 591) compared to the original images; we see them in the classifications upon which activities are filtered (kicking and punching as specific crime patterns); and we see them related to what is called the 'overall picture' of the police situation, when activity recognition is merged with other data. However, what machines achieve here is precisely not a phenomenal Gestalt perception in the sense of Christian von Ehrenfels (1890), but an act of ultimate (binary) classification (for example, do we deal with a conspicuous activity or not?), based on statistical threshold values.

In security contexts, such classifications are in the service of forecasting and are intended to legitimize preventive action. In predictive policing, for example, a software like PRECOBS (Pre Crime Observation System), which was also tested in some German police stations, uses offense data from the recent past in order for police authorities to make predictions in which area repeat crimes (mainly residential burglaries) are most likely to occur within the next 72 hours (cf. Egbert/Leese 2021; Perry et al 2013; Ferguson 2017).[9] What I would like to emphasize in relation to predictive policing is the conservative and normative dimension of patterns, which I have elsewhere called the "*temporal vector* of patterns" (Schabacher forthcoming: 160; original emphasis). According to Mareile Kaufmann, Simon Egbert and Matthias Leese, the respective programs reinforce the "epistemological authority" of patterns in policing (2019: 684), however developing different "styles" of pattern identification (ibid.: 680) with own rationalities and conceptions of crime that in turn inform police work: "They [patterns, G.S.] give form to and formalize different

9 Website of LogObject Deutschland Gmbh 2021: https://logobject.com/en/solutions/precobs-predictive-policing/ (accessed March 31, 2023).

understandings about crime, which are in turn based on specific ideas of governing crime. This makes patterns political" (ibid.: 684). Four implications of this pattern politics are highlighted by the authors: Firstly, patterns emerge only where regularities exist: "Patterns can only capture offenses that follow rules" (ibid.). Thus, a solitary crime cannot occur. Secondly, the future is not extrapolated from live data, but from past data; patterns are therefore "conservative" (ibid.: 685). Thirdly, they exhibit a "self-reinforcing logic" (ibid.: 687), because assumptions about crime patterns feed back into policing cultures by establishing a direct link between assumed pattern and the efficiency of respective police action. Finally, patterns alter the general relationship between crime and norm: From this perspective, criminal behavior must be regular, otherwise it could not be captured by patterns (ibid.). Patterns thus normalize crime without stimulating reflection on motives and causes (ibid.), which is why predictive policing has discriminatory and stigmatizing effects.

The considerations of Kaufmann, Egbert and Leese highlight the political-cultural implications of reinforcing and habituating (crime) patterns based on regularity and repetition. Together with the described German tests on AI-based surveillance systems in public spaces, it can be shown how the regularity of patterns informs practices of predicting, for example, dangerous situations. Thus, it is first-order patterns that inform AI systems at the level of training data: This is equally true for the fact that, in the context of human pose estimation, rapid striking and standing close together are understood as expressions of aggression and fight, that a lying person or an unaccompanied suitcase at a train station are perceived as deviant, or that burglaries are more likely to be expected where burglaries have already occurred. Although in all three cases the patterns of danger are easily recognizable even without AI systems – they are culturally familiar 'templates' – this is rarely highlighted in the context of AI systems.

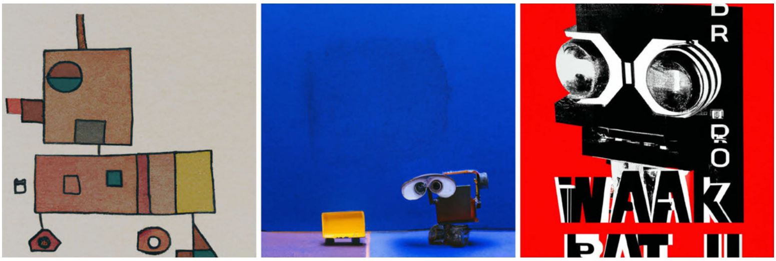
4. The work of patterns

What is at stake in the question of predictive analytics is made clear by Rainer Mühlhoff in his plea for "prediction privacy" (2023). Mühlhoff (2023: 3) refers to the regulation of the currently unregulated possibilities of economic actors to match data of individuals with anonymous mass data in such a way that individual predictions become possible. One thus encounters the becoming-environmental of surveillance discussed at the beginning of the previous section in a more generalized form: The prediction concerns information on all conceivable human categories (gender, ethnicity, purchasing behavior, age, health, sexual orientation, etc.) (cf. Hirschauer 2021) and is generated on the basis of individual data of the person concerned (usage, tracking, or activity data) in comparison to anonymous mass data. By operating in this way, AI systems do not foresee a future that exists independently of them, but rather they modulate the future according to their own specifications: "Algorithms 'manufacture' with their operations the future they anticipate" (Esposito 2022: 11). In doing so, AI systems are having a self-fulfilling performativity (Rona-Tas 2020; on the logic of prevention see Bröckling 2012), they structure and govern our (image of the) future and are thus "world-shaping instruments" (Lazzaro/Rizzi 2022: 16).

Accordingly, the phenomena discussed with respect to security research and predictive policing can also be formulated in more abstract terms: It is not only about the hope of preemption generally associated with AI systems, i.e., the proactive action that anticipates the future and prevents an undesirable outcome of things. It is also about a serious problem that all such automated detection systems have and that is intimately related to their pattern-based nature. For due to their training being based solely on things that already exist, predictions can only vary them virtuously; ultimately, however, a crime warning remains directed at such events that one already knows in principle, just as a purchase recommendation is oriented toward transactions that have already been made. This orientation towards the past can also be related to Wendy Chun's critique of the "homophily" of network research. For, as Chun argues, network analyses follow the paradigm of similarity; this has the effect of weakening the importance of difference in favor of self-similarity, which reinforces the segregation of societies (2021: 81–137). However, insofar as homophily itself is to be understood as a form of patterning in which the repetition of similarity is rewarded (not least because this is easier to calculate than difference), the kind of reference to the past that also played a role in crime predictions is evident here: "Because […] predictions rely exclusively on past regularities, the future made present in the here and now is impoverished and reduced to a mere repetition of the possible, of what has already happened at least once" (Lazaro/Rizzi 2022: 13).

But how does this apply to the supposed creativity of AI systems? As we came to know large language models such as ChatGPT or DALL-E in the past year, AI systems are quite capable of producing aesthetic content. True to its name, a portmanteau of Dali and the Pixar garbage robot WALL·E, DALL-E creates images based on prompts. The underlying artificial neural network operates on billions of parameters trained with text-image pairs from the Internet so that it can convert text into pixels. Such a "'prompt design'" and the associated "'promptology'" have two sides (Bajohr 2022: 67): Although the AI remains without consciousness and thus "dumb" (ibid.: 66), what it produces is no longer mere syntax, but rather "dumb meaning". Thus, interaction with these systems becomes a feedback loop between artificial and human meaning: "Not only does the machine learn to correlate the semantics of words with those of the images we have given it, but we learn to anticipate the limitations of the system in our interaction with it" (ibid.: 67). In particular, styles are patterns that can be readily addressed by prompts. Thus, to ask DALL-E to 'paint' the WALL·E robot in a Paul Klee style leads to quite appropriate results, just as with the corresponding request to Yves Klein or Barbara Kruger, the typical blue or large-scale text-photo combinations are generated (fig. 11).

Figure 11: Pictures generated by DALL-E 2. Courtesy of the author.



Seen in this way, AI's repertoire is quite broad. As Roland Meyer correctly observes, in this context style is no longer a historical category; instead, styles are "typical visual patterns extracted from a latent space of possible images accessed through generative (and often iterative) search queries" (Meyer 2022: 107), i.e., monetizable "images about images, filtered through language" (ibid.: 108). Still, beyond the legitimate question of copyright violations, forgeries, and data hallucinations by such systems,[10] which, despite their training (reinforcement learning), nonetheless also produce much fake knowledge in flawless prose, the more important point is: The produced artifacts are "*statistical*

10 See, for example, the pending lawsuit on consumer harm caused by the practices of Open AI and Microsoft (Kang/Metz 2023).

art" (Pasquinelli 2019: 15; original emphasis). AI systems such as DALL-E or ChatGPT produce only the most probable, that is the statistically reasonable, answers on the basis of their (large amount of) training data.

AI systems are thus characterized by a limit that Matteo Pasquinelli very aptly calls "*undetection of the new*" (ibid.; original emphasis). At the core of machine learning lies the "inability to predict and recognise a new *unique anomaly*" (ibid.: 14; original emphasis), because every anomaly, even a social or political one, would be the creation of "a new code or rule" (ibid.: 16). And that is precisely what AI systems cannot do. Rather, they represent a constantly further "standardized world", which is why their most decisive effect on society consists in a "social *normalisation*" (ibid.: 17; original emphasis). Are the patterns of AI therefore de facto stereotypic stencils? In a certain way they are. They are, because AI is not able to produce negation, lack, or workaround. There is no place for surprise in the sense of revaluations. And they are, too, because there is never anything like 'the new': Every invention is a re-combination of existing entities or concepts.

5. Conclusion

To conclude, I would like to highlight four aspects that seem significant to me for the pattern regimes associated with AI technologies in general.

Firstly, there is the vision of simplification. With new technologies such as AI systems, environments become more complex because the entanglement of different actors becomes denser and less manageable. Promises of a fundamental simplification of communication, work or control through automated systems are thus de facto accompanied by the constant complication of the concrete constellations. In an ethnographic analysis of a township in eastern South Africa, Thomas Kirsch (2019) very convincingly shows how the introduction of security technologies leads to a recursive securitization – "*security needs to be secured*" (ibid.: 124; original emphasis). To continue, one can easily add such recursive structures for other contexts: security also requires maintenance, it requires energy, it requires trust etc. As AI systems are embedded within socio-technical-*discursive* infrastructures, they will never represent technical effects and solutions alone, but will concern the respective structures as a whole. Therefore, they can be seen as mediators of knowledge, of societal relations as well as of cultural and aesthetic perspectives.

Secondly, pattern recognition systems are part of a politics of rationalization and convenience. On the one hand, an important reason for the enforcement of AI systems is the optimization of operational processes and human resources through automation. For example, ChatGPT is claimed to be able to relieve clinical staff of burdensome documentation duties through its autocompletion capabilities. The consumer sector on the other hand focuses on convenience, allowing passengers to pass through gates without contact, to pay more quickly with face recognition payment systems (FayPace, Paybyface), and to complete homework with less effort due to using a large language model. From a cultural and media critical perspective, it should not only be noted here that it is questionable what the greater efficiency or freed-up time can be used for. In view of the capitalist logic driving these changes, it is to be assumed that no 'free space to do others things' will emerge, but only that new areas will become calculable for economic value creation. Rather, it must be emphasized that their application close to everyday life (smart home, smart driving, etc.) will lead to a familiarization with AI technologies that will make their presence fade into the background of functioning infrastructure, making them more and more invisible.

Thirdly, there is the scientific legitimation respectively authentication of AI technologies. Within the scientific-economic complex, the scientific use of AI technologies, for example in the medical field or in biology, legitimizes, ennobles even, their use in incomparably more critical areas such as security. Science thus contributes to the social acceptance of AI, without it having to be covered in detail by the findings obtained by AI systems. And although proprietary AI systems have a black-boxed status, interestingly enough, this lack of transparency that is based on corporate policies seems to even increase rather than decrease the public belief in capabilities of these systems. The approach of Explainable AI, which aims at elaborating methods to make the functioning of artificial neural networks (more) transparent, must be seen as an attempt to deal with this problem (cf. Samek et al. 2019); this is equally true for efforts to clarify the different uses and horizons of crucial terms (e.g., 'autonomy' or 'agents') (Powers/Ganascia 2020), the emphasis on the need for decidedly political action (McQuillan 2019), and the call to pay more attention to the production of large data sets as well as to the movement of data through the sciences (Leonelli 2020).

Finally, the pattern reference of AI technologies, that is, their recourse to stencils (templates) in the sense of feature spaces and classification schemes, can be seen as their normative dimension, which is discursively invisibilized.

In that AI technologies constantly find new correlations seemingly 'on their own' (what I have called second-order patterns), the operations of stenciling, gridding, and classification that are at the outset and indispensable for training AIs remain strangely unobserved. This is why correlation can so easily be mistaken for causation, even though we know it is not the same thing (cf. Pasquinelli 2019: 14), and why differences of degree can be interpreted as differences of kind (cf. Mackenzie 2017: 149). This blending of two understandings of patterns – the repetitive stencil and the statistical correlation, the ornamental and the numerical patterns – is what I take to be representative of the politics of patterns of AI technologies.

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Images

Fig. 1: Ernst Haeckel (1904): Kunstformen der Natur, Leipzig/Wien: Bibliographisches Institut, Plate 84 (Diatomea).

Fig. 2: Mandelbrot, Benoit B. (1983): The Fractal Geometry of Nature. Updated and Augmented, San Franscisco: Freeman and Company, Table 44, p. 44.

Fig. 3: Ancient tilings from Portugal. After Simoes 1969. Branko Grünbaum/Shephard, G. C. (2016 [1987]): Tilings and Patterns. Second Edition, Garden City andNew York: Dover Publications, p. 7.

Fig. 4: Baby Cap. Riego de la Branchardière (1848): The Knitting Book, 3rd ed., London: Simpkin, Marshall, and Co, pp. 44–45.

Fig. 5: Lewis F. Day (1887): The Anatomy of Pattern, London: Batsford, plate 3.

Fig. 6: Jacquard loom with clapper tacker. Musée d'art et d'industrie de Saint-Étienne, France. photographie: Hélène Rival, November 27, 2012.

Fig. 7: Brassaï, Graffiti from the Series III: "Naissance du visage" (left and middle) and IV: "Masques et visages" (right). Untitled. Gelatin silver prints. c. 1930. Print run c. 1950. MACBA Collection. MACBA Foundation. © Estate Brassaï, 2023.

Fig. 8: Golda, Thomas/Kalb, Tobias/Schumann, Arne/Beyerer, Jürgen (2019): "Human Pose Estimation for Real-World Crowded Scenarios." In: 2019 16th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS), Taipei, Taiwan, p. 1.

Fig. 9: Golda, Thomas/Cormier, Mickael/Beyerer, Jügen (2022): "Intelligente Bild- und Videoauswertung für die Sicherheit." In: Dieter Wehe/Helmut Siller (ed.), Handbuch Polizeimanagement. Polizeipolitik – Polizeiwissenschaft – Polizeipraxis. 2nd rev. and expanded ed., Wiesbaden: Springer, p. 1493. Edited version of the image.

Fig. 10: Cormier, Mickael/Clepel, Aris/Specker, Andreas/Beyerer, Jürgen (2022): "Where are we with Human Pose Estimation in Real-World Surveillance?" In: IEEE/CVF Winter Conference on Applications of Computer Vision Workshops (WACVW), Waikoloa, HI, USA, p. 597.

Fig. 11: Pictures generated with DALL-E 2 (https://labs.openai.com), Gabriele Schabacher 2022.