



Image Platforms

Kind of Blue

Social Media Photography and Emotion

Michelle Henning

Abstract

This paper considers emotion recognition and sentiment analysis in relation to social media photographs. It addresses this as part of a larger regime of surveillance and control, in which photographs are treated as symptoms for a diagnosis, and are quantified as data. Automated emotion recognition approaches are capable in principle of analysing the visual qualities of social photos insofar as these can be measured and represented numerically. In reducing the photograph to data, they select out features of the image, as a means to explain or describe a mental state that lies behind or beyond the image. To treat photographs as emotionally expressive goes against the historical idea of the photograph as objective recording. Originally, the idea that photographs could move their viewers was linked to the sense of photography as detached documentation. Today, more and more people take and share photographs as part of a larger shift in emotional culture, which places a therapeutic sense of self at the heart of economy and governance. Yet while people use mobile phone photos as a means of expressive documentation and self-representation, emotion recognition relies on a behaviourist and positivist model that is indifferent to their intentions and to culture, and which is premised on a myth of total knowledge.

Keywords

Photography, Social Media, Emotion Recognition, Behaviorism, Emotional Capitalism

Kind of Blue: Social Media Photography and Emotion

Automated techniques of mood tracking, emotion recognition and sentiment analysis are currently on the rise across several industries, drawing on massive amounts of data accumulated via people's social media feeds and mobile phone apps. They are part of new developments in artificial intelligence (AI) and affective computing (computing that concerns itself with emotion and affect). They classify and analyse text, emojis, images and video. Emotion detection algorithms also

sort through data on facial, vocal and bodily behaviours supplied by cameras, microphones and other less visible sensors built into mobile phones, such as the accelerometer and gyroscope. These tools (some of which are publicly and commercially available) are machine learning systems, trained on datasets labelled by armies of low paid casualised workers including Amazon Mechanical Turk workers (Zylinska 2021: 242-249). Their uses vary and include brand reputation management, recruitment, targeted marketing, political campaigning, academic research, policing, border control and healthcare.

Emotion recognition or sentiment analysis tools are controversial for several reasons. They involve not only the identification and prediction of emotional states but, inevitably, the attempt to shape or direct them. Arguably, such tools, deployed by the social media platforms, have contributed to the heightening of political polarisation. They also raise issues of respect for privacy and for human autonomy, as participants rarely, if ever, give informed consent (Andalibi/Buss 2020; Wongkoblap/Vadillo/Curcin 2017). Furthermore, since mental health is connected to emotional expression, they may transgress laws and medical ethics relating to health data (Schneble/Elger/Shaw 2020).¹ Developments in machine learning mean that the methods by which people are classified are increasingly black-boxed and unavailable to human interpretation (Wongkoblap/Vadillo/Curcin 2017). The use of psychological profiling and facial recognition are considered particularly problematic. Facial recognition systems emerge from a biometrics industry tightly linked to state security legislation and are trained on datasets with inbuilt discriminatory assumptions about race and gender such as the ImageNet dataset (Gates 2006; Shankar et al. 2017; Crawford/Paglen 2019). Their use for purposes of emotion detection also notoriously relies on a disputed biologicistic classification of discrete emotions and supposedly universal expressions, derived from the work of Paul Ekman, which also raises doubts about the validity of its results (Leys 2010). Nevertheless, the great majority of emotion detection studies now make use of facial recognition.

Profiling is used to predict people's actions, preferences or responses, as the computational sciences draw on psychological scales originally devised for therapeutic purposes (Stark 2018: 206). It has been argued that individuals are increasingly acclimatised to psychological profiles as a means of self-understanding or self-objectification – for example, via online quizzes or early internet dating sites (Illouz 2007: 75). Yet most people have no control over, and little insight into, how their social media posts are being used to construct profiles. Concerns have been raised about the “performative power” of these profiles, which provoke feelings

1 In 2017, a systematic review of 48 English language articles using social media for predictive analytics in mental health noted a general neglect of ethical issues by these studies, and that none of the studies used clinical diagnosis as their measure for depression, using surveys instead (Wongkoblap/Vadillo/Curcin 2017).

and engineer behaviours, often on the fly (Stark 2018: 213). Although the notion of profiling suggests something static, social media feeds can be adjusted in real time, dynamically and responsively, as part of an ongoing process of mood-tracking, which works to ensure people remain “hooked” to their devices (Davies 2017).

In the following discussion, I set out to add a new perspective to the growing literature critiquing emotion recognition, by considering the role of photographic images. Currently, the analysis of the visual qualities of photographs (as opposed to the objects depicted in them) is not a major aspect of sentiment and emotion detection and prediction. Nevertheless, scores of international university research teams have showcased projects using social media photos for “depression detection” and sometimes in relation to the identification of personality traits (some of these are discussed below). It is unclear to me to what extent such studies are also being done by the social media platforms themselves, so my examples derive from these academic studies.² To read them is to experience a strange historical vertigo as the discussion of “convolutional neural networks” collides with old-fashioned aesthetic strictures, and claims about faces and personality that seem to have come straight from the 19th-century pseudo-sciences of physiognomy and phrenology. If I seem impatient with such studies, it is first because many combine what I consider bad science (such as Ekman’s biologicistic classification of the emotions) with bad aesthetic theory, baking into their technology arbitrary judgments about what is “good” and “interesting” and what makes “aesthetic sense”; and second, because they are almost always framed as a public health good (e.g., for suicide prevention), and are at best naive regarding the other obvious applications for their methods (e.g., to discriminate against depressed people or to select “agreeable and conscientious” personality types in job recruitment).³

Photography and Self-Expression

The fact that social media photographs are being seen as a valid resources for this kind of study is a consequence of at least three factors. First, there is the direction taken in contemporary AI research, which supports the accumulation of vast amounts of data and inevitably takes in the huge volumes of photographs being

2 I read overviews of the field such as Wongkoblap/Vadillo/Curcin 2017, and trawled through academic databases such as PubMed and IEEE Xplore for articles and conference papers from the past five years.

3 In 2019, Business Insider reported that Facebook was using a suicide risk detection algorithm, although not in the EU, where it would breach the General Data Protection Regulation (GDPR), and that this raised concerns about data privacy (Goggin 2019). The phrase “agreeable and conscientious” is used in Liu et al.’s 2016 paper on how personality traits could be predicted through social media profile pictures.

generated daily by people with mobile phone-cameras. Kate Crawford summarises that it is now “common practice for the first steps of creating a computer vision system to scrape thousands – or even millions – of images from the internet, create and order them into a series of classifications, and use this as a foundation for how the system will perceive observable reality” (2021: 96). Studies describe these as “images collected from the wild” (e.g., Balouchian/Foroosh 2018; Vadicamo et al. 2017). The phrase “in the wild” has some specific meanings in the computer sciences, referring to data or technologies that are currently in the public domain and in public use, or no longer under the control of their makers, or to datasets that are “*not constructed and designed with research questions in mind*” (Ang et al. 2013: 39, original emphasis). Such data is also referred to as “foraged” and “found”. As the metaphors suggest, social media images are considered fair game for researchers, a view underpinned by the assumption that they are reducible to “data” and are therefore merely “raw” material ripe for analysis (Gitelman 2013).

A second factor is the growth of stock photography, the influence of which is clearly evident in these datasets of images from “the wild”.⁴ For example, a 2018 study boasted “the largest dataset of images collected from the wild” using keyword searches on Flickr and the Bing internet search engine (Balouchian/Foroosh 2018: 1932). Yet as their own illustration reveals, the images are classic stock and stock-style images, which the search algorithms already push to the top: “happiness” is attached to photographs of white pregnant women taken in the so-called magic hour, in natural settings with shallow depth of field, their arms folded around their bellies; images of graduating students, cheering and smiling in groups, again with the background thrown out of focus; posed images of good looking, casually dressed young white people on a summer’s day, grouped around a table laden with food, or around a barbecue, or gathered on a rock to watch the sunset. No-one is pulling the wrong face, no-one has their eyes closed, no head blocks another, nothing jars. These images are emphatic, promotional images, designed to *illustrate* concepts and sentiments. They tell us nothing about the emotional state of the photographer or of the person who put the image into the public space.

A third factor, and the one I will focus on here, is that people do take photographs as a means of self-expression, so that it does not seem outrageous to claim that such photographs might thereby reveal emotion. Researchers in affective computing justify their studies on the basis that people upload images to “display their sentiments and emotions” (Doshi/Barot/Gavhane 2020). It seems reasonable to judge social media photographs to be sources for emotional data, if users themselves seem to be treating them as subjective and expressive. This may seem self-evident, but as I will argue, it represents a change in the culture and practice

4 On stock photography and picture agencies, see Frosh 2003 and Blaschke 2016.

of vernacular photography. Conceptualising photographs as primarily media for emotional self-expression is as new as treating them as data.

For the purposes of this argument, I have artificially separated still photographs from text, emoji, graphics and video. This does not reflect the contexts in which we encounter photographs, which are increasingly hard to discern or distinguish from video (especially in the cases of “live” photographs or animated gifs), and which are invariably surrounded by text, and frequently accompanied by reaction buttons (pseudo-emoji). However, this narrowing of focus will allow me to tease out what is most distinctive about the growing trend of using photographs as a means to analyse the feelings of the people taking them. Although the idea of the photographic image as subjective and expressive may seem fairly conventional today, it stands in stark contrast to early ideas about photography as an objective, mechanical way of picturing the world.

Historically, narrative film, television and video, more often than still photography, have been understood as emotionally expressive, able to make use of the emotionality of music, storytelling and performance. In photography, the tendency of the camera to record everything without hierarchy seemed to give it both scientific objectivity and emotional flatness, even though early viewers of photographs actually responded with astonishment, horror and awe at the new technology. In the mid-19th century, theories of the aesthetic encounter largely excluded photographs, which art historians and critics tended to dismiss as affectless because authored by a machine: the photographer’s status was as a mere “operator”, the camera a “slavish imitator” (for a quick summary, see Brown/Phu 2014: 10-13). Photographers struggled to have their work accepted as art because of this, and the notion of an expressive or subjective photography was controversial for several decades. The pictorialist photographers of the late-19th century worked hard to give atmosphere and aura to their pictures, to imprint them with the stamp of an author, and to situate them visibly in the iconographic traditions of art. Their pictures were denigrated for their pretension, their staged effects and fakery, particularly after the rise of documentary, “straight” photography and new objectivity in the 1920s and ’30s.⁵

Against my claim that (outside of certain art contexts) photography was not seen as emotionally expressive, one might point to the fact that family or vernacular photographs have always been treasured, emotionally significant objects. Throughout the 20th century, photography companies exhorted people to take photographs as a means to create a personal (though standardised) record of their

5 As Elspeth Brown and Thy Phu note, many writers on photography have until recently tended to disavow feeling as a legitimate aspect of photography theory and criticism despite the extensive influence of Roland Barthes’ *Camera Lucida* (1980), a book that prioritises the author’s own affective response to photographs (Brown/Thu 2014: 2-3).

own lives, to share experiences with people, and to keep in touch with relatives and friends at a distance. These pictures quickly became “fetishes” – objects of human attachment and superstition, worn in locket and carried in wallets, and emotionally difficult to destroy. As Roland Barthes recognised, this emotional quality of the image was not separate from, but entirely tied to its presumed objectivity, its apparent ability to record that which has been, with very little mediation. We fetishise the physical photograph because of what it represents – superstitiously, to tear a picture of a lover is to hurt them. As well as a meditation on the emotional pull of photographs, Barthes’ *Camera Lucida* is also about the difficulty in separating the photograph from its referent, from the real. Elsewhere, Barthes observed that it is precisely the emotional detachment of the camera that leads to the shocking nature of images of war and violence: the shock is inseparable from its brute factual recording (Barthes 1979). To say then, that photography was not (or not usually) a medium of subjective emotional expression is not to say that it did not provoke emotions. On the contrary, it was its presumed ability to record a scene in a way that was uncoloured by subjective vision that seemed to make a photograph capable of moving a viewer.

The historical tensions between the photograph’s claim to mechanical objectivity, its uncertain position as art, and its use in popular practices of self-documentation form a backdrop to present uses of social media photography as a mode of self-expression.⁶ Today, people are encouraged to photograph to communicate, not just in a deictic way (“I was/am here”) but expressively (“this is how I feel”). This is not to say that the documentary aspect of the photograph has been lost; far from it – the conversational or social photograph extends the documentary function of photography. As Nathan Jurgenson says “this documentary habit burrows into consciousness. [...] Life is experienced as increasingly documentable and perhaps also experienced *in the service of* its documentation, always with the newly accessible audience in mind” (Jurgenson 2019: 12, original emphasis). But this practice of documentation is not constrained by a truth to nature or commitment to recording the facts of a situation: instead, something is documented with a view to attaching a witty caption or garnering likes, to construct an image of oneself and one’s life for others, or to remind one’s future self of good times. Self-expression, self-presentation and documentation are mutually connected practices. Perhaps they always have been aspects of snapshot photography, but the notion of taking a photograph as a means of subjective expression takes on a new emphasis in the context of the ability to immediately circulate the image through a mobile phone.

6 This is a brief and very partial summary informed by a wide range of historical-theoretical studies, too many to list here. My own take on this history is presented at length in Henning 2018.

As this brief historical summary implies, I consider mobile phone and social media photographs to be cultural artefacts. I disagree with Jurgenson's claim that art historical discourse about photographs is irrelevant to this kind of practice. Jurgenson seems to reduce art history to art appreciation and debates about aesthetic value – about “good” photographs – and he claims that “the center of conceptual gravity for describing how people communicate with images today should be less art historical and more social theoretical” (Jurgenson 2019: 9). While I sympathise with his argument that photographs need to be understood as communication media, and indeed with much of what he says about the “social photo”, here I will use theories of art as well, not only because they offer nuanced ways of understanding visual culture, some of which are perfectly compatible with the social photo, but also to critique the positivism inherent in this data science approach to social media photographs via Georges Didi-Huberman's critique of positivist approaches to art history.

A New Symptomology

It is easy to imagine that the most concerning issues in relation to social media photography are to do with privacy and surveillance, given the place of cameras in surveillance and photographs in revealing private information. Certainly, emotion recognition can be understood as a significant development in what Shoshana Zuboff describes as “surveillance capitalism”, where human beings are tapped or “mined” for ever hungrier data markets (Zuboff 2019). As a 2018 article describing a report by Tractica, a market intelligence firm, on this expanding “market for sentiment and emotion” enthuses:

Accelerated access to data (primarily social media feeds and digital video), cheaper compute power, and evolving deep learning combined with natural language processing (NLP) and computer vision are enabling technologists to watch and listen to humans with the intention of analyzing their sentiments and emotions. (Omdia 2018)

Being watched and listened to, without one's consent (or with little knowledge of precisely what one may have consented to), without knowledge of precisely when it is happening, and without direct access to or control over the data thus produced, nor over the various other actors to whom it is disseminated, certainly constitutes a violation of privacy, but surveillance extends far beyond this. For Michel Foucault, surveillance is a means by which bodies become subject to power, rendered “docile and knowable”, their behaviours subject to “progressive objectification and [...] ever more subtle partitioning” (Foucault 1979: 172-173). For Zuboff, contemporary surveillance capitalism is premised on the extractive process of transforming experience into data, which she refers to as “rendition”. She describes affective computing and sentiment analysis as “a burgeoning new domain of rendition and

behavioral surplus supply operations” (Zuboff 2019: 282). This process breaks with one of the principal aspects of older modes of surveillance – the emphasis on visual observation. Matthew Fuller writes, “surveillance in the present context applies very little to acts of seeing”, instead it collects traces or what Fuller calls “flecks of identity” – “a trail of triggers and tokens” (2005: 149).

A token is a small symbolic gesture or a piecemeal or partial representation, but it also has the older meaning of a *symptom*. For example, in Daniel Defoe’s *Journal of the Plague Year* (1722), “tokens” describes the visible symptoms that bespoke the bubonic plague, the black swellings or “buboes”. Social media photographs, reduced to data, are treated by emotion recognition AI as symptoms or tokens. Carlo Ginzburg sees “symptomology” as a mode of diagnosis using “superficial symptoms or signs, often irrelevant to the eye of the layman” (1980: 12). These are the almost imperceptible traces produced involuntarily and without conscious control. Ginzburg writes: “It is one thing to analyse footprints, stars, faeces (animal or human), colds, corneas, pulses, snow-covered fields or dropped cigarette ash; and another to analyse writing or painting or speech” (ibid.: 24). He connects the spread of symptomology across a wide range of disciplines to “the emergence of an increasingly clear tendency for state power to impose a close-meshed net of control on society” (ibid.: 24).⁷

The new surveillance would *not* be a symptomology for Georges Didi-Huberman, who conceives of symptoms in the Freudian sense, where the telling detail is not the “last word” but part of a “signifying chain, sequence or *thread*” (Didi-Huberman 2005: 231, original emphasis). For Freud, the observable symptom is never a direct expression of the unconscious but is the result of a certain work or set of processes (such as repression, condensation or displacement). To read the visual symptomatically is not to look “for some supposed explanatory ‘key’ to the image” but to address the “work of figurability” (ibid.: 262). Didi-Huberman uses the term to suggest how intelligibility emerges from something which does not fully cohere or which exceeds representation.⁸

In “depression detection”, the social photo is treated as a means to diagnose the emotional state of the person who took or posted the photograph: it is a symptomology in Ginzburg’s sense, not Didi-Huberman’s (indeed, I am going to suggest Didi-Huberman’s symptomological approach as a corrective or antidote to this diagnostic use of photos). The photograph is read almost as an extension of the body, like the digital traces of gestures, movements and speech. In this sense it is taken to be an “expression”. This has nothing to do with the conscious self-expression of the individual. As part of a larger dataset, the photograph becomes expressive regardless of its maker’s intention to express anything. This expression

7 Ginzburg’s example is Alphonse Bertillon’s anthropometric police database, which combined standardised photographs with verbal description, and later, fingerprints.

8 *Figurabilité* is a neologism used in the French translation of Freud’s “The Interpretation of Dreams” for the German word *Darstellbarkeit* (Parsons 2005: xviii).

is a surface effect of something happening beneath or behind the surface. What is sought behind the image is not the author, since an author is a figure conceived as having a certain amount of interpretative authority over their own work (Barthes 1968; Foucault 1980). Nor is it the unconscious, since there is no interest in the complexity of an individual psyche here: this symptomology is indifferent to the individuals it diagnoses. It seeks to directly know their emotional or affective states regardless of intention and regardless of any unconscious drives shaping or inhibiting these. These algorithmic detectives are indifferent to the intended or imagined audience, too. The expressive photo is treated as a kind of emotional outburst thrown into the void.

Tokens are also things we *exchange*, and the people exchanging photographs on social media experience these photographs as conversational and social. This is why Jurgenson calls the practice “social photography” (Jurgenson 2019). It is this social function that makes this such a rich seam for the emotion-miners to tap, because a big part of social communication is self-expression. As Jurgenson says, “for those communicating through social images, their informational qualities are a means to the end of expression” (ibid.: 18). From the perspective of emotion detection, however, expression produces information. Yet expression is also performative, its literal content mattering less than its practice: much social photography is “phatic communication” which centres around keeping in touch, building a sense of community, through performative statements which are first of all gestures, including the gesture of taking the photograph (Frosh 2012: 133; Miller 2016: 87). This lends a deliberate triviality or lightness to social media exchange (just as people verbally exchange observations about the weather, for example). Thus, emotion recognition as a kind of “mining” of either trivial or intimate expressions may seem disproportionate or intrusive.⁹

This affective turn is starting to shift the ways in which image-data is understood. Already, writers on the digital networked image argued that the digital photographic image had become a carrier for metadata more significant than its visible content (Rubinstein/Sluis 2013). This changes now that AI can decode visible content, having been trained on datasets (frequently on ImageNet) which are effectively taxonomies of objects in images. As various writers have pointed out, the AI is subject to the human bias built into the training set, which assigns

9 For instance, the research participants in a study by Nazanin Andalibi and Justin Buss were asked to imagine that social media sites had analysed their posts using computational techniques to “infer their emotional states”. The participants considered emotions to be intimate and personal things, nuanced and hard to understand even for the person experiencing the emotions, and several found the idea of algorithms reading their emotions through their images as creepy or scary on the grounds that they had no control over this reading and what was done with it (Andalibi/Buss 2020).

fixed meanings to visual objects in highly questionable ways (Denton et al. 2020). Now, the affective turn in the computer sciences moves the question from what images represent to what they *express*. Emotions and expression are associated with the sensual qualities of images, with embodied experience and with social relations. Nevertheless, as we shall see, the formal qualities associated with expression are not divorced from data or immune to quantification. In a digital image, they are quantities as well as qualities.

For example, colour is to a great extent a subjective perceptual experience, dependent on brains and eyes but also on culture, thus the experience of colour famously varies between language groups, between individuals, and even for the same individual from moment to moment. Yet colours are also quantifiable as different wavelengths of visible light or electromagnetic radiation and, in the context of digital media, as hue and saturation values. Several studies use these to classify images (e.g., Reece/Danforth 2017; Guntuku et al. 2019; Lin et al. 2020). In one psychological “depression detection” study, colour is described as part of “the wealth of psychological data encoded in visual social media, such as photographs posted to Instagram” (Reece/Danforth 2017: 1). The study concludes that “photos posted by depressed individuals tended to be bluer, darker, and grayer” and that depressed people were more likely to use monochrome filters (*ibid.*: 7-8).¹⁰ Effectively, it claims, blue Instagram posts were a sign of the blues.

Reece and Danforth’s automated analysis isolated hue and saturation values from other aspects of the photograph (such as composition and form, or what was depicted in the image, for example). Although the findings of the machine learning system correlated well with the (subsequent) diagnosis of participants as depressed, it did not correlate with the labels applied by human evaluators, and they comment “when people rated a photograph as sad, that impression was unrelated to how blue, dark, or gray that photo was” (*ibid.*: 9). This seemed to puzzle the researchers, since “semantically these descriptions seem like they should match well with one another, as well as link to depression” (*ibid.*: 9). Not only does this ignore the metaphorical character of linguistic colour expressions, it ignores the way colour meanings vary with context: a grey kitten, a blue sea, a Blue Note album cover or a black and white vintage magazine image do not necessarily convey sadness. While colours affect people’s moods or emotional states, and our reactions to colours involve a strong physiological and visceral aspect, colour meanings change. In the 19th century Goethe associated bright colour with “uncivilized” peoples, and monochrome with “refinement” (Taussig 2009: 3). The

10 They write “when depressed participants did employ filters [which they rarely did], they most disproportionately favored the ‘Inkwell’ filter, which converts color photographs to black-and-white images [...]. Conversely, healthy participants most disproportionately favored the Valencia filter, which lightens the tint of photos” (Reece/Danforth 2017: 8).

colour palettes of mid-20th-century cinema were likewise sometimes deliberately restrained, to avoid accusations of vulgarity and imply sophistication (Higgins 2007; Brown 2009; Street 2011). Like mid-century cinema or 19th-century fashion, Instagram has its own changeable grammar, its own mutating sets of implicit rules and taste cultures, which impact on people's uses of the platform.

Possibly the authors of this and similar studies would respond that I am making a category error, since machine learning does not concern itself with meaning, but simply makes correlations between data, here between "blue, dark and grey" photographs and a tendency to depression. Nor is any claim being made about causation. What matters instead is merely that the correlation exists. Yet the quasi-magical ability of machine learning to find correlations across vast quantities of data gives the impression of ever-growing and exhaustive knowledge, even when (as here) the obviously cultural and linguistic nature of these correlations should give us pause. Supported by the ideological belief in the objectivity of machines and automated processes – just as in the early years of photography, mechanical objectivity is taken as what Lorraine Daston and Peter Galison (2007) call an "epistemic virtue" – these correlations are sufficient to be acted on: to treat blue and grey images as factors or markers indicating suicide risk, for example. Antoinette Rouvroy explains in an interview:

Once signals have been detected, the person in question will be treated as if they have already "contracted" the risk or already "actualised" the danger, and may then, for example, have their life insurance cancelled. It is not about acting on causes but about acting preemptively on effects and in a way that is beneficial to those who purchase or design the algorithm, be it to increase profits or control. (Rouvroy 2020: 1-2)

Feature Extraction

In these studies, colour is reduced to one of the "features" of an image, subjected to "visual feature extraction" alongside other visual elements – such as compositional devices, sharpness and blur, foreground and background. Features are not always objectively measurable aspects of an image (such as hue and saturation) but often very subjectively arrived at. For example, in one study, which used extracted features to "score" images for their "aesthetic sense", the features included compositional balance, whether the image follows the rule of thirds, had symmetry, "good/interesting lighting" and so on (Guntuku et al. 2019: 239). The "neural network" becomes a kind of automated photography competition jury, albeit a very rigid one with deeply traditionalist aesthetics. The study concluded that "images posted by depressed and anxious users tend to be dominated by grayscale, low arousal images lacking in aesthetic sense" (ibid.: 244). However, aesthetics are not hard and fast rules but cultural standards, subject to historical

change and reinvention. The rule of thirds is a compositional device modelled on older devices such as the golden section, and lighting conventions and styles also vary historically, as do ideas about the virtues of symmetry. Specific and rather clichéd cultural expectations are thus built into the algorithm.

While a digital image is, as Bernard Stiegler (2002) explained, “discrete” in its very structure, meaning entirely amenable to disassemblage and reassemblage (which in turn makes the image able to travel), it does not disassemble as an image in the way that a sentence can be taken apart into words or a word into letters. It is up to the researcher or the AI network to decide where to make the cut, to decide what must be “extracted” and what deemed waste, to define what counts as a salient “feature”. This is how something as ambiguous as an image and as fuzzy as aesthetics can enter the purview of systems which only “see” data, and for which, as Geoffrey Bowker puts it, “If it’s not in principle measurable, or is not being measured, it doesn’t exist” (2013: 170). Arguably, to treat photographs as data is to ignore to a large extent the explicit positions they adopt vis-à-vis the world, since “data means – and has meant for a very long time – that which is given prior to argument” (Rosenberg 2013: 36). To treat photographs as data is to assume their givenness, and to assume that the act of observing or analysing them can be culturally neutral.

In the humanities, there is a tendency to associate big data studies with a kind of distant reading, set against an older art of close reading (cf. Herrnstein-Smith 2016). Yet actually, these kinds of analyses operate at shifting scales, moving between the detail and the whole. In this regard, sentiment and emotion mining resemble the art historical approach that, as Didi-Huberman says, “postulates that the whole visible can be described, cut up into its components [...] and wholly accounted for” (2005: 231). The “whole visible” in our case is the corpus, the colossal and ever-growing accumulation of images on social media. Didi-Huberman is discussing painting, and a mode of art history in which positivism (the approach that sees knowledge as that which is scientifically verifiable) combines with a “badly-understood Freudianism” such that every detail is treated as concealing something which is “hidden behind it” (ibid.: 231). Instead of addressing the painting in its full material presence, an attempt is made to see through it, to find in the detail a motive for the painting as a whole. Here again, there is a parallel: papers in affective computing often assume that emotion is a measurable fact of the image, something embedded in it, rather than an intangible, complex and relational quality. Studies of social media images propose that images “reflect”, “reveal” and “display” users’ mental states, and that they can “have” emotions which can be quantified as emotion values, or that emotions are “hidden behind” images (e.g., Kim et al. 2017; He et al. 2019; Huang/Chiang/Chen 2019; Guntuku et al. 2019; Lin et al. 2020).

Cutting up, partitioning or dividing the image into “features” becomes an exhaustive exercise: witness the way different studies in the affective computing field propose new techniques, new methods to parse the visual image. Each one

claims to attend to an aspect (scale, context, comparison between foreground and background) ignored by all previous studies. What Didi-Huberman says about the positivist attention to the detail in painting pertains here, too, it “verges on pure theoretical delusion” (2005: 236). It is an optimistic delusion, a belief that the image can be explained, that something as overdetermined and irreducible as a painting (or in our case a social photo) can be made “clear and distinct” (ibid.: 237). Against this, he posits the concept of the *pan*, the painterly elements that are not quite one thing or another, the points at which representation dissolves into abstraction and pigment.¹¹ Didi-Huberman’s symptomology is thus concerned not with the symptom as an effect of a cause, but with such incoherent, ambiguous and overdetermined symptoms or signifiers.

One might object that it is inappropriate to transfer Didi-Huberman’s argument about paintings by Vermeer and Brueghel to social photos which are more throwaway, more conversational, much less carefully contrived and crafted, and less tangibly material. Although he is keen to emphasise the specificity of painting, Didi-Huberman himself notes that in photographic images, the painterly “pan” finds its equivalent in the accidents and blurs that “‘point’ us beyond any *that-has-been*” (ibid.: 265, original emphasis).¹² So we might expect to find these elements in vernacular photographs, especially those that are *least* contrived and crafted. Although social photos may be cleaned and standardised by the mobile phone camera software and by processing within an app, and although accidental blur may be unlikely, they still retain something of the excessiveness of the photograph that early theorists noted: the non-hierarchical nature, the irrelevant detail, the odd intrusions that fail to cohere as representation. Unlike stock photos, they are non-emphatic and imperfect images, even if they aspire to the same clean mediocrity. These accidental elements are irreducible to “features”, and they form an excess or waste, which cannot be accounted for in the system or quantified as data.

The theoretical delusion that an image can be exhausted by interpretation is driven by a positivism that seeks absolute knowledge and total visibility. This totalising positivism expands the technical means of collection, observation,

11 Didi-Huberman argues that this seeking out the detail is destructive, not just of the object, but of the observer themselves, as if they redirect toward themselves “the first, violent act of disintegration” (2005: 233). This “drama of the detail” (ibid.: 234) is perhaps too complicated to address properly here.

12 Didi-Huberman is referring to Barthes, whose concept of *punctum* is close to the concept of *pan*. These concepts differ, not because “one of the two notions originates in painting and the other in photography”, but because Barthes conceives of the *punctum* in indexical terms: “the world reverts to depositing itself on the image” (Didi-Huberman 2005: 264). As Didi-Huberman explains, “In this sense, the *punctum* should be construed not as a symptom of the image, but as a symptom of the world itself” (ibid.: 265).

calculation and measurement, in the assumption that ultimately nothing can escape “capture” in the form of data. In photography theory and history, the term “positivist” is most often invoked in relation to the tendency to treat photographs as visible proofs of an external reality, but it also characterises ways in which photography and other technologies can be deployed as part of a set of protocols or procedures to suppress subjectivity and objectively yield the “facts” (Daston/Galison 2007: 115-190). This form of positivism makes its way into data science. As Ed Finn says, the dominant computational ideology or vision is also a colonising or conquering one: “the maximalist idea that all complex systems will eventually be made equivalent through computational representation” (2017: 43).¹³ The search for the sentiments and emotions “behind” images has fallen for what Didi-Huberman calls the “positivist myth of the omni-translatibility of images” (Didi-Huberman 2005: 3).

Behaviourism and the Measurement of Emotions

The shift to photography as a major form of self-expression and self-presentation is taking place in the context of a larger historical change, particularly in Western capitalist countries, towards what Eva Illouz (2007) terms “emotional capitalism”.¹⁴ She describes this as a therapeutic model organised around self-reflection, soft communication skills and “emotional intelligence”, which became central to the 20th-century capitalist economy, first between the 1930s and the 1970s in the United States, and then increasingly elsewhere. It replaced older distinctions between private and public spheres and between acceptable emotions (differentiated by gender), but maintained the vision of the self-interested individual (*homo economicus*), for whom “healthy” emotions are personal, not collective. Central to this new “emotional culture” is an increasing emphasis on the public performance of the private self (ibid.: 5). The prompts on social media platforms exhorting you to “share” what you are “feeling” or express what is “on your mind”, are invitations to participate in such a public performance. This performance is complicated, as it has different registers, since communicating with you on the same platforms

13 This is despite the fact that information theory and computing begin with the idea of information as uncertainty, and are underpinned by notions of indeterminacy and probability (Finn 2017: 43). Indeed, it is probabilistic approaches to AI which have driven the mass accumulation of data regardless of its future uses (Crawford 2021: 99-103).

14 The term describes a distinct aspect of 20th-century capitalism, especially in the USA, but there is some overlap with Zuboff’s characterisation of surveillance capitalism insofar as the latter makes use of the “behavioural surplus” produced through emotional expression, and elicits emotional communication in order to generate surplus.

are intimate friends, work colleagues and people you have never met – even people that you are not sure are actually people at all. The context of emotional capitalism creates a demand for self-expression, but this does not necessarily entail trying to directly communicate feelings. Instead, you may express yourself by using social media photos to represent your experiences, your tastes (including your visual aesthetic) and your ideal self-image. The image filters provided by different apps work as affect-management techniques, offering a means of adding instant atmosphere or mood but at the same time they can also be understood as indicators of taste and preference, part of this larger performance of self.

To use photography expressively involves making aesthetic and technical choices on the basis of “truth to feeling” rather than on the basis of whether the image represents the world “as it is”. I refer to this as “affective realism”, by which I mean any practice with photography where the measure of the photograph’s realism lies in its correspondence, not with a neutrally observable reality but with subjective, felt and emotional experience. Affective realism does not necessarily require an image to conform to what is or was objectively present in the world, but rather to express the experience of an individual – in this respect it is solipsistic, since its only reference points are one’s own experience and existence.¹⁵ It contradicts the historic association of photography with a realism characterised by neutral, unfeeling or disinterested recording. The yardstick of this affective realism is not only how well the individual judges the image to correspond to their own experience and the feelings that came with that experience, but also how well it seems to communicate that to others (gleaned from reactions, comments and so on).

It is likely that many people posting social media photographs want to convey something of the world as they experience it, something of their subjective worldview, without stopping to analyse precisely what feelings they might evoke or express.¹⁶ While people taking and posting social photos may conceive of them as a means of communicating their own subjective experience, they have not necessarily subscribed to the idea that images are about expressing emotions, nor have they necessarily set out consciously to express a specific feeling through the image. Although emotion recognition and sentiment analysis studies tend to assume that users are expressing emotions via images, the techniques themselves are indifferent to intentionality. This is because they are premised in behaviourist

15 My use of the term “affective realism” is related to the literary and artistic concept of realism, rather than the psychological sense, defined by Lisa Feldman Barrett and Jolie Wormwood as “the tendency of your feelings to influence what you see – not what you think you see, but the actual content of your perceptual experience” (2015).

16 An expert practitioner of affective realism would perhaps have a clear idea of what emotions they want to communicate. This suggests a practice such as that of so-called “creative photographers” who use high-end cameras and image-manipulation software to produce “expressive” images.

approaches to the emotions, which treat them as observable characteristics, rooted in the assumption that feeling and cognition are essentially discrete: our interpretation of our own feelings is no more reliable than that of an outside observer (Leys 2010: 89). Bracketed off from this are all sorts of intentions, desires and internal conflicts.

Originally, behaviours were understood as the bodily actions and expressions of an individual, but when emotion recognition algorithms are applied to social media posts, the “behaviours” are at one remove – including such things as written expression, jokes and memes, music selections, photographs and videos; things that a cultural theorist would understand as cultural artefacts, however minor or quickly produced. Culture does not simply communicate emotion directly, but makes use of complex techniques and devices such as metaphor. Since metaphors may be well-worn, deeply embedded and linked to our own embodied experience of the world, it is easy to mistake them for universal or natural forms of expression: so, a sunset can convey a pleasure in melancholy, or a solitary figure on a hill can convey loneliness. The same photo could be read as merely deictic: it points to the sunset or the figure and says “look at this!” or “we are here”.

The tendency to view visual imagery as pure or direct (or “natural”) emotional expression is perhaps partly a legacy of the positivist notion of the arts as a sphere dedicated purely to emotional expression, which is not knowledge-producing. This view assumes that emotion is opposed to cognition, not recognising how, as Nelson Goodman argued, “emotions function cognitively” in aesthetic experience (1976: 248).¹⁷ Thus, the communication of emotions is assumed to be something which happens reflexively, regardless of things such as conscious intention, tacit knowledge, and newly fashionable or historically embedded modes of visual practice. Additionally, behaviourist approaches to emotion recognition conceive of emotions as able to be separated from the immediate social interaction and broader culture, and therefore disregard the situated relationship between the person responding or posting, their imagined or intended audience, and any complex conscious or unconscious motivations they may have for posting a photograph.

Rejecting the cultural specificity and diversity of emotional expression (both facial and pictorial), behaviourism universalises and naturalises human emotional behaviour while at the same time individualising it (Leys 2011: 438). Against this, I would view emotional expression as fundamentally relational, an element of the interaction between people, images and contexts. Emotions appear natural precisely because they are so deeply cultural. As Illouz argues, emotions are congealed or compacted with cultural meaning, and

17 See also Brown/Phu (2014) on the relation between feeling, thinking and ethical action in photography.

it is this compact compression which confers on them their energetic and hence pre-reflexive, often semi-conscious character. Emotions are deeply internalized and unreflexive aspects of action, but not because they do not contain enough culture and society in them, but rather because they have too much. (Illouz 2007: 3)

James Elkins writes (about people crying in front of art): “strong emotions shut down our ability to reflect” (2001: 17). But even where we are “overcome” by emotion in response to a cultural artefact, this is never simply a biological response to stimuli. As Illouz suggests, the more profound the emotion, the more culturally entangled it can be. Many of the strongest gusts and waves of uncontrollable emotions are inseparable from cultural and social context, as Elkins’ example of the connections between Stendhal syndrome, Romanticism and Baroque art makes clear.¹⁸

If the behaviourist stimulus-response model seems so poor in the face of such phenomena, its great advantage is that it works at scale. In large scale automated studies, behaviourist models seem to come into their own. There is no need to identify the intentions behind a million people clicking “like” on an image, to be able to identify characteristics that guarantee an image’s likeability and enable that to be reproduced. All that is needed is for patterns to be identified and correlations made. Nevertheless, this requires emotions and their cultural expression to be translated into discrete, stable, measurable values. Following Darwin and Ekman, psychologists and neurologists have classified six to eight basic emotions. A similar classification is in operation in Facebook’s current design, which includes seven possible reactions: “like”, “love”, “care”, “haha”, “wow”, “sad”, “angry”. Human users of Facebook might see the reaction button as a means of communication, but from the platform’s perspective they enable users’ responses to posts to be measured and classified. The identification of discrete universal emotions allows for “commensuration”, which means making qualitative differences into quantifiable ones, and “textualisation”, which means “locking” emotions into texts or language (Illouz 2007: 32, 71). The Facebook reaction buttons, which (unlike emoji) have fixed textual meanings, provide a good example of how textualisation and commensuration work together.

The attempt to make emotional expression quantifiable and manipulable arrived in the mid-20th century, although the classification of emotions began

18 Stendhal syndrome was a set of symptoms exhibited by tourists, mostly at the Uffizi Gallery in Florence, starting in around the 1820s and manifesting in symptoms such as crying, fainting, fevers and hallucinations (Elkins 2001: 32-33). Elkins describes it as a consequence of a tourism which “sticks to the old Romantic war-horses, treating people to a heady mixture of genius worship and expectations as inflated as they are unfocused” and the first encounter with the intense, sensual and provocative aesthetics of Baroque paintings (such as those of Caravaggio) (ibid.: 35).

much earlier in Darwin's 19th-century experiments, which influenced Ekman's psychological theory of facial expressions, which in turn powerfully shapes contemporary facial recognition and emotion tracking. As Ruth Leys summarises, the supposedly basic emotions map onto universal, biologically-determined facial expressions that culture and socialisation are thought to only mask and moderate (2010: 70). Both Darwin and Ekman used sets of photographs to demonstrate and test their theories (Leys provides an extensive description and critique). This way of understanding emotions serves not only the field of behaviourist psychology, but also emotional capitalism more broadly, because it enables emotional life to be chained to "the logic of economic relations and exchange" as part of a "vast process of rationalization of intimate relations" (Illouz 2007: 6, 30). It is a precondition for the extractive approach to emotions characteristic of surveillance capitalism.

The Ruse of Personalisation

The identification of discrete universal emotions enabled them to be transformed into objects of governance, as well as fungibles or "behavioural surplus". Antoinette Rouvroy and Thomas Berns explain how "algorithmic governance" aims to regulate possible behaviours, through the transformation of our behaviour and environment into data, and through statistics (Rouvroy/Berns 2013: xiv). These processes do not produce static profiles, but dynamic "real-time" systems. Their alibi is personalisation:

They enrich our daily life's cognitive experience with dynamic and individualised informational content. Their celebrated capacity to detect, sort, evaluate and, most importantly, predict our desires and preferences, needs and propensities, and to customise and adjust deliveries, services and offers to our individual profile as if it knew us better than ourselves, spares us time and discomfort. (Rouvroy 2011: 125)

Such processes of personalisation have been critiqued for reducing people's informational horizons. This is what Eli Pariser describes as "filtering" – the production of personalised search results, news feeds and advertising that result in a narrowing of experience (Pariser 2011). Some researchers have argued that filtering has not produced the enclosure in "bubbles" that Pariser assumed, but it does not follow that personalisation is merely harmless or convenient. Instead, it is a mode of shaping conduct, tailoring people to the product rather than the other way round.¹⁹ This idea of oppressive personalisation recalls the technical image feedback loop described by Vilém Flusser in 1985:

19 It does so "by tailoring sales strategies (the way of presenting the product, of pricing it, etc.) to each person's profile": i.e. market segmentation (Rouvroy/Berns 2013: xiii).

This feedback enables the images to change, to become better and better, and more like the receivers want them to be; that is, the images become more and more like the receivers want them to be so that the receivers can become more and more like the images want them to be. (Flusser 2011: 55)

Rouvroy and Berns argue that the aim is to “accelerate flows”: ideally, the individual should act and respond to prompts in a reflexive fashion “without forming or formulating a desire”, avoiding any detour or gap between stimulus and response (Rouvroy/Berns 2013: xiii-xiv). Digital behaviourism promises to give us what we want before we even know we want it by listening to our bodies (via involuntary expressions, unconscious actions and movements), but also by reading our photos. At the same time, it promises to furnish research with information that appears objective and rational because technologically acquired and computational, free from human bias and subjectivity, much as photography did in the 19th century. Personalisation turns out to be nothing of the sort, since the human “person” here is irrelevant.

Algorithmic governance is premised on statistical doubles with which the person has no relationship and which are at odds with their own perceptions and representations of themselves (ibid.: xvii). The mass of social media photographs is part of the raw material of these digital, statistical doubles. The myth of omnitranslatability is the guiding principle of the rendition processes that turn physical existence, actions and behaviours into digital tokens or data-points.²⁰

In conclusion, while there appears to be a contradiction between how photographs are increasingly understood as subjective and expressive, and the positivist and behaviourist approaches used to attend to them, I have tried to demonstrate that these two things are interdependent. The promise of photography today is to represent subjective, lived experience, and to help one express oneself or even build a sense of self – of taste, memory, appearance, connection to others – through taking, posting and sharing images. Apps and mobile phone cameras facilitate this with easy-to-use filters, colour and composition adjustments, retouching and so on. The transformation of photography into a subjective means of expression is connected to the vision of the internet as a space of personalisation. Yet personalisation is a ruse of systems that are indifferent to persons. It is used to generate an excess of “wild” data to be “mined”, “harvested” or “foraged”. New machine learning and AI systems, some developed on the back of spurious claims about social goods, produce unrecognisable statistical doubles whose eventual purpose is likely to be increased control over people. These systems not only simplify

20 The term is a little misleading insofar as these doubles are not coherent entities. The process of translation of images into data is also a process of slicing and disaggregating rather than the construction of composite doppelgangers. Or as Matthew Fuller puts it, “control has no need of individuals per se, only as referents: as scalar nodes in the flows of cash, commodity, and behavior” (2005: 152).

the emotionally and visually complex, they bracket off cultural signification or symbolic action, ignore practices of sociability and community, disregard people's own accounts of themselves and their reality, and ignore the contradictions, ambiguities and accidents inherent in the social photograph.

Acknowledgements

The author would like to thank Bernadette Buckley and Rod Dickinson for their advice and suggestions for an earlier spoken version of this paper, Jordana Blejmar and John Parish for reading and commenting on this version, and Rowan Lear for drawing my attention to the work of Antoinette Rouvroy.

References

- Andalibi, Nazanin/Buss, Justin (2020): "The Human in Emotion Recognition on Social Media: Attitudes, Outcomes, Risks." In: Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems, pp. 1-16.
- Ang, Chee/Bobrowicz, Ania/Schiano, Diane/Nardi Bonnie (2013): "Data in the Wild: Some Reflections." In: *Interactions* 20/2, pp. 39-43 (<https://interactions.acm.org/archive/view/march-april-2013/data-in-the-wild>).
- Balouchian, Pooyan/Foroosh, Hassan (2018): "Context-Sensitive Single-Modality Image Emotion Analysis: A Unified Architecture from Dataset Construction to CNN Classification." In: 25th IEEE International Conference on Image Processing (ICIP), pp. 1932-1936.
- Barrett, Lisa Feldman/Wormwood, Jolie (2015): "When a Gun Is Not a Gun." In: *The New York Times Sunday Review*, April 17 (<https://www.nytimes.com/2015/04/19/opinion/sunday/when-a-gun-is-not-a-gun.html>).
- Barthes, Roland (1973 [1957]): "The Great Family of Man." In: *Mythologies*, London: Paladin Books, pp.100-102.
- Barthes, Roland (1979 [1957]): "Shock Photos." In: *The Eiffel Tower and Other Mythologies*, New York: Hill and Wang, pp. 71-73.
- Barthes, Roland (1984 [1980]): *Camera Lucida*, London: Fontana.
- Blaschke, Estelle (2016): *Banking on Images from the Bettmann Archive to Corbis*, Leipzig: Spector Books.
- Bowker, Geoffrey (2013): "Data Flakes: An Afterword to 'Raw Data' Is an Oxymoron." In: Lisa Gitelman (ed.), "Raw Data" is an Oxymoron, Cambridge, Mass.: MIT Press, pp.167-171.
- Brown, Elspeth H./Phu, Thy (2014): "Introduction." In: Brown, Elspeth H. Brown/ThyPhu (eds.), *Feeling Photography*. Durham, NC.: Duke University Press, pp. 1-25.

- Brown, Simon (2009): "Colouring the Nation: Spectacle, Reality and British Natural Colour in the Silent and Early Sound Era." In: *Film History: An International Journal* 21/2, pp.139-49.
- Guntuku, Sharath Chandra/Preotiuc-Pietro, Daniel/Eichstaedt, Johannes C./Ungar, Lyle H. (2019): "What Twitter Profile and Posted Images Reveal about Depression and Anxiety." In: *Proceedings of the International AAAI Conference on Web and Social Media* 13, pp. 236-246.
- Crawford, Kate/Paglen, Trevor (2019): "Excavating AI: The Politics of Images in Machine Learning Training Sets." (<https://excavating.ai>).
- Crawford, Kate (2021): *The Atlas of AI: Power, Politics, and the Planetary Costs of Artificial Intelligence*, New Haven: Yale University Press.
- Daston, Lorraine/Galison, Peter (2007): *Objectivity*, Cambridge, Mass.: Zone Books/MIT Press.
- Davies, William (2017): "How are We Now? Real-Time Mood-Monitoring as Valuation." In: *Journal of Cultural Economy* 10/1, pp. 34-48.
- Defoe, Daniel (2003 [1722]): *A Journal of the Plague Year*, London: Penguin Books.
- Denton, Emily/Hanna, Alex/Amironesei, Razvan/Smart, Andrew/Nicole, Hilary/Scheuerman, Morgan Klaus (2020): "Bringing the People Back In: Contesting Benchmark Machine Learning Datasets." In: *Proceedings of ICML Workshop on Participatory Approaches to Machine Learning* (<https://arxiv.org/abs/2007.07399v1>).
- Didi-Huberman, Georges (2005 [1990]): *Confronting Images: Questioning the Ends of a Certain History of Art*, Pennsylvania: Penn State Press.
- Doshi, Udit/Barot, Vaibhav/Gavhane, Sachin (2020): "Emotion Detection and Sentiment Analysis of Static Images." In: *2020 International Conference on Convergence to Digital World-Quo Vadis (ICCDW)*, pp. 1-5.
- Elkins, James (2001): *Pictures and Tears: A History of People Who Have Cried in Front of Paintings*, London: Routledge.
- Finn, Ed (2017): *What Algorithms Want: Imagination in the Age of Computing*, Cambridge, Mass.: MIT Press
- Flusser, Vilém (2011 [1985]): *Into the Universe of Technical Images*, Minneapolis: Minnesota University Press.
- Foucault, Michel (1979): *Discipline and Punish: The Birth of The Prison*, Harmondsworth: Peregrine Books.
- Foucault, Michel (1980): "What is an Author?" In: *Language, Counter-Memory, Practice: Selected Essays and Interviews*, Ithaca: Cornell University Press.
- Fuller, Matthew (2005): *Media Ecologies: Materialist Energies in Art and Technology*, Cambridge, Mass.: MIT Press.
- Frosh, Paul (2003): *The Image Factory Consumer Culture, Photography and the Visual Content Industry*, London: Bloomsbury.
- Frosh, Paul (2012): *The Poetics of Digital Media*, London: Polity.

- Gates, Kelly (2006) "Identifying the 9/11 'Faces of Terror': The Promise and Problem of Facial Recognition Technology." In: *Cultural Studies* 20/4-5, pp. 417-440.
- Ginzburg, Carlo (1980): "Morelli, Freud and Sherlock Holmes: Clues and Scientific Method." In: *History Workshop* 9, pp. 5-36.
- Gitelman, Lisa (ed.) (2013): "Raw Data" is an Oxymoron, Cambridge, Mass.: MIT Press.
- Goggin, Benjamin (2019): "Inside Facebook's Suicide Algorithm: Here's How the Company Uses Artificial Intelligence to Predict your Mental State from Your Posts." In: *Business Insider*, January 6 (<https://www.businessinsider.com/facebook-is-using-ai-to-try-to-predict-if-youre-suicidal-2018-12>).
- Goodman, Nelson (1976): *Languages of Art: An Approach to the Theory of Symbols*, Indianapolis: Hackett.
- He, Xiaohao/Zhang, Huijun/Li, Ningyun/Feng, Ling/Zheng, Feng (2019): "A Multi-Attentive Pyramidal Model for Visual Sentiment Analysis." In: 2019 International Joint Conference on Neural Networks (IJCNN), pp. 1-8.
- Henning, Michelle (2018): *Photography: The Unfettered Image*, London: Routledge
- Herrnstein-Smith, Barbara (2016): "What Was 'Close Reading?': A Century of Method in Literary Studies." In: *Minnesota Review* 87, pp. 57-75.
- Higgins, Scott (2007): *Harnessing the Technicolor Rainbow: Color Design in the 1930s*. Austin: University of Texas Press.
- Huang, Yu-Ching/Chiang, Chieh-Feng/Chen, Arbee LP (2019): "Predicting Depression Tendency Based on Image, Text and Behavior Data from Instagram." In: *Proceedings of the 8th International Conference on Data Science, Technology and Applications (DATA)*, pp. 32-40.
- Illouz, Eva (2007): *Cold Intimacies: The Making of Emotional Capitalism*, London: Polity Press.
- Jurgenson, Nathan (2019): *The Social Photo*, London: Verso Books.
- Kim, Hye-Rin/Kim, Yeong-Seok/Kim, Seon Joo/Lee, In-Kwon (2018): "Building Emotional Machines: Recognizing Image Emotions through Deep Neural Networks." In: *IEEE Transactions on Multimedia* 20/11, pp. 2980-2992.
- Leys, Ruth (2010): "How Did Fear Become a Scientific Object and What Kind of Object Is It?" In: *Representations* 110, pp. 66-104
- Lin, Chenhao/Hu, Pengwei/Su, Hui/Li, Shaochun/Mei, Jing/Zhou, Jie/Leung, Henry (2020): "Sensemood: Depression Detection on Social Media." In: *Proceedings of the 2020 International Conference on Multimedia Retrieval*, pp. 407-411.
- Liu, Leqi/Preotiuc-Pietro, Daniel/Samani, Zahra Riahi/Moghaddam, Mohsen E./Ungar, Lyle (2016): "Analyzing Personality through Social Media Profile Picture Choice." In: *Proceedings of the International AAAI Conference on Web and Social Media* 10/1 (<https://ojs.aaai.org/index.php/ICWSM/article/view/14738>).

- Miller, Daniel (2016): *Social Media in an English Village*, London: UCL Press.
- Pariser, Eli (2011): *The Filter Bubble: What the Internet is Hiding from You*, London: Penguin Books.
- Parsons, Michael (2005): "Introduction." In: César Botella/Sára Botella (eds.), *The Work of Psychic Figurability: Mental States Without Representation*, Hove: Brunner-Routledge, pp. xvii-xxiii.
- Rosenberg, Daniel (2013): "Data Before the Fact." In: Gitelman, Lisa (ed.), "Raw Data" is an Oxymoron, Cambridge, Mass.: MIT Press, pp. 15-40.
- Rouvroy, Antoinette (2011): "Technology, Virtuality and Utopia: Governmentality in an Age of Autonomic Computing." In: Mireille Hildebrandt/Antoinette Rouvroy (eds.), *Law, Human Agency and Autonomic Computing*, London: Routledge, pp. 119-140.
- Rouvroy, Antoinette/Berns, Thomas (2013): "Algorithmic Governmentality and Prospects of Emancipation: Disparateness as a Precondition for Individuation through Relationships?" In: *Réseaux 177/1*, pp.163-196.
- Rouvroy, Antoinette (2020): "Algorithmic Governmentality and the Death of Politics: An Interview with Antoinette Rouvroy." In: *Green European Journal*, March 27 (<https://www.greeneuropeanjournal.eu/algorithmic-governmentality-and-the-death-of-politics/>).
- Rubinstein, Daniel/Sluis, Katrina (2013): "Notes on the Margins of Metadata: Concerning the Undecidability of the Digital Image." In: *photographies 6/1*, pp. 151-158.
- Schneble, Christophe Olivier/Elger, Bernice Simone/Shaw, David Martin (2020): "Google's Project Nightingale Highlights the Necessity of Data Science Ethics Review." In: *EMBO Molecular Medicine 12/3* (<https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7059004/>).
- Shankar, Shreya/Halpern, Yoni/Breck, Eric/Atwood, James/Wilson, Jimbo/Sculley, D. (2017): "No Classification without Representation: Assessing Geodiversity Issues in Open Data Sets for the Developing World." 31st Conference on Neural Information Processing Systems (NIPS 2017), Long Beach, CA, USA (arXiv preprint arXiv:1711.08536).
- Stark, Luke (2018): "Algorithmic Psychometrics and the Scalable Subject." In: *Social Studies of Science 48/2*, pp. 204-31.
- Stiegler, Bernard [1996] (2002): "The Discrete Image." In: Stiegler, Bernard/Jacques Derrida, *Echographies of Television: Filmed Interviews*, Cambridge: Polity, pp. 147-74.
- Street, Sarah (2011): "Negotiating the Archives: The Natalie Kalmus Papers and the 'Branding' of Technicolor in Britain and the United States." In: *The Moving Image: The Journal of the Association of Moving Image Archivists 11/ 1*, pp.1-24.
- Taussig, Michael (2009): *What Color is the Sacred?*, Chicago: The University of Chicago Press.

- Omdia (2018): "Emotion Recognition and Sentiment Analysis." March 6 (<https://omdia.tech.informa.com/OM011970/Emotion-Recognition-and-Sentiment-Analysis>).
- Vadicamo, Lucia/Carrara, Fabio/Cimino, Andrea/Cresci, Stefano/Dell'Orletta, Felice/Falchi, Fabrizio/Tesconi, Maurizio (2017): "Cross-Media Learning for Image Sentiment Analysis in the Wild." In: Proceedings of the IEEE International Conference on Computer Vision Workshops, pp. 308-317.
- Wongkoblaph, Akkapon/Vadillo, Miguel A./Curcin, Vasa (2017): "Researching Mental Health Disorders in the Era of Social Media: Systematic Review." In: Journal of Medical Internet Research 19/6, e228 (<https://www.jmir.org/2017/6/e228/>).
- Zuboff, Shoshana (2019): *The Age of Surveillance Capitalism: The Fight for a Human Future at the New Frontier of Power*, London: Profile Books.
- Zylinska, Joanna (2021): "Undigital Photography: Image-Making beyond Computation and AI." In: Tomas Dvorak/Jussi Parikka (eds.), *Photography Off the Scale*, Edinburgh: Edinburgh University Press, pp. 231-252.