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A comparative study of algorithmic–user classification practices in online dating: a human–machine learning process

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ABSTRACT
Dating-app graphical user interface (GUI) structures for data collection contain categories that enable classifying users algorithmically and classifying users between each other to define their sexuality and find a date. Indeed, app providers define categories that mediate the users' bodies and interactions to present themselves, and these categories ultimately serve app algorithms for recommending profiles. Categories establish a main reciprocated mediation between algorithms and users that is explored in this article to shed new light on the way Big Data shapes human–algorithmic interactions in online dating. However, online dating research pays little attention to classification processes from the perspective of the user, although classification is key to algorithm function for codifying sexuality. Using a qualitative analysis of 40 participant situated interviews, I examine the way dating-app users make sense of predefined categorical structures and their underlying classification processes, within 26 platforms. The results show that actors learn to integrate algorithmic logic into their common knowledge, as well as to challenge the algorithmic logic, and thus produce new conventions to classify their emotional states, physical attractiveness, and sexual preferences.

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1. Introduction

This article focuses on how dating-app users' sexuality and ways of expressing affection are shaped by the way their bodies are codified in digitized contexts. This codification occurs through two main sociotechnical processes related to the so-called Big Data phenomenon: data collection and algorithmic processing. These are both essential to contemporary computing systems, using from the least to the most sophisticated techniques of artificial intelligence.

Data collection and algorithmic processing are studied indirectly and separately in the online dating literature, either from the user perspective or from the developer perspective. Broadly speaking, the user perspective focuses on profiles' data and design to understand individual self-presentation practices and sexual activity (see Gibbs, Ellison, and Lai 2011; Fernandez and Birnholtz 2019; Zytko et al. 2021) or how algorithmic systems present profiles to the user (see Masden and Edwards 2015; Parisi and Comunello

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2020). The developer perspective provides insights into the integration of gendered stereotypes and discrimination practices within the system's design (see Pidoux, Kuntz, and Gatica-Perez 2021; Bergström [2019] 2022).

The originality of this article relies on the reciprocated mediation that I identified between sociotechnical processes and their human nexus. This is achieved via classifications[1] for understanding dating-app algorithms (despite the fact they are secret and proprietary; see Pasquale 2015) in a new light: what matters to users. I study how users build expertise from their interpretations of algorithmic signals within specific offline and online situations to gain knowledge about their own sexuality. The objective is to compare users' expertise to the way algorithms both collect data and try, in turn, to acquire knowledge about human sexuality and affection. To this end, I analyze aspects of dating apps that mediate agency between apps and users, such as user practices, interface design, data-categorical structures, and affordances such as liking a profile. Instead of focusing on one perspective, my approach is different: it simultaneously considers 'how the machine algorithmically thinks about humans' and 'how humans learn to grasp what they think the machine algorithmically thinks about them'.[2]

1.1. Human categories for algorithmic classification

Embodied interactions in dating apps are shaped by the conventions that app providers like Tinder, Meetic, Bumble, AdultFriendFinder, ROMEO – PlanetRomeo – and their staff team define for data collection and algorithmic processing. Dating-app conventions are established by a datafication process: individual traits and actions are translated into data, made possible thanks to the use of variables defined with categories and numerical values. This enables algorithms to classify human sexuality. For instance, the website AdultFriendFinder translates a woman's bust into a variable called 'bra size', indicating the size categories of a bra that the user has to declare in their profile. The variable is presented with predefined measurements given by the website like '32B': the number indicating the size of the band around the woman's torso, and the letter indicating the breast cup size. In a similar vein, the mobile app Romeo datafies the user's 'dick size' with the following categorical values: 'S, M, L, XL, XXL'.

These conventions facilitate the collection of a vast amount of data from multiple users within a structure that is homogeneous; this allows algorithms to compute calculations quickly. Fiore and Donath (2004) highlighted this 'data collection standardization' based on the dating-app profile structures. More specifically, when collecting data, categories are used because they are decidable and finite criteria for computing calculation in a programming language. They are 'the nature of algorithmic inputs' that are fed into a function in order to define a desired output (Brown, Davidovic, and Hasan 2021). Dating apps are developed as 'recommendation systems' (Xia et al. 2016), which are computing systems using algorithms for recommending items like a profile, a song, or a book to users based on the statistical analysis of their data. These systems use, for instance, machine learning algorithms to present profiles to users, based on categories that classify users' preferences according to the 'behavioural and declarative data' (Xia et al. 2016) that are collected on platforms. For instance, the number of persons contacted online, the height declared in the user profile, and the age of all users viewing the same profile. However, while matching algorithms classify some human characteristics, they are excluding others that do not fit the app's conventions. For instance, algorithms in apps like CoffeeMeetsBagel ignore certain preferences declared by the users via graphical user interfaces (GUIs), and provide profile recommendations that discriminate specific users according to their ethnicity (Hutson et al. 2018). In other apps, there is also the case of gender discrimination when using facial analysis algorithms (Scheuerman, Paul, and Brubaker 2019). While not the case with all algorithmic input–outputs, the majority of structures designed for data collection are categorical and establish a main mediation via GUI between developers coding algorithms and the 'recipient of the output of the algorithm (the classification decision)' (Burrell 2016, 1). In this context, the recipient is the human's sexual and affective body that is being algorithmically classified on dating apps for computing profile recommendations.

Dating apps design profile forms where the user can declare physical, sexual, and emotional individual traits. For instance, a comparative study shows that 21 dating apps require users to declare 'individual capital'; this defines an 'individual's psychological, morphological and health factors like dreams, skills, erogenous body parts, sexually transmitted diseases' (Pidoux, Kuntz, and Gatica-Perez 2021, 13). These forms guide users on how they should evaluate themselves and others (Chaulet 2009). Therefore, for algorithms and other users, categories act as 'conventions for the statistical equivalency of personal qualities' (Desrosières 2014, 38).

Consequently, dating-app structures contribute to 'sexual datafication' by 'codif[ying] users' desires into a visual, structural, and linguistic order', while directing the audience's gaze (Saunders 2020, 58). This is a 'coded gaze': a view that is embedded and propagated by coding systems that makes users recognizable to algorithms via categories, and enables individuals to be understood in relation to how they are seen by others (Cotter et al. 2021). In this sense, datafication is directly linked to algorithmic classification; a process that remains underexplored in online dating. One study of the Chinese Blued dating app (Wang 2020) stresses that sexuality is datafied and exposed accordingly by the users. This datafication is possible through restricted categories such as: height; weight; sex roles; tags for body type and personality; what the user is looking for; relationship status; race; scales from 1 to 10 or high vs. low; and metrics such as the *yanzhi* algorithm to measure attractiveness from a person's face. Hence, the app produces an 'algorithmic sociality' (Wang 2020), which means users interact with others based on predefined algorithmic choices.

Classification is a matter of concern to sociologists studying algorithmic development practices on other types of platforms because of the 'social injustice and discriminatory results' they can produce (Burrell 2016; Bechmann and Bowker 2019). In the implementation of machine learning algorithms applied to Facebook data, data collection has been approached as a development process of classifying the user population according to software engineer choices (Bechmann and Bowker 2019). In the study of Facebook's classification system for targeting advertisements, scholars (Cotter et al. 2021) have shown that user data are translated into categories based on the company's economic choices, design of algorithms, and the interests of advertisers and users. The user provides 'digital-trace signals' as 'explicit expressions' of interests. These 'signals' might include 'likes' on a page, which inform algorithms how to sort the users via inferences for category imputation (Cotter et al. 2021). Thus, users are a key human nexus for algorithmic classification practices that has been little studied from the perspective of the user.

1.2. Categories for user self-presentation

To present themselves, users take advantage of dating-app structures for creating a profile. Users know that specific categories like sporting activities are more often selected by users to craft an ideal self. Users also find new practices to work around the limitations of the platform for self-description (Ellison, Heino, and Gibbs 2006). Other scholars insist that, in general, self-description pages are ignored by users (Zytko, Grandhi, and Jones 2014, 2018). The exception is the case of the Grindr app, where profile information is recalled during online conversations to achieve a goal or to complete missing information (Licoppe, Rivière, and Morel 2016). Gender categories enable users to clarify their identity before entering into contact with another user (Fernandez and Birnholtz 2019). In an environment where there is high uncertainty about the other person, users rely on the profile-page categories to increase trust about the interlocutor's identity (Gibbs, Ellison, and Lai 2011) or, conversely, to protect the user's privacy by not providing too much information. This gives the user a sense of control over the other person's gaze (Sannon, Bazarova, and Cosley 2018). Some users lie about their age to embellish their portrait (Hancock, Toma, and Ellison 2007); others do not fill in the information and prefer to engage in conversation (Zytko et al. 2018). The categories can be mobilized offline during the face-to-face meetings by Meetic users (Kessous 2011), which suggests the categories predefined by apps serve a purpose beyond the online environment.

These previous studies highlight users' agency over platforms in two modalities defined by Duguay (2020, 32; original emphases), as '*on-label use* – a platform's explicitly prescribed purpose as determined by its design constituency' and '*off-label use* – activity outside of, or contrary to, on-label use. Off-label use can be expected or unexpected' (Duguay 2020, 32). However, these studies do not directly address the question of algorithmic classification; a core feature of 'algorithmic culture' (Striphas 2015) shaping everyday life socialization mediated by computational processes that are entangled with an economic and socio-political system.

1.3. Dating and sexuality as market logic

Dating apps create profiles defined as 'casting molds' (Olgado, Pei, and Crooks 2020) that build a 'market logic' in the dating industry by two means: by requesting users to provide data that are aggregated and resold by companies; and by framing users within 'digitally-mediated capital accumulation' practices where they become 'rational actors' that are required to shape 'individual traits as commodities' and produce a 'romantic exchange value' in the app (Olgado, Pei and Crooks 2020). Olgado, Pei, and Crooks (2020) highlight that users have limited freedom when creating a profile, because users can only choose from predefined options fixed by the system; they have little control over their profile presentation and visibility unless they pay. In this sense, categories facilitate 'profit extraction' and establish 'non-neutral infrastructures' that give dominant power to platforms (Olgado, Pei, and Crooks 2020).

Data structuration on dating apps forms what Eva Illouz (2020) calls 'scopic capitalism'; a visual economic logic constituted by the association of the beauty, fashion, sports, and media industries. For Illouz (2020), women are devalued via image production for self-presentation; they are reduced to, and consumed as, merchandise by their sexualized bodies. More specifically, in her analysis of pornographic sites, Saunders (2020) shows that the industry crafts a sexual datafication through the hyper-categorization of the female body, female behaviour, and race.

Categories have been studied (Pidoux, Kuntz, and Gatica-Perez 2021) in 22 dating apps. The results show applications either imitate or counter-imitate each other. This mimetic-distinctive dynamic builds the dating experience according to four classes: 'communitarian sex-driven', 'quick dating', 'full commitment', and 'diversity'. These classes reinforce and reproduce hegemonic views about dating, gender, and sexuality. Hence, dating-app 'classifications are both conceptual (in the sense of persistent patterns of change and action, resources for organizing abstractions) and material (in the sense of being inscribed, transported, and affixed to stuff)' (Bowker and Star 2000, 289).

Taking the standpoint of app providers, the assumption is that the digital and economic logic formats social actors' representation as 'statistical bodies', which reduces the self to a set of quantifiable descriptors (Rouvroy 2013). However, if categorical data structures have agency over users, these structures are integrated into communities of practices that shape each other.

As has been shown in a study (Liu and Graham 2021, 8) of the Chinese COVID-19 contact-tracing app 'Health Code', user perception shapes the meaning of processes, such as data collection and algorithm implementation, and the socio-cultural dynamics. For instance, researchers identified that users doubt the app's accuracy after hearing misjudgements about the algorithms, or the data type collected. One user finds the app algorithms insignificant because it uses geolocation to estimate a person's risk status without knowing more about the user's context. At the same time, scientists found that the majority of cases were asymptomatic, and that patients do not know how to identify their own risk status and how this could be done effectively through the app (Liu and Graham 2021, 8). In the context of online dating, Albury et al. (2017, 6) highlight that together 'user practices, business models and app functionality co-evolve'. Although the app harvests user-behaviour data to improve and monetize the system, users learn to game the app to improve their chances of finding a potential partner (Albury et al. 2017). Users 'challenge developers' concentration of power over a technology's purpose' (Duguay 2020, 31).

Previous studies have contributed to an understanding of the ways in which technology changes cultural norms around dating and building impressions of human sexuality (Ellison, Heino, and Gibbs 2006), or, inversely, how social practices change norms within technologies (Duguay 2020). I extend the online dating literature by demonstrating that dating and sexuality conventions are shaped reciprocally between algorithms and users through a 'human–machine learning process' (Pidoux 2021) that builds a new online and offline dynamic that is founded both in mathematical logic (following algorithmic principles) and common-sense knowledge.

Apps classify users and their sexuality, via categorical structures that feed algorithms. Users retroactively shape the categories computed, through the ways the users engage with the app when they present themselves and evaluate other users using different classification processes. In this article, I present a novel reciprocated analysis of classification practices in online dating**,** building upon a body of interdisciplinary literature on dating-app interfaces and human interaction with technologies from the human and social sciences. Notably, I draw on works situated in science and technology studies, algorithm and software studies, human–computer interaction, computer-mediated communication, and media studies. This literature is particularly relevant for the study of user–algorithmic interaction. Indeed, human–computer interaction scholars show that dating-app users are particularly interested in 'learning collectively about the system' (Masden and Edwards 2015) from the interface design and external sources. Consequently, 'the definition of a type of algorithm for ranking user preferences and its advertisement by the companies encourage users to perform strategically to generate a reputation-based authenticity: hence, users become experts entangled with technical systems' (Duguay 2017, 360). This is a contrasted fact with recent analysis in 'algorithmic awareness' studies (Gran, Booth, and Bucher 2020) where users of other recommendation platforms are unaware of algorithms' logic. Another study (Parisi and Comunello 2020) analyzes how Tinder users develop 'algorithmic imaginaries' (Bucher 2017, 31), that is, 'the way in which people imagine, perceive and experience algorithms and what these imaginations make possible'. Parisi and Comunello (2020) present three types of user perceptions: an effective support of homophily (getting results similar to the user); generic understanding based on geographical proximity; and systematic exploration of the mechanics by modifying the profile information. These studies, however, are not interested in understanding the algorithm design choices: a critical point made by Wang (2020).

From a set of 26 dating apps, and based on a qualitative analysis of 40 participant interviews, I present empirical evidence of the way human and non-human actors make sense of predefined categorical data structures and the underlying classification processes by interacting with each other to find a date or a partner. The ethnomethodology (Garfinkel 1984) allowed me to investigate the human–machine reality from a situated analysis of practices, including a precise description of the categories framing this reality.

My results show that users recognize that self-presentation and browsing practices must be in the categorical forms given by the app. Hence, users distinguish themselves from the interface and acknowledge that they are crafting an image for the algorithms in order to attract others. As such, users both follow the app conventions and reject them to apply their own common-sense knowledge built between users. Despite this distinction from the machine, users integrate quantification practices that are specific to the algorithm logic. Therefore, users behave in part as the machine taught them, but trust their common-sense knowledge and integrate their own practices beyond what is encouraged by the app. Consequently, I also show the extent to which algorithms can only grasp a partial view of a user's reality.

The following section presents the method used, and the dating-app and participant samples. Section 3 presents the results of interviews where user practices were analyzed in relation to the design of the dating-app categories and in contrast to algorithmic behaviour. Section 4 develops the human–machine learning process and its implication for dating and sexuality-related practices based on a discussion of the findings, before concluding with research perspectives for porn studies.

2. Method: situated interview study

In this study, I used qualitative data from 40 interviews with dating-app users. The study adhered to ethical procedures and to a data management plan concerning personal data that was approved by the EPFL Human Research Ethics Committee (HREC), No. 007-2018/ 22.02.2018.

Semi-structured face-to-face interviews were conducted and audio-recorded by the researcher between November 2018 and June 2020. Recordings ranged in length from 26′31″ (minimum) to 1′44′22″ (maximum), with a mean of 45′18. The transcriptions were made by a professional transcriber and the researcher.

Empirically, I engaged in an offline observation setting where I engaged with social actors while they used a dating app, in order to explore with them the contingencies that come with their practices of creating a profile and browsing other users (two standardized tasks in online dating). More specifically, the participants were asked to use the app during the interview while the researcher adopted the role of a learner. For instance, users were requested to show the researcher how to create a profile, browse profiles, and edit a profile, based on questions such as: please show me how you create a profile in the dating app that you use the most; how did you obtain those matches; and how do you find other users? This method of inquiry is aligned with Garfinkel's (1984) ethnomethodology, where social practices are a continuous achievement carried out through actions that are understood *in situ*. This ethnomethodology has been adopted to examine the role of algorithms in interactions with users during a 'walking experience' (Ziewitz 2017), which means to move around and find addresses following algorithmic decisions with another person. In Ziewitz's (2017, 3) study, 'algorithms are considered as figures for making sense of observations'. He posits that engaging with algorithmic 'situational dynamics enables the understanding of human reasoning'. As pointed out by Olgado, Pei, and Crooks (2020), using ethnomethodology to study dating apps enables a better understanding of data structures from the user perspective, and of the context in which they are used beyond the interface's market logic. Indeed, online dating practices are dependent on individual life trajectories and contextualized with offline practices (Hsiao and Dillahunt 2017).

Participants were mainly recruited in the French-speaking part of Switzerland through three means: the author's personal website; flyers posted at two universities and in public spaces such as supermarkets and city centre bars; and via dating apps by creating a female profile account – in the description, the account indicated the research and the intention of recruiting interviewees.

The recruitment was guided by the diversity of dating apps used by participants. To define dating-app diversity I first considered the sex[3] options and the combinations available in the app, which are women seeking women AND men OR women seeking men. Second, I considered the innovative elements advertised in the app's website or media coverage. These two factors are relevant as dating apps are created according to a marketing logic that draws on population segmentation strategies based on sexuality (Bergström [2019] 2022), and because technological innovations are created by advertising a new or improved component from another app to ensure market penetration (Akrich 1995). There were 26 different dating apps used by the participants. Simultaneously using or trying multiple apps (maximum five) was a recurrent practice. The mean was two apps; the four main apps used by participants (in descending order) were Tinder (n = 23), ROMEO –PlanetRomeo (n = 7), Parship (n = 2), and Celibataire.ch[4] (n = 2). Despite the interest in recruiting users from different dating apps, the majority of participants in the sample used Tinder, reflecting the app's popularity.

The following demographic information was collected, as it was declared in the app: users' age, sex, and sexual preference when seeking other users. The participant sample was composed of 40 participants (25 male, 15 female).[5] Twenty-nine participants sought a member of the opposite sex, 11 sought those of the same sex, and three sought both. The mean age was 32 years (range 20–66 years). The influence of age and gender factors on the result was not investigated. However, in the interviews, the participants identified sexual orientation as an important factor for interacting with the app (see 'profiling' and 'swiping reactivity' practices in Section 3).

The interview analysis is part of a doctoral thesis that covers other types of practices (see Pidoux [2021] for more details). In this article, the analysis is limited to recurrent classification practices. I do not claim that the sample is representative of user practices or the user population in a given app, nor do I claim that users have one typical practice as a planned strategy. Users combine multiple practices, sometimes contradictory, and they change them constantly according to every profile that is browsed. The aim of the study was to identify the diverse practices of classification that are common across several platforms.

3. Results

This section presents the user practices for making sense of online dating when creating a profile and browsing profile recommendations. From the interview analysis I define five main practices: elicitation and omission; profiling; swiping reactivity; allusion; and hesitation. I define each practice according to the observations in the study. The definitions are supported by the literature in social sciences and online dating research. For each practice I present the user's actions when interacting with the machine and other users. Certain practices rely on the design conventions in the GUI, but actions are also reviewed without those explicit conventions, through a direct interaction with users online or offline and the common knowledge they build together.

3.1. Elicitation and omission

The first user practice is elicitation and omission. Eliciting is an action to confirm who the user is and who they are not by choosing a particular category provided by the app. It is a form of declaration that means projecting an image to display to others. It is also an action for being seen and being selected.

User1 explains how to complete the profile page:

> There are a lot of possible questions, you can 'ask'. In 'Talents', the prompt: 'I want to be better at' describes a position we have in front of the world. That is to say, if I choose a title in relation to another it's because I would like to formulate it in a certain way. I would like to direct the gaze on myself in this way.

In OkCupid, 15 questions are mandatory during the registration process. However, there are more than 5000 prompted questions from which the user builds a profile. Consequently, the user learns to make choices and be selective in order to elicit the information that projects a desirable image for others to see, as algorithms would do in a finite and decidable way.

User23 explains how he chooses to elicit an occupation to avoid being classified under another occupation, as a form of confirming who he is not. The declarative category in the profile page enables him to acknowledge that this is a twofold process of self-presentation and selection:

> [I check] the photos, I think. It is the age, the photos, I think that is not insignificant either. The fact that I'm presenting myself as university staff means that I'm not a bricklayer. It's sad to say. Sometimes I see myself too, I think, I project myself and I say to myself: 'No but, me, with a plumber, he may be pretty but it's not going to happen'. It's not insignificant that Tinder allows this kind of thing to be displayed. So I just put that I am a student at the University but people can really put their job, their company. So if I want someone [working at] Nestlé, there you have it.

In contrast to other observations (Zytko, Grandhi, and Jones 2018; Potarca 2020), not all categories are ignored during the self-presentation process: users learn to select the categories that matter, with the aim of filtering users and therefore guiding the gaze of the ones that they prefer.

Some apps request the users to assign a weight to categories, a measurement that indicates to algorithms and other users the relevance of the category. In practice, this means declaring in advance who can find the user or not. For instance, on OkCupid, each match question presents the user creating a profile with predefined answers. It also presents the answers the user expects others to choose. The app then asks the user to declare the importance ('a little', 'somewhat', 'very') of the answers chosen. This information is used by the algorithm to know what profiles to recommend based on a hierarchical classification that is appropriated to users. User1 explains:

> There are questions that are a bit political, like 'Should evolutionism and creationism be taught side by side in school?' I put that I thought that creationism had no place in school for example, but that I accepted that others […] answer that both evolutionism and creationism should be taught. I had put that answer as really important because I wanted that to be a discriminating factor in the sense that I didn't want to come across people who had put 'Evolutionism has no place in school' and who had their debate based on that because I would have pissed them off in three seconds, so I'm really using that to discriminate.

This is an 'expected use' as programmed by the app (Duguay 2020) as it is necessary for providing an algorithmic output. After the user chooses the questions, selects a predefined answer, and assigns the answer expected from another user a corresponding weight, each question corresponds to a 'match category' such as 'religion' defined by the app. Later, when browsing another user profile, a percentage of each match category is calculated and displayed to the user as a compatibility score for the potential couple. This weight assignation corresponds to a task aimed at matching algorithms that humans can integrate into their own reasoning via the GUI, either explicitly – as this case illustrates – or implicitly.

One user implicitly weights the category to reflect how others can perceive and classify the profile. User13 noted:

> On Bumble [in the 'looking for' field] I have this 'I don't know yet', which I think is the more honest thing. I prefer having a relationship to being single if it's a good relationship but I prefer being single than in a bad relationship. This 'don't know yet' is the most obvious but even if I am just looking for a one-night stand, the only thing is that when using 'I am

> looking for something casual' my metric goes down, because girls think you are only on Bumble, that you hook-up with several girls a week, which is not even true. But you get this impression of somebody that makes somebody really ineffective […] Nobody is really interested in speaking to somebody who is just doing this, right?

This user learned that it is important for others to elicit what he is looking for via the app conventions, but he also assumes that each possible answer has a social value that can classify him accordingly and that serves as his personal reputation metric. In this way, users learn to rank their sexuality, just as algorithms would, in order to guide a desired output. Online dating enables users to classify themselves and measure their attractiveness, thus 'segregating undesirable qualities' (Bowker and Star 2000). For users, however, elicitation is combined with the information that they hold about building a reputation when seducing.

In contrast to elicitation, omission is the action of not declaring specific information to avoid being classified in a way that will disqualify the user as a potential date. User13 states how he completed his profile on Bumble:

> As you can see, I can put in my job, or fill in other information, which I don't do […] Height is important to all girls as always […] Smoking, I started again […] Dogs, I don't care about them, so I don't answer about dogs. Politics, religion, star signs, and kids. [I don't fill in the zodiac] because I'm a Scorpio, and a lot of people hate Scorpios.

Algorithms can read omission as a null input value, and cannot interpret why this value is missing from a predefined field. In contrast, users have the judgement capacity of omitting conventions that are defined by the app and that do not converge with the user's common-sense knowledge for projecting a desirable image. The practice is key for protecting users' privacy while increasing their chances of finding a date beyond the algorithms' constraints. Omission can be read as a form of 'resistance' to classifications and standards (Bowker and Star 2000).

3.2. Profiling

The second user practice is profiling. When seeking profiles, profiling means building personal inferences to classify users and to form an opinion about them. Profiling relies on declared categories provided by another user correlated with user experiences.

User1 remarks on which questions on OkCupid become a convention in forming specific types of profiles:

> It's the same keywords that often reappear on the site […]: 'Anarchist', 'political', 'feminist', 'vegan', it's crazy, 'extreme right' or anything political, 'capitalism' too, it's repeated all the time, you see, 'overflow', 'the bourgeoisie', 'patriarchy', it's always coming back. Generally there's a style of personality on OkCupid. Even the questions [users display frequently] are 'If I were to be sent to jail I would be arrested for' […] There are quite a few people who are a bit militant, so they typically display [that question]. It's people who belong to a rather specific type […]. There are more conventional ones, there are less conventional ones.

Here it is apparent that not only do algorithms codify self-presentation practices via categories, but users also learn to assemble these categories to form a type of profile based on the patterns observed. This process enables users to classify others according to their own categories ('a bit militant') available in their common knowledge.

User6 also infers profile types from the picture, according to face and body features that matter to him:

> The people who are mentally similar to me also have the same physical traits or ways of dressing […] For example, I listen to a lot of heavy metal, so long hair for the guys and short hair and piercings for the girls. I suppose that they are interested in [metal]. It is a bit cliché, but sometimes it works.

The user is simultaneously profiling by similarity ('listening to heavy metal music') and gendered asymmetry ('short hair for women') according to his own profile. In a machine learning experiment, pictures from Tinder were collected to predict interest, a 'like', in new user profiles based on past 'likes' given by classifying facial features (Jekel and Haftka 2018). The classification models were constructed and tested 'in either 120 or 1280 input dimensions' (Jekel ans Haftka 2018) extracted from another dataset (see Jaton [2020] on mathematical ground-truths) outside Tinder for identifying faces. In the experiment we can see that the algorithm assumes that a user likes a profile according to a high number of facial features previously defined by developers; each feature has an attributed numerical value that makes it possible to establish a mathematical distance with a new entity such as a dating-app profile in a given matrix (see Burrell [2016] on mathematical matrices). As a result, a new profile that has similar facial features to somebody previously liked by another user will be recommended by the algorithms because they are considered to be in mathematical proximity. In contrast to this way of classifying users' desirability, I show that users select the features that have a meaning and match with their social world. Users can rely on categories provided in the app, but they reassemble them to infer a type of profile that makes sense to them both online and offline.

3.3. Swiping reactivity

The third user practice is swiping 'reactivity', which, as Boullier (2019, 5) describes, 'captures the user's attention in the platform by a state of alertness'. This alertness is based on the reaction to novelty, which produces excitement to keep using the app. Reactivity increases significantly when browsing profiles through the swipe gesture designed by Tinder. The gesture enables a rapid evaluation of profiles, with a simple finger gesture to indicate a like or dislike for classifying users in a binary way (Duguay 2020). User9 explains:

> I look at the pictures, I swipe, my first filter is physical. I don't even look at the text. I only look at the text when I like the person, otherwise I don't. Sometimes when I like the person I don't even look at the text, in order to go faster.

Swiping creates a desire to spend more time on the platform in order to see more profiles, at a fast rate. Users refer to this practice as 'a game', rather than as 'dating'. Swiping at speed increases reactivity, which in turn induces an automated behaviour (stimuli–response) that one user identified as a disassociation of the physical gesture from cognitive reflexivity. As User10 states:

> I am a little bit selective […]. Normally you want to get rid of it as soon as possible because […] the girls are more picky than the boys […]. But if my mind can tell my finger okay don't do this, normally I stop, but it depends.

This observation confirms a study describing user swiping practices on Tinder as 'involuntary reflexes' made by mistake or without analyzing the choices (David and Cambre 2016). When defining declared preferences according to a user's swiping behaviour by design, algorithms can only calculate in a limited way users' choices without grasping whether the choices are meaningful. Furthermore, I observed an algorithmic logic of optimization in users that consider themselves disadvantaged with respect to the recommendation system. Users swipe right, or like, massively on all profiles to increase their chances of matching. This was a strategic practice recalled by heterosexual and homosexual men, as well as gay women, who identify as a minority group on Tinder. Thus, users browse and stay alert so as to not miss the 'opportunity' of finding a date. According to Auray (2013), this kind of reactivity is a designed 'opportunistic reactivity' that does not enable a curious exploration. Curiosity invokes an openness to discovering things by chance, and not by following pre-designed reactions to stimuli. As it stands, dating-app providers increase user engagement by programming user attention according to economic logic; this is achieved through pervasive Big Data processes such as the collection of more granular and diverse data in an accelerated way. Instead, dating-app providers could enhance algorithms' design according to what matters to users, to explore (and protect) the diverse fluidity of human affection and sexuality in different situations.

3.4. Allusion

The fourth user practice is allusion. Allusion is a preference for avoiding declaring some information through an explicit category, and is stated implicitly in the profile. User29 adopts the practice of alluding to a specific goal in a free-text field for targeting some users: 'When I started using these apps, after I got used to them, I used the code word "enjoy life" [that] means "I'm looking for sex". I used this as my code'. The actor assumes the other person accepts, or is looking for, the same outcome, which requires the code to be interpreted and understood as common knowledge. Another user acknowledges the way these allusions are tested in practice and that they do not work sometimes. User36 says:

> I added the phrase 'I do not yet have any children' after I realized that, for lots of men, this is no longer a possibility. But this doesn't filter that much after all. For me, it is pretty clear that I am open to having children but I did not want to write that 'I absolutely want them'. But then men contact me and, when I bring up the subject, they say 'Ah, in fact I really don't want any'.

This practice shows that users learn that there are times when it is better to not express certain sexual intentions and relationship outcomes in a definite way via categories, as the algorithm does. However, when users target a specific goal, they might not know whether motivations are guaranteed according to the other user experiences; these motivations are thus unpredictable, compared to the ways in which an algorithm predicts an output. This practice further shows that algorithms cannot interpret users' textual practices, for instance via automated text analysis, without grasping users' common knowledge.

Beyond what can be declared in dating apps, one study (Timmermans and De Caluwé 2017) of Tinder claims there are 13 motives for using the app. Moreover, Sumter, Vandenbosch, and Ligtenberg (2017) show that motivations are fed by offline encounters (if and when users meet their matches). Although dating apps allow users to fill in a variety of goals, users themselves have to manage the ambiguity of the motivations of the other person they are meeting. The ambiguity is produced because motivations are dynamic, as they change according to the accumulated experience. As the findings show, defining specific outcomes is a practice learned over time after becoming a regular user (User29) or when trying to avoid a certain desired outcome (not wanting to have children) based on past experiences (User36).

3.5. Hesitation

The final user practice is hesitation, a state of doubt that enables users to review their actions. Using the swiping affordance and categories given by the app, users do not perform actions systematically by classifying others, nor do they have clear preference criteria for choosing others. Instead, they review their preferences and practices based on what is emotionally, physically, and sexually attractive according to the situation, and any salience can make them change their opinion.

User21 illustrates this hesitation when swiping:

> Swiping confronted me with new questions to consider. Shouldn't I choose someone who is a good fit for me? Someone who seems to be a good fit, because the pictures and the description are not much to go on. You can't know exactly. Should I still choose someone who fits me more and maybe, like that, it could work? But at the end of the day, for now, discovery brings more for me.

In the same vein, User11 illustrates this hesitation according to different features identifiable either in the personal description, or on the physical evaluation:

> There, for example, I would have put no directly. I often look at the description because I find it interesting that sometimes, when there is someone I would have said no to physically, their description can make me change my mind. Or someone where, physically I would have said yes, the description can also make me change my mind. Then I look at the pictures, and then I say yes or no.

Here, 'no' refers to giving a dislike and 'yes' to giving a 'like' on the profile.

Social actors should be understood by the plurality of their actions, which include disruptive moments, sometimes in contradiction, such as hesitation when building a judgement (Boltanski and Thévenot 2006). Hesitations mark a misalignment with the meaning of the interaction, as expressed by the algorithms and translated by the actor in situ. Algorithms cannot perform when lacking key data. Users, on the other hand, are able to do so through a type of human interpretive procedure known as the 'et cetera principle' (Leiter 1980, 174). On the one hand, a person 'assumes that [another person] can fill in the unstated but intended meanings in the [communication] despite deliberate or presumed vagueness due to acquired routine practices (the et cetera assumption)'. On the other hand, s-he 'assumes that the [something will be said] at a later point in the conversation that will clarify the ambiguous expression (retrospective and prospective sense of occurrence)' (Leiter 1980, 174). Algorithms are not able to deduce and supplement information in this way to replace an unstated meaning. Instead, they require a mathematical decision in every operation.

This section analyzed five user practices according to dating-app categorical structures by contrasting algorithmic classification to human classification for building a common knowledge. In the following section I develop a process describing how users and algorithms are learning together to classify dating practices and sexuality.

4. Discussion: human–machine learning

Dating-app algorithms are protected by 'commercial trade' (Pasquale 2015), which renders difficult 'algorithmic accountability' (Wieringa 2020) as suggested in other types of companies. However, dating-app users have access to enough components to 'think like the algorithms do in mathematical terms' (Burrell 2016). I have demonstrated this throughout the analysis of dating-app categories that user practices rely on and that constitute an important mediation between users and algorithms. Users adopt app conventions to define their sexuality by leaning on finite, decidable, and logic processes mediated by categories. I confirm that the algorithmic sociality observed in Blued (Wang 2020) is also present in the variety of platforms studied in this article. Furthermore, I show that users are not only socializing in an algorithmic way. Instead, I posit that users are integrating algorithmic logic into their daily life experiences of dating and sexuality, which are mediated through categorical GUI structures.

Burrell (2016) explains that, in contrast to algorithms, humans make interpretations, build meaning, find semiotic relationships, produce narrative analyses, and learn to make sense of situations through their capacity for reasoning. I also demonstrated Burrell's (2016) claim through studying concrete user practices in online dating. For instance, when creating a profile, users learn to omit information according to the meanings they attribute to app categories and to allude to implicit preferences to avoid being classified. Furthermore, I show that users also build classifications based on their personal experiences and categories. This forms the actor's common-sense knowledge in online dating.

Classification is not merely a computational task; it is an interpretive procedure for experiencing the social world. Ethnomethodologists call this classification process 'typification'; it enables members in society to experience and make sense of the social world. Ethnomethodologists have shown that common-sense knowledge is constructed in part by 'the stock of knowledge at hand, [which] consists of social types or idealizations of people, objects, and events that serve as points of inference and action' (Leiter 1980, 5). However, everyday life typifications are potentially equivocal and have multiple meanings. Knowledge has situated meanings: there is no neat and logical ordered storehouse of information and typifications, as the sense is context dependent. A stock of knowledge is heterogeneous (Leiter 1980, 6). This is fundamentally distinct from the way algorithms build classifications via definite categories that are necessary for creating an output that is the result of a binary decision.

Common-sense reasoning cannot be disassociated from logical reasoning that also serves human learning, as cognitive psychology has shown (Kahneman 2013; Houdé 2019). In online dating, users interact with both algorithms and other users, in mediation with categories, among other GUI components. Therefore, they inherit a particular algorithmic logic that is embedded within a power structure ruled by a market logic. I refer to the combination of common-sense and computational logic reasoning, a process which builds new conventions about dating and sexuality, as 'human–machine learning'. In particular, I showed that the classification practices enable users to understand both how algorithms behave in a definite and decidable manner for computing, and how other users behave in an ambiguous and undecidable manner due to common sense. Indeed, users accumulate experiences both online and offline which allows them to build a common-sense knowledge about dating and sexuality that creates a community of practice entwined with, or in opposition to, the machine. This common-sense knowledge is crucial for reviewing every actor's reality *in situ*.

4.1. Dating and sexuality as user–algorithmic interactions

In this article I have shown how dating apps guide users to classify their emotional states, physical attractiveness, and sexual preferences via categories that are materialized throughout online interfaces and offline interactions. This process of 'sexual datafication' (Saunders 2020), or datafication more broadly, is directly linked to how algorithms are designed. Users integrate algorithmic logic into their common knowledge, and thus produce a new dynamic of dating and sexuality. Categories enable the algorithmic logic to be readable to users. Therefore, users integrate skills and knowledge related to calculation, explicitness, and optimization in a computational way. However, the algorithmic logic is challenged or resisted by users thanks to their human capacities that go beyond mathematical operations. Hence, I show that dating and sexuality is a reciprocal dynamic between algorithms and users.

When interacting with dating-app interfaces, users become aware of how they are classified by algorithms and how they, in turn, classify others. This classification process is an advantage to users as it enables them to project a desirable image in order to attract other users when entering the market where they are required to assess a high volume of profiles. As a consequence, users' focus is less on choosing a potential date, but rather on discarding the undesirable ones.

Empirical data allowed me to compare multiple platforms and understand user practices with situated interviews. In the elicitation and profiling practices, I showed that categories teach users to define their emotions and morphologies, as well as measure their sexual desirability, as algorithms do, according to a model embedded in the app interface. In the swiping reactivity practice, I showed that users evaluate their interest in other profiles through the swipe gesture by classifying users' attractiveness in a binary way at high speed. This is a new, accelerated way of assessing attractiveness, in contrast to the way that couple formation requires negotiating preferences through time (Kellerhals, Widmer, and Levy 2004).

I showed that users learn to resist algorithmic classification through omission and hesitation practices. Users know that seduction does not require them to declare everything about their sexuality. They also resist the apps' categories when a curious exploration makes them hesitate about who to date or how to define physical attractiveness.

Finally, in the allusion practices I show that users learn that being more indirect about their motivations increases their desirability. In contrast to algorithmic logic, they communicate in an ambiguous and coded way through their own textual cues that are tested with others. Moreover, when gaining experience within the app, they learn that there are no guarantees in guiding the audience gaze by displaying some statements that do not help them to filter undesirable users.

Within this twofold process of classification and being classified, the sociological preoccupation lies in the fact that users integrate algorithmic logic into their common knowledge via the GUI to seduce and define their sexuality. This process can create a tension between performing to gain visibility in the app and building relationships offline.

Online dating illustrates a larger phenomenon of datafication and classification that requires further study by social and human scientists interested in questions of gender and sexuality. Through the reciprocal approach on classifications explored in this article, further research in porn studies can contribute to deconstructing the artificial intelligence methods that are now being applied on algorithmic recommendation systems for establishing romantic and sexual affinities. Categorical structures are a standardization practice for data collection that is present across platforms, and their agency on porn culture and economy has only recently begun to be explored (Saunders 2020).

Notes

1. I extend Bechmann and Bowker's (2019) work on classification practices on Facebook (now Meta). The authors limit their work to the developers' perspective.
2. I developed this double perspective in Pidoux (2021), inspired by two main distinct works (Burrell 2016; Pasquinelli 2019).
3. I use sex to define sexual orientation because dating apps target users through male/female binary sex combinations (M–M, F–M, M–F, F–F or both F–M–F, M–F–M). Sex is a mandatory field on the registration page that predefines the categories available in the profile, despite the fact that some apps offer myriad gender identities at later stages.
4. Celibataire.ch is a dating website popular in French-speaking Switzerland and is very similar to OkCupid, one of the most popular dating apps worldwide (see downloads: https://wiki.personaldata.io/wiki/Item:Q3555). Like OkCupid, Celibataire is based on a quiz with a high number of questions to compute a score between two profiles. For the sake of familiarity, here will be given examples of OkCupid also used by this research participant sample.
5. It was particularly difficult to reach women who were willing to speak about their experiences with dating apps. This issue requires further study.

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