DESIGN DELLA COMUNICAZIONE | SAGGI OPEN ACCESS | 05

EDITED BY SALVATORE ZINGALE

DESIGN MEETS ALTERITY

CASE STUDIES, PROJECT EXPERIENCES, COMMUNICATION CRITICISM

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La collana Design della comunicazione nasce per far emergere la densità del tessuto disciplinare che caratterizza questa area del progetto e per dare visibilità alle riflessioni che la alimentano e che ne definiscono i settori, le specificità, le connessioni. Nel grande sviluppo della cultura mediatica la presenza del Design della comunicazione è sempre più trasversale e in continua espansione.
La comunicazione richiede un sapere progettuale là dove la cultura si fa editoria, dove i sistemi di trasporto si informatizzano, dove il prodotto industriale e i servizi entrano in relazione con l'utente. Il Design della comunicazione è in azione nella grande distribuzione dove il consumatore incontra la merce, nella musica, nello sport, nello spettacolo, nell'immagine delle grandi manifestazioni come nella loro diffusione massmediale. La collana è un punto di convergenza in cui registrare riflessioni, studi, temi emergenti; è espressione delle diverse anime che compongono il mondo della comunicazione progettata e delle differenti componenti disciplinari a esso riconducibili. Oggetto di studio è la dimensione artefattuale, in tutti i versanti del progetto di comunicazione: grafica editoriale, editoria televisiva, audiovisiva e multimediale, immagine coordinata d'impresa, packaging e comunicazione del prodotto, progettazione dei caratteri tipografici, web design, information design, progettazione dell'audiovisivo e dei prodotti interattivi, dei servizi e dei sistemi di comunicazione complessa, quali social network e piattaforme collaborative.
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Design Meets Alterity

Case Studies, Project Experiences, Communication Criticism

FrancoAngeli

Contents

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Data, Algorithms and Otherness
The Erasure of the Other

1. Introduction: algorithms, data, bias and otherness

Imagine we query a search engine for two sentences and compare the results: "unprofessional hairstyles for work" and "professional hairstyles for work" (fig. 1). We will find a grid composed of images of black women with natural hair on one side and, on the other, a catalogue of photos of white, coiffed women (Alexander 2016). Now imagine to use a tool to automatically translate sentences from a language that has no gender pronouns into one that does have them: the algorithm performing the translation will assign the masculine pronoun to sentences that refer to actions such as "driving a car" and "trading", while it will use the feminine pronoun to translate sentences that describe actions such as "taking care of children" or "dancing" (fig. 2). These two examples outline the perimeter within which this paper moves: if we understand as "other" what is alien to predominant tenets and identity structures, what are the effects of increasingly delegating decisions and interpretive acts to automatic and computational processes? What is the contribution that designers may give in this scenario?

In this contribution, we reflect on the critical issues related to the use of Artificial Intelligence (AI) and Machine Learning algorithms. We focus on their connection to data, and we introduce some concepts that describe data as artefacts influenced by the biases, sensitivities, and interpretations of those who produce and use these data, as opposed to the positivist and technocentric conception that sees data as a neutral and objective tool for analysing social and cultural phenomena. Next, we highlight the relation between Machine Learning (ML) and data, and we present some strategies that are useful to narrate the acts of non-inclusion embedded in the operation of algorithms. While reviewing these strategies, we compare two complementary approaches. On the one hand, we illustrate a series of systematic *in-vitro* approaches that aim to reconstruct and understand the

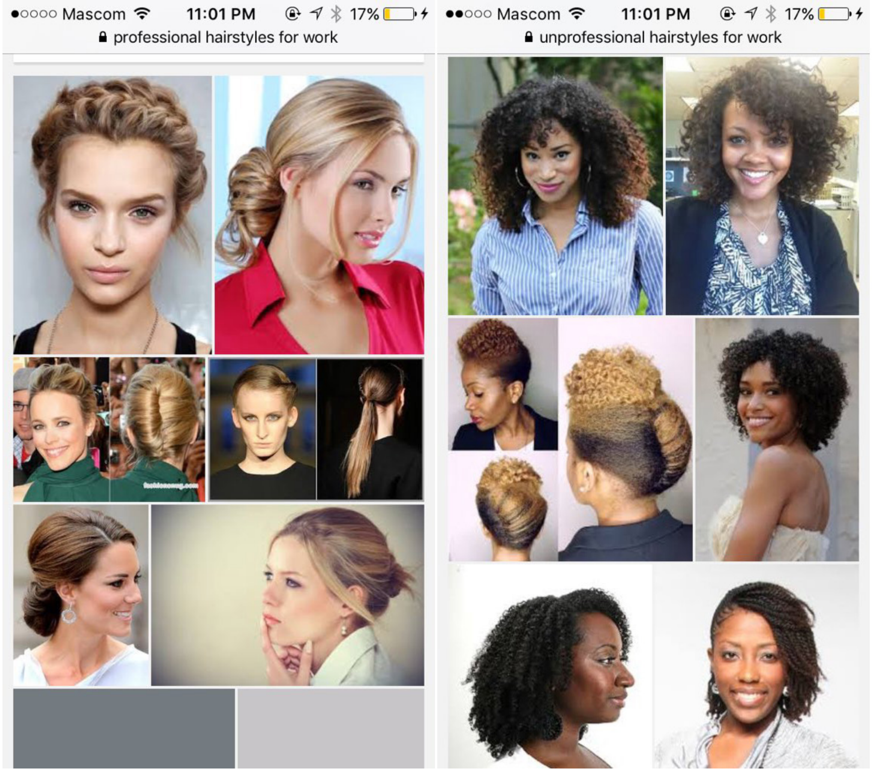

Figure 1. Screenshot of Google Image search engine. Image search results for "non-professional hair for work" (right) and "professional hair for work" (left) on Google. Source: <https://archive.ph/Goyz2>, online on 31 December 2023.

often opaque processes governing the operation of various algorithms. On the other hand, we give an account of experiences that map the effects of these technologies *in-the-field*. These examples seek to collect anomalies in the operation of algorithms in everyday life, trying to find out what escapes algorithmic classification systems. These latter works, which we may call *catalogues of errors*, constitute a stepping stone to the exploration of algorithmic otherness and to the realisation of more inclusive technologies.

2. Critical views on data

Data are of different natures, and we can generally distinguish them into quantitative and qualitative data. Our discussion herein exclusively deals with the former, which are related to the application of statistical and

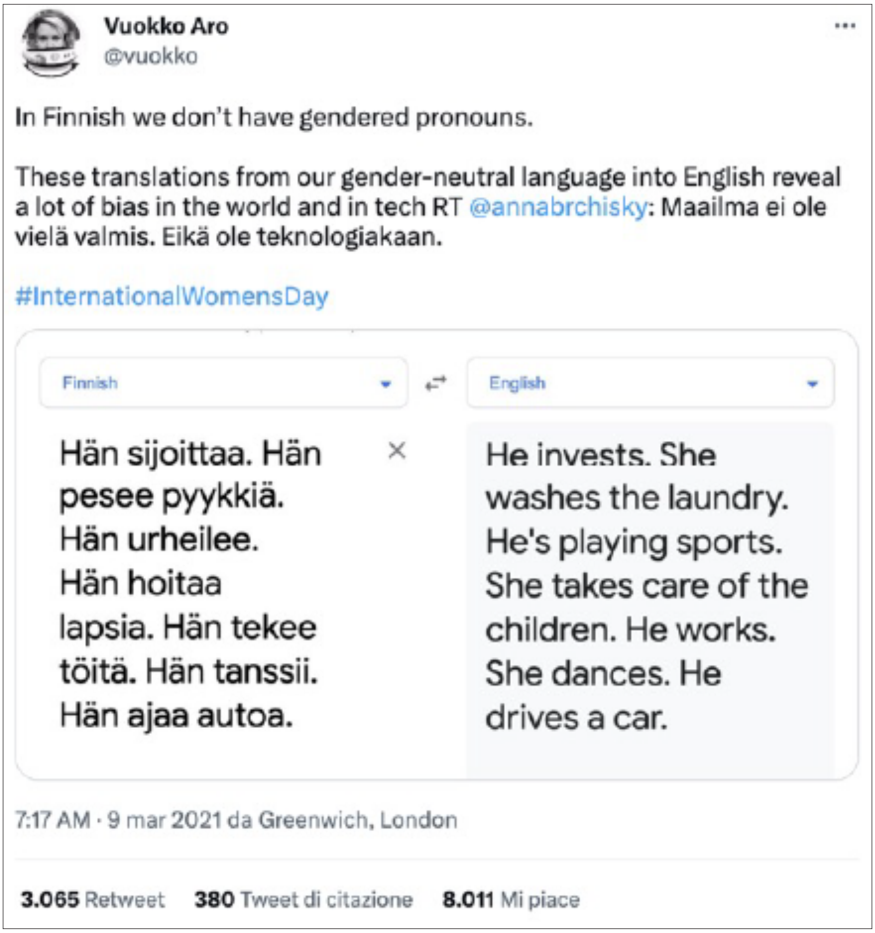

Figure 2. Screenshot of the Google Translate application. Automatic translation of a series of sentences from Finnish to English. <https://archive.ph/DzQtB>, online on 31 December 2023.

computational methods and support the creation of Artificial Intelligence. The following reflections help to understand the cultural context in which the different strategies for inspecting and criticizing the work of algorithms are situated.
Some IBM advertisements claimed the ability to use data to make accurate predictions about the future (Gitelman 2013). The Wikileaks organisation speaks of the data it receives and releases in terms of «evidence of the truth» (Manchia 2020). The narrative that describes data as transparent

and overt entities («The fundamental stuff of truth itself», Gitelman 2013), which is dominant in certain contexts, is opposed by a view according to which data are artefacts strongly influenced by the social, historical, and political environment in which they are produced (Kitchin 2014). It is a common belief that data are collected, entered, compiled, stored, processed, extracted, visualised, and only then, at the end, also interpreted. Interpretation is often thought of as a final step in the process of data transformation and use, but, actually, every aspect of working with data can be said to be an interpretive act (Gitelman 2013). Data must be generated, and consequently they conceal arbitrary choices and preserve a distance from the phenomenon they represent. Drucker (2011) provided a good summary of this thinking and introduced the term *capta*, as opposed to *data*: «capta is "taken" actively while data is assumed to be a "given" able to be recorded and observed». We collect data to create models[1] of the world in response to specific needs and following certain patterns of interpretation that inevitably lead us to select some specific aspects of the phenomenon under study (Drucker 2020).

The aura of objectivity that is often associated with data appears in visualisation practices following well-defined strategies: using two-dimensional viewpoints, clean layouts, geometric figures, and the inclusion of data sources (Kennedy 2016). There is, however, a discourse that positions data visualisations as situated artefacts, created in a specific historical, political, and social context, and that necessarily integrate and repurpose the point of view of those who build them (Kirk 2016), in a way similar to what according to Haraway (1988) also occurs for knowledge, which also and necessarily has a situated nature.

Even in the field of Digital Humanities, following lengthy reflections on distant reading[2] (Moretti 2000), a reflection has emerged that highlights how the application of computers in literary studies is probably limited to the

1 As McCarty explained, models are tools supporting knowledge and created with a specific purpose: «To an observer B, an object A* is a model of an object A to the extent that B can use A* to answer questions that interest him about A». Models neglect several aspects of the world, especially when they are created to support computational processes. In these cases it is necessary to remove all forms of ambiguity, since computational processes accept only what can be expressed in explicit forms (McCarty 2004).

2 Distant Reading employs the usage of computers in literary research. It was introduced by Franco Moretti and can be described as the ability to massively analyse large quantities of literary texts.

analysis of surface features. Indeed, the data derived from these practices are unable to return many of those aspects that are essential for the study of literature, including aspects related to the subtext and ambiguity-bearing elements necessary to set in motion the human work of interpretation and attribution of meaning (Rommel 2004; Marche 2012). To do this, scholars rely on traditional close reading practices (Hayles 2012), precisely because data are not capable to account for the complexity of a literary text.

Although reflections on the subjective, situated, and interpretive dimensions of data are rapidly expanding in a number of research fields, data continue to be subject to a process of *naturalization*: they tend to be regarded as neutral objects not to be questioned as the traces of their histories and contexts of creation have been lost (Denton et al. 2021). This approach becomes particularly problematic as we draw attention to the role of data as instruments of power, capable of perpetrating imbalance and discrimination. The collection and use of data is burdensome in terms of financial and intellectual resources; therefore the groups and minorities who fail to represent themselves through data are subject to control from those who have the ability to create these representations (D'Ignazio and Klein 2016, 2020).

3. Data, algorithms and training sets

The last decade has seen the return of something that calls us on to re-think about the role of data in representing reality: the Artificial Intelligence algorithm and, in particular, Machine Learning. Although the first Artificial Intelligence and Machine Learning systems were conceived as early as after World War II (Russel and Norvig 1995: 2), they have recently become part of technologies we use in everyday life such as automatic translators, image recognition systems, and streaming platforms (O' Neil 2016).[3] With an ever-increasing availability of data, and increasing efficiency of computational tools, it has been possible to design tools capable of performing a variety of functions, from the most analytical such as value prediction and classifications, to the most playful ones such as editing images automatically.[4] Plat-

3 Besides, most recent generative AI tools such as ChatGPT and MidJourney, must be considered.

4 Moreover, generative AI tools such as MidJourney, Stable Diffusion and Dall-E allows for generating images from scratch starting from textual or visual prompts.

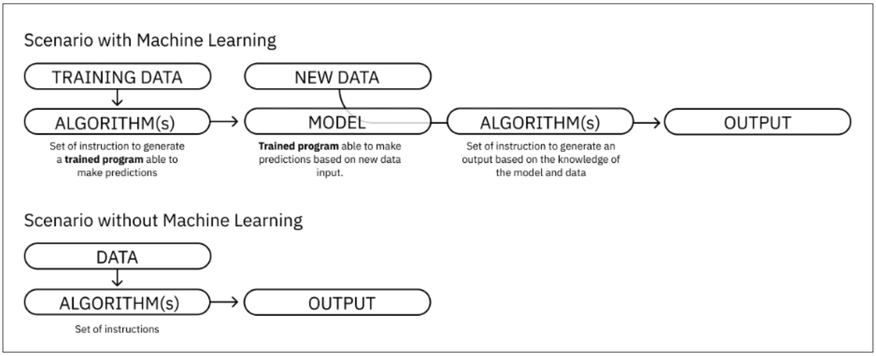

Figure 3. Summary diagram showing the relation between the components of a Machine Learning system compared with a non-ML system. Source: authors.

forms such as Facebook[5] and Instagram[6] use algorithms to profile their users. Similarly, search engines leverage these algorithms to organise their proposed results. Video streaming services such as Netflix[7] and Amazon Prime[8] profile users and, through recommendation algorithms, show them content in line with their interests. Technologies such as facial recognition, used for instance in the unlocking of smartphones, can recognise the content of images and leverage classification principles to identify subjects and objects. In addition, AI and ML algorithms are exploited for prediction purposes in financial or urban security contexts (O'Neil 2016; Diakopulos 2013). These functions are not mutually exclusive but often overlap with each other and different algorithms are used synergistically. For example, a streaming service such as Netflix profiles the user and recommends content. Similarly, an insurance service can predict the user's financial situation only after profiling the user.

Machine Learning is a specific form of AI (Russel and Norvig 1995: 2) that allows computational systems to learn notions without explicit programming. In this context, the ML algorithm is the entity responsible for creating a model through a process of training (fig. 3).

5 <https://www.facebook.com/>.
6 <https://www.instagram.com/>.
7 <https://www.netflix.com/browse>.
8 <https://www.primevideo.com/>.

During this process, large amounts of data, known as *training datasets*, are provided to the algorithm for it to learn notions that are stored into a model, which is later used to perform new actions independently from its creator. For instance, a Machine Learning model aimed at classifying pictures of dogs and cats will be trained with training datasets containing pictures of dogs and cats associated with their common name "dog" or "cat". During the training process, the model learns to identify differences and similarities between the entities, and once the training is over, it will be able to classify new pictures of dogs and cats that are not associated with their common name. Within this particular context, data have paramount significance as they are the fundamental source for developing models. Notably, web-based, manually annotated lists of datasets are accessible and are employed in the training of Machine Learning models.
In this regard, some thought needs to be given to the nature of training sets. First, the process of labelling images is manual, carried out by humans with time-consuming processes (e.g., «~1,250,000 images annotated by hand»[9]), and is subject to the biases of those who manually label the images. The term bias comes from the field of cognitive science and represents a form of misinterpretation caused by prejudice (Friedman and Nissenbaum 1996) which may be embedded in the act of labelling images. On the other hand, given the amount of resources required to generate a labelled dataset, it is common for the same dataset to be used on multiple occasions, which causes stagnation of biases and inaccuracies in models (Koch et al. 2021). For example, imagine that people tasked with manually annotating thousands of photographs of animals have only seen dogs and lions in their lifetime: most likely, images of cats will be labelled as lions and the model might learn to classify as a lion what is actually known as a cat.
The type of training that makes the most use of this type of dataset is "supervised training", where the algorithm "teaches" the model to recognise notions included in a dataset labelled a priori. The algorithm exploits the logics chosen by its designers to recognise certain properties of the data it has to process; these logics determine the features that the algorithm will auton-

9 <https://en.wikipedia.org/w/index.php?title=List_of_datasets_for_machine-learning_research&oldid=1192517147>, online on 31 December 2023.

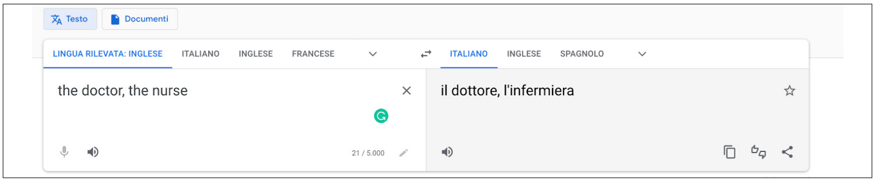

Figure 4. Screenshot of the Google Translate application. Automatic translation of two neutral terms in English that are given a gender in the Italian translation. Retrieved on 20/02/2023. Source: <https://archive.ph/HXgvx>, online on 31 December 2023.

omously consider as relevant.[10] Once the training is finished, the validation phase is carried out, in which a new dataset (or a non-labelled portion of the training dataset) is used to validate the model. During this process, biases may emerge from inappropriate labelling or category disparity. For example, if the training dataset does not have a balanced proportion of cat and dog images, the model will likely need more images to fully learn all the properties of either category. Such strategies to validate, diagnose, and improve models require technical computer skills that are not always accessible.

However, bias and prejudice may also emerge serendipitously during the use of systems that make use of ML algorithms. For example, why do well-known English-Italian automatic translators translate "the doctor" with the masculine determinative article and "the nurse" as feminine? Figure 4 shows the bias built into Google Translate, but the same can also be observed in products from other companies, such as DeepL.[11] Probably, the training dataset that was used to train the algorithm contains the issues and unbalances that are observable in society and included more examples of male doctors and female nurses, although female doctors and male nurses also exist.

The glossary of terms and practices illustrated so far helps to outline the close relation between the operation of algorithms and the vast amounts of data that are used for their "training". Thus, a landscape emerges where the intertwining of machines, human input, and big data generates and perpetuates discriminations that can influence the effects algorithms have in various areas of our daily lives.

10 The various methods used for training include "unsupervised", "semi-supervised", and "reinforced" methods which do not require integrally labelled datasets (Russel and Norvig 1995: 2).

11 <https://www.deepl.com/>.

4. Tracing the operation of algorithmic machines

How can the biases and discriminations of classification systems that underlie ML algorithms, which are often opaque and private (Rudin 2018), be made visible? How is it possible to "trace" (DiSalvo 2009) and make evident the working of these algorithmic machines, to which our society increasingly delegate important decisions? First, the need emerges of a clear disclosure of the rules governing the algorithmic processes of classification and prioritization, namely the need to understand what is included and what comes first and what later. The term *disclosure* (Introna and Nissenbaum 2000) refers to the demand for full and complete exposure of how algorithms work. However, this demand faces a number of obstacles. First, the opacity and inaccessibility of these algorithms is particularly lucrative for companies, it is part of their business strategy and sometimes it is necessary to prevent cyber attacks (Rudin 2018; O' Neil 2016). Second, fully understanding how complex algorithms work requires technical knowledge, which the ordinary user often lacks. Finally, simply disclosing the rules governing an algorithm does not resolve issues related to its unintended discriminatory effects.

5. In vitro approaches: reverse engineering and algorithmic auditing

In response to the limitations of the (often unexpected) demand for disclosure of algorithms' operation rules, we observe a number of approaches aimed at empirically testing the operation and effects of these technologies. These strategies originated in computer science and then quickly spread to other fields and aim to look inside the black boxes of algorithms through controlled experiments. In this section, we report on some of these strategies through some better-known examples.

Reverse engineering (RE) (Diakopulos 2013) is a widely recognised strategy that aims to scrutinise a machine's components and functions across multiple levels of complexity by simulating a validation process.[12] In the context of ML algorithms, RE leverages the only available access points for researchers, which are inputs and outputs. In the supervised ML paradigm, the inputs consist of unlabelled raw data or images to be edited, while the output is the model's learned response, such as newly labelled data or mod-

[12] <https://www.treccani.it/vocabolario/reverse-engineering_(Neologismi)/>, online on 31 December 2023.

ified images. By undertaking a systematic process of observation, documentation, and comparison of multiple sessions, RE can effectively reveal any instances of bias and discrimination. Although reverse engineering is a technique used in many fields, when applied to the study of algorithms, it can allow for a better understanding of the relation between input and output that, in some cases, allows for the understanding and copying of private models (Tremer et al. 2016).[13] Figure 2 offers a good example RE applied to AI algorithms by showing how a systematic inquiry conducted on specific inputs (i.e., translations of the same ungendered pronoun) shed light on the biases embedded in the algorithms that process the translation (i.e., the gender biases related to professions).

Another approach is *algorithmic auditing* (Sandvig et al. 2014), which draws from the tradition of independent evaluations performed by external bodies to assess the quality of products and services, or the financial soundness of companies and organisations. The auditing of an algorithm consists in a massive and systematic evaluation of its performance by inputting data and analysing the results while exploiting the participation of multiple users. An empirical audit could entail adopting a "sock puppet" approach wherein auditors fabricate simulated users[14] and input specific classifications of harmful, harmless, or ambiguous content to evaluate the system's outputs and ascertain their alignment with the expected compliance standards.

When multiple human users are involved who are asked to perform the same actions, it is called *collaborative auditing* (Sandvig et al. 2014: 14-15). The sole difference between a sock puppet audit and a collaborative audit is that in the latter, the tester is a human being.

A particular form of collaborative auditing is *crowdsourcing auditing* in which groups of researchers involve users willing to collaborate through a public call (Sanna et al. 2021); the goal, again, is to analyse malfunctions, which may reveal discrimination or exclusionary phenomena. This technique has proven particularly effective in observing the learning levels of different image recognition systems. One example was the "Gender Shades" project (fig. 5), which analysed and compared the performance of different face rec-

13 As in the case of Florian Tramer who, by exploiting systematic observation of inputs and outputs, reconstructed how Big ML and Amazon Machine Learning work and programmed a new algorithm with the same predictive capabilities as the previous ones (Tremer et al. 2016).

14 It is likely that false user accounts or traffic generated programmatically will be used to achieve this.

Gender Classifier	Darker Male	Darker Female	Lighter Male	Lighter Female	Largest Gap
Microsoft	94.0%	79.2%	100%	98.3%	20.8%
FACE++	99.3%	65.5%	99.2%	94.0%	33.8%
IBM	88.0%	65.3%	99.7%	92.9%	34.4%

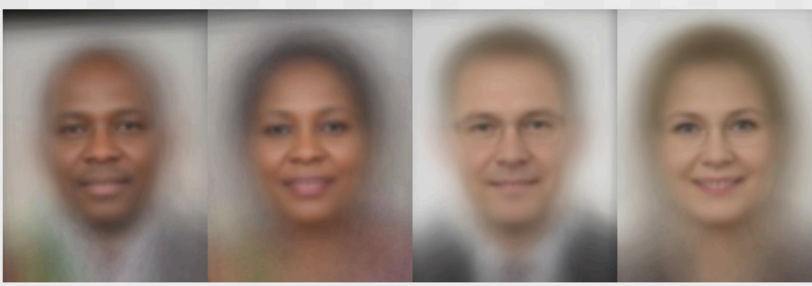

Figure 5. Result of the Gender Shades project (Buolamwini and Gebru 2018), in which different facial recognition systems are analysed for their ability to recognise faces of different ethnicities and genders. Researchers divided images in four groups, and here they are displayed as overimposed composites. Source: <https://archive.is/lnNbb>, online on 31 December 2023.

ognition systems (IBM, Microsoft, and Face++). By looking at inputs and outputs, the researchers showed that facial recognition systems have lower accuracy rates in identifying dark-skinned female people due to an under-representation of gender and ethnicity in one of the training datasets analysed (Buolamwini and Gebru 2018). Figure 5 summarises the results of the aforementioned research by comparing the results of face classifications conducted with algorithms produced by different companies.

Typically, reverse engineering is applied to specific cases where the aim is to reconstruct a process, structure, or a way of organizing knowledge represented by an algorithm. In contrast, algorithmic auditing is implemented in more extensive contexts, such as the investigation of digital platforms such as Facebook and Amazon, with the objective of identifying operational patterns and profiling, without explicitly revealing the logic of operation of the underlying algorithms.

6. In-the-field approaches: catalogues of errors and collections of glitches

Alongside the analytical strategies illustrated so far, an emerging approach can be identified that, while not claiming to be exhaustive, makes a valuable contribution to debates concerning algorithmic exclusion. In what follows we examine projects aimed at producing what we define *catalogues of algorithmic errors*. These works focus on documenting the moments when the output of an algorithm is perceived by the user as unexpected or against expectations. As opposed to *in-vitro* approaches, these experiments aim at documenting the malfunctioning of algorithms *in-the-field*. The premise is that through the documentation of these moments it is possible to peek inside the black boxes of these technologies. Through the glitch, understood as a brief moment of misalignment or malfunction of the algorithm (Meunier et al. 2019), it is possible to get a glimpse, albeit a momentary one, inside the abstractions, completely foreign to human perception (Paglen 2016), that govern these technologies. Perhaps the most famous case worth mentioning dates back to 2015, when a Twitter user shared an image showing how image recognition algorithms in the Google Photos app classified his dark-skinned friends as "gorillas" (Vincent 2018). A term that describes these moments well is "algorithmic troubles" (Meunier et al. 2021): problematic events in which visible errors allow one to question what it means to be (or not to be) analysed, profiled, classified by algorithms of various kinds. The experiences we report on in this section thus forgo the ambition of explaining the "underlying" structures of the results that algorithms produce, but rather set out to collect their unexpected and often problematic behaviours. The collection process is accomplished unsystematically and through rudimentary data extraction methods. Glitches are saved and archived by capturing images from the screen, making use of the screenshot as a photographic witnessing tool (Frosh 2018; Ben-David 2020), or other vernacular data collection solutions (Nešović 2022). The work of collection (through more or less structured archives) makes it possible to give meaning to individual episodes and builds true samplers of what escapes the classification logics of algorithms. From this point of view, the experiences described in this section work on the rhetorical figure of the catalogue as a meaning-making device (Veca 2011): it is through collection and juxtaposition that each individual episode takes on a new meaning, precisely by virtue of its being shown in relation to other episodes. In a certain sense, these catalogues can be considered as "practical lists" whose elements, although very different from each other, undergo a kind of "contextual pressure" (Eco 2019) that makes them be perceived as a unified group. These catalogues of errors can take many different forms: from the more traditional image galleries, to formats that exploit the grouping logics of the very platforms where the errors are collected, such as the chains of content that can be created with threads on Twitter.[15]

Among the best-known cases worth mentioning is the ImageNet Roulette project (Crawford and Paglen 2019), which works on algorithmic image classification processes, exposing some of the most problematic, offensive, or more simply bizarre labels found in the "people" category of one of the most widely used training sets for automatic image recognition. When a user uploads a photo, the application returns an image showing the detected face and the label that the classifier has assigned to the image. The application purposely returns particularly disturbing labels. The project is accompanied by an image gallery of some of the most offensive and discriminatory labels, extracted from the dataset on which the tool is based.

While ImageNet roulette is a catalogue designed by two researchers, there are similar experiences that are the result of collective action. In 2020, when a Twitter user posted an image containing their face and another person's face, they realised that the platform's algorithm that determines how an image is cropped favoured his Caucasian face and excluded his African American colleague's from the preview (Hern 2020). This initial revelation initiated a collective experiment where several platform users tested the same cropping mechanism with disparate images. The result is a catalogue of errors and distortions of the image cropping algorithm that can be accessed by scrolling through users' posts.

A similar strategy is that of the @algoglitch[16] account. The profile, which aims to "account for collective sensitivity to algorithmic computations", collects and shares community-submitted screenshots documenting the problems people experience in their daily encounters with algorithms.

15 The Twitter platform allows for the creation of "threads", i.e., chains of comments in which reflections and images can be linked from a single post.

16 <https://twitter.com/algoglitch>.

The result is a catalogue of a broad spectrum of algorithmic "misalignments" and errors: misclassifications, misplaced product recommendations and suggestions, content moderation problems, and, obviously, wrong machine translations. These episodes, which the authors of the collection call "algorithmic troubles", document the limitations of algorithms in performing various actions (recognizing, identifying, classifying, prioritizing, translating).
Although the cases illustrated in this section document very different algorithmic situations, and the formats of the collections mentioned herein are of different types (installations, image galleries, collections of screenshots), a thread can be identified that connects these experiences. These catalogues (of errors, deviances, misalignments, glitches, and troubles) are a first step toward determining what otherness means. Through the collection of items and situations which elude algorithms, they hint at what is possible but escapes classification systems. If identity is fixed (and identity defined through algorithms is even more so), these collections represent a sampling (albeit incomplete) of what is excluded or considered "other" by algorithmic classification systems. Collecting these anecdotes can be seen as an initial approach to creating more inclusive algorithms.

7. Conclusion

This text addresses the discourse on otherness in light of the pervasive presence of algorithmic technologies in every sphere of common life. Indeed, an increasing number of actions (classifying, predicting, analysing, selecting, generating) are being delegated to algorithmic systems that, following trained models, perform them in semi-autonomy. The optimistic view that envisions an automated and efficient society has been quickly replaced, at least in some cases, by the consideration that these technologies are characterised by the same biases and limitations as the societies that design them. Therefore, within this landscape, asking what constitutes the other for an algorithm is of utmost importance. Rather than reflect on this question from an abstract point of view, we made a brief survey of the strategies available for tracing the operation of algorithmic machines, with a focus on those devoted to the analysis of biases and limitations. We compared systematic in-vitro experiments that aim to identify the underlying structures of the results produced by algorithms with strategies that merely collect problematic results in thematic catalogues. The latter, working on the collection of malfunctioning moments of artificial intelligences, allow for the exposure and tracking of the failure of algorithms to adequately consider what comes out of classification logics. In the face of increasingly massive use of algorithms in various design domains, it emerges the risk of "weaponised" design (Tactical Tech 2018), understood as a practice that does not take into account the negative, exclusive, and harmful effects of design. We envision error catalogues as a useful tool for a more responsible approach to design that makes use of algorithms. A kind of sampler of otherness, constantly changing, that can be consulted to design with algorithms in a more equitable and inclusive way.

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The **QUESTION OF ALTERITY** has become fundamental to understanding contemporary societies, which are increasingly multicultural, multi-ethnic and intersectional. That which is **OTHER** poses questions that one is not used to answering, poses itself as a term of contradiction, questioning established certainties and beliefs.
Alterity is a field yet to be explored, especially when one wants to move from theoretical reflection, inevitable and necessary, to transformative praxis.
Reflection on alterity leads to the **ABANDONMENT OF ALL FORMS OF CENTRALISM**. Acceptance of a culture based on the recognition of alterity and mutual responsibility requires overcoming anthropocentrism and androcentrism, but also Eurocentrism and logocentrism, that is, the domination of some forms of communication and signification over all others. Today, it is legitimate to think that the design dimension can also undertake research paths that highlight **THE NEED TO RECOGNISE THE OTHER**: from migratory flows to gender cultures, from social fragility to mental health, from cultural distances to the difficulties of social integration, etc. This is the direction in which the essays in this volume are heading. Design culture has the right tools to promote innovative and open visions of relations between people, peoples, and languages.

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