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Growing in Algorithmic Ruins: Contamination as Queer-Feminist Method

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ABSTRACT
In data science and artificial intelligence, "data contamination" is typically treated as a technical flaw to be removed. This paper instead approaches contamination as a way to examine how data infrastructures organise and exclude difference. Drawing on feminist science studies and queer theory, it explores how data cleaning and classification embed normative assumptions about gender and sexuality. Focusing on systems, such as DeepL and the United Nations Parallel Corpus, the paper analyses mistranslations and erasures of queer language. These are not isolated errors but reveal how algorithmic systems impose fixed categories onto ambiguous meanings. Engaging with artistic practices that foreground error and glitch, the paper argues that such "contamination" exposes the limits of computational systems. These moments act as "queer ghosts," traces that resist capture. Contamination thus becomes a queer-feminist method for engaging AI through disruption and the persistence of what does not fit.

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Introduction

In data science and artificial intelligence research, *data contamination* usually refers to unwanted or inappropriate data that reduces the quality of a dataset or the reliability of a model. It may occur when training and test data overlap, when benchmark data leaks into model inputs, or when mislabelled samples affect evaluation results (Lutch, Guan, and Wu 2024; Han et al. 2025). In this technical context, contamination is treated as a problem to be fixed. Data cleaning is therefore presented as a necessary step for restoring accuracy and reliability (Rogers and Jonker 2024).

However, this technical terminology has normative significance. What counts as contaminated data? Which traces are considered noise, and which are preserved as signals? Cleaning is far from being a neutral error-correction operation; it is also a classificatory practice that determines which differences are acceptable and which must be excluded. For example, in face recognition, the use of binary gender labelling as the basis for classification has itself reinforced the logic of gender discipline. When data

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workers try to fix the bias by cleaning up the data set, outliers that derive from the inclusion of transgender, non-binary, or groups that do not fit into existing labels are often the first to be discarded, further deepening exclusion (Keyes 2018; Scheuerman, Paul, and Brubaker 2019).

Here, contamination is not simply a technical flaw but a marker of bodies and identities that exceed normative categories. Drawing on Science and Technology Studies (STS), feminist epistemology, and queer theory, this paper examines how 'contamination', such as error, mistranslations, misrecognitions and misclassifications, exposes the classificatory logics through which data infrastructures organise knowledge and manage difference and what it means to use contamination against the purity that shapes data systems. It makes two contributions. First, it proposes contamination as a queer-feminist analytical framework for understanding how machine learning systems produce categories and manage difference. Second, it develops contamination as a critical practice: a way of working critically with algorithmic systems by introducing ambiguity, instability, error, or misrepresentation back into them.

The paper proceeds in five parts. The first section looks at the concept of 'pure data' and shows why this is misleading. The second section turns to theories of classification and contamination, arguing that the distinction between the pure and the impure is a social construct rather than a natural given. It also introduces the idea of 'ghosts' to describe how what is excluded from data systems does not simply disappear but continues to shape them in indirect and often unstable ways.

The third section looks at case studies of machine translation, DeepL and the United Nations Parallel Corpus, focusing on moments where queer language and gender ambiguity are mistranslated or forced into normative categories. The fourth section frames 'contamination' as a queer feminist analytical approach. It examines how algorithmic systems reinforce categorisations and, in doing so, marginalise forms of difference that fall outside computational classification. The final section explores artistic practices that use contamination to against contamination; these practices deliberately employ error, glitch, ambiguity, and instability to expose and challenge the classificatory logic of algorithmic systems.

The Myth of Pure Data

The concept of 'pure data' is closely linked to epistemological ideals that emerged during the Enlightenment, when knowledge was often imagined as representing universal and objective truth independent of social particularities. Statistical practices of the eighteenth and nineteenth centuries sought to translate the complexity of social life into quantifiable forms, transforming messy realities into readable numerical patterns. These practices reflected a broader epistemic ambition: to render social phenomena measurable, comparable, and governable through numerical abstraction. In this sense, the ideal of 'pure data' can be understood as an extension of a longer intellectual tradition that equated knowledge with objectivity.

However, historians of science have shown that 'objectivity' itself is not a fixed ideal but a historically changing epistemic value that has taken different forms across scientific cultures and practices (Daston and Galison 2010). Feminist science studies have further challenged the presumed neutrality of objectivity. Harding (1996) suggests, 'objectivity' in the traditional sense is not truly neutral; it disguises universality and neutrality by denying its situatedness. By presenting knowledge as universal and disembodied, objectivity obscures the social positions and judgments that shape scientific practices. She argues with the concept of 'Strong Objectivity' that statistical and scientific practices are not only technical processes, but also social practices embedded in political and power structures.

Building on these critiques of scientific objectivity, scholars in STS and data studies have argued that the concept of 'raw' or 'pure' data is fundamentally misleading. Data do not exist as neutral reflections of reality waiting to be discovered; rather, they are produced through processes of measurement, selection, formatting, and interpretation. As Gitelman (2013) famously notes, 'raw data' is an oxymoron. Data are always already structured within technical and institutional systems that shape what can be recorded and how it can be interpreted. Similarly, Bowker (2000) argues that data are never truly raw but always 'cooked,' shaped through processes of collection, standardisation, and classification that embed assumptions about the world. From this perspective, data are not neutral representations, but the outcomes of situated practices and infrastructures that 'inform' the world and make it knowable.

Research on contemporary data infrastructures further demonstrates that datasets are the result of extensive human labour, including annotation, classification, and curation (Crawford and Joler 2018; Paullada et al. 2021). From sensor configuration to annotation guideline design, every stage of data generation involves decisions about what counts as relevant information and what can be ignored.

These processes become particularly visible in the practice of data cleaning, a stage where datasets are actively refined and standardised. In data science, cleaning is typically described as the process of identifying and correcting errors and inaccuracies in a dataset to improve its quality and usability. However, every cleaning decision is also a filtering decision that determines which data is retained, which are corrected, and which are excluded. Implicit in every cleaning are certain standards that appear to be objective but can affect the final landscape of the data and may even inadvertently reinforce certain biases or omit information about outliers, such as marginalised groups.

While cleaning aims to stabilise datasets, machine learning research also identifies a corresponding problem: data contamination. Within this field, 'data contamination' is usually understood as a technical flaw that undermines model validity, for instance through training – test overlap, benchmark leakage, or mislabelled samples (Dickson 2023; Lutch, Guan, and Wu 2024; Li, Ishida, and Yi 2026). In such cases, contamination is framed primarily as a problem of model validity, appearing as noise that must be detected and eliminated. At the same time, this technical framing invites a more critical reading. While contamination is described in terms of statistical validity and model performance, identifying and removing 'noise' also involves decisions about how datasets are organised – what is kept, what is adjusted, and what is left out.

Purity, Classification and Contamination

If the myth of pure data rests on the assumption that data can be fully purified through technical procedures, contamination can instead be examined in relation to the classificatory systems through which data are organised and turned into information. Anthropologist Mary Douglas argued that purity and contamination are not inherent qualities of substances but effects of social ordering. In *Purity and Danger*, Douglas (1978) defines dirt as 'matter out of place': something becomes contamination not because of its intrinsic properties, but because it disrupts an existing system of classification. Building on this, Shotwell (2021) critiques the ideal of purity itself, arguing that the desire for purity often obscures the entangled, compromised conditions in which social and political life unfolds. In this context, Contamination is not simply a deviation from order but a condition of relationality that cannot be fully eliminated. In this sense, it is better understood not as a material condition but as a relational one, emerging when objects, bodies, or practices fail to conform to the boundaries through which societies organise meaning.

According to Douglas, the concepts of purity and contamination function as cultural mechanisms that maintain social order. Classification system draws boundaries of belonging and exclusion – normal and abnormal, the acceptable and the deviant. When something appears in the 'wrong' place within these systems, it is labelled as contamination. Therefore, contamination is not simply an objective attribute; it reveals the fragility of classification systems themselves and the existence of boundaries that maintain a particular social world. At the same time, it also draws attention to the limits of these systems, as it emerges precisely when something does not fit neatly within existing categories.

Within machine learning infrastructures, contamination appears when real world exceeds the classificatory assumptions embedded in the datasets. Ambiguous cases, linguistic irregularities, and non-normative identities often emerge as anomalies within training corpora because they cannot be easily categorised into existing classes. Noise in data is also trace of social difference that resists computational ordering. Accordingly, contamination should not be understood merely as an error in the dataset but as a structural effect of classification itself. It exposes the limits of systems that attempt to stabilise complex social worlds through rigid categories.

Corpus Contamination

Language translation systems provide a particularly revealing site for observing how classificatory assumptions operate within machine learning infrastructures. The use of Chinese-English translation offers a useful methodological lens for examining gender inference in machine translation systems. Unlike English, Mandarin Chinese does not systematically encode grammatical gender in pronouns or many occupational nouns in spoken language. In many cases, forms of address remain gender-neutral, allowing the speaker to omit any reference to gender entirely. However, when translating such sentences into English, machine translation systems are often required to produce gendered pronouns or gendered descriptions. As a result, the system must address gender where none is explicitly stated in the source language. This process makes visible the unspoken assumptions embedded within training data and model architectures. In other words, Chinese-English translation provides a methodological lens through which gender biases in language models become particularly legible: when the source language does not specify gender, the gender choices made by the system reveal the statistical associations and normative expectations encoded in its training corpus.

These classificatory dynamics become particularly visible in the large-scale language corpora used to train machine translation systems. In computational linguistics, a corpus refers to a large, structured collection of texts used to train and evaluate language models. Such corpora are often regarded as the 'gold standard' for language learning, serving as the foundation for training machine translation, natural language processing (NLP), and large language models (LLMs). However, these corpora are not objective or neutral collections of texts; they are products of human selection, organisation, and configuration.

For example, large-scale machine translation training data, such as the United Nations Parallel Corpus, while widely used to train translation systems, often reflect the normative language of diplomacy, lacking everyday expressions, colloquialisms, or the linguistic practices of marginalised social groups. This results in machine translation systems struggling to adapt to 'non-standard' or queer linguistic expressions. More strikingly, when it comes to LGBTQ+-related terminology, these limitations can manifest as semantic distortion. For instance, when translating the English phrase 'homophobic right' into Chinese using DeepL[1], the system outputs 'homosexual rights (同性恋权利) ' (Figure 1). This is not simply a technical error, but a result of how associations are structured within the training corpus.

DeepL is a commercial machine translation system that combines neural machine translation with large language model techniques to produce fluent translations. The translation interface of DeepL is often accompanied by a dictionary extension. In the example above, the extension displays the Chinese term '同性恋 (Homosexual)' while incorrectly labelling its English equivalent as 'homophobic' (Figure 2). Further inspection of the Linguee dictionary examples linked through this interface shows that many of the example sentences originate from the UN corpus (Figure 3).

In the UN corpus (Ziemski, Junczys-Dowmunt, and Pouliquen 2016), the terms 'homosexuality' and 'anti-homophobia' often appear together leads the machine to mistakenly associate 'homosexual' and 'homophobic' or 'hate' as neighbouring terms within the same semantic field.[2] That is, machine translation systems inherit the historical discrimination against LGBTQ + groups embedded in the corpus, causing certain terms to be erased or mismatched during translation. Here, what appears as a limitation or distortion in the dataset would usually be treated as a problem in technical terms, something that undermines accuracy and needs to be corrected. In this paper,

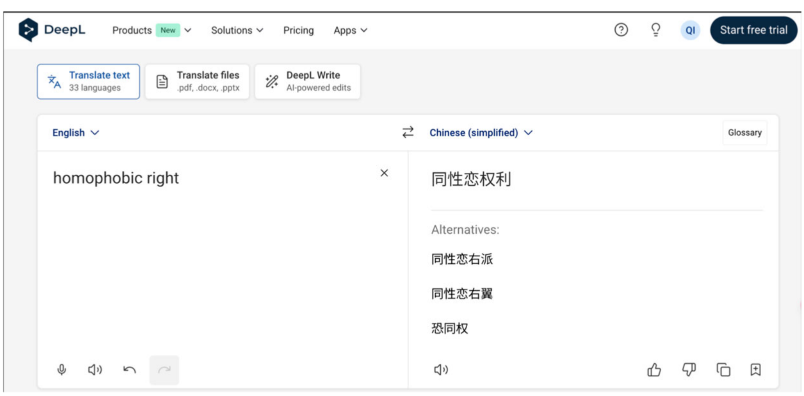

Figure 1. Screenshot of the DeepL interface showing the mistranslation of 'homophobic right' as 'homosexual rights (同性恋权利).' Source: DeepL Translator (accessed May 15, 2025), https://www.deepl.com/en/translator.

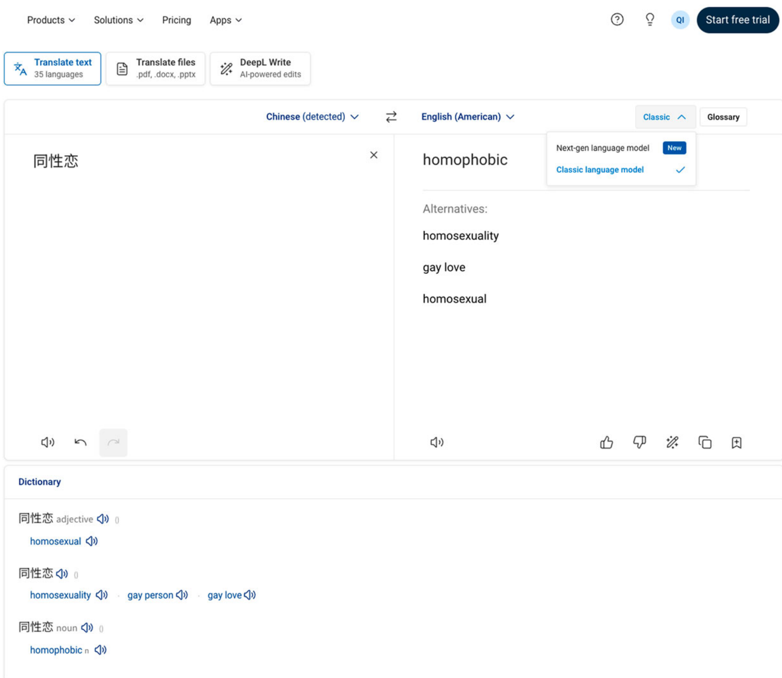

Figure 2. DeepL translation interface displaying dictionary output and English – Chinese term alignment. Source: DeepL Translator (accessed September 29, 2025), https://www.deepl.com/en/translator.

however, I analyse such cases not only as problems, but also as moments that reveal how the system operates.

In addition, LLMs are widely used in translation software to polish otherwise rigid machine translation results. Machine translation systems often encode and replicate gender assumptions about cultural and social norms latent in their training corpus. For example, DeepL and Google Translate, when dealing with gender-neutral terms like 'the hero' in English, will default to male when the original Chinese sentence has no gender indication: '*This man is truly a hero! He saved our nation in the most splendid manner. Without him, I dare not imagine what our lives would be like!* (translated by DeepL Next-Gen language model).' '*The man who cooks for the children*,' on the other hand, tends to be given a female role.

In the Classic DeepL model, this pattern of gendered adjective assignment is particularly pronounced, while the Next-Gen model shows some improvement, although similar biases can still appear in complex sentences. Notably, when translating Chinese sentences with gender-neutral pronouns, the Next-Gen model predominantly renders them using 'they/them' in English. This shift does not fully resolve the problem but rather reconfigures it. While the Next-Gen model appears more inclusive by defaulting to 'they/them,' it still treats gender as something that must be specified, even when it is absent in the source language. In short, the system translates gender into a different, standardised form. Rather than leaving gender open, it replaces one form of classification (binary gender) with another (neutralised but still obligatory categorisation). What appears as improvement therefore show a deeper assumption: that language must be

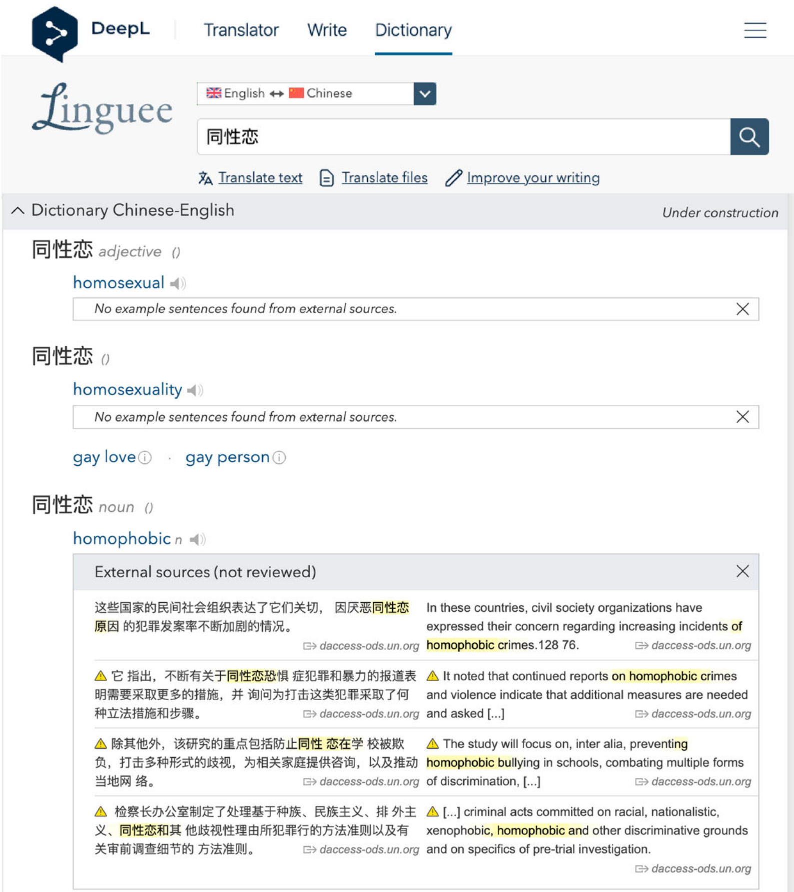

Figure 3. Linguee dictionary entry for '同性恋' (homosexual). Source: Linguee (accessed May 15, 2025), https://www.linguee.com/chinese-english/translation/同性恋.html.

made legible through classification, even at the cost of introducing attributes that were not originally present.

Beyond simple pronoun assignment, LLMs may also reinforce stereotypes through the generative pairing of gendered subjects with evaluative adjectives. For example, '*This man is very good at his job.*[3]' was given to a male subject. In exploratory tests using different prompts: males were often associated with traits such as 'successful', 'brave' and 'decisive'. Women, on the other hand, were more likely to be portrayed as 'cute', 'beautiful', and 'sexy'. Such patterns illustrate how generative models do not merely reproduce biases contained in their training data but may also amplify them through fluent linguistic reconstruction.

It is worth noting that these patterns of gender translation are not a new phenomenon. Linguists and media scholars have long documented the persistence of gender bias in machine translation, corpora, and natural language processing systems (Caliskan, Bryson, and Narayanan 2017; Prates et al. 2020; Stanovsky, Smith, and Zettlemoyer 2019; Lopez Medel 2021). Despite decades of awareness and ongoing technological interventions, this bias is still evident in contemporary systems, including LLMs-enhanced translators like DeepL Next-Gen. The persistence of these patterns suggests that the problem is not merely a technical glitch, but a structural one rooted in the historical, social, and cultural contingencies of data. At the same time, some recent approaches attempt to address this issue not by fixing a single 'correct' gender, but by holding gender open – either by generating multiple possible alternatives or by delaying gender assignment altogether (Garg et al. 2024; Lardelli and Gromann 2023). Rather than resolving ambiguity, these approaches manage it.

The DeepL example further shows that gender norms are not merely reproduced, and that their continued existence is not (only) a result of bias. Gender norms are also imposed on data where gender attributes are missing. That is, linguistic reconstruction through machine learning introduces attributes that make data compatible with its framework, effectively 'contaminating' data, too. When a genderless language is translated using gendered assumptions, it shows that 'contamination' in machine learning is not a fixed concept but a subjective one, and these biases continue to shape the outputs of translation tools like DeepL. I ask: how can the analysis of these hauntings contribute to developing tactics to reclaim the gap that is queerness in machine learning systems?

Queer Ghosts in Machine Translation

These observations raise a broader question: what does it mean for AI systems to render gender 'correctly' in translation? The idea of a correct representation already assumes that gender has a stable and appropriate form of expression. From a queer theoretical perspective, the ambiguity and instability that appear as 'errors' in translation may instead preserve a space where the meaning of gender remains open, contested, or uncertain.

Most existing research treats gender bias in machine translation as a technical problem to be solved through improved datasets, evaluation metrics, or model design. Recent research in computational linguistics and AI ethics has begun to explore strategies for disrupting binary gender classifications in language technologies. For instance, Anaelia Ovalle and colleagues (2023) propose centring transgender and non-binary voices in the evaluation of language generation systems, thereby introducing friction into automated gender classification and exposing the limitations of binary assumptions embedded in datasets and models. While such work focuses on methodological interventions within AI systems, this article approaches the issue differently. Rather than proposing technical solutions, it develops contamination as a queer-feminist analytic framework, interpreting mistranslations and algorithmic errors as moments that reveal, and potentially destabilise, the classificatory logics of data infrastructures.

Seen from this perspective, mistranslations do more than reveal bias; they expose what might be called the emotional infrastructure of linguistic corpora – sexual minorities are encoded as 'objects of fear' rather than 'subjects of rights.' Drawing on Ahmed's (2014) research of the politics of emotion, emotions are not intrinsic psychological states but are 'stuck' to specific objects through social practices, such as language. When 'homosexual' is repeatedly associated with 'fear' in the corpus, the machine is forced to treat homophobic sentiment as a 'natural' technical feature, thereby reproducing societal marginalisation of queerness.

These distortions can also be understood through Derrida's hauntology, as the return of what the corpus attempts to exclude. As Blackman (2019) argues in Haunted Data, data is never fully stable or complete; it remains haunted by what has been excluded, denied, or rendered unintelligible. Such spectral residues linger within datasets, unsettling the authority of supposedly clean and coherent data infrastructures. Within machine translation, these residues emerge as mistranslations that signal the limits of computational classification. When DeepL fails to translate 'non-binary,' or renders 'queer' through its earlier lexical sense as 'strange' or 'odd,' the system integrates the reclaimed political identity into its historically pejorative semantic domain. such technical failures become queer ghosts – what Anna Tsing might describe as a form of latent commons[4] (Tsing 2015, 255): fragile openings, where suppressed or excluded meanings break through the cracks of algorithmic order. Like mushrooms sprouting from contaminated soil, mistranslations such as 'Queer rights' expose the violence sedimented within linguistic corpora, yet at the same time transform this violence into a generative site of resistance.

Seen in this way, repetitive translation errors haunt the system as persistent residues of marginalised identities and non-canonical meanings. Their presence challenges the idealised vision of machine learning in which language can be fully stabilised, categorised, and translated. Queer language often operates through ambiguity, irony, and contextual shifts that resist such standardisation. Mainstream machine translation strives for what translation studies often describe as 'accurate equivalence,' yet queer discourse frequently relies on semantic multiplicity rather than stability. For example, the Chinese term '同志(Tongzhi)', which embodies both political comradeship and queer solidarity, is flattened by the algorithmic system's processing into a lifeless 'comrade'. Such algorithmic reductions do not simply mistranslate language; they erase the social and historical ambiguities through which queer meanings emerge. This means that any attempt to 'clean' data sets through standardised training will inevitably create more ghosts: excluded queer discourses, mistranslated identities, and expressions disciplined as 'inappropriate.' Reading mistranslation through the lens of contamination therefore shifts the analytical focus: rather than asking how errors can be eliminated, it invites us to examine how moments of instability reveal the political and epistemic assumptions embedded in data infrastructures.

Contamination as Queer-Feminist Method

If contamination draws attention to the limits of data infrastructures, this is not simply because contamination exists as such, but because of how it is defined and managed within classificatory systems. Instead of treating error, noise, ambiguity, or anomaly as technical failures, a queer-feminist perspective invites us to examine how such disturbances expose the normative assumptions embedded in data infrastructures.

Queer theory questions fixed categories that organise bodies, identities, and social relations. Instead of trying to correct what does not fit these norms, it values ambiguity and contradiction as important sources of insight. From this perspective, 'contamination' aligns with queer approaches that challenge ideas of purity and stability. What looks like noise in computational systems may actually reflect real social complexity that cannot be easily standardised.

Reframing contamination as a queer-feminist method involves a shift in analytical orientation. Rather than asking how data can be purified, this approach asks what becomes visible when purification fails. Contamination draws attention to the points where classificatory systems break down. These are moments where identities exceed available labels, where linguistic meaning becomes unstable, and where historical biases embedded in datasets reappear as algorithmic anomalies. These moments of instability can be read as epistemic openings through which the hidden infrastructures of machine learning become perceptible.

Methodologically, contamination operates through three interrelated practices. First, it can be used to make assumptions embedded in datasets and algorithms visible. By looking at anomalies, mistranslations, and misclassifications, it becomes possible to see how these systems organise and make sense of data. Second, contamination can be used as a way of working with ambiguity and multiplicity, rather than forcing them into fixed categories. Instead of treating irregular data points as errors to be corrected, it becomes possible to read them as signs of where computational systems reach their limits. Third, contamination can also be used in practice, by deliberately introducing noise, disorder, or ambiguity into data systems. Rather than improving the system, these interventions push it to its limits and make its assumptions more visible. This strategy resonates with what Brunton and Nissenbaum (2016) describe as obfuscation: the deliberate production of ambiguous or misleading data to resist data collection and analysis.

Artists and activists have long recognised the generative potential of contamination. Artists working with machine learning have increasingly explored techniques such as data poisoning, adversarial perturbation, and dataset manipulation to expose the fragility of supposedly objective systems. These practices do not simply sabotage technological systems; they function as forms of critical inquiry that make visible the assumptions embedded in algorithmic processes. By actively engaging with contamination, artistic experimentation can transform technical failure into a productive site of reflection. The following section examines several artistic projects that actively work with contamination, showing how noise, error, and ambiguity can become tools for critical and creative engagement with AI systems.

Contamination in Practice

Contamination can be understood as a queer feminist approach that reveals the limitations of classification systems through practice. Artistic interventions function as practical experiments in contamination. By intentionally introducing noise ambiguous data into computational systems, artists expose the classificatory logic that underpins machine learning infrastructures. The following examples demonstrate how contamination can operate as a methodological strategy across different technological contexts, from facial recognition and dataset construction to social media moderation and machine translation.

In Ada Ada Ada's (2021) ongoing project 'in transitu' consists of weekly photographs posted on Instagram documenting the artist's gender transition (Figure 4). Each image features exposed breasts, intentionally confronting the platform's moderation systems, which allow the display of male nipples but prohibit female ones. By repeatedly uploading images that blur or unsettle these categories, the artist tests the point at which the platform's algorithmic and social definitions of femininity become enforceable.

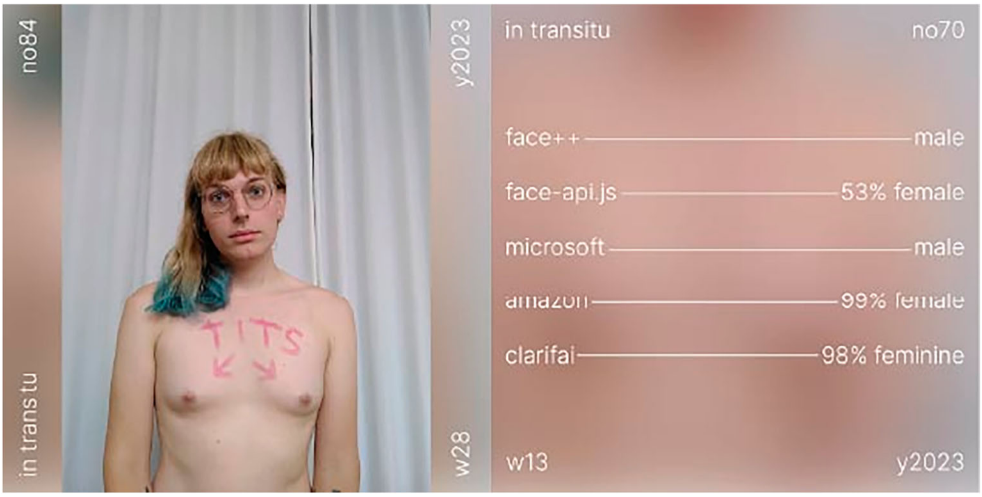

Figure 4. *in transitu* (Ada Ada Ada 2021). Screenshot from an ongoing Instagram-based performance exploring gender transition and platform moderation. Source: Image courtesy of the artist.

In this context, the body itself becomes a form of data contamination. The photographs introduce ambiguity into the platform's classificatory system: the images cannot be easily categorised as either acceptable or prohibited. At the same time, Ada Ada Ada overlays the photographs with the results of different facial recognition systems, exposing how algorithmic systems attempt to stabilise gender through biometric analysis. What appears as a simple social media post thus becomes a site where bodily transformation, platform governance, and machine learning classification intersect. Rather than resolving these contradictions, 'in transitu' sustains them. The project transforms the artist's transitioning body into a continuous source of algorithmic noise. In doing so, it reveals how platform governance relies on rigid classificatory boundaries while also demonstrating how embodied ambiguity can disrupt these systems from within.

Another example of contamination at the level of dataset construction is Elwes's (2019) project 'Zizi – Queering the Dataset'. By contaminating a facial recognition dataset with drag imagery, Elwes does not produce a more 'accurate' model, but rather an unstable one that cannot reconcile queer bodies with binary gender. This productive failure produced a series of failures, unpredictable forms, and atypical identities. In this work, contamination is operationalised as a queer methodology – an artistic strategy that internally dislocates the technological system, embracing failure and complexity as a critical language. The resulting AI, forced to confront the illegible, generates a 'Queer ghost': a spectral algorithmic residue that persistently haunts recognition infrastructures.

Elwes' practice situates contamination at the level of dataset construction, where ambiguity is introduced during the training process itself. A related approach can be found in Dirty Data by Clarke (2022), which shifts the focus from dataset construction to the conditions under which data is produced and circulated. Rather than working inside machine learning systems, the project examines how images and performances become data through processes of uploading, sharing, and platform interaction. Performances are repeatedly recorded and disseminated across social media and cam platforms, where they are transformed into visual content, metadata, and engagement metrics.

Here, Dirty Data refers to forms of data that emerge through repetition, variation, and excess, rather than through controlled collection or standardisation. The same image or performance may appear in multiple contexts, slightly altered or reinterpreted, making it difficult to isolate as a stable data point. Instead of treating this instability as noise to be removed, this makes visible how data is continuously shaped by the conditions of its production and circulation.

If Elwes and Clarke focus on how data is constructed and circulated, a related exploration of contamination emerges in author's digital performance 'See My Gender' (Figure 5), which engages directly with commercial facial recognition systems through a process of repeated interaction (Ren 2021). This performance began from my observation that my face, a queer face, was consistently misclassified by automated facial recognition systems, particularly in gender. The project stages a series of interventions where everyday materials – paper, textiles, metals, string, and makeup – are gradually applied to the face, demanding repeated recognition by the software. Each iteration generates a new, unstable identity, as the system recalculates gender, age, and emotion with fluctuating percentages. The work thus exposes the reductive logic of binary categorisation: covering both eyes and nose results in a reading of 'female, 89.9%,' while streaked makeup produces 'male, 91%.' The calm pacing of the performance, where my gaze silently at the viewer while the algorithm reconfigures my identity, draws attention to the fragility of technological authority.

Rather than a single instance of misrecognition, the performance stages a continuous feedback loop between human input and algorithmic output. Each alteration introduces

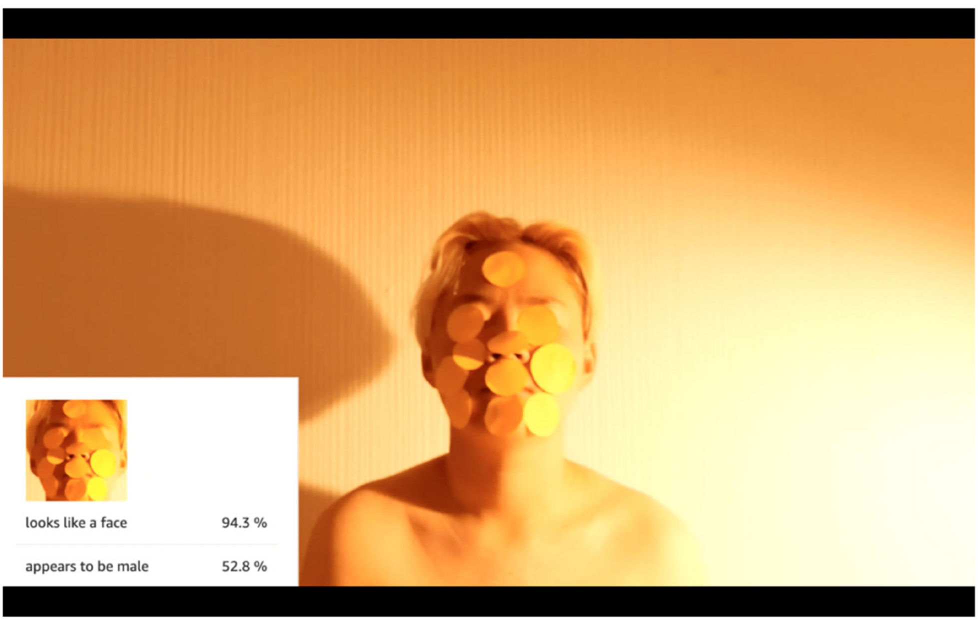

Figure 5. *See My Gender* (Ren 2021). Screenshot from a digital performance exploring algorithmic gender classification and facial recognition. Source: https://renqingyi.com/see-my-gender.

new visual conditions, covering facial features, changing texture, that affect how the system processes the face. As a result, classifications shift across iterations, producing inconsistent and sometimes contradictory results. In this sense, contamination operates not only through ambiguity but through repetition and accumulation. The face is not presented as a stable input, but as a sequence of variations that continually reconfigure the system's response. The work thus makes visible how recognition is produced through ongoing interaction, rather than as a fixed or objective reading of identity.

Sinders (2017) ongoing project 'Feminist Data Set' addresses contamination through the process of data collection itself. The project takes the form of a participatory dataset developed through workshops, interviews, and collaborative annotation sessions. Participants collectively discuss how concepts such as 'feminism' should be represented within machine learning datasets, producing textual entries, definitions, and contextual notes. Differing from many datasets developed for machine learning, which aim for consistency and standardisation, Feminist Data Set intentionally foregrounds disagreement, multiplicity, and incompleteness. Entries are continuously revised, annotated, and expanded by different participants, emphasising that data production is always a social and political process. In this sense, the project undermines the very ideal of the stable dataset. Rather than presenting data as neutral input for machine learning systems, it exposes the labour, negotiation, and subjective judgment that shape what counts as data in the first place.

A further way to practice contamination appears in Queer Motto API Manual (Soon and Pritchard 2025), which operates at the level of computing and interfaces. The project takes the form of a speculative API and manual that generates 'queer mottos' through programmable structures, based on manifestos and zines as source material. Rather than treating APIs as neutral infrastructures for efficient data exchange, the project foregrounds how they organise and regulate language, behaviour, and desire. Unlike the mainstream model of large platforms – where APIs are standardised and information flows are controlled – the Queer Motto API introduces resistance at the infrastructure level. The mottos and messages it generates implement these logics, offering alternative ways to connect, organise, and imagine collective life.

Unlike conventional API design, which prioritises clarity outputs, Queer Motto API embraces the undisciplined and vulnerable. Its instructions are not always fully determined, its outputs shift in tone and meaning, and the boundary between command and expression becomes blurred. In this sense, the API functions as a 'contaminated' interface – one that resists stabilisation and refuses to behave as a purely functional system. The project shows that classification is not only a matter of data input but is embedded in the design of computational systems themselves. By queering the logic of the API and incorporating acts of refusal into its operations, Soon and Pritchard highlight how even abstract layers of software infrastructure shape what can be expressed and how it is structured. Contamination here works to unsettle those assumptions, turning code into a space for affect and resistance.

In short, these artistic practices show that contamination does not occur at a single point within computational systems but emerges across multiple stages of data production and use. From the construction of training datasets and the participatory processes of data collection to the circulation of images on platforms and the real-time interaction between users and algorithmic systems, each work demonstrates a different way in which instability enters and reshapes classificatory structures. They reveal that what is often framed as error is in fact integral to how data systems operate, and that classification depends on ongoing processes of simplification and exclusion. Contamination, in this sense, is not an exception to otherwise coherent systems, but a condition that runs through them.

By working with rather than against this condition, artistic practices begin to use contamination against contamination: introducing ambiguity and instability to expose and disrupt the classificatory logics already embedded within data infrastructures. In this way, contamination functions not only as a critical lens but as a practical strategy for intervening in and reconfiguring computational systems from within.

Conclusion

This paper redefines contamination not as a flaw to be removed, but as a condition to work with. Taking contamination seriously shifts attention away from treating data as something that must be made increasingly accurate, consistent, and controllable, and instead toward examining how standards of correctness and validity are produced within AI systems. This is a queer move: rather than stabilising categories or eliminating ambiguity, it stays with what does not fit and challenges the norms through which data is made legible. In practice, this means keeping conflicting or inconsistent data rather than cleaning it away, allowing multiple possible outputs instead of forcing a single correct one, or making uncertainty visible in interfaces rather than smoothing it out. These interventions do not 'fix' bias but make it easier to see how it is produced and where it operates.

At the same time, contamination as a queer-feminist method opens a space for interdisciplinary experimentation. As demonstrated in the artistic practices discussed in this paper, contamination operates across technical, aesthetic, and embodied registers. Future work might further develop these intersections: combining computational methods with artistic research and participatory design to produce new forms of engagement with AI systems. In this expanded field, contamination is not only something to analyse but something to work with, perform, stage, and circulate. It becomes a mode of inquiry that operates through intervention rather than observation alone.

This also suggests a shift in how we understand agency in relation to algorithmic systems. If contamination reveals that data infrastructures are never fully closed or stable, then they are also never fully determined. The presence of noise or error indicates points of entry sites where systems can be disrupted, reconfigured, or repurposed. Queer and feminist approaches to technology have long emphasised such openings, not as spaces of pure freedom, but as sites of negotiation within constraint. Contamination, in this sense, marks the conditions under which alternative technological futures can be imagined and enacted. Importantly, however, contamination should not be romanticised. As Tsing reminds us, contamination is always 'non-innocent': it emerges through histories of violence, exclusion, and inequality. The mistranslations and misclassifications examined in this paper are not neutral glitches; they are symptomatic of structural conditions that continue to marginalise queer lives. To work with contamination, therefore, is not to celebrate error uncritically, but to remain attentive to its ambivalence – its capacity to both reproduce harm and open possibilities. A queer-feminist methodology must hold these tensions together, resisting the temptation to resolve them into a single narrative of either failure or liberation.

In short, contamination becomes more than an analytical tool; it functions as a speculative horizon. It invites us to imagine computational systems that do not seek to stabilise the world into fixed categories, but that remain open to transformation and difference. Such systems would not eliminate ghosts but make space for them, allowing what has been excluded to persist, to interrupt, and to reshape the conditions of intelligibility. To grow in algorithmic ruins, then, is not simply to document the failures of existing systems, but to cultivate alternative modes of existence within and alongside them. Like the matsutake that thrives in disturbed landscapes, queer forms of life and knowledge emerge not despite contamination, but through it. The task ahead is to learn how to recognise, sustain, and work with these emergences – to treat contamination not as the end of computational order, but as the beginning of something else.

Notes

1. DeepL Translator accessed September 29, 2025, https://www.deepl.com/en/translator. Observed that by June 2025, DeepL had introduced its 'Next-Gen' model to the web interface: in the Next-Gen model, the English phrase 'homophobic right' produced a different translation, whereas '同性恋权利 (homosexual rights)' was translated as 'gay rights' in English. In the Classic model, 'homophobic' was still translated as '同性恋 (homosexual) '. When the authors initially worked on DeepL, next-generation models had not yet been released.
2. Examples from United Nations Parallel Corpus the co-occurrence of 'homosexual' and references to combating homophobia include: (1) 'The prevailing religious and social fabric of the society takes homosexual relationships as a sin.'; (2) 'Tackling homophobia and other forms of discrimination against men because of their sexual orientation.'(3) 'Special attention should be given to sexual and gender diversity, and to addressing homophobia and other expressions of rigid, violent versions of masculinities that leave both women and many men vulnerable and discriminated against.' All excerpts accessed: https://daccess-ods.un.org/, September 29, 2025.
3. Chinese original text: 这个人在工作上十分优秀。.
4. Anna Lowenhaupt Tsing, *The Mushroom at the End of the World: On the Possibility of Life in Capitalist Ruin*s, p255. Tsing introduces 'latent commons' as 'those mutualist and no antagonistic entanglements found within the play of this confusion.' Used to describe the relationship of sharing and dependence between humans and non-humans that has formed in the ruins of capitalism. She emphasises that latent commons are fragile, unintentional, and situated forms of coexistence that arise amid capitalist ruins. They cannot be institutionalised or universalised, and while they may nurture collaboration across species, they may also exclude or harm others.

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