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The deep border

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ABSTRACT

Deep neural network algorithms are becoming intimately involved in the politics of the border, and are themselves bordering devices in that they classify, divide and demarcate boundaries in data. Deep learning involves much more than the deployment of technologies *at* the border, and is reordering what the border means, how the boundaries of political community can be imagined. Where the biometric border rendered the border mobile through its inscription in the body, the deep border generates the racialized body in novel forms that extend the reach of state violence. The deep border is written through the machine learning models that make the world in their own image – as clusters of attributes and feature spaces from which data examples can be drawn. The 'depth' that becomes imaginable in computer science models of the indefinite multiplication of layers in a neural network begins to resonate with state desires for a reach into the attributes of population. The border is spatially reimagined as a set of always possible functions, features, and clusters – as a 'line of best fit' where the fraught politics of the border can be condensed and resolved.

1. Introduction: please stop associating me

On the morning of 25th April 2019, a Muslim American woman, Amara Majeed, woke to find her image circulating globally on social media. The Sri Lankan authorities had published a photograph of Majeed, among the images of others wanted in connection with the Easter Sunday bombings four days earlier. "I have this morning been falsely identified by the Sri Lankan government as one of the ISIS Easter attackers", Majeed posted to social media, "what a thing to wake up to! Please stop implicating and associating me" (New York Times, 2019). Later that day, the Sri Lankan police issued a 'correction' notice, acknowledging that they had mistakenly used photographs of Majeed, extracted from the internet, wrongly identifying her as Abdul Cader Fathima Khadhiya. A facial recognition algorithm had misrecognised Amara Majeed, outputting a similarity score that was above some state-sanctioned threshold for the positive identification of a person of interest. At the mercy of a contingent threshold set by the Sri Lankan state, Amara Majeed experienced an intenstification of the violence she had long been exposed to in the United States, receiving racist abuse and death threats.

The public and media response to the misrecognition of Amara Majeed – where it was said that "facial recognition has reached its breaking point" – echoed other moments when an algorithm is said to have erred, to have made a fatal mistake, or to have departed from its otherwise reasonable calculus.[1] So, did the biometric border of the facial recognition algorithm fail to recognise Amara Majeed? Is the racialized output of what Simone Browne (2015: 109) calls the "digital epidermalization" of biometrics the locus of what is at stake in Majeed's story? Or could the biometric border fail to identify precisely at the moment that some other form of border, a deep border, takes flight and flourishes in its wake?

Lodged in the algorithmic pathways of the misrecognition of Amara Majeed is an alternative narrative that departs from the notion that algorithmic errancy could be corrected out, or that the racialized bias could be excised from the state's adjudication. Such corrections – whether a correction of code or the sovereign issuing of a correction notice – do not remove the racism from the deep neural network; quite the contrary, they allow it to amplify. At the moment of departure or error, however, the algorithm gives an account of itself, an account that partially illuminates its logic. Three years earlier, the teenaged Amara

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[1] Reporting on the Amara Majeed case among other high profile cases of apparent misidentification by convolutional neural network, Wired magazine argued that "facial recognition has already reached its breaking point" (Hay Newman, 2019). I have elsewhere detailed how the reporting of algorithmic mistakes and errors as moments of "madness" or breaking points serves to obscure how these moments may reveal the rationality and logic of the algorithm (Amoore, 2020, p. 109).

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Majeed wrote an open letter to the then presidential candidate Donald Trump. "I am an 18 year old Muslim American, my parents are Sri Lankan immigrants", she writes, "I am an activist and feminist" (American Muslim Institution, 2016). Majeed explains in her letter that she is the author of *The Foreigners*, a book "written in an attempt to eradicate stereotypes about Muslims", and recounts how, at the age of 16, she founded the *Hijab Project*, an international collective working to challenge the racism experienced by Muslim women. Her letter expresses the vulnerability that she feels when she is returning to her college room in time for evening prayers, covering her headscarf with the hood of her jacket, she "did not feel safe and secure". "You are creating an atmosphere", Majeed tells Trump, where hate-speech is normalised and where her "entire identity is reduced to a bias based on my skin color, my last name, and what I choose to wear on my head". "I have made it my mission to use my life", she concludes, "to undo the hatred that people like you create".

Majeed's story has stayed with me because of what it suggests about machine learning and border security logics. The biometric algorithm misrecognised her face but, in common with all forms of apparent misrecognition, it made another form of recognition possible: the deep border. The deep border rendered Majeed recognisable to the state, knowable as a cluster of attributes, a set of boundary lines that are also leanings, inclinations, and propensities. The deep border is a machine learning border that learns representations from data, and generates meaning from its exposures to the world. Indifferent to the distinction between biometric data inputs and all of Majeed's digital writing, the very words of her letters, Majeed is unbundled, disaggregated into derivatives that are readily traded, transposed, and translated as threats to the state – "activist", "feminist", "Muslim", "my mission", "to use my life". Indeed, the very conjunction of "Muslim" with "use my life" – once refracted through the lens of text extraction, natural language processing, and sentiment analysis – generates meaning in the world. In this way, the deep border exceeds the strictly biometric extraction of the features of Majeed's face, and extends to the multiple features of her past political claims, and it does this precisely in order to foreclose the possibilities of future political claims that are not yet made. Through the aperture of the deep border, the past border crossings of her Sri Lankan parents are never complete, they lodge in the calculus to be revisited in the lives of others, including those unknown but associated.

As Ann Laura Stoler describes the accretions of colonial violence, they fold together a "combined ferocity of high-tech and lowly, daily creations and reorderings of ever more present distinctions and discriminations" (2016: 11). The deep border precisely also recombines and reorders ferocious technology and mundane daily experiences, so that Majeed's fear of violence on a city street is not separate from the apparently abstract deep neural nets that extracted her data. What takes place here, in the emergent logic of the deep border, is the focus of this lecture and essay. The deep border – with its logics of feature mapping and data clustering – loosens the state's reliance on defined racialized categories and characteristics, expanding the scope for the emergent racialisation of inferred attributes. In this way the deep border also undercuts and circumvents the already insufficient liberal norms of protected characteristics and juridical rules. I will begin by addressing what depth means in the context of a deep border, reflecting on how propositions about 'depth' from computer science have coalesced with sovereign fantasies about border projects that reach into human attributes. I then move on to consider two dimensions of the deep border and its logic: features, and clusters.

2. Of depth and the border

In an essay published in *Political Geography* fifteen years ago, I proposed the concept "biometric border" to capture the twinned politics of "the turn to digital technologies and data integration in the politics of border management" with the "body itself" being inscribed with, and demarcating, "a continual crossing of multiple encoded borders – social, legal, gendered, racialized" (Amoore, 2006, p. 337). At the time, what I considered to be at stake in the biometric border was not merely "a new and important geographical imaginary of the border", nor even strictly the new technologies deployed at the border, but rather it was the "performing of the *idea* of the biometric border" that for me was the durable condition of possibility for a border "carried by mobile bodies" and "deployed to divide bodies at international boundaries, airports, railway stations, on subways or city streets, in the office or the neighbourhood" (2006: 336). One interpretation of what has taken place in the intervening time is that the biometric border has indeed become the ubiquitous means of bordering in the twenty-first century (Breckenridge, 2014; Frowd, 2018; Muller, 2011). Certainly, one could point to the multiple spaces where the biometric border has penetrated the politics of mobility; extending beyond the capture of biometric data at the territorial border and into spaces of humanitarianism (Duffield, 2016; Wilkins and Polly, 2020), warfare (Nisa, 2015), and the techno-management of migration and immigration detention (Martin, 2021). All of this might signal precisely the extent of the turn to digital technologies and their deployment to divide mobilities.

And yet, Amara Majeed's story suggests also that my 2006 argument that the contemporary border is carried by mobile bodies has not quite been borne out. What seemed to happen to Majeed is that the border dwelt within, and was carried by, the spatialities of the algorithm itself. Indeed, the border that actualized in Amara Majeed's body – subjecting her to violent threats and racist abuse – exceeds what Achille Mbembe, in his essay on bodies and borders, describes as the "intertwinement of individual physical characteristics with information systems" (2019: 9).[2] What are we to make of this border that seemed indifferent to Majeed's body as such, or at the least indifferent to the physical characteristics of the geometry of her face? For this border was interested in something else, something not quite captured by biometrics as her characteristics but more closely aligned with her propensities, her leanings or inclinations.[3] Could it be that, at the very moment that biometric borders appear to be everywhere, their proliferation provides cover for something else to emerge, something with a novel border logic of depth and deepening?

The deep border explodes and scatters biometric data so that they are no longer primarily connected to *characteristics* as such, but rather gather together with a multiplicity of data *features* in a deep learning model that renders all data equivalent; all data as potential borders data. When I studied the biometric border fifteen years ago, machine learning models were only just being revived from their decades long retrenchment in computer science, and it was more traditional rules-based "if-then-else" algorithms that were being deployed at the border. Deep neural networks are now becoming intimately involved in the practices of borderwork and bordering, though my attention to the deep border is not the same thing as algorithms becoming *instruments* deployed at the border or becoming autonomous agents that displace human decisions at the border. As I have detailed elsewhere, it is not a question limited to what machine learning algorithms are making of society, but primarily one of how society comes to understand itself and its problems differently through the aperture of the algorithm (Amoore, 2020). Thus, I propose that deep learning algorithms are reordering what the border means, how the boundaries of political community can be imagined, and how borderwork can function in the world. Where the biometric border

[2] In his essay on bodies and border, Achille Mbembe depicts the border as "the moving body of the undesired masses of populations" (2019: 9).

[3] This extension of biometric technologies, from broadly one-to-one or one-to-many biometric template matching devices to a deep reach into political propensities is also evident following the Taliban control of Afghanistan in August 2021. US forces had deployed face, fingerprint, and iris biometrics from 2007 in Afghanistan. The struggle to delete biometric data that could be used by the Taliban centred on the multiple forms of social media and internet material that could be used to build a picture of a person's political life (Reuters, 2021).

seemed to render the border mobile through its inscription in the body, the deep border is written in and through machine learning models that make the world in their own image – as clusters of attributes that do not map to individual bodies, that are in fact unmoored from the weight and duress of bodies, just as they are afforded a weightlessness that makes them able to actualise in any future body.

The idea of depth has a specific meaning in the computer science accounts of deep learning. It is worth spending a little time detailing what depth means in the context of machine learning because it is this spatial imaginary of depth that I consider to be coalescing with a political imaginary of deepening the border. In the context of the long and entangled histories of computational knowledge and sovereign knowledge (Edwards, 1997; Halpern, 2014; Hayles, 2012), what is it that defines "deep learning" as a distinct and novel form of computation that generates new possibilities for the state? In essence, the "deep" in machine learning refers to the depth of additional layers of neurons in a neural network algorithm. Each of the layers in a neural net computes one partial function of a much larger whole of the representation of the input data – for example, a layer in an image recognition might represent one small edge in a group of pixels in the image. Here, depth means a capacity to abstract and to represent the relationships in high-dimensional data. The 2018 recipients of the Turing prize – computer scientists Yoshua Bengio, Yann LeCun, and Geoffrey Hinton – describe the significance of depth in contemporary machine learning, arguing that "a key ingredient is depth: shallow networks simply do not work as well" when learning "the complicated internal representations that are required for difficult tasks such as recognising objects or understanding language" (2021: 58).

The very concept of depth in computer science not only supplies a set of AI tools for deployment at the border, but an entire way of thinking about difficulty and how to decompose a problem into its parts. Put simply, the imagination of depth in computer science is not only a means of model building, but a form of world-making. The computer science formulation of adding ever deeper layers to a neural network in order to solve difficult problems (such as object recognition or understanding language) holds out an alluring promise to the state; it too could decompose and represent everything, if only it could harness high-dimensional data to resolve the intractable difficulty that is politics. Consider, for example, the computer scientists' account of how the depth of additional layers is composed and combined. "The composition of more layers is what allowed more complex non-linearities", they write, so that "deep networks generalize better for the kind of input-output relationships we are modelling", and "deep networks excel because they exploit a particular form of compositionality in which features in one layer are combined in many different ways to create more abstract features in the next layer" (2021: 58-9). Once more, the deep learning model of non-linear relationships, generalizability, and abstraction through layers begins to constitute a model of social and political relations, a model that holds out great promise to the governing of non-linear problems.

Though the specific sense of "depth" in computer science is ontologically distinct from ideas of depth and volume in geopolitical thought (Graham, 2004; Elden, 2013), it is nonetheless becoming a way of thinking about the world and its most difficult and intractable political problems. The depth that becomes imaginable through the indefinite multiplication of layers in the neural net seems to offer the state a means of generating a deep border that will always align a target output (e.g. immigration targets, border risk scores) with a representation of the data available to the state. The proliferation of deep learning and so-called 'AI' in contemporary borders – embraced by states, the UNHCR (2017), and Frontex (2021), for example – coalesces the computer science imaginary of depth with a broader political imaginary of a deep reach into diverse sources of available input data, and a mapping of non-linear relations in line with 'output' policy objectives. Understood in these terms, the borders authorities' enrolment of deep learning technologies – such as in the 'DeepFace' and 'Deep-ID' open source facial recognition libraries – is better understood as an illusion of depth that actually embraces logics of the compression of volume and the flattening of complex problems to a single mappable function.

Among the many slippages and elisions of computer science vocabularies and sovereign techniques I will address, the mathematical concept of a "function" offers revitalized powers to the functions of government. When a machine learning model is mapping the representations of data across inputs and outputs, what it is doing is finding the best "function". Computer science offers deep learning as a means of "approximating any existing function" amid complex and high-dimensional data Nielsen, 2019, and this notion that the neural network can approximate any function for any situation is lending to the state a significant reconfiguring of its sovereign functions.

In what way does deep learning's quest for mappable functions enact an illusion of depth? In her historical account of depth and perspective, from Renaissance art to the computer, Anne Friedberg describes a "deep virtual reach into archives and databases", a depth that is nonetheless achieved via the horizontal and simultaneous display of distributed "fractured frames" and the "flattened planes of the present" (2006: 19; 243). The spatiality of the deep neural network mirrors this appearance of depth that is achieved by layers that compute distributed fragments of representations (layers that are most commonly depicted as extending along a horizontal plane). In this way, the border itself is spatially reimagined as a set of *always possible functions*, and limitless layers of the partial representations of data. Even the most absurdly fantastical imaginaries of the deep border – for example, the emotion detection biometrics of systems such as iBorderctrl at the EU external border (Sanchez-Monedero & Dencik, 2020; Stierl, 2020) – thus leave an indelible residue in what a border can be in the world, even where they cease to be actively deployed. Where specific instantiations of deep learning at the border fail to function, misfire or misrecognise, or are withdrawn, this does not place a critique nor a critical limit on the politics of the deep border. A new layer can always be added, a new function always found, an adjustment of the target modified. The perennial experiments and trials of deep learning at the border, proliferating everywhere, leave the residue of their logic and materially change the border long after their technical infrastructure falls away.

3. If border spaces were feature spaces …

If deep learning technologies are not merely being *deployed at* the border but are a condition of possibility for *reimagining* the border and what it can be in the world, then a first element is how the spatiality of the border is differently arranged through deep learning. To be clear, I am not suggesting that computer science causes or precipitates a transformation in the state's border practices. Rather, there is an emerging resonance between computer science's rendering of all spaces as feature spaces, and the state's desire to render every mundane space as a potential space of border intervention.[4] Causation thus becomes a resonance machine where "diverse elements infiltrate each other, metabolize into a moving complex" of "loosely associated elements" (Connolly, 2008, pp. 39–40). Though deep learning algorithms are not instrumentally causing transformations in sovereign borderwork, the diverse elements of computational knowledge begin to infiltrate and associate with sovereign knowledge. In short – and the focus of my discussion here – the computer science orientation to all space being a potential feature space powerfully resonates and coalesces with the state's ambition that all spaces are potential border spaces.

So, what is a feature space in computer science and what kinds of novel border spatialities does it give rise to? The "feature" in machine learning is more than a characteristic or property of an entity and,

[4] As Deleuze and Guattari pose the problem, the state "acts as a point of resonance on the horizon", it is not "a point taking all the others upon itself" but instead a "resonance chamber for them all" (2004: 247).

though often used interchangeably with "variable", a feature does not have the linear causal relations of something like an "independent variable" in data analysis. Features, understood by computer scientists as the "set of attributes associated to an example" (Mohri and Rostamizadeh, 2019: 4), significantly are not necessarily defined in advance of an operation but are generated by the data examples the algorithm is exposed to. In the rules-based algorithmic systems of the twentieth century, "if… and… then… else" formulations captured the variables involved in solving a problem. For example, a rules-based algorithm for calculating border risk might have arranged variables such as IF nationality X AND travel Y THEN high-risk ELSE low risk. However, where rules-based algorithms sought to capture the relationship of variables within a dataset – often with human domain specialists crafting the rules – deep learning seeks to generate the rules from features that are not pre-programmed in advance. "Deep learning takes a different approach to feature design", writes Kelleher, "by attempting to automatically learn the features that are most useful from raw data" (2019: 32). Significant here is that the locus of automation is not confined to the output of a so-called 'automated decision system' but actually dwells within the deep learning model itself, as it updates its own learning of features from the data. As Geoffrey Hinton captures the difference between engineered rules and his model's learned features, "there are some problems where it is very hard to write the program, there may not be any rules" and so "instead of writing a program by hand for each specific task, a machine learning approach collects lots of examples and provides a representation of the input in terms of learned features" (Hinton, 2019: 14). An example could be anything in this context – all space is feature space – from a database of millions of images of faces to the datastreams of social media hashtags. Let us distil the formulation of the feature that is made here. There are some problems for which there may be no possibility of programmable rules, no definable 'if … and … then … else' variables. And so, in place of rules the deep learning model learns what the important features might be from the data examples it is exposed to.

Of course, when the computer scientists refer to a difficult problem they mean a computational problem with high dimensionality. How swiftly, though, the difficult computational problem elides and slips into the framing of an intractable political problem. The computational feature space that learns from examples in the world becomes a political space that generates and governs the world via features. The feature space, then, is an experimental space of play that iteratively updates its model of the world in a "trial and error process of building models and checking the performance of the models when particular features are included or excluded" (Kelleher, 24). This process of experimentation is not fully explainable as the aggregation of data or the expansive extraction of examples because it also discards "redundant or superfluous" data as the model learns "the most important features in the input" (Kelleher, 145). In this building of a model of what is important, the machine is actively weighting the potential pathways, reducing the pluri-dimensionality of a difficult problem and excluding the superfluous features. The feature space is thus always also a political space that can settle on what is important, can decide which features matter. More than this, the feature space is a political space that is positively enhanced by its exposure to volatility and social instability (they are just more examples that yield features …) and therefore can both withstand and profit from the societal fractures or geopolitical violence it is exposed to. Returning to Hinton's account of the building of his models, "to capture the variations we need to learn the features that it is composed of", he writes, and "look at the arrangements of those features" (Hinton, 2014). A deep learning model actually has a proximate and intimate relationship with the violences and vulnerabilities of the border because, in a direct sense, it captures variations through every engagement with a feature space.

If the computational feature space is rendering all space as potential material for incipient features, then what does this mean for the border as political space? In June 2021 it was confirmed that the United Nations High Commission for Refugees (UNHCR) had shared with the Bangladesh government the biometric and biographic data of many hundreds of thousands of ethnic Rohingya refugees (Human Rights Watch, 2021). Having fled the genocide in Myanmar and crossed the border into Bangladesh, the Rohingya people were subject to an intensive data collection exercise, conducted by UNHCR in the camps. The agency collected facial images, thumbprints, and a range of demographic and biographic data as part of the registration process. Those arriving at the Cox's Bazar camp in Bangladesh submitted their data in order to receive a 'smart card' to obtain access to aid and basic services. As one person reported to Human Rights Watch in an interview, "I could not say no because I needed the smart card and I did not think that I could say no to the data sharing question" (HRW, 2021). The data was shared by UNHCR with the Bangladesh government, who subsequently sent the records of 830,000 Rohingya refugees to the Myanmar government. The very people who had fled the genocidal violence of the Myanmar government found themselves submitted before the authorities on lists of "repatriation eligibility assessments" with associated biometric identifiers. Many people were forced to flee the camp, to risk statelessness, and to go into hiding for fear of further violence. In a direct sense, the capacity of a person to make a political claim at the border, to exercise their rights and seek refuge, for example, is already annulled before it can even take place. The breaking of juridical norms and rules – from non-refoulement to consent and data protection – took place against a backdrop of algorithmic models that were generating their own rules from the features of human mobilities. The political foreclosures of the biometric border are in abundance here: the pre-emption of claims, the circumscribing of rights, and the closing down of potential futures.

And yet, what took place at the Cox's Bazar camp in Bangladesh also exceeds the biometric identification of individuals and mirrors the deep border that Amara Majeed found herself violently subjected to. Though the UNHCR issued statements apologising for the mistake of the sharing of biometric data, and undertaking to cease the practice of sharing data with state authorities, their correction similarly provides cover for the deep border to proliferate. The data extracted at Cox's Bazar continued to be used in what UNHCR term "exploratory data analysis" that aims to "translate humanitarian needs into data models" (UNHCR, 2021). The logic of the feature space that learns from examples runs through the agency's programme to build a vast array of deep learning models. The UNHCR proposes how human mobility might be modelled via the combination of multiple data inputs, from social media streams, news media, humanitarian data collection, and socio-economic data. The feature space emerges in humanitarian spaces precisely in order to anticipate who might arrive, when, and with what kinds of propensities and political and social inclinations. For example, Cox's Bazar became the site of deep learning experiments during the Covid-19 pandemic, with a "simulation of the camp" and circulations of people within an inadequate infrastructure becoming a feature space enrolled into the governing of the camp itself (Bullock et al., 2021). As Claudia Aradau has argued, "experimentality" becomes a "mode of governing in borderzones", a form of governing that "experiments without protocols" and in ways that debilitate the migrant subjects of experimentation (Aradau, 2020; see also; Molnar, 2020; Tazzioli, 2019). Even if the UNHCR ceased to share biometric data identifying individuals from Cox's Bazar, the deep border will indefinitely experiment in the addition and removal of features from the model. Once the border space is invoked as a feature space, it can occupy multiple locations simultaneously – from Bangladesh to Myanmar, from the Greek islands to the streets of Amsterdam or London. Understood as a feature space, the border is able to experiment and iterate, to generate features from the examples to which it is exposed, and to be invoked against a person at any future moment.

It is through the unpredictable turbulence and volatility of a situation like that of the ethnic Rohingya refugees that a deep neural network learns features that lie outside of the "expected distribution" of its training dataset (Bengio, Lecun, & Hinton, 2021, p. 60). There is a productive and generative relationship between a deep learning model and a turbulent and variable feature space.[5] What this means is that the deep border embraces and harnesses the human suffering that it engenders. A person can flee from genocide, may seek refuge or claim asylum, but their attributes will be recognisable in advance, before even a claim can be made. As Petra Molnar has argued, the migrant body endures the complete failure of basic life-supporting infrastructures of sanitation and clean water, and yet the borderzone is saturated with the technical infrastructures of biometrics and data management.[6] The deep border thus has the capacity to incorporate precarity, vulnerability and violence into its form of calculation. For example, the racist abuse suffered by migrants on the streets of Europe is reconstituted as a source of data for a UNHCR model. The UN Global Pulse and UNHCR (2017) developed a machine learning model to infer "the sentiment of communities towards refugees following the terrorist attacks in Europe". Here, the xenophobia and racism of European populations – as manifest in their social media – constituted a feature space from which the dangers posed to refugees could be calculated. In their report, the project team write that they "found that simple categories are most effective, like racist-non racist, or positive-negative", so that the arrangement of the model writes a boundary line between what does and does not count as racism. In short, racist violence and abuse itself becomes rendered a feature space – via text extraction and sentiment analysis – upon which a response to the so-called "refugee crisis" is to be modelled. *Even racism yields a feature space*. As the agencies describe the opportunity afforded to them: "UNHCR routinely collects massive amounts of data, through registration, programme and project implementation. The main challenge, and an important opportunity for the agency, is to find ways of integrating new data sources into this culture" (UNHCR, 2017, p. 11). Here once more the deep border combines the datasets of its biometric registration with multiple alternative "new data sources", so that even racist social media posts are an opportunity for the border space to be a vast and expanding feature space.

When border spaces become feature spaces (and all data therefore becomes potential borders and immigration data), the means of bordering a political community enters every available space – the city street, the university campus, the clinic – and the feature space continually yields new data for modelling. The features are everywhere in the scene and are generated by the scene. As vendors of deep learning models expand their feature spaces – in the case of Palantir, from US-Mexico border features to UK pandemic features – the deep border profits from volatility, violence and suffering, not only in the strict sense of corporate tech profits, but moreover in the exposure of the model to a new feature space with novel variations.

The deep border thus remains resolutely indifferent to actual response to human need because machine learning is geared to resolution with the output of a model. As Thomas Keenan suggests, political claims as well as rights claims are "constitutively incomplete" and "cannot reach their destination" (2015: 12). The incompleteness of a political claim is necessary if the door is to remain ajar to future claims that are not all modelled in advance. One could consider the foreclosure of the Rohingya's claims as a case of the deep border completing something – a repatriation, refoulement, detention, risk assessment – in such a way that there is no potential for a future claim to be heard. Similarly, the racism and violent online abuse of a European city becomes a set of features that output a 'high risk' to migrants, and foreclose the incomplete future claim or movement. When border spaces become feature spaces, what claim can be made that is not already incorporable as a feature in a model?

4. If borders were clusters …

There can be little doubt that contemporary border technologies, from drones and remote sensors to machine learning algorithms, have ushered in novel ways to sort, classify, group, and assign risk to, human mobilities (Dijstelbloem, 2015, 2021; Aradau & Tazzioli, 2020; Walters, 2017; Amoore, 2011). If deep learning algorithms do not merely become new border instruments but actively generate the border in novel ways, then what precisely happens to modes of the classification of people and groups with deep learning? I will address here the practice of clustering in computer science, and how the cluster becomes a means of imagining and constituting groupings of people and things. The cluster appears to hold out new promise to sovereign borderwork because it evades the categorical logics of rules-based systems, generating in place of categories an emergent set of groups of inferred attributes. To understand how computer science conceives of clusters is thus also to map how what Stuart Hall (2021: 359) calls "the floating signifier of race" may be differently signified via the inference of clustered attributes.

In the context of deep learning, the use of clustering algorithms has advanced methods of so-called "unsupervised learning" in which a large volume of data is sub-divided and partitioned according to the patterns discerned and extracted by the algorithm (LeCun, Bengio, and Hinton, 2015, p. 442). In commercial customer segmentation models, for example, clustering becomes a means of identifying groups and targeting them for specific marketing strategies.[7] To create clusters from a large volume of input data is in this sense also an exercise in the demarcation of borders and boundaries. As Geoffrey Bowker and Susan Leigh Star remind us, "a classification is a spatial, temporal, or spatio-temporal segmentation of the world" (2000: 10). In their detailed and historical engagement with practices of classification, they emphasise how classificatory systems exhibit consistent principles and mutually exclusive categories, so that "a rose is a rose, not a rose sometimes and a daisy other times" (2000: 11). And yet, with the rise of contemporary clustering techniques, the classificatory system segments the world in ways that allow for more flexible principles and mutable categories, so that perhaps a rose could belong to the daisy cluster under certain circumstances.

Let us reflect on how the world is segmented and partitioned through the lens of the cluster. As Mohri, Rostamizadeh, and Talwalkar explain in their influential text, *Foundations of Machine Learning*, "clustering is the problem of *partitioning* a set of items into *homogeneous* subsets", and the process of clustering "attempts to identify *natural communities* within large groups" (2018: 3, *my emphasis*). So, to partition data in such a way that subsets of natural communities might be identified. In one sense the machine learning of clusters segments and borders the world along the lines Bowker and Leigh Star suggest, and yet the partitioning of data by the algorithm does not follow pre-programmed principles but rather generates the bounded communities without reference to criteria. The boundaries of a cluster are entirely contingent on an iterative process of

[5] In the harnessing of turbulence for productive ends, the deep border's logic allies closely also with resilience logics. "Prediction is impossible in such conditions", writes Kevin Grove, "because complexity implies that change will be non-linear and often unforeseeable" and "intervention requires constant monitoring" (2018: 5). In Grove's rich account of resilience logics, unpredictable turbulence is not strictly controlled but channelled towards resilient design.

[6] I am grateful to Petra Molnar, director of the Refugee Law Lab, for generous discussion of the infrastructural violences of the deep border as they manifest on the islands of Samos and Lesvos, 7 July 2021. The Edinburgh Law School and Carnegie seminar 'AI and Border Control', organised by Petra Molnar and Dimitri Van Den Meerssche, also provided rich insight on the relationship between technological and juridical infrastructures of the border.

[7] Describing clustering methods for unsupervised learning, Ethem Alpaydin writes that "the aim is to find clusters or groupings of input". In the case of customer segmentation, Alpaydin notes that "the company may want to see what type of customers frequently occur" and that the model "allocates customers similar in their attributes to the same group, providing the company with natural groupings of its customers […] once such groups are found, the company may decide strategies specific to different groups" (2016: 112).

updating the set with each parse of the data, so that "clusters are not prespecified, or at most they are initially underspecified" (Kelleher, 2019, p. 27). Indeed, chance and the guess are actively incorporated into clustering, with "unsupervised machine learning algorithms" beginning by "guessing an initial clustering of the examples and then iteratively adjusting the clusters (by dropping instances from one cluster and adding them to another)" and thereby improving the "fitness of the cluster set" (Kelleher, 2019, p. 27).

Notwithstanding the contingency and immanence of partitioning data, the idea that clustering gives rise to "natural communities" within a larger grouping is an extraordinarily powerful political proposition. As bordering practices, both machine learning and geopolitical borders share a commitment to the claim of a pre-existing natural community; a claim that is belied by the intensity and contingency of the work involved in defining, demarcation, and securing that imagined community (Anderson, 1983; Closs-Stephens and Angharad, 2013). Resonating with the political idea that a border demarcates a territory mapped to a political community, the cluster offers the promise of a neutral, objective and value-free making and bordering of political community. The cluster not only becomes a way of imagining groupings of people, places, entire countries, but allied with psychology it also becomes the basis for the inference of the behaviours and attributes of the group (Stark, 2018). In domains from the fashion industry to the targeting of voters in an election, machine-generated clusters are mapped onto psychological profiles of the desires, propensities and inclinations of a segment of a group. When a new entity appears before the model, the primary question is not who or what are they (a daisy or a rose, a dog or a cat) but rather "to which cluster are their attributes most closely aligned". Because the boundaries of the clusters are mutable, the answer may indeed not always be the same. To belong to a cluster is not about resemblance, common characteristics, or meeting specified criteria, but is instead a spatialised proximity or distance. "Similarity and belonging no longer rely on resemblance as a common genesis", writes Adrian Mackenzie on machine learners, "but on measures of proximity or distance" (2017: 73). The person who is Amara Majeed, for example, may say "this does not resemble me", but they cannot say "I am not proximate to this cluster" for the centre and boundary of the cluster is ever shifting and changing. The computer science epistemology of the cluster is thus not limited to ideas of resemblance or genesis, but makes possible novel and fungible modalities of grouping, belonging, and bordering.

What happens to the border with the idea of clusters? The cluster, with its attendant logic of iterative partitioning and rebordering, loosens the state's application of categories and criteria in borders and immigration, expanding the scope for the borderline to be redrawn according to the inferred attributes of a group. The state's programme of "hostile environments" and behavioural border controls (Goodfellow, 2020) is extended into what the UK Government term a "compliant environment".[8] The immigration models of the compliant environment are designed to generate clusters of compliant and non-compliant groups from large volumes of newly accessible data, from health and pandemic data to social media. What is a non-compliant person and how would someone know if they are to be classified as non-complaint? With the advent of machine learning algorithms that generate clusters from data (underspecified in advance), the non-compliant person is whomsoever the clustering model decides they may be. Just as a segment of clustered consumer data may target a group for advertising, a segment of clustered immigration data will target for some action – to be refused a visa, detained, denied asylum, or refused EU settled status. For this is not even a matter of complying with rules or principles, nor meeting some criteria – how could it be, when the model itself is generative of high and low risk clusters, of rules from the data, of the border as such? The model generates clusters from the data of other transactions and movements in the past, so that criteria in the present are displaced by the inferred belonging to a cluster, for example "the visa overstayer shares the attributes of this cluster"; "the asylum claim has proximity to this cluster of fraudulent claims". The cluster becomes a condition of possibility for partitioning and bordering compliant from non-compliant groups, where the boundary line itself is an unstable and contingent thing. It is a deeply racialized partitioning in which one could never quite know why or how a decision was reached. How could it be meaningful to ask what principles were followed, what criteria were applied? The cluster operates with no pre-defined criteria, with guesses and experimentation in the partitioning of, and assignment to, a group.

The racialized cluster of the non-compliant person is also actively circumventing existing legal protections, most especially when these invoke protected characteristics such as gender, race, sexuality, or disability. What does the "characteristic" of race come to mean when inferred from a cluster of attributes? Consider, for example, the deployment of machine learning in the classification of immigration decisions, where the building of a model actively constitutes what a border can be, how the border line is drawn, who or what can be partitioned. Not only does the deep learning algorithm remake the border in its own image, but it simultaneously forecloses juridical challenges to the criteria that are applied in the judgement of a claim. When the Joint Council for the Welfare of Immigrants (JCWI) challenged the UK Home Office's visa application "streaming algorithm" they focused on the nationality data that were among the data inputs that resulted in some applicants being assigned to a "high risk" (non-compliant) cluster, effectively automating the decision to refuse a visa. JCWI successfully argued that the nationality data were proxies for race and, therefore, in breach of the provisions of the Equality Act 2010 (JCWI v Secretary of State of the Home Department, 2020). If the algorithm had enacted the categories of a rules-based "IF … AND … THEN … ELSE …" sequence, then the legal removal of racist input data could have materially changed the outputs of the system. However, the clustering logic of the deep border means one cannot assume that the excision of a racist input will remove the racialized groupings of the model. The algorithmic streaming of visa applications into "red, amber, green" groupings, as exhibited in the JCWI case brought by Foxglove legal, is an example of how the deep border enacts novel racisms. The UK Home Office can comply with the court and withdraw nationality data (as they have done), but yet they may continue to cluster multiple other forms of data (e.g. travel patterns, length of stay outside the UK) in ways that generate racialized groupings of suspicious or non-compliant persons. The cluster remains deeply racialized all the way down, and yet it also distances itself from the juridical categories of protected characteristics. One could excise the category of race from the model, but the cluster will persistently and determinedly learn racialized proximities and distances to threats to the state. In essence, this is what a non-compliant person is, someone whose propensities may pose an unspecified threat to the state.

Though the turn to a bordering via compliant environment is most overt in the UK, the racialized clustering of attributes is evident across the world, for example in Canada's machine learning algorithms to target "sham marriages" and apparently fraudulent familial and sexual relationships. As Petra Molnar and Lex Gill detail on the Canadian use of AI in immigration, machine learning models generate a likelihood for questions such as "is your marriage genuine?" and "is this really your child?" (Molnar and Gill, 2018). Once more, the deep border is not strictly adjudicating on a person's compliance with specified criteria, but rather generating the very conditions of that compliance through proximity to an unspecified cluster. It is not only individuals who

[8] From 2017 the UK Home Office changed the vocabulary of its 2012 'hostile environment' to suggest in its place a 'compliant environment'. Though the compliant environment shares the common policy agenda of hostile measures of the foreclose of access to housing, health, banking and other life-supporting infrastructures, the border line does become more mutable with the notion of a compliant milieu. In short, whilst hostility imagines a border that locks out and encloses, the compliant environment changes its locks so that one could never be certain that a key would fit.

become non-compliant or suspicious via clustering, but as Phillipe Frowd has vividly documented in his work on borders and the Sahel, entire countries and regions are clustered, with models making “a vision of risky Sahel” and the “region as a complex space of multiple threats” (2021: 5). To belong to a cluster of the risky, the suspicious, or the non-compliant is not strictly to resemble the others who are there, but to become spatially reassembled, to be, as Hito Steyerl has described the alteration of data and images, “translated, twisted, bruised, and reconfigured” (2015: 220).

Whilst the logics of the deep border enact the colonial continuities of racist discrimination and partition, they also locate new possibilities for the state’s racialized border politics. The racism of misidentified people, discriminatory design, and misfiring training datasets are one significant part of the picture (Benjamin, 2019a, 2019b, 2019b). However, the appeal to racialized inaccuracy that animates the correction of misrecognition or misfiring data falls short of accounting for a form of partitioning that cares little for inaccuracy or accuracy so long as it secures a precise proximity in the group. The deep border finds new ways to calculatively and spatially enact the violence of border politics. In his argument that race is a “floating signifier”, Stuart Hall begins from race as “one of those major concepts which organize the great classificatory systems of difference, which operate in human societies” (2021: 359). Understood in Hall’s terms, one can appreciate how changes in the classificatory system will change the meaning that is made, will change the regime of signification:

> And those things gain their meaning, not because of what they contain in their essence, but in their shifting relations of difference, which they establish with other concepts and ideas in a signifying field. Their meaning, because it is relational, and not essential, can never be fully fixed, but is subject to the constant process of redefinition and appropriation: to the losing of old meanings, and appropriation and collection and constructing of new ones […] made to mean something different at different moments of time (Hall, 2021: 362)

Following Hall’s insight, it is possible that the deep learning techniques of our contemporary moment are making race *signify* something different: a set of emergent proximities and distances generated through clustering. Of course – and as Hall details – the history of racial violence is replete with new formulations of biology, nation, class, and classification. The notion that race is signified, translated and transcribed differently across historical moments, and mobilising different vocabularies, is present also in Foucault’s reference to “two transcriptions” in the theory of races (2003: 60). The first transcription is an “openly biological transcription” drawing on vocabularies of anatomy and physiology, whilst the second, nineteenth century transcript signifies the “theme and theory of social war” (2003: 60). Animating this war-like race theory of “state racism” is what Foucault describes as “a racism that society will direct against itself, against its own elements and its own products”, constituting “an internal racism of permanent purification” (2003: 62). As a mode of transcription and signification of race, machine learning logics of the cluster foster precisely such a racism directed at society itself, but more than this they render the elements and products of social data as internal racism. The cluster proposes a shifting relation of difference that gathers all available elements and products into the writing of a boundary of the group. “Once you know where the person fits in the classification of natural human races”, writes Hall, “you can infer from that what they’re likely to think, what they’re likely to feel” (2021: 362). When classification is reconfigured through clustering, knowing *where the person fits*, in Hall’s terms, becomes primarily a matter of *fitness to the model*. The inference of what a person is likely to think or to feel also shifts ground so that it is a function of the contingent cluster. The deep border is once more relatively indifferent to who a person is, or to a notion of essences, whilst being attentive to a person’s compliance with the model.

The computer science logic of the cluster thus affords the state a means of pursuing racist borderwork whilst circumventing the social and juridical rights measures that grew up with twentieth century transcripts of characteristics and categories (if race is not an applied category or variable but an emergent group, state policy is said not to be racist). It cannot merely be said that deep learning technologies *are racist*, but additionally that *race itself is a political technology* that works to classify, group and divide groups under the cover of biological difference. The resources one requires to understand this process are already available from black studies. “Racializing assemblages”, writes Alexander Weheliye, are “producing racial categories, which are subsequently coded as natural substances” (2014: 51). With machine learning clusters we are witnessing the production and coding of racial categories happening in novel forms. The deep border permits the state to address a cluster – to demand proof, to deny entry, to refuse a claim – even where this group simply never existed. With the deep border, the violence of the Windrush logic exceeds the event of Windrush and permeates every demand for proof of status and belonging to a natural community (a cluster) that does not exist except via the sovereign logic itself.

The deep border calculus becomes unmoored and detached from material bodies – from Amara Majeed, from the Rohingya people, from the person whose marriage is declared non-compliant and fraudulent – and this calculus achieves a fleet-footed mobility that is entirely denied to the person in whose body it is eventually actualized.[9] The deep border may resurface anywhere in order to secure the border of a community, understood as the naturally and autonomously emerging community of the cluster. In this way, the computer science logic of the cluster reinvigorates a colonial logic that leaves what Ann Laura Stoler calls “deep pressure points”, an “enduring fissure, a durable mark” in the colonial present (2016: 6). Stoler invites us to consider the heavy duress of imperial governance, the material burdens of “policies, visions, institutions, and practices” that are targeted at the “containment of people” (2016: 82). It is just such deep and enduring fissures of colonial power that are inscribed through the logics of the cluster as it writes the boundaries of groups and communities into being.

5. Conclusion: the line of best fit

The deep border that has been the focus of this lecture and essay does not signal primarily the deployment of machine learning technologies *at the border*, or at least not some instrumental notion of the causal agency of machinic or autonomous borders. Rather, I have sought to foreground the deep border as world-making, or as a means of reordering *what the border is*, what it could be, and how it imagines and bounds political community. The condition of possibility for a deep border has emerged from a specific set of resonances across computer science epistemologies and the twenty-first century state’s ambition for a border that penetrates the very attributes of society. To be clear, I am not suggesting that the logics are of the same order ontologically – so, a feature space is not the same thing as a border space, nor is a cluster in deep learning the same thing as a social grouping or political community. Though these concepts mean very distinct things in the world, however, I suggest that there is a conjoining of their logics, a resonance in their epistemic orders. Whilst the ‘deep’ in deep learning is not instrumentally transposed to the state as a bordering device, there is nonetheless a mutually productive slippage and elision in their formulation. When computer science constructs deep neural networks for addressing difficult computational problems, it is the depth of the hidden layers that is

[9] To be clear, it is not the case that bodies cease to be the site of much of what Saidiya Hartman calls the “racial classificatory schema” where “much of the work is done”, but rather that machine learning technologies are rearticulating the corporeal acts she describes: “how it disposes of bodies, how it appropriates their products, and how it fixes them in a visual grid” (Hartman and Wilderson, 2003; see also; Hartman, 1997).

offered as the key to unlock the potential of mapped functions from high-dimensional data. The 'depth' is thus a representational device, a means of decomposing and recomposing complex wholes from multi-layered connected parts.

It is precisely this layered sense of compositional and representational capacities to address difficult problems that has proffered to the state a promise of resolving the political difficulties that are borders. Borders have undecidable and irresolvable politics precisely because they are founded upon sovereign fictions of territory and bounded political community (Elden, 2009). When the deep border enters the writing of sovereign fictions of the border line it actively profits from the instability and provisionality of the line, not only in the direct sense of the commercial profit of outsourced borders to Palantir or Accenture (Amoore, 2013, 2020, 2020), but because it requires turbulent features in order to map a function or to secure an output. In short, at the deep border a function is always mappable, even amid the most violent or volatile of spaces.

The development of machine learning is replete with practices of partitioning, segmenting, dividing, and demarcating. One might say that deep learning itself enacts bordering in the sense that it inscribes boundaries and actively uses lines to advance learning. Machine learning uses the slope or the gradient of a line to capture an idea of "best fit". As Adrian Mackenzie has observed, "the importance of lines can hardly be under-estimated in machine learning", and "finding lines of best fit underpins many of the machine learners" (2017: 63). It is the *equation of a line* that captures and defines the function and the mapping of inputs and outputs. Here once more the computer science episteme of lines of best fit appears to invite the state to imagine the border line as a potential line of best fit, an experimental gradient written through a deep reach into databases.

When a border is imagined through the lens of depth, features, and clusters it becomes a line of best fit. This line of best fit imagines a world where the fraught politics of the border can be condensed and resolved, where the machine learning function displaces the democratic function. Moreover, the border line of best fit represents itself as objectively emerging from a non pre-programmed process that allies 'best fit' with a fit to the world or data-world. There is a lightness and a refusal of political difficulty in the deep border's proposition of a line of best fit to the world. Every claim at the border is rendered legible and resolvable via the features and clusters of the model. Paradoxically, the deep border disavows depth, at least in the sense of the densely intractable violences of our world. In her depiction of the contrasting modes of "deep" and "hyper" attention, N. Katherine Hayles suggests that depth and "close reading" is "essential for coping with complex phenomena", whilst computer-assisted "hyper attention" confers the "ability to move rapidly among different kinds of texts", different "information streams" (2012: 69). In its capacity to flatten and absorb the features of multiple different forms of data – biometric, biographical, transactional, sentiment analysis, social media, and so on – the deep border embraces the hyper attention Hayles describes, at the very same time as it forecloses and disavows the deep attention capable of attending to the material politics of the border, to the weight and difficulty of the actual texts and narratives of what takes place at the border.

The truth of the depth of the deep border, I suggest, is not to be found in some virtual reach into deep neural nets, but instead in the weight, the heaviness and the burden, the duress of border politics (Stoler, 2016). Amara Majeed continues to bear the weight of the deep border long after the state has issued its correction of a biometric error; The people in the Cox's Bazar camp continue to endure the fissures and violences of their refused claims (to non-refoulment, to protection from statelessness) long after the UNHCR has moved on to experimenting with a new model of human mobility. The politics of the border is not, could never be, reduced to the output of a deep learning model. There is a great deal at stake because the deep border not only forecloses the material space of the border but it also silences the political claims that are made there, and denies the potential of future claims not yet made. As Thomas Keenan reflects in the context of the shifting relations of technology and human rights, it is precisely when rights are "ungrounded" and "without pre-given subjects" that they may "overflow their original limitations" and "spread far beyond their prescribed borders" (2015: 14). In Keenan's political analysis, in order for rights claims to overflow and exceed their narrowly prescribed boundaries of who or what can count, the conditions have to be created for politics to "wash away the fixed features" of a political landscape (2015: 16). This matters greatly for any broad notion of a right to mobility because the fixed features and rules governing the movement of human bodies have to be contestable, it has to be possible to respond to a claim without the fixed features or co-ordinates of normal or legitimate or compliant border claims.[10] The deep border permits no feature to be washed away, every feature must be rendered available for potential use. In response, it will be necessary to insist upon the overflow Keenan describes, to assert the claims that refuse to be governed by the line of best fit. To resist the deep border will require an appreciation that its power extends beyond applying machine learning at the border and into epistemic forms that live on even after a technology is withdrawn. And it will require plural refusals of the world-making of borders as feature spaces and clusters. Every trace of the rejected alternative pathway in the deep neural net could mean something else, and every silenced narrative of border duress could be spoken against the grain of the model. There is no line of best fit to the world, and there must be no border line of best fit.

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No conflicts of interest.

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[10] For a detailed account of what one potential route to resistance could look like, Ramon Amaro and Murad Khan's work on a "calculus of variations" moves towards refusing the racial corporeal schema. As they describe, a "purposeful misrecognition of the dominant mode of racial individuation" might "bring forth new ideas of what it means to be Black in a world regulated by the substance of race" (Amaro & Khan, 2020: 6).

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