EXPLAINABILITY FOR IDENTIFICATION OF VULNERABLE GROUPS IN MACHINE LEARNING MODELS

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ABSTRACT

If a prediction model identifies vulnerable individuals or groups, the use of that model may become an ethical issue. But can we know that this is what a model does? Machine learning fairness as a field is focused on the just treatment of individuals and groups under information processing with machine learning methods. While considerable attention has been given to mitigating discrimination of protected groups, vulnerable groups have not received the same attention. Unlike protected groups, which can be regarded as always vulnerable, a vulnerable group may be vulnerable in one context but not in another. This raises new challenges on how and when to protect vulnerable individuals and groups under machine learning. Methods from explainable artificial intelligence (XAI), in contrast, do consider more contextual issues and are concerned with answering the question “why was this decision made?” Neither existing fairness nor existing explainability methods allow us to ascertain if a prediction model identifies vulnerability. We discuss this problem and propose approaches for analysing prediction models in this respect.

1 Introduction

Algorithmic fairness has grown as a sub-discipline in artificial intelligence (AI) and data science to address the ethical and legal issues that arise with algorithms being involved in decision making, classification, pattern identification and prediction (Barocas et al., 2019; Rodolfa et al., 2020). The primary ethical concern with algorithmic decision-making is to ensure that using machines to make or aid decisions does not negatively impact the ethical values of justice, autonomy and non-maleficence we want to follow as humanity (Floridi and Cowls, 2019).

In decision-making that involves some type of resource allocation, such as jobs, grades, loans, etc., the law affords special protections to protected groups, typically characterised by an identifying feature that one cannot change, such as race or a minority background. Within algorithmic fairness, group fairness research and engineering is concerned specifically with identifying protected groups and requiring that (approximate) parity of some statistical measure across all of these groups is maintained (Chouldechova and Roth, 2020). Thus, group fairness indirectly seeks to ensure that automated decisions are not contingent on the membership to the protected group.

Beyond automated decision-making for resource allocation, machine learning is increasingly used to predict the behaviour and personality traits of individuals from their digital traces, see for example (Kosinski et al., 2013; Thieme et al., 2020). These predictions are then used to make decisions about people, decisions that include resource allocation and also tailoring of services and offers (Slavkovik et al., 2021). In some contexts and for some groups this pattern matching can be unethical to use, particularly when a vulnerable group of people is being identified from their digital traces with the purpose of exploiting their vulnerability. Such use directly violates the ethical principles of justice, autonomy and non-maleficence.

Vulnerable groups are recognised for protection under international human rights law Nifosi-Sutton (2017). Vulnerability signifies an actual or potential exposure to harm and as such, this term can potentially encompass anyone, given the right situation. Thus, the definition of a vulnerable group is context-dependent and thus the number of vulnerable groups and ways to exploit them is practically infinite. This makes the identification of a vulnerability for a particular
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context challenging. As Rodrigues Rodrigues (2020) observes, “while the technical solutions proposed thus, are good steps forward there have been many calls to pay greater regulatory, policy and ethical attention to fairness, especially in terms of protection of vulnerable and marginalised populations”.

We are here concerned with the problem of machine learning being used for the purpose of exploiting the vulnerability of a vulnerable group of people. Specifically, we ask the question: **how can you tell that a prediction model identifies a vulnerability?** Although this question concerns fairness in treatment of groups (it is unfair to exploit vulnerabilities), its answer cannot be tackled using existing group fairness measures and definitions, since these compare distributions of classifications between groups Mehrabi et al. (2019). Although this question concerns understanding what a machine learning trained model actually does, its answer cannot be tackled by methods of explainable artificial intelligence (XAI) either (Barredo Arrieta et al., 2020; Stepin et al., 2021; Burkart and Huber, 2021; Islam et al., 2021; Winfield et al., 2021).

To demonstrate that machine learning models have the power to identify vulnerable groups, we give an overview of the state of the art in machine learning use in psychology for the purpose of identifying people with specific mental health issues and properties. We focus on those mental states for which it is easy to see that they can under some circumstances constitute a vulnerability. We do not intend this survey to constitute a judgment on what is or is not a vulnerability. We discuss what fairness and explainability are today as tools for achieving ethical AI and discuss why they do not offer sufficient protection against the abuse of vulnerabilities. We propose approaches to comparing machine learning models and discuss their applicability. We intend for the proposed approach to act as substitute while no XAI methods capable of directly addressing the problem of identifying modelled vulnerability exist.

We consider that our work directly contributes to improving the transparency of ML models. Additionally our contributions to AI ethics are

1. a motivation for XAI not previously addressed,
2. a motivation to expand fairness research towards concerns for vulnerable groups,
3. an initial approach towards addressing the possible misuse of ML models for exploiting vulnerable groups.

The paper is structured as follows. In section 2, we define vulnerability for our context and discuss the literature analysing machine learning methods for identifying vulnerability. In section 3, we give a brief introduction to fairness in machine learning and how this relates to modelling vulnerability. We also briefly introduce XAI, and discuss the necessary capabilities of an XAI method for assessing vulnerability fairness. Arguing that no XAI method with the necessary capabilities presently exists, we propose a subsidiary method in section 4. Finally, we summarize our work in section 5 and propose future studies.

## 2 State of machine learning and vulnerability

To understand the possible impact that machine learning can have on identifying and exploiting vulnerable groups, we need to fix a definition of vulnerability and understand the capabilities of machine learning and big data in identifying vulnerable groups.

**Vulnerability:** We define, for the purposes of this article, a vulnerable group as follows. A vulnerable group, or a group at risk, is a group of people for which there is a good reason to suspect that its members have special difficulty in making autonomous choices or are not in full control of their actions. It is “the quality or state of being exposed to the possibility of being attacked or harmed, either physically or emotionally.” (Lexico lex (2022)). For this reason, the vulnerable groups can be potentially exposed to additional forms of harm. An intuitive example of a vulnerable group are children.

### 2.1 Social media data for assessing mental health

Already in 1982, Oxman et al. Oxman et al. (1982) showed that patients could be classified into groups suffering from depression and paranoia based on linguistic speech analysis. Most forms of mental health disorders cannot be reliably laboratory tested, and their diagnosis is usually based on self-reports made by the patient and a mental status examination (Martin, 1990). At the same time, an increasingly large body of literature supports that social media data can be – and is being – used directly to detect and predict mental disorders in individuals. The systematic review by Wongkoblap et al. (2017) and the more recent Aboureihani Mohammadi et al. (2020); Thieme et al. (2020), provide overviews of machine learning used to predict mental health from social network data, reporting that machine learning methods are increasingly replacing more traditional forms of data analysis.
At the same time, there is a tremendous increase in availability of relevant data, including data sets constructed exactly for the purpose of identifying mental health conditions. For instance, the large data set SMHD (Self-reported Mental Health Diagnoses) Cohan et al. (2018) contains social media posts from Reddit users with mental health conditions, matched with control users.

A variety of studies show that data from social media can be used to predict individual well-being (Schwartz et al., 2016) as well as future mental illness (Thorstad and Wolff, 2019). Particularly well explored is depression (De Choudhury et al., 2013; Schwartz et al., 2014; Orabi et al., 2018; Eichstaedt et al., 2018; Tadesse et al., 2019; Alghamdi et al., 2020), including self-harm (Yates et al., 2017), and anorexia (Ramírez-Cifuentes and Freire, 2018). Quantifiable signals in Twitter data relevant to bipolar disorder, major depressive disorder, post-traumatic-stress disorder and seasonal affective disorder were demonstrated by Coppersmith et al. (2014), who constructed data-based models capable of separating diagnosed from control users for each disorder.

While data based tools assessing mental health can certainly be used to help vulnerable individuals – suicide prevention tools have for instance been available on Facebook for more than ten years (Callison-Burch et al., 2017) – their existence raises several concerns: The general desirability of subsequent interventions has not been democratically agreed upon. Whether the use of data for this purpose can really be characterised as voluntary for Facebook users is not clear, as evidenced by e.g. the public dispute of the study ‘Experimental Evidence of Massive-Scale Emotional Contagion Through Social Networks’ (Kramer et al., 2014), including its editorial expression of concern. Showing that social media data can be used for emotional contagion – “leading people to experience (…) emotions without their awareness” –, this study together with the existing body of literature lead to the conclusion that not only can data and machine learning models be used to detect emotional states and mental health conditions, but that such models are already being successfully developed.

### 2.2 Mental health as an exploitable vulnerability

While it is difficult – and outside our aim – to analyse the underlying causal patterns, depression and anxiety, including individuals having a negative view of themselves, coincide with mental conditions that lead to compulsive behaviours. For example, Lejoeux et al. (1997) conclude that “Compulsive buying is frequent among depressed patients. In most cases, the behavior is associated with other impulse control disorders or dependence disorders and a high level of impulsivity.”, and similarly, Lejoeux et al. (2002) conclude that “Our data emphasizes the frequency of association between ICDs (impulse control disorders) and major depression, and 29% of the depressed patients also had an ICD”. Shopping as a coping behavior for stress also is investigated in Hama (2001), who report that “more stress release was found with larger amounts spent …”. McElroy et al. (1996) state that “Although no studies directly compare a cohort of ICD patients with a cohort of mood disorder patients, available data suggest that ICDs and bipolar disorder share a number of features: (1) phenomenologic similarities, including harmful, dangerous, or pleasurable behaviors, impulsivity, and similar affective symptoms and dysregulation …”. These are exactly the kind of behaviours social media usage is likely to reflect, probably even before they are discovered clinically or by the individuals themselves (Eichstaedt et al., 2018).

This insight must be combined with the knowledge that data based models for identifying and predicting mental health are used for commercial purposes. For example, a leaked Facebook document reported by The Australian (ArsTechnica, 2017) revealed that the platform uses data based models to identify young, meaning down to 14 year old, individuals feeling vulnerable, i.e. “worthless”, “insecure”, “stressed”, “defeated”, “overwhelmed”, “anxious”, “nervous”, “stupid”, “silly”, “useless”, and “a failure”. Furthermore, the document, marked “Confidential: Internal Only”, outlines how Facebook can target “moments when young people need a confidence boost”, and reveals an interest in helping advertisers target moments in which young users desire “looking good and body confidence” or “working out and losing weight”.

As stated by Inkster et al. (2016): “A key ethics challenge for using social networking site data (…) will be to ensure that vulnerable individuals have a comprehensive and sustained understanding of what participation involves…”. We fully agree with this conclusion, and argue that most users of social platforms do indeed not have such a comprehensive and sustained understanding. Sadly, this is neither a novelty nor a controversial stance. However, we also argue that this problem exists on two levels, one level being the mere flow of information, or desire of social media platforms to
inform users of how their data is being used. The second level is more subtle as well as technical, since “understanding
of what participation involves” requires an understanding of the models used to analyse the data of the individual. Such
understanding of non-interpretable models is at present often not possible, commonly referred to as the “black box”
problem in machine learning and artificial intelligence.

This must be considered in light of the observation that the reviews quoted in the beginning of this section – (Wongkoblap
et al., 2017; Aboureihani Mohammadi et al., 2020), reporting the general tendency of machine learning methods
replacing traditional forms of data analysis – consequently report an increase in non-interpretable models being used to
detect mental health disorders.

3 Shortcomings of fairness in XAI

3.1 Fairness in AI

Fairness in artificial intelligence is concerned with protecting the ethical value of justice. The justice principle is
centered around how people are treated and embodies the idea that decisions about individuals should be based on just
arguments, the consequence of which is that similar people are treated similarly. Justice also embodies the concern that
members of a group are not discriminated against in resource allocation, but also in how they are represented in a wider
context (Miller, 2021). For example, having persistent unjust negative portrayal of groups in the public sphere gives
rise to representational harms when those negative portrayals are embedded in machine learning models Abbasi et al.
(2019).

Fairness in machine learning has been particularly concerned with classification by supervised learning algorithms
when applied to decision-making about, or, involving people. Fair machine learning as a discipline studies how to
identify, avoid, and mitigate unjust discrimination in allocating a desirable resource with classification (Chouldechova
and Roth, 2020). Group fairness in particular is concerned with ensuring that decisions to recommend allocating of a
resource, such as for example a job interview, are not directly or indirectly biased with respect to a legally protected
feature of the applicant, such for example race.

The existing definitions of machine learning fairness compare, in some way, the amount of desirable allocations among
groups identified by some, typically protected, features (Verma and Rubin, 2018). A notable shortcoming of these
definitions is that an individual cannot know whether fairness in the sense of such definition is satisfied. This is because
each individual only has access to their own decision, or classifications, and almost never to all the decisions. The latter
is necessary to establish whether any of the group fairness definitions hold. Furthermore the group fairness definitions
do not capture context: while a race of a person does not change, a person may be part of a group that can be vulnerable
to discrimination in some context or for some duration, but not in another context or outside of a time period. Examples
of features that identify groups in this later sense are those that correlate with temporary mental or physical impairments.

We are connecting fairness in machine learning and XAI, because we are looking to further the protection of the ethical
principle of justice as well as other ethical principles that can be of concern, such as autonomy and non-maleficence.
The fundamental question of fairness is “Is a particular group in treated unjustly or harmed?”. The group in question
can be defined by protected attributes, such as race, religion, gender, etc. In addition, groups can also be characterised
by vulnerability, which is not defined in terms of protected attributes, or otherwise defined by law, and consequently
not easily identified. What we do know, however, is that both protected and vulnerable groups are being identified by
AI models. Our fairness question in the following is thus are vulnerable people being targeted disproportionately?,
regardless of whether the vulnerability in question is due to belonging to a protected group or whether it exists in some
contexts but not in others.

In machine learning, a dataset is a collection of phenomena described by characterising feature values; each data point
corresponds to one phenomenon represented by the same features. A data set is labeled if each data point is assigned
a label, which can be either a subset of a finite set of possible classes or a continuous value. In supervised machine
learning, a prediction model is trained using labeled data. The prediction model associates, hopefully with a high degree
of certainty, the feature values, and correlations among these, of a phenomenon with a class. The literature overview
in section 2 evidences that machine learning can be used to train prediction models that associate individuals with a
variety of psychological traits. This directly creates the possibility to build prediction models that identify vulnerable
individuals.

It is easy to argue that prediction models that identify vulnerable individuals or members of vulnerable groups should
not be pursued1. While the question of whether machine learning or any AI-based method should all be used to
identify vulnerable people is outside our scope, we are concerned with the problem of how we can ascertain whether

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1See for example Wang and Kosinski (2018) and the challenges raised by ethicists and by computer scientists.
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A particular prediction model does in actuality identify vulnerable individuals or groups. A model can identify vulnerable groups or individuals accidentally, or deliberately in order to exploit their vulnerability. Both accidental and deliberate identification in such prediction models can lead to a violation of at least the ethical principles of justice, non-maleficence and autonomy.

3.2 Explainable artificial intelligence (XAI)

As large, complex, and non-interpretable machine learning models have become popular, the field of XAI has gained increased interest in the machine learning research community and literature. Its aim is to increase the amount of information available from a given AI system in a way that is understandable by humans. The technical challenge in explaining machine learning models to humans is that the former generate their results by operating on high dimensional correlations that are beyond the interpretive capabilities of human scale reasoning (Leslie, 2019).

While the need for explainability has become apparent and widely addressed with the recent rise in popularity of machine learning based systems, the relevance of explainability is not limited to machine learning models. Although XAI did not crystallise as a field until fairly recently Gunning and Aha (2019), the non-interpretable nature of AI systems has long been a cause of concern. For example, this concern – then for the dominant AI system on the market, the expert systems – was addressed in 1985 by Bell (1985), stating that it is problematic when “the problem [expert systems] are dealing with is not or cannot be understood”.

A number of surveys on XAI are available, and the interested reader is recommended Barredo Arrieta et al. (2020). However, despite a large number of surveys and an increased interest in the field, no common consensus has been reached regarding benchmarks, approaches, or even terminology. Terms such as ‘explainability’, ‘explicability’, ‘transparency’, and ‘interpretability’ are often used interchangeably. We do not contribute to the discussion on terminology, but instead use the term ‘explainability’ throughout, and follow the definition by Miller (2019): Explainable AI refers to an explanatory agent revealing underlying causes to its or another agent’s decision making.

Explainability is highly relevant for safety critical applications, including autonomous systems (Danks and London, 2017) and medical applications (Aman et al., 2020), where erroneous decisions can potentially be fatal, for accountability (Kroll, 2015; Breidbach and Maglio, 2020) and liability (Kingston, 2016). Another commonly cited motivation for producing explanations is the General Data Protection Regulation (GDPR), where the explanation requirement is specifically aimed at individuals whose data are processed. However, we argue that explainability is not limited to areas governed by law, privacy sensitive applications or applications where accountability must obviously be managed: The AI community must address that vulnerable people can be and are being targeted – as evidenced by the large body of literature demonstrating that machine learning can be used on non-privacy protected and publicly available data to reveal mental illness, mental disorders, and other vulnerabilities in individuals. The process of addressing this must involve developing XAI methods detecting when and which vulnerabilities are being exploited. In particular, such XAI methods must

1. explain which features and exact combination of features characterise the different groups the model identifies,
2. explain the model’s latent features in such a way that these can be compared directly to psychological traits.

This information can then be combined with information from psychology to assess whether the model has modelled vulnerability. However, no XAI methods with the capabilities described above exist as of today, and the second point might even require creating concepts we humans do not have. We therefore propose a subsidiary methodology that can be used and developed further while the XAI community addresses these challenges. Our proposed methodology is detailed in section 4, and is based on comparison of models.

4 Proposed approach

Vulnerability is not directly represented by data features, and must thus be deduced. While age is something that can be a data feature, human beings don’t have e.g. “depression” written somewhere on their body, and no single behaviour is directly related to depression. Psychological conditions that can form the base for vulnerability are ascertained by psychologist who in turn have to use self-reported feelings and behavioural tendencies to find out whether a person has a mental illness or vulnerability – or a machine learning model can use data containing language or behavioural patterns to construct latent features representing mental illness or vulnerability in a person. However, if a model is

Note, however, that it is not clear what the GDPR’s right to an explanation implies (Edwards and Veale, 2017; Wachter et al., 2017; Selbst and Powles, 2017).
not specifically constructed to detect a vulnerability, how can we be sure that it hasn’t constructed latent features representing vulnerability, and exploits these to achieve its goal?

4.1 Comparing models

We here discuss how models can be “semantically” compared. Assume that we want to know whether a given prediction model identifies individuals from the vulnerable group of individuals $V$. One way to check is by constructing a dataset using the characterizing features that the model is trained on, from both members of group $V$ and non-members of $V$. We can then set thresholds $\epsilon_1$ and $\epsilon_2$, and check whether at least $\epsilon_1\%$ of the group $V$ members are assigned the same label and at most $\epsilon_2\%$ of the non-group $V$ members are assigned it. This test is intuitive, but not practical.

Building data sets is expensive, especially under requirements such as the ones we need here. We need for example that the data set is representative of a specific group which is identified by a psychological condition that cannot be tested for. This cost of data set building increases for every vulnerable group we would like to check, which could potentially be a large number. Instead of building data sets to perform a test of the sort just described, we therefore suggest a different approach, involving one model per vulnerability or combination of vulnerabilities of interest, as defined in the following.

Model $A$ deliberately identifies personality traits that identify members of a particular vulnerable group $V$ by assigning label $a_1$ to individuals that have those traits and $a_2$ to individuals that do not have them. Model $B$ is the model under scrutiny, that potentially identifies members of group $V$. For simplicity, we assume that model $B$ also does binary classification and assigns labels $b_1$ and $b_2$. We can then compare directly how many of the individuals $V$ who were assigned label $a_1$ by $A$ are also assigned the corresponding label $b_1$ by $B$. The method is depicted in fig. 1. Note that the features each model is trained on (the blue and purple in fig. 1) need not be the same in order to give the two models the same information about an individual’s vulnerability; most behavioural data are proxy variables.

We illustrate this method using a constructed but not unrealistic example: Model $A$ can be designed to use data from a platform such as Facebook to identify whether a user has an ICD (impulse control disorder), i.e. $a_1$ denotes having an ICD and $a_2$ denotes being unlikely to have an ICD. Model $B$ can be a commercially applied model for targeted advertisement on the same platform, labelling $b_1$ users that are likely to buy a certain product, and $b_2$ users that are not likely to buy the product. If, upon comparison of models $A$ and $B$, a large number of users labelled $a_1$ are also labelled $b_1$, we can conclude that it is likely that model $B$ is in fact exploiting the vulnerability detected using model $A$, in this case ICD.

We assume that we can find a trained model $A$ that we know identifies a particular group of people considered vulnerable in a given context. Specifically, model $A$ assigns a positive label to the individuals that belong to group $V$ and a negative label to the individuals that do not. We now want to compare a model $B$ to model $A$, assuming for simplicity that model $B$ also performs a binary classification of membership of some group $X$. We define:

- The true positive set $TP_V$: the set of cases (individuals) for which a predicted belonging to $V$ by $A$ overlaps with actual belonging to $V$;
- The false positive set $FP_V$: the set of cases (individuals) for which a predicted belonging to $V$ by $A$ overlaps with actually not belonging to $V$;
- The true positive set $TP_X$: the set of cases (individuals) for which a predicted belonging to $X$ by $B$ overlaps with actual belonging to $X$;
- The false positive set $FP_X$: the set of cases (individuals) for which a predicted belonging to $X$ by $B$ overlaps with actually not belonging to $X$;
- The margin $\epsilon$, a small real number.

We can now define the following classifier independence notions. To study whether classifier $A$ is independent from classifier $B$, given an individual $i$ that has been labeled both by $A$ and $B$, we consider the following conditional probabilities

\[
P(i \in TP_X \mid i \in TP_V) = \frac{P(i \in TP_X \cap TP_V)}{P(i \in TP_V)} \leq \epsilon \quad (1)
\]

\[
P(i \in TP_X \cup FP_X \mid i \in TP_V) = \frac{P(i \in (TP_X \cup FP_X) \cap TP_V)}{P(i \in TP_V)} \leq \epsilon \quad (2)
\]

\[
P(i \in TP_X \cup FP_X \mid i \in TP_V \cup FP_V) = \frac{P(i \in (TP_X \cup FP_X) \cap (TP_V \cup FP_V))}{P(i \in TP_V \cup FP_V)} \leq \epsilon \quad (3)
\]

Eq. (1) requires that the probability of an instance being correctly assigned to the group $X$ by model $B$ conditional upon it being correctly assigned to the vulnerable group $V$ by $A$ be at most $\epsilon$. In order to use this requirement, the actual
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member of the vulnerable group \( V \) as well as of the group \( X \) must be known. Especially for a loosely defined group, such as a target group for an advertisement, the latter might be difficult to faithfully represent.

Eq. (2), on the other hand, requires that the probability of an instance being assigned – correctly or not – to the group \( X \) by model \( B \) conditional upon it being correctly assigned to the vulnerable group \( V \) by \( A \) is at most \( \epsilon \). The use of this requirement only depends on knowing the actual membership of the vulnerable group \( V \), as all instances classified as positive by model \( B \) are counted.

To summarise, both Eqs. (1) and (2) require knowing true labels, i.e. in this case actual class membership. Furthermore, being conditional upon only cases where model \( A \) correctly identifies positive membership of the class \( V \) could amount to an over-reliance on the correctness of this model.

In contrast, Eq. (3) requires that the probability of an instance being assigned to the group \( X \) by model \( B \) conditional upon it being assigned to the vulnerable group \( V \) by \( A \) be at most \( \epsilon \). Using this requirement does not rely on knowing the actual membership of either group \( V \) or \( X \), as it only counts positive classifications from both models: It measures the probability of model \( B \) doing a positive classification, conditional upon \( A \) doing a positive classification. This method can thus be applied given access merely to model \( A \), and not labelled data describing vulnerable individuals, which is favourable especially from a privacy perspective.

A note on the threshold value \( \epsilon \): Ultimately, empirical research is needed to identify a good value for this parameter. Clearly, a smaller \( \epsilon \) corresponds to a smaller tolerance for differences between the compared models, which translates to an increased chance of not catching the model identifying vulnerable groups. On the other hand, a large tolerance may result in too many models being flagged. The appropriate choice of \( \epsilon \) depends on the kind of users on the platform or represented in the data of model \( B \).

Lastly, our proposed method of comparing models does not fulfill any of the requirements in the list in section 3.2: it is not an XAI method, and it does not explain which features characterise the different groups identified by model \( B \) nor what are the latent features of model \( B \). Instead, it relies upon the assumption that model \( A \) has correctly modelled vulnerability, and that any model which behaves similarly to model \( A \) is consequently likely to have modelled vulnerability as well.

Figure 1: The model \( A \) (top, purple), known to identify vulnerable individuals, can be used to test whether model \( B \) (bottom blue), developed for some other purpose, is likely to have modelled vulnerability in individuals in order to achieve its objective. We want to check whether the classifications done by the two models are statistically dependent, and details are described in the text.
4.2 Traditional methods

For completeness, we briefly outline how we see traditional fairness and XAI methods can be used to assess whether model $B$ is likely to exploit vulnerability, provided model $A$.

**Fairness.** Given that the the training data for model $B$ is available, we can add a vulnerability column. This additional feature is a Boolean “vulnerability feature” (or indicator) whose value is true when the individual represented by the data point is labeled by model $A$ as member of group $V$ and false otherwise. A new model $B'$ is trained on this extended data set, and we can use standard fairness definitions (Verma and Rubin, 2018) to check whether model $B'$ shows a bias with respect to the vulnerability feature, which for the sake of the test plays the role of a protected attribute.

**XAI.** If there exists an overlap between the features used to train models $A$ and $B$, then we can use traditional XAI methods to obtain attributive explanations (Štrumbelj and Kononenko, 2014; Datta et al., 2016; Shrikumar et al., 2016) for both models. Attributive explanations aim to answer the question “to which extent have the different features contributed to the outcome of the model?” If we observe that the two models attribute similar importance to the same features, we can regard it as likely that the two have modelled the same underlying properties, and would therefore identify the same individual(s).

4.3 Modelling vulnerability

We have to acknowledge the challenges associated with the creation and use of models of the kind denoted “model $A$” in this paper, namely models trained to identify a state that can constitute a vulnerability. The development of such models requires diagnostic, meaning sensitive and privacy protected, information about individuals. Hence there are many challenges and professional requirements that need to be met for safe and ethical handling and development of such models (Stachl et al., 2020).

It has been argued\(^3\) that models with such capabilities should not be developed due to the risk of abuse. However, we argue that the existence of models of type $B$, meaning models accidentally or covertly having the capabilities of identifying vulnerabilities, constitutes a far greater risk of abuse. This opens up a discussion on proportionality which is common in privacy law, and outside the scope of this paper. However, we wish to point out the interesting trade-off that arises as developing type $A$ models helps divulge type $B$ models, while focusing the attention on the difficult questions, including: Who should develop type $A$ models? Who should be trusted with using type $A$ models to test type $B$ models already deployed? Can type $A$ models be distributed, or does their containing latent features describing vulnerability force us to consider them as containing sensitive information?

We most adamantly do not intend to argue that all platforms using models trained on publicly available behavioral data should also ask their users to provide sensitive data about their mental health status, in order to develop type $A$ models for testing.

5 Summary and future work

We have discussed an approach for finding out whether a data based AI system exploits vulnerabilities, namely comparison to other systems built to model specific properties. Since no XAI method exists that can uncover which vulnerabilities - represented by latent features in a model - are being used to target individuals, we propose a substitute method. This method consists in comparing the model of scrutiny to one known to detect vulnerabilities. While we regard this and similar approaches as useful, they depend on systems modelling the specific properties being developed and available. The logical conclusion from this is that uncomfortable and controversial models, namely models trained to identify a state that can constitute a vulnerability, should indeed be developed, for use in comparisons such as the ones described in this paper, while no other methods that do not rely on comparison are available. We also conclude that addressing the overarching challenge of knowing which properties a system has modelled is an important focus for explainable artificial intelligence (XAI).

Beyond explainability, understanding when models are the same or different adds value to transparency. Until now, comparing two machine learning models has amounted to either comparing the efficiency of the models – see e.g. Naghibi and Pourghasemi (2015); Ahmed et al. (2010) – or the data on which they were trained. We expand upon this in this paper, and argue that since data sets are representations of the real world, then if two data sets represent the same phenomena, and models trained on them partition that phenomenon in the same way, those prediction models are in fact not different.

\(^3\)See for example Agüera y Arcas et al. (2022) for the discussion regarding ML use in detecting sexual orientation.
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The first line of further work is to explore the practical usability of our approach, and compare it with what we outline as traditional XAI and fairness approaches. This work is not without its challenges. We need to find a model that predicts a mental state or age (model A) and a model that predicts something else (model B). While the vast literature in machine learning and psychology might be hoped to contribute good choices for model A, models of type B would be much more difficult to find, as these do micro-targeting and are not likely to be released by companies. After model A and B have been found, individuals serving as appropriate subjects for providing data for classification from both models must be recruited. This in itself is work that is ethically sensitive and would require consultation with psychology experts, as well as proper ethical evaluation and approval before proceeding.

6 Acknowledgments

The authors thank Daniel Vidali Fryer for discussions about the conditional probabilities describing the independence of two classifiers. I. S. is grateful for support received by the Research Council of Norway and the industrial partners of the EXAIGON project (grant no. 304843).

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