From What to How: An Overview of AI Ethics Tools, Methods and Research to Translate Principles into Practices

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Statement of Funding: This research was funded by the Digital Catapult
Statement of Contribution: LK and LF contributed equally to this article

Abstract
The debate about the ethical implications of Artificial Intelligence dates from the 1960s (Wiener, 1960) (Samuel, 1960). However, in recent years symbolic AI has been complemented and sometimes replaced by (Deep) Neural Networks and Machine Learning (ML) techniques. This has vastly increased its potential utility and impact on society, with the consequence that the ethical debate has gone mainstream. Such a debate has primarily focused on principles—the ‘what’ of AI ethics (beneficence, non-maleficence, autonomy, justice and explicability)—rather than on practices, the ‘how.’ Awareness of the potential issues is increasing at a fast rate, but the AI community’s ability to take action to mitigate the associated risks is still at its infancy. Therefore, our intention in presenting this research is to contribute to closing the gap between principles and practices by constructing a typology that may help practically-minded developers ‘apply ethics’ at each stage of the pipeline, and to signal to researchers where further work is needed. The focus is exclusively on Machine Learning, but it is hoped that the results of this research may be easily applicable to other branches of AI. The article outlines the research method for creating this typology, the initial findings, and provides a summary of future research needs.
1. Introduction

As the availability of data on almost every aspect of life, and the sophistication of machine learning (ML) techniques, has increased (Lepri, Oliver, Letouzé, Pentland, & Vinck, 2018) so have the opportunities for improving both public and private life (Luciano Floridi & Taddeo, 2016). Society has greater control than it has ever had over outcomes related to: (1) who people can become; (2) what people can do; (3) what people can achieve; and (4) how people can interact with the world (Floridi and colleagues, 2018a). Yet, growing concerns about the ethical challenges posed by the increased use of ML in particular, and Artificial Intelligence (AI) more generally, in society, threaten to put a halt to the advancement of beneficial applications, including in data science (Mittelstadt, 2019), unless handled proportionately.

Balancing this tension between the need to support innovation, so that society’s right to benefit from science is protected (Knoppers & Thorogood, 2017), with the need to limit the potential harms associated with poorly-designed AI (and specifically ML in this context), (summarised in figure 1) is challenging. ML algorithms are powerful (Ananny & Crawford, 2018) socio-technical constructs that raise concerns that are as much (if not more) about people as they are about code (Crawford & Calo, 2016). Enabling the so-called dual advantage of ‘ethical ML’— so that the opportunities are capitalised on, whilst the harms are foreseen and minimised or prevented (Floridi and colleagues. 2018)—requires asking difficult questions about design, development, deployment, practices, uses and users, as well as the data that fuel the whole process (Cath, Zimmer, Lomborg, & Zevenbergen, 2018). Lessig was right all along: code is both our greatest threat and our greatest promise (Lessig, 2006).

| Ethical Concern          | Explanation                                                                                                                                 |
|-------------------------|---------------------------------------------------------------------------------------------------------------------------------------------|
| Inconclusive Evidence   | Algorithmic conclusions are probabilities and therefore not infallible. This can lead to unjustified actions. For example, an algorithm used to assess credit worthiness could be accurate 99% of the time, but this would still mean that one out of a hundred applicants would be denied credit wrongly. |
| Inscrutable Evidence    | A lack of interpretability and transparency can lead to algorithmic systems that are hard to control, monitor, and correct. This is the commonly cited ‘black-box’ issue. |
| Misguided Evidence      | Conclusions can only be as reliable (but also as neutral) as the data they are based on, and this can lead to bias. For example, Dressel & Farid, 2018 found that the COMPAS recidivism algorithm commonly used in pretrial, parole, and sentencing decisions in the United States, is no more accurate or fair than predictions made by people with little or no criminal justice expertise. |
| Unfair outcomes         | An action could be found to be discriminatory if it has a disproportionate impact on one group of people. For instance, Selbst, 2017 articulates how the adoption of predictive policing tools is leading to more people of colour being arrested, jailed or physically harmed by police. |
| Transformative effects  | Algorithmic activities, like profiling, can lead to challenges for autonomy and informational privacy. For example, Polykalas & Prezerakos, 2019 examined the level of access required to personal data by more than 1000 apps listed in the ‘most popular’ free and paid for categories on the Google Play Store. They found that free |
Apps requested significantly more data than paid-for apps, suggested that the business model of these ‘free’ apps is the exploitation of the personal data.

Traceability: It is hard to assign responsibility to algorithmic harms and this can lead to issues with moral responsibility. For example, it may be unclear who (or indeed what) is responsible for autonomous car fatalities. An in-depth ethical analysis of this specific issue is provided by (Hevelke & Nida-Rümelin, 2015).

Figure 1: Ethical concerns related to algorithmic use based on the ‘map’ created by Mittelstadt and colleagues (2016).

This might seem like an incredibly tall order. However, rising to the challenge is both essential and possible. Indeed, those that claim that it is impossible are falling foul of the is-ism fallacy where they confuse the way things are with the way things can be (Lessig 2006), or indeed should be. It is possible to design an algorithmically-enhanced society pro-ethically1 (Floridi 2017b), so that it protects the values, principles, and ethics that society thinks are fundamental (Floridi 2018). This is the message that social scientists, ethicists, philosophers, policymakers, technologists and civil society have been delivering in a collective call for the development of appropriate governance mechanisms (D’Agostino & Durante, 2018) that will enable society to capitalise on the opportunities, whilst ensuring that human rights are respected (Luciano Floridi & Taddeo, 2016), and fair and ethical decision-making is maintained (Lipton, 2016).

The purpose of the following pages is to highlight the part that technologists, or ML developers, can take in this broader conversation. Specifically, section 2 discusses how efforts to date have been too focused on the ‘what’ of ethical AI (i.e. debates about principles and codes of conduct) and not enough on the ‘how’ of applied ethics. Section 3 outlines the research planned to contribute to closing this gap between principles and practice through the creation of an ‘applied ethical AI typology’, and the methodology for its creation. Section 4, summarises what the typology shows about the low availability and maturity, as well as skewed distribution, of tools and methodologies available for practical AI ethics. Section 5, argues that there is a need for a more coordinated effort, from multi-disciplinary researchers, innovators, policymakers, citizens, developers and designers, to create and evaluate new tools and methodologies, in order to ensure that there is a ‘how’ for every ‘what’ at each stage of the Machine Learning pipeline. Finally, section 6, concludes that this will be challenging to achieve, but it would be imprudent not to try.

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1 The difference between ethics by design and pro-ethical design is the following: ethics by design can be paternalistic in ways that constrain the choices of agents, because it makes some options less easily available or not at all; instead, pro-ethical design still forces agents to make choices, but this time the nudge is less paternalistic because it does not preclude a course of action but requires agents to make up their mind about it. A simple example can clarify the difference. A speed camera is a form of nudging (drivers should respect the speed limits) but it is pro-ethical insofar as it leaves to the drivers the freedom to choose to pay a ticket, for example in case of an emergency. On the contrary, in terms of ethics by design, speed bumps are a different kind of traffic calming measure designed to slow down vehicles and improve safety. They may seem like a good idea, but they involve a physical alteration of the road, which is permanent and leaves no real choice to the driver. This means that emergency vehicles, such as a medical ambulance, a police car, or a fire engine, must also slow down, even when responding to an emergency.
2. Moving from Principles to Practice

As the call for ‘AI governance’ has got louder, the number of available Ethical Codes of Practice for AI has increased. Currently (April 2019), there are at least 70 publicly available sets of ethical principles and frameworks for AI. The list includes documents produced by industry (Google, IBM, Microsoft, Intel), Government (Montreal Declaration, Lords Select Committee, European Commission’s High-Level Expert Group), and academia (Future of Life Institute, IEEE, AI4People). The hope is that these principles, as abstractions (Anderson & Anderson, 2018), can act as normative constraints (Turilli, 2007) on the ‘do’s’ and ‘don’ts’ of algorithmic use in society. This is a worthwhile aim, and a necessary building block in the creation of an environment that fosters ethical, responsible, and beneficial AI. However, the mere existence of these principles does little to bring about actual change in the design of algorithmic systems, leading to accusations of ‘ethics washing’ and feelings of ‘ethics fatigue’ (Floridi, 2019).

The issue is that, whilst these principles—which (at least in Europe) are largely based on the bioethical principles of beneficence, non-maleficence, justice and autonomy, and the concept of ‘explicability’ (Floridi and colleagues, 2018)—provide a useful framework for what ethical AI looks like, they do not tell developers how to design it. The gap between principles and practice is simply too large. This is risky: unless mechanisms are developed to close this gap, the lack of guidance may (a) result in the costs of ethical mistakes outweighing the benefits of ethical successes (even a single critical ‘AI scandal’ could stifle innovation); (b) undermine public acceptance of

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1 See these two repositories: Algorithm Watch. The AI Ethics Guidelines Global Inventory © April 2019: https://algorithmwatch.org/en/project/ai-ethics-guidelines-global-inventory/ and Winfield, A. (18 April 2019): An Updated Round Up of Ethical Principles of Robotics and AI. http://alanwinfield.blogspot.com/2019/04/an-updated-round-up-of-ethical.html

2 Google's AI Principles: https://www.blog.google/technology/ai/ai-principles/

3 IBM's everyday ethics for AI: https://www.ibm.com/watson/assets/dau/pdf/everydayethics.pdf

4 Microsoft's guidelines for conversational bots: https://www.microsoft.com/en-us/research/uploads/prod/2018/11/Bot_Guidelines_Nov_2018.pdf

5 Intel's recommendations for public policy principles on AI: https://blogs.intel.com/policy/2017/10/18/naveen-rao-announces-intel-ai-public-policy/

6 The Montreal Declaration for Responsible AI: https://www.montrealdeclaration-responsibleai.com/the-declaration

7 House of Lords Select Committee on Artificial Intelligence: AI in the UK: ready, willing and able?: https://publications.parliament.uk/pa/ld201719/ldselect/ldarti/100/100.pdf

8 European Commission’s Ethics Guidelines for Trustworthy AI: https://ec.europa.eu/futurium/en/ai-alliance-consultation/guidelines

9 Future of Life’s Asilomar AI Principles: https://futureoflife.org/ai-principles/

10 IEEE General Principles of Ethical Autonomous and Intelligent Systems: http://alanwinfield.blogspot.com/2019/04/an-updated-round-up-of-ethical.html

11 Floridi, L. and colleagues. AI4People—An Ethical Framework for a Good AI Society: Opportunities, Risks, Principles, and Recommendations. Minds and Machines 28, 689-707, doi:10.1007/s11023-018-9482-5 (2018).
algorithmic systems; (c) reduce adoption of algorithmic systems; and (d) ultimately create a scenario in which society incurs significant opportunity costs (Cookson, 2018).

Avoiding these opportunity costs is crucial, and so the social need for means of translating between the ‘what’ (ethical principles) and the ‘how’ (technical requirements) (Dignum, 2017) is growing. Complexity, variability, subjectivity, and lack of standardisation, including variable interpretation of the ‘components’ of each of the ethical principles, make this challenging (Alshammari & Simpson, 2017). However, it is achievable if the right questions are asked (Green, 2018);(Wachter, Mittelstadt, & Floridi, 2017a) and closer attention is payed to how the design process can influence (Kroll, 2018) whether an algorithm is more or less ‘ethically-aligned.’ Thus, this is the aim of this research project: to identify the methods and tools available to help developers, engineers and designers of ML specifically (but we hope the results of the this research may be easily applicable to other branches of AI) reflect on and apply ‘ethics’ (Adamson, Havens, & Chatila, 2019) so that they may know not only what to do or not to do, but also how to do it, or avoid doing it (Alshammari & Simpson, 2017).

3. Methodology

The first task was to design a typology of applied AI tools, for the very practically minded ML community (Holzinger, 2018), to embed reflection on the ethical principles of beneficence, non-maleficence, autonomy, justice and explicability (Floridi and colleagues, 2018)) into the ML pipeline from pre-processing, to use by the end user (Holzinger, 2018). To do this, the ethical principles were combined with the stages of algorithmic development outlined in the overview of the Information Commissioner’s Office (ICO) auditing framework for artificial intelligence and its core components,13 as shown in Figure 2, to encourage ML developers to go between design decision and ethical principles regularly.

13More detail is available here: https://ai-auditingframework.blogspot.com/2019/03/an-overview-of-auditing-framework-for_26.html
The second task was to conduct a thorough literature review (in Scopus14 and arXiv15) and Internet search using the terms outlined in Table 3. The original search returned more than 800 results. A review of the abstracts or website introductions was then conducted to refine this list (articles, blogs, reports, websites, online resources and conference papers were checked for relevance, actionability by ML developers and generalisability across industry sectors) to 253 sources that provide a practical or theoretical contribution to the answer of the question: ‘how to develop an ethical algorithmic system.’

14 Scopus is the largest abstract and citation database of peer-reviewed literature: scientific journals, books and conference proceedings: https://www.scopus.com/home.uri

15 Arxiv provides open access to 1,532,009 e-prints in the fields of physics, mathematics, computer science, quantitative biology, quantitative finance, statistics, electrical engineering and systems science, and economics: https://arxiv.org/
| Search Term(s)          | Number of saved Scopus results | Date of search |
|------------------------|-------------------------------|----------------|
| Public Perception      | 3                             | 14/02/2019     |
| Intellectual Property  | 10                            | 14/02/2019     |
| Business Model         | 3                             | 14/02/2019     |
| Evaluation             | 7                             | 14/02/2019     |
| Data Sharing Agreement | 1                             | 14/02/2019     |
| GDPR                   | 33                            | 13/02/2019     |
| Impact Assessment      | 6                             | 13/02/2019     |
| Counterfactuals        | 59                            | 13/02/2019     |
| Privacy by design      | 18                            | 13/02/2019     |
| Data minimisation      | 18                            | 13/02/2019     |
| Bias                   | 5                             | 13/02/2019     |
| Harm                   | 18                            | 13/02/2019     |
| Responsible Technology | 231                           | 12/02/2019     |
| Regulation             | 47                            | 06/02/2019     |
| Ethical                | 120                           | 05/02/2019     |

*Figure 3: Full list of terms used for literature search (Number of saved results from Scopus listed). All were searched with AND Machine Learning OR Artificial Intelligence OR AI*

The third, and final task, was to review the recommendations, theories, methodologies, and tools outlined in the reviewed sources, and identify where they may fit in the typology. The ultimate ambition is to ensure that there is a choice of mature tools in each box of the typology (this is not the case currently), so that ML developers have aids to ethically-informed design at each stage of the process. For example, as illustrated in figure 2, a developer looking to ensure their ML algorithm is ‘non-maleficent’ (unlikely to cause harm related to privacy or security issues) can start with the foundational principles of privacy by design (Cavoukian and colleagues, 2010) to guide
ideation appropriately, use techniques such as data minimisation (Antignac and colleagues, 2016), training for adversarial robustness (Kolter & Madry, 2018), and decision-making verification (Dennis and colleagues, 2016) in the train-build-test phases, and end by launching the system with an accompanying privacy audit procedure (Makri & Lambrinoudakis, 2015).

What is revealing about this example, and what makes it illustrative of one of the overarching limitations of many of the tools included in the typology, is that all the techniques referenced are currently in the academic research stage and, although promising, they require more work before being ‘production-ready.’ This current lack of ‘market-testing’ means that applying ethics still requires considerable amounts of effort on behalf of the ML developers (even when there are open-source code libraries available documentation is often limited and the skill-level required for use is high), undermining one of the main aims of developing and using technologically-based ‘tools’: to remove friction from applied ethics.

The full typology is available here [https://tinyurl.com/AppliedAIEthics]. It is important to note that the purpose of presenting it is not to imply that it is ‘complete’ nor that the tools and methodologies highlighted are the best, or indeed the only, means of ‘solving’ each of the individual ethical problems. It is more a proof of concept. How to apply ethics to the development of ML is an open question that can be solved in a multitude of different ways at different scales and in different contexts (Floridi, 2019a). Instead, the goal is to provide a brief snapshot of what tools are currently available to ML developers to encourage the progression of ethical AI from principles to practice and to signal clearly, to the ‘ethical AI’ community at large, where further work is needed. It is with the intention of starting this conversation that an overview of the findings is presented in the next section.
4. Initial Findings

It is evident, by simply looking at the typology (see figure 4 above), that interest in the practice of ‘ethical ML’, and thus the availability of tools and methods, is not evenly distributed across the ML pipeline. Currently, most attention for all the ethical principles is focused on interventions at the early input stages (Binns, 2018b) (business and use-case development, design phase and training and test data procurement) or at the model testing phases. For example, the review failed to identify tools or methods for ensuring value-alignment (beneficence) at the deployment stage, and found very few tools or methods for promoting autonomy (the user’s ability to exercise their rights (Floridi and colleagues, 2018)) during the middle building and testing phases. Several factors may have influenced this skewed distribution of interest, but three are likely to have been more influential:

1. at least in Europe, the introduction of the European General Data Protection Regulation (GDPR)\cite{17};
2. a focus on the need to ‘protect’ the individual over the collective; and
3. the lack of clarity around definitions of key terms.

They are interrelated, but for the sake of simplicity let us analyse each separately.

4.1 Legislative influence

In Europe, the introduction of the GDPR in May 2018, with its threat of large fines for inappropriate collection or processing of data\footnote{A guide to the implications of the GDPR is provided by the ICO here: \url{https://ico.org.uk/for-organisations/guide-to-data-protection/guide-to-the-general-data-protection-regulation-gdpr/}} and supposed right to an explanation (Wachter, Mittelstadt, & Floridi, 2017b) has clearly had a significant impact on the ML research community, concentrating attention on methods to ensure non-maleficence (privacy and security), autonomy (consent), and post-hoc explanations. This is understandable but concerning.

The GDPR may, like all regulation, prove to have unintended consequences in terms of incentivising some types of research over others and promoting minimum adherence over best practice. For example, it has clearly encouraged a focus on privacy and explicability over the promotion of autonomy in design choices and done very little to encourage competition to be the \textit{most} ethical system (Luciano Floridi, 2018). The risk is that being compliant may be seen to be good enough. This is evident in the case of the ‘the right to an explanation’, where a focus on achieving what can be termed a minimum-viable-explanation has encouraged the ML research

\footnote{The word “failed” is used because it is important to note that this does not mean that such tools do not exist, but that they did not come up in our search, are available only as proprietary solutions, or are currently only available in theory and not in practice.}

\footnote{The GDPR can be viewed in full here: \url{https://eur-lex.europa.eu/legal-content/EN/TXT/?qid=1532348683434&uri=CELEX:02016R0679:20160504}}
community to focus on mechanisms that can inform users (Wachtter, Mittelstadt, & Floridi, 2017b) in a simplified manner of how the inputs are related to the outputs. This may be necessary but is not sufficient, because such mechanisms—e.g. LIME (Ribeiro, Singh, & Guestrin, 2016), SHAP (Lundberg & Lee, 2017), Sensitivity Analysis (Oxborough and colleagues, 2018)—do not really succeed in helping developers provide meaningful (Edwards & Veale, 2018) explanations that give individuals greater control over what is being inferred about them from their data.

4.2 An individual focus

Few of the available tools surveyed provide meaningful ways to assess, and respond to, the impact that the data-processing involved in their ML algorithm has on an individual, and even less on the impact on society as a whole (Poursabzi-Sangdeh, Goldstein, Hofman, Vaughan, & Wallach, 2018). This is evident from the very sparsely populated ‘deployment’ column of the typology. Its emptiness implies that the need for pro-ethically designed human-computer interaction (at an individual level) or networks of ML systems (at a group level) has been paid little heed. This is most likely because it is very difficult to translate complex human behaviour into simple to use, generalisable design tools.

This might not seem particularly important, but the impact this has on the overall acceptance of AI in society could be significant. For example, it is unlikely that counterfactual explanations19 (i.e. if input variable $x$ had been different, the output variable $y$ would have been different as well) will do anything to improve the interpretability of recommendations made by black-box systems for the average member of the public or the technical community. If such methods become the de facto means of providing ‘explanations,’ the extent to which the ‘algorithmic society’ is interpretable to the general public will be very limited. And counterfactual explanations could easily be embraced by actors uninterested in providing factual explanations, because the counterfactual ones provide a vast menu of options, which may easily decrease the level of responsibility of the actor choosing it. For example, if a mortgage provider does not offer a mortgage, the factual reason may be a bias, for example the gender of the applicant, but the provider could choose from a vast menu of innocuous, counterfactual explanations—if some variable $x$ had been different the mortgage might have been provided—e.g., a much higher income, more collaterals, lower amount, and so forth, without ever mentioning the gender of the applicant. All this could considerably limit the level of trust people are willing to place in such systems.

19 See for example (Wachter, Mittelstadt, & Russell, 2017) (Johansson, Shalit, & Sonntag, 2016) (Lakkaraju, Kleinberg, Leskovec, Ludwig, & Mullainathan, 2017) (Russell, Kusner, Loftus, & Silva, 2017).
This potential threat to trust is further heightened by the fact that the lack of attention paid to impact means that ML developers are currently hampered in their ability to develop systems that promote user’s (individual or group’s) autonomy. For example, currently there is an assumption that prediction = decision, and little research has been done (in the context of ML) on how people translate predictions into actionable decisions. As such, tools that, for example, help developers pro-ethically design solutions that do not overly restrict the user’s options in acting on this prediction (i.e. tools that promote the user’s autonomy) are in short supply (Kleinberg, Lakkaraju, Leskovec, Ludwig, & Mullainathan, 2017). If users feel as though their decisions are being too curtailed and controlled by systems that they do not understand, it is very unlikely that these systems will meet the condition of social acceptability, never mind the condition of social preferability which should be the aim for truly ethically designed ML (Luciano Floridi & Taddeo, 2016).

4.3 A lack of consistency

Producing tools to fill in the white space on the typology is likely to be challenging. There is a distinct lack of agreement on what the aims of such tools would be. Key terms such as ‘fairness’ (Friedler, Scheidegger, & Venkatasubramanian, 2016) (Kleinberg, Mullainathan, & Raghavan, 2016) (Overdorff, Kulyanych, Balsa, Troncoso, & Gürses, 2018), ‘accountability’, ‘transparency’ (Ananny & Crawford, 2018) (Turilli & Floridi, 2009), and ‘interpretability’ (Doshi-Velez & Kim, 2017) (Guidotti and colleagues. 2018) (Bibal & Frénay, 2016) have myriad definitions, and sometimes (e.g. in the case of ‘fairness’) many statistical implementations that are not compatible and require informed decisions about trade-offs. Indeed, in some instances, definitions of the same concept directly contradict each other (Friedler and colleagues. 2016) and recently there has even been debate as to whether black boxes are as problematic as popular opinion makes them out to be (Holm, 2019). This makes it almost impossible to measure the impact, ‘define success’, and document the performance (Mitchell and colleagues. 2019) of a new design methodology or tool. Without a clear business case, that is, in the absence of a clear problem statement and a clear outcome, it is hard for the ML community to justify time and financial investment in developing these much-needed tools and techniques.

This issue stems from the fact that the entire field is imbued with subjectivity (Bibal & Frénay, 2016) and the relative success of ethical-alignment—from ideation through to operation at scale—is also context-dependent. Yet there seem to be few tools available to help ML developers deal with this subjectivity and associated complexity. For example, at the “beneficence → use-case → design” intersection, there are a number of tools highlighted to help elicit social
values. These include the responsible research and innovation methodology employed by the European Commission’s Human Brain Project (Stahl & Wright, 2018), the field guide to human-centred design,\textsuperscript{20} and Involve and DeepMind’s guidance on stimulating effective public engagement on the ethics of artificial intelligence.\textsuperscript{21} However, although they are useful, such methods offer limited guidance on how to deal with value pluralism (i.e. variation in values across different population groups). Without this guidance, the values that are embedded and protected by design tools are likely to be perceived as imposed and paternalistic, and restricted to those of the groups in society that have the loudest voices. In other words, there has been little attention paid to the potential for ‘value bias’ to develop at scale.

5. A way forward
Social scientists (Matzner, 2014) and political philosophers (from Rousseau and Kant, to Rawls and Habermas) (Binns, 2018a), are used to dealing with the kind of plurality outlined in section 4, and to thinking about the interaction between individual level and group level ‘ethics.’ This is why Nissenbaum argues for a contextual account of privacy, one that recognises the varying nature of informational norms (Matzner, 2014) and Kemper & Kolkman, (2018) state that transparency is only meaningful in the context of a defined critical audience. However, the ML developer community may be less used to dealing with this kind of complexity, and more used to scenarios where there is at least a seemingly quantifiable relationship between input and output. As a result, the existing approaches to designing and programming ethical ML fail to resolve what Arvan, 2018 terms the moral-semantic trilemma, as almost all tools and methods highlighted in the typology are either too semantically strict, too semantically flexible, or overly unpredictable (Arvan, 2018).

Overcoming this nervousness of social complexity, embracing uncertainty, and accepting that: (1) AI is built on assumptions; (2) human behaviour is complex; (3) algorithms can have unfair consequences; (4) algorithmic predictions can be hard to interpret (Vaughan & Wallach, 2016); (5) trade-offs may be inevitable; and (6) positive, ethical features are open to progressive increase but are not bounded between 0 and 1 (e.g., an algorithm can be increasingly fair, and fairer than another algorithm or a previous version, but makes no sense to say that it is fair 100% in absolute terms, compare this to the case of speed: it makes sense to say that an object is moving quickly, or that it is fast or faster than another, but not that it is fast 100%), is likely to be highly beneficial for the development of applied ethical tools and methodologies for at least three reasons.

\textsuperscript{20} http://www.designkit.org/resources/1
\textsuperscript{21} https://bit.ly/2HKNpPh
First, embracing uncertainty will naturally encourage ML developers to ask more probing and open (i.e., philosophical) questions (Luciano Floridi, 2019b) that will lead to more nuanced and reasoned answers and hence decisions about why and when certain trade-offs, for example, between accuracy and interpretability (Goodman & Flaxman, 2017), are justified, based on factors such as proportionality to risk (Holm, 2019). Second, it will encourage a more flexible and reflexive approach to applied ethics that is more in-keeping with the way ML systems are actually developed: it is not think then code, but rather think and code. In other words, it will encourage a move away from the ‘move fast and break things’ approach towards an approach of ‘make haste slowly’ (festina lente) (Luciano Floridi, 2019a) . Finally, it would also mitigate a significant risk posed by the current sporadic application of ethical-design tools and/or methods during different development stages, of the ethical principles having been written into the business and use-case, but coded out by the time a system gets to deployment.

To enable developers to embrace this valuable uncertainty, it will be important to promote the development of tools, like DotEveryone’s agile consequence scanning event,22 that prompt developers to reflect on the impacts (both direct and indirect) of the solutions they are developing on the ‘end user’, and on how these impacts can be altered by seemingly minor design decisions at each stage of development. In other words, ML developers should regularly

a. look back and ask: ‘if I was abiding by ethical principles \( x \) in my design then, am I still now?’ (as encouraged by Wellcome Data Lab’s agile methodology (Mikhailov, 2019) and

b. look forward and ask: ‘if I am abiding by ethical principles \( x \) in my design now, should I continue to do so? And how?’ by using foresight methodologies (Taddeo & Floridi, 2018) (Floridi & Strait, forthcoming) such as AI Now’s Algorithmic Impact Assessment Framework (Reisman, Schultz, Crawford, & Whittaker, 2018)).

Taking this approach recognises that, in a digital context, ethical principles are not simply either applied or not, but they are regularly re-applied or applied differently, or better, or ignored as algorithmic systems are developed, deployed, configured (Ananny & Crawford, 2018) tested, revised and re-tuned (Arnold & Scheutz, 2018).

Although clearly beneficial, this approach to applied ML ethics of regular reflection and application will not be possible unless (i) the skewed distribution of tools in the typology is balanced out and (ii) acceleration of tools maturity level from research labs into production environments. To achieve (i)-(ii), society needs to come together in communities comprised of multi-disciplinary researchers (Cath, Wachter, Mittelstadt, Taddeo, & Floridi, 2017), innovators,

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22 Full details of DotEveryone’s Consequence Scanning Event: https://doteveryone.org.uk/project/consequence-scanning/
policymakers, citizens, developers and designers (Taddeo & Floridi, 2018) to foster the development of: (1) common knowledge and understanding; and (2) a common goal to be achieved from the development of tools and methodologies for applied AI ethics (Durante, 2010). These outputs will provide a reason, a mechanism, and a consensus to coordinate the efforts behind tool development. Ultimately, this will produce better results than the current approach, which allows a 'thousand flowers to bloom' but fails to create tools that fill in the gaps (this is a typical 'intellectual market' failure), and may encourage competition to produce preferable options. The opportunity that this presents is too great for us to wait, the ML research community should start collaborating now with a specific focus on:

1. creation of tools that ensure people, as individuals, groups and societies are given an equal and meaningful opportunity to participate in the design of algorithmic solutions at each stage of development;
2. evaluation of the tools that are currently in existence so that what works, what can be improved, and what needs to be developed can be identified;
3. commitment to reproducibility, openness, and sharing of knowledge and technical solutions (e.g., software), also in view of satisfying (1) and supporting (2);
4. evaluation and creation of pro-ethical business models and incentive structures that balance the costs and rewards of investing in ethical AI across society, also in view of supporting (1)-(3).

6. Conclusion
The realisation that there is a need to embed ethical considerations into the design of computational, specifically algorithmic, artefacts is not new. Both Alan Turing and Norbert Weiner were vocal about this in the 1940s and 1960s (Turilli, 2008). However, as the complexity of algorithmic systems and our reliance on them increases (Cath and colleagues, 2017), so too does the need to be critical of pro-ethical (Floridi, 2016) AI governance (Cath, 2018) and design solutions. It is possible to design things to be better (Floridi, 2017), but this will require more coordinated and sophisticated approaches (Allen, Varner, & Zinser, 2000) to translating ethical principles into design protocols (Turilli, 2007).

This call for increased coordination is necessary as this research has shown that there is a skewed distribution of effort across the ‘Applied AI Ethics’ typology. Furthermore, many of the tools included are relatively immature. This makes it difficult to assess the scope of their use (resulting in Arvan’s 2018 ‘moral-semantic trilemma’) and consequently hard to encourage their
adoption by the practically-minded ML developers, especially when the competitive advantage of more ethically-aligned AI is not yet clear.

Constructive patience needs to be exercised, by society and by the ethical AI community, because the question of ‘how’ to meet the ‘what’ will not be solved overnight, and there will definitely be mistakes along the way. The ML research community will have to accept this, trust that everyone is trying to meet the same end-goal but also accept that it is unacceptable to delay any full commitment, when it is known how serious the consequences of doing nothing are. Only by accepting this can society be positive about the opportunities presented by AI to be seized, whilst remaining mindful of the potential costs to be avoided (Floridi and colleagues. 2018).
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