Monsters, Metaphors, and Machine Learning

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ABSTRACT
Machine learning (ML) poses complex challenges for user experience (UX) designers. Typically unpredictable and opaque, it may produce unforeseen outcomes detrimental to particular groups or individuals, yet simultaneously promise amazing breakthroughs in areas as diverse as medical diagnosis and universal translation. This results in a polarized view of ML, which is often manifested through a technology-as-monster metaphor. In this paper, we acknowledge the power and potential of this metaphor by resurfacing historic complexities in human-monster relations. We (re)introduce these liminal and ambiguous creatures, and discuss their relation to ML. We offer a background to designers' use of metaphor, and show how the technology-as-monster metaphor can generatively probe and (re)frame the questions ML poses. We illustrate the effectiveness of this approach through a detailed discussion of an early-stage generative design workshop inquiring into ML approaches to supporting student mental health and well-being.

Author Keywords
Machine Learning; UX design; Generative Metaphor; Monster Theory

CCS Concepts
•Human-centered computing → Interaction design theory, concepts and paradigms;

INTRODUCTION
> "Monsters do a great deal of cultural work but they do not do it nicely. They not only challenge and question, they trouble, they worry they haunt. They break and tear and rend cultures, all the while constructing them and propping them up. They swallow up our cultural mores and expectations, and then becoming what they eat, they reflect back to us our own faces, made disgusting or, perhaps, revealed to always have been so." [112, p.1]

A recent headline in the Guardian, a UK newspaper, warned of *"Franken-algorithms: the deadly consequences of unpredictable code"* [146]. This headline is an example of a familiar trope in media representations of new or unfamiliar technologies, which sees the technology characterized as being monstrous, or being discussed with reference to some particular monster from popular culture. Similar examples have focused on artificial intelligence (AI) ethics [66], and warnings about how machine learning (ML) might be targeted and manipulated [58]. This 'technology-as-monster' metaphor is perhaps most widely associated with genetically modified organisms (GMOs), which became commonly known as 'Frankenstein foods', starting in early 1999 as GMOs first came to prominence, e.g. [91, 148, 115], and continuing with regularity since, e.g.[94, 64, 111]. However, it has also been applied to nuclear energy and weapons [18, 50], and CRISPR gene editing [141]; and its use extends beyond particular technologies to include more general discussions of scientific breakthroughs [28, 83]. Common across all of these examples is a reflection of the fear that technology may become uncontrollable, and wreak havoc and disruption.

The appearance of a technology-as-monster metaphor is often a response to claims which can seem to be over-optimistic, even hubristic, particularly with regard to solving major societal challenges. For example, with regards to AI and ML we find claims such as, "[i]n the next 3 decades natural and artificial intelligence will become one. We'll live indefinitely, and become a billion times more intelligent" [84]. While [116] states, "Just as electricity transformed almost everything 100 years ago, today I actually have a hard time thinking of an industry that I don't think AI will transform", and "almost all of this massive economic value of AI is driven by one type of AI, by one idea, and the technical term is supervised learning". Similar claims are made for medical diagnosis [106]; universal translation [37] (even as far as inter-species translation [72]); recruitment and HR [155, 117]; predictive policing [25, 26]; and criminal justice [131, 113]. This brave new world is exemplified in an internal Google video [137] in which ubiquitous data collection will lead to decoding human behavioral sequences, so that behavior tracking can become behavior directing, and thereby offer "benefits to this generation, to future generations, and to the species as a whole". Utopian visions of AI also surrounded cybernetics research in the 1960s [5], and then too the technology-as-monster metaphor was present as a response. For example, in leading cybernetician Norbert Weiner's invocation of Golem [169, pp.49-69]. The awe and fear seen in these examples, and in responses to them, perhaps being evidence of an algorithmic [5] or technological[118] sublime.

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Repeated use of the technology-as-monster metaphor points to an underlying duality in discussions that cast AI and ML, which are typically used interchangeably in popular media, as simplistically magical or fearsome. It is these public conversations that frame the context into which new products are released, and which provide the backdrop to user experience (UX) designers' interactions with research participants. To overcome this duality, and find deeper value in the technology-as-monster metaphor, we revisit what it means, and has meant, to be monstrous, and use this understanding to offer UX designers a generative lens with which to approach ML. Because ML is a particular form of AI computing that uses statistical probabilities to make predictive calculations based on examples from training data, we draw connections between ML and monsters by considering the role monsters have played in *prediction* and *classification*. To explore the generative potential of the technology-as-monster metaphor, we also look at practices associated with *creating* monsters. Our starting point is an etymology of the English word monster, and our backdrop is informed by insights from authors such as Law and Haraway who have previously used monsters as a lens to bring entanglements of culture-nature-science-technology into view [69, 89]. Our intention is to (re)interpret the technology-as-monster metaphor as a reminder to be thoughtful when designing, implementing, and making use of ML. We illustrate our approach, and show the effectiveness of probing ML through a monster lens, with detailed examples taken from an early-stage generative design workshop in which we brought together UX designers, ML experts, and domain stakeholders, to inquire into ML approaches to supporting student mental health and well-being. This paper responds to challenges UX designers face working with ML [42], and contributes to the CHI community's understanding of generative metaphor [140].

A Brief Introduction to Mary Shelley's Frankenstein

The monster most commonly called upon in contemporary discussions of technology, at least in English speaking media, is the creature from Mary Shelley's *Frankenstein, or the Modern Prometheus* [144]. Shelley's novel tells a morality tale of an unfortunate creature who has been brought into the world and then abandoned by a human creator who is unwilling, and unable, to acknowledge and take responsibility for his creation [170, pp.307-316]. Frankenstein's creature is arguably the first modern monster, arriving as the Enlightenment takes hold and questioning the new relationship of science and nature [68]. It is also the monster most fully adopted into Western pop culture [54], where it more closely resembles the grotesque amalgam of stolen corpses, with bolts through its neck and a murderer's brain, which emerges via Boris Karloff's acting and Jack Pierce's makeup design in the 1931 movie. It is often this is relatively one dimensional pop culture notion of Frankenstein, in which the name seems to reference the creature rather than its creator, that becomes the metaphorical reference in discussions of technology. However, like other authors for whom the story has become an important touchstone, e.g. [1, 71, 153], we draw on Mary Shelley's original conception, and will return to this from time-to-time as we inquire into the monstrous, and (re)configure the technology-as-monster metaphor.

DESIGNING WITH MACHINE LEARNING

ML is a not so new technology, having been an area of active research for at least fifty years, e.g. [133, 135]. It is neither arcane nor obscure, with numerous textbooks e.g. [49, 171], introductory articles e.g. [38], and online resources e.g. [63] produced that cover the topic. However, recent work has highlighted how challenging a material it can be for UX designers to work with, e.g. [42, 173, 172, 24]. There are many reasons for this, including that unlike systems driven by heuristic rules, ML operates in a way that is strangely different from how we commonly understand human intelligence. Instead it applies statistical methods to produce output that can be difficult to explain and which can make seemingly bizarre errors with no obvious 'common sense' explanation [177, 178]. ML also has a different relation to data than is typically familiar for UX designers. In ML systems, data are large and dynamic, and *learning* implies that data will change over time. Moreover, domain and application specific data are often scarce or non-existent at early-stage design, meaning that trained models will not be available during prototyping [42, 175].

The current upturn in HCI research interest around ML has produced interaction guidelines [4], and new design approaches that attempt to make AI 'unremarkable' [174] or address users' expectations [80]. However, the challenges posed by ML in UX practice result in designers typically deferring technical understanding to software engineers. This has been found to be the case with regards to those designers experienced in working with ML [173], as well those whose experience with ML is limited [42]. Furthermore, experienced designers do not consider an in depth understanding of the algorithms and computer science underpinning ML necessary for their work [173]. This is not entirely surprising, and neither should it necessarily be concerning, as design is typically collaborative, with professionals from different domains contributing particular knowledge, skills and experience [29, 44, 122, 139, 101]. However the primary concerns of software engineers, which are typically optimization and efficiency, measured through the comparative performance of different algorithms e.g [23, 30, 171], differ in important respects from those of UX designers [88]. Therefore, designers need to frame and facilitate wider consideration for a system's users and contexts of use [12, 65, 107], including ethical and societal concerns [55, 124], for example through the conscious and explicit use of metaphor [104, 105]. We demonstrate how this can be achieved in our example workshop.

METAPHOR AND DESIGN

Metaphor has played a crucial role in the development of human thought, with metaphors of embodied experience in the world now understood to be the foundation of abstract conceptual systems [85]. Its particular importance to design process and practice came to the fore following the metaphoric turn [109], heralded by Schön e.g. [140] and Rittel & Webber e.g [132]. Metaphor underpins the process of translating between familiar design types [126, 139] and particular situations that enables a familiar aspect from the designers' repertoire to become generative of new phenomena [138, p.269] through designers' seeing-as and doing-as [138, p.138]. By renaming and re-describing a familiar process using a different but equally familiar term, knowledge associated with the second process is brought into consideration with regard to the first. This use of *generative metaphor* [140] enables new features relevant to the problem at hand to be perceived, and offers new perspectives that may lead to a (re)framing. For example, Schön describes how a researcher's insight that a "a paintbrush is a kind of pump" reframes the design process for synthetic paintbrush bristles. Within collaborative design processes, the gestation and development of such generative metaphors can be complex, and happen over an extended period. This process is described in detail with regard to the development of the 'plant a seed' metaphor, which provides a common ground for domain experts and designers to guide the design of a media architecture installation at the botanical gardens in Aarhus, Denmark [44].

Metaphors also provide a mediating mechanism, acting between low-level episodic experiences and high-level symbolic semantics to facilitate design exploration and creative ideation [90]. They provide elements from which designers can build and test theories [138, p.319], and a spotlight that reveals some aspects of a concept whilst simultaneously concealing others, thereby offering the means through which problems are defined and resolved [147]. The use of metaphor in interaction design is often particularly explicit, e.g. the computer desktop or file system, and reified as a design tool [19, 96]. Metaphors therefore often connect form and meaning in digital artifacts, and act as a semantic resource and material reference to facilitate user interpretations of design perspectives [78]. Metaphors also offer a route through which mental models might be explored during user research [129], and a mechanism to support problem reframing [97]. Metaphors shift the focus of attention to suggest a novel view of the situation and offer specific design options [105], and they can act as a lens for meta-analysis [15]. The power and pitfalls of particular design metaphors are seen through their manifestation in artifacts [70]. In summary, metaphors can be both representational tools showing how to use a complex artifact and rhetorical devices that invite deeper thinking. They help us to understand the situation at hand, share competing stakeholder perspectives, and generate new and creative responses to the challenges posed. The choice and use of metaphor is crucial to design. We build on this previous work to show how reinterpreting the familiar technology-as-monster metaphor can offer UX designers a lens though which to approach the difficult material of ML.

(RE)INTRODUCING MONSTERS

> Monsters are our children. They can be pushed to the farthest margins of geography and discourse, hidden away at the edges of the world and in the forbidden recesses of our mind, but they always return. [31, p.20]

While monsters seemingly emerge across many different cultures and times [62, p.1], our particular view of the monstrous comes through a largely Western European lens. However, examples from other cultural traditions, such as yōkai from Japan, the Yeti from Nepal, Arabic ghouli, and Chinese dragons, have infiltrated and influenced this Western monster culture, and retain a presence in our analysis.

Warnings from Predictive Monsters

The English word *monster* is generally considered to be derived from *monstrum* the noun form of the Latin verb *monere* (to remind, warn, instruct, or foretell) [11, p.2] [130, p.399], denoting the strange, unnatural, and unusual, and meaning "that which reveals" [62, p.9], an omen, or "portent of something unforeseeable" [17, p.3]. Closely associated with the Latin verb *monstrare* (to show or display), it arrives via the Old French *monstre*. Collectively, "monstrosities, *monstra* are named from an admonition, *monitus*, because they point out something by signaling or symbolizing" [62, p.9]. In antiquity, Roman use of *monstra* typically referred to signs from the gods, to omens or predictions of future travails; and *monstrum* to unnatural things attached with prophetic significance, which may be alive, but that are "against nature... like footed serpents and two-headed men" [56, p.108-111]. The birth, or stillbirth, of animals or children with congenital abnormalities was considered monstrous, and would require sacrificial action to avoid the misfortune they predicted. For example, conjoined twins might be considered a sign of political upheaval [48, p.128].

The view that 'monstrous' human and animal births were a warning of divine displeasure continued into medieval Europe [56, p.116]. Initially during this period, such births were taken as signs of a whole community's sinful practices, foretelling of natural catastrophes such as floods or plagues that would come in punishment. However, as the ideas associated with liberal individualism emerge, 'monstrous' births increasingly become signs of an individual's errors, and they come to serve as a way through which crimes that were otherwise difficult to detect, most notably adultery, might be identified. [34, pp.54-55]. The etymology of monster as warning and omen, unnatural and therefore predictive is somewhat forgotten in contemporary use, and the 'monstrum' has become "a glyph that seeks a hierophant" [31, p.4]. Today we identify deviant behavior using ML. For example, by making predictive warnings in policing [25, 26, 16] and in criminal justice risk assessment [131, 113, 77, 145].

Monsters and Classification

There is a strong human desire to place order on a chaotic world, to identify and label, to classify, characterize, and sort [22, pp.1-5]. In early Western encyclopedia, such as Cicero's 'On Divination' (44 BCE), and Pliny's 'Natural History' (c.77-79 CE), or Augustine's 'City of God Against the Pagans' (c. 426 CE), and Isidore of Seville's 'Etymologies' (c. 600-625 CE), divine categorizations of monsters are found side by side with scientific attempts to incorporate them into the order of the 'natural' world. These works include catalogs of 'nature' and 'monstrosity', such as anomalous animal and human births and bodies (e.g. conjoined twins, giants and dwarfs, or those with superfluous or missing body parts), and monstrous races who live at the edges of the world, such as the Cynocephalus (dog-head) and Sciapod (one footed dwarf) [34, pp.50-51]. In this way, the boundaries of what can be considered 'human' and 'natural' versus what must be seen as 'monstrous' and 'unnatural' are marked out. These attempts to mark and demarcate 'natural' and 'supernatural' worlds, are echoed in catalogs of yōkai produced in Japan during the

Edo period (c.1603-1867 CE). Encyclopedia from this period, such as Wakan sansaizue (c.1713 CE), include illustrated catalogs of yōkai alongside descriptions and illustrations of plants, animals and constellations [51, pp.30-48]. Yōkai, typically associated with everyday places and natural features, are the groupings of supernatural creatures, monsters, or spirits, that bridge spiritual and material realms [52, pp.135-136]. They are hybrid and ambiguous, and can be mischievous trouble makers, even murderous, yet also creatures of entertainment. Today, classification is among the most common tasks undertaken by ML [38], and can tell us much about what might be considered 'unnatural' or 'monstrous' [13]. For example, Facebook's image recognition algorithms have identified breastfeeding mothers as 'pornographic' [73].

Creating Monsters

Any classification system leaves things that don't fit neatly into the categories created. These are the hard to recognize things, the things made invisible, the 'residuals' [149]; and they are the materials from which monsters are created. Monsters are brought forth from the imagination, in dreams and fantasy; in cultural metaphor, literature, and art; in popular fiction, TV, and movies; in storytelling and in ritual. Monsters such as Cyclops and Scylla, Humbaba, and Grendel, are found in the Odyssey, Gilgamesh, and Beowulf; each a root of European literary culture [33]. Monsters also defy time and distance. Godzilla is awakened from pre-history, and the Terminator returns from the future; there are posthuman cyborg monsters, and alien monsters from outer space. Monsters are intentionally brought to life in order to embody the unknown and unseen. However, recognizing the unknown requires reference to the known, and so we create monsters using familiar parts, but put them together in strange combinations. Dragons, for example, may include reptilian-like bodies and wings reminiscent of birds-of-prey.

Creating and identifying monsters during rituals helps release participants from their everyday constraints and from commonsense constructions of social reality. In rituals, a 'liminal period' is created, with a freedom to pose primitive questions and play with ideas of existence [158, 159]. Rituals can help change perception, and permit knowledge that would otherwise not be known [39, p.64-65]. They are a time when participants call on, create, and experience monsters; mixing the magical and the mundane in a way that encourages or forces them to rethink features of their environment, and reconsider their relationship to people and things they may otherwise take for granted [158, pp.105-106]. This is often undertaken through bricolage [150, p.11], with participants repurposing everyday items. Similar practices can also underpin interaction design activities, e.g. [161, 9, 136], and creating monsters from everyday items is one example of how we use the technology-as-monster metaphor generatively.

Returning to Mary Shelley's Frankenstein

Rituals and rites of passage traverse the mundane and the magical, and infuse the familiar everyday with mythical things. Similarly, in encyclopedia from Japan's Edo period and from Roman or medieval Europe, there is often no clear distinction made between observation, document, and fable in attempts to place order on and understand the world, [51, p.40] (with reference to [53, pp.140-141]). However, following the seventeenth century, and as materialist explanations became increasingly preeminent, monstrous bodies became objects of scientific study (e.g. for the surgeons like John Hunter who employed grave robbers to assist in acquisitions), and attempts were made to explain the secrets of life through experiments in vitalism (e.g. by Galvani and Volta). This provided the backdrop, and possible sources of inspiration, for the first of the modern monsters, Frankenstein's creature [11, pp.130-133]. As this process has continued, and culture and nature have become more divided, our concept of the monster has become increasingly one dimensional, and Mary Shelley's creature replaced by Boris Karloff's. Our aim in this section has been to (re)introduce the monster and offer a reminder of a more complex and nuanced history of human-monster relations. In the following sections we will first show how this can be applied to ML, and then illustrate how it is used generatively in UX design through an example workshop.

MACHINE LEARNING AND MONSTERS

Even those ML applications subsequently most associated with harmful bias were probably not developed with bad intentions. Their likely aim was to use statistical analysis of data to respond more 'objectively', and limit and/or mitigate prejudice. However, in ML as elsewhere, the social and the technical are irreducibly entangled. Technology is not neutral [81], and the notion of objective or raw data is both oxymoronic and undesirable [21, p.184]. Some ML systems surface and amplify long-existing problems, e.g. [77]; while for others, what at first appears to be an example of familiar discrimination, turns out to be new phenomena emerging from data-driven markets [86].

Machine *Learning* is itself a metaphor applied to help us get to grips with particular forms of computing. A typical ML application, uses statistical inference to make a predictive calculation based on the probability that an example of input signal is similar to some class of entity recognized from its training data. For example, spam filters attempt to predict whether a user will value a particular email message based on its similarity to the examples of other email messages (both spam and non-spam) it was presented as training data. However, simple descriptions of ML applications belie their complexity. A ML algorithm, which might appear to be discrete and unitary in the abstract, is likely to be implemented across different modules, in numerous snippets of code written by different people; and which are distributed through a large and complex program, running on different computers, and potentially located in different domains [40]. This algorithm is embedded within sociotechnical structures, and moulded by communities of practice [7]; it is intimately tied to particular data, with which it will co-evolve [40]; and it may appear not as a singular technical object, but rather as unstable, multiple, enacted in use [142]. All this helps to create the ambiguous edge places and overlooked spaces where monsters emerge, but which go unnoticed in simple 'book' descriptions. A generative technology-as-monster metaphor can help surface complexity in these assemblages, and raise a warning to proceed with care.

ML Prediction and Monstrous Omens

Prototyping interactions with ML applications is a major challenge for UX designers [42]. This is in part because the predictive outputs ML produces from statistical inferences are based on patterns identified in the formal properties of data, including training data. For example, a recommender engine is trained on flows of customer data over long periods of time, identifying patterns in labeled meta-data, before starting to provide useful predictions [7]; and predictive policing is built on years of annotated crime statistics, demographics, and assorted other data [16]. The ML models used to generate predictions from these data are typically intentional black-boxes, opaque even to the data scientists and software engineers who design, select and implement them [27]. This has led at least one leading ML researcher to compare the practices of data science and ML research to alchemy [127]. Yet data scientists not only select and evaluate algorithms, they also act as ML interpreters, and so may be compared to priesthoods in Roman antiquity and medieval Europe who would interpret monstrous births as omens and predictions. The role of interpreter can also be taken on by UX or user interface designers who simplify the statistical inference ML produces so that it becomes meaningful to end-users, or by information workers who interpret and summarize algorithmic outputs, e.g. intelligence officers for predictive policing [167].

ML needs interpreting because its algorithms work with a data set's formal properties to find regularities and commonalities, and it produces analyses unknowable in terms of the application's domain. It is humans who give an account of these patterns and reduce complex collections of data points into defining characteristics and narratives, e.g. about categories of people such as "pregnant women, dual-income Minneapolis families in the market for a new car, disaffected voters, or people likely to cheat on their taxes" [40]. In the case of recommender engines, these calculations are interpreted to produce predictive publics of 'customers like you', which aim to personalize suggestions, underpin and validate recommendations, and invoke a virtual community the shopper is invited to feel an affinity with [61].

Despite its apparent dynamism, predictive ML is typically based on an assumption that relatively stable classifications exist [102], often built on ground truth labeling undertaken by low-paid crowdworkers [20]. ML predictions may draw strong conclusions from relatively little user information, and from engineers and data scientists tweaking algorithms based on what 'looks right' or on approximations of 'user satisfaction' [61]. This is the 'magic' that invokes promises of predictive efficiency, rather than the often undervalued work of gathering, cleaning, labeling, and curating data [156]. Ignoring this work, and paying scant critical attention to the provenance of data, creates opportunities for unexpected and unwelcome outcomes when ML applications are in general use [14]. We use monsters generatively, to acknowledge these areas of uncertainty and to foreground hidden assumptions.

ML Classifiers and Monstrous Categories

Classifiers are the most mature and widely used form of ML [38], and typically work by learning to recognize the differences between categories which in themselves remain relatively fixed [102], using ground truth most often provided by large sets of (often manually) labeled data [164]. These data are subject to, and embed, assumptions and practices adopted in collection and curation [166]. Data acquisition practices (e.g. selective sampling, survey design, and stroke capture), data preparation practices (e.g. structuring data to remove unwanted dimensions, and cleaning data to remove junk), and data labelling practices (e.g. selecting category options for a classification system), each present opportunities to capture unacknowledged disparities and biases, which are instrumental in embedding particular 'features' that mediate how a ML algorithm perceives the world [20]. For example, the way in which survey questions are framed and presented, and responses are collected, has a large impact on the data subsequently available [157]. Also, the transformations necessary to match data to schema, and in response to missing or unexpected values, result in data being excluded [128]; and the categories selected, and therefore the residuals created, result in certain social groups being hidden, e.g. [134]. Errors in classification can typically be explained with reference to the data ML algorithms are exposed to in training, e.g. in the tendency for image recognition algorithms to falsely identify 'sheep' in photos of a grassy hill [143].

Like the ancient encyclopedia that listed conjoined twins as 'monstrous' births and presented distant peoples as 'monstrous' races, today's ML applications can (often uncomfortably) reveal what may be considered monstrous now. Preexisting patterns of discriminatory exclusion and inequality, which are being surfaced by widespread data mining [13], may previously have been less visible; suspected but hidden. ML classifications have produced examples of racial bias in risk assessments for criminal sentencing [77, 145], recommended an app locating sex offenders to users of gay dating app Grindr [6] and resulted in photo apps that automatically labelled some black users as gorillas or asked if Asian users were blinking [32]. Other people may be rendered invisible by classification systems used to organize data [134], and be made 'monstrous' as a result [110]. Yet the instability and potential strangeness of ML classifications can also be a source of generative potential, e.g. in relational classification [92], and a source of inspiration for new forms of human-machine collaboration [93], perceptual engagement [35], and human-ML co-performance [82]. While ML may at times be treated as if it were a form of magic [45], its models are shaped by examples of previous human activity, and so are models of a particular cultural context. Assumptions, biases, and lay people's interpretations typically only enter the picture after an application is publicly released [14]. Approaching the design of ML applications aware of the places monsters may lurk, provides an early warning and encourages designers to probe into uncertainty and become familiar with the unknown.

Returning to Mary Shelley's Frankenstein (Again)

> "It is not the case that we have failed to care for Creation, but that we have failed to care for our own creations. We blame the monster, not the creator, and ascribe our sins against Nature to our technologies. But our iniquity is not that we created our technologies, but that we have

> failed to love and care for them. It is as if we decided that we were unable to follow through with the education of our children" [87].

The story of Dr Frankenstein [144], and how he is unable and unwilling to care for the creature he brings into the world, reminds us of our responsibility towards and for the things we create. We should not think of technology as simply being instrumental in helping humans achieve goals, because these goals and technologies are often irreducibly inseparable [165]. Neither should we see designing technology as simply the creation of discrete objects with intrinsic meaning, but rather as the "cultural production of new forms of practice" [154]. Content creators and information producers find a strong compulsion to (re)make themselves and their products to become recognizable to ML search algorithms [61], and the adoption of image recognition and autonomous guidance systems changes the role of aircraft pilots [57, p.100]. ML applications are also performative. Targeted advertisements for flights may not only change the market share for a particular airline, but also change the wider market for flights if, for example, other airlines change their schedules in response [102]. Similar performative interactions are found in high frequency financial trading [10, 103], and academic writing [75]. The technology-as-monster metaphor shines light on ML, and the story of Frankenstein reminds us that the products and services we design have implications beyond those we can easily foresee. This reminder gained contemporary resonance when Microsoft briefly launched their next generation chatbot Tay on Twitter. Just like Frankenstein's unfortunate creature, insufficient consideration was given to life beyond its metaphorical 'release', and the offensive and abusive language it 'learned' to spit out resulted in its almost immediate shutdown [114].

A GENERATIVE MONSTER METAPHOR

> "Monsters remind us that our environment is *not* always controllable. The earth keeps changing, and we must continue to adjust; we must continue to be creative and heroic in our efforts to bring order to the chaos constantly threatening us, and thus to accept the monstrous even while trying to keep it at bay" [48, p.131].

For all their apparent ubiquity, monsters are embodied in particular moments. They defy easy categorization, having an intimate association with 'otherness' [69] that incorporates a complex mix of fear, desire, anxiety and fantasy [31, p.4]. Yet their strangeness is typically made up of otherwise familiar parts. They may be part human and part animal, such as in the Minotaur's mix of man and bull, or created from parts of different animals, such as a Griffon's mix of lion and eagle. They may signify sinful practice and warn of divine retribution [34, p.55], but they can also become a focus of desire and escapism. Exotic geographies were populated with Cyclops and Cynocephalus, but also with Amazons and Hermaphrodites, "bodies through which the possibilities of other genders, other sexual practices, and other social customs can be explored"[31, p.17]. Vampires seduce their victims, and the allure of the Siren's song called sailors to a fearful death. Descriptions of these distant or rare monsters brought the edges of the world closer to the realm of the knowable, with an implication that such places could be (re)visited with at least partial understanding of their dangers [163, p.390]. This is perhaps because,"as soon as one perceives a monster in a monster, one begins to domesticate it ... to compare it to the norms, to analyze it, consequently to master whatever could be terrifying in this figure of the monster" [36, p.386].

The capacity for monsters to act not only as a warning, but also as an introduction to the unknown and unfamiliar, encourages generative use of the technology-as-monster metaphor. It supports alternative ways of seeing-as and (re)framing, and surfaces new possibilities for inquiry into the situation at hand. From reported encounters with the monstrous races of Greco-Roman antiquity and monstrous births of medieval Europe [34, pp.50-51], to explorations of posthuman teratology [100], we see how engagement with metaphorical monsters unveils assumptions about humanity. We create monsters to act as a comparison that (re)anchors the 'natural', the 'normal', the 'human'. Sex and sexuality, gender, race, religion, and disability, which have each posed ethical challenges to ML, e.g. [77, 145, 6, 32], have also all been a focus for locating 'humanity' and thereby identifying 'monsters' [110, 121, 151, 160, 59].

ML is also increasingly present in mundane everyday artifacts, e.g. in lighting made by Phillips [1], thermostats made by Nest [2], and toothbrushes made by Kolibree [3]. These, and other examples of domesticated ML (e.g. Siri, Alexa, and Google Assistant), aim to make lives easier, more efficient, and more connected; and the benefits they offer appear to multiply for people with certain disabilities [108]. However, these artifacts may also encourage unrealistic expectations [99], or fail to respond in a way that follows user intent [176]. A typical ML response to issues such as these would be to collect more data for training and evaluation. Viewing this response through the lens of a technology-as-monster metaphor might prompt other reflections. What if users' relationships with domestic ML too closely resemble those of Seymour and *Audrey II* in 'Little Shop of Horrors' or Billy and *Gizmo* in 'Gremlins'? In these movies, seemingly tame companions turned out to have rapacious appetites, and a tendency for destructive, anti-social behavior. The metaphor reminds us that social media can have a downside [162, 3, 95], and that ML is a key technology in the development of business practices that have become known as 'surveillance capitalism' [179]. For UX designers the challenge is how to use ML in ways that are meaningful to users and supportive of their needs and wants, while bringing joy and surprise to the things we design without being or appearing to be creepy. ML based artifacts should be like the Scully and Mike who find the secret of children's laughter at the end of Monsters Inc., not the monsters who jump out of closets to scare us at the beginning of the movie. To encourage this type of reflection, we have designed a set of monster cards (e.g. Figure 1) for use in ideation workshops. These are similar to cards that are familiar in both interaction design research, e.g. [67, 98], and UX design practice, e.g. [74]. Each card contains an image representing a particular monster or monsters, the name of the monster, a brief descriptive text, and a prompt

[1] http://www.futureoflight.philips.com/home
[2] https://nest.com/thermostats/
[3] https://www.kolibree.com/en/

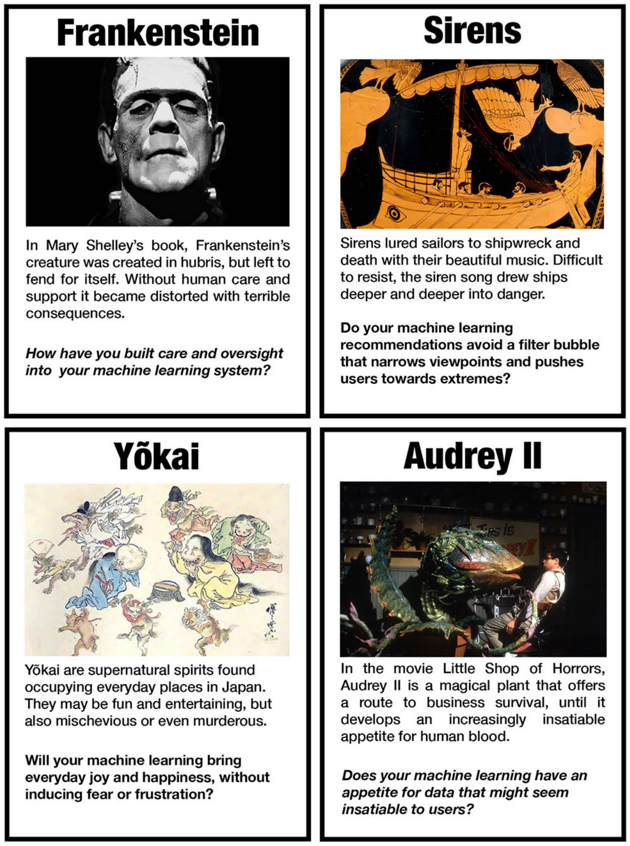

Figure 1. Examples of the monster cards we use for prompting reflection during UX design of ML applications. Each card contains an image of a particular monster, a brief description of that monster, and a prompt that links the monster to ML.

Figure 2. Examples of the everyday objects used as materials for making monsters during workshops.

Figure 3. Participants making monsters in our student mental health and well-being workshop.

that links the monster to some aspect of ML. The role of the cards when used individually is to ask specific questions of ML, but considered collectively they encourage wider reflection on ML design. Blank template cards allow workshop participants or other design collaborators to introduce new monsters and new ML concerns. In the following section we describe in detail another example of our generative use of the technology-as-monster metaphor, a workshop format that employs the metaphor to surface uncertainty and highlight unspoken assumptions, and which can include activities that utilize these cards. We use this workshop to probe ML projects at their outset, and highlight the need for core UX design skills, such as empathy and contextual insight, to be brought to the forefront.

'Where Be There Monsters?'

In this section we introduce *"Where Be There Monsters?"* a UX workshop for early-stage design in projects where ML is a likely technology choice. This work builds on research into generative design workshops that support design inquiry for interactive systems through structured activities with tool kits and making, e.g. [136, 43, 9]. Similar tool kits and workshop techniques are also common in UX design practice [60]. In this workshop, we bring together domain experts, and UX and ML professionals, to explore the data and ground truth that inform ML, and the predictions and recommendations typical of ML outputs. We illustrate our discussion with examples taken from a workshop concerned with how ML might be used in support of student mental health and well-being.

Using the technology-as-monster metaphor

In this workshop we employ the technology-as-monster metaphor as a way of revealing assumptions and highlighting uncertainty. Using familiar examples such as Frankenstein's creature and yōkai (via Pokémon), and drawing on the etymology of monster as a warning, the monster is introduced as an ambiguous creature that represents the unknown. Our focus is not on detailed technical aspects of designing with ML, but rather on discovering issues that may otherwise only become apparent in use as 'unforeseen circumstances'. Participants are asked to identify the problematic or uncertain places from which monsters may emerge, describe what might cause a monster to appear there, and to bring the monster forward by naming it and giving it form. Each monster embodies a particular concern, and the power of the technology-as-monster metaphor lies in the way it prompts participants to identify and name these concerns. This is because once they have been identified, described, and named, participants can begin to consider how these monsters might be domesticated and tamed, and how the concerns they represent might be mitigated or avoided.

Making Monsters

Each workshop starts with participants making a monster from everyday materials (Figure 2). This is a time limited activity, typically 5 minutes. Participants are asked not to stop and think, but simply to make any monster that comes into their heads and make it quickly (Figure 3). This activity acts as an ice breaker and warm up. The monsters are then put to one side and brought back into focus towards the end of the workshop.

Identifying inputs and outputs

The locus of this workshop format is the space between data that ML applications are built on and recommendations or predictions they might make. We seed exploration of this space by listing some likely origin and destination points. In our example workshop, these were signs or symptoms that might raise concerns about student mental health and well-being, and examples of interventions that have proved effective. These were derived from: National Alliance on Mental Illness [120], U.S. Department of Health and Human Services guidelines for educators [119], the American Psychiatric Association [125], and UC Berkeley's Greater Good Science Center [46]. To start mapping the space between these origin and destination points we ask participants to brainstorm sources and types of data that might be used to indicate signs or symptoms, and following this we brainstorm ideas for implementing interventions. This starts to frame our inquiry.

Mapping islands and monsters' hiding places

To move between the inputs and outputs that might describe our application we use hexagonal worksheets (Figure 4) based on the 5WsH creativity technique [76, p.66], and similar to those described in reports of previous co-design workshops [41]. These represent key aspects of ML, typically: data, ground truth, and recommendation (or prediction). Each of these is investigated in turn, with participants working collaboratively to answer the questions posed, see Table: 1. The responses participants give to these questions are then collectively critiqued with the aim of revealing where it is that things are unknown or uncertain, and locating places where monsters might be waiting to emerge. Here we might use monster cards (Figure 1) as an additional prompt or guide. We then highlight these places with monster stickers to act as a visible reminder and warning.

(Re)making, naming, and describing monsters

Once a route between data and recommendation has been mapped out, and we have marked the warning signs for monsters, we turn to addressing particular concerns. We return to the monsters created at the outset of the workshop as a starting point to explore the warnings we have identified. Participants are asked to select any monster, other than the one they themselves had made. They are then given a brief opportunity to develop this monster and decide its story. We provide a template to guide thinking about the monsters' back-stories. Participants are asked to name their monster, to tell what their monster warns us of, to say whether we should fear their monster (and why or why not), and finally how we might start to domesticate their monster. Participants are then each asked in turn to place their monster into the map at a warning point of their choice, and share their monster's tale.

Question	*Aspect text*
Who:	owns these *data*?
	defines *ground truth*?
	are *recommendations* for?
What:	*data* will be used?
	does *ground truth* describe?
	recommendations?
Why:	use these *data*?
	this *ground truth*?
	these *recommendations*?
Where:	will *data* come from?
	does *ground truth* come from?
	do *recommendations* go?
When:	will *data* be available?
	was *ground truth* defined?
	are *recommendations* made?
How:	will *data* be obtained?
	will *ground truth* be labeled?
	are *recommendations* decided?

Table 1. Listing of questions on the hexagon worksheets that are used in each of the three rounds of mapping ML concerns with 5WsH creativity technique.

In our student mental health and well-being workshop, one group had identified so much uncertainty around ground truth for the classroom performance data they aimed to use, that a monster called simply 'Ground Truth' (see Figure 5) was introduced. This monster was a warning about assuming their data was a valid indicator for mental health concerns. It should be feared because untrustworthy data could label students without strong basis. However, we might start to domesticate this monster with a culture shift so that discussion of these labels was less scary, and also by understanding that one source of data was not enough to make a decision in a valid way.

(Re)framing Inquiry

A generative metaphor brings forward new perceptions, explanations, and inventions, and brings new features relevant to the problem at hand into focus [140]. Schön introduces the term through the example of the 'paintbrush-as-pump', describing how a group of researchers are tasked with developing synthetic paintbrush bristles. Following a moment of inspiration, in which one researcher notes that a "a paintbrush is a kind of pump", inquiry is focused on the space between the bristles, which do not facilitate the easy flow of paint. This instigates a transformation, re-framing the questions posed, and leading to a design for synthetic bristles that gently curve when pressed against a surface. In Schön's words, generative metaphors "select for attention a few salient features and relations from what would otherwise be an overwhelmingly complex reality. They give these elements a coherent organization, and they describe what is wrong with the present situation in such a way as to set the direction for its future transformation" [140].

Figure 4. Examples of 5WsH hexagons from our student mental health workshop, with monster stickers highlighting assumptions and areas of uncertainty. This example includes an empty data hexagon that was added when it became apparent that data on students self-reported mental health were necessary for recommendations, but hadn't been considered.

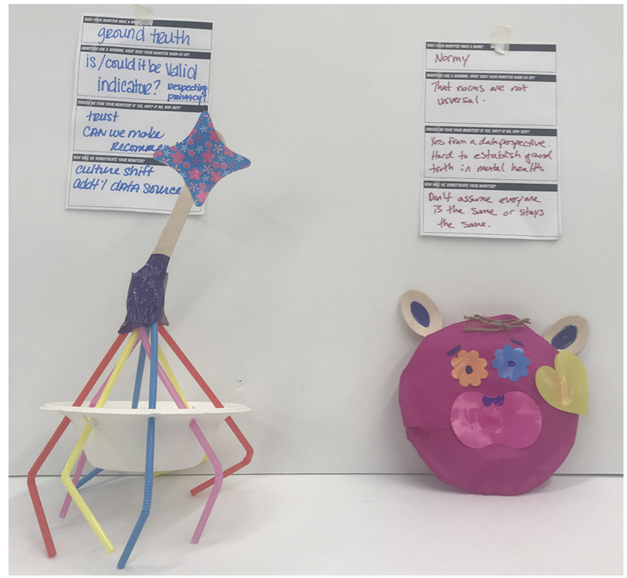

Figure 5. 'Ground Truth' and 'Normy', monsters from the student mental health and well-being workshop, shown with the notes outlining their story.

If, as research suggests, UX designers are typically deferring important questions about the design of ML applications to software engineers [42, 172], we should not be surprised if the situation becomes framed around questions of optimization and efficiency [23, 30, 171], rather than consideration for contexts of use [12, 65, 107] and ethical concerns [55, 124]. Assumptions and biases which may escape notice when design and development are driven and assessed primarily by technical constraints (e.g. because offending results are considered aberrations), typically only enter the picture after an application is publicly released [14]. The technology-as-monster metaphor, and the workshop activities it has inspired, begin to address this imbalance by providing a lens that brings into focus uncertainty around particular areas that warrant extra attention and caution. They offer a mechanism for selecting salient features and relations from within complex situations, organizing them in such a way that they present a coherent description of what is wrong in the present understanding of the situation, and posing questions that re-frame how the situation might be approached.

In our student mental health and well-being workshop, one group had been working on an idea that combined different location, credit card, and activity data, to track changes in behavior that might indicate early signs of concern. While there had been some uncertainty discussing data, and a warning had been raised about *when* ground truth (i.e. a baseline of behavior against which troubling changes might be compared) would be defined, it was inquiry into recommendations that identified a monster which caused these earlier stages to be revisited and a reframing proposed. The key moment came with regard to identifying *who* recommendations should go to. This was because the group realised that their intervention was aimed at students who did not identify as needing help with mental health issues, yet they were aiming to collect ground truth data interactively through student participation in therapy sessions. This shone light on the unspoken assumption that baselines for ground truth could be transferable, and raised a warning that 'normal' mental health could be a monster. Following this reframing, the group identified a new need for data about self-reported mental-health that would have to be addressed (in Figure 4 this is the empty 5WsH hexagon at the top). A monster called 'Normy' (see Figure 5) came out of this group. It was a warning that norms are not universal, and should be feared because determining baselines to obtain ground truth is hard with regard to mental health. To start domesticating this monster it should not be assumed that everybody is the same or that they stay the same. As in Schön's paintbrush-as-pump example, the technology-as-monster metaphor is here bringing salient features from a complex reality to the foreground, organizing them so that they describe what is wrong in the present situation, and setting the direction for inquiry that may instigate its future transformation. As one participant said, "Normy shows us there is no normal".

Supporting Design Collaboration

Design is often a collaborative activity, with specialists from across different domains needing to share practice knowledge and expertise in order to work effectively with challenging materials [29, 101, 122]. One way in which this is achieved, is through exploring shared metaphors [44, 139]. In this workshop we brought together different stakeholders, including: UX designers, ML experts, students, and student welfare professionals. One role that the monster plays in this workshop is as a clearly visible manifestation of uncertainty and dangerous assumptions. Once a potential monster hiding place has been identified and marked, it is harder to ignore and move on. The monster is a reminder and warning that the uncertainty might return as future danger.

As discussed earlier, in our student mental health and well-being workshop one group found ground truth so challenging that it became a monster's name. In this group, participants wanted to collect data 'that didn't make judgements' but instead just showed changes in patterns of behavior. However, the group's ML expert was able to show that it was unlikely this could be avoided, as ML needs labeled examples for training and evaluation. Solving this proved to be beyond the group in the time allotted this workshop. For example, how would they define student attendance as problematic? Is there an institutional norm? A class norm (defined by the syllabus)? Is it simply under 80%? How might this relate to potential mental health issues? Ground truth remained something that was complicated for other group members to understand, but in this instance, the ML expert had shown that it was not enough to just say, 'we don't want to collect data that are making judgments about people'. In another example from this same group, the student welfare expert explained that in her professional role, safety rather than privacy might be the main concern; and that providing help for students, making sure they are OK, is the priority. This insight challenged participants to consider whether the same might be appropriate in an ML context. In this workshop, the technology-as-monster metaphor is used to foreground and materialize these concerns. The figure of the monster occupies particular points of uncertainty, and challenges participants to confront assumptions that otherwise might be baked in at an early stage. A purely technical response to such challenges is likely to be insufficient, and so the monster also points to opportunities for UX designers to bring empathy, contextual insight, and sensitivity to a product's hedonic dimensions, to designing with ML.

Moving Beyond Transparency and Explanations

HCI research into ML often focuses on explaining algorithmic decision-making or making it more transparent to users [2, 79, 152, 168]. However, transparency and explanations have limitations [8], and the particular problem of black-box algorithms may itself be overstated [123], as similar problems are likely to have been seen before, e.g. with relational databases [47]. Yet many of the problems currently associated with ML applications are likely to remain if the provenance and validity of ground truth data are not probed with sufficient critical rigor. In each of the previous examples from our student mental health and well-being workshop the key conversations were around the availability and validity of ground truth data. In each case, assumptions that may have been missed, or simply remain unchallenged 'to be dealt with later', were foregrounded and major issues raised early. Greater transparency is important, and clearer explanations may mitigate problems by helping users to understand ML outputs. Raising concerns about the provenance and quality of data prior to its adoption might prevent them happening in the first place.

WHY MONSTERS

> "Monsters are to be feared, but also are generative spaces, places to question, wrestle with uncertainty, resist easy classifications, name power."

The 'Where Be There Monsters?' workshop ends with each participant completing a postcard asking them to briefly tell us about monsters and machine learning. The quote above is from a participant in our student mental health and well-being workshop, and nicely highlights how the monster is a prompt and locus for dialogue. Throughout the workshop we use the technology-as-monster metaphor as a reminder to take care and be responsible. We also use it to show that, rather than being fixed, meaning is an ongoing translation effort. ML can be opaque and unpredictable, and produce unforeseen outcomes; and yet it also presents opportunities and offers breakthroughs in diverse areas. Monsters help us to mark out territories of concern at an early stage of design and point to where exploratory inquiry may be most needed. Our workshops allow these questions to be posed, and provide stakeholders from across disciplines a platform to discuss what might otherwise be considered the exclusive domain of data scientists and ML experts. We use the lens of a generative technology-as-monster metaphor to focus UX concerns towards activities earlier in ML pipelines than might otherwise be the case, and as tool to (re)frame the questions and challenges UX might pose for ML. We do not view ML as either magical or terrifying, but acknowledge that it may be both. The monsters we look for are complex, ambiguous, and challenging. They occupy uncertain spaces that border the known and unknown. Even when those spaces are part of the familiar everyday. Our monsters are not always fearful, and should not be always be avoided; but we should always listen for their warnings.

CONCLUSION

In this paper we have taken the familiar technology-as-monster metaphor as a starting point for inquiry into machine learning (ML), and shown how it can be employed by user experience (UX) designers who work with this challenging material. We have described how in popular use the metaphor references a monster that has lost much of its ambiguity and nuance over time, to become increasingly one dimensional; and so we have revisited historic human-monster relations to reveal how the metaphor can shine new light on ML. We have then demonstrated how by reconsidering our understanding of the technology-as-monster metaphor it can become generative. We have presented a workshop format that exploits this generative potential, and illustrated its effectiveness through detailed descriptions of an example workshop. This paper contributes to how HCI understands generative metaphor, provides a lens through which we might approach ML, and responds to the challenges ML poses for UX design.

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