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Machine Learning, Music and Creativity: An Interview with Rebecca Fiebrink

Simon Holland and Rebecca Fiebrink

The following interview was conducted in London and Milton Keynes by Skype. It has been lightly edited for clarity.

Abstract Rebecca Fiebrink is a Senior Lecturer at Goldsmiths, University of London, where she designs new ways for humans to interact with computers in creative practice. As a computer scientist and musician, much of her work focuses on applications of machine learning to music, addressing research questions such as: ‘How can machine learning algorithms help people to create new musical instruments and interactions?’ and ‘How does machine learning change the type of musical systems that can be created, the creative relationships between people and technology, and the set of people who can create new technologies?’ Much of Fiebrink’s work is also driven by a belief in the importance of inclusion, participation, and accessibility. She frequently uses participatory design processes, and she is currently involved in creating new accessible technologies with people with disabilities, designing inclusive machine learning curricula and tools, and applying participatory design methodologies in the digital humanities. Fiebrink is the developer of the Wekinator: open-source software for real-time interactive machine learning, whose current version has been downloaded over 10,000 times. She is the creator of a MOOC titled “Machine Learning for Artists and Musicians.” She was previously an Assistant Professor at Princeton University, where she co-directed the Princeton Laptop Orchestra. She has worked with companies including Microsoft Research, Sun Microsystems Research Labs, Imagine Research, and Smule. She has performed with a variety of musical ensembles playing flute, keyboard, and laptop. She holds a PhD in Computer Science from Princeton University.

Simon Holland

Music Computing Lab, Centre for Research in Computing, The Open University, UK
e-mail: s.holland@open.ac.uk

Rebecca Fiebrink

Department of Computing, Goldsmiths, University of London, UK
e-mail: r.fiebrink@gold.ac.uk



Photo credit: Shelley Glimcher

Holland: How did you first become involved in HCI research?

Fiebrink: I came into my PhD, back in 2006, with an interest in music information retrieval. At that point in time, even though machine learning had been used in music performance systems much earlier by people like David Wessel, there wasn't a lot of focus in looking at how machine learning techniques could be used in performance, or by creative practitioners, and so I saw an opportunity. I was surrounded by people who were experimental musicians and composers, and I got really interested in the question of what might happen if we took some of the techniques that I saw gaining traction in the ISMIR¹ community and put them in the hands of creative practitioners. When I started that work, I didn't necessarily approach it from a very formal HCI standpoint, but I was very interested in making tools that were usable by other people who weren't me—I wanted to understand what composers wanted to do with these tools, and not just have everything be driven by my own ideas. So I very naturally found that HCI gives a set of methodologies and perspectives and modes of evaluation that supported the work I wanted to do.

Holland: Do you make music yourself?

Fiebrink: Not as much as I used to! Since coming to Goldsmiths, I haven't had an ensemble that I'm active with, and the kind of electronic music that I make is very much social. I'm not a solo performer, but even when I was working with the Princeton Laptop Orchestra and SideBand (when I was at Princeton before moving to Goldsmiths), I often looked at the creative work that I was doing as having dual functionality. From one perspective, it was simply fun —engaging in crea-

¹ International Society for Music Information Retrieval Conference

tive expressive activities that brought me satisfaction for their own sake. But at the same time, as a researcher, I was able to justify taking the time to do it from the perspective of ‘dog fooding’—in the sense that if I’m going to make a tool that other people are going to use, it’s always a good idea for me to make sure that it’s at least good enough to support my own practice. And so I approached it from that perspective. Obviously, I’m going to listen to other people and work with participatory design processes, but at the same time I like to complement that with my own hands-on work —trying to get to the heart of how I might make my tools more efficient, or recognising that there possibilities that I’m only really going to find by getting my hands dirty.

Holland: Many researchers come to work of this kind from a perspective of being a performer or a composer but it’s interesting that you mentioned that your work started in part in the context of music information retrieval - can tell us a bit more about that?

Fiebrink: My background is multifaceted. I have an undergraduate degree in computer science and I also have an undergraduate degree in flute. I did a master’s degree in music technology, and during my master’s I became really interested in music information retrieval, but I was also doing some side projects that were more related to NIME,² so my interests were always quite broad. So while I don’t approach my work with the main goal of making things for me to use in my own performance work, I can speak the same language as performers, because I have a lifetime of experience being a performer.

Holland: What influences affect the way you develop your work?

Fiebrink: I’m drawing on a lot of different perspectives in my work. I am a computer scientist and a programmer. I also take ideas from what’s happening in the machine learning community and what’s happening in the music information retrieval community. Certainly, being able to prototype new technology myself is crucial to the way that I look at the space of possibilities. It allows me to engage in really hands-on participatory experimental processes, when I’m making stuff and people are trying it out - as opposed to being limited to approaches that are more removed – for example simply trying to observe and understand people’s existing practices.

Also, many of the research questions that I’m most interested in are not just technical research questions; there are wider questions about things like: What is machine learning good for? How do we make better tools for creative practitioners? What should creative practitioners learn or know about particular technical practices in order to use tools effectively? How do we educate people or build interfaces that might feel well matched to what people already know?

² New Interfaces for Musical Expression

I have a fundamental interest in advancing and expanding the types of creative practices that people can do with technology - I would say that's my main motivation as opposed to simply 'how I can make a better algorithm?'

Holland: When you're working on research that involves music does it have implications any wider than music?

Fiebrink: Definitely, yes. When I did my PhD work I was focusing quite explicitly and narrowly on music and on building tools for electronic musicians and composers - but there are immediate applications to other domains. It's not a big leap from thinking about building a gesturally controlled musical instrument to building a gesturally controlled game or building interactive art installations. The approaches I began developing in my PhD work can be applied in any situation in which people are interacting in a space with sensors, where information about what they are doing influences some aspect of what the computer is doing. After my foundational work with musicians, I started working with folks who wouldn't necessarily describe themselves as musicians, but who were doing creative stuff with sensors in closely related fields. In addition to just building useful tools, aspects of my research involve trying to understand what it really means to support composers or musicians in their practice. And that intersects with fundamental questions about what it means to support people involved in any kind of creative practice in any domain.

For instance, I draw a lot on work by folks like Ben Shneiderman, Celine Latu-lipe, and Scott Klemmer, who have studied creative practices in a variety of domains, as well as how technology can be used to support those practices. When we make and evaluate technologies for use in creative practice, we've got to consider different factors than when we are trying to develop a better user interface for more mundane tasks. For instance, we want to make it really easy for people to prototype an idea so that they can get a hands-on feeling for whether their idea is any good. And we want to make it easy for people to explore lots of ideas in a given space, rather than forcing them to commit to one initial idea.

Making musical interfaces contributes back to this body of work in a few ways. Certainly, some of my research validates some of these design guidelines that have been proposed for creative technologies, and informs a more nuanced understanding of how they play out in musical contexts. Additionally, one of the big themes in my work is about making interfaces that allow people to communicate embodied practices and ideas to the computer. When you try build expressive musical interfaces with computers, you notice right away that keyboards and mice aren't great interfaces for embodied expression. And likewise, computer programming languages are not ideal for communicating ideas about human movement, or imagined relationships between movement and sound. Building good interfaces for music performance—and for the design of performance systems—demands an awareness of the importance of the body. These issues manifest quite clearly in music, but of course they're shared across a lot of other fields.

Holland: For people who don't know, tell us a little about your PhD.

Fiebrink: My starting point was asking what might be needed to enable musicians and composers to use machine learning in their work—without requiring them to get a PhD in computer science first! In order to explore that, I built a lot of software prototypes and iteratively workshopped them with a group of composers. One outcome of this work was the software I ended up building, called Wekinator (Fiebrink, Trueman and Cook, 2009; Fiebrink, 2011). Wekinator allows anyone to apply machine learning in real time, for instance to sensor, audio, or video data. I've continued to develop and release Wekinator, and it's now been downloaded over 10,000 times. It's used in a lot of teaching around the world. A more research-oriented outcome of my PhD work was the finding that, that in order to make machine learning useful and usable to people doing things like making new instruments, it turns out that a lot of conventional assumptions and practices around machine learning aren't appropriate. For example, this idea that you have a ground truth dataset that you want to model as accurately as possible goes out of the window - because what people often care about is solving some bigger creative problem, or building something that functions within a particular context - and the training dataset may actually be quite malleable. For instance, you may start with one data set and build a model that models that dataset quite well, but when you try to use the model to make music, you find that it doesn't exactly support what you wanted to do musically, as a person. In that situation, you might be able to change that training data to give better results. So a main outcome of this work was identifying human-in-the-loop processes that make sense for applying machine learning to creative problems, and of course Wekinator embodies those ideas in the types of interactions with machine learning and data that it supports.

Holland: There are certain criteria for whether research is successful and other criteria for whether musicians or creative people think you're helping them. Is there a tension between these two things, and if so, how do you navigate it?

Fiebrink: There's often a tension between those things. I'm happiest as a person when I'm making things that are useful to people, but I make my department happiest when I'm publishing highly cited research papers! Sometimes the first thing does lead to the second, but not always. Sometimes, for instance, it's hard to communicate the particular challenges and goals of computer music to a broader set of reviewers, for example HCI paper reviewers. I don't necessarily think that's a bad thing, but it's a fact of life. It can be hard to try to tell the story of why solving a particular problem in computer music can be of interest beyond the computer music community.

Another obvious issue is that some of the evaluation methods that are expected at venues like CHI (the premier international conference on Human-Computer Interaction) are very different from what you would want to do in practice to understand whether you have built something that's useful for musicians or not. Some of the things that are really meaningful for me - in understanding if the thing I built works - need to take place over really long timescales. Has something been adopted and propagated over a period of years? Or at a very local level - this tool that I

built for this music teacher, are they still using it, or are they developing a curriculum around it? So there are all sorts of factors. You generally can't measure whether one musical interface is better than another using established criteria - you're often building technology to enable something totally new and the criteria may change. Developing new technology often entails developing new evaluation methods as well, so there's all sorts of challenges.

Holland: Have you developed any strategies for explaining work that straddles these boundaries to HCI referees, or does it have to be ad-hoc?

Fiebrink: A bit of both. In terms of general strategies, one approach is to link it to existing threads of research in the HCI community. So, for example, my work with interactive machine learning and music is not just about music, it's also relevant to a larger space filled with people who maybe couldn't care less about music but who might be interested in how we can improve machine learning systems by putting humans in the loop. So I feel I have something useful to say about that and I've written some papers where you can talk about creative use cases of using machine learning in the interface as a complementary perspective in other perhaps more traditional or unambiguous use cases.

There is a similar situation with the discourse around what makes a good creative technology such as the work that Celine Latulipe is doing. There's a thread of that woven through the CHI community where I can currently engage and bring a different set of perspectives and show what machine learning can bring to creativity.

So I think it's good that you have to contextualize your work against the types of things that a particular community cares about – but I'm not always successful!

Holland: Are there areas where music interaction still has lessons for mainstream HCI?

Fiebrink: That's a good question. One of the challenges for musicians and people who research in music is that often we're not particularly good at articulating what makes something a positive experience or an engaging interface, or at any rate articulating that in ways that naturally suggest linkages to HCI. That doesn't mean that they're not there. One thing about music and the arts is that there's a tradition of practice-based research and there's a tradition of self reflection on one's work. You can find this done well in different music conferences, for instance, where somebody writes a paper as a composer and talks about their rationale for doing things the way that they do. Obviously auto ethnography is not a new method, but a lot of those papers are fascinating to read and may perhaps contribute to the dialog around formalizing and refining methods of this kind and importing them into other fields. That's something that I do feel is appropriate and valuable. In my work, when I interview people who use my software, I'm getting information of that kind, and trying to try to understand as deeply as possible why they're doing what they're doing and all the different factors that that come into play when they're composing a piece. I think that some methods and findings of

this kind can be encapsulated as case studies, but perhaps there is more to be understood and articulated methodologically.

Holland: Are there things that mainstream HCI knows about that music HCI is neglecting?

Fiebrink: Not that come to mind immediately! I can't think of any HCI papers that I've read recently where I think oh that would be great to apply to music and nobody's done anything like that before. That's not to say they aren't out there but in general I feel like there is a contingent of people within the music community who are pretty on top of what's happening in the HCI community!

Holland: What are you researching at the moment?

Fiebrink: Well, I have one set of projects continuing to look at ways of making end-user machine learning more usable, especially in creative contexts. For instance, we're looking at how to make feature selection and engineering by musicians or artists easier, because that's something that Wekinator doesn't do and other tools don't do, and it's a problem that deep learning doesn't always solve - even though many people think it does! Feature engineering is still one of the big practical barriers to people using machine learning in creative work, especially when they have small datasets and they're applying machine learning to unique modeling problems.

I've got another project with collaborators in Northamptonshire, working with music therapists and kids with disabilities, where we are looking at how to build better on-the-fly instrument-making tools. The seed for this project was the vision that a music therapist could sit down with a kid with potentially quite severe physical disabilities and use machine learning techniques like those in Wekinator to quickly make a customized, sensor-based musical instrument. With input from kids and therapists, this idea has now branched out into a few different directions. For example, once we provide users with an easy-to-use interface for doing the machine learning, what else is required in order for music therapists and teachers to effectively build curricula around these instruments? What kind of music and sound-making capabilities should they have? How can we build tools that allow kids with disabilities - and kids without disabilities who are playing acoustic instruments, for example - to participate collaboratively in music classrooms?

Holland: Does this line of work carry a responsibility to ensure it's sustainable?

Fiebrink: Yes. Making things sustainable is always tough without sustainable funding. But my approach is always at a minimum to make it open source and free to download, to provide as much documentation as we can in different formats, and to strive to develop a community of users.

We also just wrapped up a project called RapidMix, which was a Horizon 2020 project. A lot of our work at Goldsmiths focused on making better machine learning tools for creative software developers. So, for example, to serve the needs of

hackers³, makers, creative coders, and professional developers working in games and audio, we crafted a programmer-level API for machine learning that you can use without needing to be a machine learning expert. This work was tailored for people who may want to use machine learning to achieve similar outcomes as Wekinator users, and thus may want to use more interactive approaches to evaluating and refining the machine learning models. For instance, the training set may be a moving target, and conventional evaluation metrics might not be as useful as just building something that you can play with in real time in order to understand how it might need to be improved.

Holland: Can you give an example of what that might have made possible that perhaps wouldn't have existed before?

Fiebrink: For example we produced an open source set of JavaScript examples making it easy to use machine learning to create flexible interactions using sensors such as those in smartphones. When we started this project, JavaScript developers making mobile or desktop apps faced steep barriers in doing this kind of thing. They had to deal with large quantities of boilerplate code and make many low-level decisions about what algorithms to use, as well as dealing with libraries that assume that your training data must be stored in a file or a database. So we made some easy to use tools as well as a lot of learning resources to help developers get started with machine learning. You can go to our API website and see a lot of examples that let you see the source code, see the executed program right next to it, and edit the code experimentally in real time. There is a suite of demos showing how to carry out the entire machine learning process, from collecting data, to training a model, to testing it out, to changing the model in real time, and showing how do that with sensors, with audio, and with video.

We're also working with JUCE (which is a pretty well known audio library), and they're about to release a set of machine learning modules for their developers that wrap our code. So it's good to see that this work is getting used.

Holland: What are the interesting problems in Music and HCI that people should be working on?

Fiebrink: My answer to this hasn't changed dramatically from what it was several years ago. For me, the big questions are still around how technology, including machine learning, can best support human creative practices. Research, including my own, has contributed to a better understanding of this, but there's still a lot to explore.

There is a lot of focus, both among machine learning researchers and the general public, on using machine learning and AI to replace people and duplicate human creative processes. I find this such a limiting viewpoint. From an artistic and humanist perspective, people derive a lot of value from making creative work, so

³ 'hackers' in the original benign sense of this word.

we need to make tools that people actually use, where we are adding value to people's lives, rather than replacing people.

There are also commercial and practical reasons to broaden the focus beyond replacing people. Some generative approaches effectively function like a big red button that you push and music comes out. That's not really so useful if you want to generate music for a particular application. Often, you are going to do a better job if the computer has more nuanced ways of taking into account information about the context, the user's goals, the characteristics that they would like to see in that finished product, and so on. Not to mention, giving people the ability to iteratively shape and refine algorithmic output has so much more potential to produce work that satisfies subjective goals that might be hard to encapsulate in a single objective function. We need approaches that more richly combine human and machine processes, if we want machine learning to flexibly integrate into real-world media creation or production contexts.

There are lots of different ways we can think about how machine learning algorithms and human creators might work together. A learning algorithm might function as a collaborator, or as a friendly adversary that challenges you or pushes back against you. We can draw on all sorts of other relationships we have with objects or people in other creative work, to find new metaphors for how we might use machine learning: we could imagine machine learning functioning like a paint brush, or a sketch pad, or a telescope; or perhaps an extension of our body, like an extra hand. Or we could build machine learning systems that take on the role of a teacher, or a critic, or an audience. When you think about it, just trying to replace a human expert is so boring.

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