# Interactive Machine Learning for Embodied Interaction Design: A tool and methodology

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## Abstract

As immersive technologies are increasingly being adopted by artists, dancers and developers in their creative work, there is a demand for tools and methods to design compelling ways of embodied interaction within virtual environments. Interactive Machine Learning allows creators to quickly and easily implement movement interaction in their applications by performing examples of movement to train a machine learning model. A key aspect of this training is providing appropriate movement data features for a machine learning model to accurately characterise the movement then recognise it from incoming data. We explore methodologies that aim to support creators' understanding of movement feature data in relation to machine learning models and ask how these models hold the potential to inform creators' understanding of their own movement. We propose a 5-day hackathon, bringing together artists, dancers and designers, to explore designing movement interaction and create prototypes using new interactive machine learning tool InteractML.

***CCS Concepts:*** • **Human-centered computing** → **Participatory design**; **Gestural input**.

***Keywords:*** interactive machine learning, movement interaction, immersive media, performance


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## 1 Introduction

As movement sensor technologies become more available, affordable and reliable, body-based interaction is now placed firmly within contemporary digital culture and the creative domain, particularly dance, interactive and immersive media [Fdili Alaoui 2019; Masu et al. 2019; Rizzo et al. 2018; Wechsler et al. 2004]. In VR, movement interaction has been shown to increase the sense of presence [Slater 2009], it can also increase users focus and attention [Wilde et al. 2017]. Discourse in HCI is now taking inspiration from embodied cognition and somaesthetic design in development of theory and process. Embracing the cultural world as a resource for designing interfaces, respecting the importance of emotion, experience and aesthetic. HCI for movement interaction can learn from dancers knowledge of the body; tacit and embodied.

## 2 Background

To accommodate the shift towards affective bodily-based interaction, there are several design approaches that exploit tacit embodied knowledge, such as those that develop movement interaction designs through physical 'bodystorming' or 'embodied sketching', by acting them out. This requires a first-person perspective on interaction design [Höök et al. 2018]and design by doing and moving [Hummels et al. 2007; Kleinsmith and Gillies 2013] as an early stage of the design process. Enactment in this way enables designers to reflect on the changing experience of movement over time, through this reflection the activities supports cycles of reflection and refinement [Márquez Segura et al. 2016].

If we are to carry on this embodied and iterative approach through to the implementation phase, we need to continue to use our body. Our second technique, Interactive Machine Learning [Gillies 2019], enables creators to implement movement designs simply by performing them, in order to provide a quick feedback to enable a rapid iterative workflow. For artists and dancers to create movement based interaction artworks they must rely on a developer to programme a way for the system to understand a particular movement. There are many issues with this design process; it is non-iterative, uses linear problem solving and means technical limitations stifle creative ideas[Fdili Alaoui 2019]. InteractML intends to give this artistic power back to the artist giving them the ability to control the machine learning system and the movement which they want to express. In the ethos of the design is not only for them to be able to use the system themselves, but for them to gain a higher understanding of how the system works and what it is capable of so they are able to create more original uses of the system and enrich their artwork.

## 3 Design Process

### 3.1 Bodystorming

We adopt the embodied sketching design approach as an ideation practice when using Interactive Machine Learning for designing embodied interaction. Following from Caramiaux et al. our method uses an adapted form of the critical incident technique; a procedure that elicits designers to recall recently lived memories from their everyday lives to apply as input for design [Caramiaux et al. 2015; Flanagan 1954]. Here, the method takes its form as a 'movement incident', where subjects are instructed to remember, from the past few days, an atypical situation in which a memorable movement contributed. This guides the designer towards their own lived experience, in line with Núñez-Pacheco and Loke's approach of focusing, based on invoking an awareness of the felt qualities of embodied experience [Núñez-Pacheco and Loke 2018]. Designers physically enact and explore their movements. Instructed to 'slow it down, speed it up, make it as big or as small as you can. Make it go wrong', the aim is to encourage embodied sketching and the embodied design ideation practices of using estrangement and defamiliarization as an exploratory method [Wilde et al. 2017]. We pose that the sense of 'play' in our method is in important part of the iterative approach. Play disarms the creator to take risks, to react quickly without dwelling on the outcome, we have found this enriches the process and gives rise to interesting results [Gaver 2000; Iivari et al. 2020].

### 3.2 InteractML

Interactive Machine Learning allows a user to iteratively build and refine a machine learning model through "cycles of input and review"[Fails and Olsen 2003] as opposed to the automated process where the algorithm classifies the data with limited customisation from the user[Ware et al. 2001]. It gives the user power to customise and control how the data is classified and what the content of the data is. In the design of InteractML the user provides training examples (movement data), classifies these examples and can iteratively edit the classification and examples.

IML is increasingly being implemented to design and build new gestural controls to allow users to create and define examples improvisationally, and to evaluate models through experimenting with controllers in real time. Several toolkits have been designed for the use of programmers such as GRT[Gillian and Paradiso 2017], RapidMix, RapidLib and ml.Lib. Tools have been designed for less expert users such as Delft AI Toolkit and Wekinator offering a graphical user interface. Wekinator[Fiebrink and Trueman 2012] was built for the creation of new musical instruments, it allows for custom mappings between gesture and computer responses. IML is also being used by programmers working with dancers to implement their artistic work[Fdili Alaoui 2019]. These are used in collaboration with the artists controlled by the programmer rather than creating tools which put the power in the hands of the dancer.

## 4 Feature Extraction

Movement features can be computationally characterized relative to a set of dimensions in space and time. The type of movement features that the InteractML system extracts are: positions, rotations, velocities and the distance between two values (for example the distance between a moving point and an object). Different types of movement might be predominantly characterised by a particular feature, for example a twisting movement is best distinguished by fluctuations in rotation values. Whereas, a movement with a clear trajectory from one point to another could be better distinguished by changes in position values.

A ML model will compare incoming movement data with recorded example data and decide on the output based on similarity. Understanding which features best characterise a movement will yield a more reliable and robust comparison for the model to make a successful decision. This is often not a straightforward choice, especially as the exact process behind a learning algorithm (described as a 'black box' by [Patel et al. 2008]) is difficult for a user, or even a ML expert, to interpret. During our research with participants using the tool at workshops and hackathons users found it difficult to choose the appropriate features. McCallum and Fiebrink research with similar tool Wekinator found that feature engineering was a necessary part of the process to be able to recognise a movement[McCullum and Fiebrink 2019].

It is feasible that the graph could take all raw data from sensors, however, for this to provide accurate results the system would need a very large dataset which is unsuitable for users of InteractML as they record the data themselves[McCullum and Fiebrink 2019]. There are similar applications which provide a set of feature extractors for users[Dudley and Kristensson 2018], however this also would not be appropriate as it would limit the movements that the users could design.

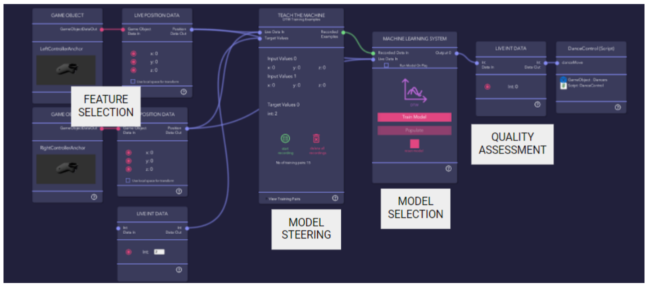


**Figure 1.** A node based graph that allows users to configure and train machine learning models within InteractML.

Experts in understanding movement computationally can draw their knowledge to analyse which features are important for a particular movement or pose. In experimentation they can draw from this knowledge comparing results with an understanding of why one is preferable. McCallum and Fiebrink found that non-expert users often changed the movement they were trying to recognise rather than finding the best features[McCullum and Fiebrink 2019], without grounding knowledge it is easier to change what your goal is then to iterate when you are unsure of why the system is not behaving in the way you want. It has also been found that iteration without this grounding knowledge does not lead to better models[Wu et al. 2019].

We need to give the users of InteractML knowledge about how to understand their movements so that the phase of experimentation can lead to the right model formation. We will be bringing this into the design of our bodystorming sessions.

## 5 Plan and Learning Goals

We propose a 5-day hackathon, bringing together artists, dancers and designers, to explore designing movement interaction using a new interactive machine learning tool InteractML [Gonzalez Diaz et al. 2019], a plug-in for Unity3D software, developed by the organising team and other colleagues at Goldsmiths, University of London. On the first and second days of the hackathon participants will gain instruction on the use of our tool (Gonzalez Diaz et al. 2019) and an insight on the interactive machine learning method the tool is built on. Initial sessions will also aim to equip participants with embodied ideation design strategies to enable them to design compelling movement interfaces that hold the potential to engage full body interaction within immersive media. The embodied ideation sessions will involve taking part in full body movement activities and comfortable clothing and footwear are encouraged. However, participants will choose the movements they make and only need to make movements they are comfortable with. We encourage participation from all along the spectrum of body motion, these experiences will provide valuable insights in the tool design. We will hold interactive sessions twice, at different times of the day, to accommodate participants attending from different time zones. These sessions will be held on Microsoft Teams and recorded to be available to stream after, we will be available on our Discord server to answer participant questions.

Over the third and fourth days, participants are encouraged to collaborate to design and develop prototypes using movement interaction in their immersive creative applications, as and when it fits with their own schedule and time zones, we will offer support over our Discord server throughout these days. As a deliverable participants will, either individually or in small groups, develop a working prototype of an immersive creative application that uses the InteractML tool for movement interaction.

On the last day, we will hold a showcase session, again with 2 opportunities to join, to accommodate participants attending from different time zones. Here participants will present their prototypes to one another, offering the opportunity for feedback and reflection. During the hackathon we will pose an emphasis on exploring methodologies that aim to support creators' understanding of movement feature data in relation to machine learning models as a learning goal. With this in mind, to close we will hold a discussion session posing the question on how working with machine learning models could hold the potential to inform creators' understanding of their own movement.

Participants will have the opportunity to join the InteractML community, where we deliver regular workshops and artist residencies, keeping interested parties up to date with the development of the InteractML tool.

The studio will be featured on our project blog, detailing the discussion outcomes and showcase participants' prototypes:
https://sites.gold.ac.uk/4i/. More formally, the studio outcomes will be written up in the form of a research paper where we will submit to academic journals and conferences in the field of HCI, including ACM TEI 2022 but also ACM CHI, ACM TOCHI and the International Conference on Movement and Computing (MOCO).

## 6 Schedule

### Day 1

2 hour interactive session on Microsoft Teams (choice of 2 sessions)

- Welcome and introductions
- Bodystorming activity

- Interactive Machine Learning presentation and InteractML demo

Morning session - 10 am CET (9am GMT)
Afternoon session - 5pm CET (4pm GMT)

**Day 2**

Offline activities with communication and materials distributed on our InteractML Discord Server.

- Simple training exercises in a learning scene in special Unity project
- Facilitated group and idea formations

5 minute presentation for feedback on Microsoft Teams, to be organised directly between us and participants

**Day 3 and 4**

Asynchronous prototype development, with ongoing support from us on our Discord Server

**Day 5**

3 hour interactive session on Microsoft Teams (choice of 2 sessions)

- Prototype presentations and feedback (2 hours)
- Discussion session (1 hour)
  - Reflection on the interactive machine learning approach and designing embodied interaction.
  - Issues relating to movement features and an understanding of movement between machine learning and humans.

Morning session - 10 am CET (9am GMT)
Afternoon session - 5pm CET (4pm GMT)

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