Scratch for Sports: Athletic Drills as a Platform for Experiencing, Understanding, and Developing AI-Driven Apps

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Abstract

Culturally relevant and sustaining implementations of computing education are increasingly leveraging young learners' passion for sports as a platform for building interest in different STEM (Science, Technology, Engineering, and Math) concepts. Numerous disciplines spanning physics, engineering, data science, and especially Artificial Intelligence (AI) based computing are not only authentically used in professional sports in today's world but can also be productively introduced to introduce young learners to these disciplines and facilitate deep engagement with the same in the context of sports. In this work, we present a curriculum that includes a constellation of proprietary apps and tools that we show to student athletes learning sports like basketball and soccer which use AI methods like pose detection and IMU-based gesture detection to track activity and provide feedback. We also share Scratch extensions which enable rich access to sports related pose, object, and gesture detection algorithms that youth can then tinker around with and develop their own sports drill applications. We present early findings from pilot implementations of portions of these tools and curricula, which also fostered discussion relating to the failings, risks, and social harms associated with many of these different AI methods – noticeable in professional sports contexts, and relevant to youths' lives as active users of AI technologies as well as potential future creators of the same.

Introduction

Richer Artificial Intelligence (AI) education opportunities is a critical rising need for youth across the world (Luckin et al. 2016). Simultaneously, there are persistent and expanding challenges regarding the access of computing and AI education opportunities, especially across social axes like gender, race, and class among others (Webb et al. 2012).

Recognizing the power of interdisciplinary education for broadening participation in STEM disciplines (Doerschuk et al. 2016), and especially computer science contexts (Lasker and Weiss 2003), we believe that centering a similar goal of creating interdisciplinary activities around AI education is a key method to contextualize it with activities that are more internally motivating, and also situate AI in activities where its utility and power are salient to learners.

With this framing in mind, we are working on developing curricula and tools that help provide bridges between sports, PE classes, and computing classes. Sports as a participatory space provides unique power and potential to enrich technology exposure and knowledge. In contrast to most formal (and even many informal) educational opportunities, sports activities like physical education classes include a whole body movement that is broadly known to help social, physical, and mental health of learners across ages (D'Isanto 2016). Additionally, it also provides a context for engaging with *body syntonicity*, an often underemphasized aspect of Papert's framework of constructionism (1978), wherein he designed Logo and corresponding physical Logo turtles with the aspect of enabling connecting with mathematical and computational concepts through learners' personal body movement.

Additionally, sports are often pursued as an extracurricular hobby and passion, engendering unique, rich cultures and providing a healthy venting space from classroom schooling (Messner, 2009). Additionally, in many contexts, they are also pursued as an avenue for life success, often in response to the academic component of schools undeserving many learners and communities (James, 2012).

As a result, we focus on enriching sports experiences of youth by introducing technology and AI exposure activities in the same, while centering student interest in physical activity. Through this bridging, we are able to provide a novel perspective into AI and its capabilities, bridge the disciplinary divide between academics and sports, and identify novel kinds of learner participation in AI education rarely seen as relevant to computing practices and learning. In this paper, we share our work in this space – describe our curricula and tools, and present preliminary findings from early implementations in formal and informal contexts.

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Related Work

Interdisciplinary Computing and AI Education

There is a vast breadth of work bridging computing and different STEM disciplines. One of the earliest and most significant thrusts in computer science education as empowered by Papert's model of constructionism (1980) itself placed a key value of learning computer science at the school level in service of understanding other concepts to a greater depth. Papert argued that creating Logo programs to understand concepts in math and other disciplines has powerful value in both learning computer science as well as math to a depth often inaccessible in school classrooms.

Building on this perspective, CT-Stem is an example of a project with numerous publicly available tools and curricula (Jona et al. 2014) which brings computational thinking education opportunities and experiences into physics, chemistry, and biology classrooms through the use of agent-based modeling examples which help develop deeper understanding of science concepts as well as make value of bridging disciplines overtly visible.

There is an extensive presence of artificial intelligence systems present in adaptive tutoring systems across numerous disciplines (Mousavinasab et al. 2021). At the same time, there is limited approach in education targeting AI concepts themselves in the context of non-computing disciplines and classrooms.

So far, AI education has been mostly only approached through numerous playful and game-based educational activities, including social AI co-drawing activities (Ali et al. 2019), robot car control games (Williams 2018), game design and development curricula (Zyda and Koenig 2008), and art generation activities (Ali et al. 2021). These projects are key frontiers in expanding access to AI education and concepts in different forms, but they are almost always situated in curricula and classrooms aimed at computing and AI education.

Outside of computing classrooms, DanceOn (Castro et al. 2022) is an exemplary project of providing culturally responsive computing education opportunities by engaging dancers in AI concepts through tools that help add visualizations and effects to their choreography.

AI (Education) in Sports

Our project builds on DanceOn's approach, as well as the work by Zimmerman-Niefield et al. (2019), who implement machine learning techniques and education among soccer players by developing sensors for them to assess their own gameplay.

To develop a fuller curriculum that engages learners across different sports contexts, our work relies on the already populous market of commercial and publicly available AI technologies for sports.

Professional sports have a long running practice of deeply engaging with players' and teams' performance statistics (Ofoghi et al. 2013) – acting as the bedrock of league industries where players are valued and traded across teams on their performance as individuals and team members.

More recently, as different kinds of AI systems and sensors have become increasingly affordable and accurate, a deeper level of analysis of athletes' participation has become commonplace. Sensors in the form of wearables are used by professional athletes (Lutz et al. 2020) as well as all kinds of people in their everyday lives to track fitness, health, amount of exercise conducted, and details of movement through different activities. While the ability of wearables to provide real time as well as cumulative detailed information about wearers' stress levels, and fitness measurements like lung capacity offer a powerful way to make gameplay and team strategies responsive to players' capacity, they have also been used to measure other activities in athletes' lives like sleep and daily movement raising concerns about privacy and ethics around these practices (Karkazis and Fishman 2017).

This is in addition to another classic way of analyzing sports – video cameras. Building on the legacy of the first captured video motion which was of a race horse, video cameras have long been used to analyze sports in action, for referee judgments, and for analyzing different player techniques. With the increasing ease of AI systems being able to commercially process video even in real-time, numerous AI-driven apps have been developed to track play information automatically, including attempts, passes, successful shots, speed of throw or hits, and many other game metrics.

Lastly, there is also a slew of sensor embedded gameballs that allow for less detailed data collection and analysis than video cameras, but sensing that tends to be more portable, and requiring lesser external infrastructure like cameras. Soccer, basketballs, golf clubs, and other kinds of racquets and balls are being developed with the ability to track patterns of how different athletes play, what provides them with real-time as well as cumulative information about their strengths, weaknesses, and ways to improve.

In the following section, we discuss specific examples of these three different kinds of sports technologies and how we have developed accompanying educational materials to make their underlying AI concepts and practices more accessible to learners.

Resources and Experiences

Given the categories of sports technologies we described, we now describe how we integrate them with educational computing tools to make underlying AI concepts explainable and modifiable for learners.

The activities we describe have been used across elementary school students to high schoolers. Centrally, most of the usage is aimed at learners from **grades 3-8**. We draw on descriptions of learner usage from a variety of contexts: **PE and library classes**; informal venues like informal **programming at parks**, libraries, community centers; and **pop-ups** as well as week long **summer camps**. Across contexts, our recruitment varies from engaging with school students who have to follow classroom curricula, drop-in attendance at sports-centered community events and registered participants at sports and STEM summer camps, At the end of each activity description, we briefly discuss how these activities reference different broad AI concepts and initiate productive conceptual conversations around.

Video Sensing: HomeCourt + Scratch

HomeCourt.AI is a camera based **iPad app** that tracks body movement to be used for a variety of training drills for basketball (and more recently, soccer) (Figure 1). It has a wide host of reaction and movement drills, which are used in numerous physical education classes as well as pro athlete training for practicing different moves, especially when off court, but sometimes also on sports spaces. It provides a uniquely appealing experience by gamifying these drills – keeping track of score and performance records, comparing on local and global leaderboards, and even running movement based eSports tournaments more recently. Additionally, it also has a functionality to record whole court matches, and track player movements, and different stats regarding the location of different attempted shots, tracking different players' accuracy and scores. While the makers of HomeCourt app do not publicly reveal the algorithms being used, we believe they are a mixture of movement, person, and object tracking, and pose detection algorithms, leading to a well packaged AI system catering to Basketball training.

Figure 1: A demo screenshot of the Homecourt app's reaction drill (taken from Homecourt's website)

We introduce the **HomeCourt app typically in a gym, or a large enough space to move freely** and start off with the reaction drill. In this drill, green circles appear for short periods of time (up to 5 seconds), and players get rewarded points for how quickly they tap these circles, i.e., for having a quicker reaction speed. Depending on access to space and basketballs, we also let learners compete on more complex versions of the reaction drill, which only progress on continued dribbling of the basketball, building players' basketball bouncing skills, alongside their ability to manage space against opponents who would be moving closer to them during an actual game.

If learners are engaging in a whole match, we also set up recording for a match – the stats of which are interesting and often surprising to almost all young players. We discuss different players' shot accuracy, movement across the space, and how they can reflect on and use the data that HomeCourt's recordings provide. We also discuss if players can think of features they would add or improve to HomeCourt if they had the ability.

These discussions have led to ideas like adding an ability to change difficulty levels with more control, noticing that the reaction drill responds to different body parts like elbows, shoulders, knees, etc and whether we can restrict this.

Following this, we inquire which of the players might be interested in making their own versions of HomeCourt. If no one is interested we simply demo the version we have made using Scratch and the Body Sensing blacks made by the Dancing with AI project (Jordan et al. 2021), which provide pose detection body skeletal detection in the form of Scratch Blocks (Figure 2). If some players do exhibit interest, we walk them through the blocks, and show how these blocks allow for choosing specific parts of the body (like wrist, hand, elbow, and others), and how to create a collision detection script which enables the different reaction circles and score keeping.

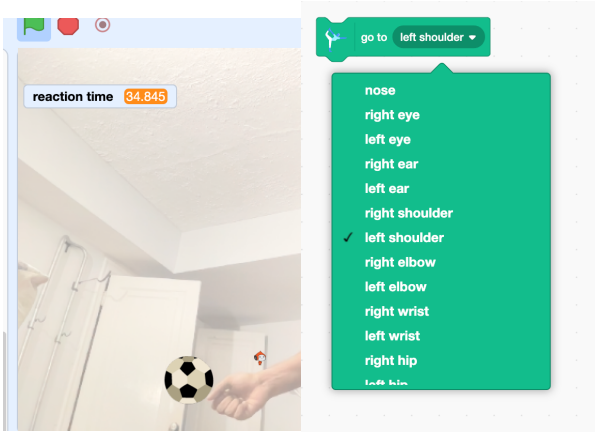

Figure 2: Screenshot of Scratch based reaction time game in action (left), and list of skeleton access provided by Body Sensing blocks

For this programming activity, we have found lower reliability with Scratch programming on iPads, so tend to use **chromebooks or any laptops with webcameras** to do this programming activity. We encourage programming players to create variations in their game to make it harder as a challenge to others in the class and make everybody compete on the different programmed versions of Scratch Reaction Time as well.

We are currently working on creating block-based access to Sports-centered object and person detection scripts, to enable learners to also create the match recording and shot tracking aspect of HomeCourt. For this, we are working on blocks that can differentiate people, track different balls like soccer and basketballs, and scoring objects like goals and baskets, to enable learners to create scripts that can identify successful shots from misses, and even track different players simultaneously to record scores in a whole match.

This activity is key in **discussing the ability of video based AI systems in helping sports practice**, which often also opens the door to discussing the usage of similar systems in their surroundings – seen on face identifying systems on smartphones, and home security systems – and the underlying ethics of regarding data access and surveillance enabled these systems (Zhang et al., 2022). More directly relevant to the extensions we show them, these extensions also provide the stage to discuss commonly implemented **pose detection** models.

Wearables: Smartwatches + Micro:bits

We introduce wearables using smartwatches which provide instant access to step counting. This activity also requires an **open space**, often best done around a track field. We ask learners to take a lap or walk a certain distance and count the number of steps they think it takes to cover that distance. After this, we have a short discussion about how they could make this task easier – most groups have at least some youth if not many who know about smartwatches and name FitBits or Apple Watches as capable devices to do the same. After a short discussion about how they think these watches work, we equip learners with a smartwatch and make them walk the same distance. We compare learners' initial count with that from the watch, and then invite learners to make their own step counters using Micro:bits. Micro:bits are a popular physical computing board with numerous in-built sensors, and are programmable through MakeCode which in turn provides a block based interface (as well as JavaScript and Python editing for the same code) (Austin et al. 2020). We follow one of MakeCode's in-built tutorials for the Micro:bit for making a step counter, which involves simply three blocks of identifying a shake and counting those as steps. We repeat the walking exercise with the smartwatch and the micro:bit worn around the wrist or ankle, and then discuss a comparison of the numbers provided by the two devices. Finally, we invite learners to try to trick the two devices into counting more steps than they walked, which is often followed by a discussion around how the smartwatches tend to not count as many "fake" movements as the micro:bit does. This creates an entry point to discuss details of what the micro:bit considers a "shake", and how smartwatches use algorithms that are trained on more data to reduce their errors in counting steps for different gaits.

We have also found promising engagement through using wearables with built-in engaging activities. For instance, the *Moov Fitness Coach* (NEX Team 2017) wearables provide exercise activities in their app – specifically a cardio boxing activity, which provides a reaction based punching drill that scores players in dialogue with graphics presented on a connected mobile app. We conduct this activity in pairs by asking players to compete on their scores. Following this, similar to other activities, we invite learners to make their own versions of the same game. This is another activity that can be done with minimal space and played even inside a classroom.

Since MakeCode's micro:bit interface does not enable easy access to interactive graphics to make a game-like interface we have made Scratch blocks and micro:Bit firmware which enables micro:bit's motion data to be usable inside the Scratch interface (Figure 3), which builds on Williams' (2018) base work on building Scratch extensions for PopBots.

Learners are able to create a basic emulation of the cardio boxing activity using shake detections and thresholds for intense movement and direction change, we are currently working on extending this work to enable **pattern detection algorithms** through Scratch blocks to be able to detect different kinds of punches. This is expected to not only be relevant for emulating the cardio boxing activity but provide valuable modules and tools for our upcoming collaborations with community boxing gyms as well.

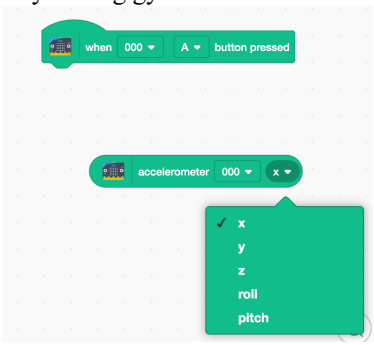

Figure 3: The main blocks in our Scratch extension that exposes motion data from micro:bits to Scratch

Ball Sensors: Play Impossible & SIQ + Micro:bits

Lastly, we show systems which have sensors embedded inside other sports objects. So far, these have centered around

game balls (in the family of handheld balls like basketballs and volleyballs). One of the easiest to implement activities we have is using the **Play Impossible Gameball** (Baden Sports 2020), which comes with a suite of games that can be played through phone and desktop apps using small game balls. These can be played in any space and are easiest to **play inside a classroom**. We ask learners to arrange themselves into 2 teams and start with the Showdown challenge around the Shake-Off game – a timed competition around which team can shake the ball faster than the other. This game, and other Play:Impossible activities, consistently receive very intense engagement. For instance, teachers who played this with their third graders told us that the Air Time games and other activities centered around tossing the ball in the air caused some minor damage to their classroom's ceilings as a result of students' excitement in play and competition.

The shake-off game is the easiest to recreate using micro:bits – a basic recreation of it is identical to the step counter which simply counts the number of times the micro:bit is shaken. This recreation works noticeably different than the impossible gameball's measurement of ball shaking amount – which again works to trigger a conversation about different algorithms for identifying different movements.

Another embedded sensor ball we have found to be very relevant on the **Basketball court**, are the **SIQ Basketballs** (SportIQ 2008). Also used by professional teams for measuring statistics and also recording play patterns, the SIQ Basketballs are proprietary basketballs that come with an app that (similar to HomeCourt) are able to measure shots, misses, trajectories of attempts, and also generate user profiles over extended gameplay. Discussions about how sensors inside a ball are able to recognize a successful shot or not often leave learners with a pending curiosity about better understanding how different kinds of movement can be so reliably identified.

These activities extend the applied AI concepts surrounding **gesture detection** from the last section, to identifying movement patterns from inside these different balls. These very often lean towards supervised learning methods since ball movements are noisy and hard to describe in a systematic pattern – especially since the location of the sensor inside the ball is constantly changing relative to the ball's center and direction of movement. We are able to discuss these concepts at varying levels of complexity and detail with learners from **high school** and above – from describing the process from collection, labelling, training, and prediction at the broadest of terms, to specifics of different learning algorithms and methods that are used for classification of such data streams. With younger learners, this activity expands the meaning of identifying aspects of activity from sensors without access to human-familiar perception (visual sensors like cameras or on-body trackers), to assess events that feel like they need such measurements.

Discussion and Future Work

In addition to the equity centered goals of foregrounding AI tools and concepts through sports, there is a critically productive form of embodied cognition and learning accessed in this modality that can benefit all learners by providing novel representations (National Research Council 2000). Analogous to Papert's concept of body synotonicity (1978) mentioned in the introduction, understanding how to implement logics for gesture recognition through data produced from a wearable, and next from inside a ball, embeds AI concepts and understandings across a novel diversity of contexts and entities for learners to think through and help develop their understandings.

In addition to more familiar ways of thinking about gestures as formed through users' own wrists or bodies, ball-embedded sensors push learners to think about gestures and extracting meaning from data through nontrivial contextual frames like how movement data from within a basketball can predict when and how it is thrown, and when it hits a backboard or goes through a hoop.

Especially related to sensor-embedded balls, we are working on formulating reliable fabrication techniques to embed programmable sensors inside balls that can retain integrity, but also have an ability to be charged over time. With this, we might be able to develop more open source and easily programmable ball-based AI learning activities.

We are extensively working on formalizing curricular tools and materials around our technological creations (currently being compiled on our project website (tiilt Lab 2022) in ways that provide more specific connections between context, age groups, and ideas that can be effectively discussed. Unsurprisingly, such a compilation not only requires many broader implementations and testing of these materials but need to be recognized for their reliance on learners' prior cultural exposures to technologies and critical discourses around technology. It is critical to center inequitable creation, usage, and impacts of different aspects of numerous (AI enabled) technologies in education, design, and discussions around the same (Ko et al. 2020).

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