
Scratch Nodes ML: A Playful System for Children to Create Gesture Recognition Classifiers

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ABSTRACT

Children are growing up in a Machine Learning infused world and it's imperative to provide them with opportunities to develop an accurate understanding of basic Machine Learning concepts. Physical gesture recognition is a typical application of Machine Learning, and physical gestures are also an integral part of children's lives, including sports and play. We present Scratch Nodes ML, a system enabling children to create personalized gesture recognizers by: (1) Creating their own gesture classes;

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CHI'19 Extended Abstracts, May 4–9, 2019, Glasgow, Scotland UK

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ACM ISBN 978-1-4503-5971-9/19/05.

<https://doi.org/10.1145/3290607.3312894>

KEYWORDS

Machine Learning; Gesture Recognition; Children.



Figure 1: Child playing with a Scratch Node device.

(2) Collecting gesture data for each class; (3) Evaluating the classifier they created with new gesture data; (4) Integrating their classifiers into the Scratch environment as new Scratch blocks, empowering other children to use these new blocks as gesture classifiers in their own Scratch creations.

INTRODUCTION

Machine Learning (ML) is a popular tool integrated into many products. As a result, more children grow up in a ML infused world. ML processes are typically "black-boxed" (i.e. their underlying processes are hidden), therefore children lack the opportunity to learn from direct experience and develop accurate mental models of basic ML processes [3]. Furthermore, children may develop inaccurate mental models, which are difficult to overcome [8]. Uncovering black-boxed processes can enhance understanding of ML, but uncovering too many may be overwhelming, preventing understanding altogether. Therefore, only some underlying processes should be uncovered [9].

Previous work has shown that direct experience with physical objects can facilitate understanding of abstract concepts [13]. More specifically, it has been shown that children are able to understand basic ML processes when they take part in the training of an accessible ML system [7]. Children can greatly benefit from support given by more experienced children, while at the same time, children who provide the support are highly motivated by their role as leaders, and can be encouraged to gain a better understanding for future interactions with children who seek their help [4, 10]. In ML experiences, children with varying levels of experience can contribute to increase engagement, participation, and understanding. A highly relevant application of ML for children is gesture recognition [12], as physical movement is dominant in children's lives. However, existing gesture recognition systems are not accessible for children, mainly because data collection and classifier accuracy verification is generally done by adults [2].

We present a gesture recognition platform, Scratch Nodes ML, that uncovers the data collection, data labeling, and classifier testing ML processes, enabling children to sample their own gestures and verify their own classifiers. Children then use those classifiers as Scratch blocks to create their own ML applications, and other children can use these gesture recognition Scratch blocks to create their own playful experiences, collaborating and taking different roles such as "data collector", "classifier trainer", and "Scratch application developer".

RELATED WORK

Recent studies indicated that some of the basic building blocks of ML are accessible and understandable to children as young as twelve years old [5, 7]. Druga et al. showed that hands-on experience with a navigating robot can refine children's understanding of the robot's AI capabilities and processes [5]. Hitron et al. indicated that children's understanding of ML building blocks is improved when they

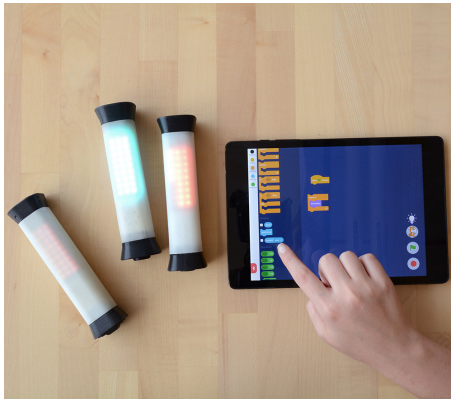


Figure 2: The Scratch Nodes system.

Scratch Nodes are physical devices designed as extensions for Scratch which allow for the use of hardware components in Scratch blocks. The devices contain multiple hardware components encased in a hard plastic case with rubber caps to afford robustness with no exposed hardware. Scratch Nodes connect to an extended Android version of Scratch running on a tablet using Bluetooth Low Energy (BLE). They contain LED lights and a speaker which can be activated using Scratch blocks in various ways, an accelerometer which sends sampled data back to the tablet, and a button which can be used as an event in Scratch. For example, these components allow for children to program a Scratch Node to play a sound whenever the button is pressed using the added Scratch blocks.

actively take part in the training process of a ML system, specifically regarding the data labeling and evaluation ML building blocks [7].

ML for children is also addressed in the industry. For example, Google has presented the AIY kits, designed to encourage children to build systems such as a voice recognition kit [1]. While this project involves ML, the underlying ML processes in it are black-boxed. Another project by Google which allows for a more direct hands-on experience with ML is the Teachable Machine [11]. In this system, users provide images as data for a computer vision algorithm. The users can then evaluate the system's ability to classify new examples.

We extend prior work with a ML-based gesture recognition system that enables children to train a classifier by sampling their own (or other children's) gestures, perform data collection, test classification accuracy, and integrate their classifier into a Scratch-based coding platform. This ML-based gesture system allows children to take part in the systematic data collection of personalized gestures and evaluation of gesture recognition, which are typically black-boxed. This hands-on experience can provide children with the opportunity to improve their understanding of selected underlying ML concepts, specifically in the gesture recognition application. In addition, the system invites collaboration as it involves both the training platform and the physical device. As such, one child can supervise the training while another child is providing the gestures data samples.

SYSTEM

Scratch Nodes ML involves a physical hardware device that sends accelerometer readings via Bluetooth to a tablet running the gesture recognition platform. The data is then used to train a gesture recognizer which classifies the accelerometer data as one of the gestures created by the child. Our implementation builds on the previously published Scratch Nodes devices [6] (see sidebar). The gesture recognition interface was integrated using Scratch 3.0. The gesture recognition process implemented in the system comprises of four essential stages (see Figure 3): (1) create a gesture class; (2) record examples of the gesture; (3) evaluate the classifier with new samples; and (4) integrate the gesture classifier as a Scratch Block.

Implementation

We implemented an extension for Scratch 3.0, in a similar way to the built-in Scratch sound editor, allowing children to create and train their own gestures instead of record their own sounds. The user creates a new gesture, names it, and then records examples of that gesture with the Scratch Node hardware device. Children can then test their new gesture class by performing physical gestures and receiving feedback from the platform on the tablet interface. The real-time feedback shows the name of the class recognized by the system on screen. After children verify their classifier works properly, they can record more examples to improve it, or generate blocks that can be used in Scratch coding.

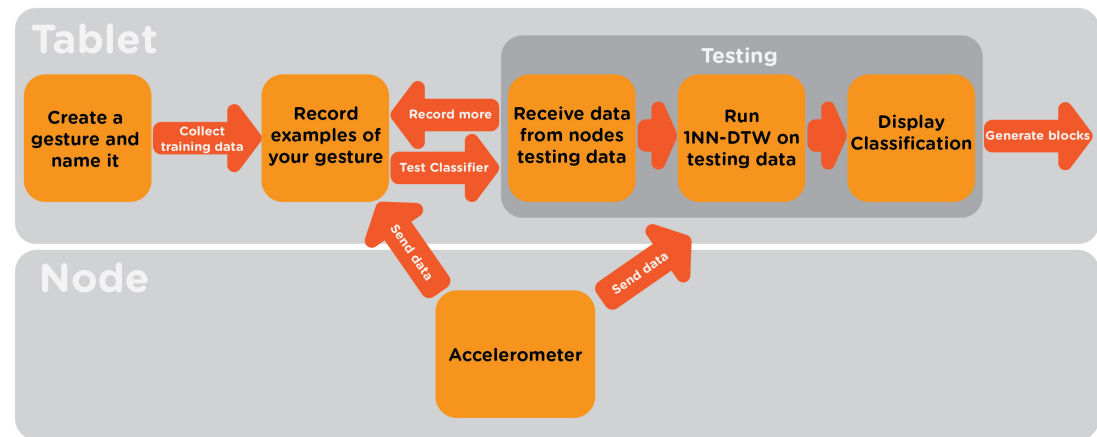


Figure 3: The system components and stages

To classify the data gathered by the children, Scratch Nodes ML uses supervised learning. The algorithm requires training examples, labeled by the children according to the gesture they represent. After a new gesture class is created and gesture examples are labeled, the algorithm uses these training examples to compare to new data. When a new gesture is sampled for testing, we run a 1NN-DTW ML algorithm to compare the stream of data coming from the device to the examples given by the user and classify it. The result of this classification is displayed to the user in real-time, with the classification changing in real-time as more gesture examples are sampled. To integrate the new gesture classes into Scratch as a Scratch block, we create a new event block which checks if a chosen gesture is performed by running the created classifier on new data from the Scratch Node. This enables children to use that specific gesture recognition classifier as a sensing event in a Scratch project. The new gesture recognition block is specific to the data the classifier has been trained with, meaning that a classifier created using gestures performed by a child will have high detection accuracy for that child, but usually not for others. We believe this "gesture specificity" will be a playful feature for children, for example letting older siblings create classifiers that work only for their younger siblings and not for their siblings' friends.

1NN-DTW Algorithm Implementation. The 1NN-DTW algorithm used in our gesture recognition classifier works in the following way: 1-Nearest Neighbor (1NN) is a ML algorithm in which every new example is classified to the same class as the training example most similar to it. In this case, our training examples are gestures collected and labeled by the child. In addition, we use Dynamic Time Warping (DTW) to find the distance between two examples, one being a training example and the

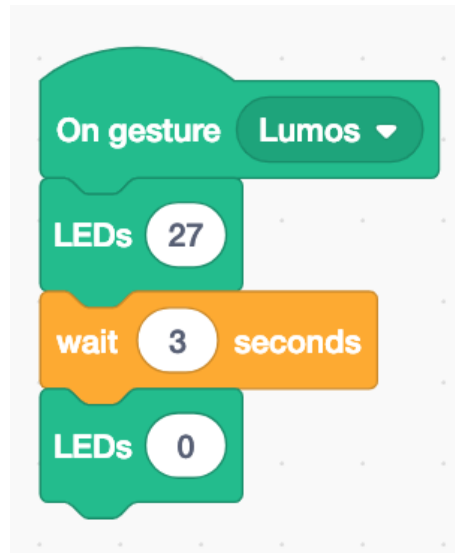


Figure 4: Code Snippet.

The code snippet above presents four stacked Scratch blocks as an implementation for the usage scenario. The first block is an Event block, generated by Scratch Nodes ML, which activates the blocks stacked under it when the "Lumos" gesture is recognized by the gesture classifier created by Dana and Tom. The blocks following the Event block will turn on all of the LEDs on the Scratch Node, wait three seconds, and then turn off all of the LEDs. With this code snippet, Tom makes the Scratch Node light up whenever he performs the "Lumos" spell gesture with the Scratch Node.

second being the testing data, and apply 1NN on these distance calculations to classify the testing data to the same class as the training example closest to it.

USAGE SCENARIO

Our system was designed as a playful way for children to add gesture recognition into their Scratch Nodes creations, and as a learning technology making ML more accessible to children through direct experience. In the following scenario we describe how children of various ages can use the system in different ways.

Usage Scenario: Harry Potter Spells Among Siblings

Dana, a 13-year-old child that has been programming in Scratch since 5th grade and follows technology-focused YouTubers, receives a new Scratch related hardware device in her Scratch after-school program, called Scratch Nodes ML. Her mentor explains that it's a new way to add Machine Learning blocks into Scratch. Dana takes the new device home, where she sees her younger brother, Tom, playing with his Harry Potter wand. Dana asks Tom to bring some duct tape, and together they attach the wand to the Scratch Node hardware device. Dana installs the new Scratch extension, and instructs Tom to perform a gesture of his favorite spell, "Lumos". They collect one sample, test it, and always get a correct "Lumos" classification. They then perform a different spell's gesture, and it's detected as "Lumos" as well. Dana suddenly understands she needs to create another gesture class, that will identify all non-"Lumos" spells. She creates it and asks Tom to perform many different spell gestures, one after the other. Tom can not believe how lucky he is, and shows off all the gestures he remembers by heart. She switches to the testing interface, and the feedback shows very low accuracy. Dana asks Tom to perform a few more "Lumos" gestures one after the other, and records them into the "Lumos" class. After a few cycles of sampling and testing, they reach detection accuracy that Dana is satisfied with. At this stage, she invites Tom to use other Scratch Nodes blocks to light up his wand when the "Lumos" spell is performed. Tom creates a project using the LED blocks (see Figure 2), and calls his parents to see his wand light up. His father, a Potter fan as well, tries it too, but the wand does not light up. They call Dana and she explains that the data collected is specific to Tom's gestures, so the system will only recognize gestures that are highly similar to Tom's.

DISCUSSION

ML processes are integrated into many products and services, but children are hardly exposed to the way ML processes operate. We present a new system, Scratch Nodes ML, making selected ML gesture recognition processes accessible to children in a playful way. Our system allows children to collect gesture data by themselves, using their own gestures or those of other children. The result is a hands-on learning experience that uncovers selected ML black-boxes and promotes trial-and-error. In

ACKNOWLEDGEMENTS

We would like to thank Netta Ofer for her help in different stages of this study. This research was supported by the Scratch Foundation.

addition, our system enables experienced Scratch users to create gesture-specific blocks for themselves and for other Scratch users to use in their projects, encouraging collaboration between children of various ages and levels of understanding. The iterative process of sampling and verification can promote formation of mental models at an early age, which can increase understanding of more complex ML processes when children learn them later in their lives.

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