Smart Toys for an Educational Framework

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Proposed study

The objective of this project is to design a toy that will learn, in order to ease frustration and reinforce success for children with autism. One of a number of challenges autistic children face is transitioning from one subject to another, specifically when transferring knowledge from one context to another. Often this triggers emotional outbursts, further hindering learning due to frustration. This study investigates the use of machine learning to support a multisensory toy to assess emotional responses while learning. Pressure, orientation, and sequence handling of the toy are some of the independent variables used to feed data to the neural network. Data from the interaction is relayed, stored, and processed using a Cloud-Fog-Device framework to inform the system's next pedagogical decision. Visualizations of the information pipeline between student and toy will map the pattern of interaction in an attempt to identify optimal and suboptimal moments to engage the student. Patterns of learning are compared across populations of children who do and do not suffer from autism, offering insight into emotional readiness.

Basis of the study

There are three forms of engagement that influence learning: behavioral, emotional and cognitive (Hannafin, 1989; Fredricks, Blumenfeld, & Paris, 2004; Dickey, 2005). Decisions made by the toy about the lesson plan will be based on monitoring each state of engagement to identify high and low sequences. Observing physical interaction is one form of monitoring behavior or emotions, akin to test scores for cognitive engagement.

Some teaching aids, such as Intelligent Tutoring Systems (ITS), have established pedagogical practices that encourage learning through repetition and scaffolded modular sequences. However, few of these systems consider the emotional or mental challenges that face children and recommend teacher or parent participation (Kulik & Flecher, 2016). Many educational games have been developed to position learning in the context of a positive (fun) experience to encourage learning, but these typically lack the flexibility to accommodate learners who struggle with the content in order to keep them engaged (Filsecker & Kerres, 2014). In education, progress is made through consistent improvements made by the student as well as adjusting for variations from that consistency. Current applications of IoT in health and transportation focus on any occurrence of anomaly detection that deviates from the current operations of a device.

Smart consumer products, on the other hand, regulate based on the consistent performance of the device where the function of labeling is binary or parametric within a fixed sample range of known input-output pairs of the function (Jordan & Mitchell, 2015), making little use of anomalous data. This study presents a framework for educational devices that use machine learning; balancing interactions that are anomalous and consistent with learning objectives as the basis for decision-making. The framework pairs Cloud-Fog-Device processes with content, context and responsiveness to user feedback that addresses the shortcomings of ITSs that dampen emotional / behavioral engagement and the prescriptive nature of lessons in educational games.

Based on the Bin et. al (2010) data mining model, the smart toy data is well formed and data types are known, requiring less servicing. The Cloud-Fog-Device layers process data collection, data management, and event processing that supports low latency and at the same time recognize the moderate severity level for predicted decisions that are poorly fit. The smart toy collects data through physical interactions and is analyzed using Fog computing, drawing comparisons between task completion rates to physical interactions to identify positive learning outcomes. Machine learning processed in the Cloud provides predictions for the best ‘next’ task, customizing each play session with the toy. Similar distributed processing models are described by Farahani et. al (2019) in their eHealth system that also require low latency responses but in educational contexts are driven by the user experience. Improvements to tailored lesson pathways are predicated on previous interactions and success or failure to complete a task. From play sessions, we expect to see patterns emerge that indicate moments of frustration, pride, thoughtfulness, and joy among other emotions that correspond to physical inputs of positive and negative learning experiences. These patterns can be used as a benchmark, adapting to any child’s emotional, behavioral and cognitive learning state as they acquire new information as well as use it in different subjects.

Implications

In an educational context, decisions made by smart objects are not highly critical–they do not involve life or death decisions–and therefore do not focus only on the anomalous response that deviates from the norm. Conversely, learning is not a consistent climb over time; it progresses, levels off and sometimes deteriorates due to interpretation, making decisions about learning pathways difficult (Gaines, 1987). The design of the toy should support an educational environment shaped by the communication between user and smart object in an effort to alleviate the need for a teacher’s time and repeated assistance. Educating autistic children in particular requires both constant monitoring and regularly mitigating mood, which is expressed through physical interaction (Schaaf et. al., 2014). This is particularly evident when switching subjects, expecting learned information to be transferred into new contexts. More importantly, the primary object is to identify patterns of learning through cognitive behavioral and emotional expressions of interaction. Haptic patterns provide a map of physical manifestation that leads to knowledge acquisition (Fogtmann, et. al., 2008). Using these maps, machine learning can react to consistent and anomalous human response appropriately easing learning by keeping children engaged.

Conclusion

In an effort to identify patterns in learning, this study examines a framework including machine learning that uses educational toys for data collection. The value of these patterns to aid teaching and bolster tutoring systems cannot be overstated. Not only does the framework have the potential to change the way we deliver education, it can also help those who struggle with the pace and complexity of typical learning environments.

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