
Paper Cubes: Evolving 3D characters in Augmented Reality using Recurrent Neural Networks

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Abstract

1 Paper Cubes is a DIY Augmented Reality (AR) Platform that uses paper cube
2 patterns and an AR application to teach computational concepts such as Neural
3 Networks in a simple and engaging manner. We present an AR representation
4 of a Recurrent Neural Network in the form of stick figures that move in the
5 user's physical space and evolve over time. We argue that using Recurrent Neural
6 Networks to drive agents in AR and in real-time can potentially help to generate
7 more interactive and engaging storytelling, gaming and learning experiences.

8 1 Introduction

9 AR is an explanatory medium that takes advantage of the physical space, objects and surfaces. It
10 gives us the opportunity to create interfaces to better understand what AI does in a visual and spatial
11 manner. Paper Cubes [2] was created to teach basic computational skills as well as more advanced
12 programming concepts such as Artificial Intelligence (AI) and Machine Learning (ML) [1] using AR
13 in a more visual and engaging way.

14 Recurrent Neural Networks (RNN) [10] are a complex concept to visualize and understand. Some
15 work has already been developed in generating more simple and engaging interfaces using neural
16 networks [3,5,7] and crowd simulation [9] in virtual environments. Norton et al. [6] presented a
17 visualization suite showing how adversarial examples fool deep learning. Teachable Machine [8]
18 is a Google AI Experiment where the user can learn about basic AI by using their camera. There
19 is also a good amount of research on endowing simulated characters with locomotion and other
20 movement skills. Heess et al. [4] demonstrated how a rich environment can help to promote the
21 learning of complex behaviors. As a result, they also presented an attractive visualization of avatars
22 and other creatures moving in space. With Paper Cubes, we extend on this idea by using the physical
23 environment and the digital affordances of AR to teach a group of characters how to avoid obstacles.

24 2 System Overview

25 Our system consists of 6 paper cubes that can be used to control and generate AR. We used Unity3D
26 to create the virtual assets and animations. We used the Vuforia SDK to detect the cubes in space.
27 Each cube has a different pattern that is recognized by the phone's camera. The Jump, Stop and Turn
28 cubes are defined as regular computing cubes. They trigger actions in AR and establish the language
29 between the physical environment and the digital content. The AI Cube generates an ongoing process
30 of improvement over time. It gives intelligence to the characters making them smarter. When the AI

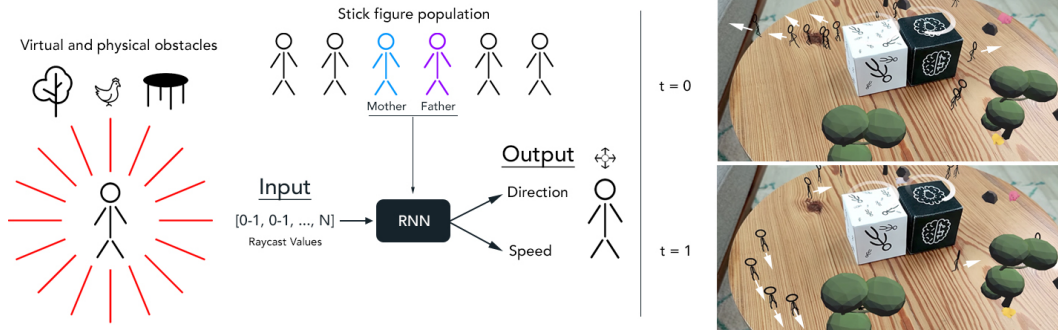


Figure 1: Paper Cubes system overview diagram and visual output in time

31 Paper Cube is placed next to the Start Paper Cube, a set number of stick figures will start walking in
 32 random directions.

33 Each stick figure is controlled by a unique RNN. The output of the network controls the actions of the
 34 stick figure, indicating direction and speed. The inputs are gathered from the stick figure's lidar
 35 system. The stick figures have a lidar-like system that detects objects close to them. This system
 36 generates a specific number of rays from the center of the stick figure outwards spread uniformly in
 37 360 degrees. This raycast system can detect virtual obstacles such as animals or trees and physical
 38 objects such as the edges of the table. The raycast system computes the distance between the stick
 39 figures and the objects around them and creates an array of floats ranging from 0 to 1. When closer
 40 to an obstacle, the value gets closer to 1. If there is no obstacle, the value is 0. This array gets fed
 41 into the RNN as the input. The output of this RNN defines the direction and speed of each stick
 42 figure. Figure 1 shows the system overview, along with the visual output at two moments in time.
 43 Specifically, in $t=0$, the stick figures run at high speed towards the edges of the table and the virtual
 44 objects. In $t=1$, the stick figures have learned how to reduce speed and change direction when closer
 45 to obstacles.

46 3 Training

47 Unlike existing machine learning approaches that typically pre-train the weights of a neural network
 48 before deployment, we wanted to experiment with the possibility of training the neural network in
 49 real-time, while the user is playing with the cubes. For this reason, we chose to use an evolution
 50 strategy and a large population of stick figures in the environment to evolve a suitable set of weights
 51 that will guide the agents to survival. In our population, there is a maximum number of stick figures
 52 (30) that can exist in the scene at the same time. Every time a stick figure disappears, another
 53 one is created. When created, each stick figure is assigned a mother and a father from the stick
 54 figures that already exist in the scene. New stick figures learn from their assigned parents. Over
 55 time, these inherited traits will increase the chance of survival and, eventually, the stick figures
 56 learn to avoid the virtual and physical objects. The example visualization of this can be seen at:
 57 <https://experiments.withgoogle.com/ar/paper-cubes>.

58 4 Conclusions and Future Work

59 We presented Paper Cubes, an example of an engaging and creative visualization of RNNs that makes
 60 AR stick figures evolve over time. Our system is helpful for learning ML concepts in the wild, using
 61 the physical environment for an interactive and playful experience. This concept can be applied to
 62 any AR system that requires autonomous behavior agents in physical space, such as interactive
 63 education, gaming and health systems.

64 In future work, we plan to extend Paper Cubes into a more dynamic platform for storytelling, creativity
 65 and learning in AR. We are planning to conduct qualitative user studies to test the effectiveness of
 66 the system with children. We will test engagement and learning performance using Paper Cubes for
 67 learning ML concepts such as RNNs.

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