

# A Model of Inverse Intuitive Physics

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## Abstract

The literature on intuitive physics reveals that our natural sense for how objects behave sometimes disregards the simplest principles of Newtonian mechanics (McCloskey, 1983). Here we set out to capture a commonsense judgement about how a ball falls in a simulated world. We model how subjects reason backwards from the ball's final position to its initial position in the world. Our interviews with subjects point to a cognitive basis for the variability that our model predicts.

**Keywords:** intuitive physics, cognitive model, probabilistic model, Church

## Background

The literature on intuitive physics reveals that, even in simple circumstances, we have serious misconceptions about how objects move. These incorrect judgements tend to resemble medieval impetus theories, which predate Newtonian mechanics and hinge on the idea that all motion is *caused* (McCloskey, 1983).

One of our commonest misconceptions concerns the forward velocity of a projectile. We often consider downward velocity but disregard forward velocity. The result is a misbelief that an object will fall straight down when in fact its trajectory is approximately parabolic (McCloskey, 1983). It isn't just children who make these errors: even "sophisticated" subjects revert back to commonsense judgements that are at odds with learned mechanical laws (Caramazza, McCloskey, & Green, 1981).

In practice, we often use intuitive physics to predict outcomes: given some initial configuration, what do we expect to occur? But here we consider *inverse* reasoning: given some final state, what do we expect was the initial configuration of the world? Our interest in inverse reasoning is due in part to a relevant example in the ProbMods book (Goodman & Tenenbaum, 2015). The design of both our simulation and model build on this example.

## Methods

Our simulations extend what is available in the ProbMods environment. We set up a local Box2D branch and modified the Physics2D JavaScript file to support new objects and functions, which we accessed in a local Webchurch environment. We added triangles as standard objects as well as a function to angle objects.

In our base simulation, a falling ball drops at random from above one of five static circles. The configuration of this world is shown below: note that the falling ball is enlarged for detail.

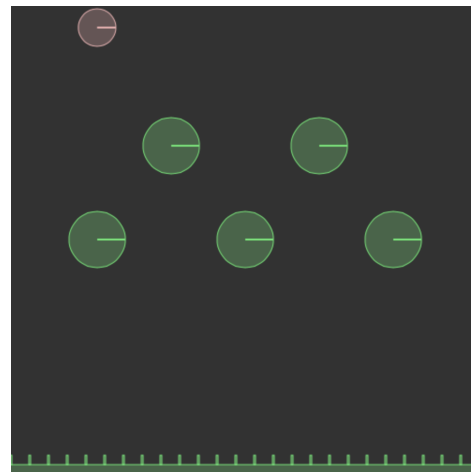


Figure 1: Base simulation

The falling ball takes on one of five initial drop sites, each corresponding to a different horizontal position that occurs with equal probability. Once the drop site is determined, the ball is offset a bit to the right or left to prevent it from coming to rest on top of a static object. The ball tips to the right or left of the static object with equal probability. For example: if the ball's drop site is 250 (above the middlemost static circle), its actual initial position is 249.9 or 250.1 with equal probability. The ball will collide with one or more static circles and come to rest in a bin at the bottom of the world. Our extended simulation is identical to the base simulation, but the static shapes are now triangles.

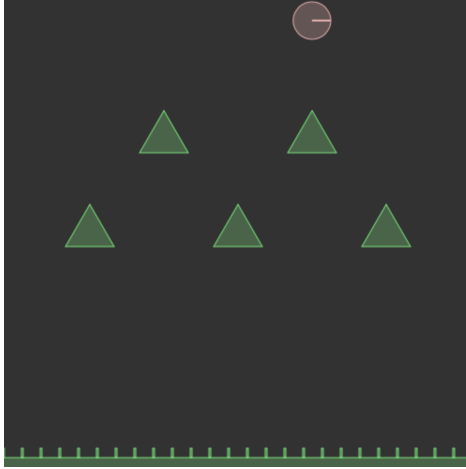


Figure 2: Extended simulation

We collected behavioral data from a population of 30 Stanford undergraduates. Each subject was presented with images of the two simulations and asked the following question: Given that the ball ends up in the middle of the world, where did it come from? We limited the ball to five initial drop sites (A, B, C, D, and E) to make our data collection precise. Subjects were informed that each drop site was above one of the static circles, and the ball could tip to the left or right. The image we presented for the base simulation is shown below.

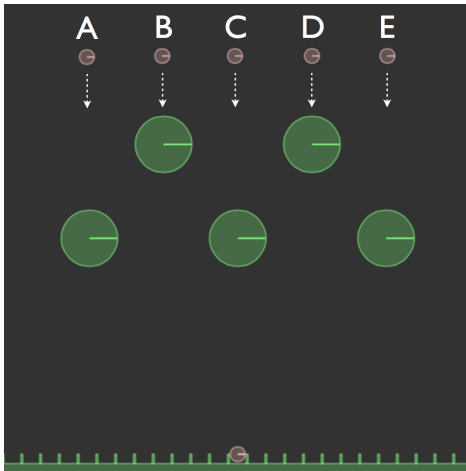


Figure 3: Base simulation behavioral cue

We model this human judgement in Church using a Metropolis-Hastings query. For each sample, the query generates a new instance of the simulation world. It forward simulates this world, and the ball takes on a final horizontal position (what we call just the “final position”). We query for the ball’s initial drop site: A, B, C, D, or E. The conditioner requires that the ball’s observed final position (here, the center of the world)

is equal to the Gaussian distribution with mean equal to ball’s final position and standard deviation equal to 10.

```
(define init-xs
  (mh-query 1000 10
    (define init-state (world))
    (define final-state
      (p.runPhysics 1000 (render init-state)))
    (getX init-state)
    (= (gaussian (getX final-state) 10) obs-x)))
```

Figure 4: Metropolis-Hastings query

## Results

For the base simulation, our behavioral data reveals that beliefs are polarized into the initial drop sites B and D, with some exception. Of the 30 subjects, 17 selected B, 12 selected D, and one outlier selected A. These percentages are shown below.

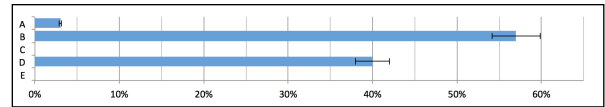


Figure 5: Base simulation behavioral data

The output from the model is predictive of the behavioral data. The model predicts that the ball’s initial drop site is B with ~52.5% likelihood and D with ~47.5% likelihood.

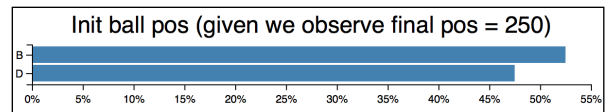


Figure 6: Base simulation model output

For the extended simulation, we find increased variableness in the behavioral data. As before, most responses are divided between B and D, but more subjects opted for A and E. Of the 30 subjects, 14 selected B, 12 selected D, three selected A, and one selected E. These percentages are shown below.

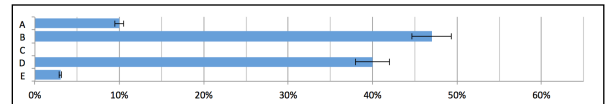


Figure 7: Extended simulation behavioral data

The output from the model appears to reflect the uptick in variableness that we see in the behavioral data. The model predicts that the ball’s initial drop site is D with

~49.7% likelihood, B with 49.5% likelihood, A with ~0.4% likelihood, C with ~0.4% likelihood, and E with some small nonzero likelihood.

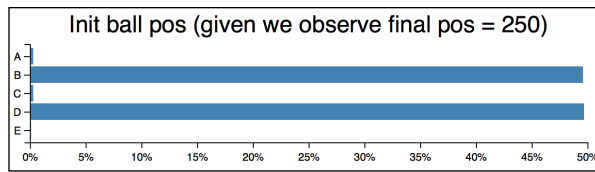


Figure 8: Extended simulation model output

## Interpretation

Even though we surveyed just 30 subjects, the model does a nice job of capturing the behavioral data for the base and extended simulations.

We find increased variableness in the behavioral data for the extended simulation. We asked subjects to recount the backwards reasoning that led to their selections. These responses point to a cognitive basis for this effect.

In the base simulation, most report that their first step was to rule out drop site C because a static circle was positioned right between the ball's final position and this drop site. The next popular step was to rule out drop sites A and E because it was hard to imagine that the ball could travel the horizontal distance from these drop sites to the center of the world. A number of subjects went further to explain that—after colliding with a static circle—the ball would tip to one side and fall straight down. Though these subjects were correct to rule out drop sites A and E, their reasoning is flawed: it is consistent with a common misconception that concerns the ball's forward velocity. These subjects consider the ball's downward velocity but disregard its forward velocity. Because the ball rolls to the left or right of the static object, it does in fact take on a positive forward velocity.

In the extended simulation, most report ruling out drop site C as before. But in contrast to the base simulation, fewer subjects rule out drop sites A and E. We find that approximately 13.3% of subjects opted for A or E when the static objects are triangles. These subjects explain that—after colliding with a static triangle below site A or E—the ball would acquire the horizontal velocity needed to reach the center of the world. These subjects are as well mistaken about the ball's forward velocity. But here, these subjects *overestimate* the ball's forward velocity.

Our results suggest that our intuitive disregard for a projectile's forward velocity is a context-dependent error. In our simulations, this error depends on the

shape of the static objects. Beliefs about the ball's forward velocity can range from complete disregard in the base simulation to overestimation in the extended simulation.

The model's output as well shows an uptick in variableness for the extended simulation. Because the model isn't reasoning quite how human subjects do, we might wonder about the basis for this added variableness. The model considers the initial and final positions of the ball across a huge number of samples.

Five drop sites amounts to just 10 possible final positions for the ball in simulation. We believe that the predictive power of the model is sensitive to how these 10 possible final positions relate to the ball's "observed" final position, which we hard-coded to be 250. It could be that—in the base simulation—the 10 possible final positions are well-behaved. That is, these positions are evenly distributed and 250 falls somewhere between a position stemming from drop site B and one stemming from drop site D.

It is perhaps the 10 (different) final ball positions in the extended simulation that add noise to the model's output. That is, these 10 positions are more clustered and 250 falls near positions stemming from three or even four drop sites.

We also acknowledge two peripheral sources of uncertainty: (1) how the ball bounces around the bins and (2) the bounciness of objects in the world. The bins make measurements of the ball's position more tractable, though it adds imprecision. The ball's horizontal position is affected when the ball bounces on top of bins. We've observed that—on a lucky bounce—the ball can circumnavigate up to three full bins. The bounciness of the world is set to reflect how actual objects collide according to their mass and velocity. But the bounciness is unknown to subjects. It could affect the behavioral data if subjects were allowed to observe the bounciness of the simulation world before recording their selections.

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## References

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