Student Research Week

A Continuum of Algorithms for Physical Reasoning

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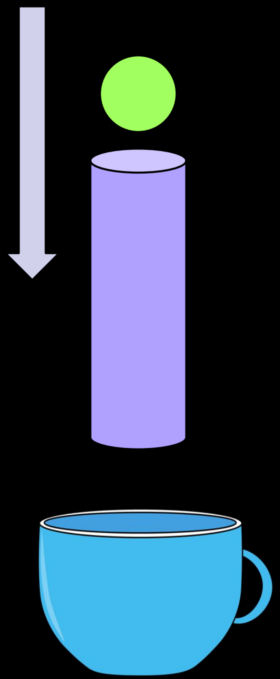
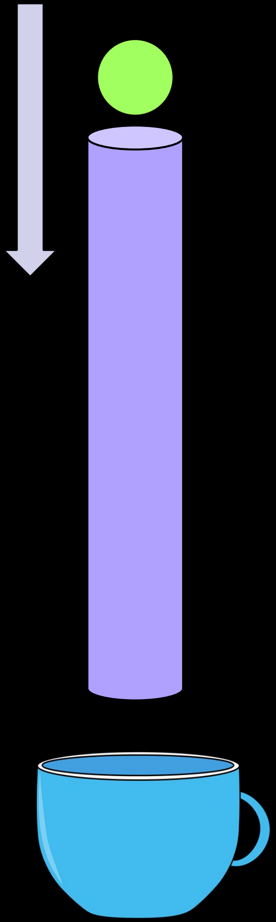


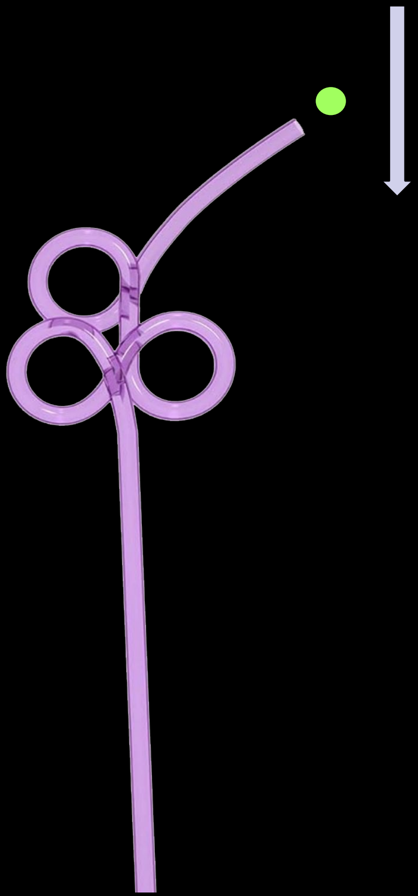
Will the ball fall into the cup?

The answer is an almost immediate 'yes'.



What if the straw is twice as long?

The answer is still an obvious ‘yes’, and it **does not take twice as long** to answer that.



Now consider dropping the ball into a convoluted straw.

The answer becomes **non-obvious**, as the bead might get stuck in the twists and turns.

The time to come up with an answer now **depends on how convoluted the straw is.**

Physical reasoning is the ability to understand and predict how physical objects and systems behave in the real world.

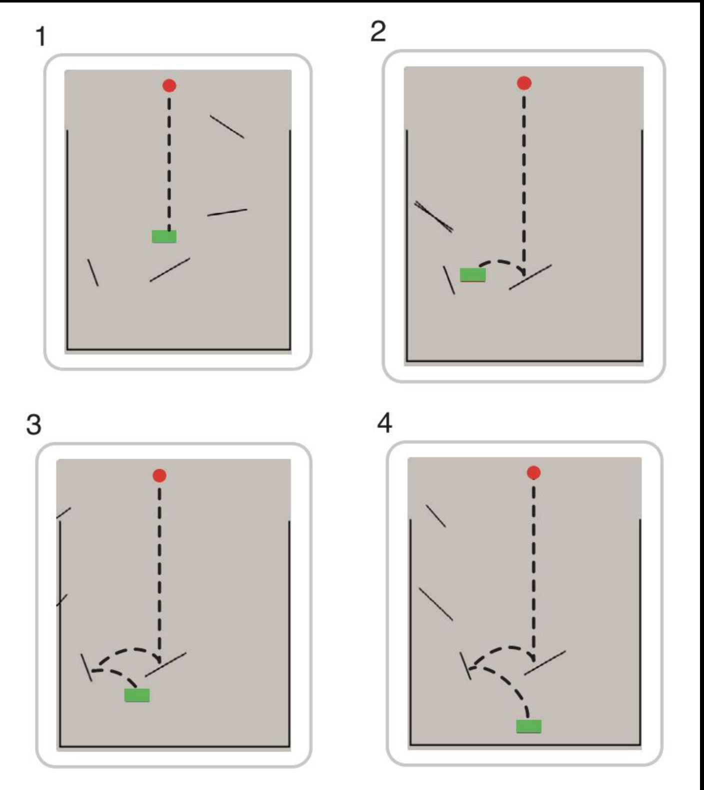
How do we derive knowledge of physics from observing and interacting with the world?

How are people able to understand everyday physical events with such ease? There are **two general hypotheses**.

1. People use an approximate probabilistic **simulation** of the world.
2. People use a collection of **abstractions** or heuristics.

Both have supporting evidence, neither fully explains human physical reasoning.

Sosa et al. proposes a **blended model** that switches between simulation and abstraction.

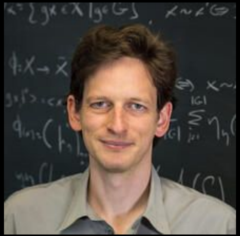


Original Paper

Blending simulation and abstraction for physical reasoning

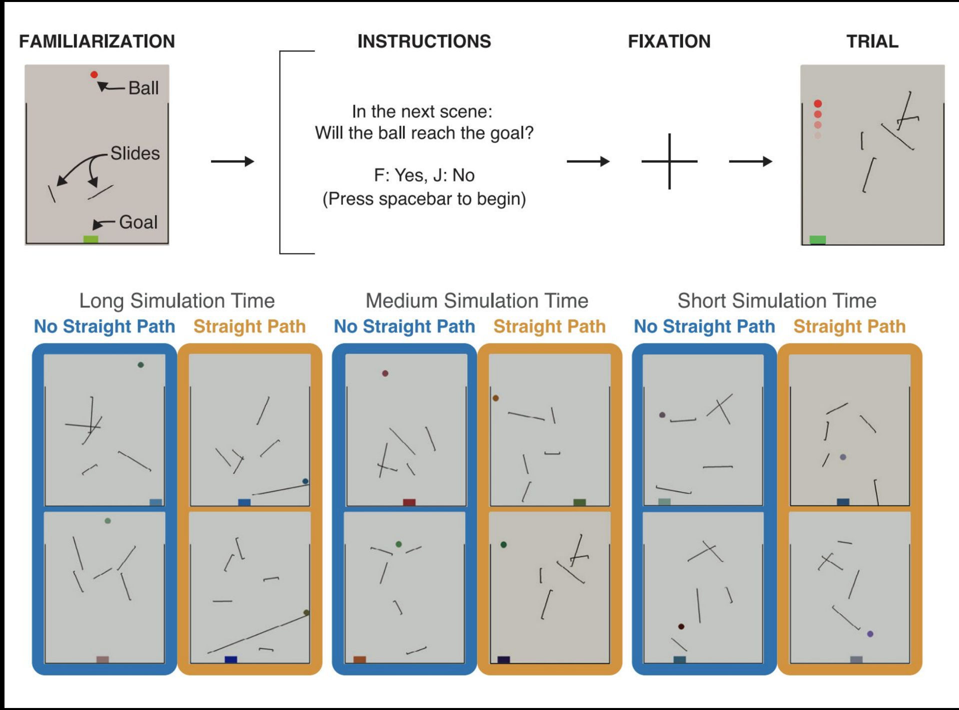
Felix Sosa
Psychology PhD @ Harvard

Sam Gershman
Professor @ Harvard Psyc



Tomer Ullman
Assistant Professor @ Harvard Psyc

Sosa, F. A., Gershman, S. J., & Ullman, T. D. (2025). Blending simulation and abstraction for physical reasoning. Cognition, 254, 105995.



Human Data

Participants watched scenarios where a ball falls towards a goal.

After 1s, the ball vanished, and people quickly decided if the ball would reach the goal or not.

Computational Models

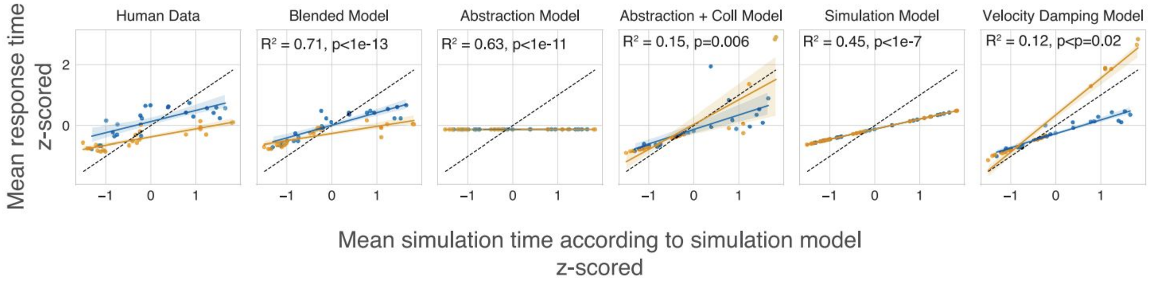
They created five computational models using five different techniques.

1. **Blended**
2. **Pure abstraction**
3. **Pure simulation**
4. Velocity damping
5. Abstraction + Coll

Table 1

Parameter estimates. N is the number of simulation steps taken by the blended model (i.e., the amount of "minimal simulation" the blended model performs per forward pass). E is the cosine similarity threshold; if the threshold is met then the blended model chooses the prediction made by abstraction over simulation. D is the length or distance of the path projection abstraction. σ is the standard deviation of the zero-mean Gaussian noise injected into the starting position of the ball. λ is the noise variance of the response generation process (see Eq. (1)). $(\beta_0, \beta_1, \beta_2)$ are the coefficients of the linear map between model outputs and response time predictions (see Eqs. (1) and (2)).

Model	N	E	D	σ	λ	β_0	β_1	β_2
Blended	5	0.9	75	(0.01, 0.01)	0.069	794.93	6.04	N/A
Pure abstraction	N/A	N/A	75	(0.01, 0.01)	0.24	1189.64	0.073	N/A
Pure simulation	N/A	N/A	N/A	(0.04, 0.04)	0.13	908.98	1.35	N/A
Velocity damping	N/A	N/A	N/A	(0.0, 1.11)	0.83	1173.52	0.069	N/A
Abstraction + Coll	N/A	N/A	37.55	(0.22, 1.33)	0.56	1228.52	−1.72	3.46

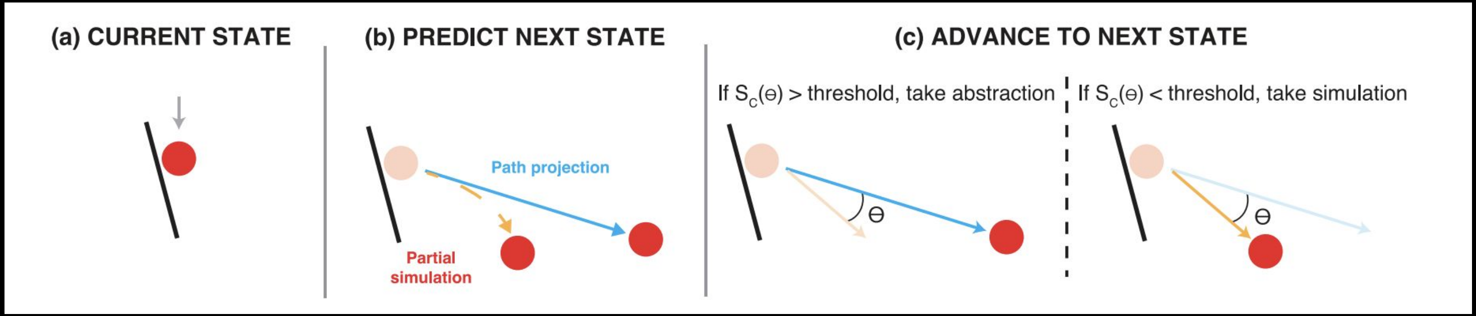


The Blended Model

Instead of exclusively using simulation or abstraction, the model dynamically selects between them in real-time based on **threshold conditions (cosine similarity).**

It balances:

1. Accuracy (fidelity of simulation)
2. Efficiency (speed of abstraction)

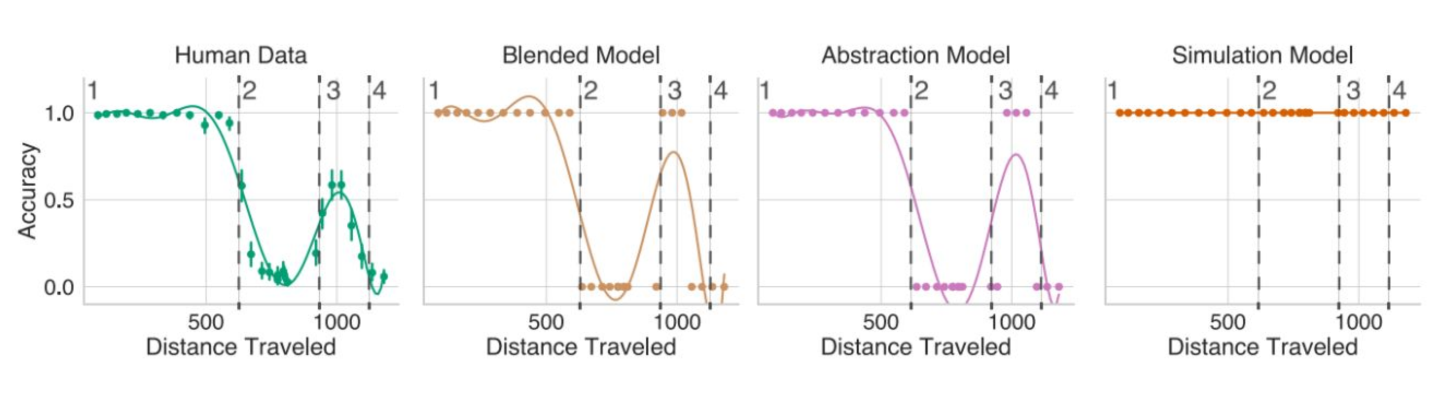


Findings

Accuracy was a non-monotonic function of distance and **fluctuated in ways predicted by the blended model**.

People make errors when abstraction fails, reinforcing the idea that they use a mix of simulation and abstraction.

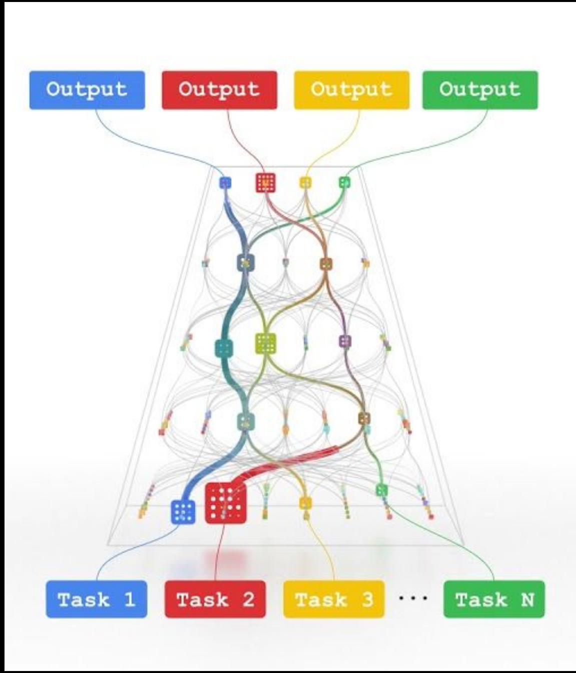
BIC favored the blended model (BIC = -41.60) over the other models of pure abstraction (BIC = -35.74), pure simulation (BIC = 81.18),



"people have access to a flexible mental physics engine, but adaptively invoke more efficient abstractions when they are useful."

The proposed model explicitly frames cognition as switching between **two distinct states**.

Rather than a binary switch, physical reasoning might involve a more fluid, **continuous spectrum of strategies**.



I believe the mind optimizes the tradeoff between fidelity and efficiency among a continuum of algorithms based **context and task demands**.

- Herbert Simon's **Bounded rationality** (1950s–60s)
- Kahneman & Tversky's **Heuristics and biases** (1970s–90s)
- John Anderson's **Rational analysis** (1990s)
- Griffith & Tenenbaum's **Optimal predictions** (2000s)
- Sam Gershman's **Computational rationality** (Present)

(Non-exhaustive list)

How do we show that the brain is not switching between two binary states but rather choosing between a continuum of algorithms?

Instead of a blended model that chooses between one kind of abstraction or simulation:

A continuum of blended models with increasingly more abstractions.

New Models

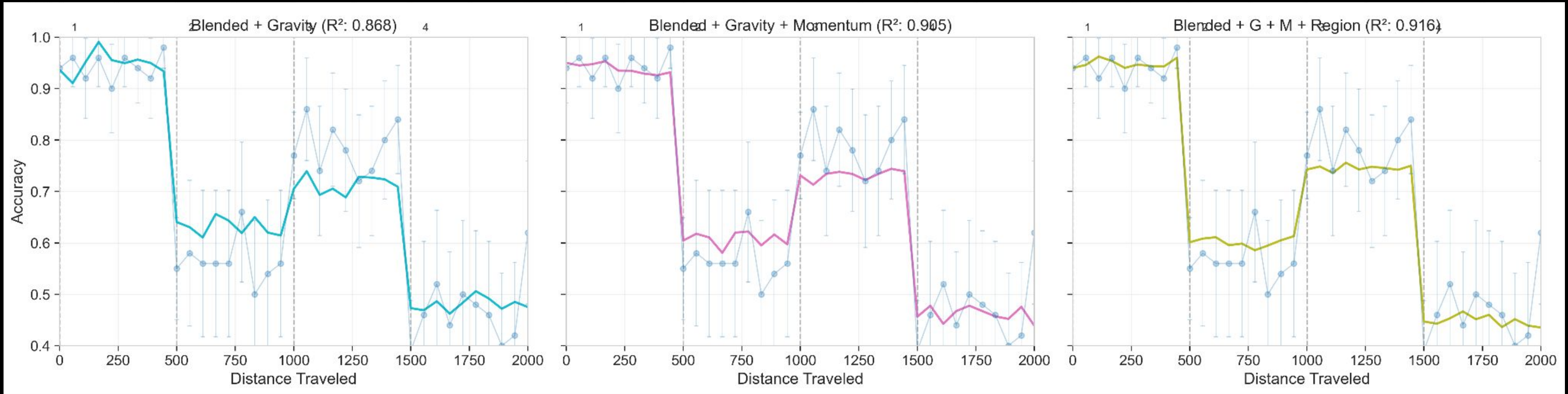
1. 100% simulation
2. 100% simulation + linear path projection (original blended model)
3. 100% s + lp + gravity projection
4. 100% s + lp + g + momentum-based projection
5. 100% s + lp + g + m + region-based abstraction

My New Models

Gravity projection: Predicts the ball's landing spot assuming only gravity acts, ignoring horizontal velocity or obstacles unless necessary

Momentum-based projection: uses initial velocity and simplified collision rules (elastic bounces) to predict the path

Region-based abstraction: divides the scene into zones (near goal, blocked zone) and predicts outcomes based on the ball's current zone, ignoring precise paths



R^2 scores (model fit to human data):

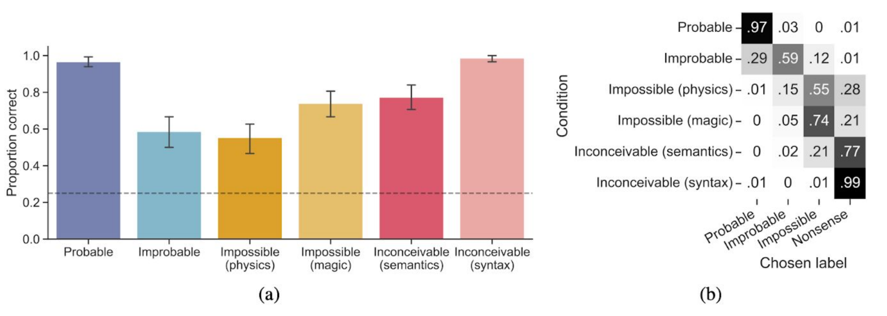
1. Original Blended Model: $R^2 = 0.7901$
2. Blended With Gravity: **$R^2 = 0.8678$**
3. Blended With Gravity and Momentum: **$R^2 = 0.9047$**
4. Blended With Gravity, Momentum, and Region: **$R^2 = 0.9156$**

Future work may explore:

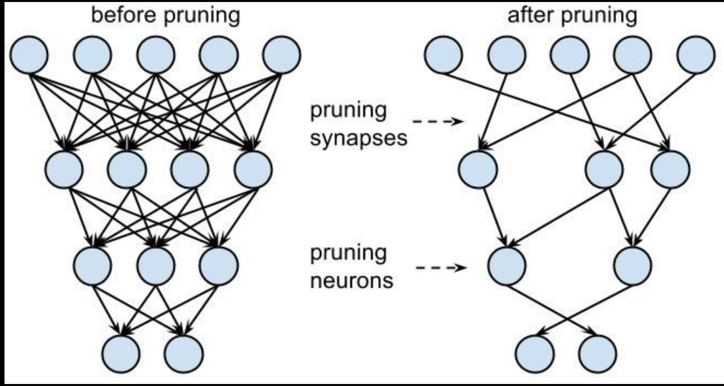
This “cognitive continuum” in other fields like **semantic categories**.

How these abstractions are created (mechanistically).

Are “abstractions” just **compressed algorithms**?



Hu, J. et al (2024)



Han, S. et al (2015)

References

Sosa, F. A., Gershman, S. J., & Ullman, T. D. (2025). Blending simulation and abstraction for physical reasoning. Cognition, 254, 105995.

Lieder, F., & Griffiths, T. L. (2020). Resource-rational analysis: Understanding human cognition as the optimal use of limited computational resources. Behavioral and Brain Sciences, 43, e1. doi:10.1017/S0140525X1900061X

Github: https://github.com/flxsosa/physics_abstraction

This research is very early-stage.
I welcome all criticism.

Questions?