Intuitive physics judgments guided by probabilistic dynamics model

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What do we mean by “intuitive physics”?

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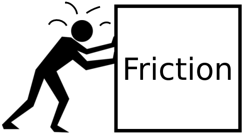
Reasoning about scenes' physical properties and dynamics using perception and background knowledge.

Why is intuitive physics difficult or interesting?

Gravity

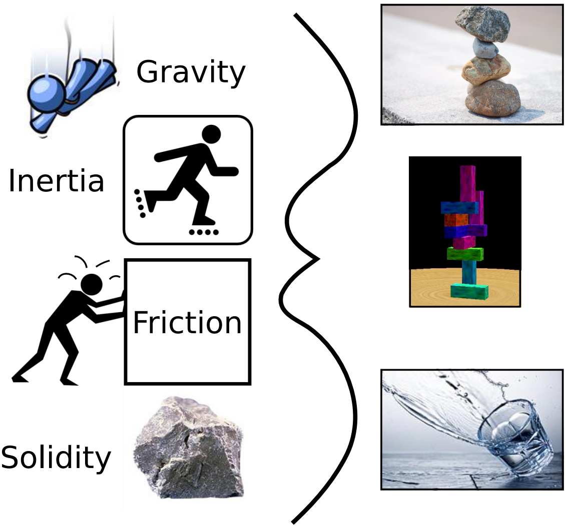
Inertia



Solidity

Few principles

Why is intuitive physics difficult or interesting?



Few principles **Many** situations

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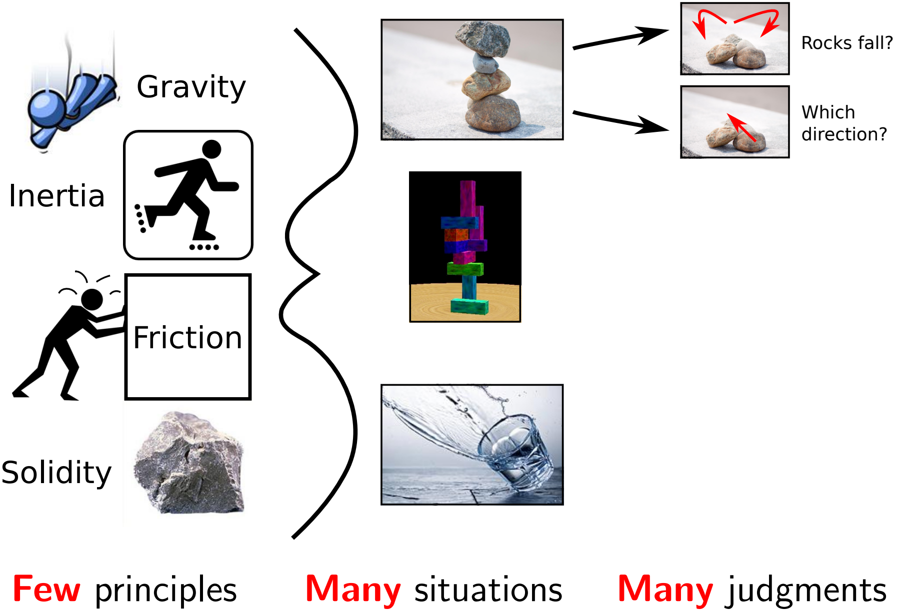

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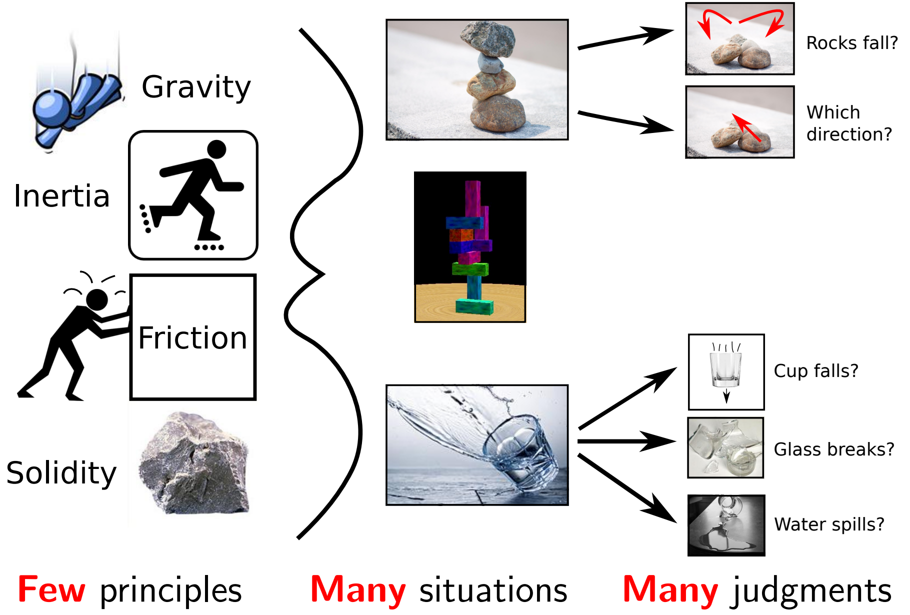

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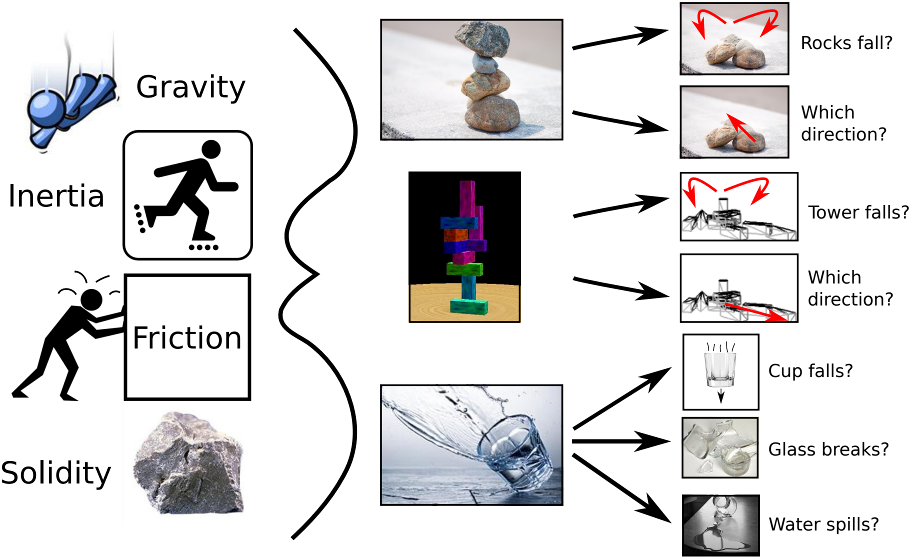

Few principles **Many** situations **Many** judgments

Previous work

Intuitive Physics

Principle-Based **Cue-Based**

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Principle-Based

(e.g. impetus principle;
McCloskey, Caramazza, Green)

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Limitation:
no quantitative predictions

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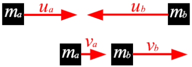

$$\frac{m_a}{m_b} = \frac{u_b - v_b}{v_a - u_a}$$

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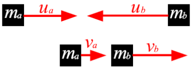

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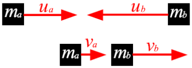

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Principle-Based, Quantitative Model

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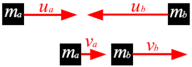

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Probabilistic Newtonian models:
Sanborn, Mansinghka, & Griffiths

Principle-Based, Quantitative Model

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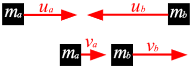

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Principle-Based, Quantitative Model

Quantitative Probabilistic Framework

Newtonian Physics

Our hypothesis

People have a **probabilistic intuitive physics** which approximates **Newtonian physics** while incorporating multiple sources of **uncertainty**

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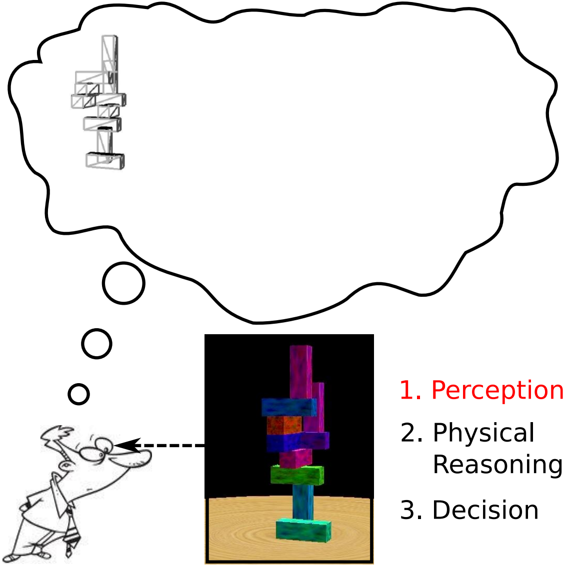

1. Perception
2. Physical Reasoning
3. Decision

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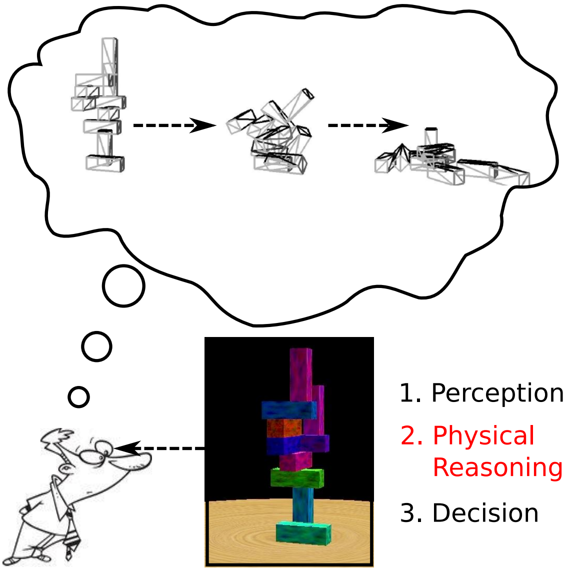

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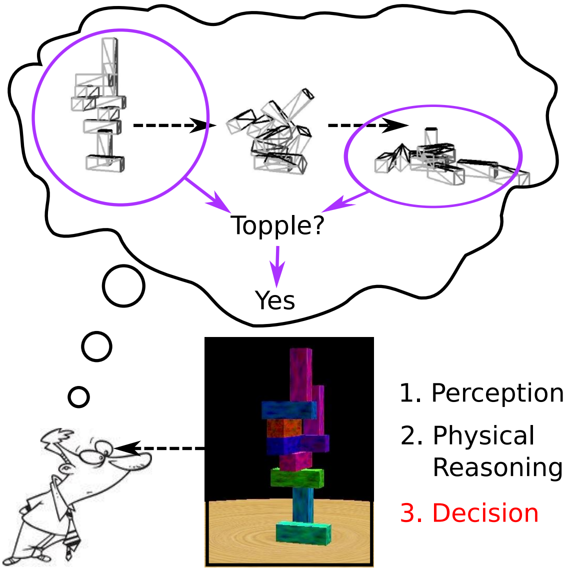

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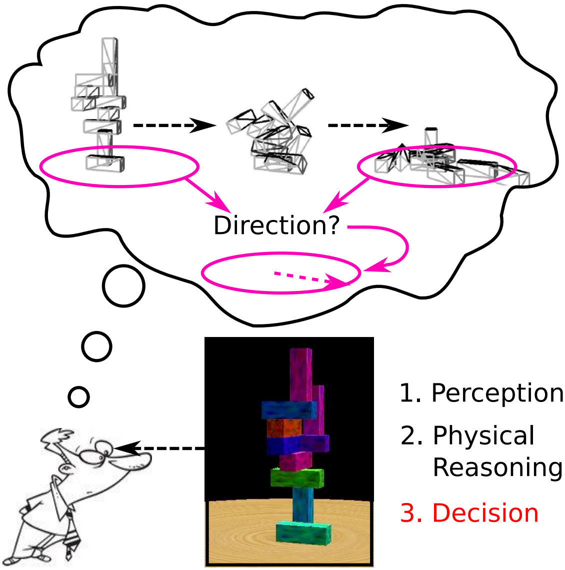
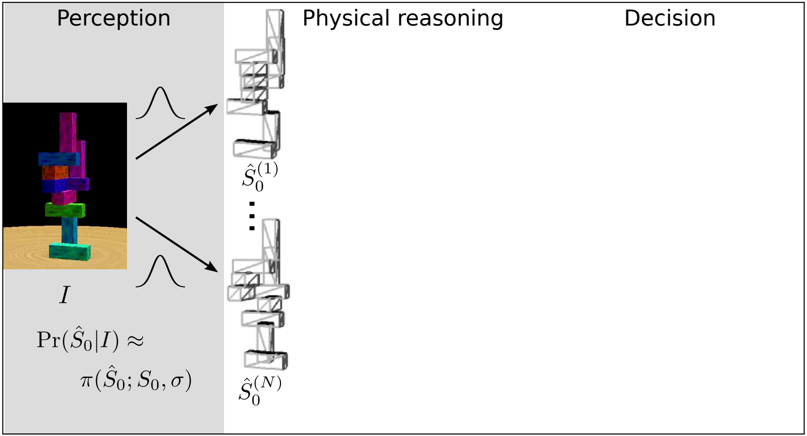
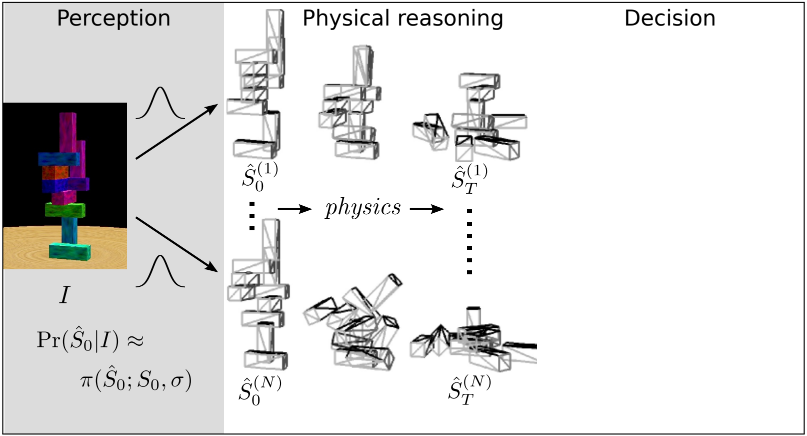


Probabilistic Newtonian model



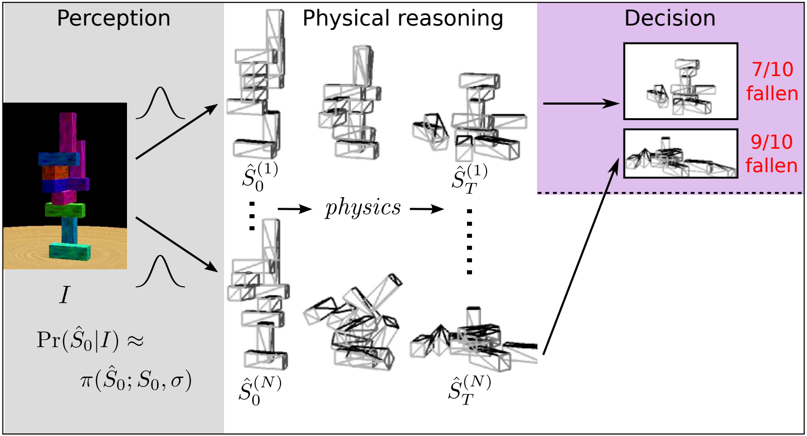
Perceive geometric, kinematic, & physical *state* of current scene under uncertainty

Probabilistic Newtonian model



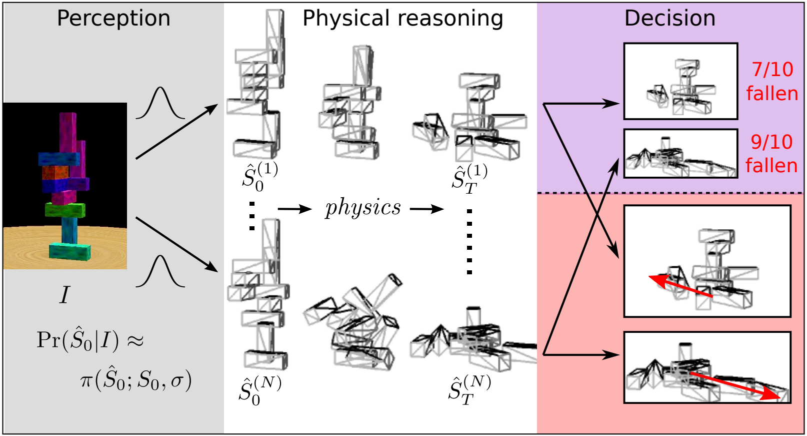
Predict *future states* through Newtonian dynamics, under constraints of: gravity, solidity, inertia, friction

Probabilistic Newtonian model



Decide about physical properties, e.g. *stability*, by comparing the current and predicted future states

Probabilistic Newtonian model



Perceptual uncertainty represented by σ

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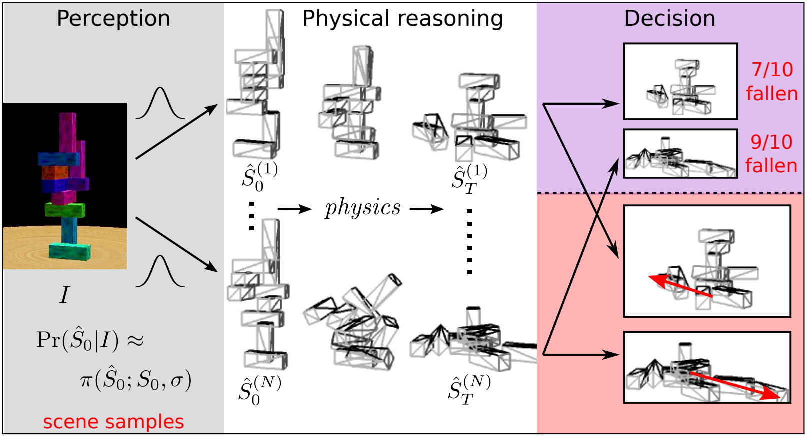

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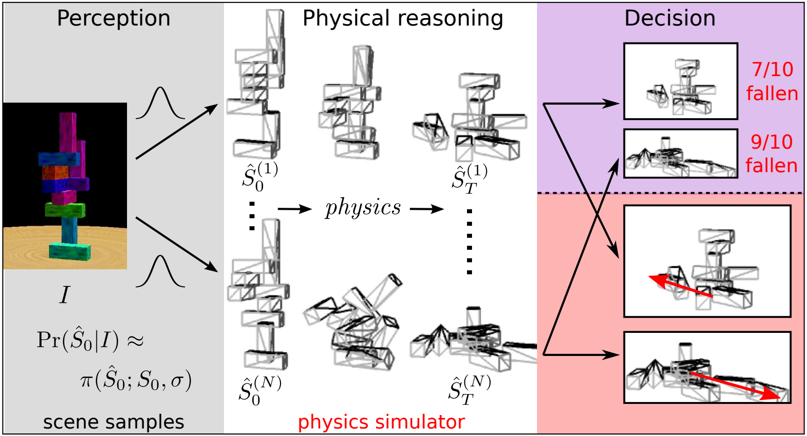

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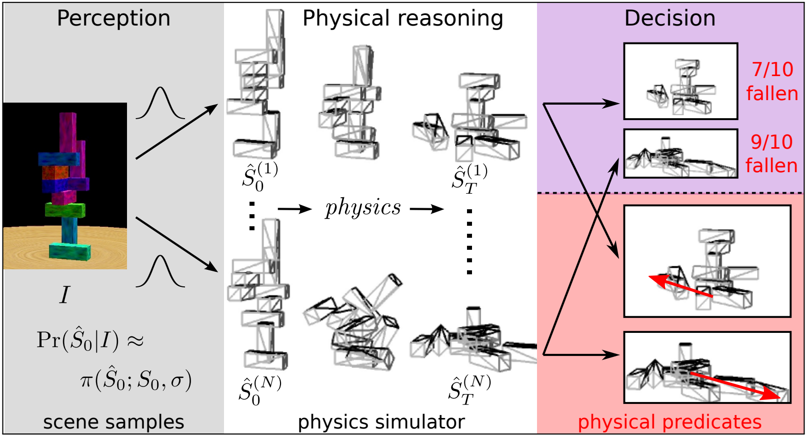

Perceptual uncertainty represented by σ

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Exclusively geometric properties, independent of physical principles, that could drive physical property judgments

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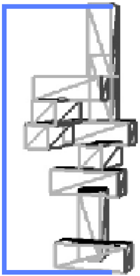
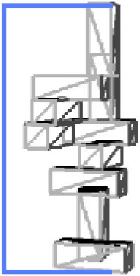


Height

Geometric heuristics

Exclusively geometric properties, independent of physical principles, that could drive physical property judgments



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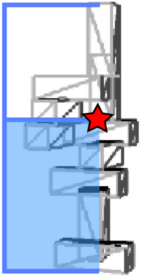

Top-Heaviness

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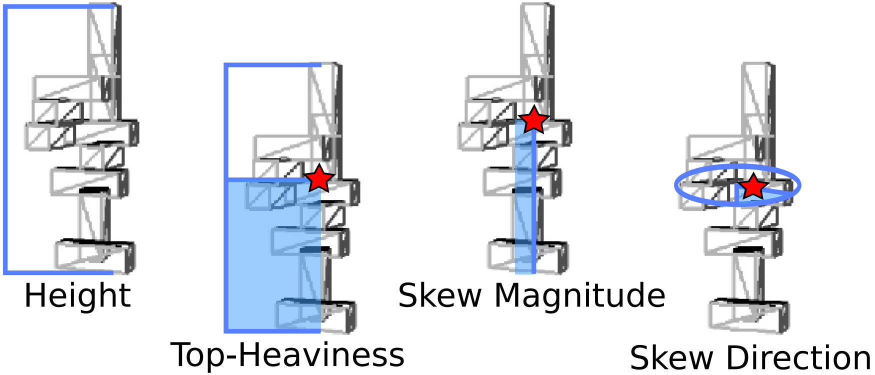
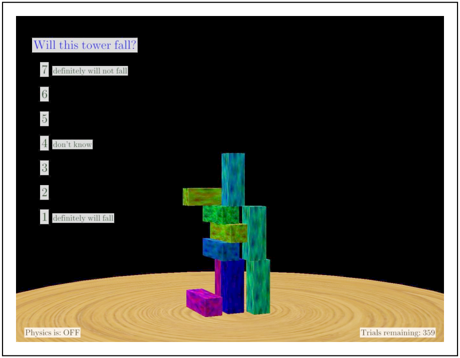


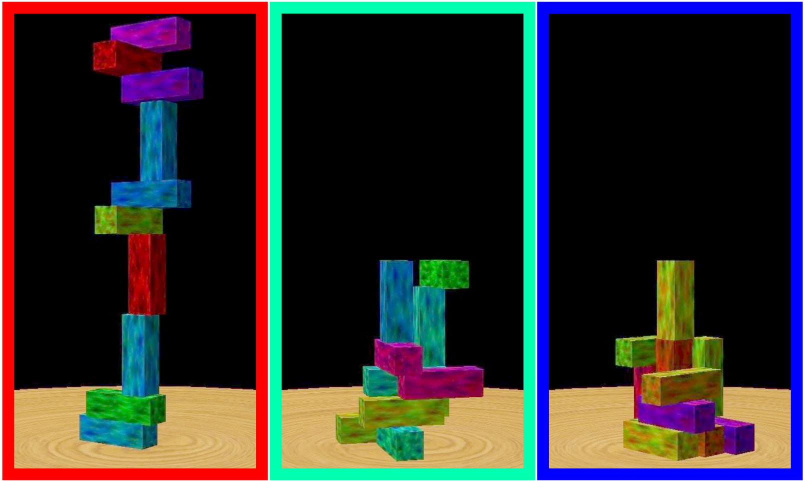
"Stability" experiment: methods



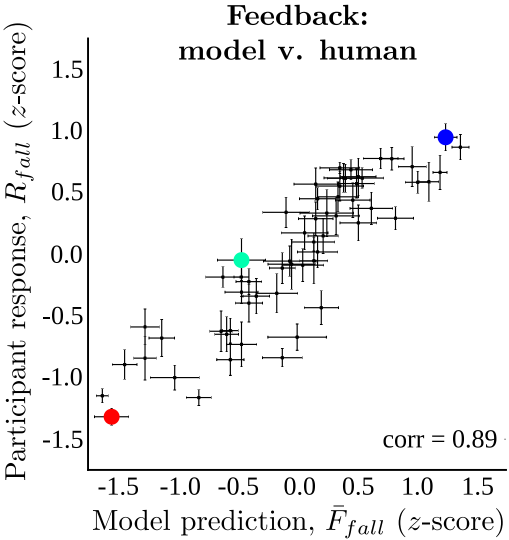
Model: % of blocks that fall

- "Will this tower fall?", scale from 1-7
- Randomly generated towers
- 60 towers
- 6 reps/tower
- $n = 10$ subjects
- *Feedback given*

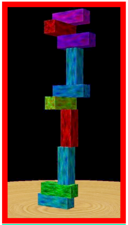
Example towers

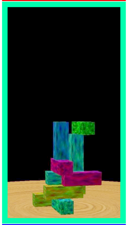


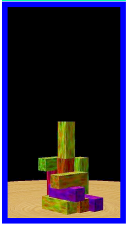
“Stability” experiment: results



$\sigma = 0.05$







Does feedback cause learning?

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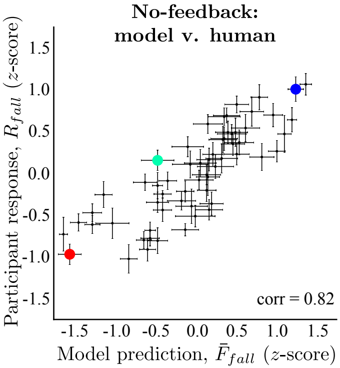

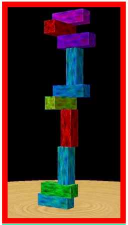

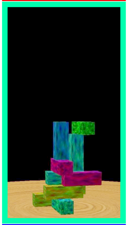

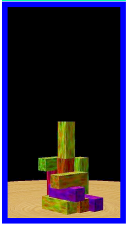

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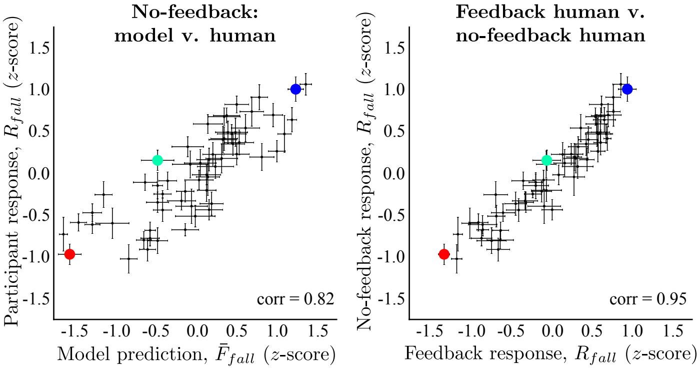

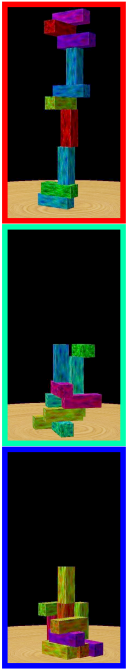

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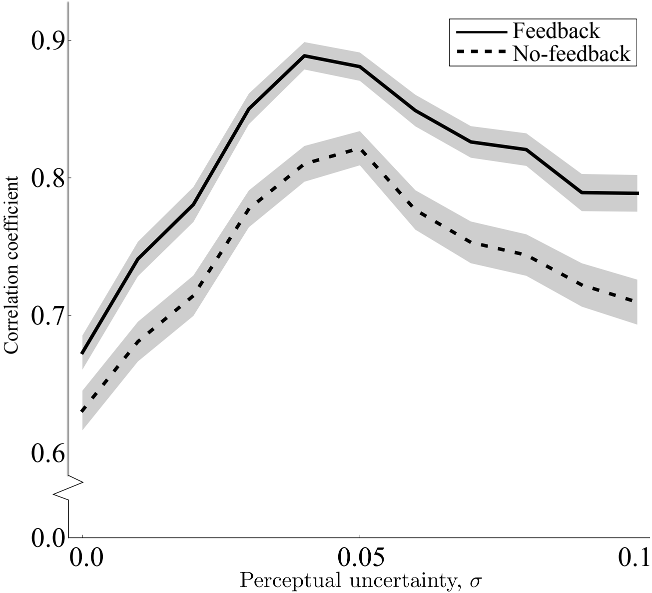
"Stability" experiment: effect of σ



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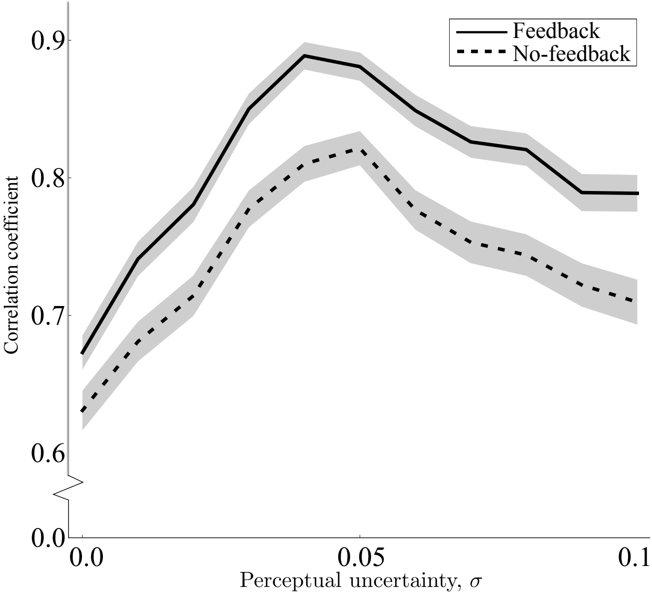

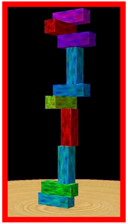

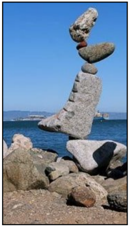

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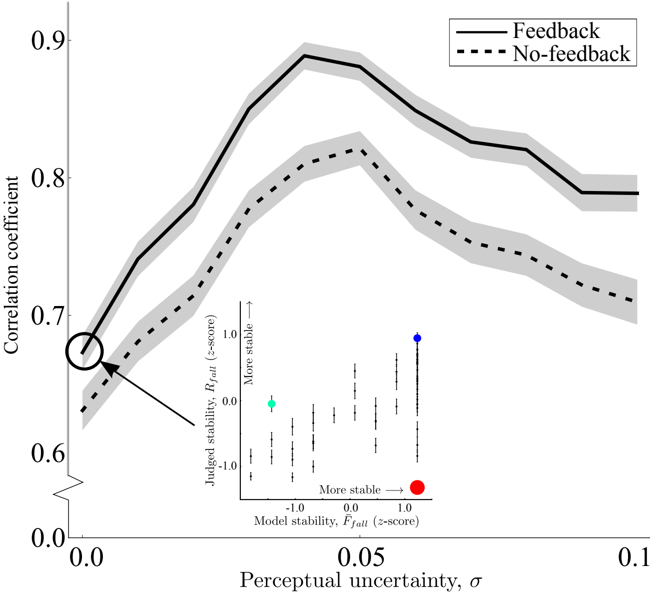

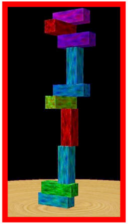

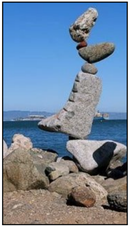

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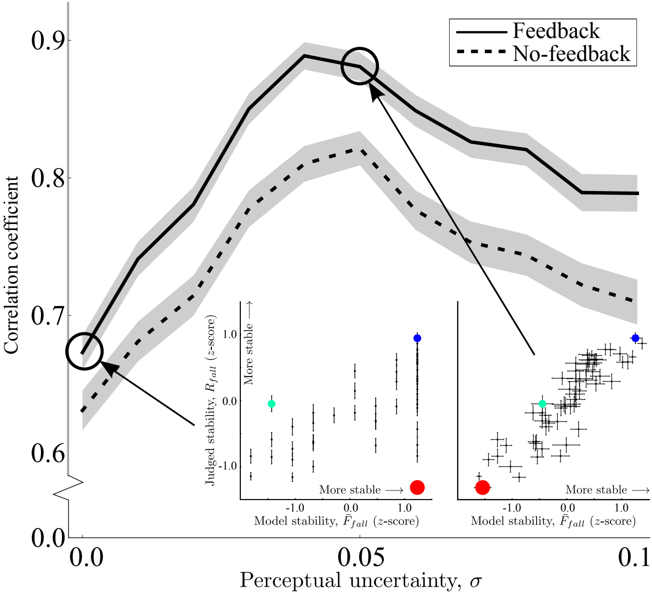

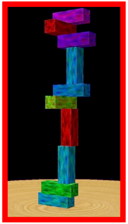

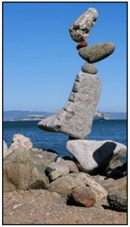

Do people use height?

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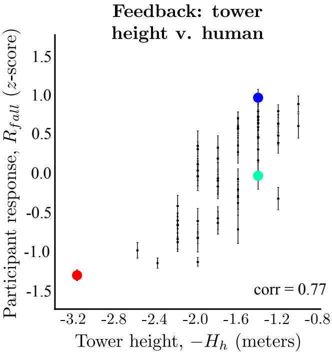
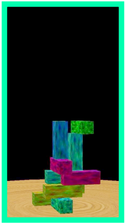
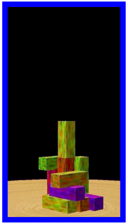


partial correlation:
height v. human (removing
model) = 0.52





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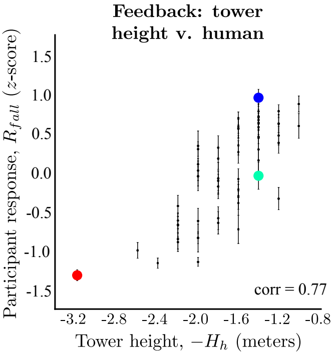

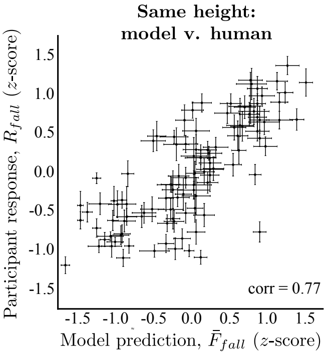

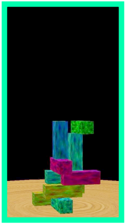

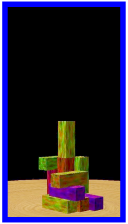

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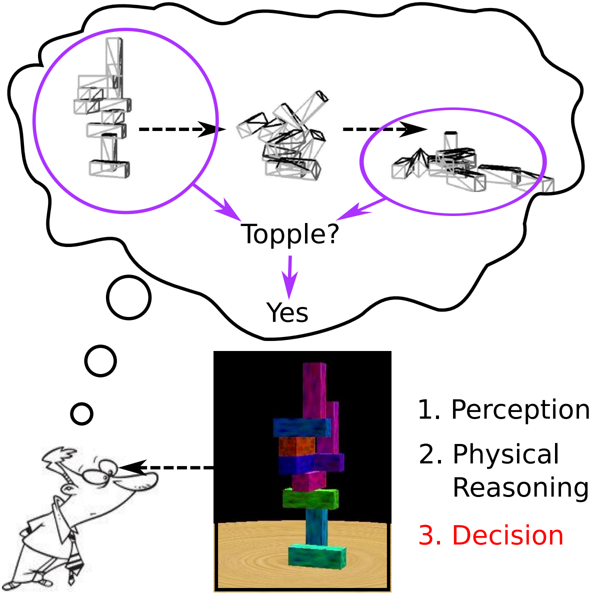
“Stability” experiment: take-home

- Probabilistic Newtonian model
  - $\rho \approx 0.89$ with humans
  - $\rho \approx 0.77$ after height removal
- $\sigma = 0.05$ provides best
- Height heuristic
  - $\rho \approx 0.52$ with humans (partial corr.)
  - Augments model with useful information

✔ **Clear influence of physical reasoning**

“Direction” experiment: motivation



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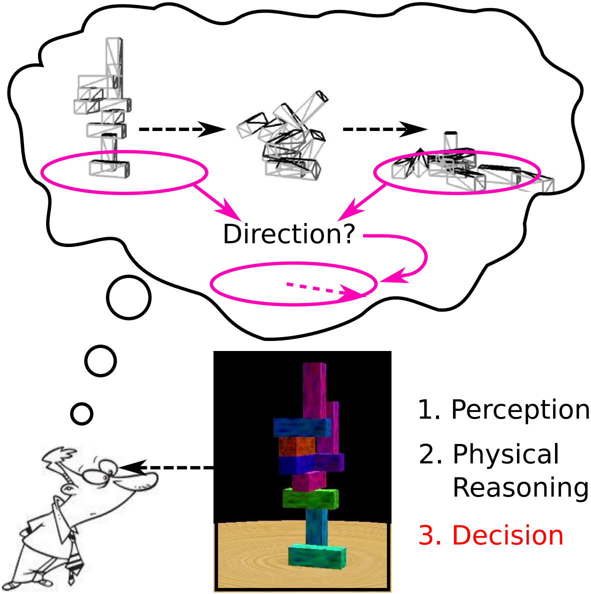

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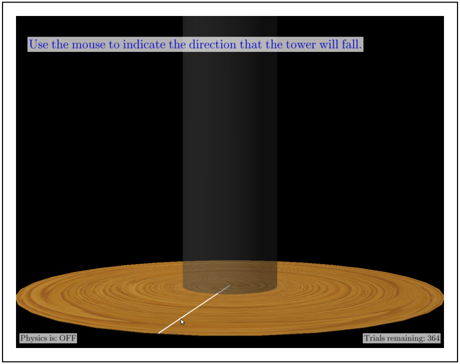
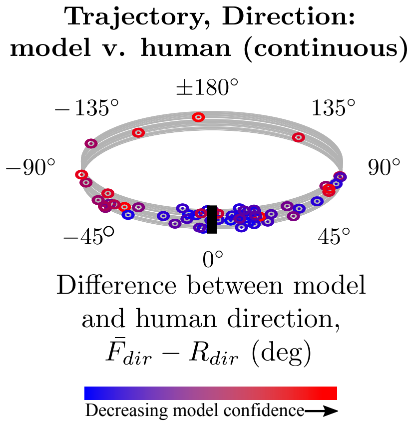


Model: angle of average block position

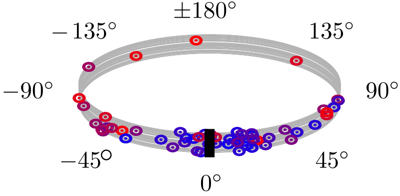
- 60 *only unstable* towers
- 6 reps/tower
- $n = 10$ subjects

“Direction” experiment: results



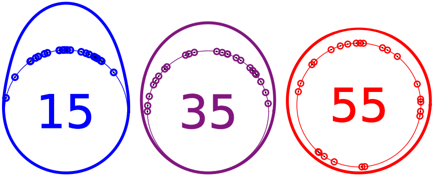
"Direction" experiment: results

Trajectory, Direction: model v. human (continuous)



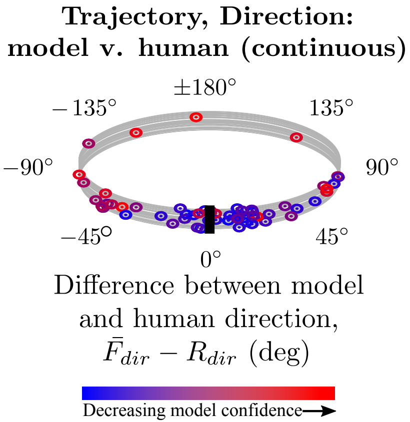
Difference between model and human direction, $\bar{F}_{dir} - R_{dir}$ (deg)

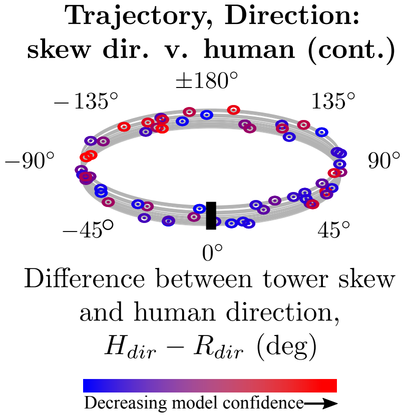
Decreasing model confidence



Towers, in order of **decreasing model confidence**

“Direction” experiment: results



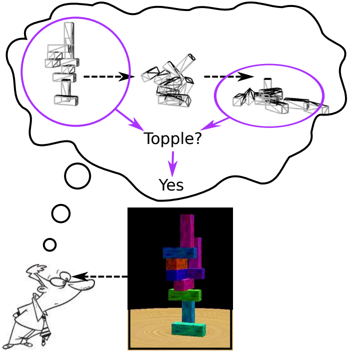


"Direction" experiment: take-home

- Model predicts human direction judgments
- Simple heuristics fail

✓ By **inputting a different predicate**, our model also predicts human direction judgments: **one** model, **many** judgments

Discussion



✓ Model: highly consistent with human **stability** *and* **direction** responses

✓ Heuristics: less predictive of human judgments

✓ Many more physical properties are predictable via interchangeable predicates: **one** model, **many** judgments

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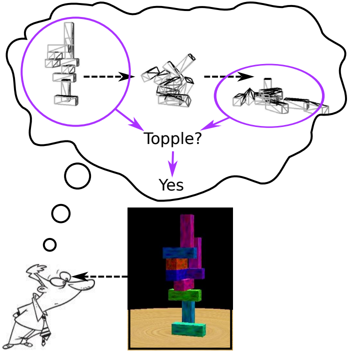

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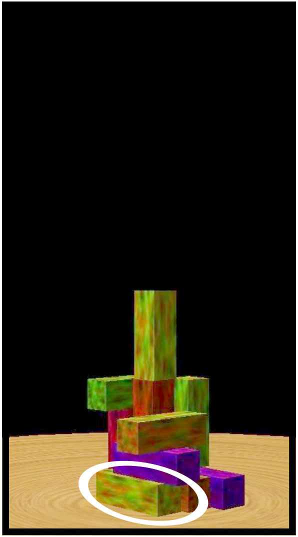
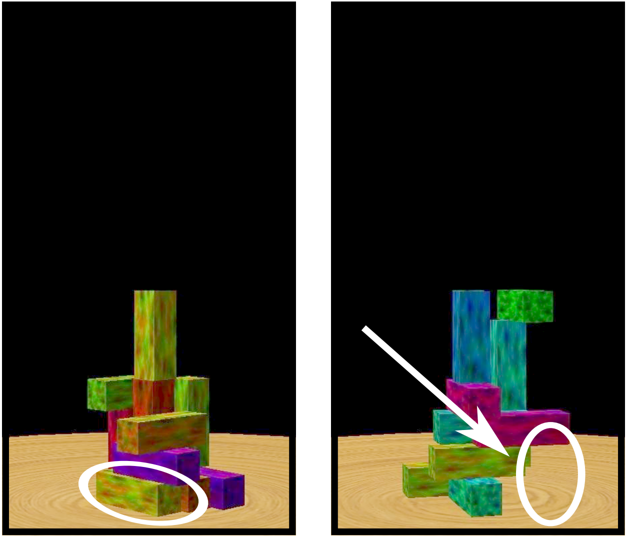
We conclude that **humans use probabilistic intuitive physics** to make judgments about physical events.

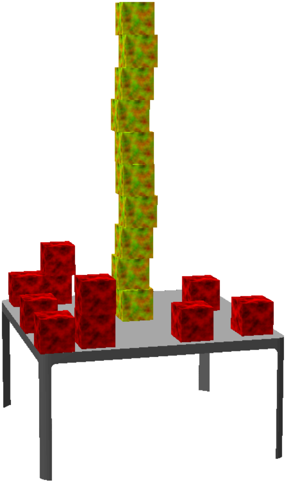
Future directions: counterfactual reasoning



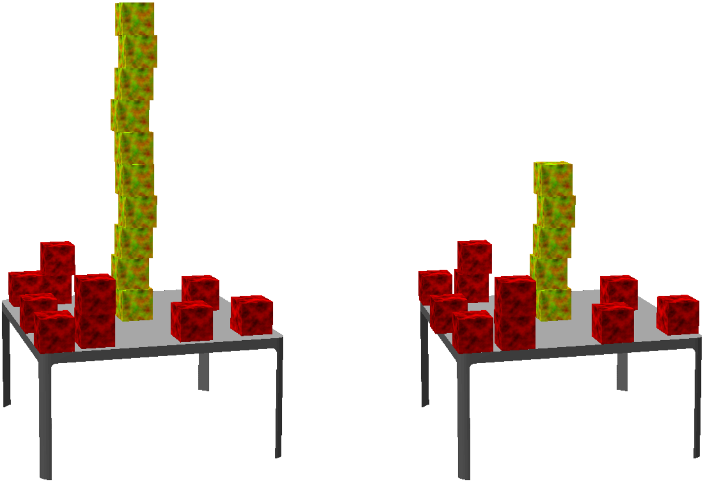
Future directions: counterfactual reasoning



Future directions: combined judgments



Future directions: combined judgments



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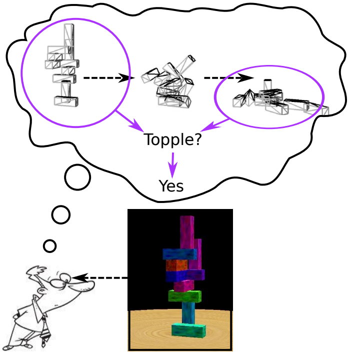
- ONR MURI 1015GNA126



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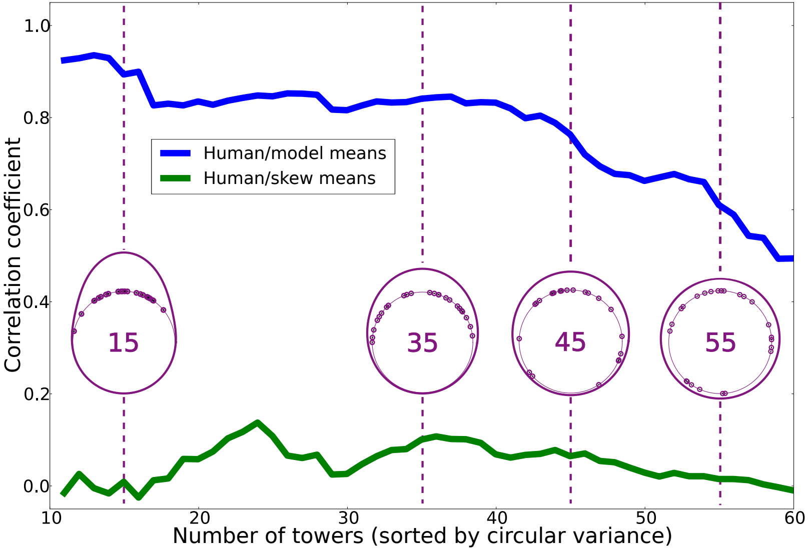
Questions?

“Direction” experiment: tower concentration



Model observer

A physical tower property is given by $f(S_0, \phi(S_0, T))$. To form a decision about the value of this property:

$$E[f(S_0, \phi(S_0, T))]_I = \int f(S_0, \phi(S_0, T)) \mathrm{Pr}(S_0|I) dS_0 \qquad (1)$$

- S_0 - initial scene state
- ϕ - physical reasoning process
- T - amount of simulation time
- I - perceived image/scene

Model observer

We approximate the probability of the initial scene state:

$$P(S_0|I) \approx \pi(S_0; \bar{S}_0, \sigma) \tag{2}$$

- S_0 - initial scene state belief
- $\bar{S}_0$ - true initial scene state
- I - perceived image/scene
- $\pi(\cdot)$ - Gaussian distribution + deterministic repel
- σ - perceptual uncertainty (std. dev. of Gaussian)

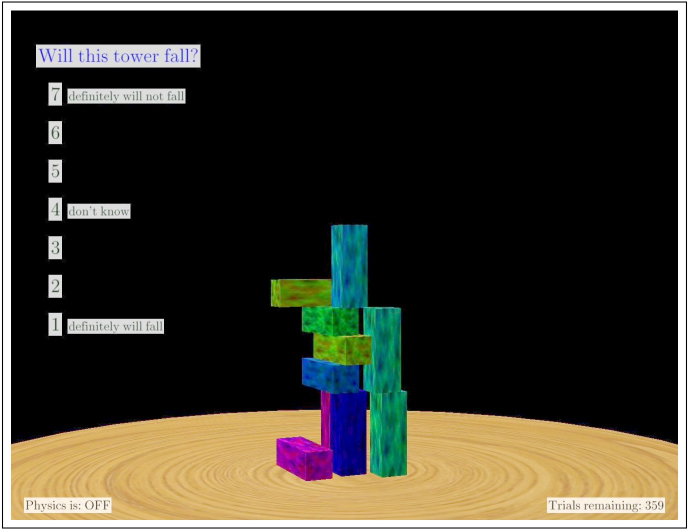
Model observer

We approximate Eqn. 1 through a Monte Carlo simulation that draws N "perceptual" samples $S_0^{(1,\dots,N)} \sim \pi(S_0; \hat{S}_0, \sigma)$:

$$\bar{F} = \frac{1}{N} \sum_{i=0}^{N} f(S_0^{(i)}, \phi(S_0^{(i)}, T)) \tag{3}$$

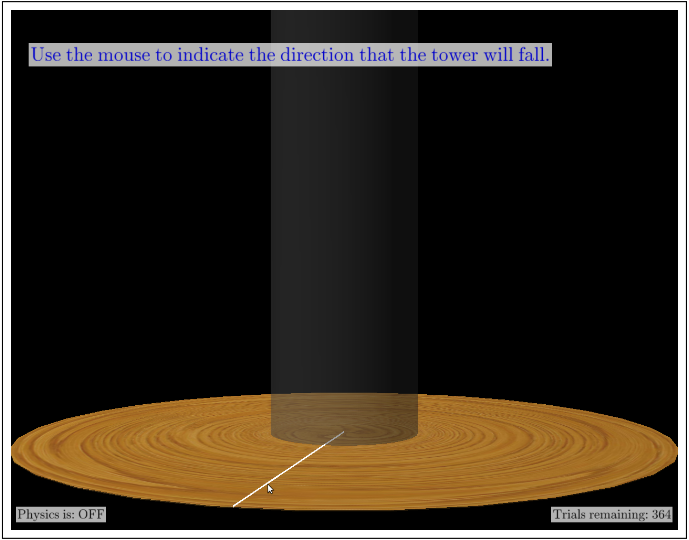
- S_0 - initial scene state
- ϕ - physical reasoning process
- T - amount of simulation time
- $\pi(\cdot)$ - Gaussian distribution + deterministic repel
- σ - perceptual uncertainty (std. dev. of Gaussian)

“Stability” experiment



Stability Video

“Direction” experiment



Direction Video

"Direction" experiment: old setup