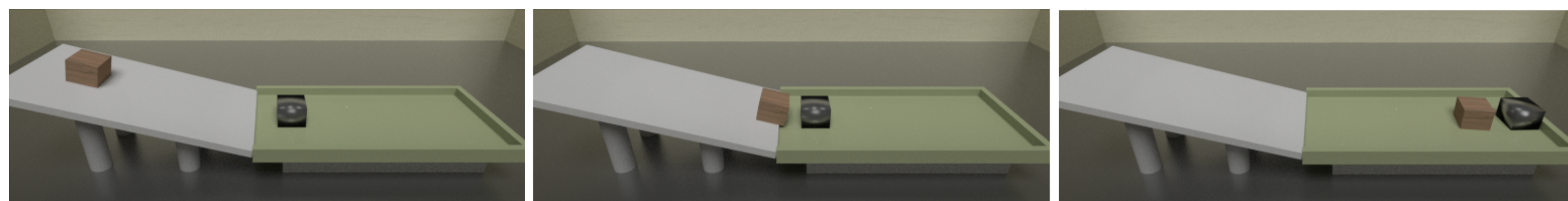


## Motivation

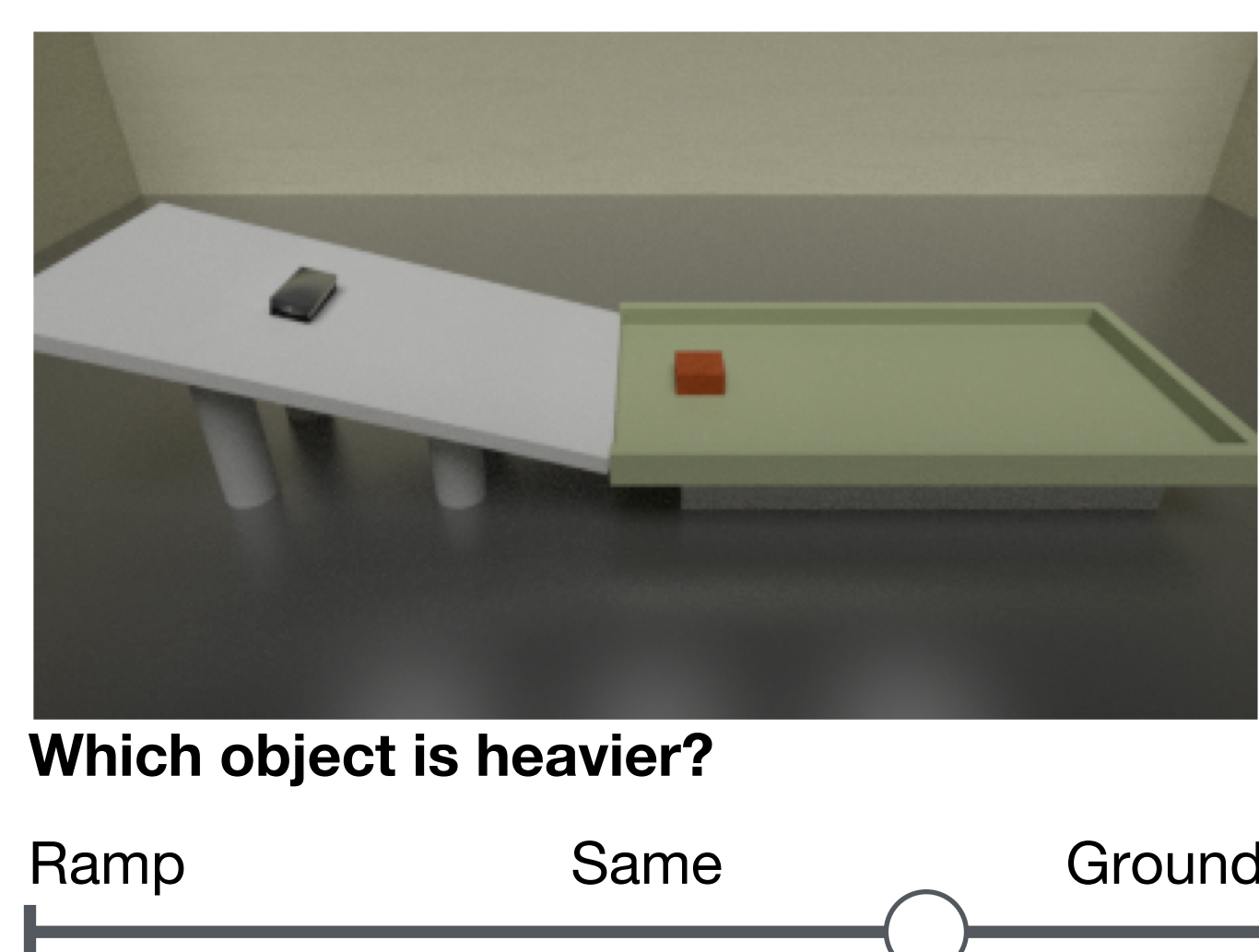
- Human scene understanding involves inferring latent causal properties – e.g., objects' mass
- These properties can be inferred in real-time from (1) texture, (2) object dynamics
- How do we do this “online” updating?
- Test via incongruencies in texture, dynamics



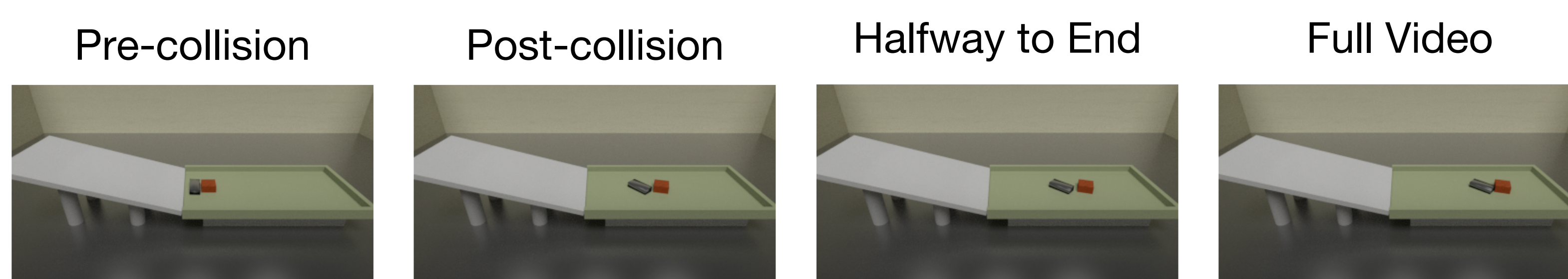
## Experiment

### Task

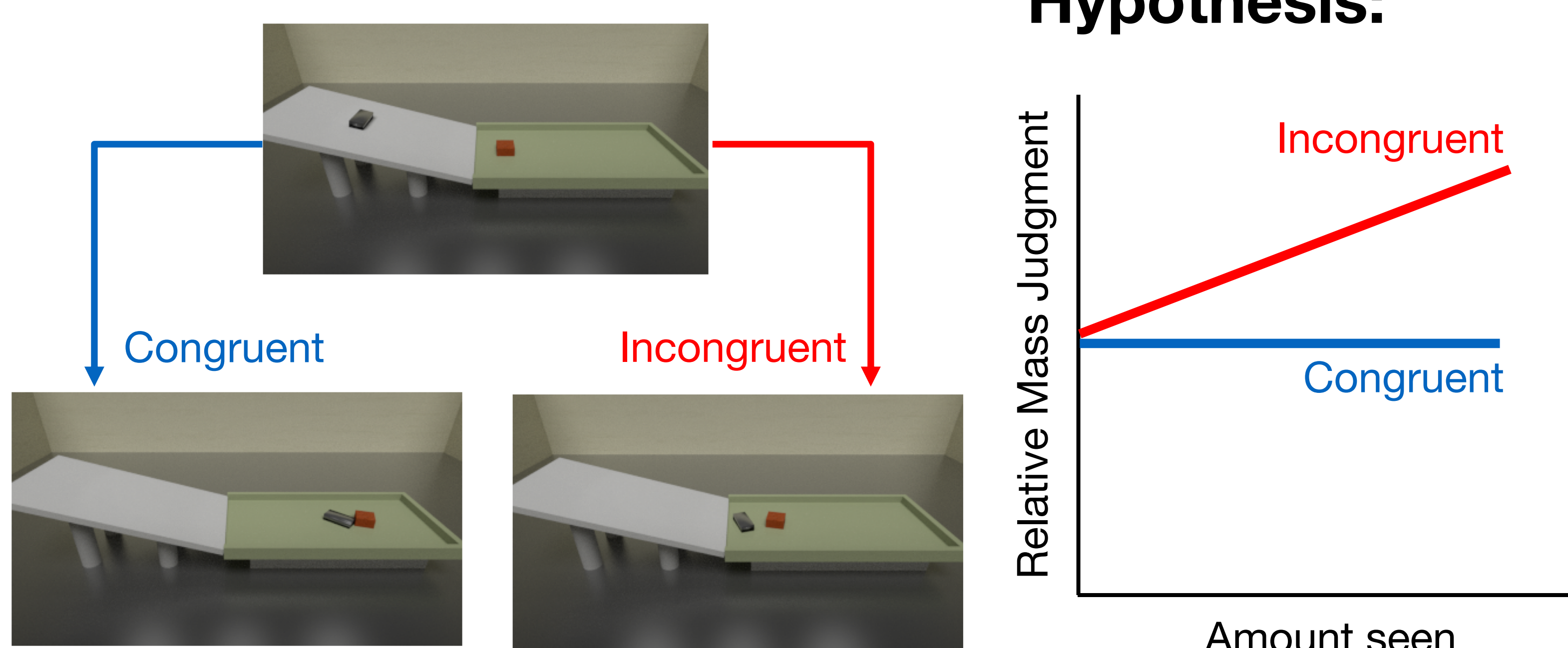
- Watch videos of dynamic collisions
- Judge relative masses



### Four video cuts / scene



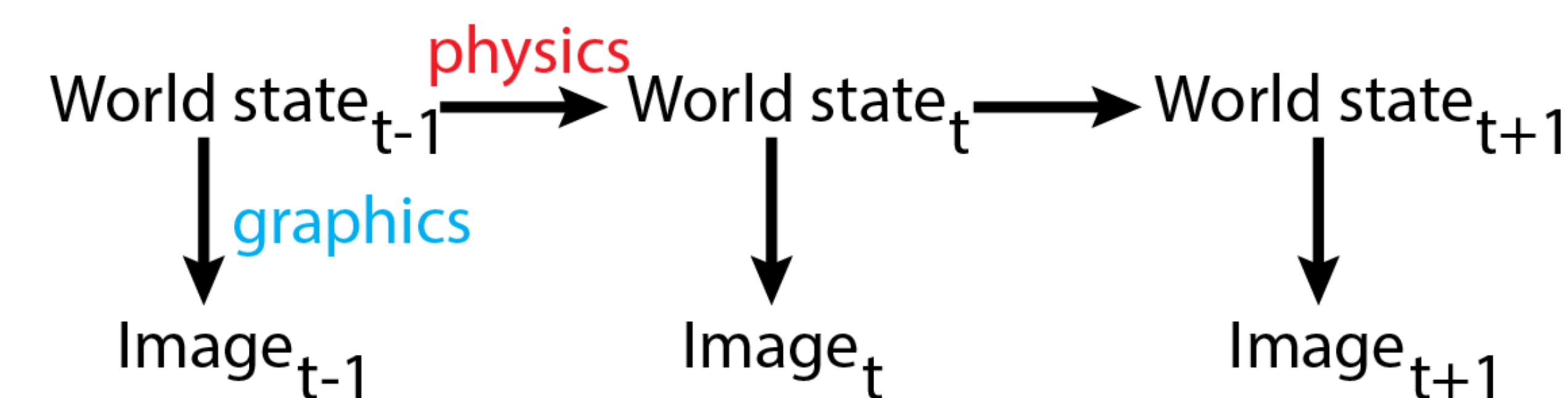
### 20% “incongruent” scenes



## Dynamic Physical Inference

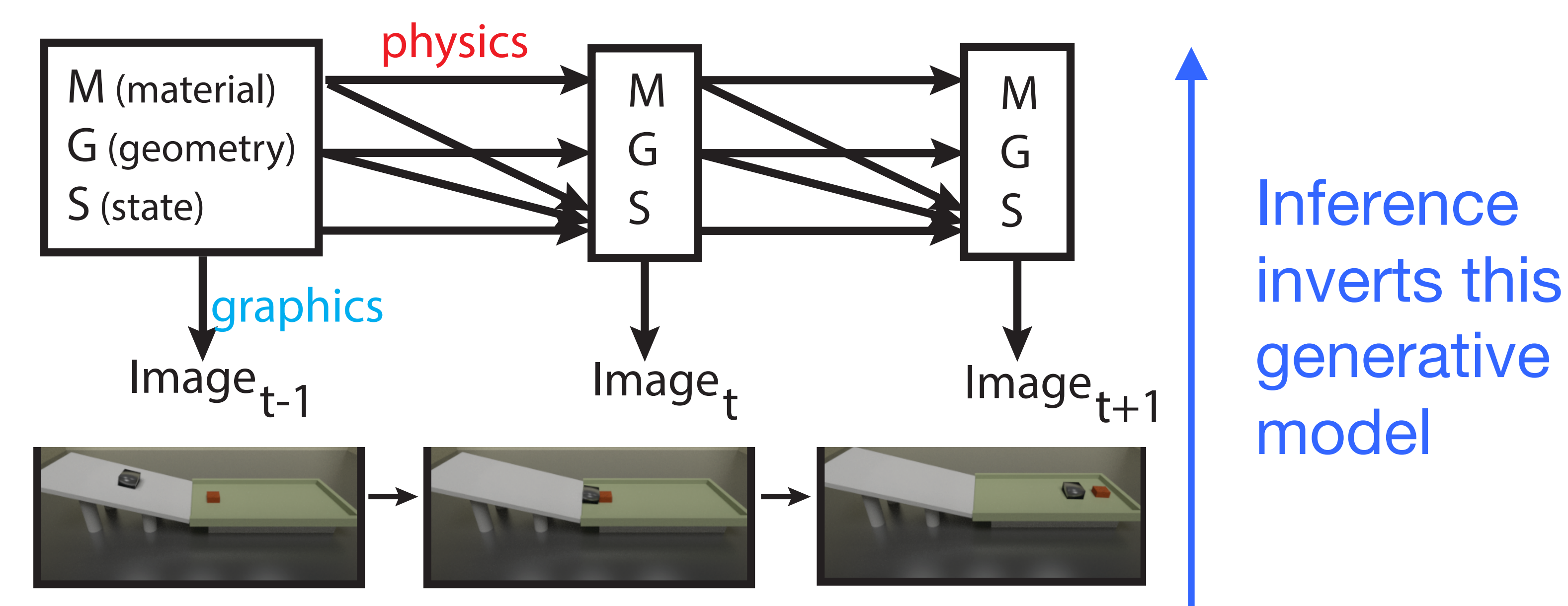
“Analysis by Synthesis:” reconstructing the scene that gives rise to sense inputs

### Generative model



Battaglia, Hamrick, Tenenbaum (2013)

### Inference problem



## Inference Models

### 1. Ideal Observer

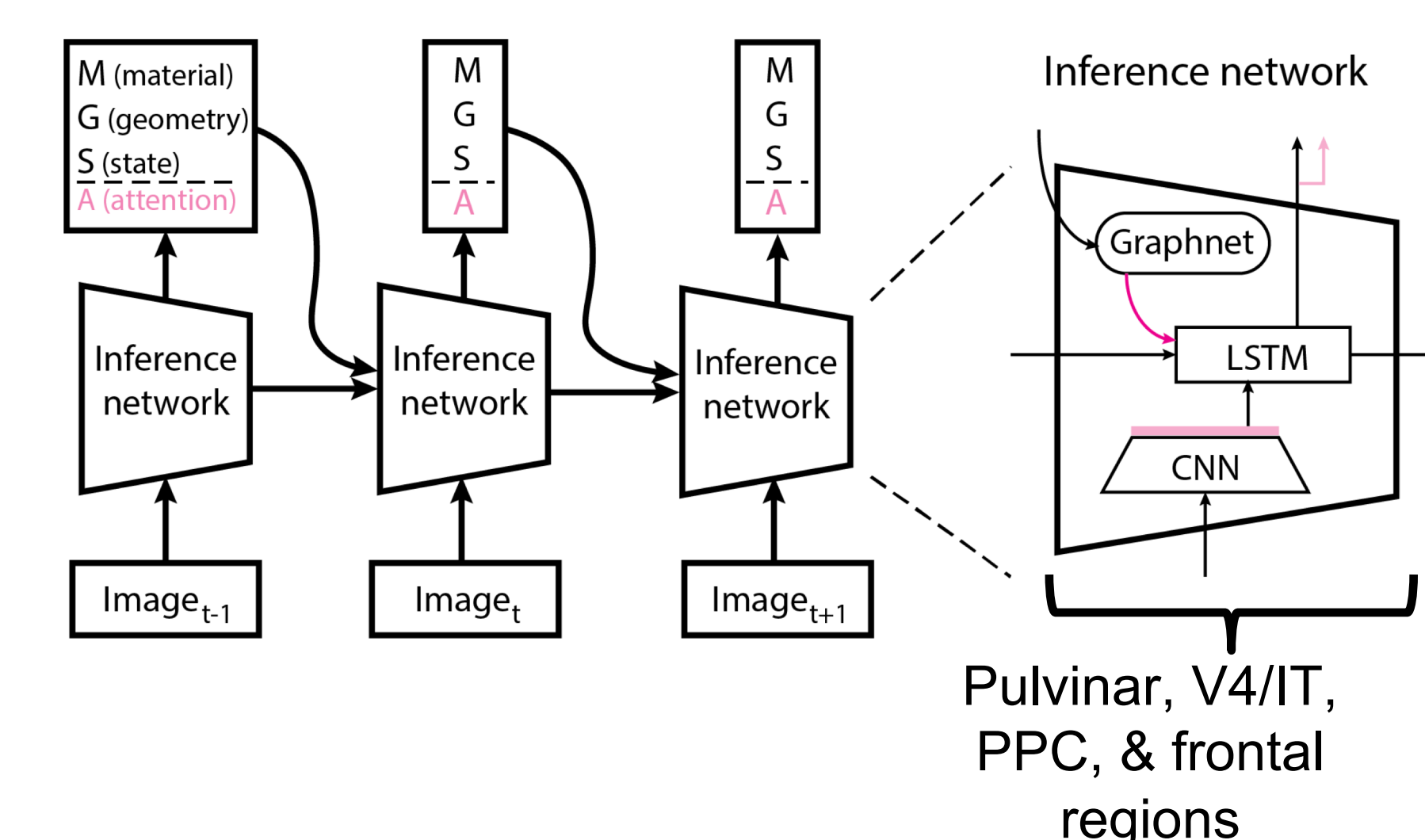
- Exact inference at each time point

### 2. Sequential Rational Process

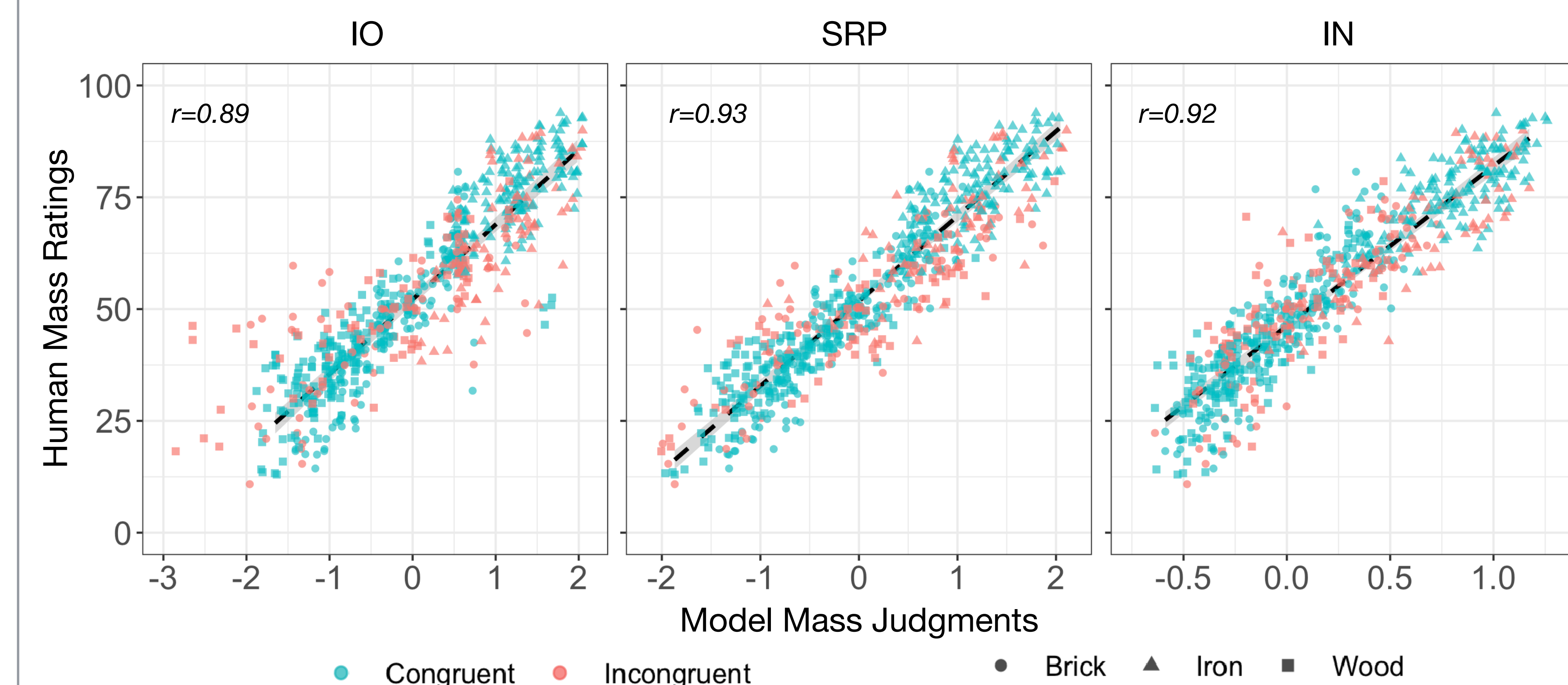
- Approximation using Particle Filters
- Resource constrained: 4 hypotheses at a time

### 3. Inference Network

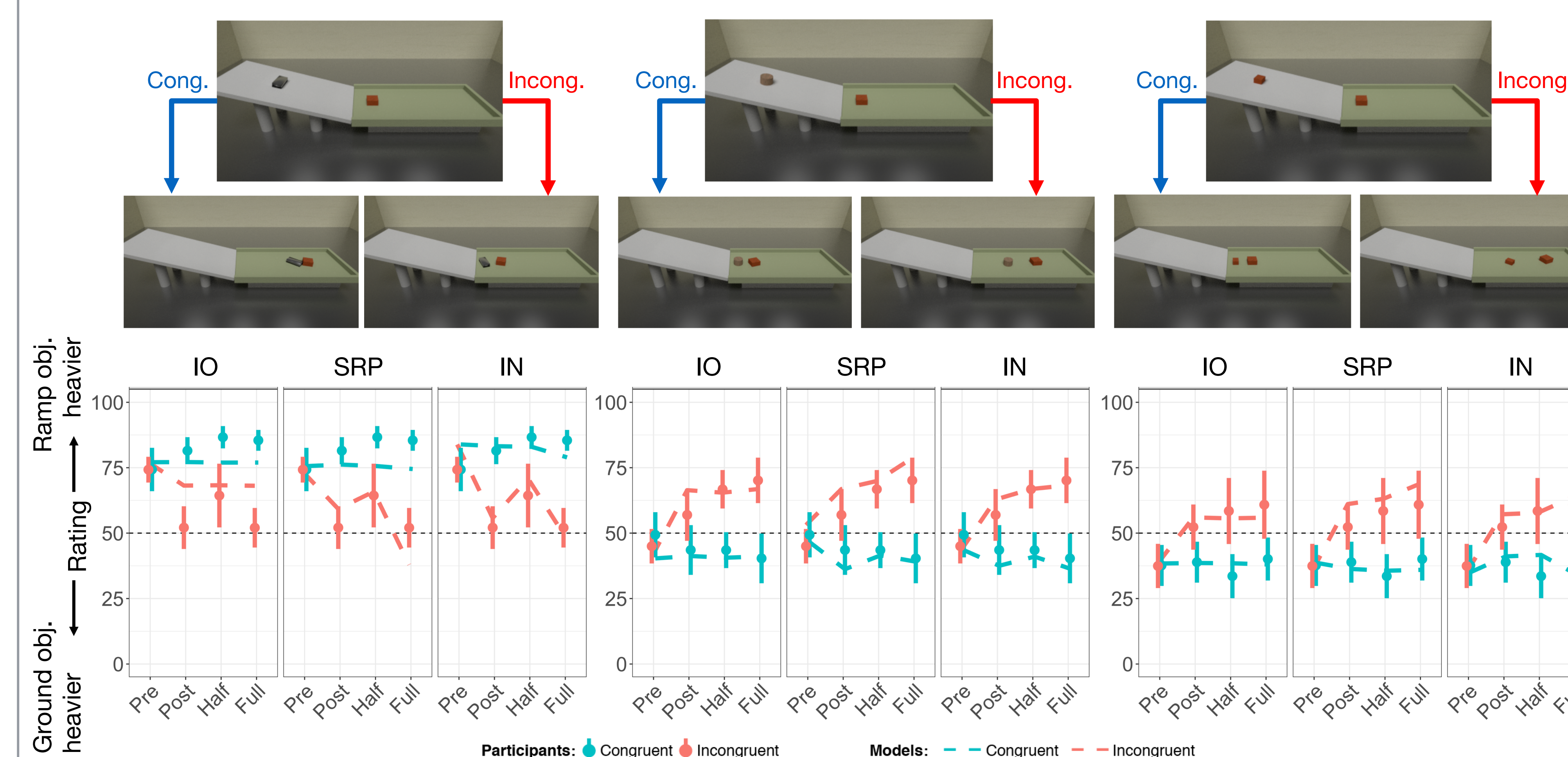
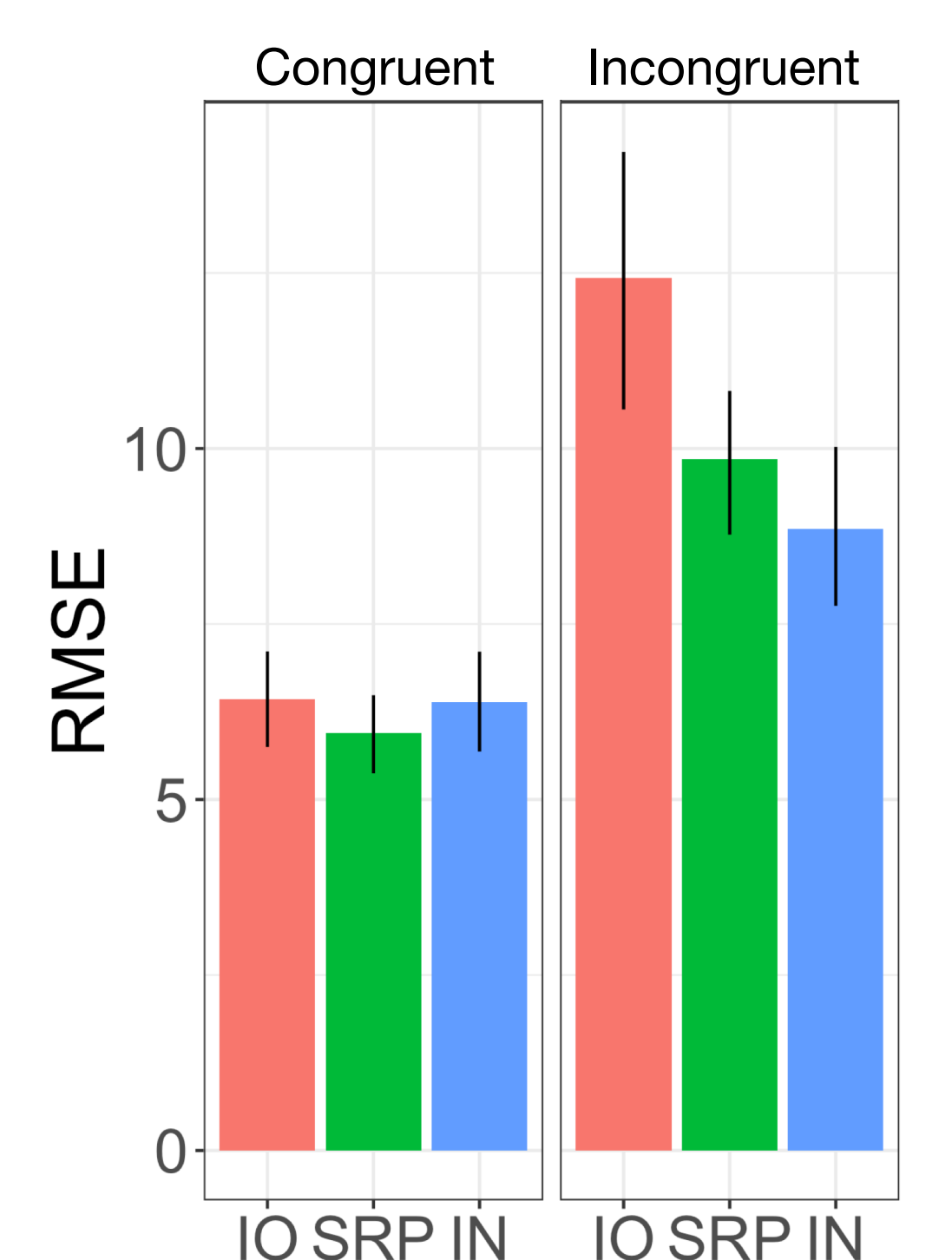
- Learns approximate inverse function
- Plausible neural mapping?



## Results



- All models explain human judgments well overall
- But fit in IO is driven by congruent trials, whereas approximate models extend well to incongruent
- Approximate models capture dynamics of human judgment over time



## Discussion

- Bayesian inference provides rich, causal explanations of sensory inputs supporting physical scene understanding
- Dynamic inference driven by efficient, approximate algorithms
- IN provides starting point for understanding physical inference in the brain

## Acknowledgments

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