Learning to understand intuitive physics from natural videos

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Joint work with: Mido Assran, Nicolas Ballas, Adrien Bardes, Laurent Najman, Emmanuel Dupoux, Mike Rabbat, Yann LeCun

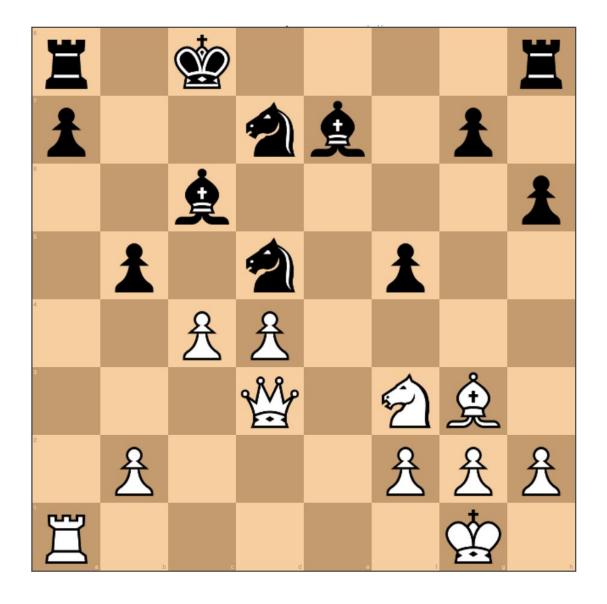






We are building embodiments of Moravec's paradox

Models are great at solving complex tasks...







... But they are terrible at tasks that are easy for us

How many Rs are in strawberry

There are two "R"s in the word "strawberry."

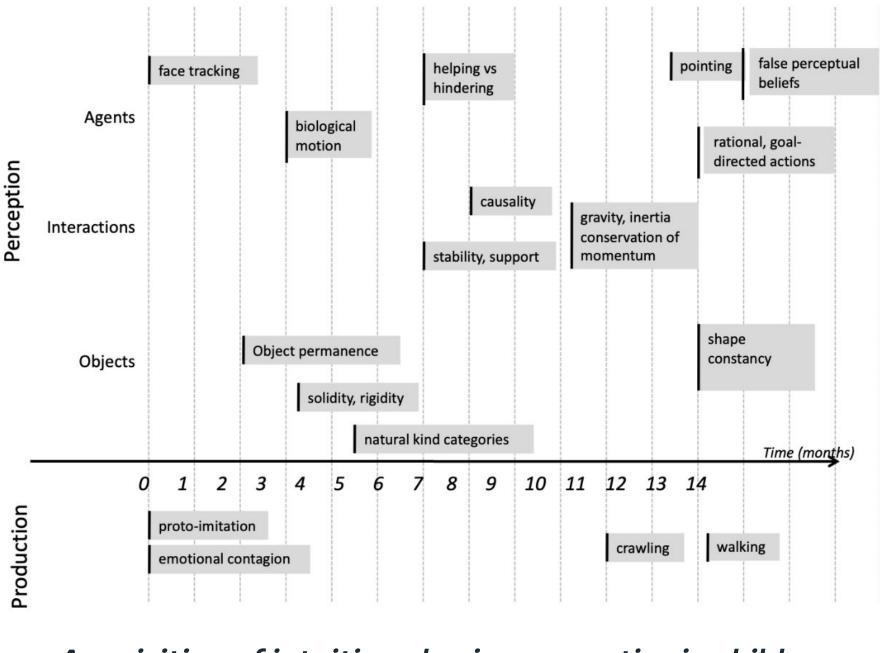
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We should focus on learning like humans

Humans acquire an understanding of the physical world at a young age:

- Object permanence (objects don't appear out of nowhere) at 3 months
- Shape constancy (objects don't change shape suddenly) at 14 months
- Walking at 14 months
- Etc

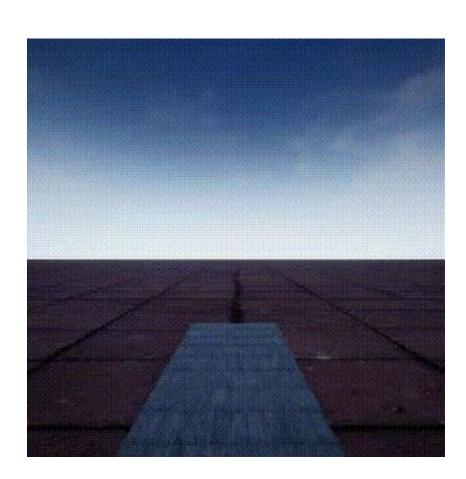
Can we build machines that acquires these almost innate concepts, and break Moravec's paradox ?



Acquisition of intuitive physics properties in children. From : https://arxiv.org/pdf/1803.07616

Intuitive physics benchmarks





Can a model find which video is impossible? *I.e. can a model detect violations of intuitive* physical laws

Existing architecture: Multimodal LLMs

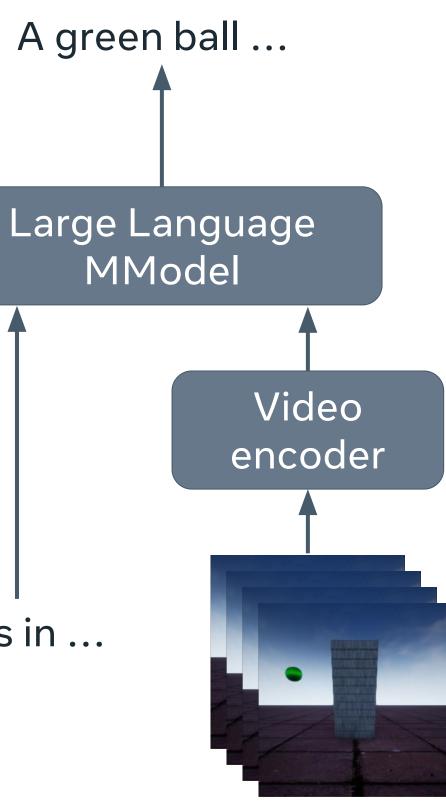
- Great at recognition tasks
- Give a textual interface

But ...

- Need huge amount of compute/data
- Video support is often an afterthought

What is in ...



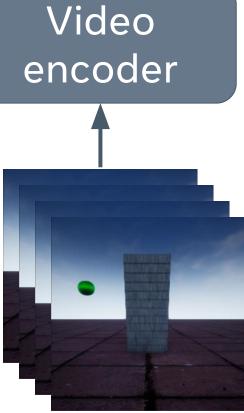


Existing architecture: Pixel Space Prediction

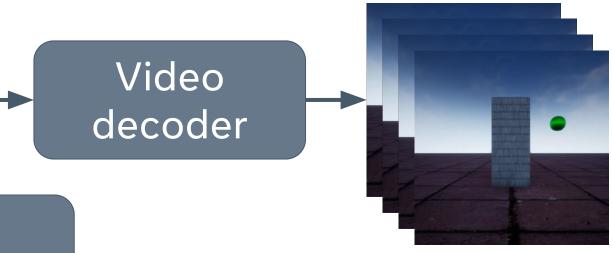
- Trained to predict the future
- We can look at predictions

But ...

- Aren't great at recognition tasks
- Focus too much on unnecessary details







These intuitive physics concepts are HARD

"The computational system generally performed poorly compared to humans"

"Existing models struggle to identify violations of these principles despite their ability to accomplish other complex tasks"

IntPhys: Riochet et. al. (2019)

"the models generally exhibit performance equivalent to, or less than, chance across all tests"

GRASP: Jassim et. al. (2024)

InfLevel: Weihs et. al. (2022)



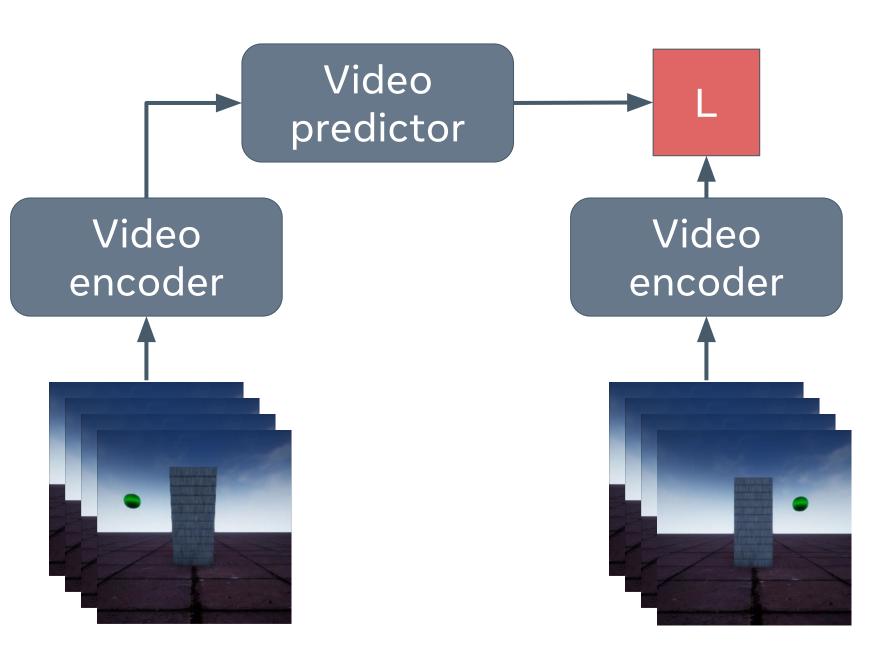
Can we to build deep learning systems that learn like humans, exhibiting human-like understanding of intuitive physics ?

What we believe should be done: Latent Space Prediction

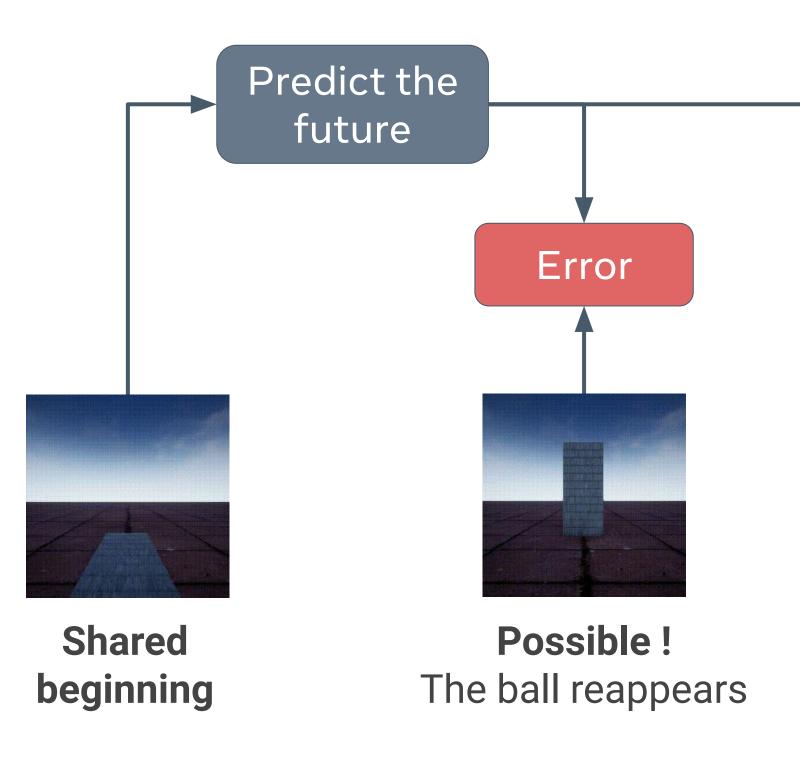
- Trained to predict in an abstract space
 - Predict the future
 - \circ Inpainting
 - \circ etc
- Great at recognition tasks

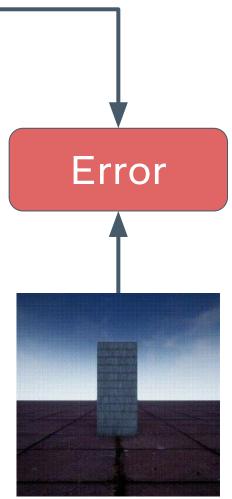
But ...

• No way to directly interpret predictions



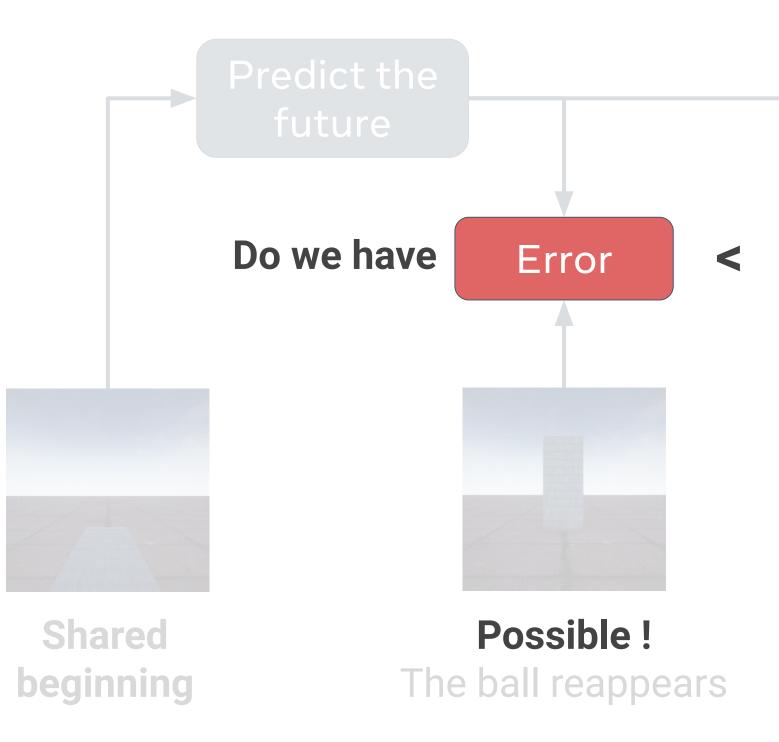
How to measure these properties: Violation of Expectation

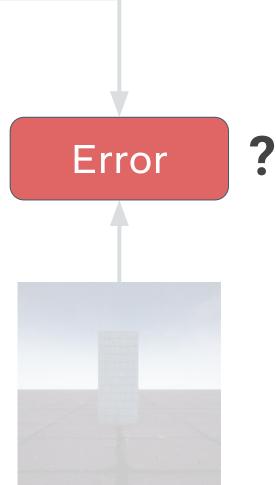




Impossible ! The ball vanished

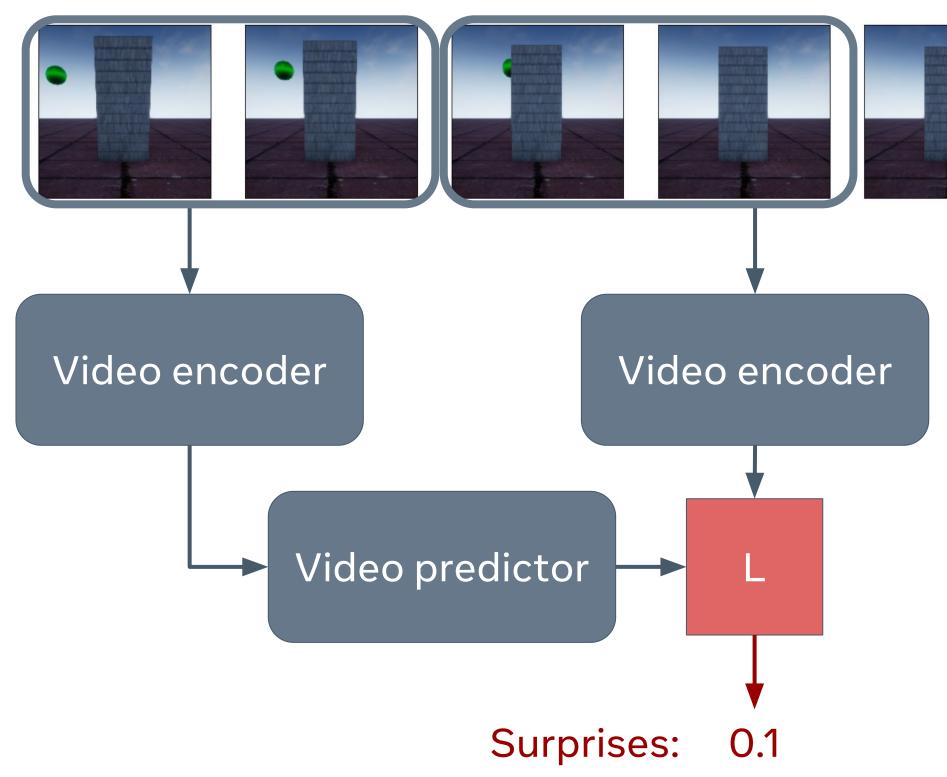
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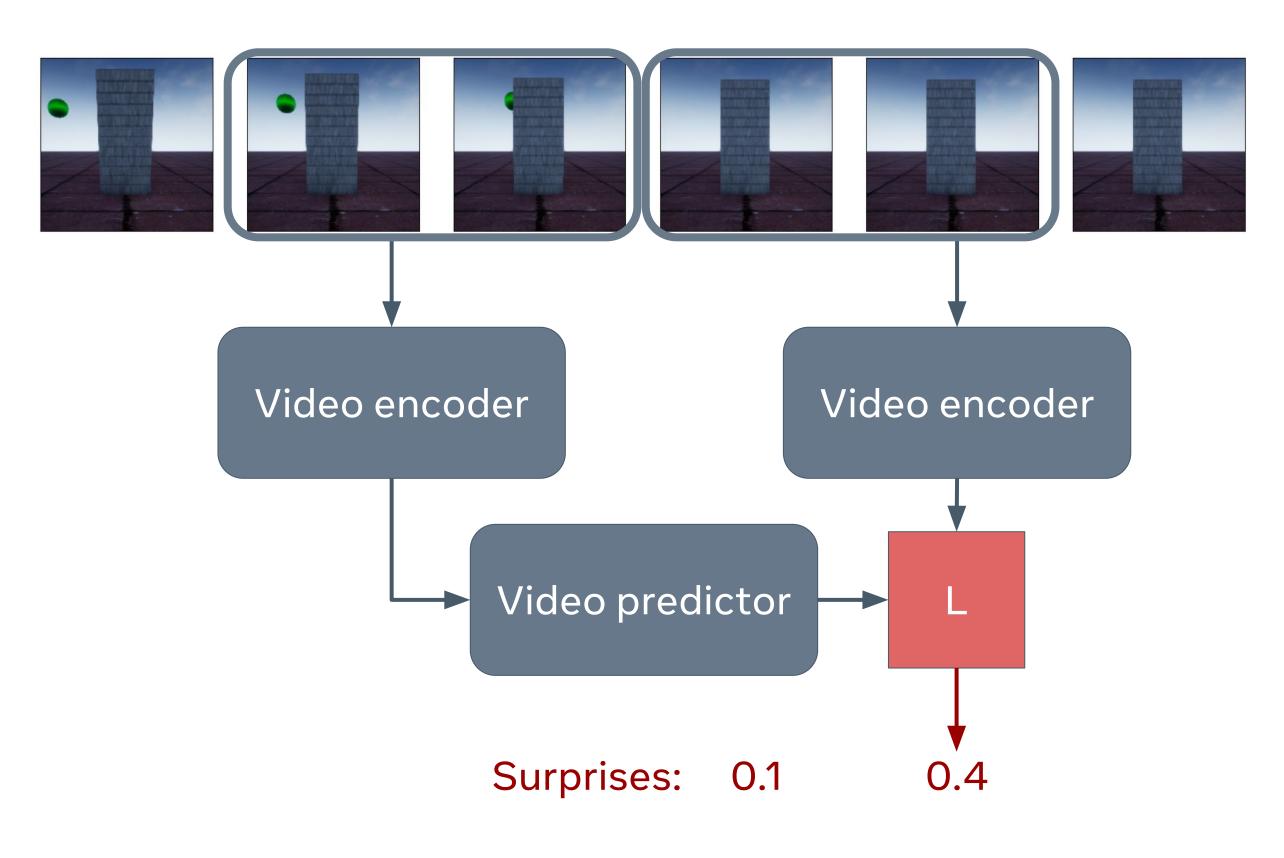
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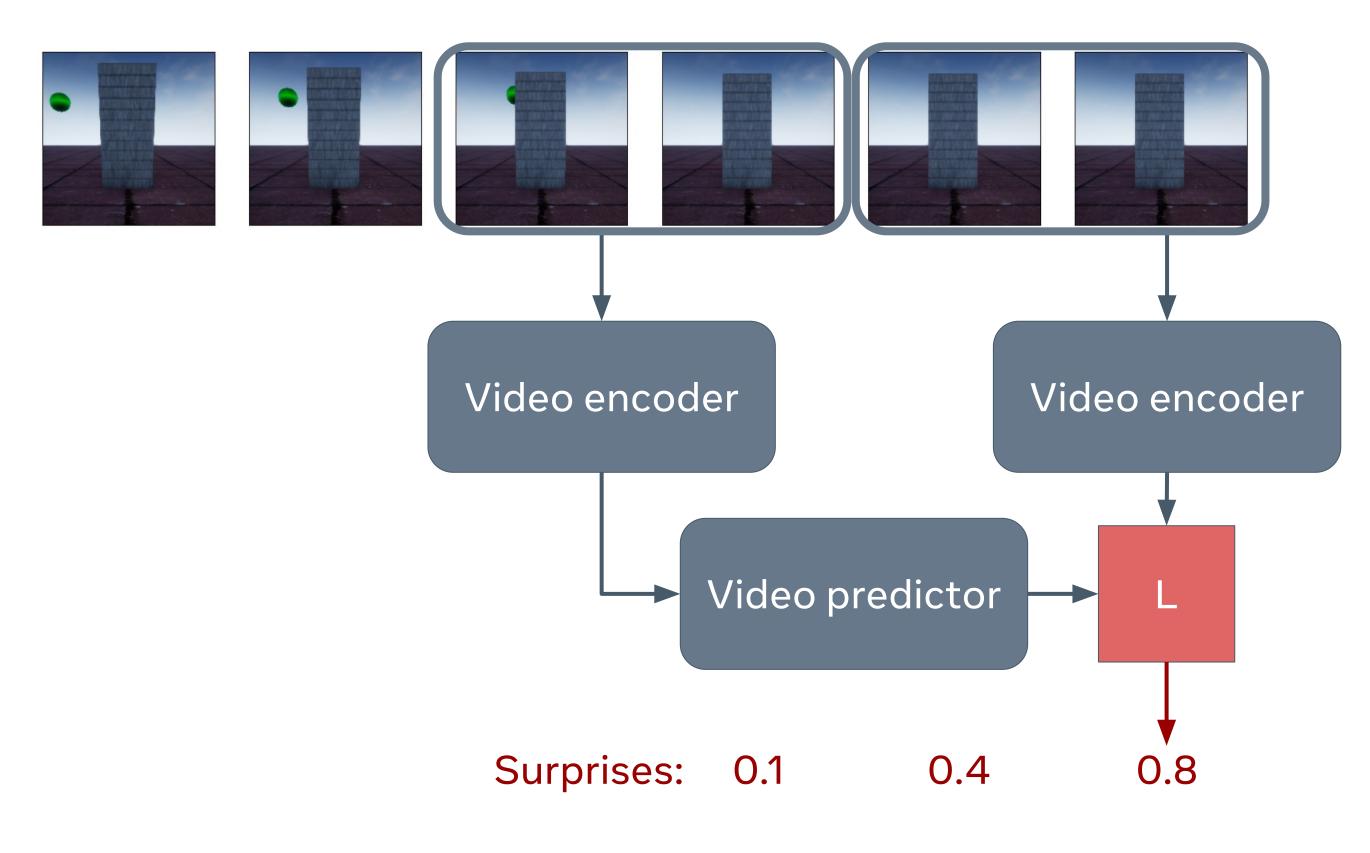
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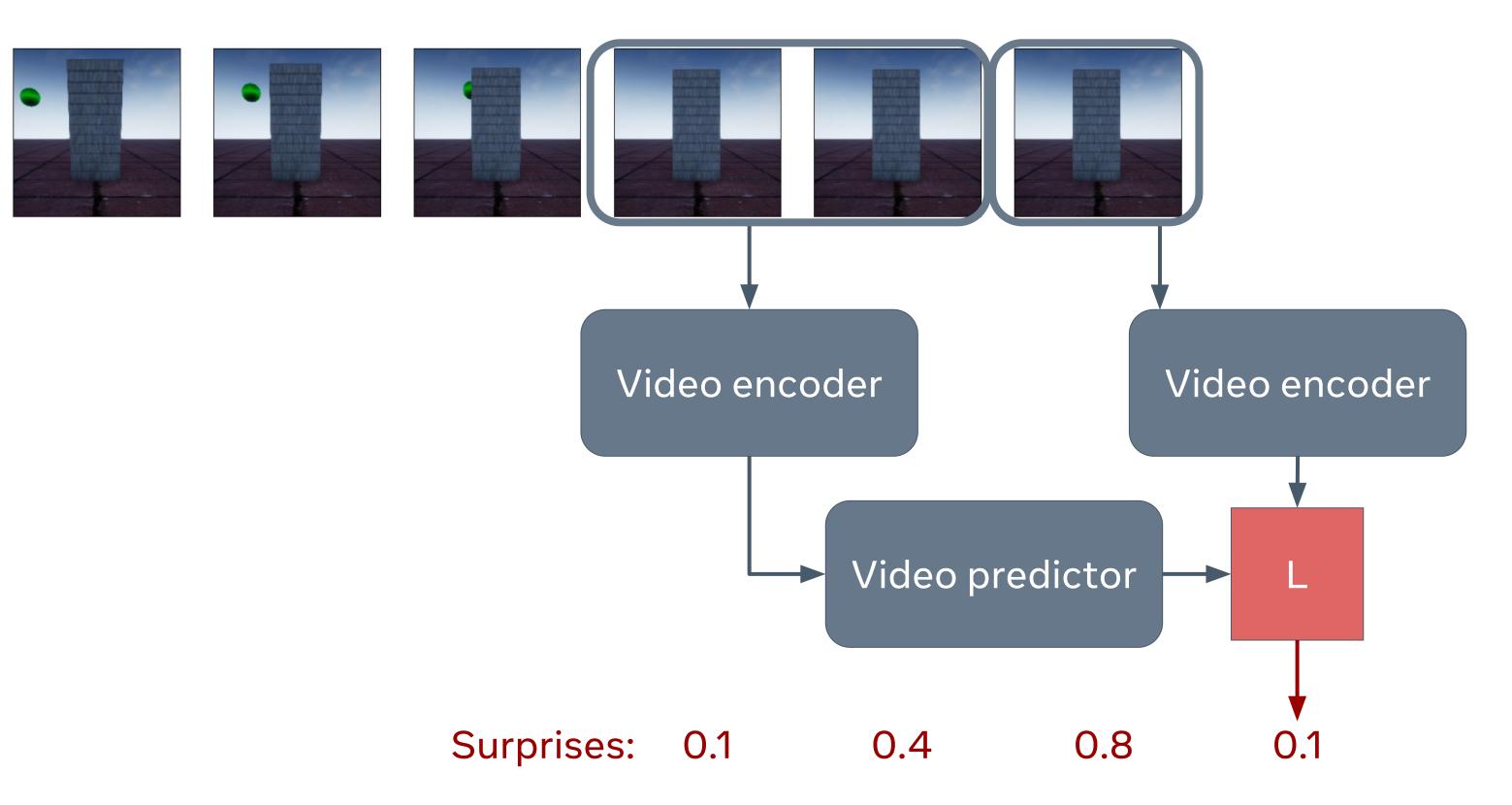


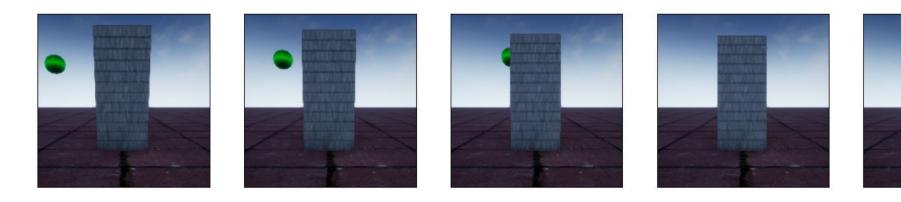




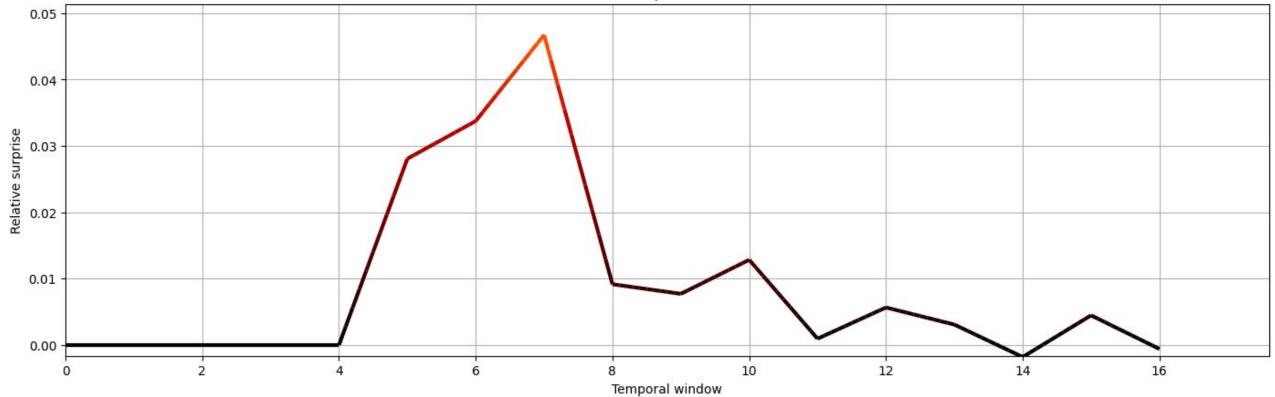




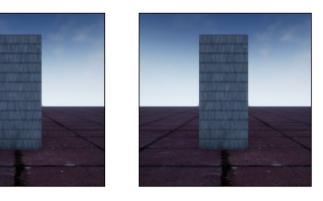




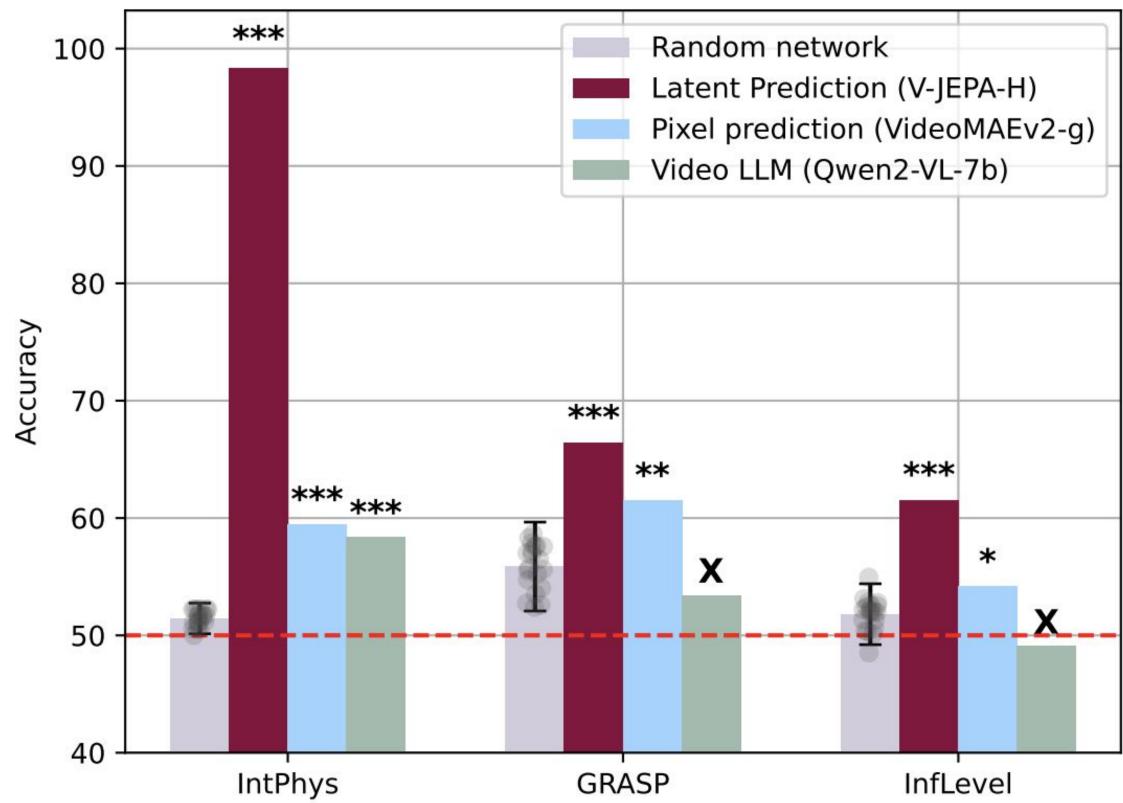
Relative surprise over time



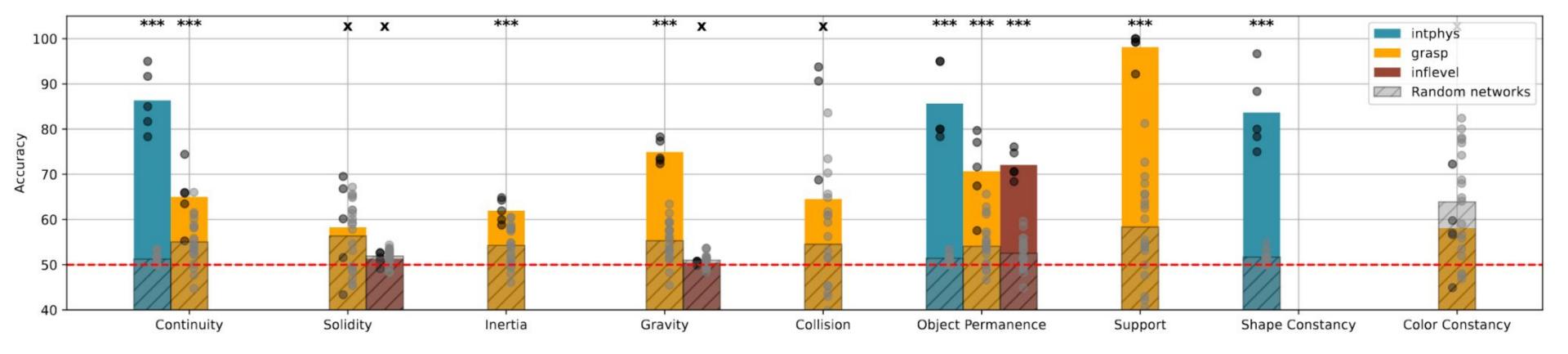
The model should show a higher surprise when something physics breaking happens



Only Latent Prediction can reliably find the impossible video

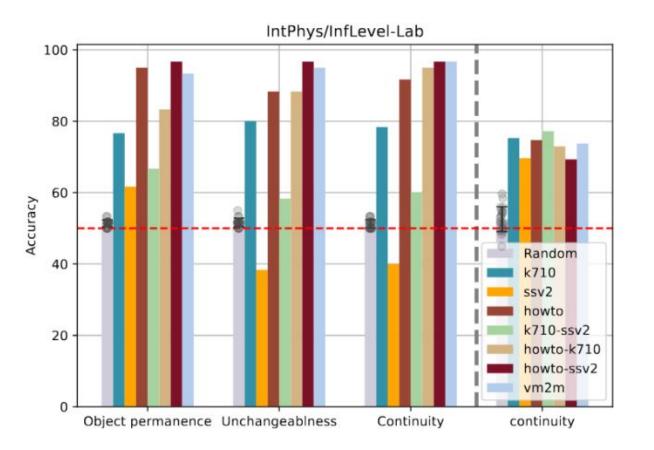


We find a non trivial understanding across properties



We find non significant performance when too much memory is requires, or when the task is flawed (a random network can sometimes perform well)

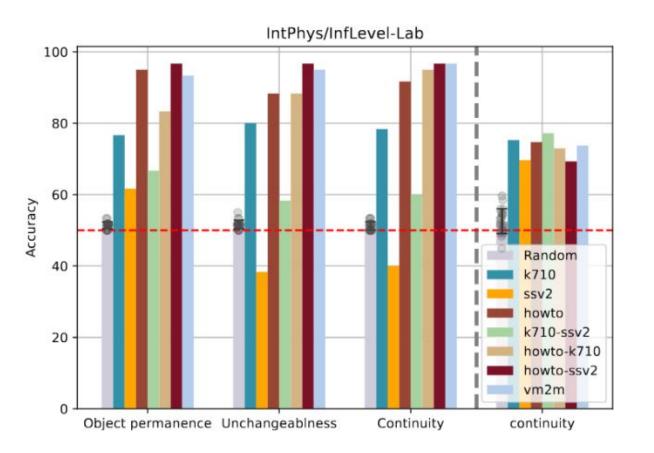
Why does this understanding emerge? The right data

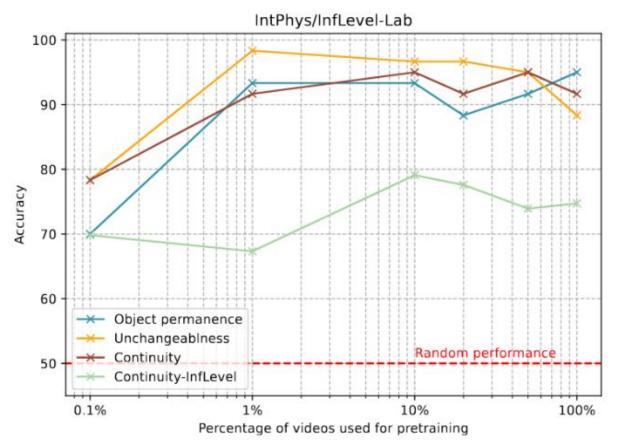


Some data sources are better than others.

Youtube tutorials are ideal.

Why does this understanding emerge? The right data





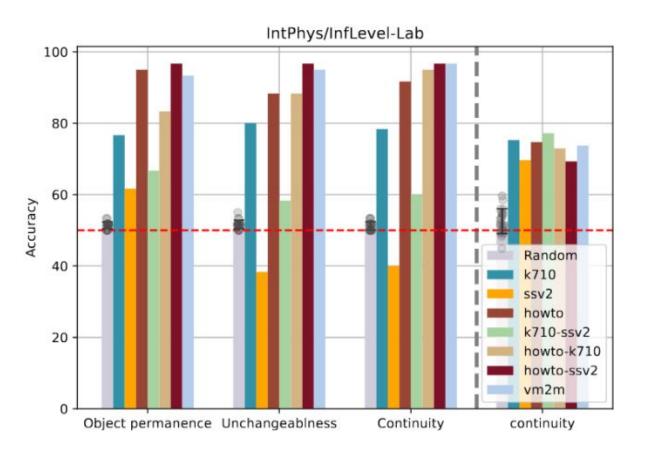
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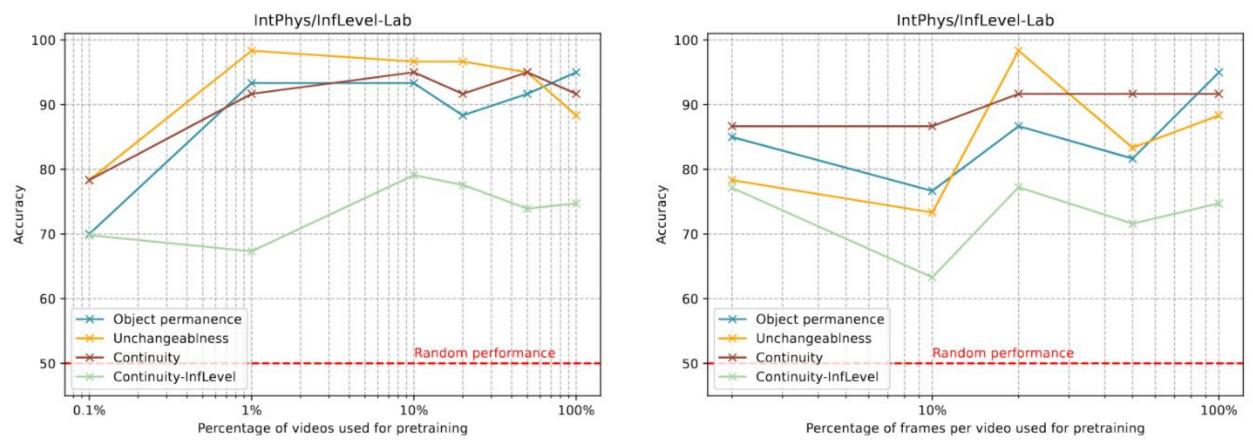
Youtube tutorials are ideal.

We only need a little bit of unique videos.

As little as 150h is enough.

Why does this understanding emerge? The right data





Some data sources are better than others.

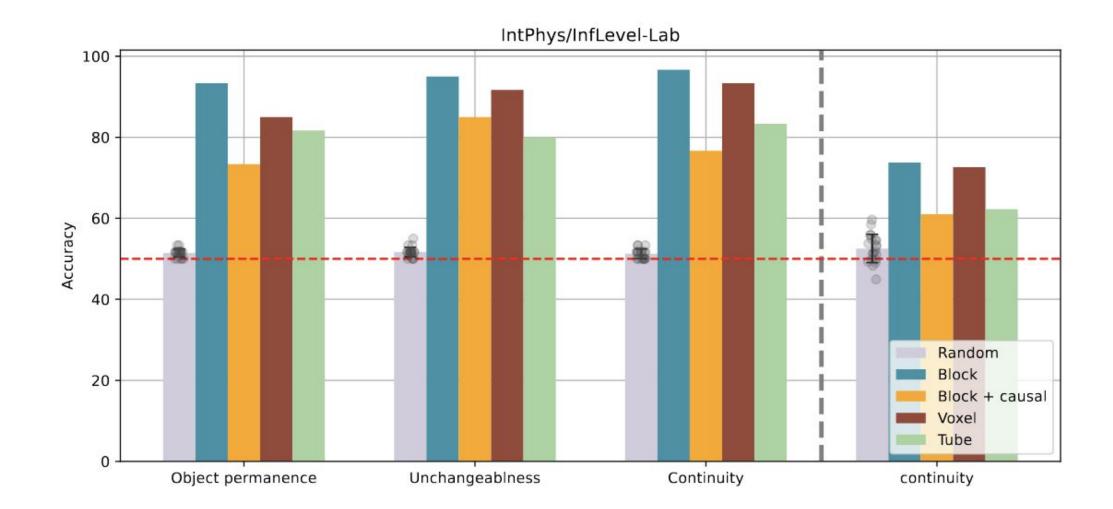
Youtube tutorials are ideal.

We only need a little bit of unique videos.

As little as 150h is enough.

It's better to see fewer videos than shorter ones.

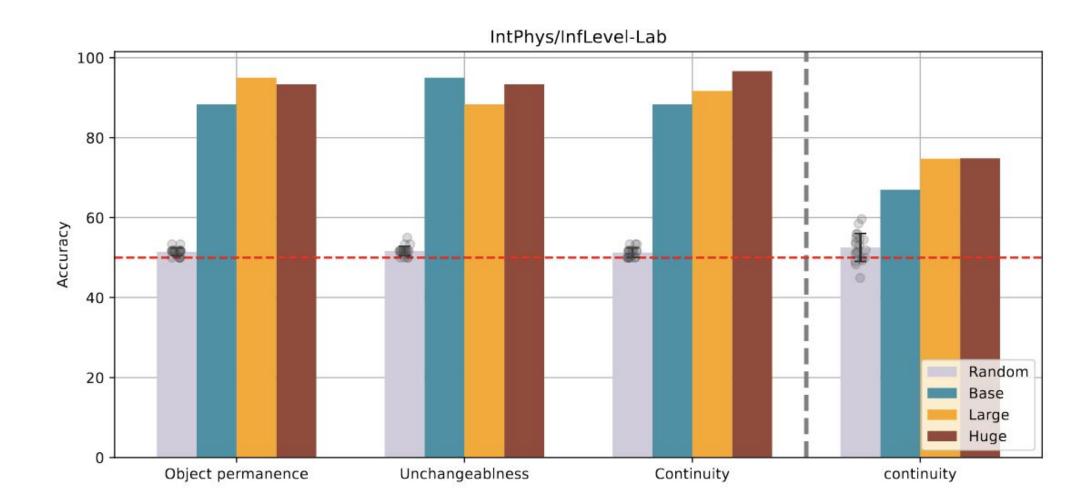
Why does this understanding emerge? The right pretraining



Different pretraining prediction tasks change performance.

The key is to predict in latent space.

Why does this understanding emerge? The right size



Bigger models are better, but 80M parameters is enough.

Compare that to 10s of billions for LLMs...

How do babies learn?

They observe the world

They interact with the world

They don't speak/read

They are young

How to translate to neural networks



They observe the world

They interact with the world

They don't speak/read

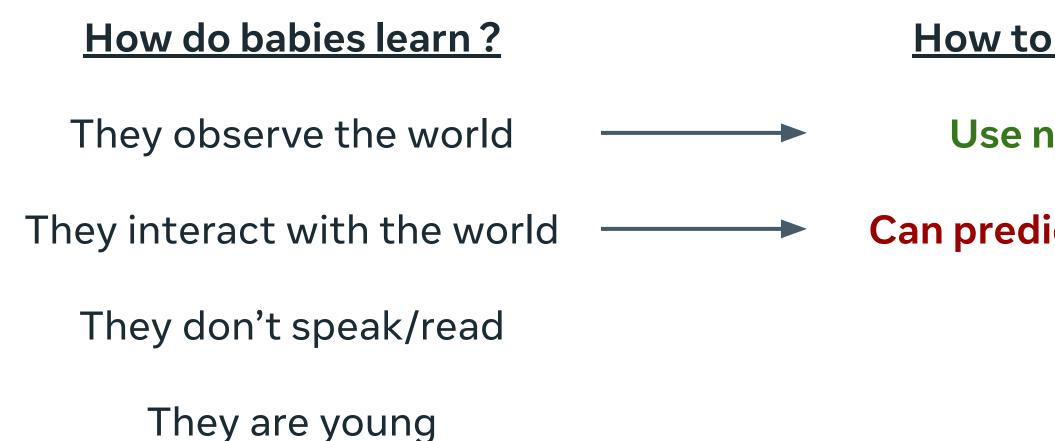
They are young





How to translate to neural networks

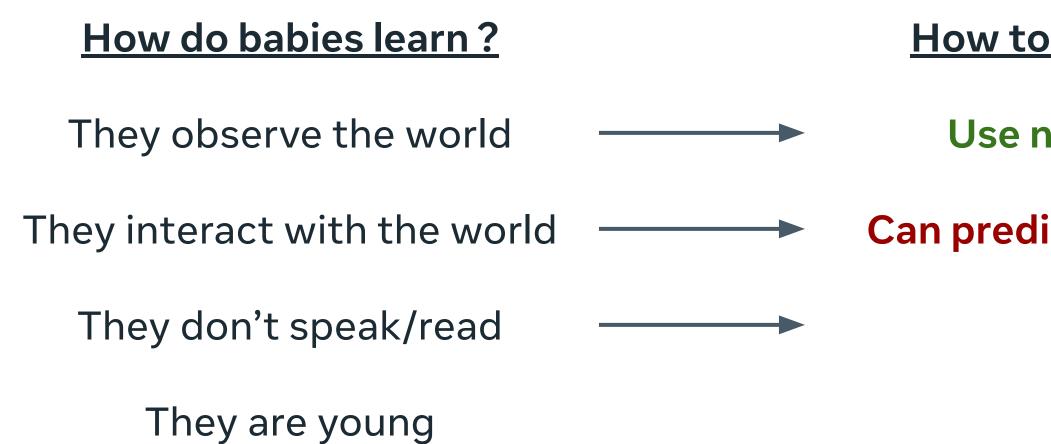
Use natural videos from the wild



How to translate to neural networks

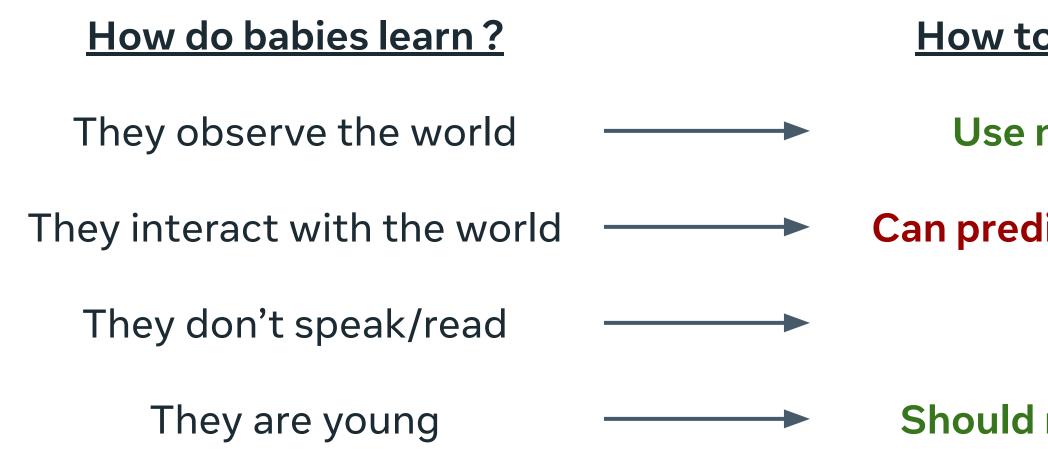
Use natural videos from the wild

Can predict the consequences of actions



How to translate to neural networks

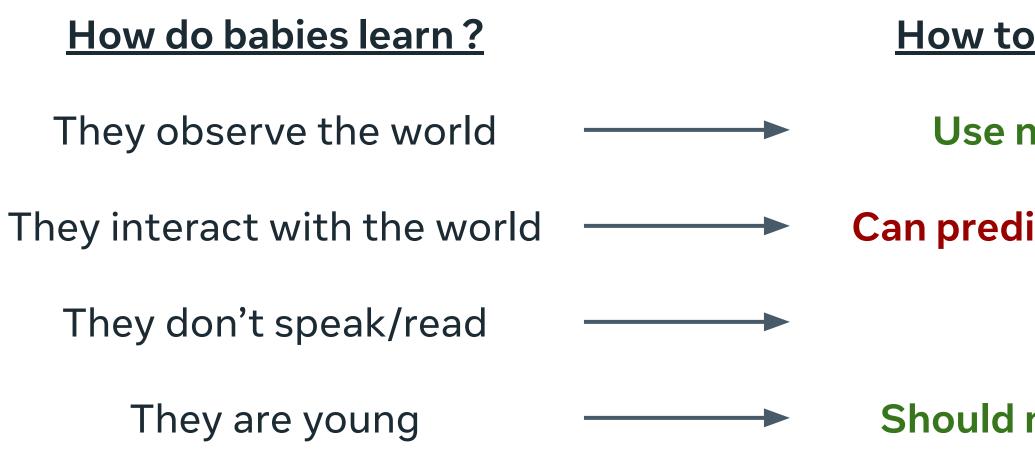
- Use natural videos from the wild
- Can predict the consequences of actions
 - No need for text data



How to translate to neural networks

- Use natural videos from the wild
- Can predict the consequences of actions
 - No need for text data

Should not need gargantuan amounts of data



Most importantly:

Latent Prediction is the only framework that understands intuitive physical concepts non trivially.

How to translate to neural networks

- Use natural videos from the wild
- Can predict the consequences of actions
 - No need for text data

Should not need gargantuan amounts of data

Take home messages

- Current deep learning approaches are very non-human in their learning, failing at simple intuitive physics tasks
- We want methods that exhibit more similarities to humans
- Latent Video Prediction offers the first non trivial performance at intuitive physics benchmarks

We should scale frameworks that learn like humans rather than scaling approaches that don't and hoping that they will exhibit human behaviour at some point.

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