Neurosymbolic AI

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IBM Research

MIT-IBM WATSON AI LAB

“Artificial Intelligence”

The evolution of AI

General AI
Revolutionary

Broad AI
Disruptive and Pervasive

Narrow AI
Emerging

▼ **We are here**

2050 and beyond

The evolution of AI

Narrow AI

Single task, single domain

Superhuman accuracy and speed for certain tasks

Broad AI

Multi-task, multi-domain

Multi-modal

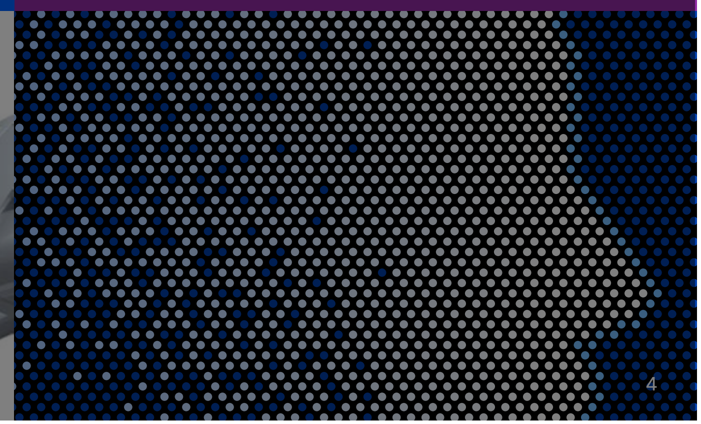
Distributed AI

Explainable

General AI

Cross-domain learning and reasoning

Broad autonomy



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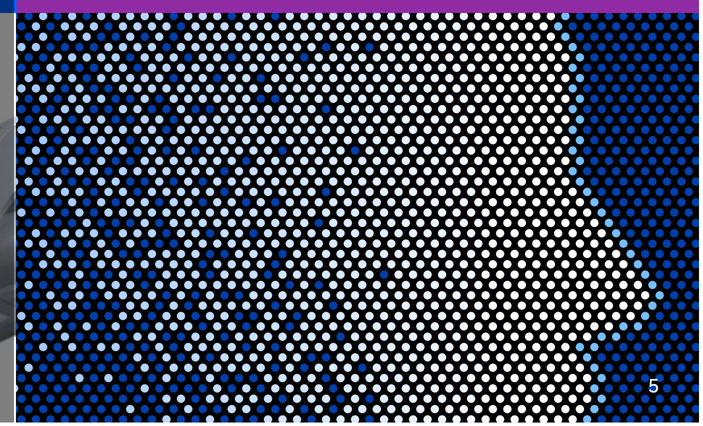

Elon Musk

Elon Musk Compares Building Artificial Intelligence To "Summoning The Demon"

Posted Oct 26, 2014 by Greg Kumparak (@grg)

17.6k SHARES

Next Story

Technology

Stephen Hawking warns artificial intelligence could end mankind

By Rory Cellan-Jones
Technology correspondent

2 December 2014 | Technology

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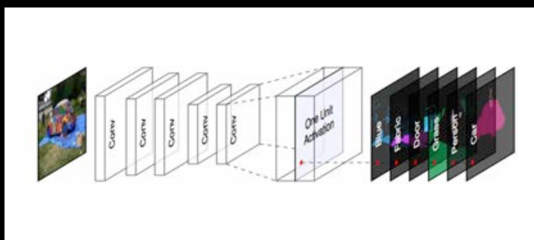
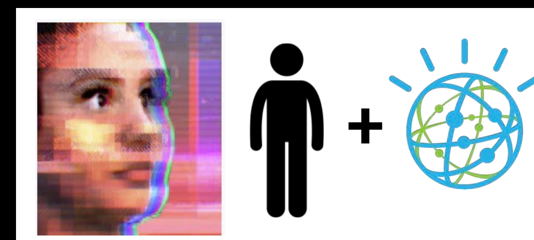
The path to a “Broad AI” toolbox

Explainability



Security

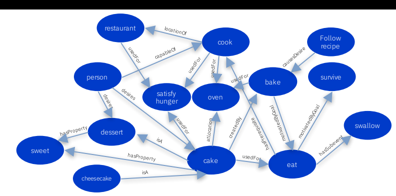
Ethics



Learn more from small data

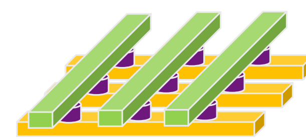
Learns to transfer

+



Reasoning

Infrastructure



Physics of AI

Platform for AI Lifecycle

Compute | Data & Models | Applications | Workflow

MIT-IBM
WATSON
AI LAB

The evolution of AI

General AI
Revolutionary

Broad AI
Disruptive and Pervasive

Narrow AI
Emerging

▼ **We are here**

2050 and beyond

So what’s “narrow” about today’s AI toolbox?

Forbes / Tech

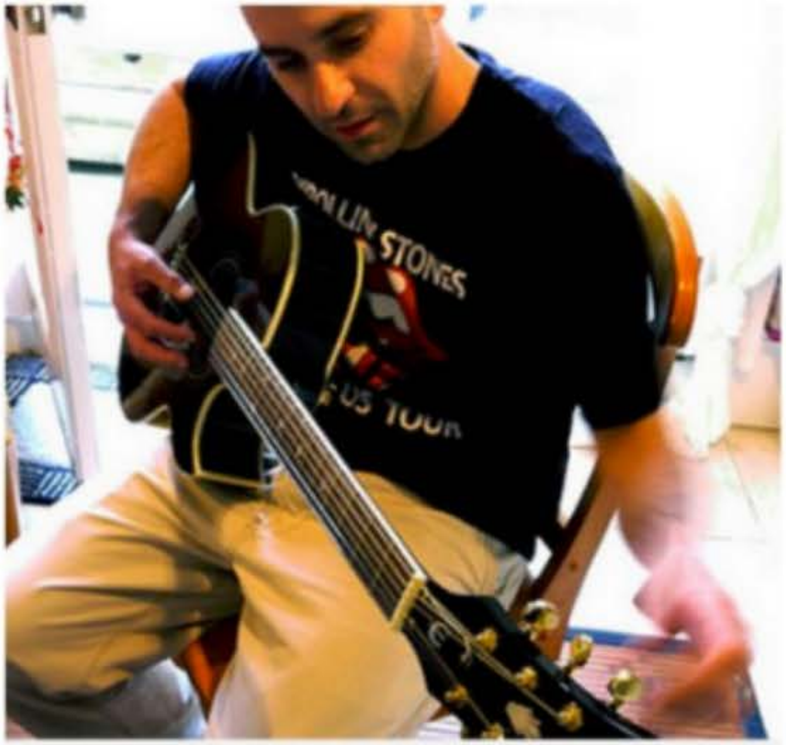
DEC 29, 2014 @ 11:37 AM   115,776

Tech 2015: Deep Learning And Machine Intelligence Will Eat The World

Anthony Wing Kosner, CONTRIBUTOR

Quantum of Content and innovations in user experience **FULL BIO**

Opinions expressed by Forbes Contributors are their own.



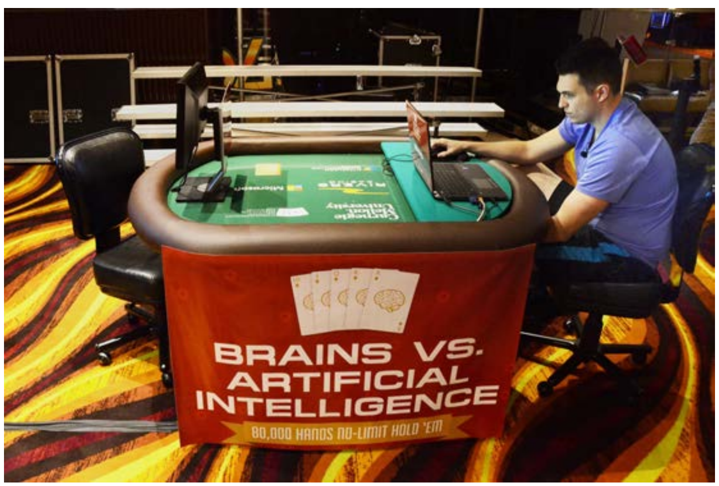
man in black shirt is playing guitar.

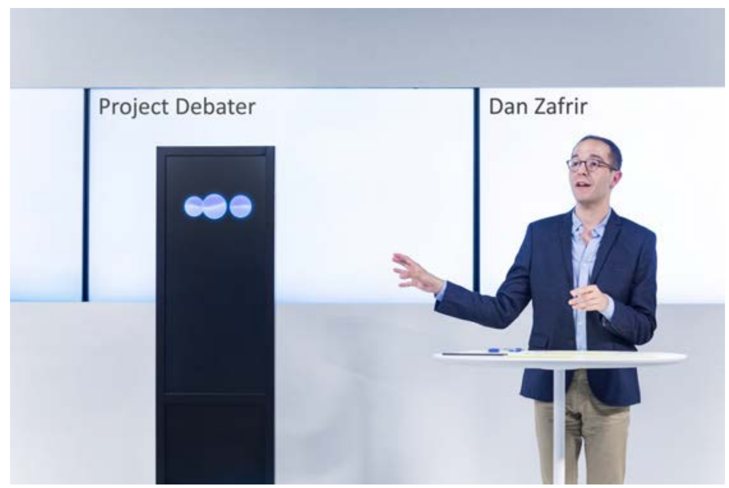
construction worker in orange safety vest is working on road.

Karpathy and Li, 2015


THINK
DENKE
$24,000
$77,147
$21,600
Who is Stoker?
$1,000
Who is Bram Stoker?
$ 17,973
$5600


AlphaGo
Lee Sedol


BRAINS VS. ARTIFICIAL INTELLIGENCE
80,000 HANDS NO-LIMIT HOLD 'EM

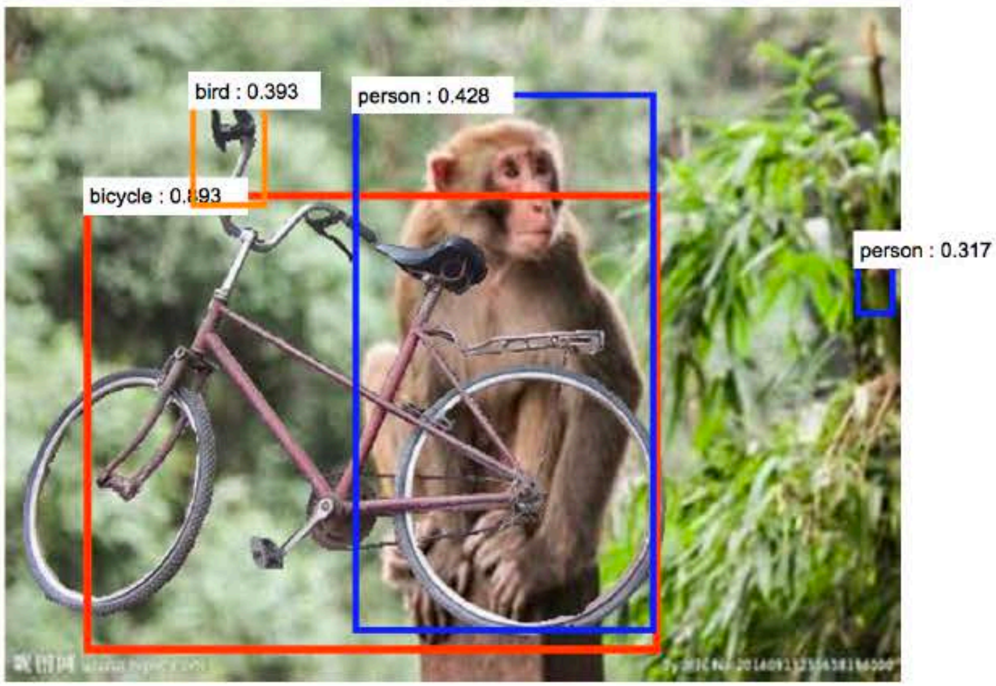

Project Debater
Dan Zafrir

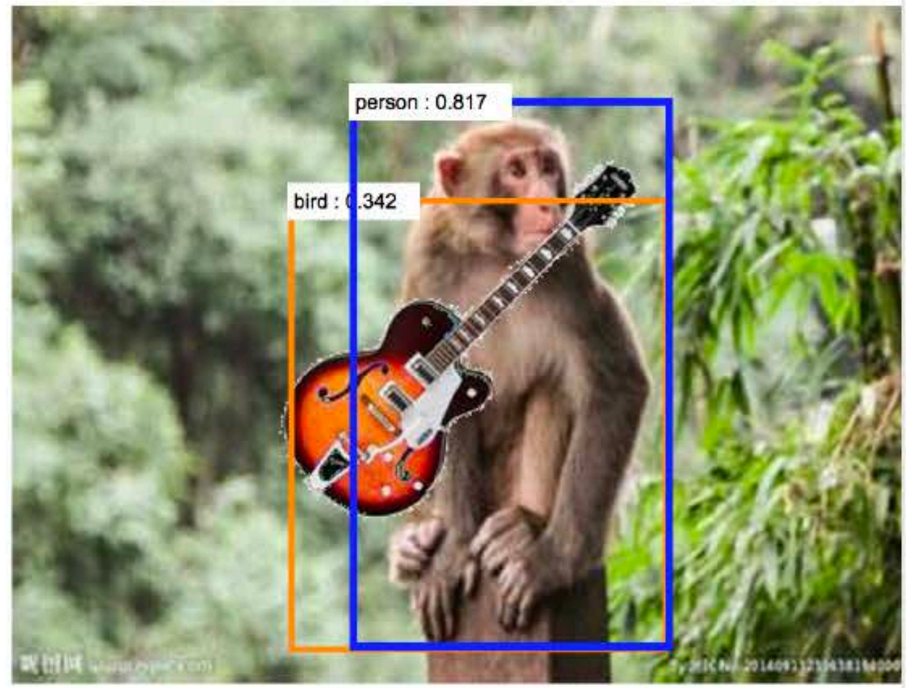
Gatys et al. 2015

Brock et al. 2018

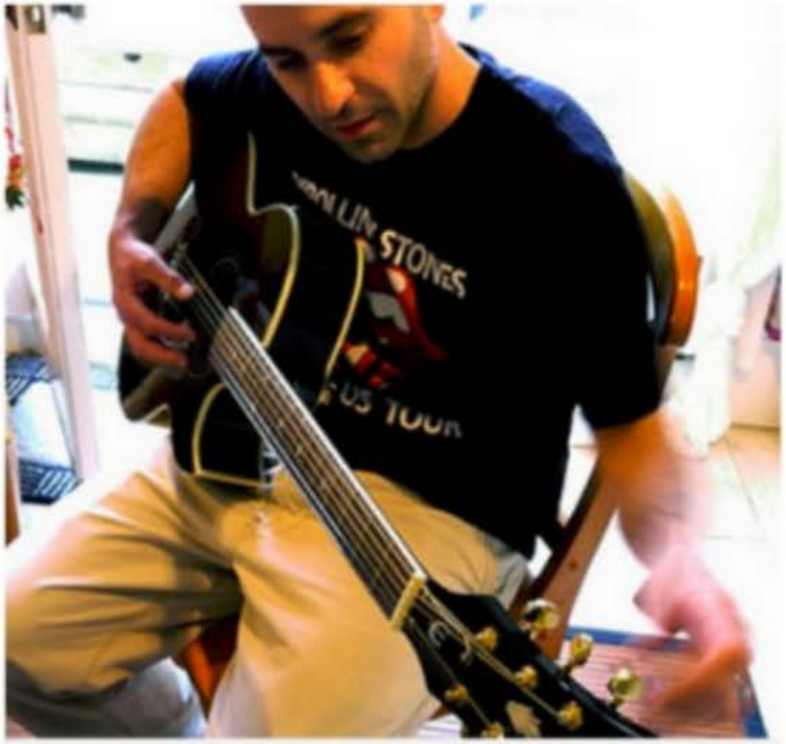
“Teddy Bear”

Meret Oppenheim, *Le Déjeuner en fourrure*





Wang et al. 2018



man in black shirt is playing guitar.

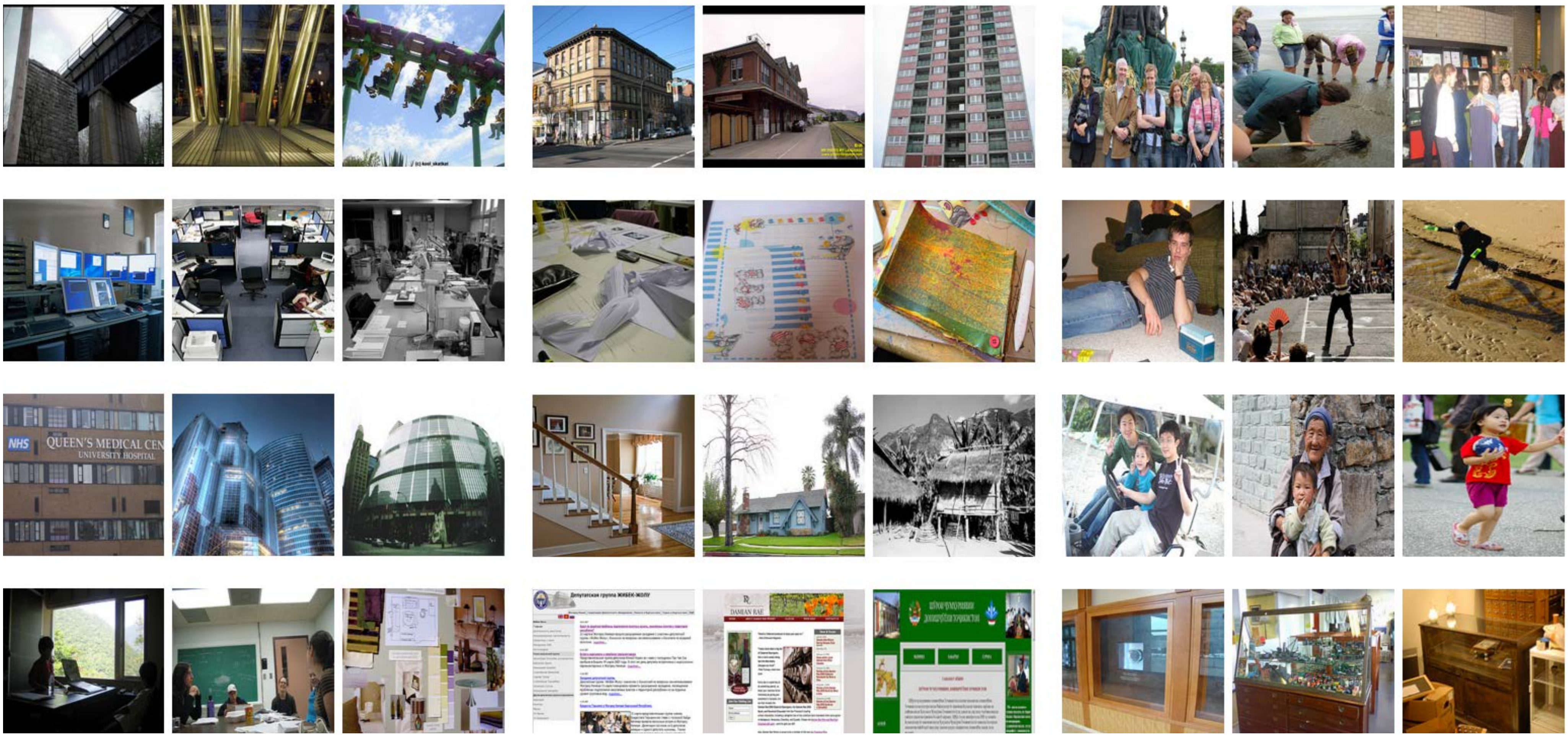
construction worker in orange safety vest is working on road.

Karpathy and Li, 2015

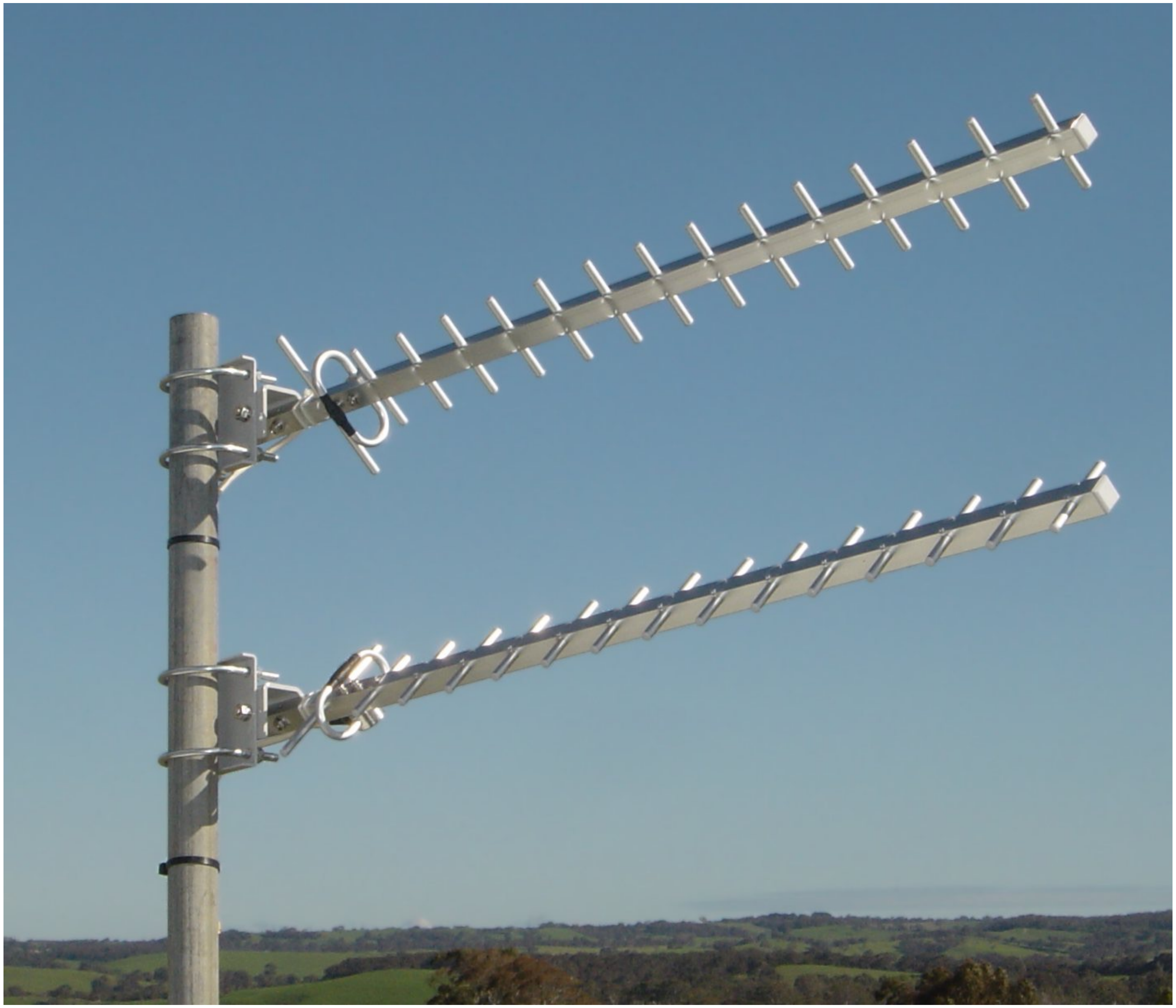
a man riding a
motorcycle on a beach

Lake, Ullman, Tenenbaum & Gershman, 2016

IMAGENET



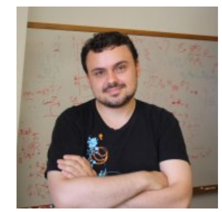
What’s this?



IMAGENET

ObjectNet

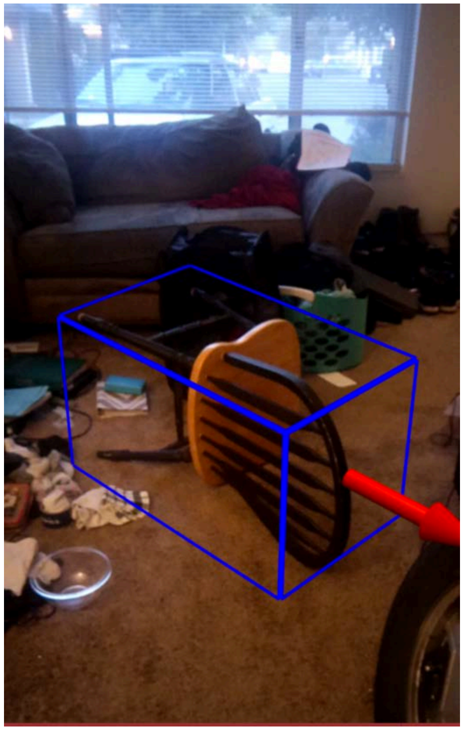
Boris Katz
MIT

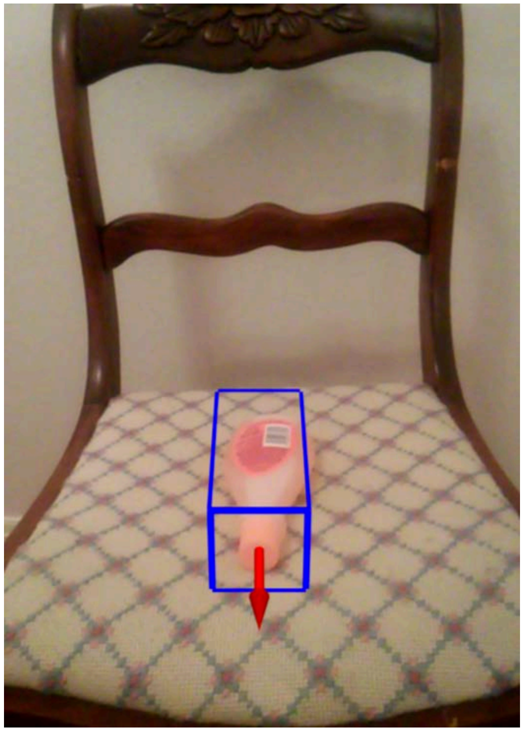


Andrei Barbu
MIT

Dan Gutfreund
IBM

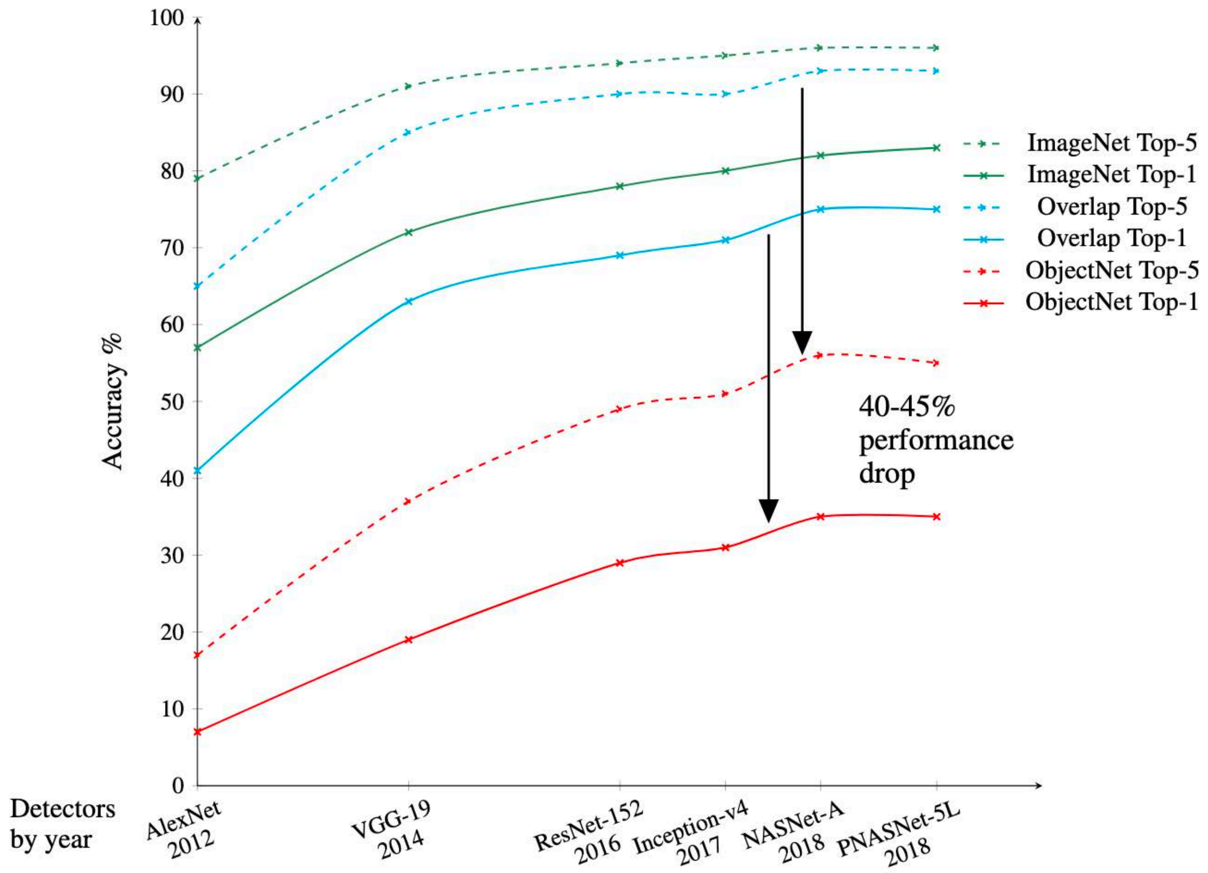
ObjectNet





- ~50K images
- ~300 object classes
- 4 different room types

Testing ImageNet-trained models on ObjectNet



Original Top-3 inferred captions:

1. A red stop sign sitting on the side of a road.
2. A stop sign on the corner of a street.
3. A red stop sign sitting on the side of a street.

Pin-yu Chen
IBM

Adversarial Top-3 captions:

1. A brown teddy bear laying on top of a bed.
2. A brown teddy bear sitting on top of a bed.
3. A large brown teddy bear laying on top of a bed.

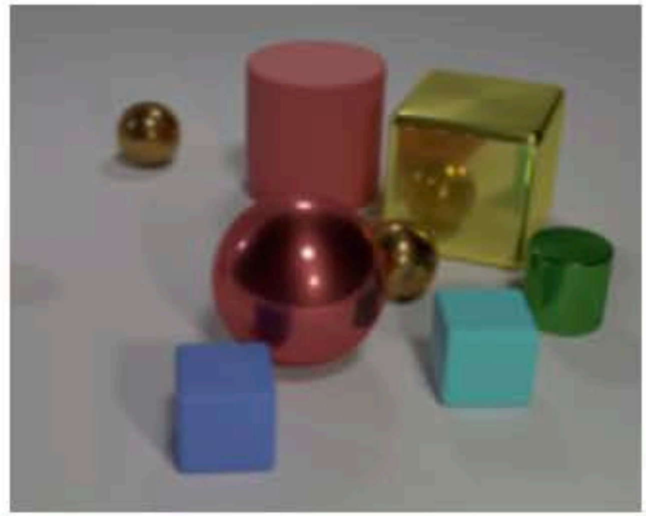
Chen et al. 2018

Xu et al. 2019

How many blocks are on the right of the three-level tower?

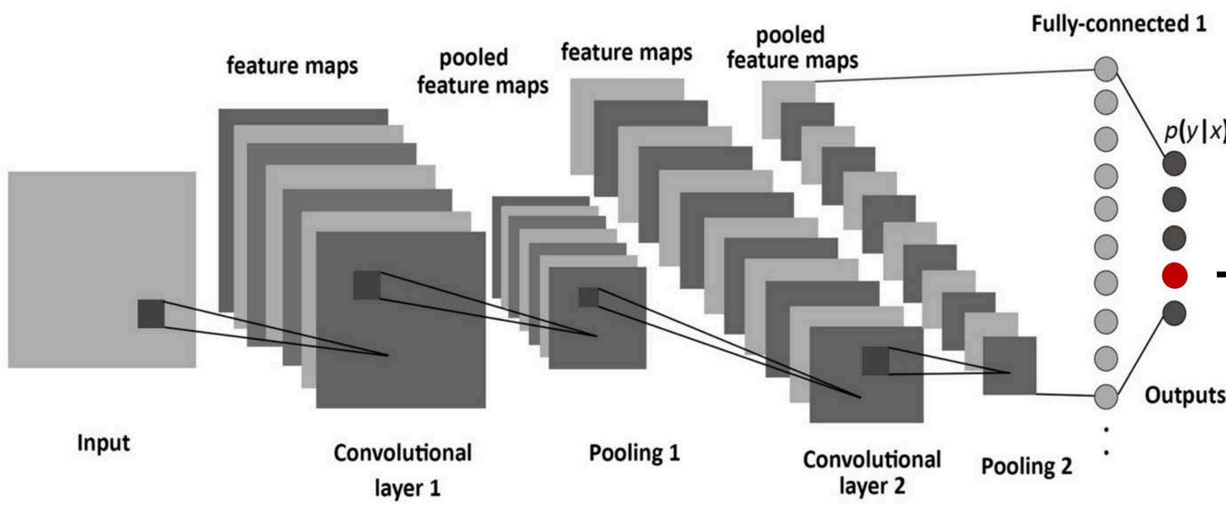
Will the block tower fall if the top block is removed?

Are there more trees than animals?



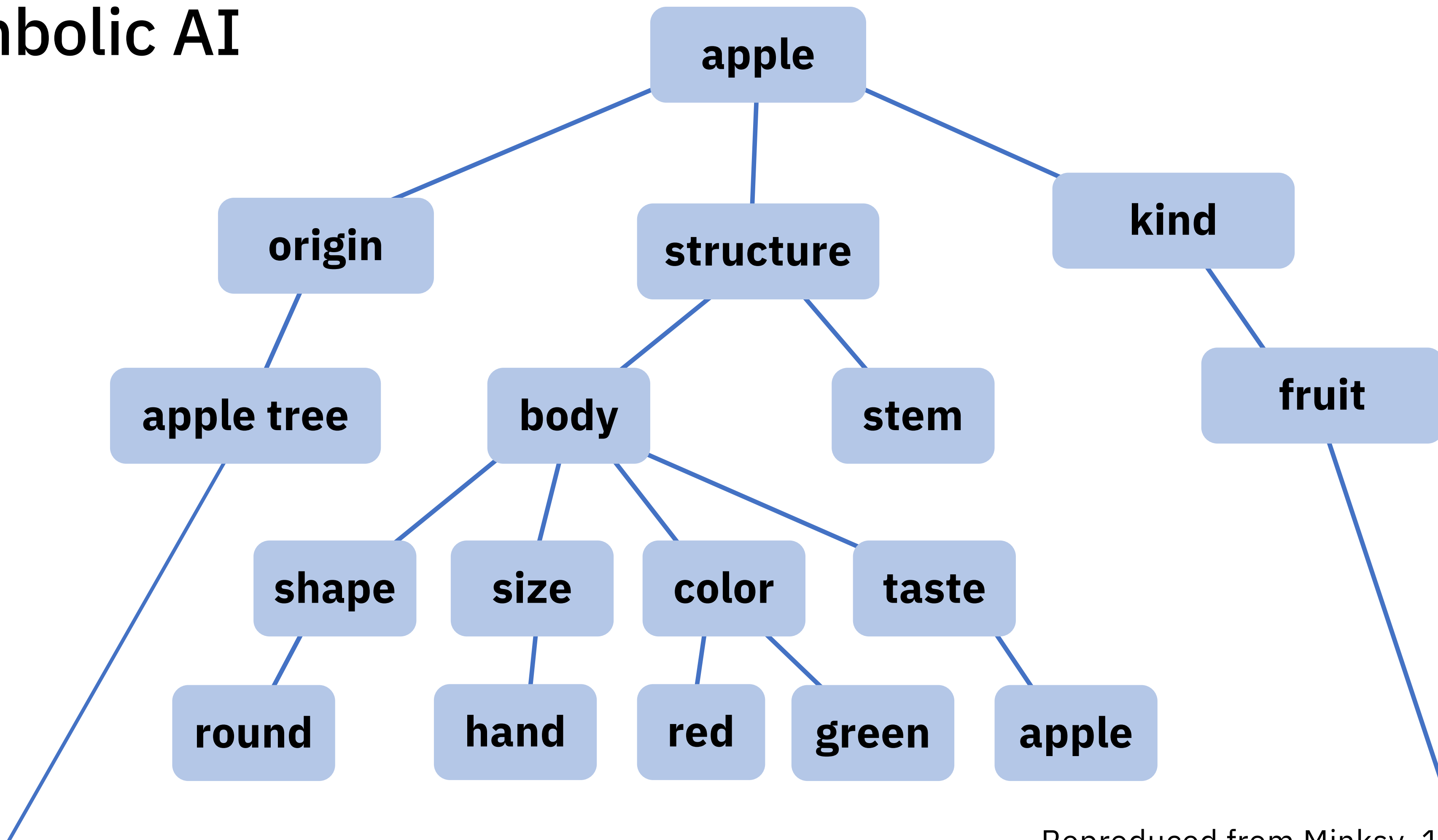
What is the shape of the object closest to the large cylinder?

Neural Networks / Deep Learning



→ “Apple”

Symbolic AI



Reproduced from Minksy, 1991

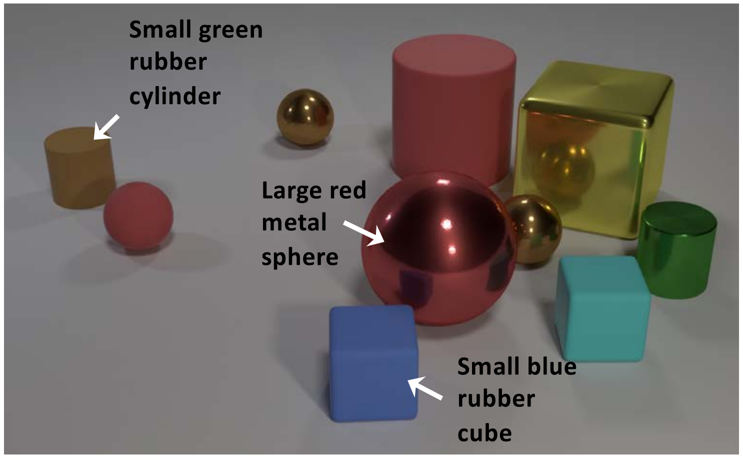
Neural-symbolic AI

Disentangling reasoning from vision and language understanding

Jiajun Wu

Chuang Gan

Joshua Tenenbaum

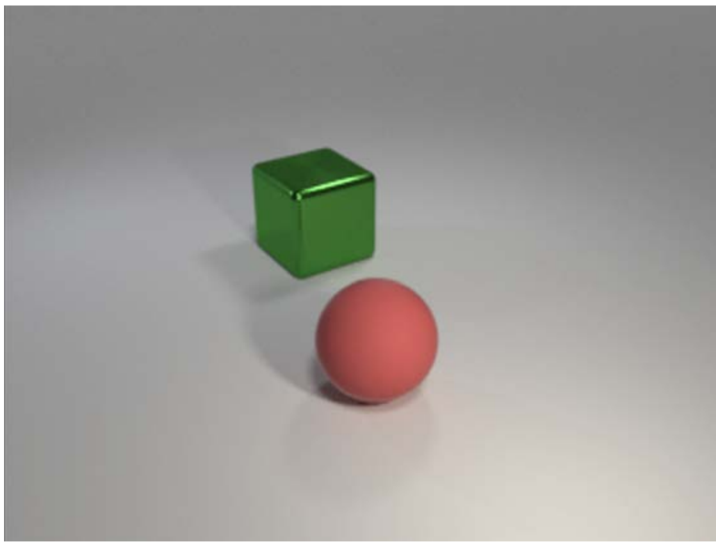


Question: *Are there an equal number of large things and metal spheres?*

Program: equal_number(count(filter_size(Scene, Large)), count(filter_material(filter_shape(Scene, Sphere), Metal)))

Answer: *Yes*

End-to-End Visual Reasoning



Visual Question Answering

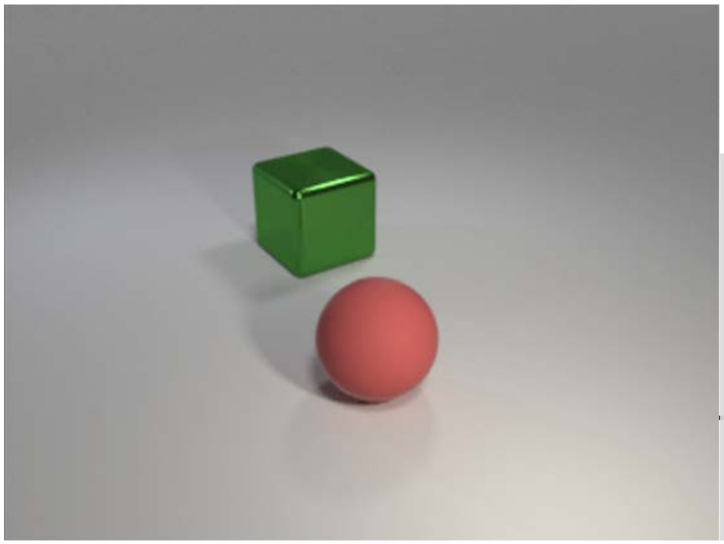
Q: What’s the **shape** of the **red** object?

End-to-End
Neural Network

A: Sphere.

NMN [Andreas et al., 2016]
IEP [Johnson et al., 2017]
FiLM [Perez et al., 2018],
MAC [Hudson & Manning, 2018]
Stack-NMN [Hu et al., 2018]
TbD [Mascharka et al. 2018]

End-to-End Visual Reasoning



Visual Question Answering

Q: What's the **shape** of the **red** object?

End-to-End Neural Network

Concept
(e.g., colors, shapes)

Reasoning
(e.g., count)

NMN [Andreas et al., 2016]
IEP [Johnson et al., 2017]
FiLM [Perez et al., 2018],
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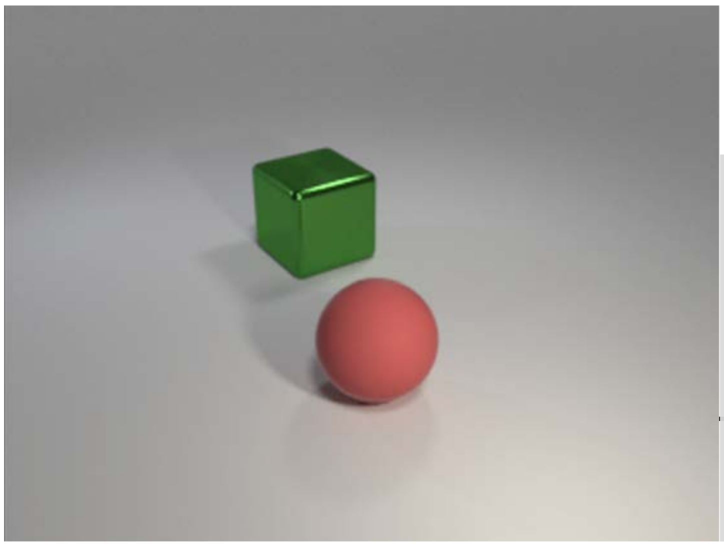
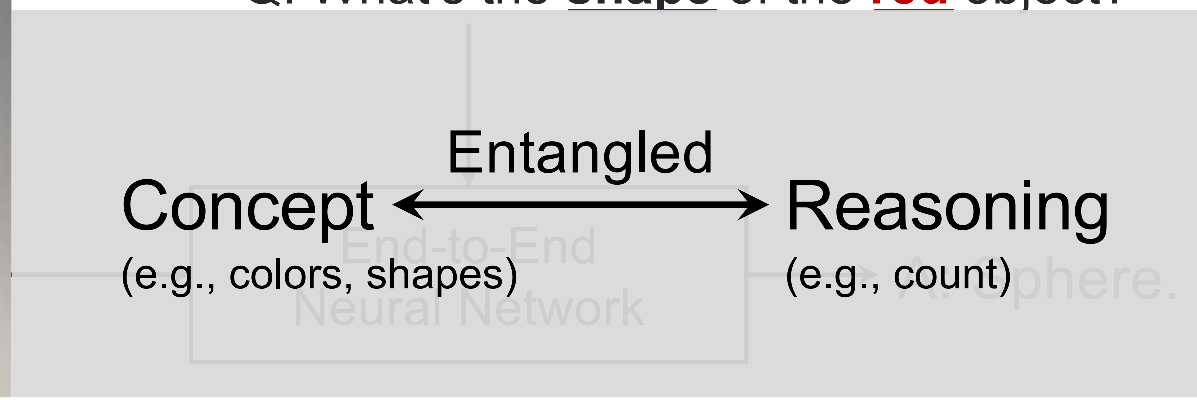
End-to-End Visual Reasoning



Visual Question Answering

Q: What's the **shape** of the red object?



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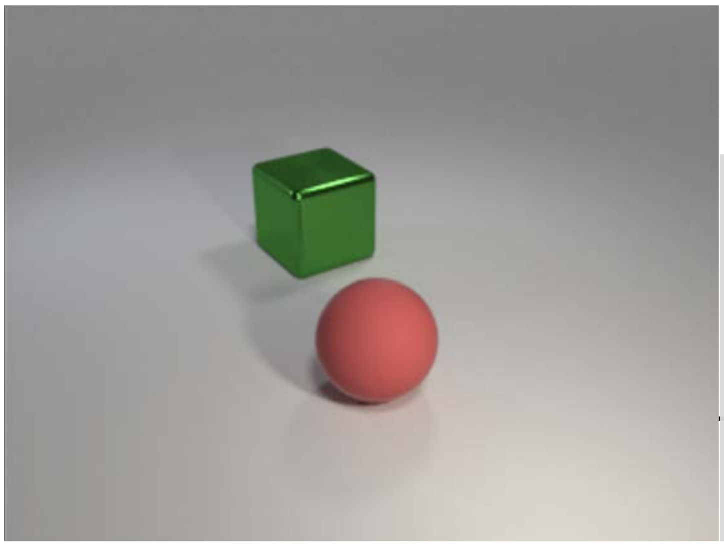
End-to-End Visual Reasoning



Visual Question Answering

Q: What's the **shape** of the **red** object?

Entangled

Concept ⟷ Reasoning

(e.g., colors, shapes) (e.g., count)

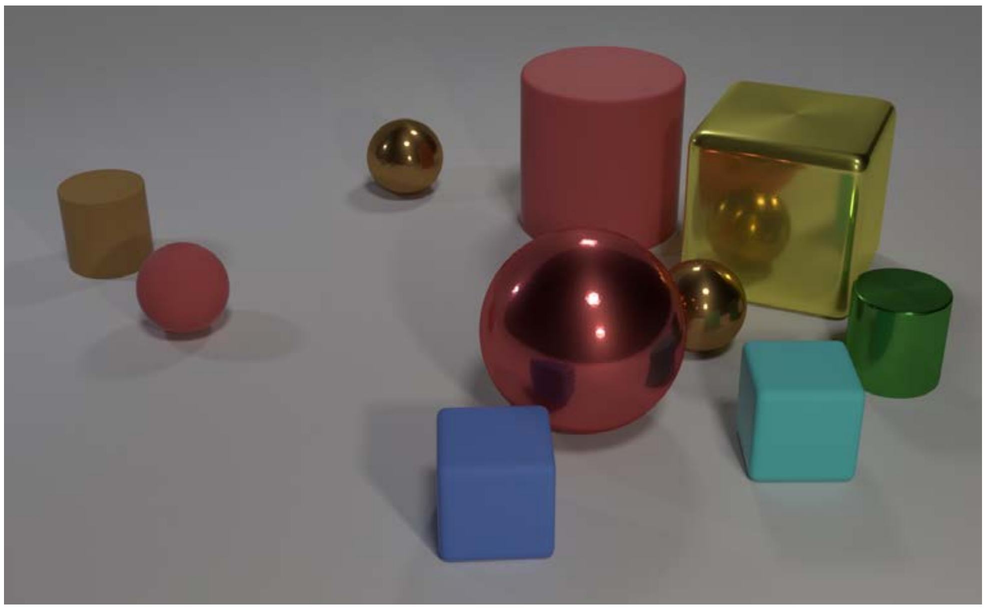
Hard to transfer

Image Captioning

Instance Retrieval

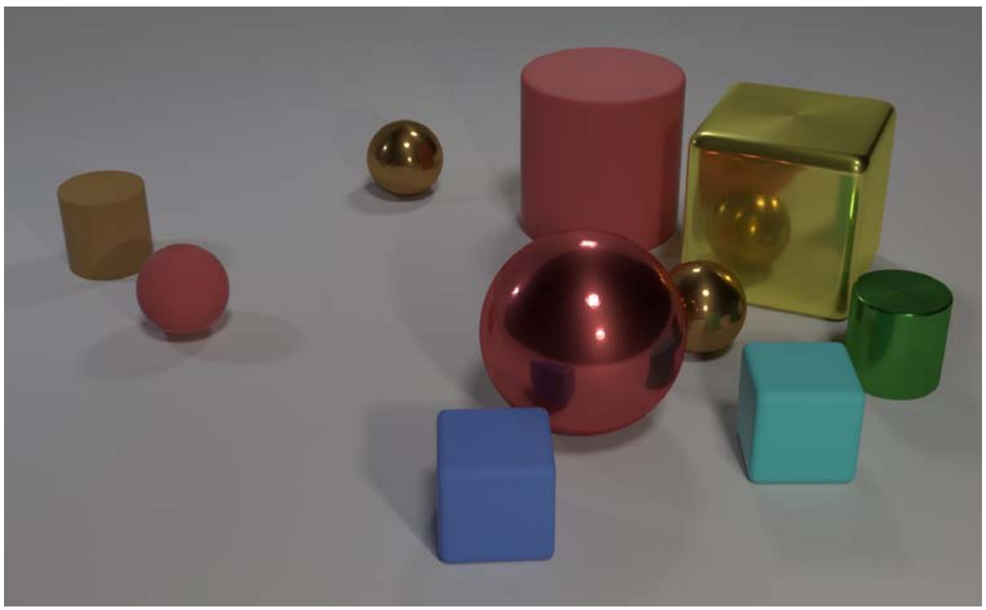
NMN [Andreas et al., 2016]
IEP [Johnson et al., 2017]
FiLM [Perez et al., 2018],
MAC [Hudson & Manning, 2018]
Stack-NMN [Hu et al., 2018]
TbD [Mascharka et al. 2018]

Task: **Visual Reasoning**



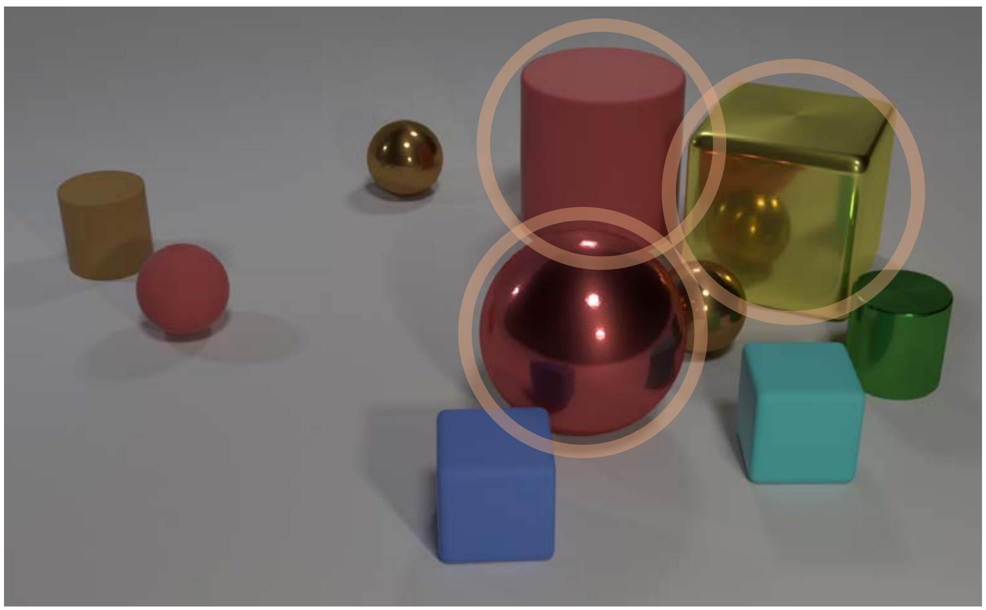
Question: *Are there an equal number of large things and metal spheres?*

Task: **Visual Reasoning**

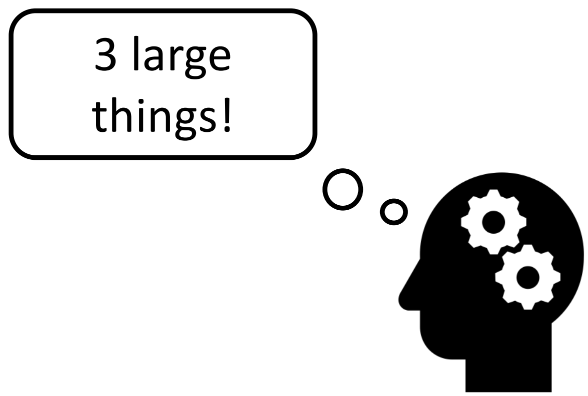


Question: *Are there an equal number of large things and metal spheres?*

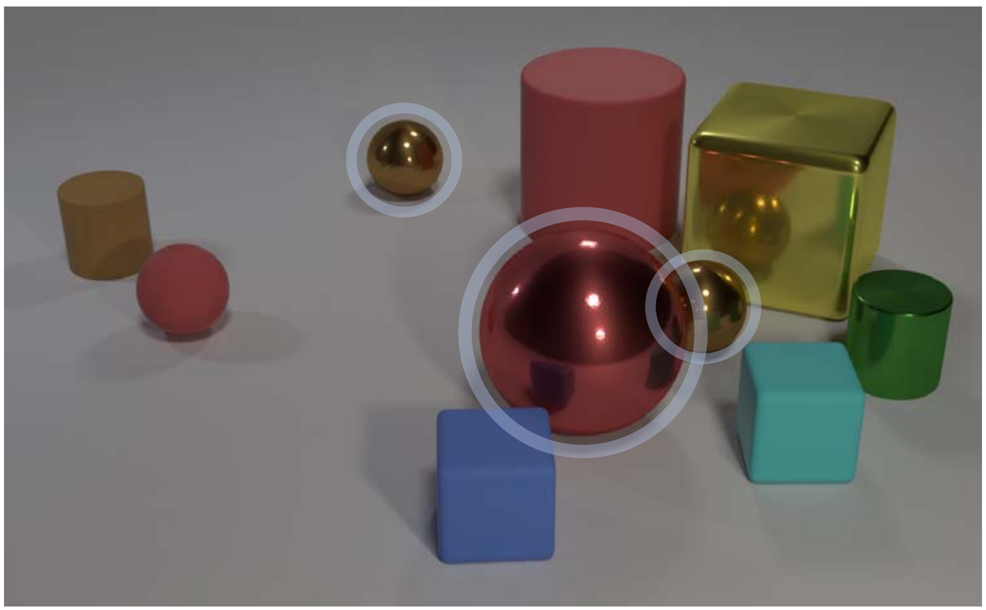
Task: **Visual Reasoning**



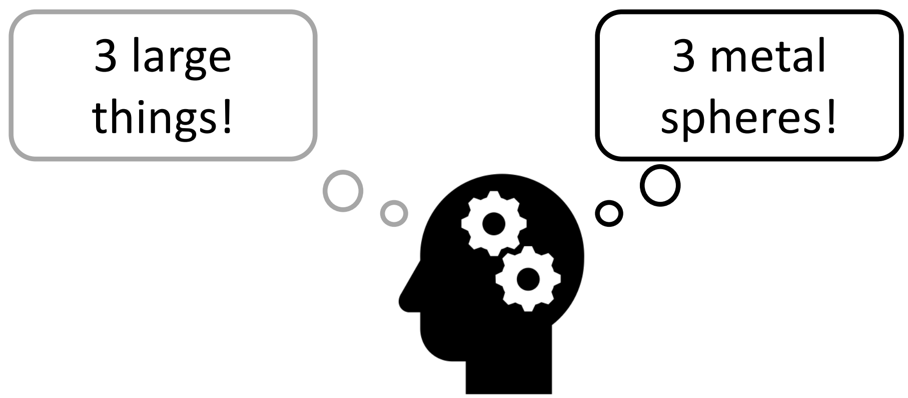
Question: *Are there an equal number of **large things** and metal spheres?*



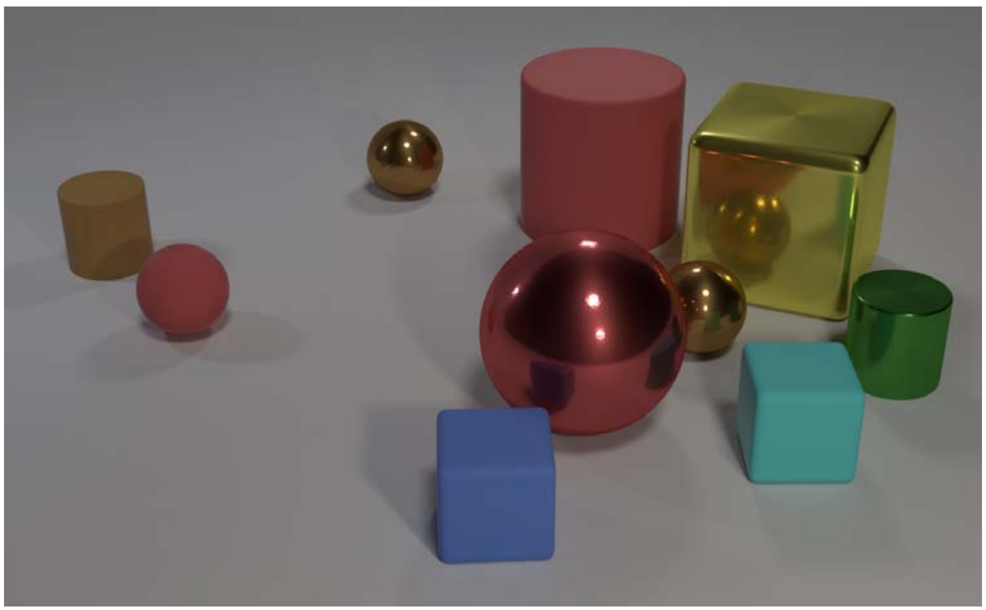
Task: **Visual Reasoning**



Question: *Are there an equal number of large things and **metal spheres**?*



Task: **Visual Reasoning**



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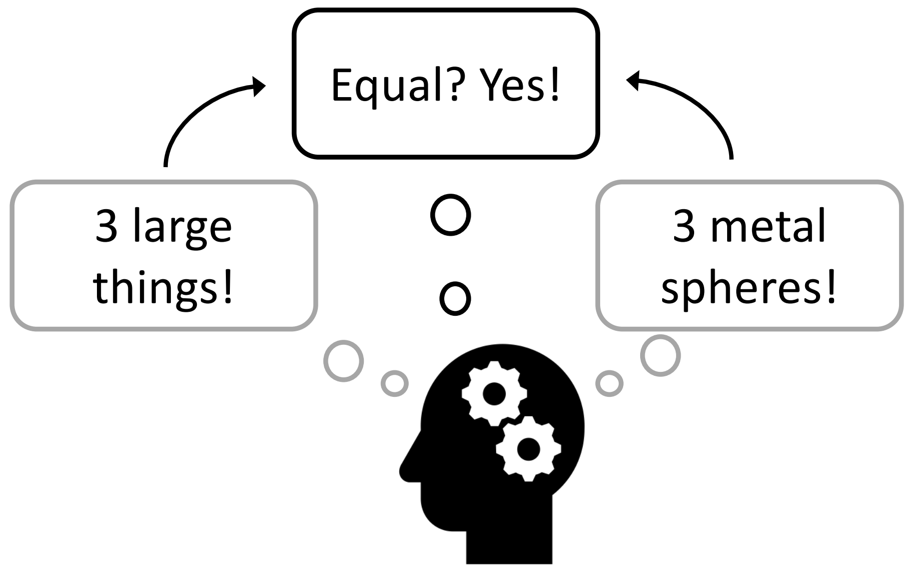
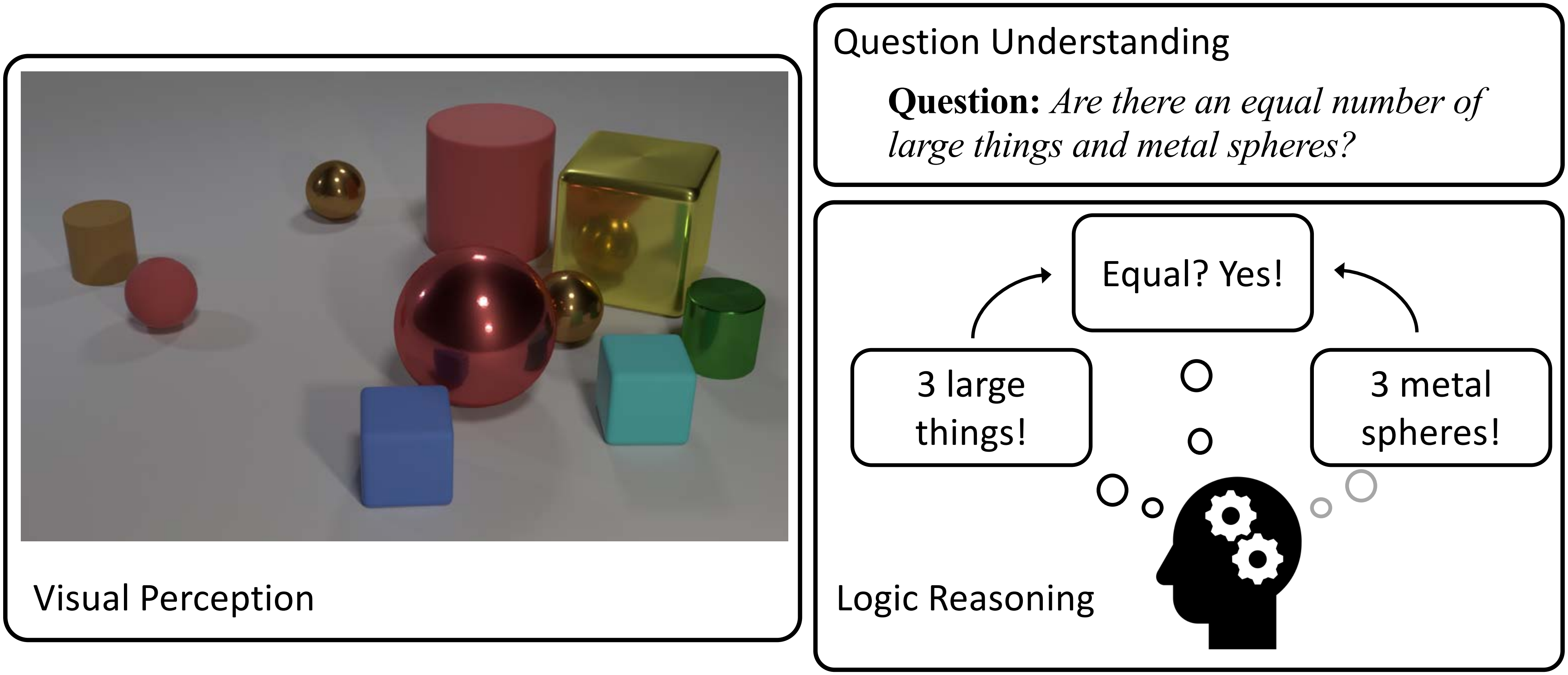
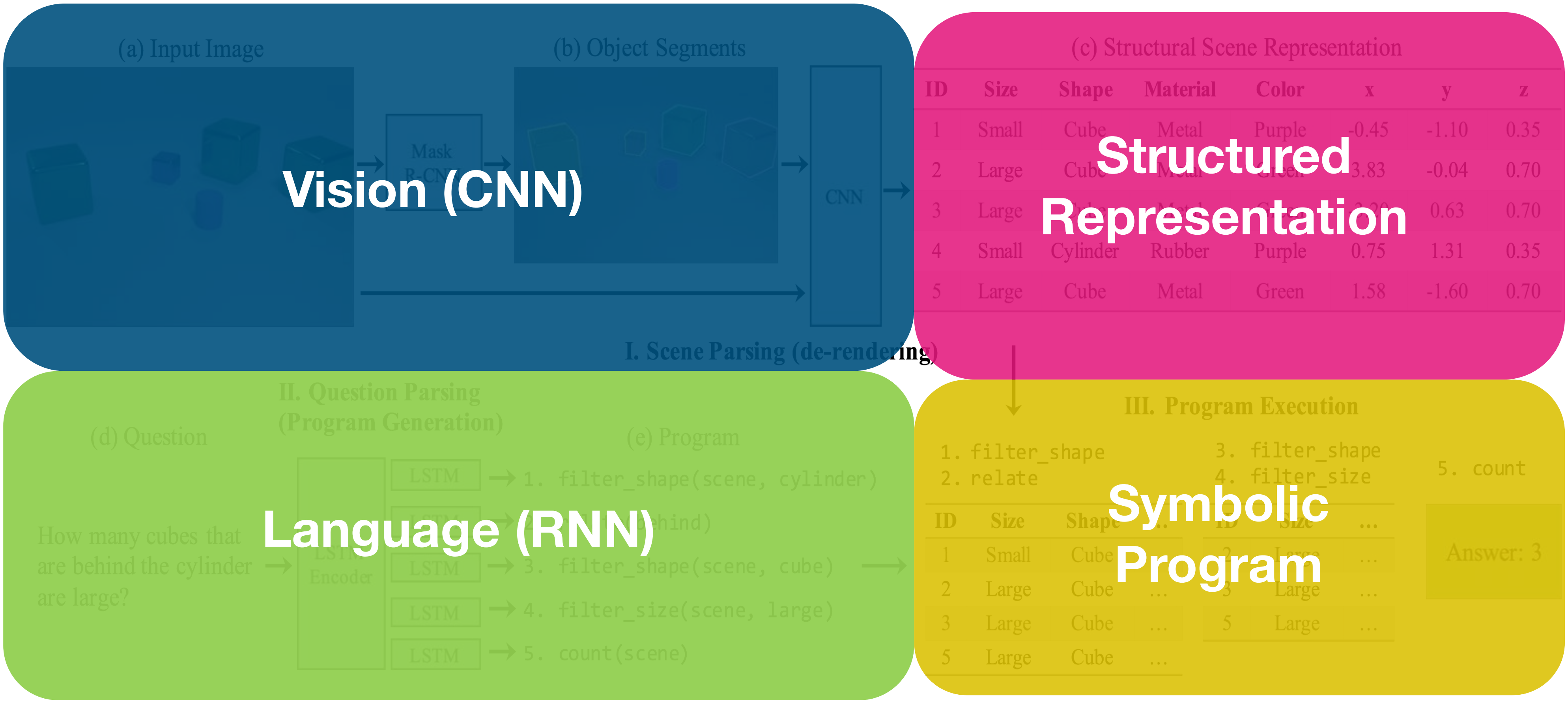


Task: **Visual Reasoning**



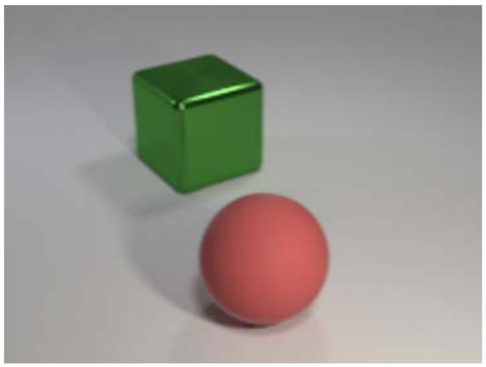


Vision (CNN)
Structured Representation
Language (RNN)
Symbolic Program
(a) Input Image
(b) Object Segments
Mask R-CNN
CNN
(c) Structural Scene Representation
I. Scene Parsing (de-rendering)
II. Question Parsing (Program Generation)
(d) Question
(e) Program
How many cubes that are behind the cylinder are large?
LSTM Encoder
1. filter_shape(scene, cylinder)
3. filter_shape(scene, cube)
4. filter_size(scene, large)
5. count(scene)
III. Program Execution
1. filter_shape
2. relate
3. filter_shape
4. filter_size
5. count
Answer: 3

NS-VQA [Yi et al. 2018]

Incorporate Concepts in Visual Reasoning

Vision



Scene Parsing →

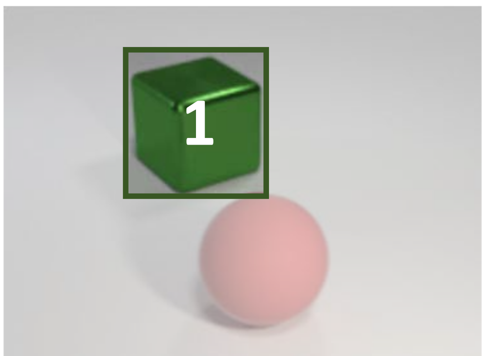
Language

Q: What's the **shape** of the **red** object?

NS-VQA [Yi et al. 2018]

Incorporate Concepts in Visual Reasoning

Vision



Scene Parsing

ID	Color	Shape	Material
1	Green	Cube	Metal

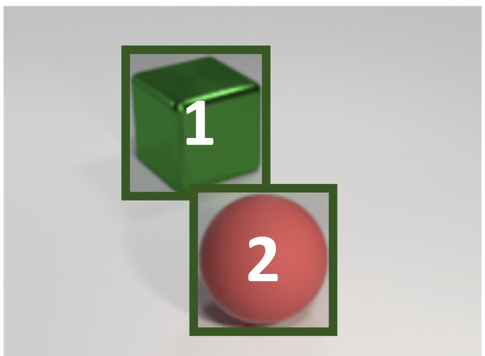
Language

Q: What's the **shape** of the **red** object?

NS-VQA [Yi et al. 2018]

Incorporate Concepts in Visual Reasoning

Vision



Scene Parsing →

ID	Color	Shape	Material
1	Green	Cube	Metal
2	Red	Sphere	Rubber

Language

Q: What's the **shape** of the **red** object?

Semantic Parsing →

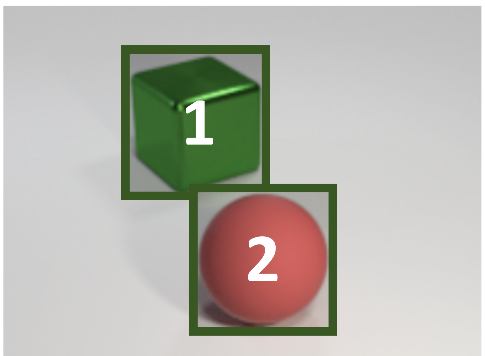
```
Filter(Red)
↓
Query(Shape)
```

Program

NS-VQA [Yi et al. 2018]

Incorporate Concepts in Visual Reasoning

Vision



Scene Parsing

ID	Color	Shape	Material
1	Green	Cube	Metal
2	Red	Sphere	Rubber

Symbolic Reasoning

Language

Q: What's the **shape** of the **red** object?

Semantic Parsing

```
Filter(Red)
↓
Query(Shape)
```

Program

NS-VQA [Yi et al. 2018]

Incorporate Concepts in Visual Reasoning

Vision

Scene Parsing

ID	Color	Shape	Material
1	Green	Cube	Metal
2	Red	Sphere	Rubber

Symbolic Reasoning

Language

Q: What's the shape of the red object?

Semantic Parsing

```
Filter(Red)
↓
Query(Shape)
```

Program

NS-VQA [Yi et al. 2018]

Incorporate Concepts in Visual Reasoning

Vision

Scene Parsing

ID	Color	Shape	Material
1	Green	Cube	Metal
2	*Red*	Sphere	Rubber

Symbolic Reasoning

Language

Q: What's the shape of the red object?

Semantic Parsing

```
Filter(Red)
Query(Shape)
```

Program

NS-VQA [Yi et al. 2018]

Incorporate Concepts in Visual Reasoning

Vision

Scene Parsing

ID	Color	Shape	Material
1	Green	Cube	Metal
2	Red	*Sphere*	Rubber

Language

Q: What's the shape of the red object?

Semantic Parsing

`Filter(Red)`

↓

`Query(Shape)`

Program

Symbolic Reasoning

Sphere

Advantage 1: **High Accuracy**

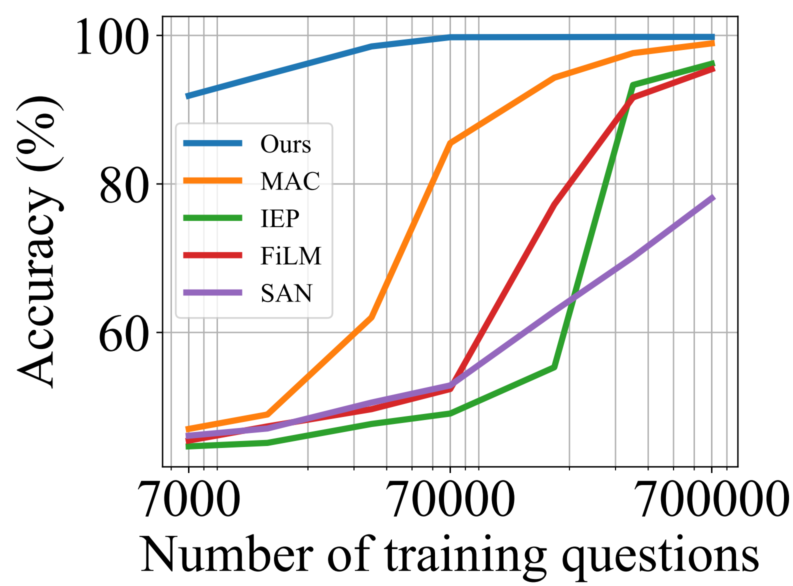
Method	Accuracy (%)
Human	92.6
RN	95.5
IEP	96.9
FiLM	97.6
MAC	98.9
TbD	99.1
NS-VQA (Ours)	**99.8**

Effectively perfect!

[Yi et al. NeurIPS 2018, Johnson et al. ICCV 2017, Santoro et al. NIPS 2017, Perez et al. AAAI 2018, Hudson et al. ICLR 2018, Mascharka et al. CVPR 2018]

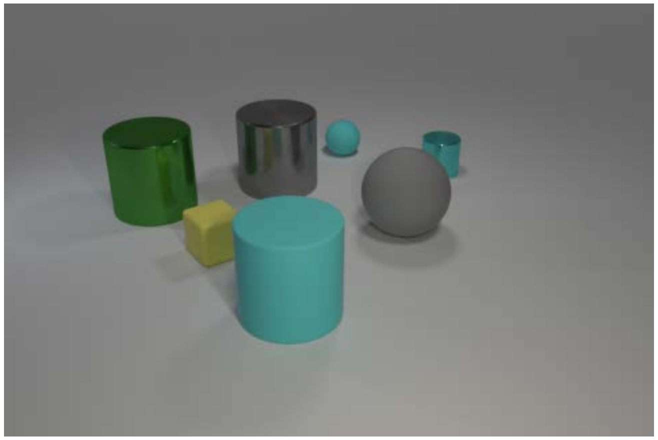
Advantage 2: **Data Efficiency**

High accuracy when trained with just 1% the of the data that other methods require



[Yi et al. NeurIPS 2018]

Advantage 3: **Transparency and Interpretability**



Question: Are there more yellow matte things that are right of the gray ball than cyan metallic objects?

```
scene
filter_cyan
filter_metal
count
...(4 modules)
scene
filter_yellow
filter_rubber
count
greater_than
```

Answer: no

[Yi et al. NeurIPS 2018, Johnson et al. ICCV 2017]

NeurIPS 2018: Neurosymbolic VQA:
Properties (e.g. “color”) and values (“red”) predefined

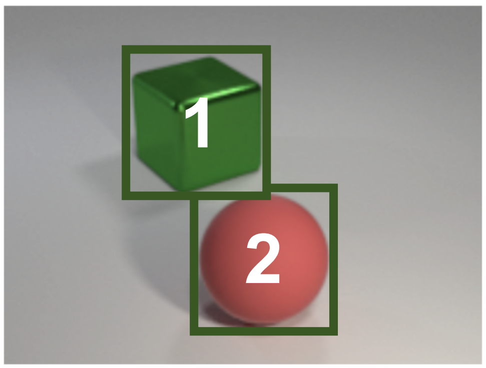
ICLR 2019: Neurosymbolic Concept Learner:
Properties predefined, can learn new values autonomously

NeurIPS 2019: Neurosymbolic Metaconcept Learner:
Autonomously learns new concepts

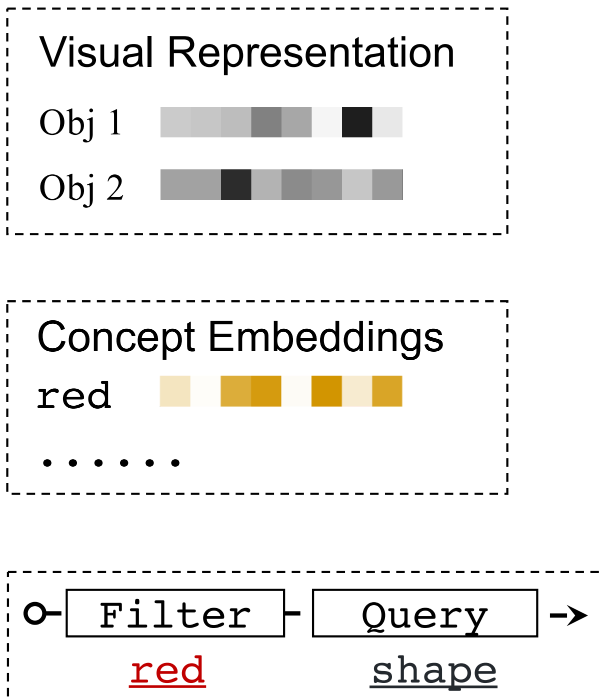
ICML 2020 (target submission):
Real world images

less predefined, more autonomous →

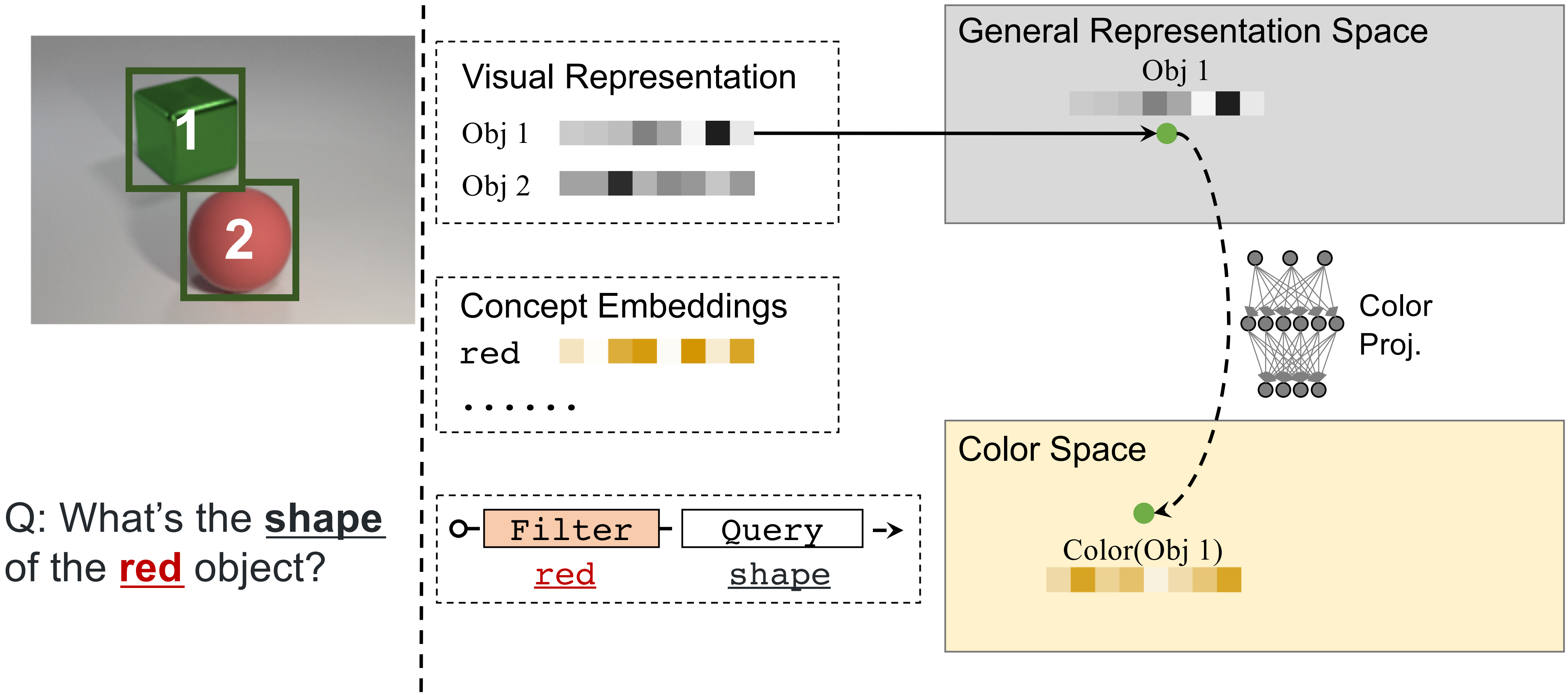
Neuro-Symbolic Concept Learning



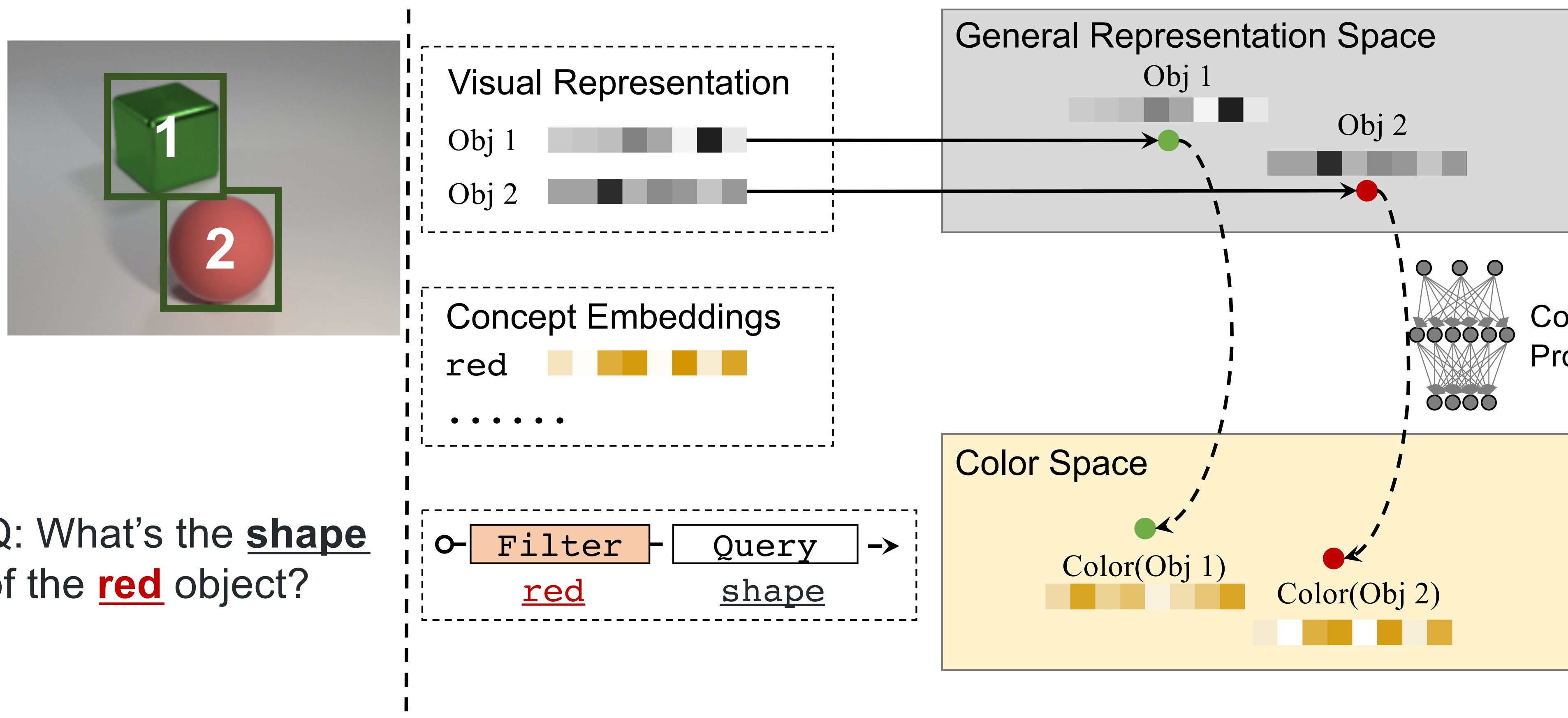
Q: What's the **shape** of the **red** object?



Neuro-Symbolic Concept Learning

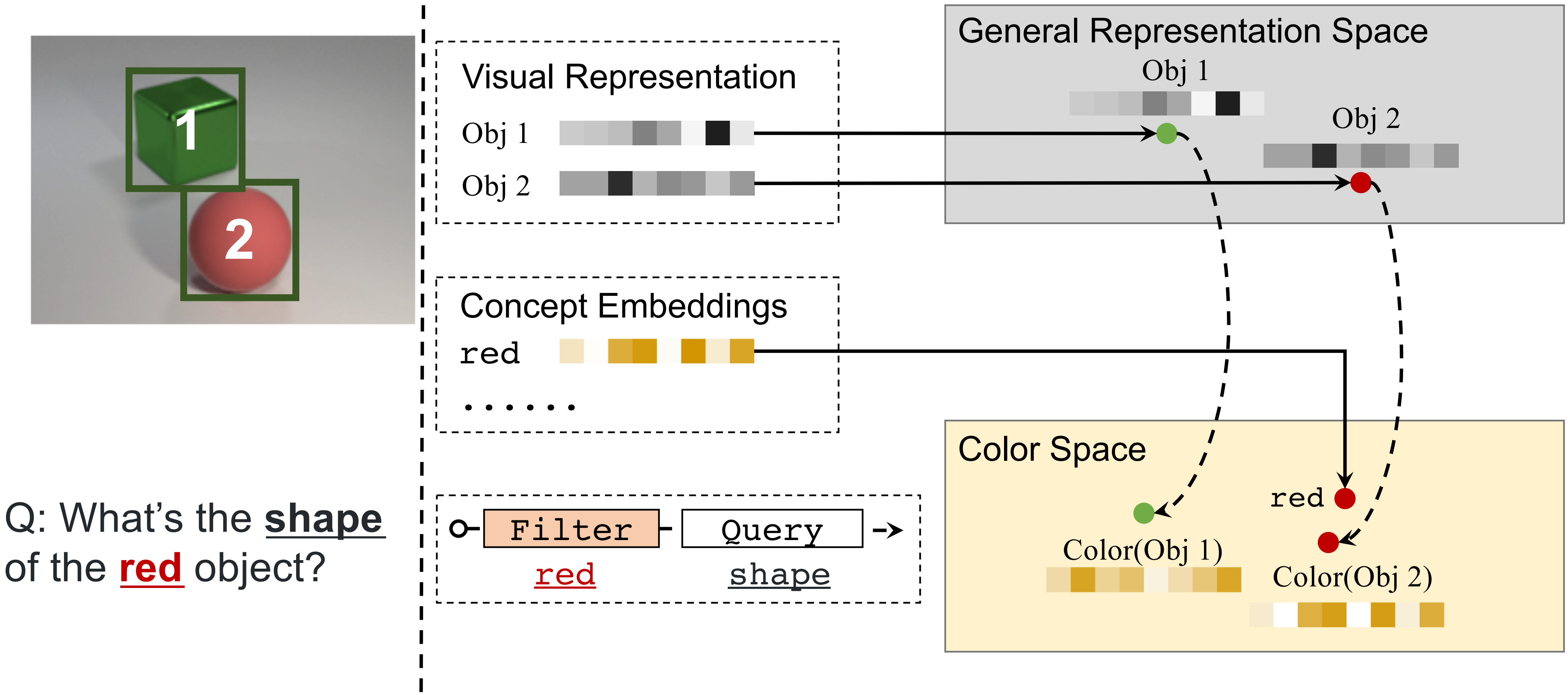


Neuro-Symbolic Concept Learning

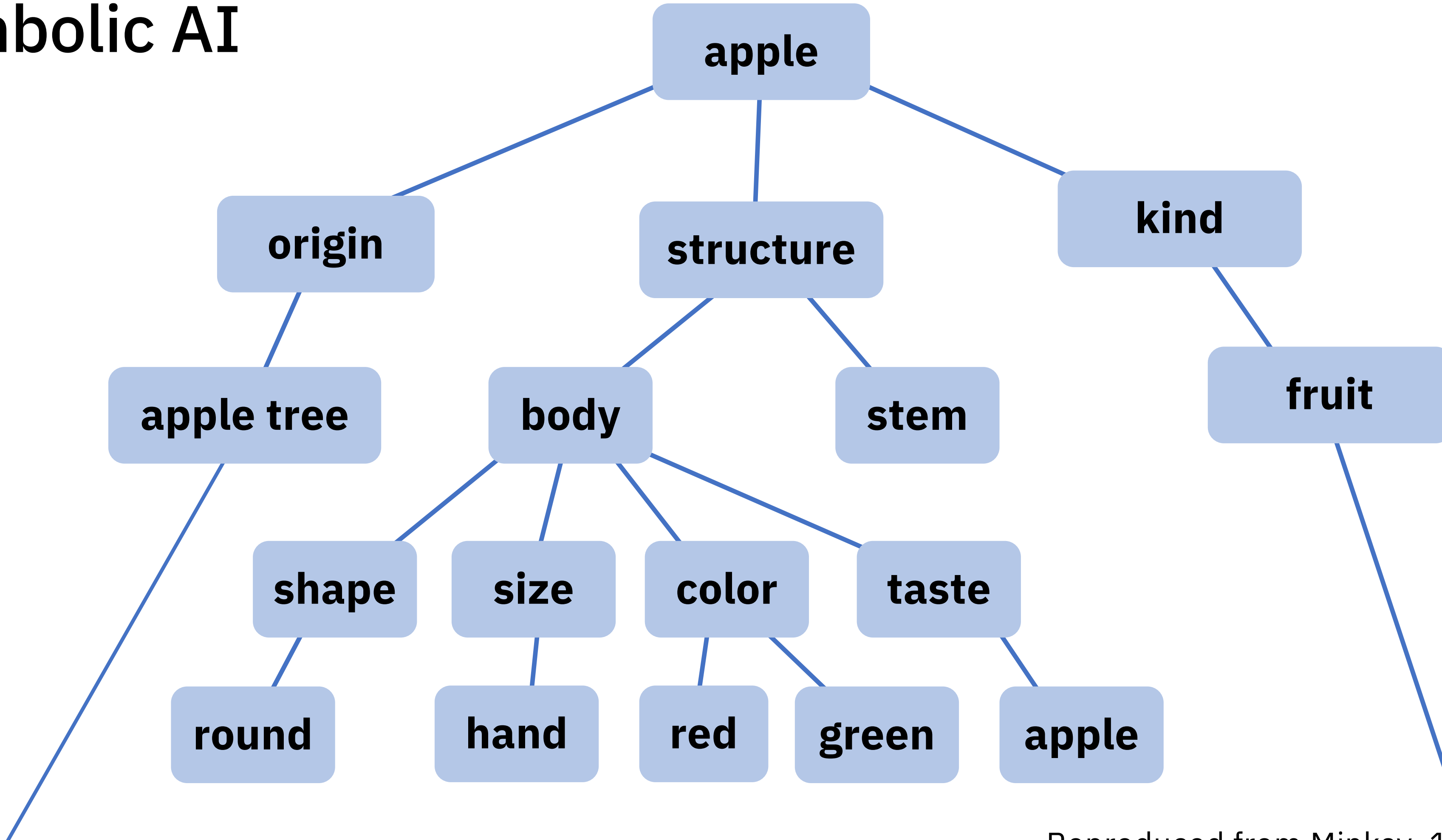


Q: What's the **shape** of the **red** object?

Neuro-Symbolic Concept Learning



Symbolic AI



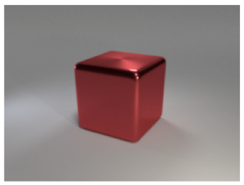
Reproduced from Minksy, 1991

Meta-concept Learning

Han et al. NeurIPS 2019

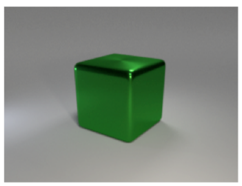
Visual reasoning questions

color: red



Q: Is there any **red cube**?
A: Yes.

color: green



Q: Is there any **green block**?
A: Yes

CLEVR
(Johnson et al. 2017)

+ Metaconcept questions

Q: Is red a **same kind** of concept as green?
A: Yes.

Q: Is cube a **synonym** of block?
A: Yes.

Laridae

Ivory Gull

Q: Is there any **Ivory Gull**?
A: Yes.
Q: Is there any **Laridae**?
A: Yes.

Black Tern

Q: Is there any **Black Tern**?
A: Yes.
Q: Is there any **Laridae**?
A: Yes.

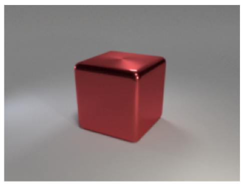
CUB
(Wah et al. 2011)

Q: Is Laridae a **hypernym** of Ivory gull?
A: Yes.

Augmenting VQA with Metaconcepts

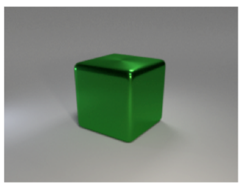
Visual reasoning questions

color: red



Q: Is there any **red cube**?
A: Yes.

color: green



Q: Is there any **green block**?
A: Yes

CLEVR
(Johnson et al. 2017)

Ivory Gull

Q: Is there any **Ivory Gull**?
A: Yes.
Q: Is there any **Laridae**?
A: Yes.

Laridae

Black Tern

Q: Is there any **Black Tern**?
A: Yes.
Q: Is there any **Laridae**?
A: Yes.

CUB
(Wah et al. 2011)

+ Metaconcept questions

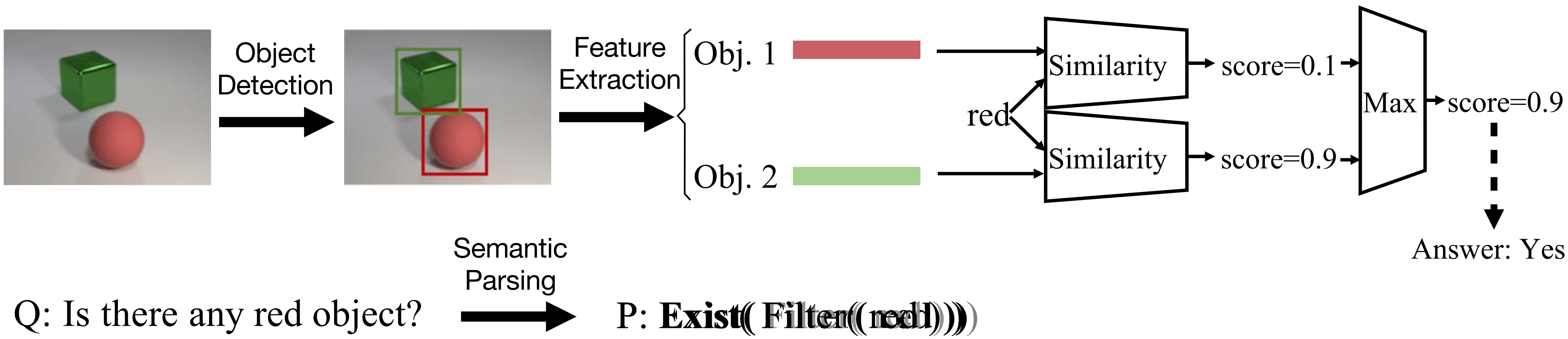
Q: Is red a **same kind** of concept as green?
A: Yes.

Q: Is cube a **synonym** of block?
A: Yes.

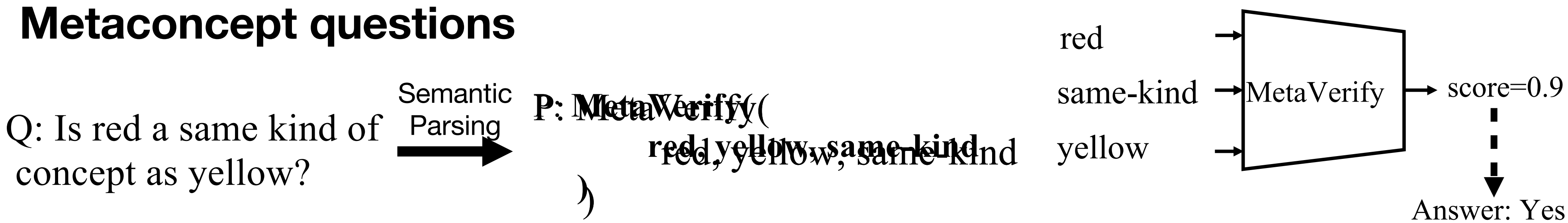
Q: Is Laridae a **hypernym** of Ivory gull?
A: Yes.

Program Execution Animated

Visual reasoning questions



Metaconcept questions



Generalization

Metaconcept Generalization

Q: Is there any *airplane*?
A: Yes

Q: Is there any *kid*?
A: Yes

Q: Is airplane a *synonym* of plane?
A: Yes

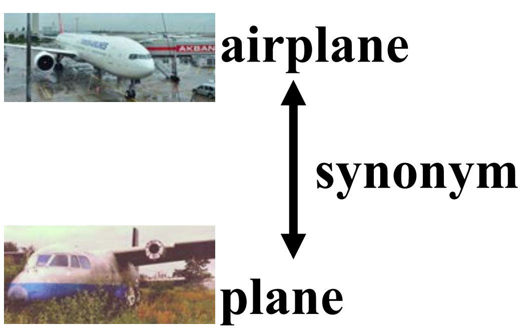
Q: Is there any *plane*?
A: Yes

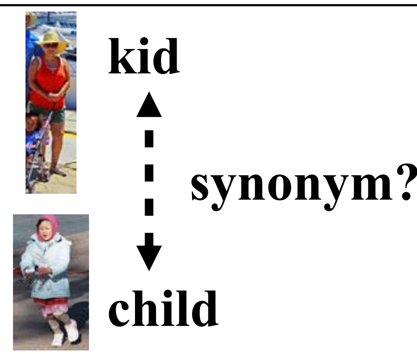
Q: Is there any *child*?
A: Yes

Q: Is kid a *synonym* of child?
A: Yes

Training

Testing: metaconcepts on unseen pairs of concepts





Generalization

Metaconcept Generalization: Results

Q: Is there any *airplane*?
A: Yes

Q: Is there any *plane*?
A: Yes

Q: Is there any *kid*?
A: Yes

Q: Is there any *child*?
A: Yes

Training

Q: Is airplane a *synonym* of plane?
A: Yes

Q: Is kid a *synonym* of child?
A: Yes

Testing

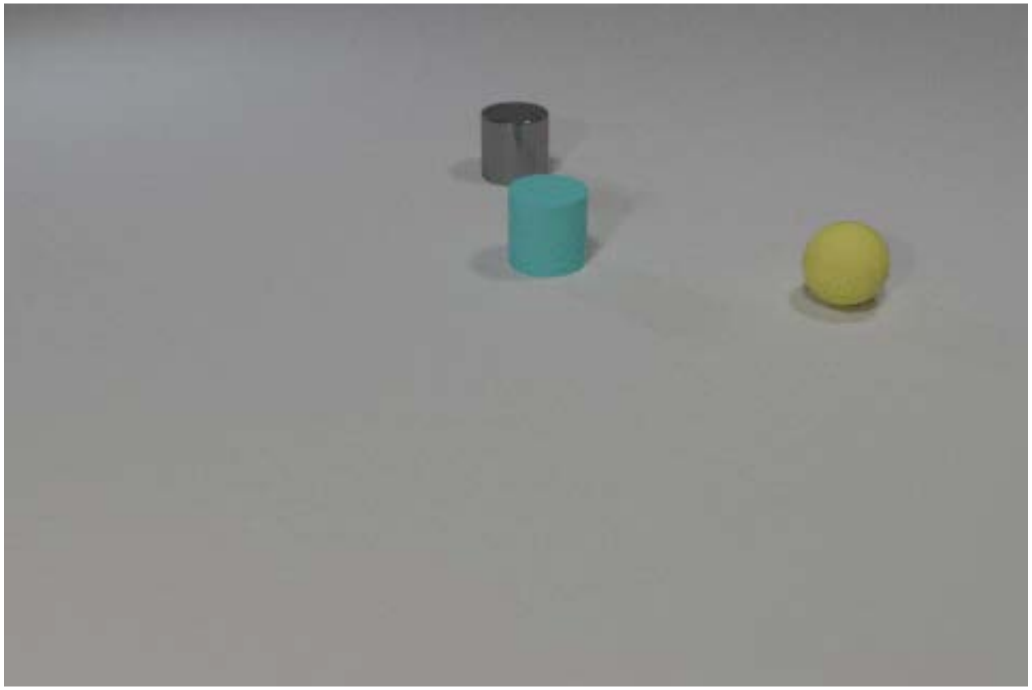
		Q.Type	GRU (Lang. Only) [Cho et al., 2014]	GRU-CNN [Zhou et al., 2015]	BERT (question ; concept) [Jacob Devlin, 2018]	NS-CL [Mao et al. 2019]	VCML
CLEVR	Synonym	50.0	$66.3_{\pm 1.4}$	$60.9_{\pm 10.6}$	$76.2_{\pm 10.2}$; $80.2_{\pm 16.1}$	$\mathbf{100.0}_{\pm \mathbf{0.0}}$	$\mathbf{100.0}_{\pm \mathbf{0.0}}$
	Same-kind	50.0	$64.7_{\pm 5.1}$	$61.5_{\pm 6.6}$	$75.4_{\pm 5.4}$; $80.1_{\pm 10.0}$	$92.3_{\pm 4.9}$	$\mathbf{99.3}_{\pm \mathbf{1.0}}$
GQA	Synonym	50.0	$80.8_{\pm 1.0}$	$76.2_{\pm 0.8}$	$76.2_{\pm 2.4}$; $83.1_{\pm 1.5}$	$81.2_{\pm 2.8}$	$\mathbf{91.1}_{\pm \mathbf{1.7}}$
	Same-kind	50.0	$56.3_{\pm 2.3}$	$57.3_{\pm 5.3}$	$59.5_{\pm 2.7}$; $68.2_{\pm 4.0}$	$66.8_{\pm 4.1}$	$\mathbf{69.1}_{\pm \mathbf{1.7}}$
CUB	Hypernym	50.0	$74.3_{\pm 5.2}$	$76.7_{\pm 8.8}$	$75.6_{\pm 1.2}$; $61.7_{\pm 10.3}$	$80.1_{\pm 7.3}$	$\mathbf{94.8}_{\pm \mathbf{1.3}}$
	Meronym	50.0	$80.1_{\pm 5.9}$	$78.1_{\pm 4.8}$	$63.1_{\pm 3.2}$; $72.9_{\pm 9.9}$	$\mathbf{97.7}_{\pm \mathbf{1.1}}$	$92.5_{\pm 1.0}$

CLEVERER: CoLlision Events for Video REpresentation and Reasoning

- Descriptive

Q: *What is the material of the last object to collide with the cyan cylinder?*

A: *Metal*

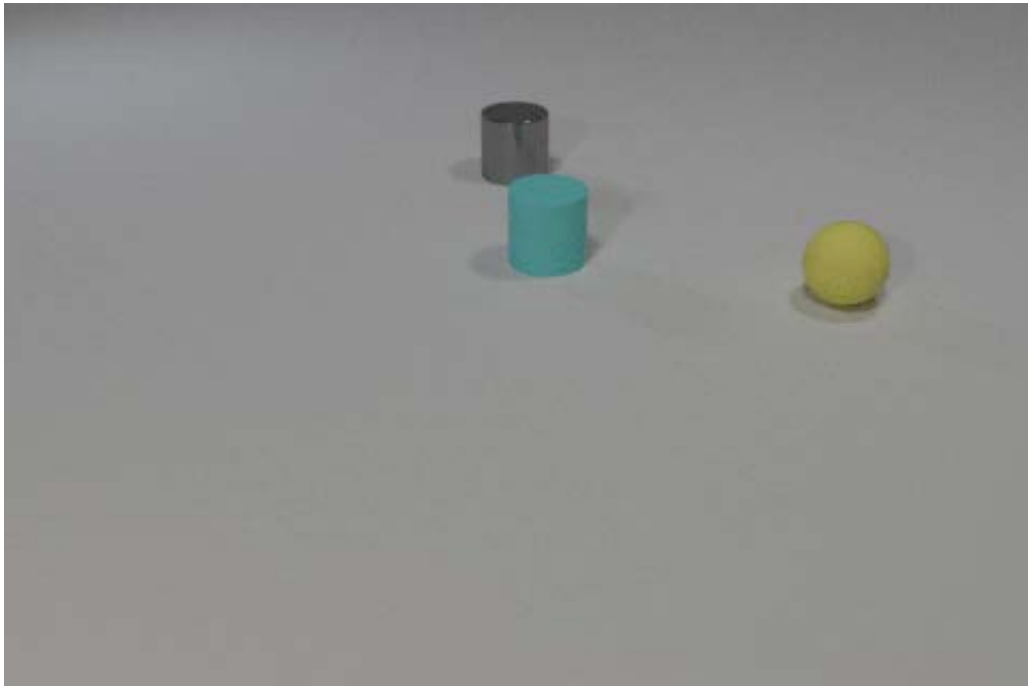


Chuang Gan w/ Kevin Xi, Yunzhu Li, Pushmeet Kohli, Jiajun Wu, Antonio Torralba & Josh Tenenbaum

- Explanatory

Q: *What is responsible for the collision between the rubber and metal cylinder?*

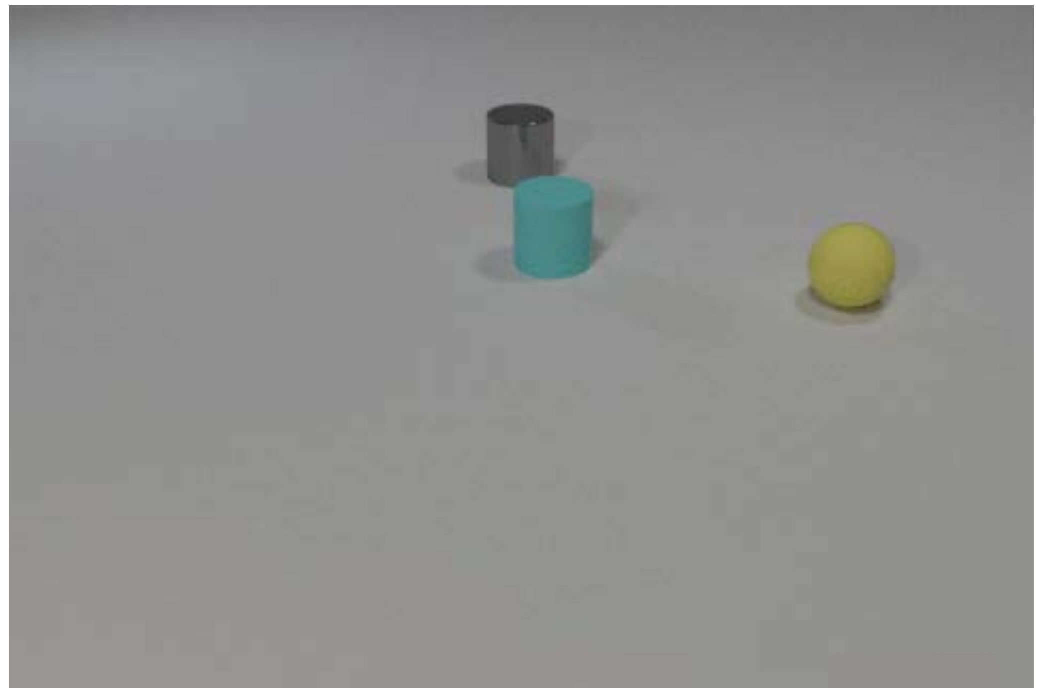
A. The presence of the yellow sphere
B. The collision between the rubber cylinder and the red rubber sphere



- Counterfactual

Q: *What will happen without the cyan cylinder?*

A. The red rubber sphere and the metal sphere collide
B. The red rubber sphere and the gray object collide

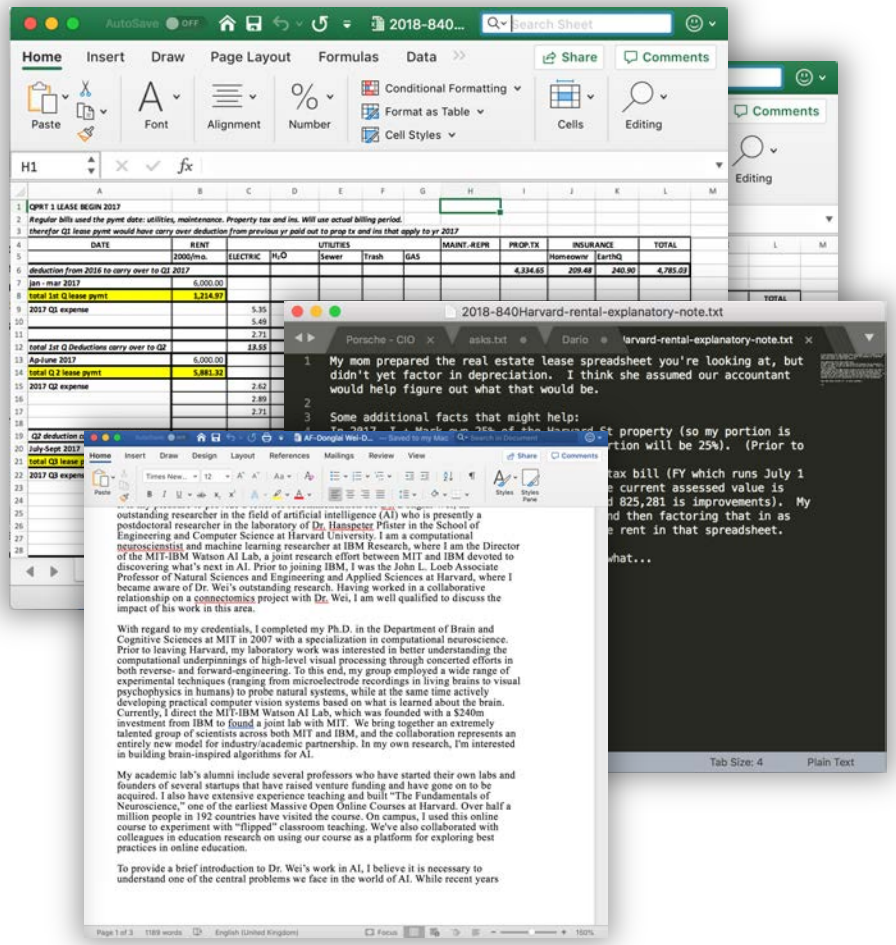


Looking Ahead

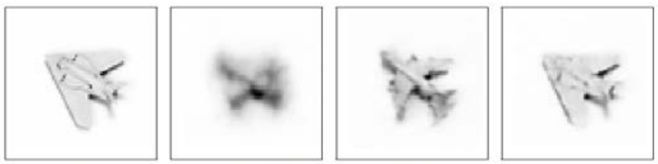
How many employees have over 10 years experience but have moved location in the last year?

What factors might contribute to better output from Factory A vs. Factory B?

Why is our database down?



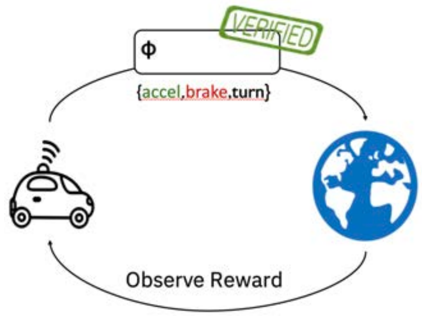
Neurosymbolic
Generative Models



(a) Target (b) β-TCVAE (c) DS-VAE with perturbed Z (d) DS-VAE

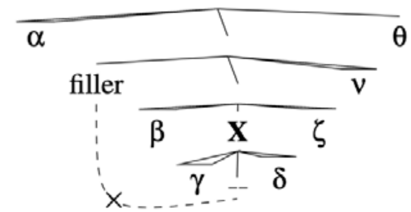
Srivastava et al. 2020 (submitted)

Neurosymbolic
Safe ML/RL



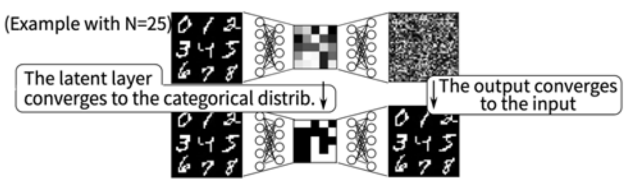
Fulton et al AAAI 2018

Neurosymbolic
NLU



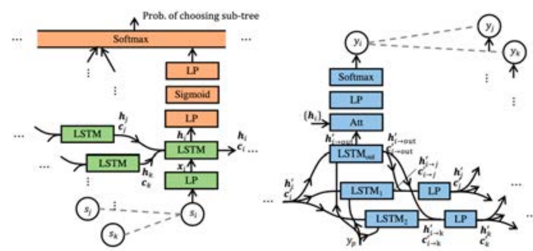
Wilcox et al. NAACL 2019

Neurosymbolic
Planning



Asai et al. AAAI 2018

Neurosymbolic
Code Optimization

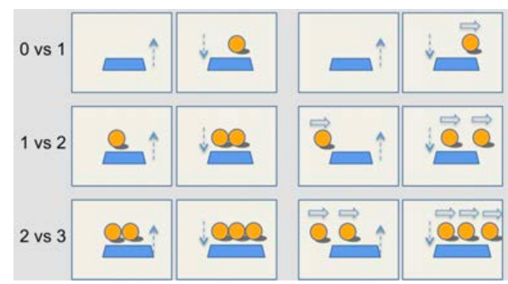


(a) The tree encoder (green) and subtree selector (orange).

(b) The tree decoder.

Shi et al. ICLR 2019

Neurosymbolic
Machine Common Sense



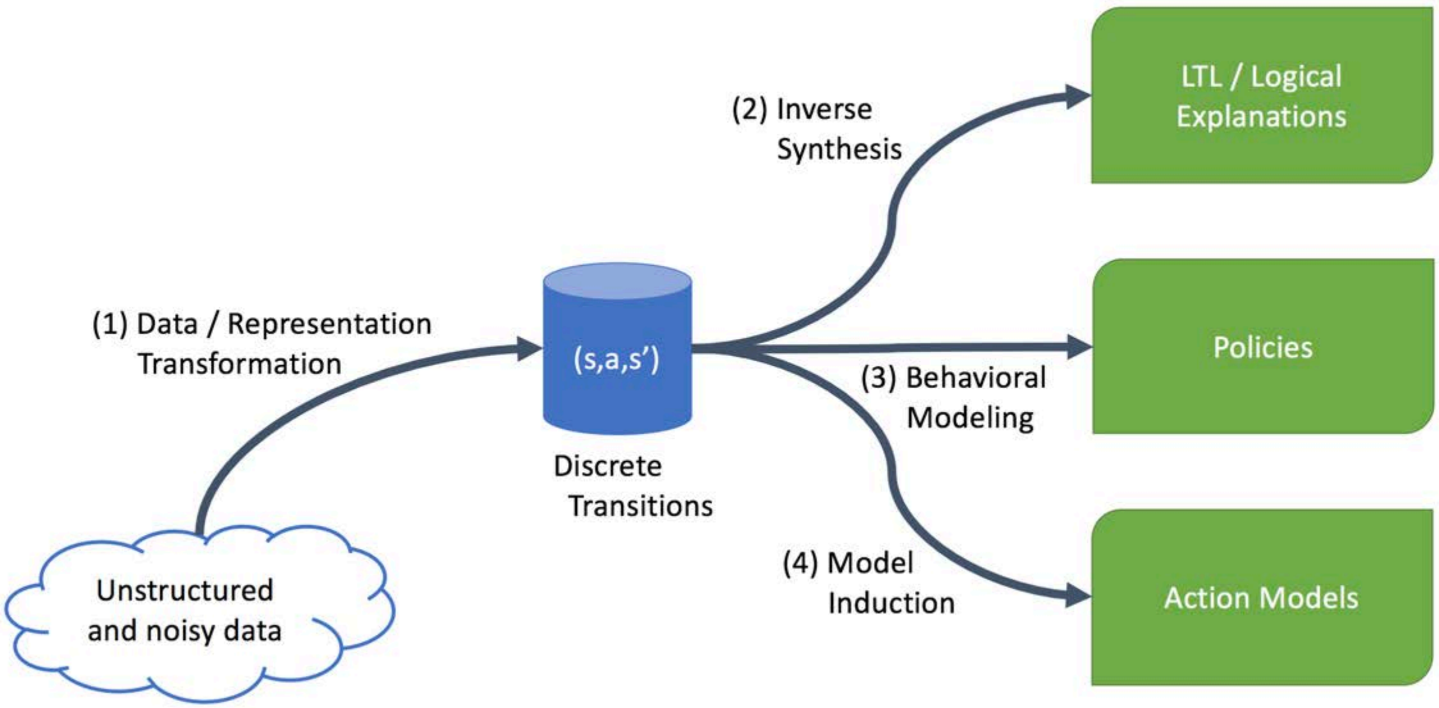
Smith et al. NeurIPS 2019

Inducing Behavioral Insight

Inferring flexible behavioral plans/policies from temporal observation data

Julie Shah
MIT

Christian Muise
IBM



```
(:action pickup

 :parameters (?b1 ?b2 - block)

 :precondition (and (on ?b1 ?b2)
                    (hand-clear))

 :effect (and (not (hand-clear))
              (not (on ?b1 ?b2))
              (holding ?b1))
)
```

Task: Induce the action theory of an environment through observations

MIT-IBM Watson AI Lab

LatPlan

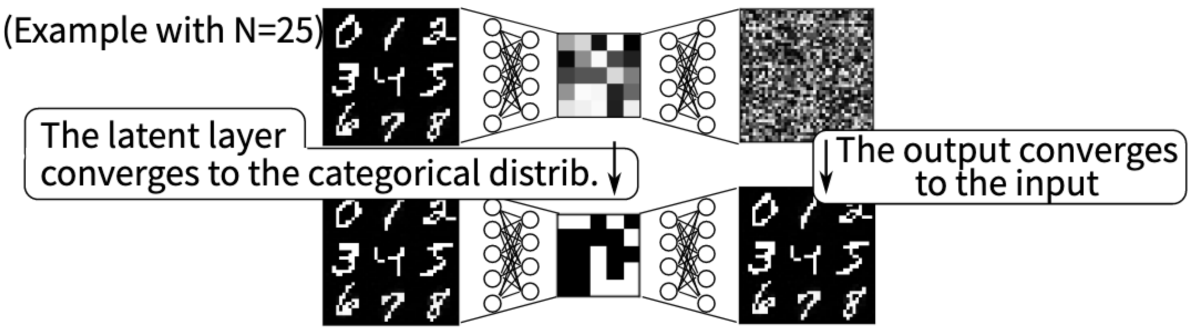
Mixing symbolic planning with neural networks

Masataro Asai
IBM

LatPlan

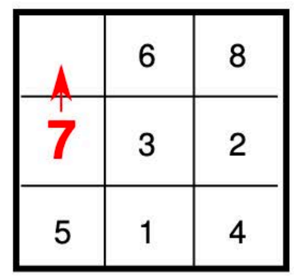
Mixing symbolic planning with neural networks

Masataro Asai
IBM

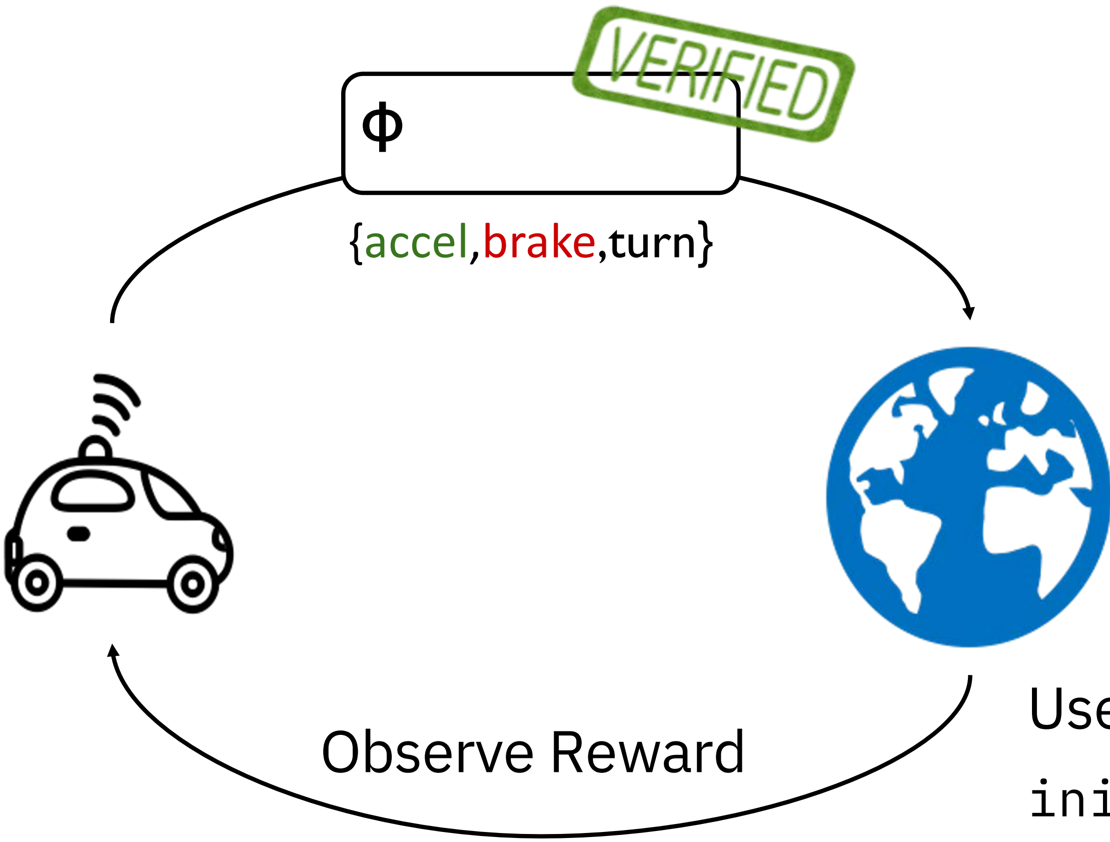


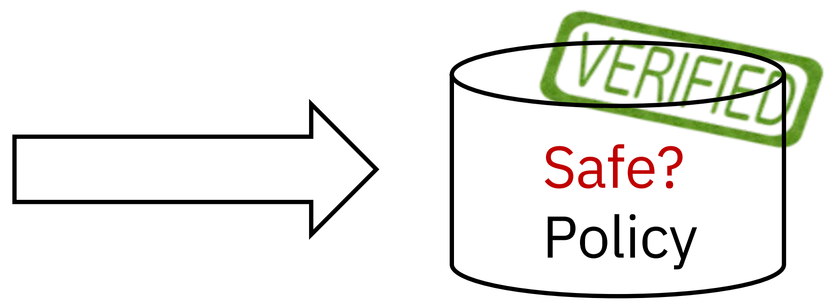
When
$Empty(x, y_{old}) \wedge$
$at(x, y_{new}, p) \wedge$
$up(y_{new}, y_{old})$;
then
$\neg Empty(x, y_{old}) \wedge$
$Empty(x, y_{new}) \wedge$
$\neg at(x, y_{new}, p) \wedge$
$at(x, y_{old}, p)$

```
;; Translates to a PDDL model below:
(:action slide-up ...
 :precondition
 (and (empty ?x ?y-old)
      (at ?x ?y-new ?p) ...)
 :effects
 (and (not (empty ?x ?y-old))
      (empty ?x ?y-new)
      (not (at ?x ?y-new ?p))
      (at ?x ?y-old ?p)))
```



Verifiably Safe Reinforcement Learning



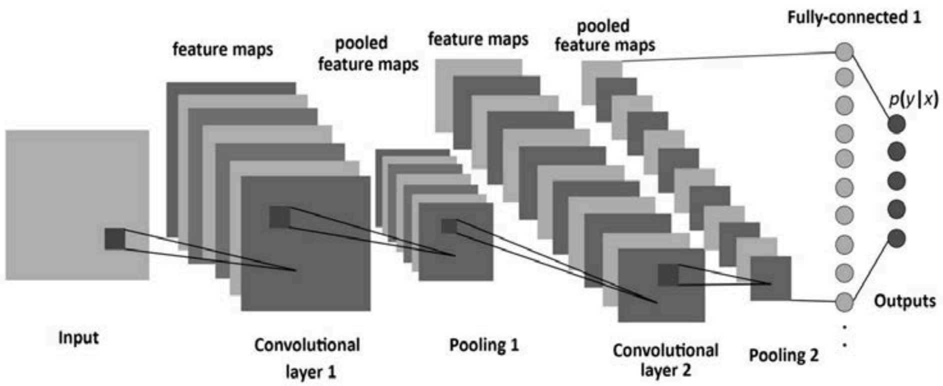


Nathan Fulton
IBM

Use a theorem prover to prove:

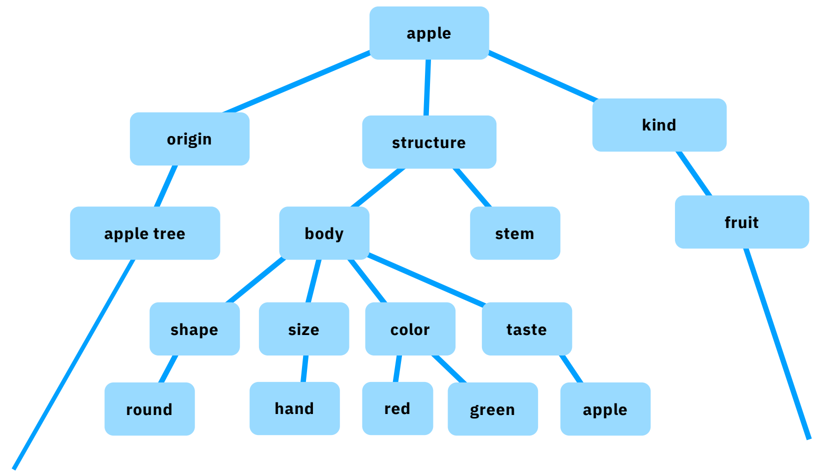
$\mathtt{init} \rightarrow [\{\{\mathtt{accel} \cup \mathtt{brake}\};\mathtt{ODEs}\}^*]\mathtt{safe}$

is correctly monitored by ϕ.



NEURAL NETWORKS

+




```
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 :parameters (?b1 ?b2 - block)
 :precondition (and (on ?b1 ?b2)
                    (hand-clear))
 :effect (and (not (hand-clear))
              (not (on ?b1 ?b2))
              (holding ?b1))
)
```

SYMBOLIC AI

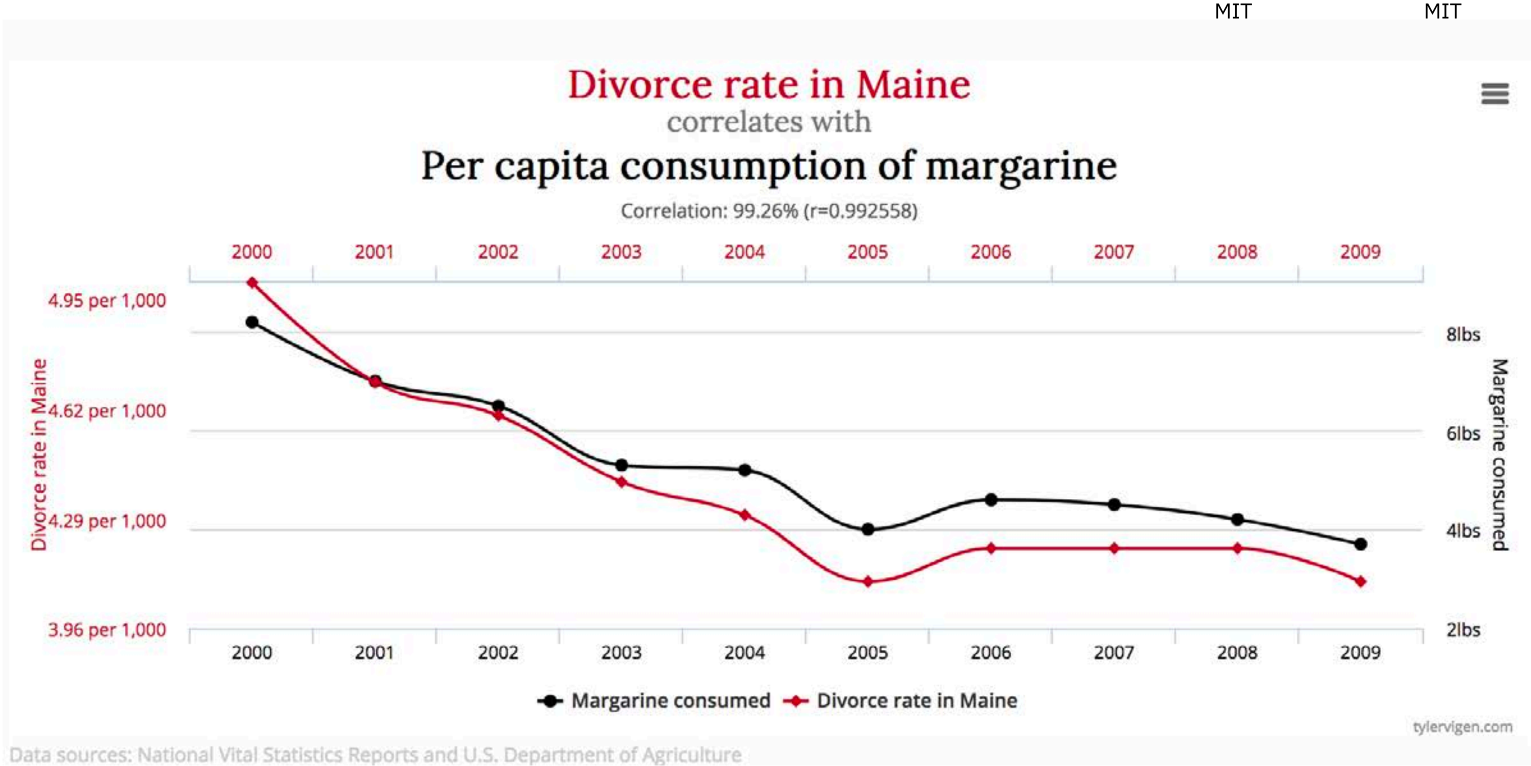
Causal Inference

Beyond Correlation—inferring and testing for causal relationships in complex systems

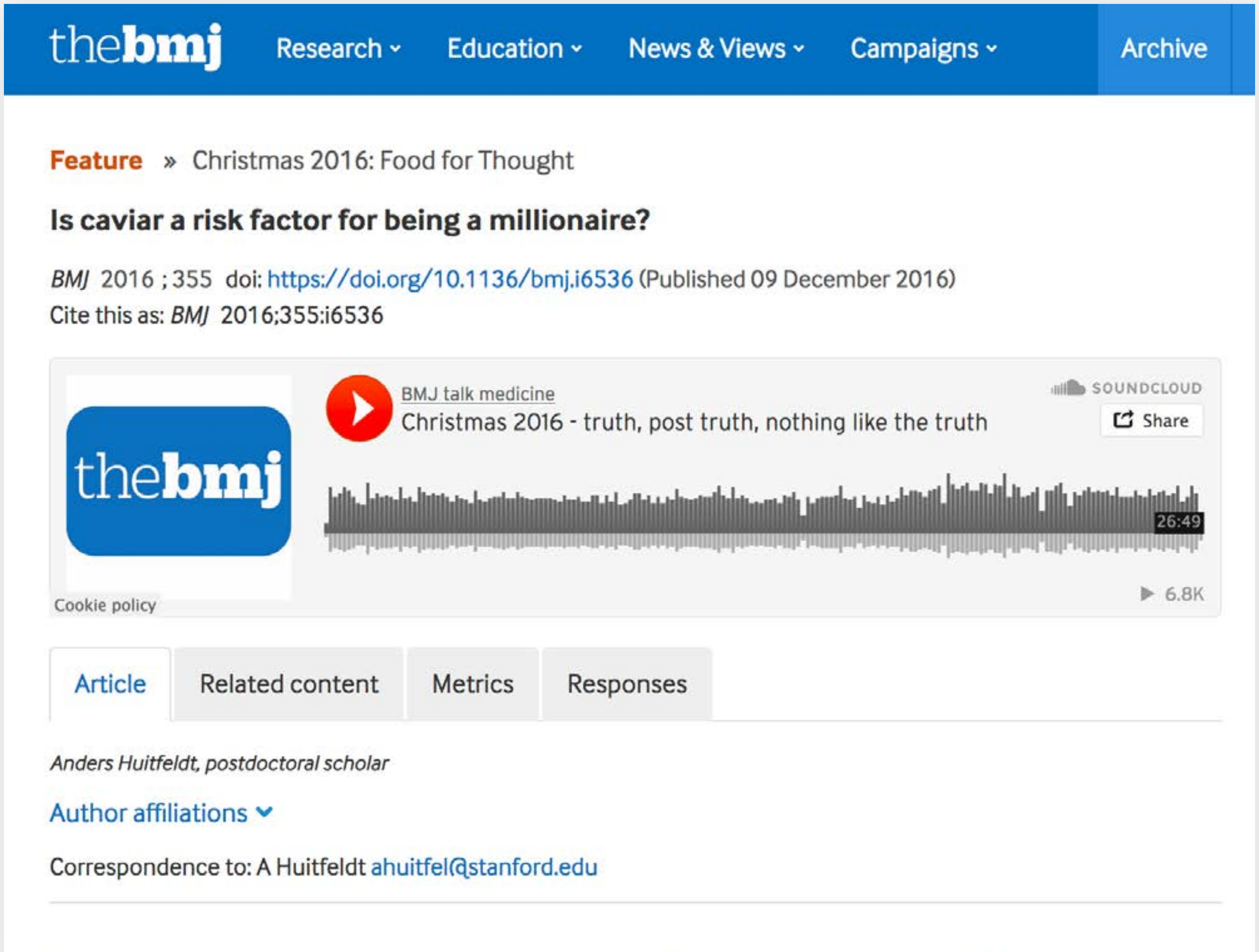
Caroline Uhler
MIT

Guy Bresler
MIT

Karthikeyan Shanmugam
IBM



http://tylervigen.com/spurious-correlations



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Anders Huitfeldt, postdoctoral scholar

Author affiliations

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