

# “Unit-testing” deep learning with synthetic data for more informative evaluation

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# Overview

- ▶ Visual question answering
- ▶ Problems with the VQA Dataset
- ▶ Evaluation methodology
- ▶ ShapeWorld generation framework
- ▶ Evaluation of FiLM on ShapeWorld

# Visual question answering

## Examples



Where is this cat laying?

Is the cat awake?

What color is the cat?



Is the cat facing the computer?

Is the cat typing?

Is the cat playing with the mouse?



What object is shining on the animal?

What objects is the cat sitting behind?

How many cats?



How many items are on the bookcase?

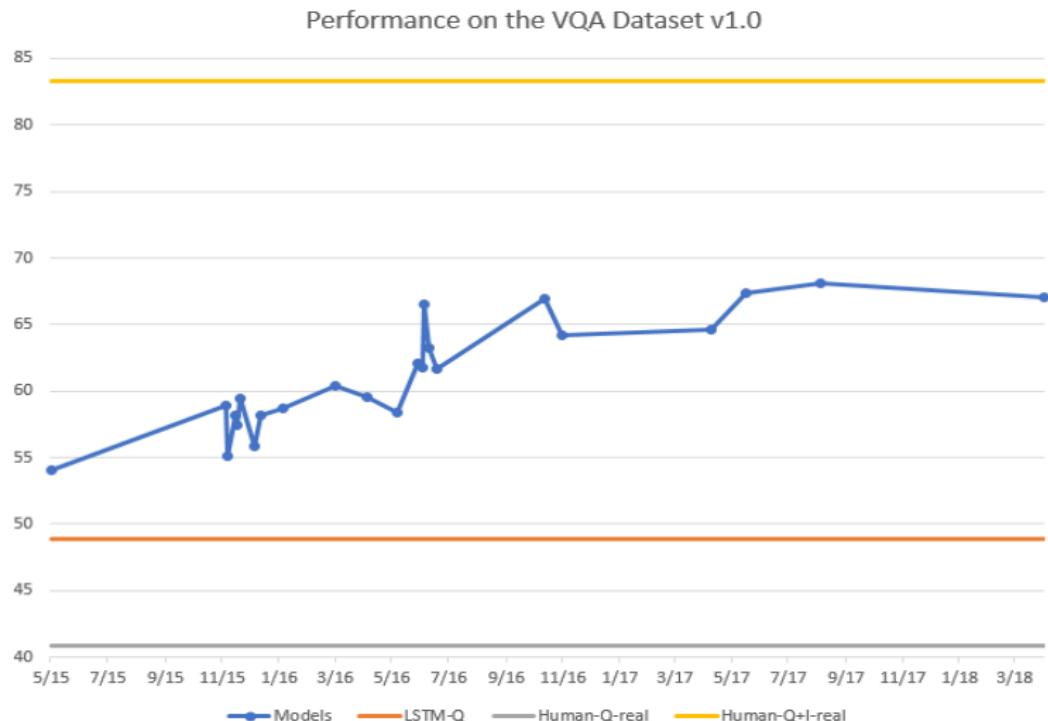
Are these two children related?

Is the dog begging for food?

⇒ **Visual Turing test?**

# Visual question answering

## Performance over time



Based on (incomplete) list of VQA papers with arXiv publication dates

# Problems with the VQA Dataset

## Question-answer biases



- ▶ What sport is...? ⇒ **tennis** (41%)



- ▶ How many...? ⇒ **two** (39%)



- ▶ Do you see a...? ⇒ **yes** (87%)

Examples from Goyal et al. (<https://arxiv.org/abs/1612.00837>)

# Problems with the VQA Dataset

Complete question/image understanding



- ▶ What...? ⇒ **umbrella**
- ▶ What season...? ⇒ **summer**
- ▶ What season of...? ⇒ **summer**
- ▶ ...
- ▶ What season of year was this photo taken in?  
⇒ **summer**



- ▶ What does the red sign say? ⇒ **stop**



Examples from Agrawal et al. (<https://arxiv.org/abs/1606.07356>) and Devi Parikh's slides (<https://newgeneralization.github.io/>)

# Problems with the VQA Dataset

## Sensitivity to question words

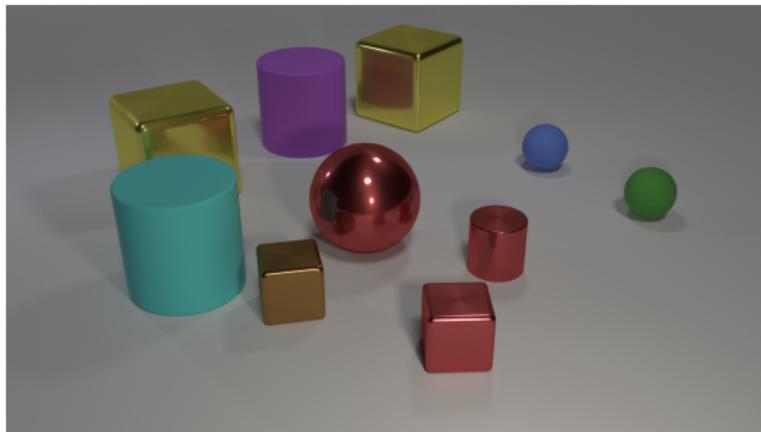


- ▶ How symmetrical are the white bricks on either side of the building? ⇒ **very**
- ▶ How **spherical** are the white bricks on either side of the building? ⇒ **very**
- ▶ How **soon** are the bricks **fading** on either side of the building? ⇒ **very**
- ▶ How **fast** are the bricks **speaking** on either side of the building? ⇒ **very**

Example from Mudrakarta et al. <https://arxiv.org/abs/1805.05492>.

# Problems with the VQA Dataset

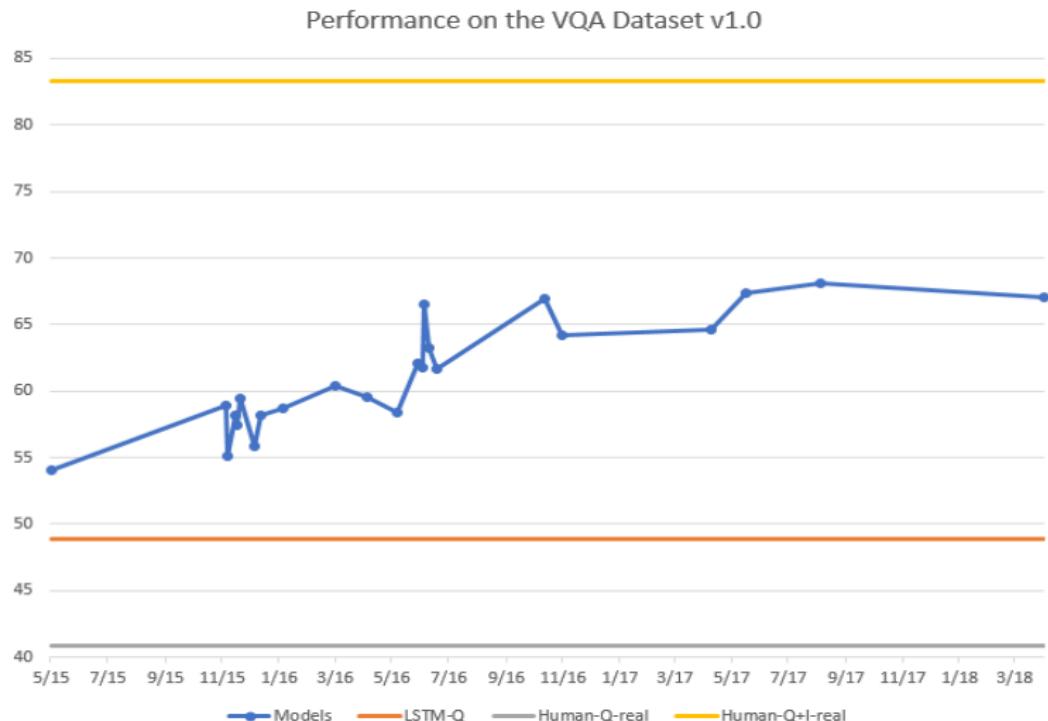
Low performance on CLEVR



- ▶ How many small spheres are there?  $\Rightarrow$  2
- ▶ What number of cubes are small things or red metal objects?  $\Rightarrow$  2
- ▶ Does the metal sphere have the same color as the metal cylinder?  $\Rightarrow$  Yes
- ▶ Are there more small cylinders than metal things?  $\Rightarrow$  No

# Evaluation methodology

Meaningful progress?



Based on (incomplete) list of VQA papers with arXiv publication dates

# Evaluation methodology

Pros and cons of crowd-sourced real-world datasets

**Solve the problem/dataset?**



Deep learning will find a way to make effective use of the data.

**Evaluate model capabilities?**



Are these datasets appropriate to investigate this question?

- ▶ Natural?
- ▶ Difficult?
- ▶ Specific?

⇒ **Synthetic data!**

# Evaluation methodology

## Other popular datasets with similar issues

### SNLI – Stanford Natural Language Inference Corpus

C: A soccer game with multiple males playing.

H: Some men are playing a sport.

→ entailment

C: A smiling costumed woman is holding an umbrella.

H: A happy woman in a fairy costume holds an umbrella.

→ neutral

C: A man inspects the uniform of a figure in some East Asian country.

H: The man is sleeping

→ contradiction

### SQuAD – Stanford Question Answering Dataset

In meteorology, precipitation is any product of the condensation of atmospheric water vapor that falls under gravity. The main forms of precipitation include drizzle, rain, sleet, snow, graupel and hail... Precipitation forms as smaller droplets coalesce via collision with other rain drops or ice crystals within a cloud. Short, intense periods of rain in scattered locations are called "showers".

(1) What causes precipitation to fall?

⇒ gravity

(2) What is another main form of precipitation besides drizzle, rain, snow, sleet and hail?

⇒ graupel

(3) Where do water droplets collide with ice crystals to form precipitation? ⇒ within a cloud

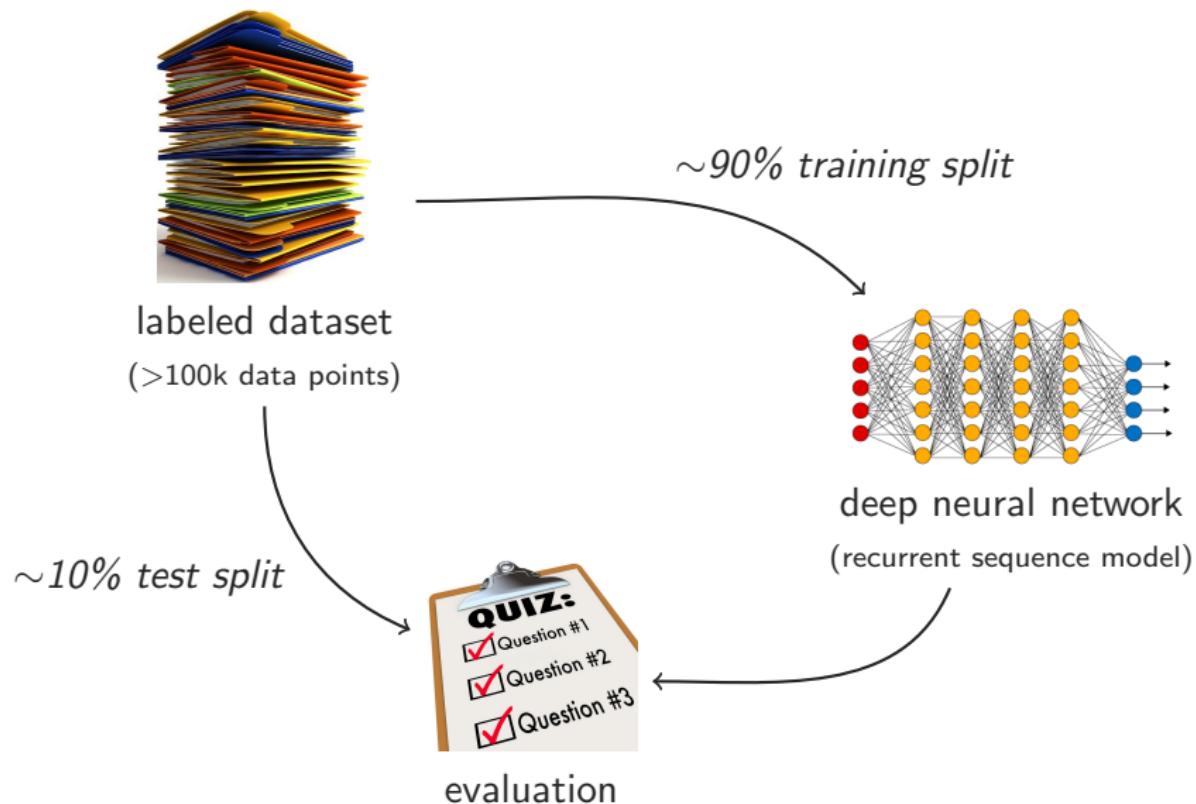
# Evaluation methodology

“Growing pains” for deep learning evaluation

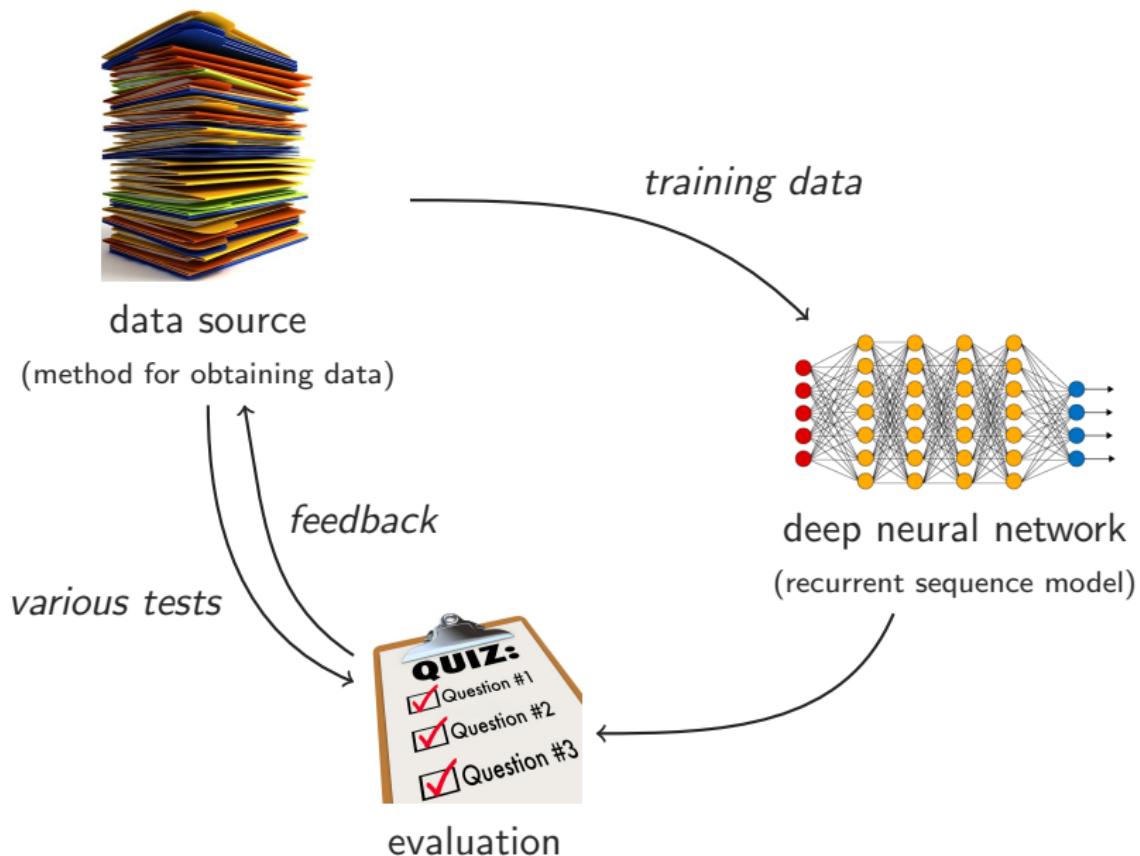
- ▶ Dataset bias and “cheating” models
  - ▶ Unexpectedly simple data and strong baselines
  - ▶ Adversarial examples with unintuitive model behavior
  - ▶ Replication and task/dataset transfer failure
- ⇒ **Symptoms of insufficient/inappropriate evaluation**

# Evaluation methodology

## Current approach

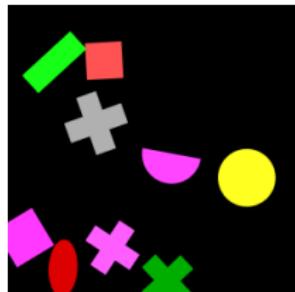


# Evaluation methodology

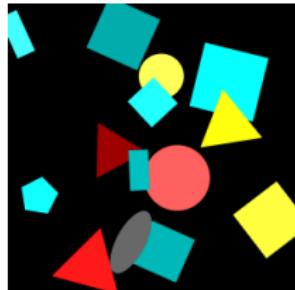


# ShapeWorld generation framework

Examples: relations and quantifiers



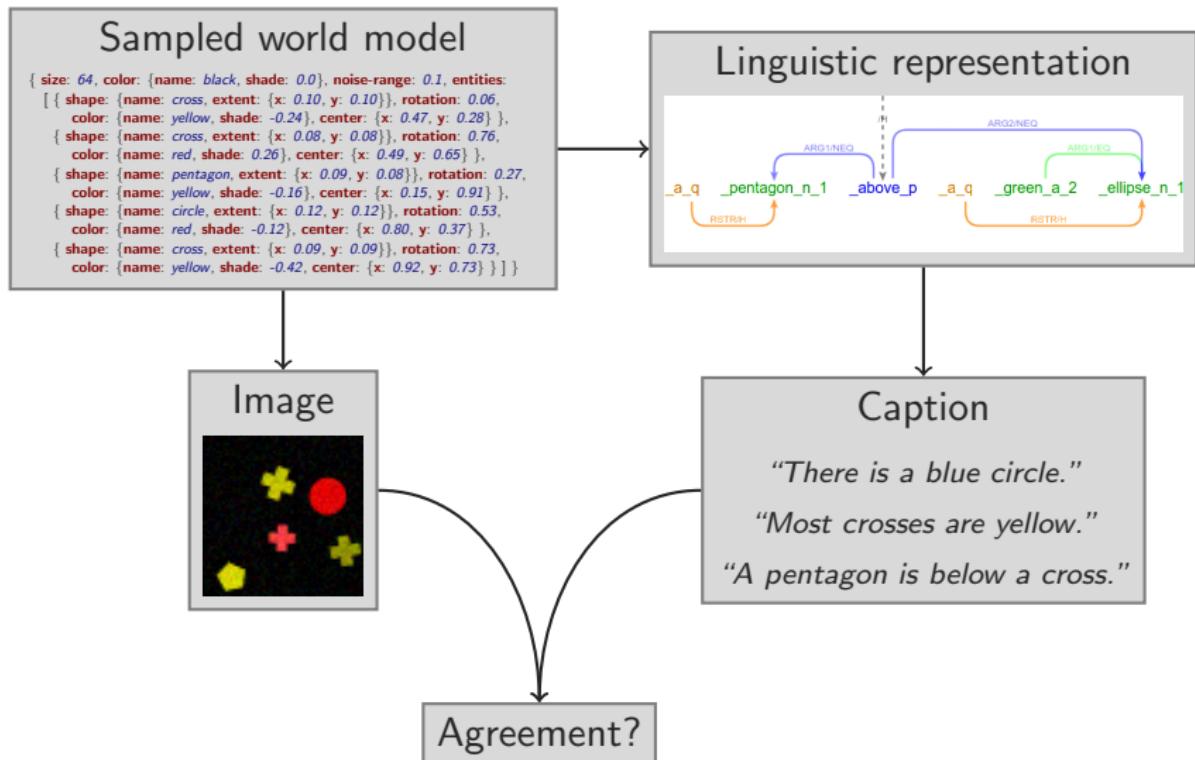
- ▶ A magenta square is to the right of a green shape.
- ▶ A yellow shape is not in front of a square.
- ▶ A circle is farther from an ellipse than a gray cross.
- ▶ A cross is not the same color as a green rectangle.
- ▶ The lowermost green shape is a cross.
- ▶ A red shape is the same shape as a green shape.



- ▶ Less than one triangle is cyan.
- ▶ At least half the triangles are red.
- ▶ More than a third of the shapes are cyan squares.
- ▶ Exactly all the five squares are red.
- ▶ More than one of the seven cyan shapes is a square.
- ▶ Twice as many red shapes as yellow shapes are circles.

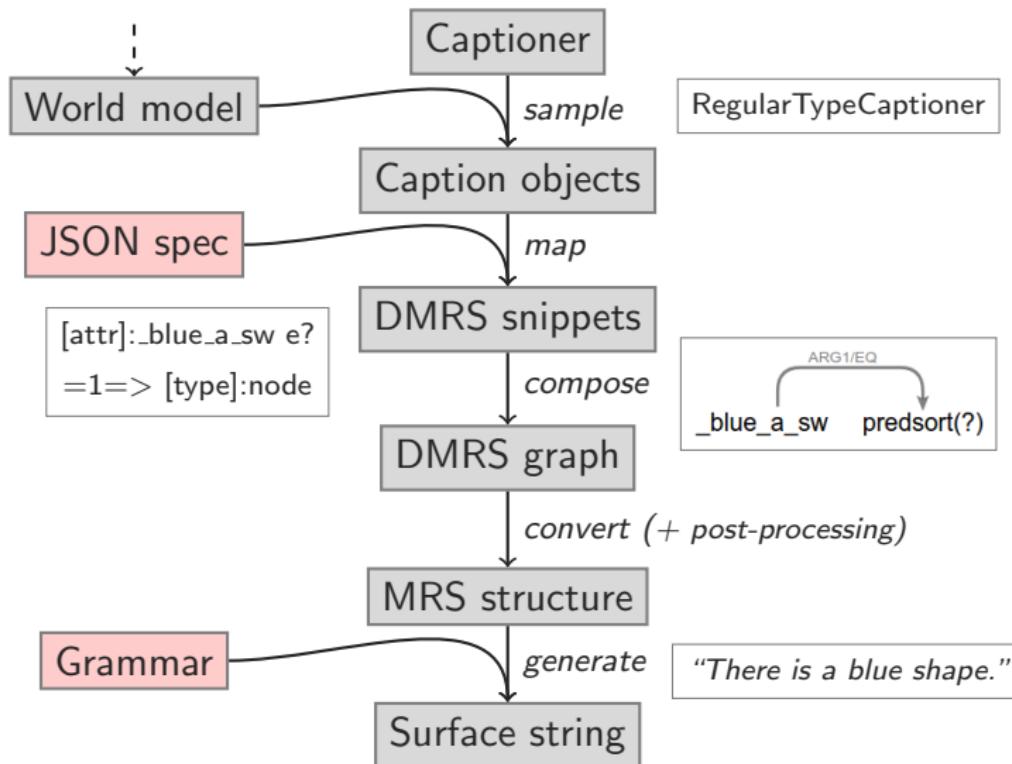
# ShapeWorld generation framework

## System overview



# ShapeWorld generation framework

## Language generation

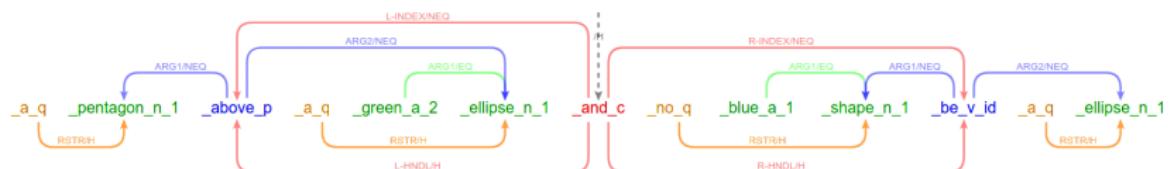


# ShapeWorld generation framework

## Compositionality

*"A pentagon is above a green ellipse, and no blue shape is an ellipse."*

↑ ERG + ACE realization ↑



↑ Internal DMRS mapping ↑

$\exists a : a.shape = pg$	$a.y > b.y$	$\exists b : b.color = gr$	$b.shape = el$	$\wedge$	$\neg \exists c : c.color = bl$	$true$	$c = d$	$\exists d : d.shape = el$
$\exists a : a.shape = pg$	$a.y > b.y$	$\exists b : b.color = gr \wedge b.shape = el$		$\wedge$	$\neg \exists c : c.color = bl$		$c = d$	$\exists d : d.shape = el$
$\exists a : a.shape = pg \wedge [\exists b : b.color = gr \wedge b.shape = el \wedge a.y > b.y]$				$\wedge$	$\neg \exists c : c.color = bl \wedge [\exists d : d.shape = el \wedge c = d]$			

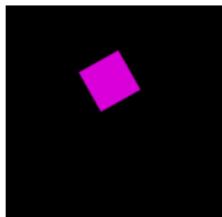
# ShapeWorld generation framework

## Design choices

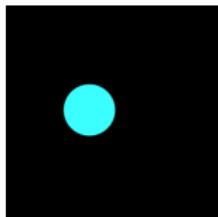
- ▶ Caption is extracted from image, i.e. world model
- ▶ Incorrect caption via minimal modification of correct one
- ▶ Three agreement values to avoid ambiguous cases
- ▶ Initialize generator/captioner values before sampling
- ▶ Various tautology/contradiction checks
- ▶ Modular and configurable

# ShapeWorld generation framework

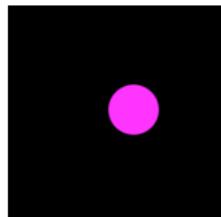
What type of generalization do we expect/desire?



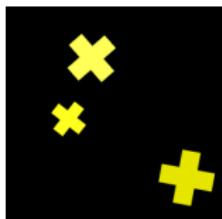
magenta square



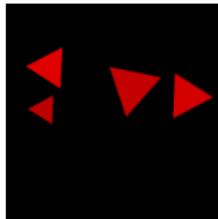
cyan circle



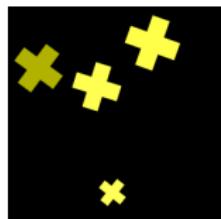
magenta circle



three crosses



four triangles

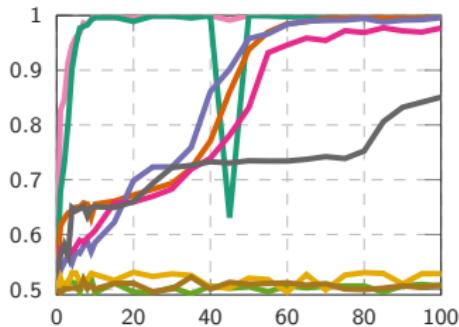


four crosses

# Evaluation of FiLM on ShapeWorld

## Results per instance type

Dataset	CNN-LSTM	CNN-LSTM-SA	FiLM	
(single-shape)	—	—	100.0	87.2
existential	100.0	81.1	100.0	99.7
logical	79.7	62.2	76.5	58.4
numbers	75.0	66.4	99.1	98.2
quantifiers	72.1	69.1	84.8	80.8
(simple-spatial)	81.4	64.8	81.9	57.7
relational	—	—	—	50.6
implicit-rel	—	—	—	52.9
superlatives	—	—	—	50.8

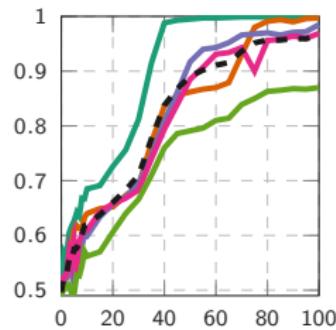


- ▶ Can relational-like instances implicitly be learned when training on a broader set of instances?
- ▶ Can relational-like instances be learned when (pre)training on simpler pedagogical instances?

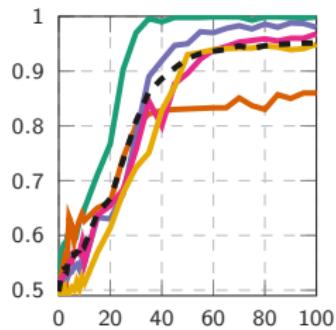
# Evaluation of FiLM on ShapeWorld

Learning from a broader set of instances

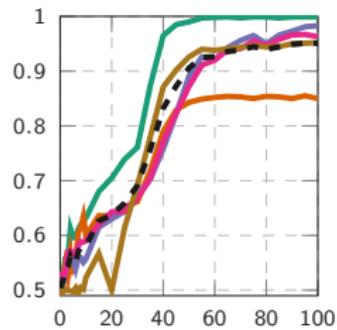
relational



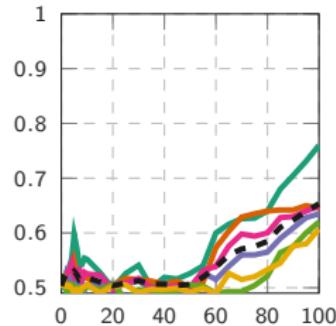
implicit-relational



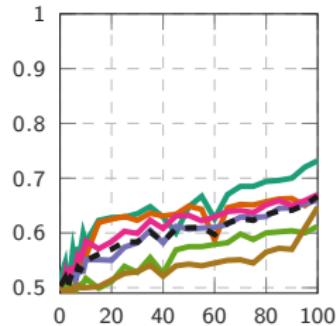
superlatives



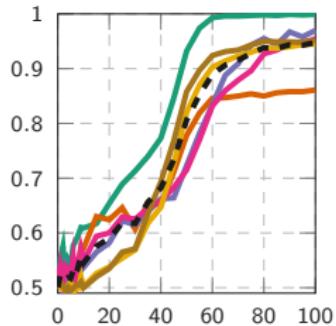
relation + implicit-rel



relational + superlat



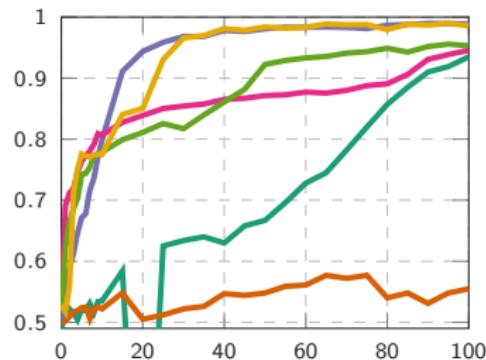
implicit-rel + superlat



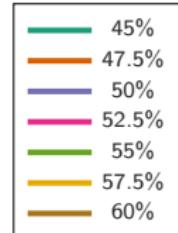
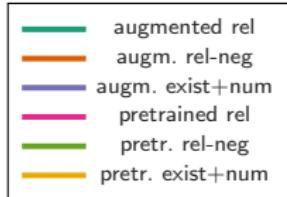
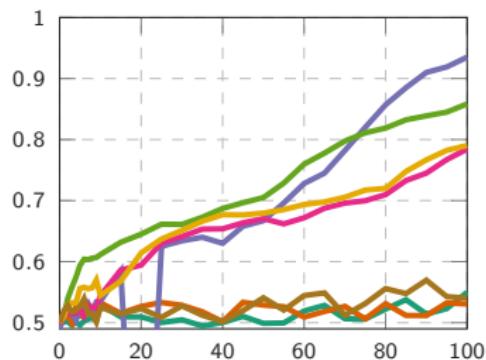
# Evaluation of FiLM on ShapeWorld

Learning bootstrapped by simpler instances

augmentation vs pretraining



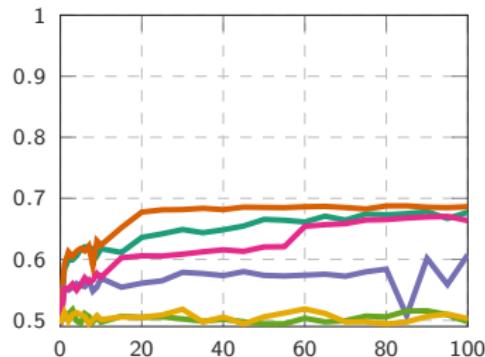
augmentation distributions



# Evaluation of FiLM on ShapeWorld

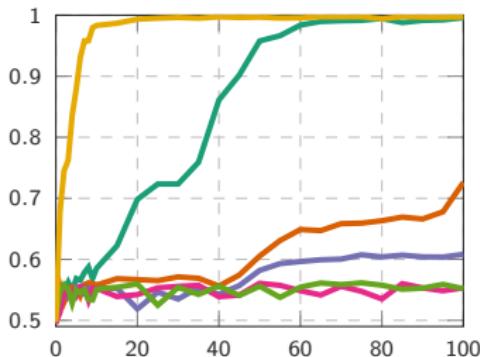
## Additional findings

pretrained ResNet doesn't work



- teal existential fixed
- orange existential trainable
- purple numbers fixed
- pink numbers trainable
- green relational fixed
- yellow relational trainable

overlapping objects impede learning



- teal overlap-free
- orange 5% numbers
- purple 10% numbers
- pink 17.5% numbers
- green 25% numbers
- yellow 25% existential

# Conclusion

## **real-world data    vs    synthetic data**

limited and expensive     $\longleftrightarrow$     unlimited amount

uncontrolled content     $\longleftrightarrow$     clean content

sparse instance coverage     $\longleftrightarrow$     targeted instance coverage

monolithic benchmark     $\longleftrightarrow$     tailored unit tests

test interpolation ability     $\longleftrightarrow$     test extrapolation ability

⇒ **Complementary evaluation paradigms**



**Thank you for your attention!**

**Questions?**