Visual Reasoning

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Topics in Deep Learning, 2017

Outline

1. Introduction
2. Datasets
3. Models

- Too much bias in VQA datasets.

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Visual reasoning vs VQA

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Visual reasoning vs VQA

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Image understanding → Visual reasoning → VQA

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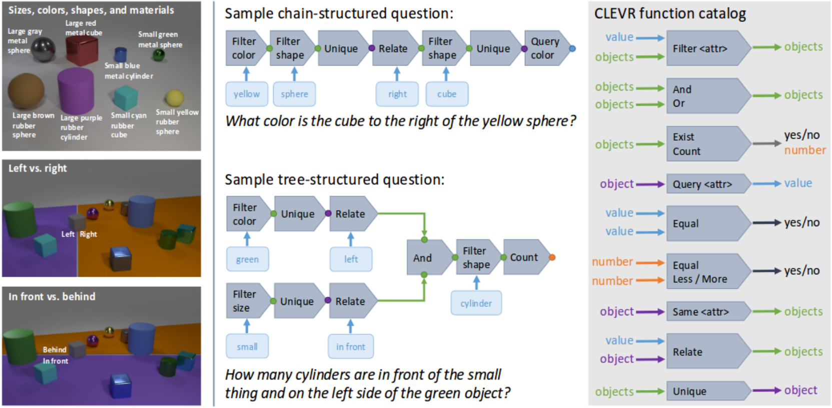
- Interface:



CLEVR

Images:

- Synthetically generated

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- 3 object shapes (cube, sphere, and cylinder)

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- Scene graph annotated
- **To generate image:** Randomly sample a scene graph. Then generate image using Blender (a tool to generate 3d images from scene graph).

CLEVR

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CLEVR

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- Example: How many red things are there? can be formed from How many $< C > < M >$ things are there?, binding the parameters $< C >$ and $< M >$ (with types color and material) with values red and nil.

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- CLEVR contains a total of 90 question families, each with a single program template and an average of four text templates.
- So to generate question: choose a question family, select values for each of its template parameters, execute the resulting program on the image's scene graph to find the answer.

CLEVR

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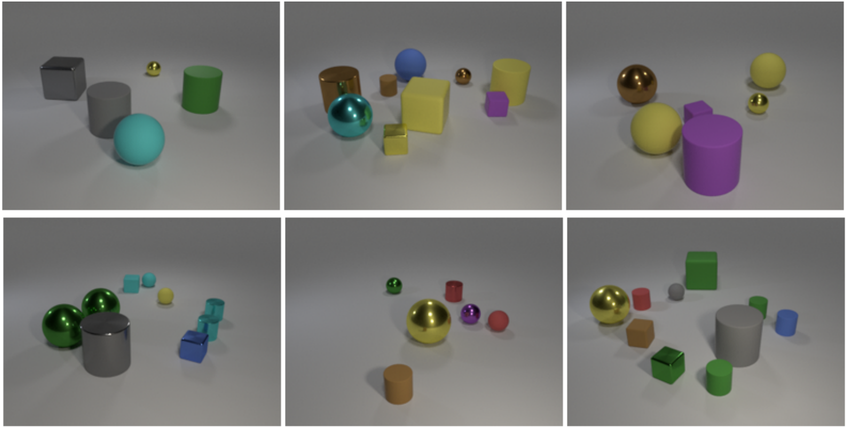
- Employ a depth-first search. At each step of assigning values to the vaiables, use ground-truth scene information to prune nodes which are guaranteed to produce undesirable questions.
- Maintain uniform question distribution across families.

CLEVR



CLEVR

```
"params": [
  {"type": "Size", "name": "<Z>"},
  {"type": "Color", "name": "<C>"},
  {"type": "Material", "name": "<M>"},
  {"type": "Shape", "name": "<S>"},
  {"type": "Relation", "name": "<R>"},
  {"type": "Size", "name": "<Z2>"},
  {"type": "Color", "name": "<C2>"},
  {"type": "Material", "name": "<M2>"},
  {"type": "Shape", "name": "<S2>"}
],
"text": [
  "What size is the <Z2> <C2> <M2> <S2> [that is] <R> the <Z> <C> <M> <S>?",
  "What is the size of the <Z2> <C2> <M2> <S2> [that is] <R> the <Z> <C> <M> <S>?",
  "How big is the <Z2> <C2> <M2> <S2> [that is] <R> the <Z> <C> <M> <S>?",
  "There is a <Z2> <C2> <M2> <S2> [that is] <R> the <Z> <C> <M> <S>; what size is it?",
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  "There is a <Z2> <C2> <M2> <S2> [that is] <R> the <Z> <C> <M> <S>; what is its size?"
],
```
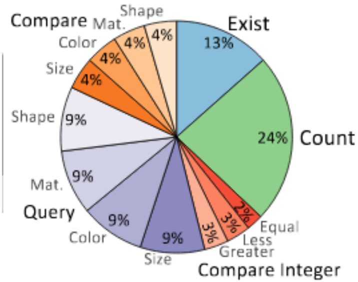

CLEVR

Split	Images	Questions	Unique questions	Overlap with train
Total	100,000	999,968	853,554	-
Train	70,000	699,989	608,607	-
Val	15,000	149,991	140,448	17,338
Test	15,000	149,988	140,352	17,335



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- Jointly train the modules and dynamically compose them into deep networks which can learn to answer the question.

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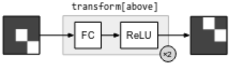
- **Inspiration:** Different architectures are needed for different tasks - CNNs for object detection, RNNs for counting.
- Decompose a question into its linguistic substructures and train a neural network module for each substructure.
- Jointly train the modules and dynamically compose them into deep networks which can learn to answer the question.
- Start by analyzing the question and decide what logical units are needed to answer the question and what should be the relationship between them.

NMNs

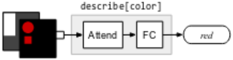
- Find: Finds objects of interest.

- Transform: Shift regions of attention.

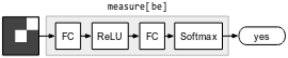


- Combine: Merge two attention maps into a single one.

- Describe: Map a pair of attention and input image to a distribution over the labels.



- Measure: Map attention to a distribution over the labels.



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- Parse the input question to obtain set of dependencies and obtain a representation similar to combinatory logic.
- For example, what is standing in the field becomes what(stand), what color is the truck becomes color(truck), and is there a circle next to a square becomes is(circle, next-to(square)).

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- Map question to the layout which specifies the set of modules and connections between them.
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- For example, what is standing in the field becomes what(stand), what color is the truck becomes color(truck), and is there a circle next to a square becomes is(circle, next-to(square)).
- The symbolic representation is mapped to a layout:
  - All leaves become find module.
  - All internal nodes become transform/combine module.
  - All root nodes become describe/measure module.

NMNs

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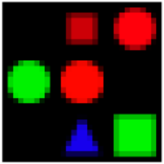
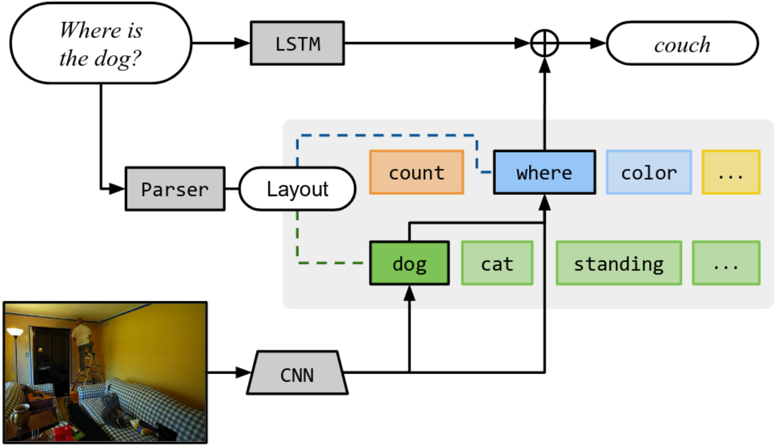
 *how many different lights in various different shapes and sizes?*	 *what is the color of the horse?*	 *what color is the vase?*	 *is the bus full of passengers?*	 *is there a red shape above a circle?*

`describe[count](`
`find[light])`
	`describe[color](`
	`find[horse])`
		`describe[color](`
		`find[vase])`
			`describe[is](`
			`combine[and](`
			`find[bus],`
			`find[full])`
				`measure[is](`
				`combine[and](`
				`find[red],`
				`transform[above](`
				`find[circle])))`

four (four)	brown (brown)	green (green)	yes (yes)	yes (yes)

NMNs



Where is the dog?
LSTM
couch
Parser
Layout
count
where
color
...
dog
cat
standing
...
CNN

Implementation details:

- Since some modules are updated more frequently than others, adaptive per weight learning rates are better.
- Training: Adadelta with standard parameter settings.
- Stanford parser has F1 score of 87%.

NMNs

Model	Overall	Count	Exist	Compare numbers	Query	Compare attribute
Human	92.6	86.7	96.6	86.5	95.0	96.0
LSTM	46.8	41.7	61.1	69.8	36.8	51.8
CNN+RNN	52.3	43.7	65.2	67.1	49.3	53.0
SA	68.5	52.2	71.1	73.5	85.3	52.3
NMN	72.1	79.3	52.5	71.4	78.9	78

N2NMNs

- NMNs are restricted to parsers for model configuration. A better model would be that learns it from the data.
- This paper learns to both parse the language into linguistic structures and compose them into appropriate layouts.
- Model has 2 parts. First, a set of co-attentive neural modules that provide parameterized functions for solving sub-tasks, and a layout policy to predict a question-specific layout from which a neural network is dynamically assembled.

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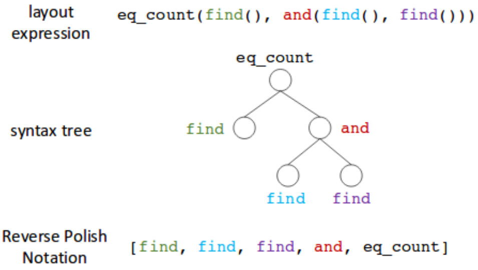
  $y = W_1^T vec(a_1) + W_2^T vec(a_2)$
- **Compare:** For complex pairwise comparison
  $y = W_1^T(W_2 sum(a_1 \odot x_{vis}) \odot W_3 sum(a_2 \odot x_{vis}) \odot W_4 x_{txt})$

N2NMNs

Layout:

- To predict the layout represent the layout in term of Reverse Polish notation and convert it to a sequence.



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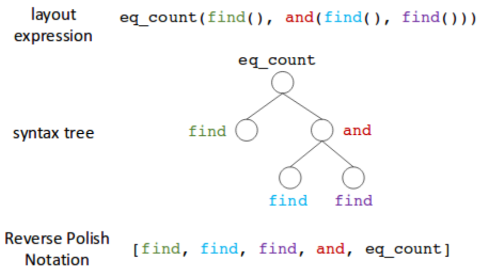

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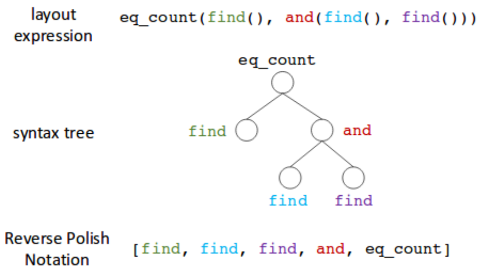

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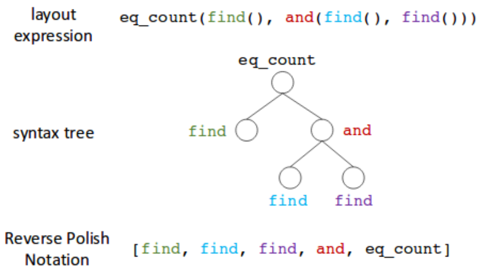

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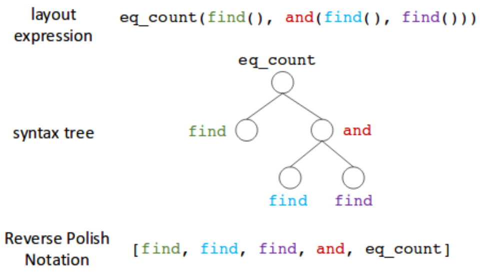

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- At each step the text features passed to the module are the attended features obtained from the LSTM

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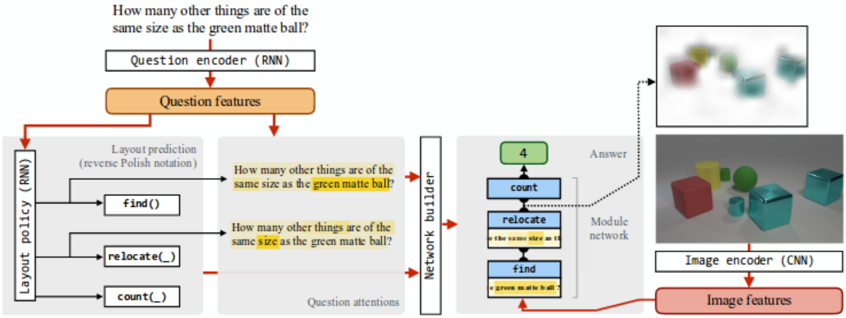
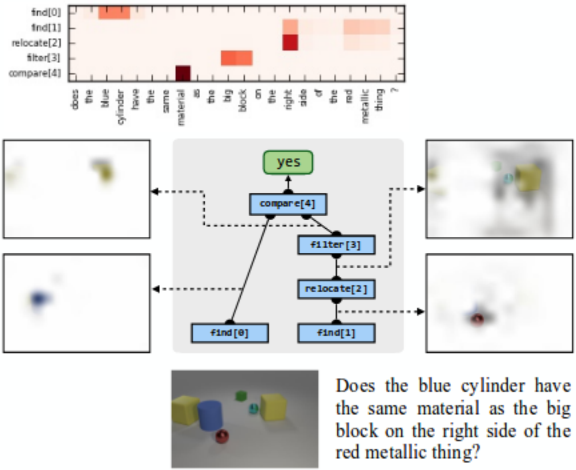
Architecture overview:



N2NMNs

Example:



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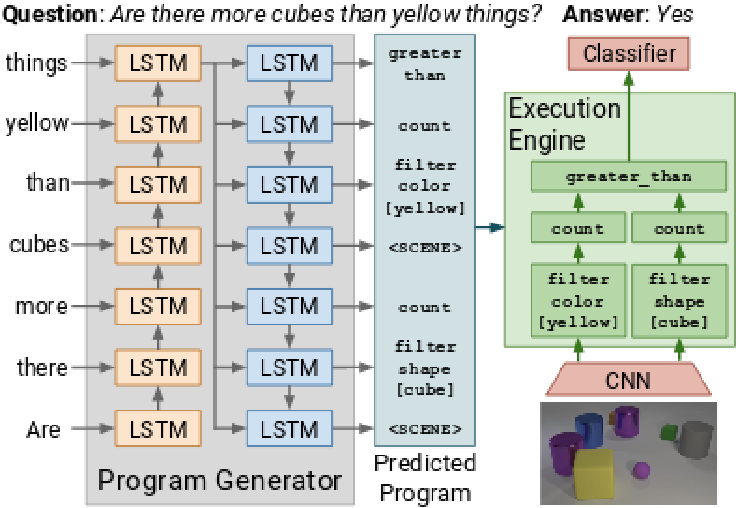

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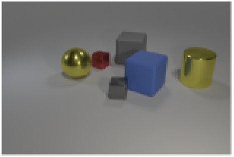
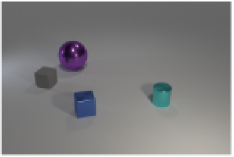
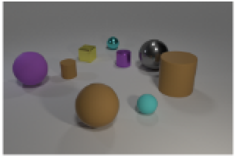


Q: *Is there a blue box in the items?* **A:** *yes*



Q: *What shape object is farthest right?* **A:** *cylinder*



Q: *Are all the balls small?* **A:** *no*

Predicted Program:

```
exist
filter_shape[cube]
filter_color[blue]
scene
```

Predicted Answer:
✓ *yes*

Predicted Program:

```
query_shape
unique
relate[right]
unique
filter_shape[cylinder]
filter_color[blue]
scene
```

Predicted Answer:
✓ *cylinder*

Predicted Program:

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equal_size
query_size
unique
filter_shape[sphere]
scene
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unique
filter_shape[sphere]
filter_size[small]
scene
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Predicted Answer:
✓ *no*

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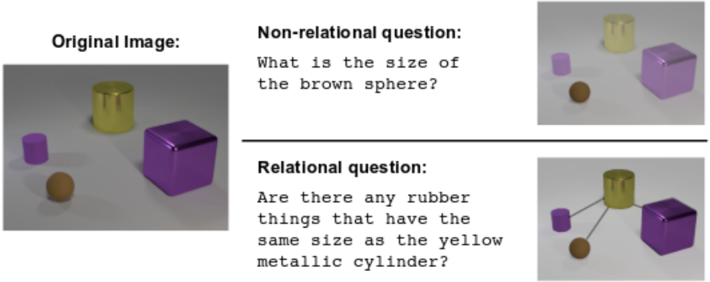

Relational networks

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- Not knowing the actual relations, RNs must learn to infer the existance of relations.

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- **RNs operate on a set of objects** RNs are order invariant of object sequence. This invariance ensures that the RN's output contains information that is generally representative of the relations that exist in the object set.

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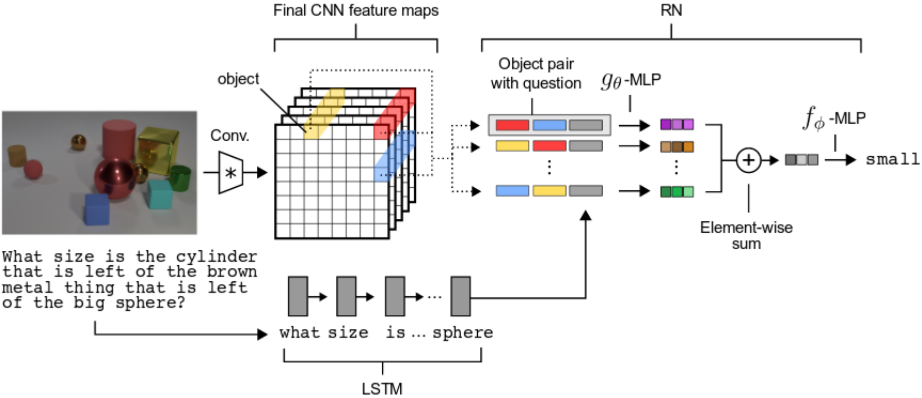

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- The paper introduces 2 tasks: We defined two separate tasks: 1) infer the existence or absence of connections between balls when only observing their color and coordinate positions across multiple sequential frames, and 2) count the number of systems on the table-top.

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- An MLP with comparable number of parameters was unable to perform better than chance for both tasks.

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- Demonstrate the RN's rich capacity for structured reasoning even with unstructured inputs and outputs.

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- FiLM can be thought of as a generalization of Conditional Normalization, which has proven highly successful for image stylization.

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- It is a scalable and computationally efficient conditioning method.

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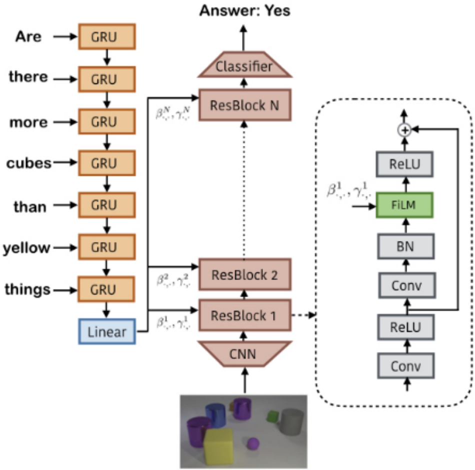
- The visual pipeline extracts 128 14×14 image feature maps from a resized, 224×224 image input using CNN.
- The CNN architecture is similar to ResNet-101 with a added FiLM module. It was pretrained on Image-Net.
- Model is trained end-to-end from scratch with Adam (learning rate 3e-4), weight decay (1e-5), batch size 64,and batch normalization and ReLU throughout FiLM-ed network.

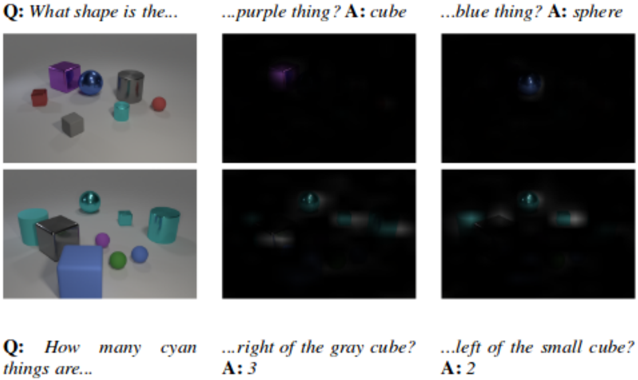
FiLM



Answer: Yes
Are
there
more
cubes
than
yellow
things
GRU
Linear
Classifier
ResBlock N
ResBlock 2
ResBlock 1
CNN
ReLU
FiLM
BN
Conv
ReLU
Conv

FiLM

- Images reveal that the FiLM model predicts using features areas near answer-related or question-related objects.



FiLM

Model	Overall	Count	Exist	Compare numbers	Query	Compare attribute
Human	92.6	86.7	96.6	86.5	95.0	96.0
LSTM	46.8	41.7	61.1	69.8	36.8	51.8
CNN+RNN	52.3	43.7	65.2	67.1	49.3	53.0
SA	68.5	52.2	71.1	73.5	85.3	52.3
NMN	72.1	79.3	52.5	71.4	78.9	78
N2NMN	83.7	85.7	68.5	83.7	90	88.7
PG	96.9	97.1	92.7	98.6	98.1	98.9
RN	95.5	90.1	97.8	93.6	97.9	97.1
FiLM	97.7	94.3	99.1	96.8	99.1	99.1

We saw 3 different innovative ways to achieve super human performance in this task.

Thank You.