HOW TO REPRESENT RELATIONS

2018. 11. 14 Naver TechTalk SNU Datamining Laboratory Sungwon, Lyu Iyusungwon@dm.snu.ac.kr

CONTENTS

- I. Introduction
- 2. Relational Inductive Bias
- 3. Relational Network
- 4. Follow-up research
- 5. SARN: Sequential Attention Relational Network
- 6. Conclusion

DEEPEST



- SNU (Based) Deep Learning Society Research, Project, Study, Competition, Discussion EE, CS, MD, IE & Naver, Kx, Sx etc Every Saturday 3PM
 - http://deepest.ai/

Projects

- Bayesian DeepLearning
- Disentangled Representation in Audio •
- Language generation using discrete latent • variable
- RL Start
- Video Super Resolution
- Trends in RNN
- PRML Study

DEEPEST

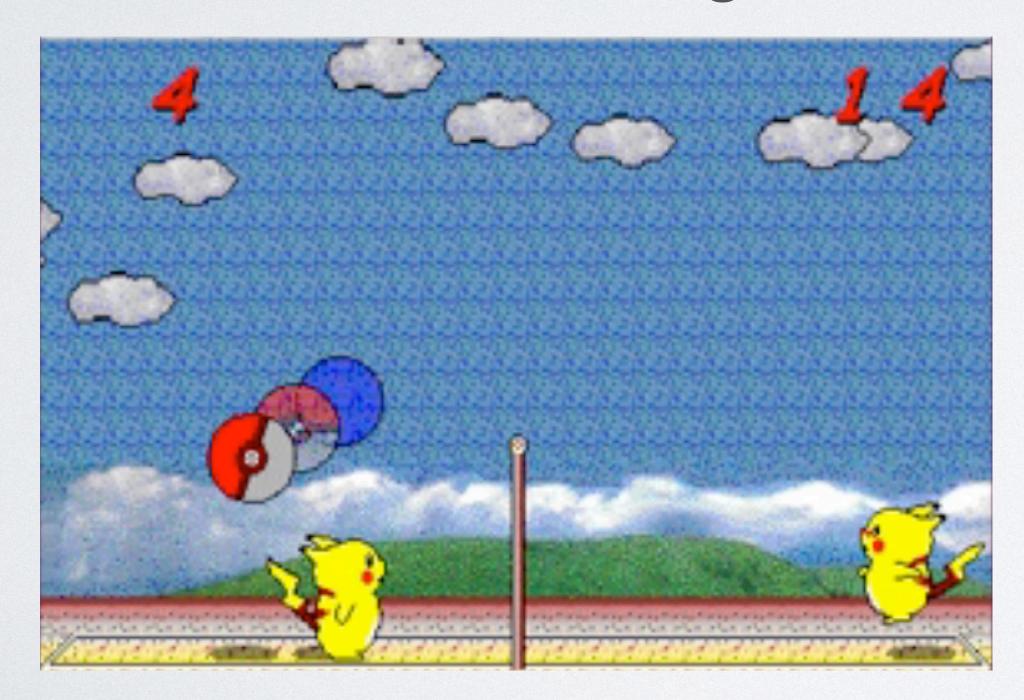
Hosting Topics

Neural Architecture Search Flow-based generative model (NICE, Real NVP, Glow) Breaking Illusion on 'PSNR' Engineering Reinforcement Learning ICML Review High Resolution Variational Auto Encoder: Beyond Pixelwise Loss Weakly-supervised Semantic Segmentation Co-Training of Audio and Video Representations Python Optimization Methods unsupervised domain adaptation 3 Issues on Current Neural Networks Speaker recognition An overview of image enhancement Introducing Magenta Neo-backpropagation, Part 2 my painful climb to score>0.80 Image to Image translation poisoning attack Visual Domain Adaptation FloWaveNet Music Generation using MIDI



My Projects •

• Training Pickachu Volleyball with Reinforcement Learning



DEEPEST

DeepClear (2018 Digital Health • Hackathon)





Sungwon Lyu

- SNU IE Data-Mining Laboratory
- https://lyusungwon.github.io/
- Interested Field •
 - Deep Learning Engineering •
 - Representation Learning with deep learning •

SPEAKER

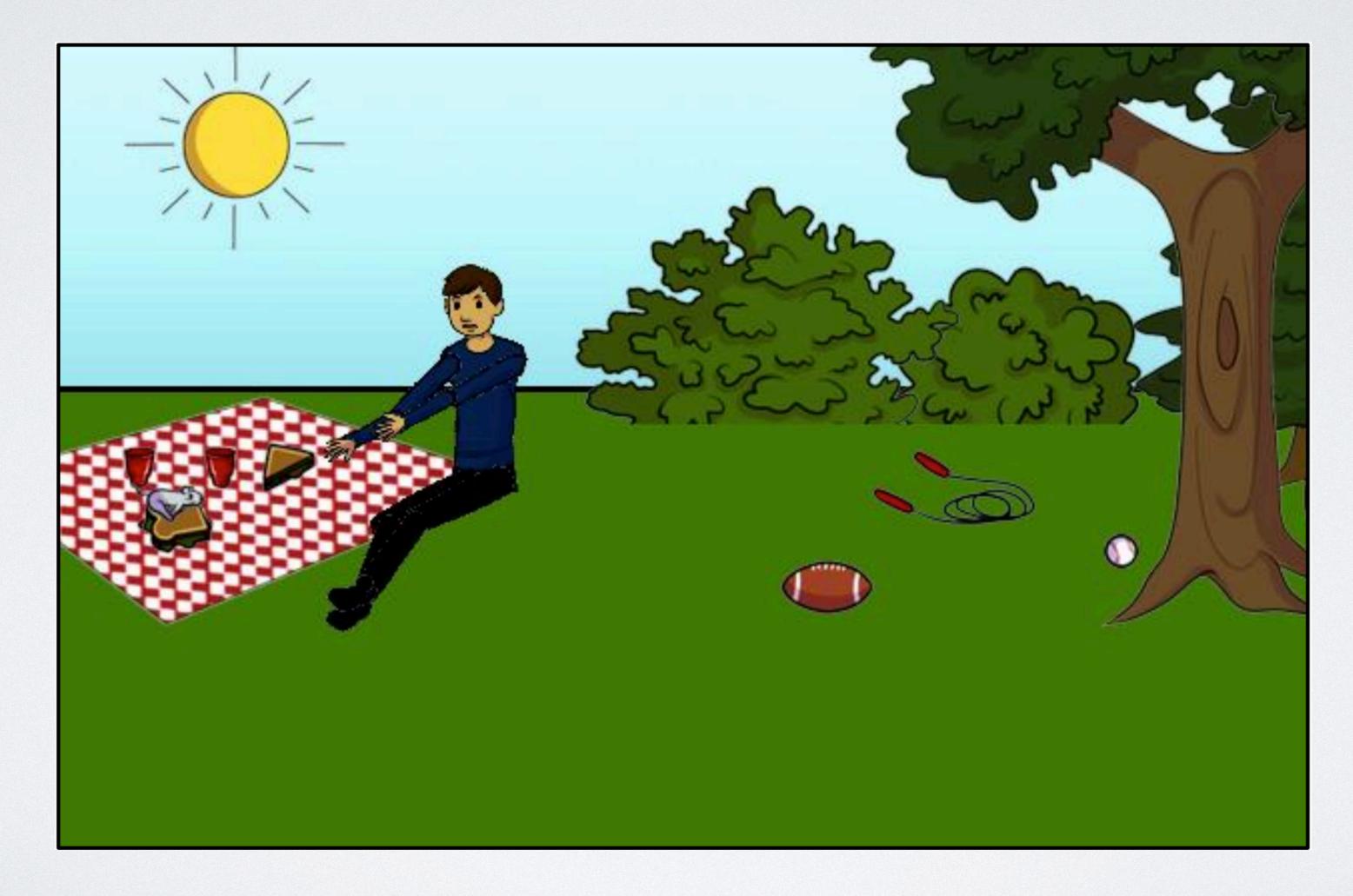
REPRESENTATION

Representation •

- Vector form (for Neural Network)
- Task Specific
- Examples
 - (beta) VAE...
 - Audio(Raw Audio) : STFT, MFCC... •
 - Text?
 - Relation? •

Image(C-H-W) : The last block of Classifier (Imagenet), latent Variable of





Source: Agrawal, Aishwarya, et al. "Vqa: Visual question answering." arXiv preprint arXiv: 1505.00468 (2015).

RELATION

RELATIONAL REASONING

Relational Reasoning

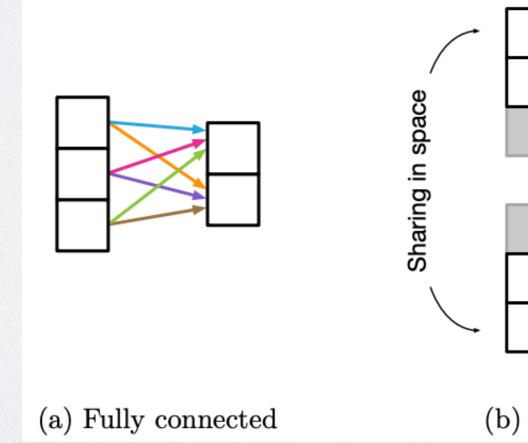
- Relational reasoning involves manipulating structured representations of entities • and relations, using rules for how they can be composed.
- Entity: An element with Attributes
 - Physical objects with a size and mass •
- Relation: A property between entities •
 - Same size as, heavier than, distance from... •
- Rule: Function that maps entities and relations to other entities and relations •
 - Is entity X heavier than entity Y?



INDUCTIVE BIAS

(or interpretation) over another, independent of the observed data.

Entities	Relations	Rel. inductive bias	Invariance
Units	All-to-all	Weak	-
Grid elements	Local	Locality	Spatial translation
Timesteps	Sequential	Sequentiality	Time translation
Nodes	Edges	Arbitrary	Node, edge permutations
		Sharing in time	
connected	(b) Convo	lutional	(c) Recurrent
	Units Grid elements Timesteps Nodes	Units Grid elements Timesteps Nodes Units Edges Edges	Units All-to-all Weak Grid elements Local Locality Timesteps Nodes Edges Arbitrary



Source: Battaglia, Peter W., et al. "Relational inductive biases, deep learning, and graph networks." arXiv preprint arXiv: 1806.01261 (2018).

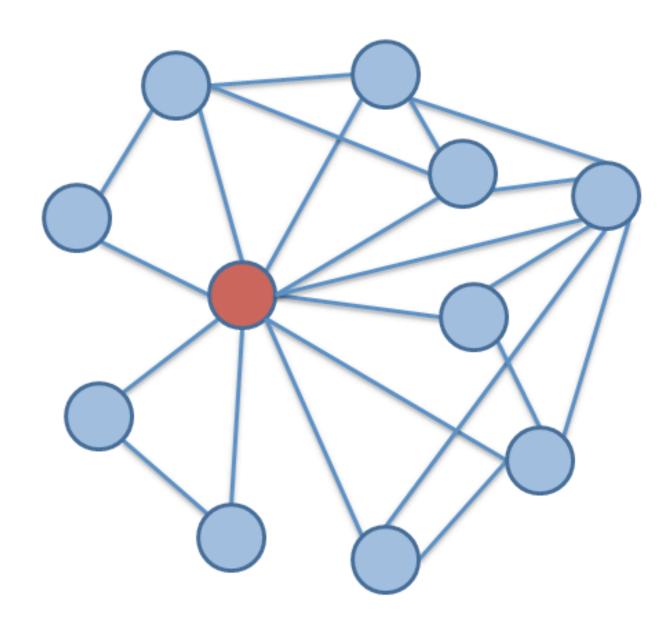
• An inductive bias allows a learning algorithm to prioritize one solution



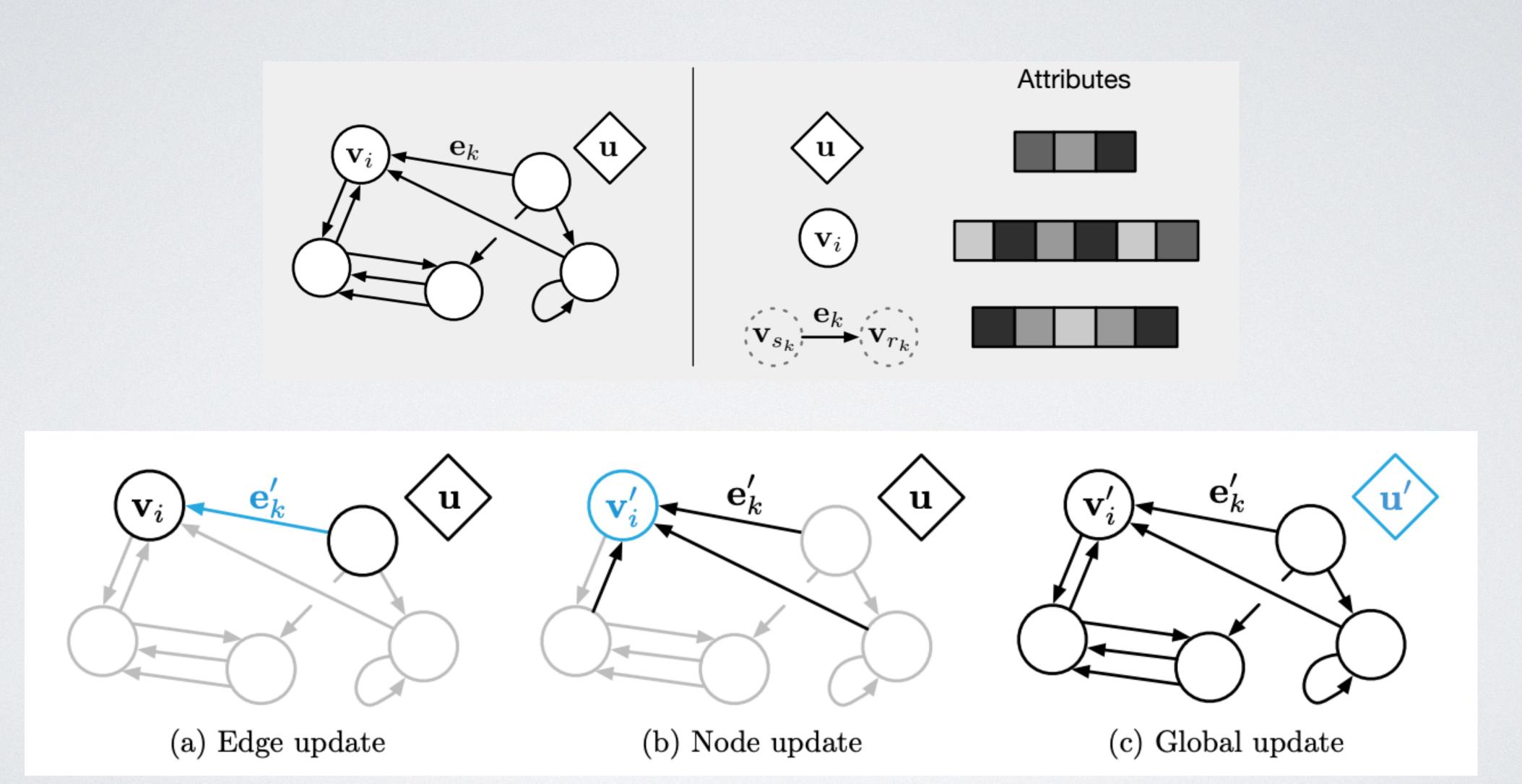
GRAPHS

• Graphs

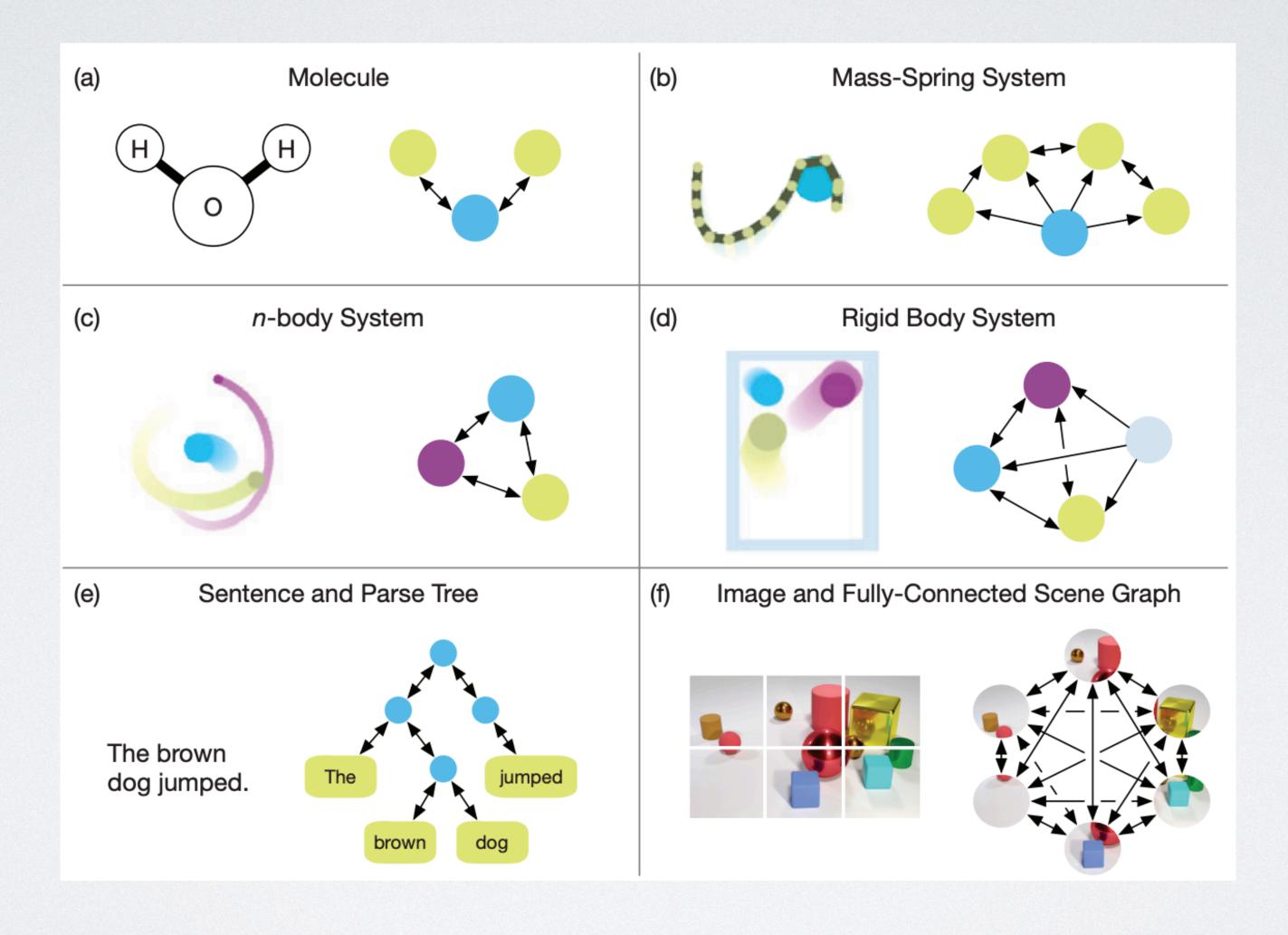
- Visual Representation for (clearly defined) entities and relations
- **REUSE** of entities and relations (Combinatorial Generalization)



GRAPH NETWORKS

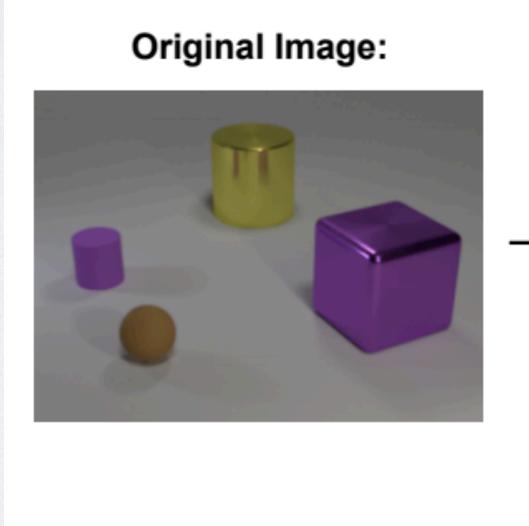


GRAPH NETWORKS



• CLEVR

- Cubes are gray, blue, brown, or yellow •
- Cylinders are red, green, purple, or cyan
- Spheres can have any color



Non-relational question:

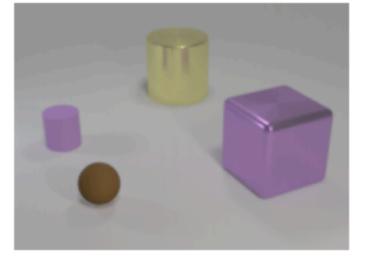
What is the size of the brown sphere?

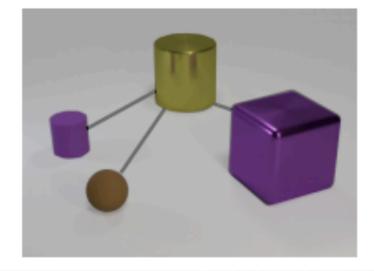
Relational question:

Are there any rubber things that have the same size as the yellow metallic cylinder?

Source: Johnson, Justin, et al. "CLEVR: A diagnostic dataset for compositional language and elementary visual reasoning." Computer Vision and Pattern Recognition (CVPR), 2017 IEEE Conference on. IEEE, 2017.









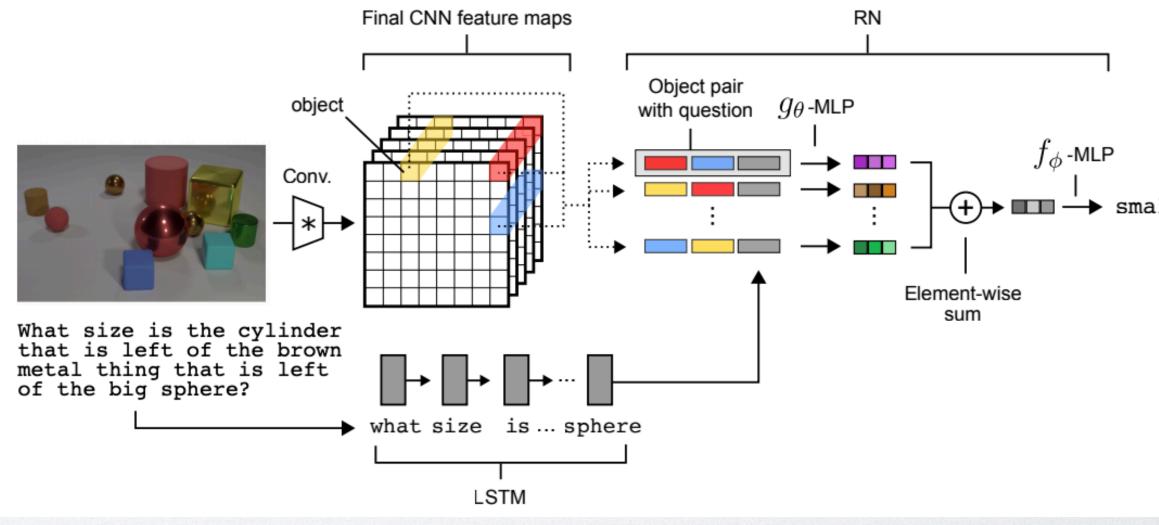
RELATIONAL NETWORK

Relational Network

$$\operatorname{RN}(O) = f_{\phi}\left(\sum_{i,j} g_{\theta}(o_i, o_j)\right)$$

- Objects: each channel of middle
 layer of Conv
- g-theta(relations), f-phi: MLP
- Order Invariance among relations
- Capture all possible relations
- Reuse of relations

Source: Santoro, Adam, et al. "A simple neural network module for relational reasoning." Advances in neural information processing systems. 2017.





RELATIONAL NETWORK

• Results

Model	Overall	Count	\mathbf{Exist}	Compare Numbers	Query Attribute	Compare Attribute
Human	92.6	86.7	96.6	86.5	95.0	96.0
Q-type baseline	41.8	34.6	50.2	51.0	36.0	51.3
LSTM	46.8	41.7	61.1	69.8	36.8	51.8
CNN+LSTM	52.3	43.7	65.2	67.1	49.3	53.0
CNN+LSTM+SA	68.5	52.2	71.1	73.5	85.3	52.3
CNN+LSTM+SA*	76.6	64.4	82.7	77.4	82.6	75.4
CNN+LSTM+RN	95.5	90.1	97.8	93.6	97.9	97.1

* Our implementation, with optimized hyperparameters and trained fully end-to-end.

Source: Santoro, Adam, et al. "A simple neural network module for relational reasoning." Advances in neural information processing systems. 2017.

RELATIONAL NETWORK

- Questions:
- All possible relations
 - A-B, A-C, A-D, B-C, B-D, C-D
 - $A \rightarrow C \rightarrow B \rightarrow A \rightarrow D$

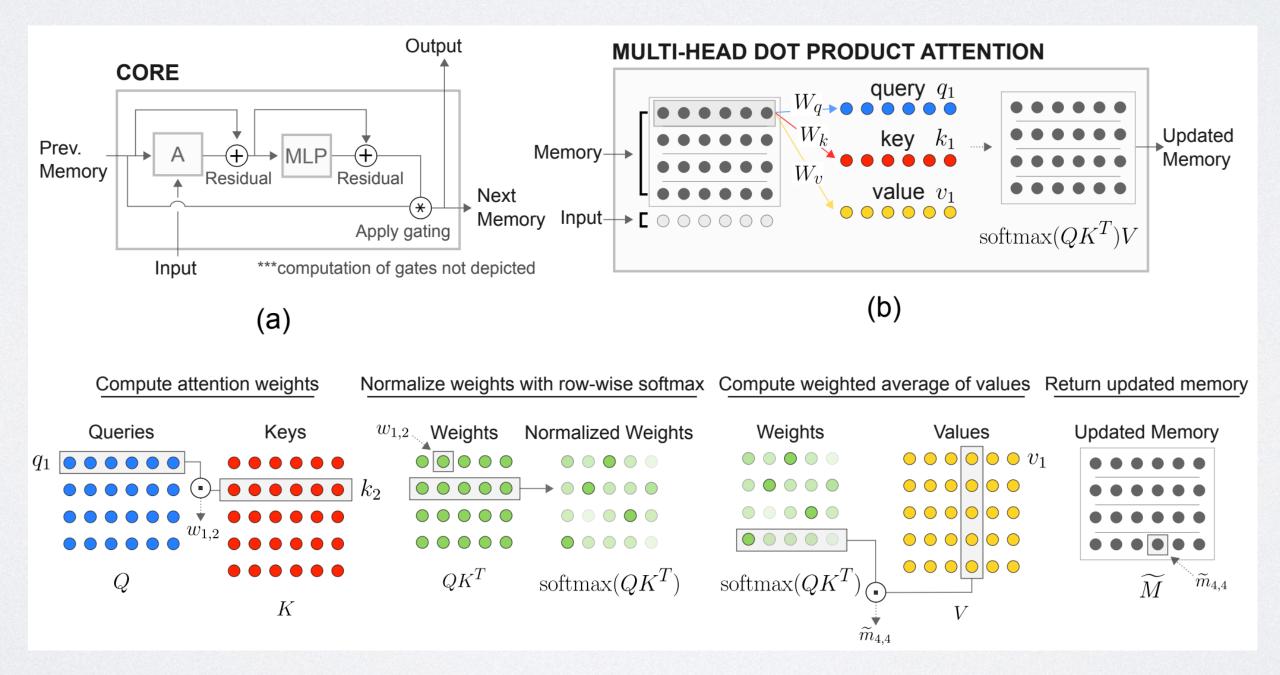
Source: Santoro, Adam, et al. "A simple neural network module for relational reasoning." Advances in neural information processing systems. 2017.

• "There is a cube that is on the left side of the large shiny object that is on the right side of the big red ball; what number of cubes are to the right of it?"



RELATIONAL NETWORK - FOLLOW UPS (1)

- Relational Recurrent Neural Network •
 - MHDPA module for relation

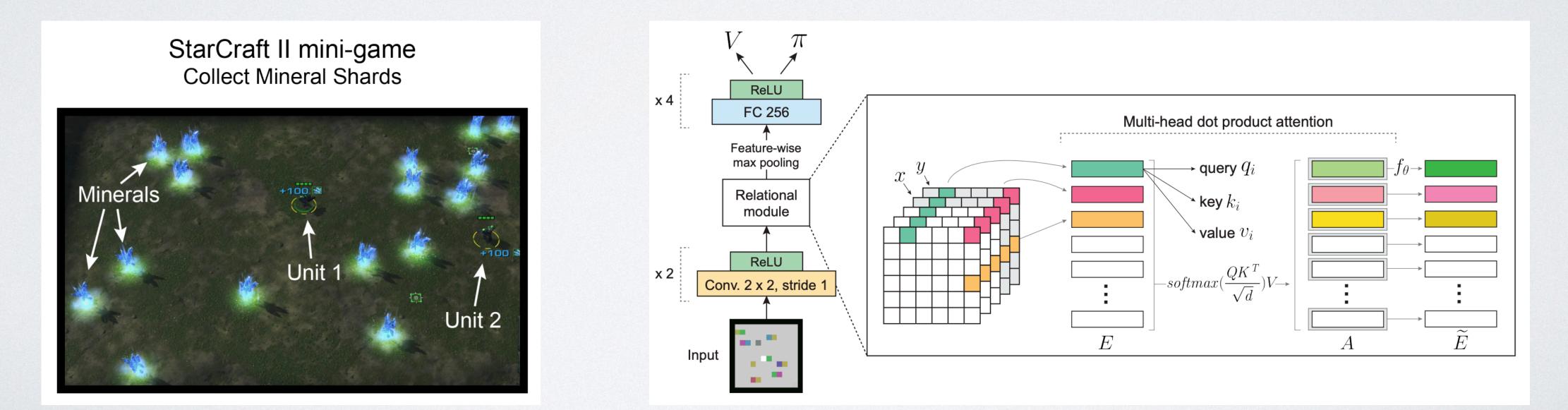


Source: Santoro, Adam, et al. "Relational recurrent neural networks." arXiv preprint arXiv: 1806.01822 (2018).

Relations among memory slots in memory augmented neural network

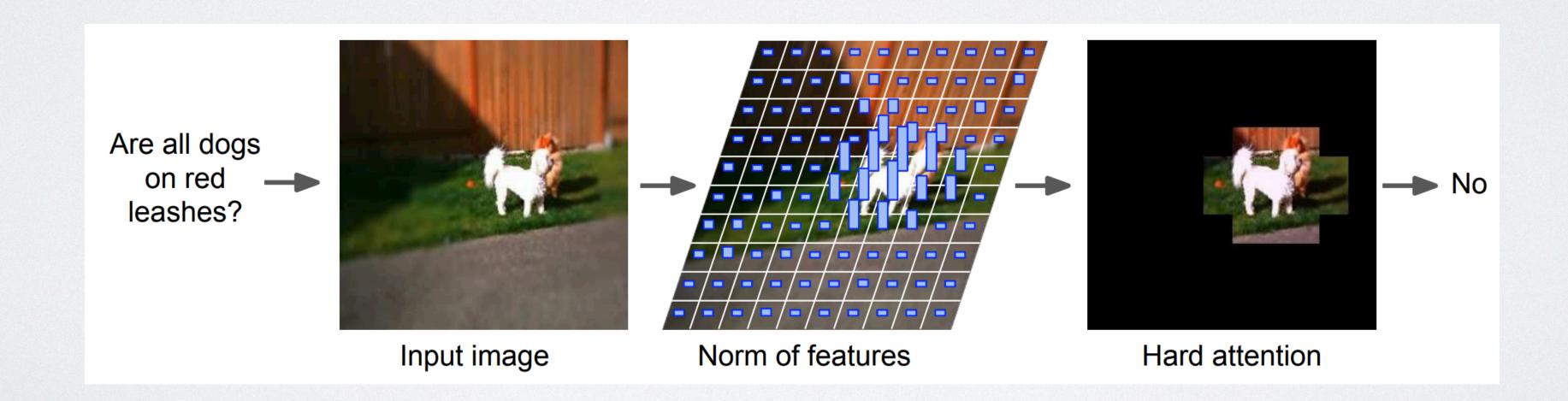
RELATIONAL NETWORK - FOLLOW UPS (2)

- Relational Deep Reinforcement Learning
 - MHDPA module for relation
 - Relational Module for reinforcement learning



RELATIONAL NETWORK - FOLLOW UPS (3)

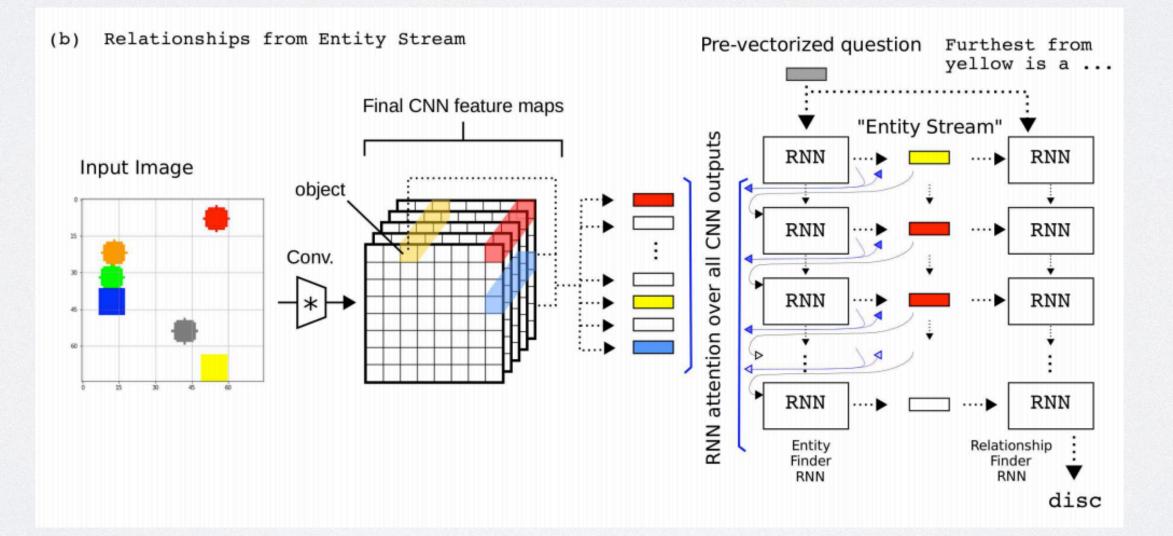
- Learning Visual Question Answering by Bootstrapping Hard Attention
 - MHDPA module for relation
 - Reduce the number of objects with hard attention



Source: Malinowski, Mateusz, et al. "Learning visual question answering by bootstrapping hard attention." Proceedings of the European Conference on Computer Vision (ECCV). 2018.

RELATIONAL NETWORK - FOLLOW UPS (4)

- Relationships from Entity Stream
 - LSTM to select Entity
 - LSTM to find Relationships
 - Reduced the number of pairings

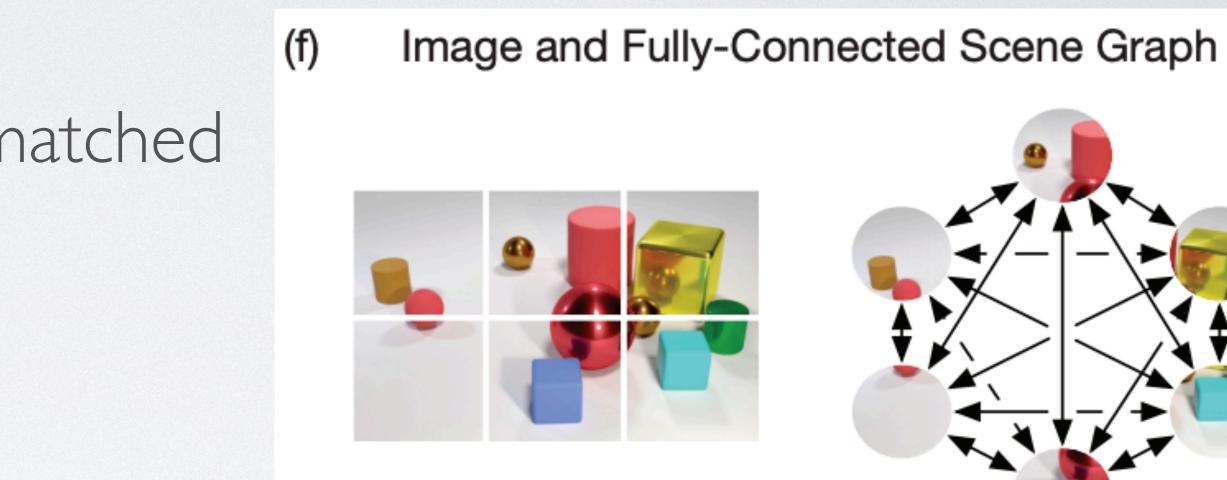


Source: Andrews, Martin, Red Dragon AI, and Sam Witteveen. "Relationships from Entity Stream."

LIMITATION OF RN

- Are they good representations of relations?
 - Objects? •
 - Fragmented / Number not matched
 - Fully Connected?
 - n^2
 - Interpretable?
 - rather from the absence.

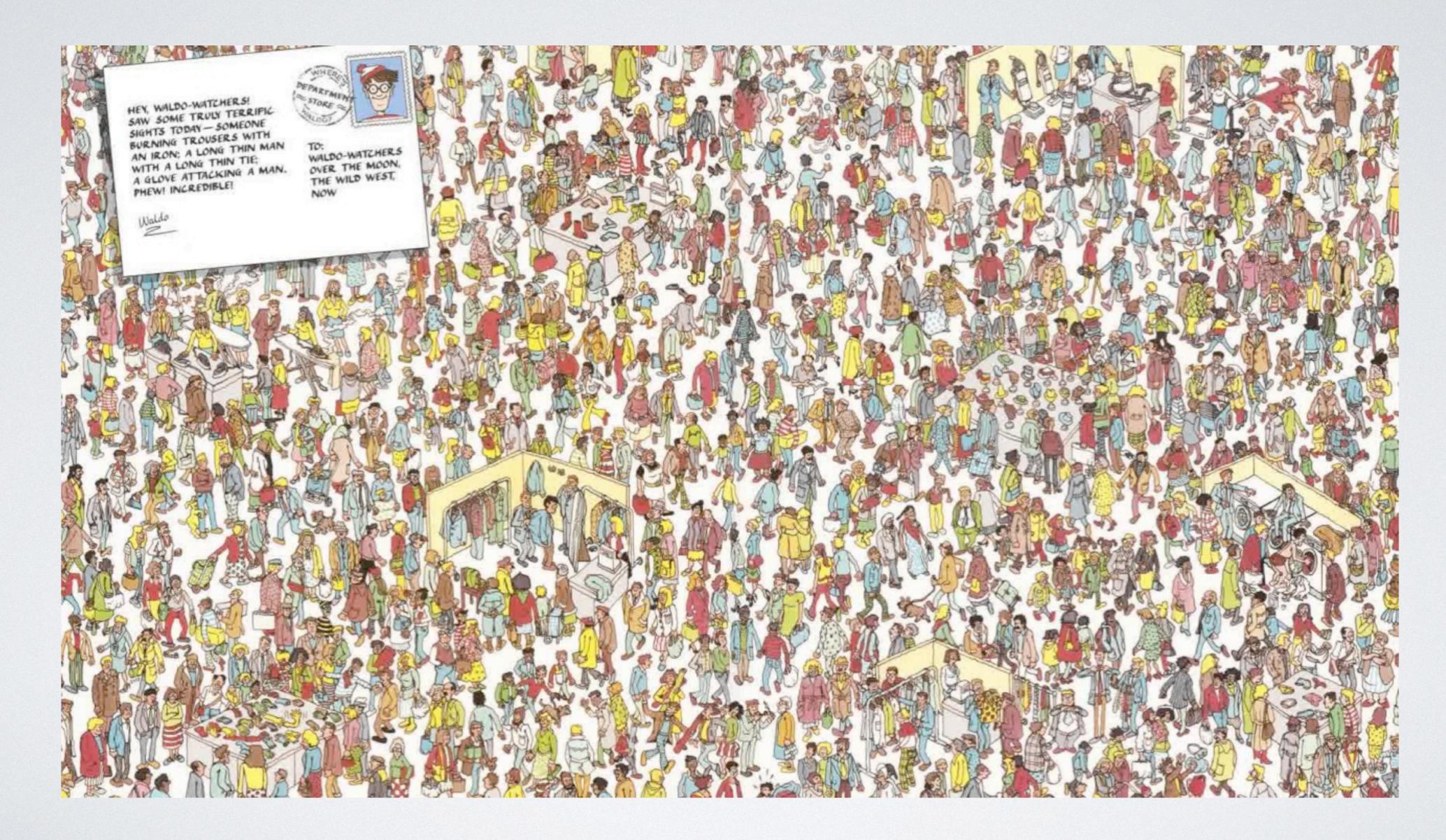
Source: Battaglia, Peter W., et al. "Relational inductive biases, deep learning, and graph networks." arXiv preprint arXiv: 1806.01261 (2018).



• Relational inductive bias does not come from the presence of something, but



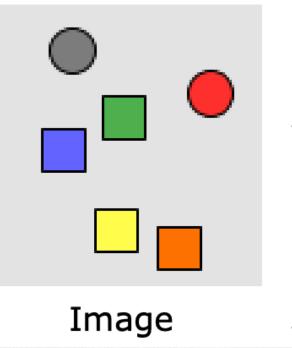
LIMITATION OF RN



SORT-OF-CLEVR

Sort of CLEVR

- 6 Objects with unique color of red, blue, green, orange, yellow, gray • • A randomly chosen shape (square or circle).
- Relational question
 - Color / shape of closest / furthest object from certain color •
 - Number of object of the same shape with certain color •

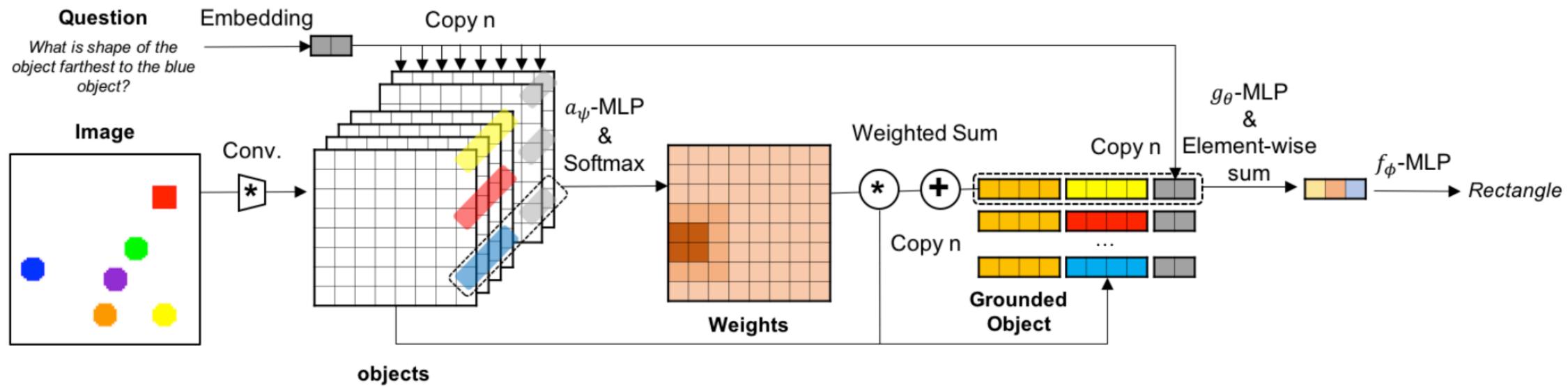


- **Non-relational question** Q: What is the shape of the gray object? A: circle

- **Relational question** Q: What is the shape of the object that is furthest from the gray object?
- A: square

SARN: Sequential Attention Relational Network

$$a_i = a_\psi(o_i, q) \quad i = 1, \cdots$$
 $ro = \sum_{i=1, \cdots, n} a_i * o_i$
 $g_{ hetaoutput} = \sum_{i=1, \cdots, n} g_ heta(o_i, q)$



\cdots, n	(1)
	(2)
(ro,q)	(3)



Result •

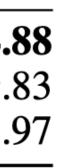
• Sort-of-clevr

Table 1: Test accuracy					
model	overall	non-rel	rel		
SARN	96.73	99.84	94.88		
RN	93.56	99.81	89.83		
base line	89.07	97.58	83.97		

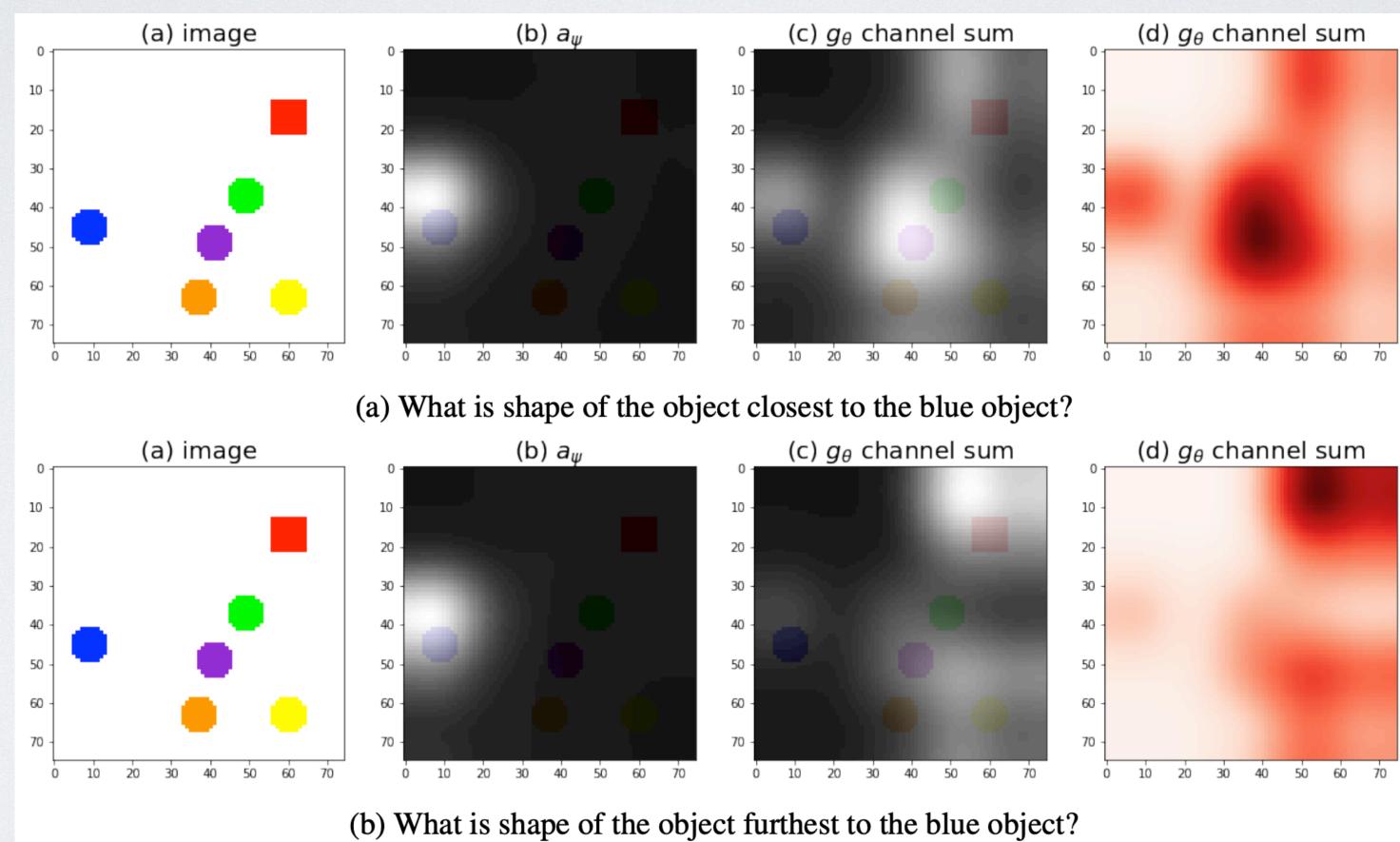
Table 2: Test accuracy: non-relational questions						
model	horizontal	vertical	shape	non-rel		
SARN	99.92	99.67	99.92	99.84		
RN	99.92	99.67	99.83	99.81		
base line	96.33	96.58	99.83	97.58		

Table 3: Test accuracy: relational questions

			•			
model	cl_col	cl_sh	fur_col	fur_sh	count	rel
SARN RN base line	86.33	93.92 88.42 88.50	84.17	90.25	99.67 100 99.33	89.



Result •



Robustness on image size and object sparsity

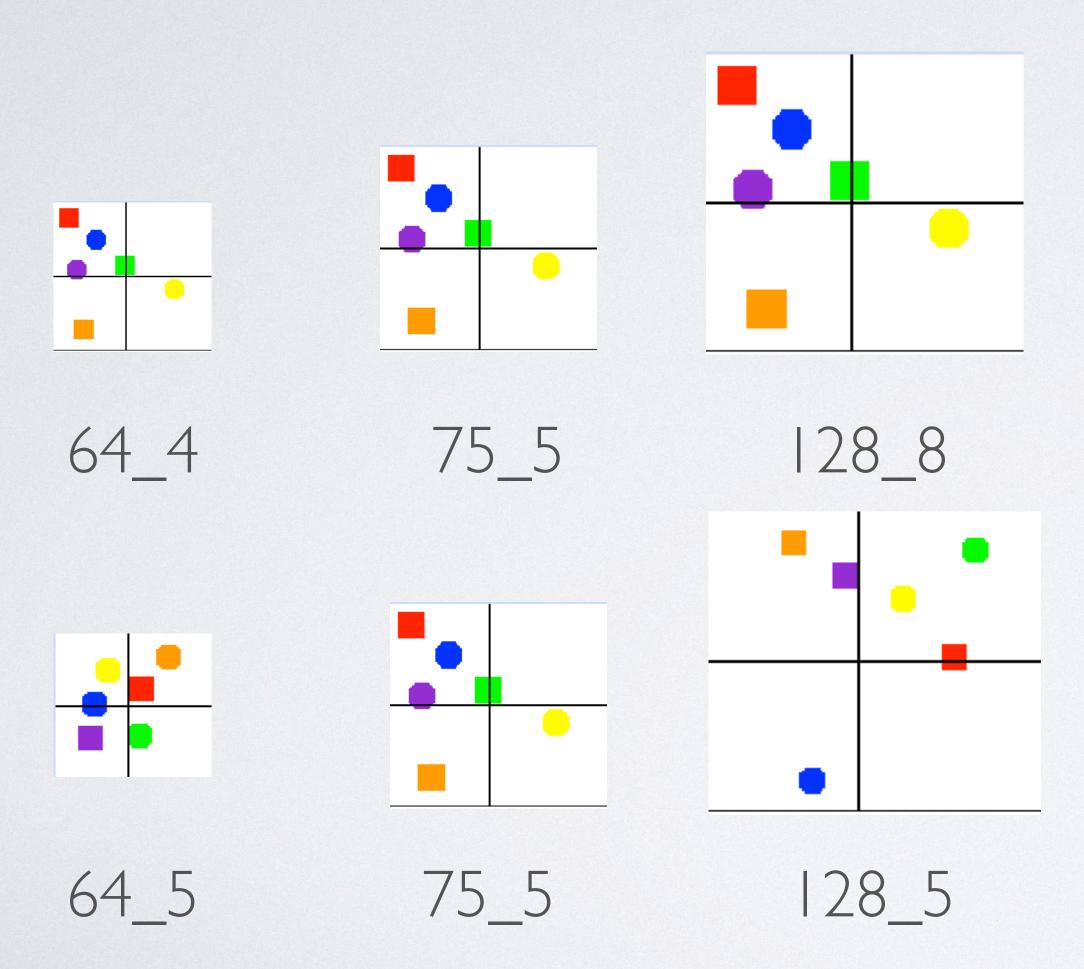
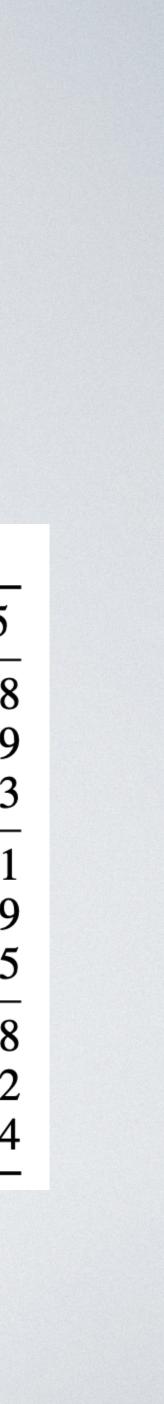


Table 4: image size-object size						
		64_4	128_8	64_5	128_5	
SARN	non-rel rel total	0.9970 0.8949 0.9345	0.9999 0.9440 0.9650	0.9948 0.8370 0.8970	0.9988 0.8669 0.9163	
RN	non-rel rel total	0.9944 0.8415 0.8989	0.9981 0.8207 0.8872	0.9964 0.8430 0.9005	0.9931 0.7719 0.8555	
baseline	non-rel rel total	0.9941 0.8120 0.8803	0.9972 0.8625 0.9130	0.9933 0.8163 0.8827	0.9978 0.8532 0.9074	



STRENGTH OF SARN

I. Computation efficiency

• n^2 -> n

2. Better Performance

3. Interpretability

FUTURE WORKS

- Lack of Chaining (yet!)
 - Memory
- Reuse of entities
 - A->C->B->A->D

CONCLUSION

- - Identify Entities (Modularity)
 - Attention / Conditional CNN •
 - **Relations** are defined from relational reasoning
 - MLP / Self-attention
 - Chaining •
 - Sum / LSTM?

• How to represent relations? = How to form a reasonable graph from image?