Iterated learning for emergent systematicity in VQA


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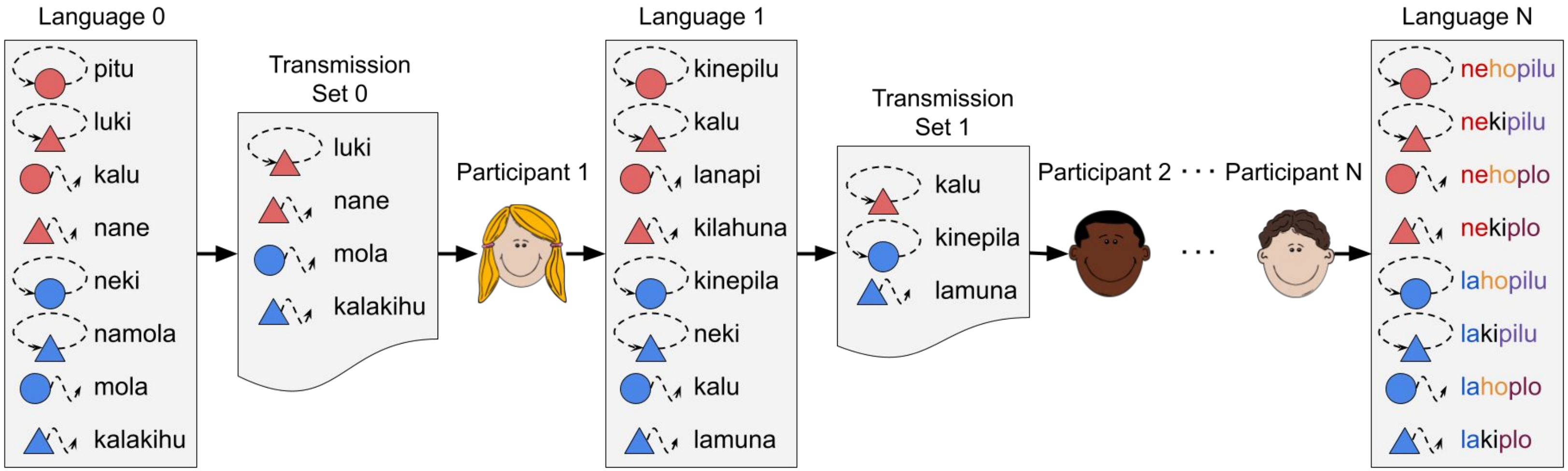
Background

Iterated learning (IL)

- [Kirby et al., 2014] The process by which a behavior arises in one individual
  - Through induction, based on observations of behavior in another individual
    - who acquired that behavior in the same way

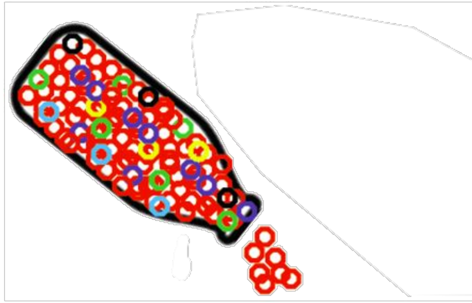
- Leads to the emergence of compositionality in human languages

Iterated learning (IL)



(based on Kirby et al., 2008; 2014)

Learning bottleneck



- Need to learn an **highly expressive** language
  - Through **limited supervision**

- Language properties likely to pass through this bottleneck become universal
  - Compositional rules are more likely to survive the transmission (Kirby, 2001)
    - Easier to learn
    - Faster to learn

  - Language properties depend on prior / inductive bias of agents

Iterated learning in machine learning

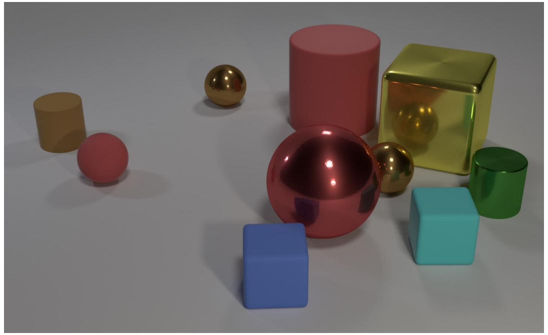
- IL in machine learning has stayed close to its cognitive science roots
    - Most of the work involves agents playing very simple referential games

      (Guo et al., 2019; Li et al., 2019; Cogswell et al., 2019; Dagan et al., 2020; Ren et al., 2020)

- **Claim**: Learning bottleneck is a fundamental way to recover structure

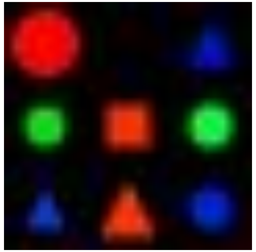
- We demonstrate this in a more complex task of **visual question-answering**

Visual question-answering (VQA)



(Image taken from CLEVR (Johnson et al., 2017))

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



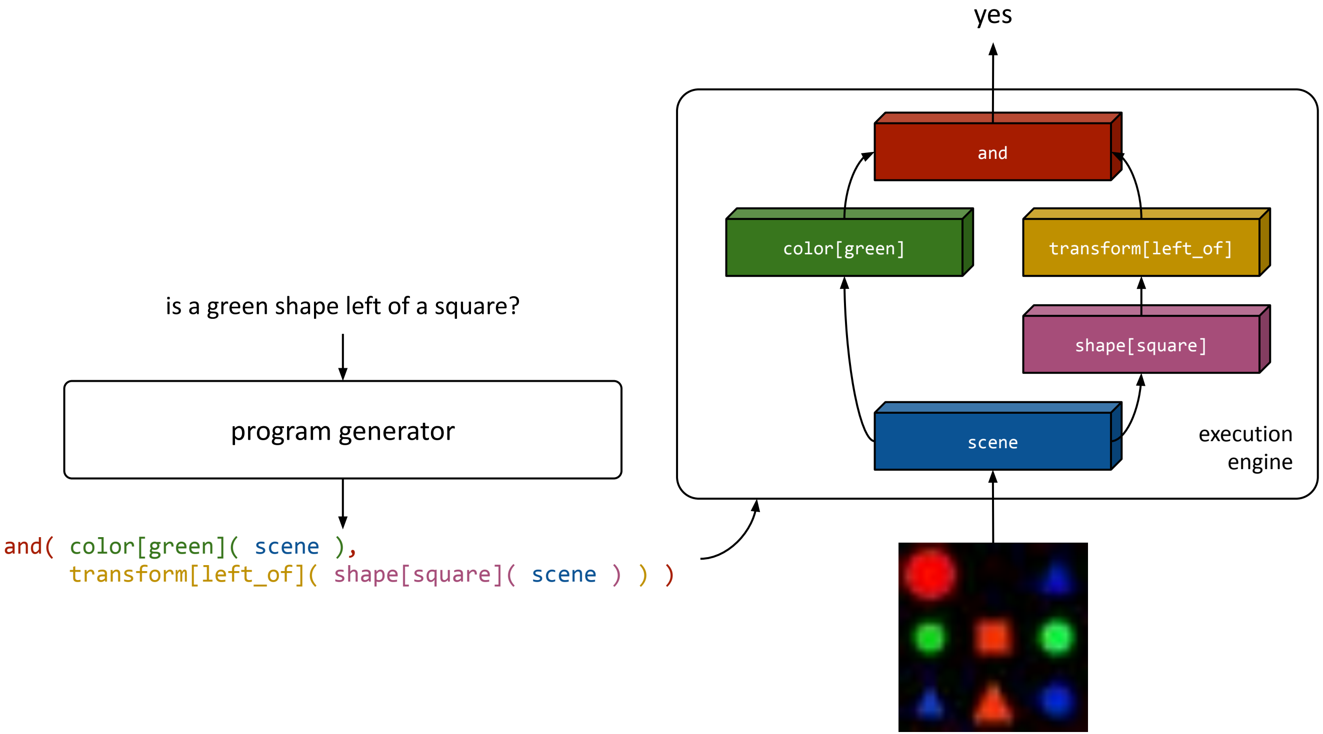
(Image taken from SHAPES (Andreas et al., 2016))

Q: Is a green shape left of a square?

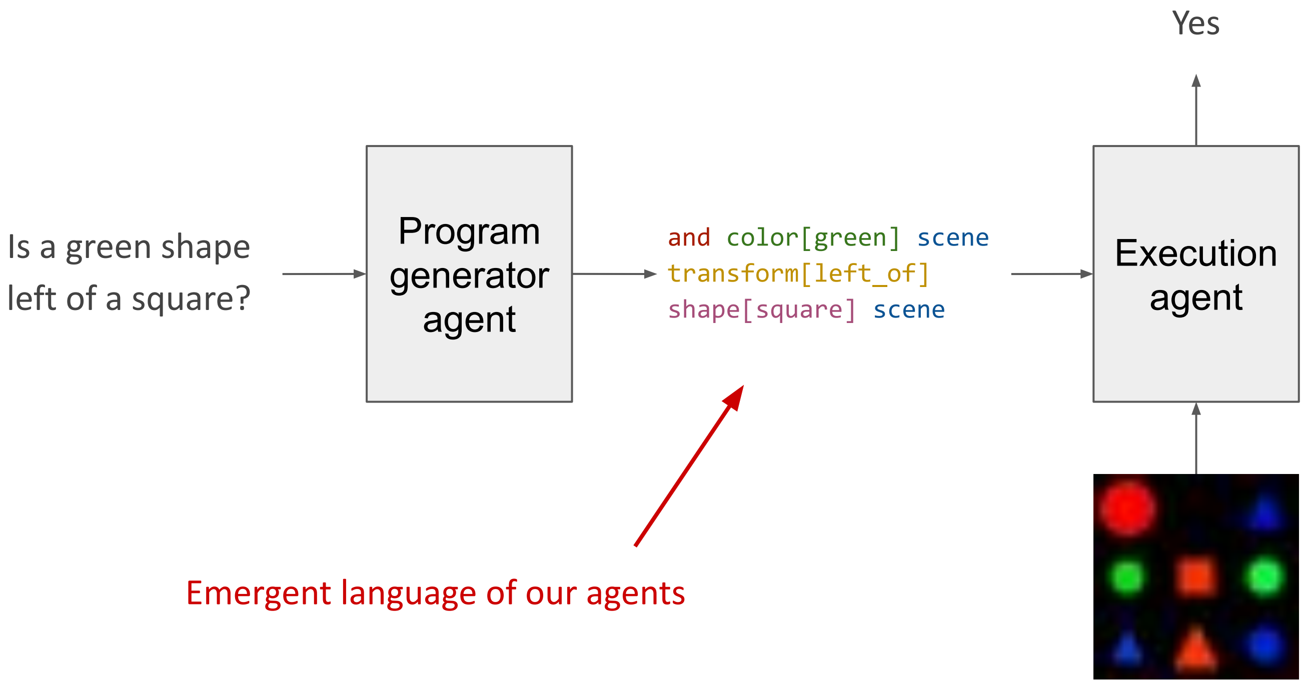
Program:

```
and( color[green]( scene ),
     transform[left_of]( shape[square]( scene ) ) )
```

Neural module networks (NMNs)



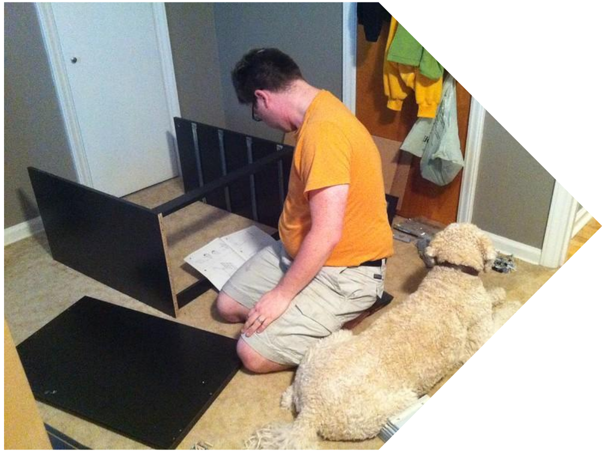
Language of reasoning in a VQA game



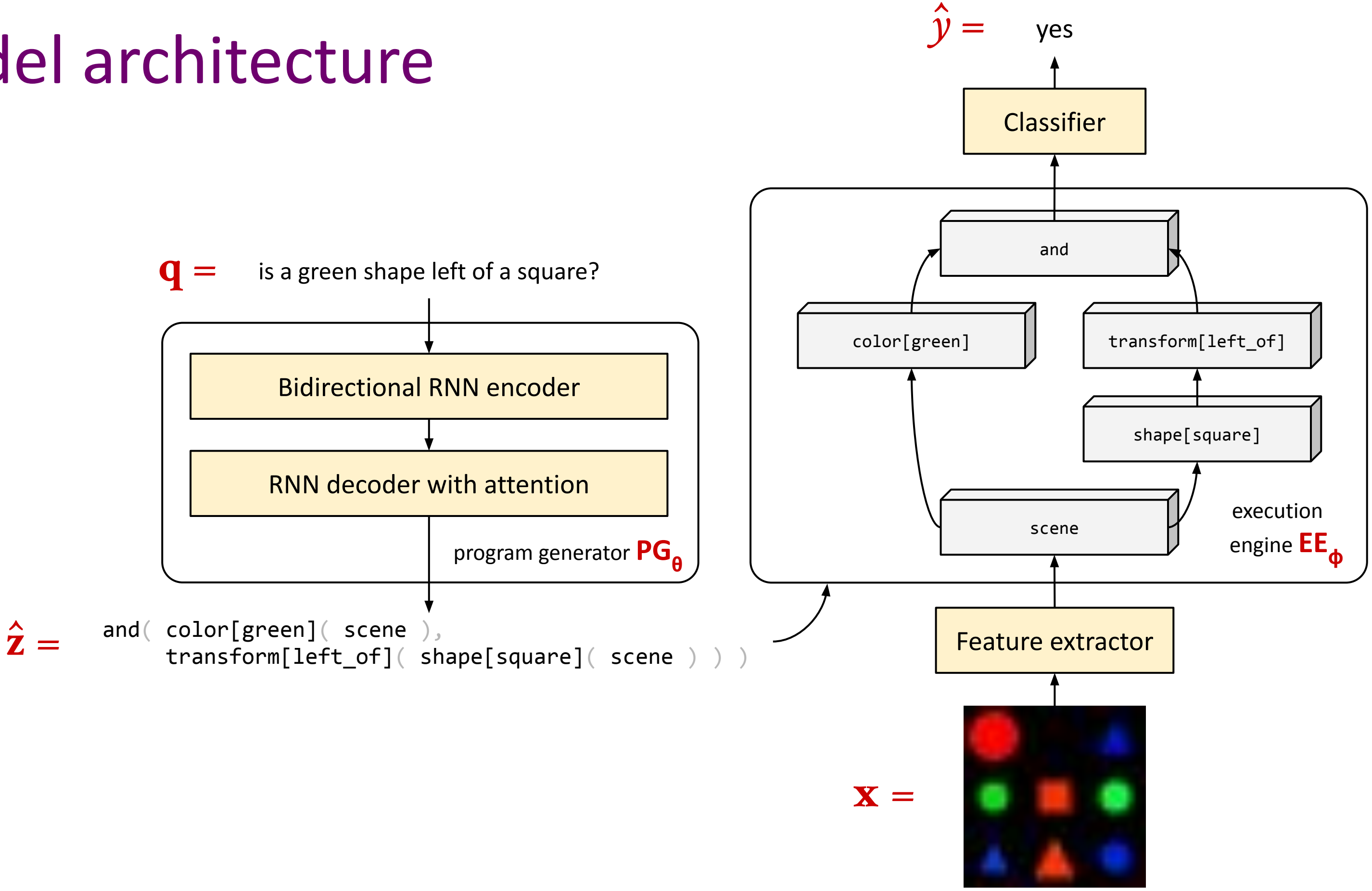
Goal: Systematic generalization

- NMNs exhibit compositionality given the *right layout*
  - NMNs can systematically generalize to SQOOP, where RelNet, FiLM, MAC fail (Bahdanau et al., 2018)
- **But**: The right layout does not emerge naturally
  - Bahdanau et al., 2018 needed to provide correct tree-structured layouts
  - Learned layouts only converged to be robust under a strong prior for the correct structure
- *Use IL to encourage structured layouts towards systematic generalization*

Method



Model architecture



Execution engine choices

	Shared module parameters	**Separate module parameters**
Tensor-valued input/output	Tensor-FiLM-NMN	Tensor-NMN
Vector-valued input/output	Vector-NMN	

Architecture from "Inferring and Executing Programs for Visual Reasoning" (Johnson et al., 2017b)

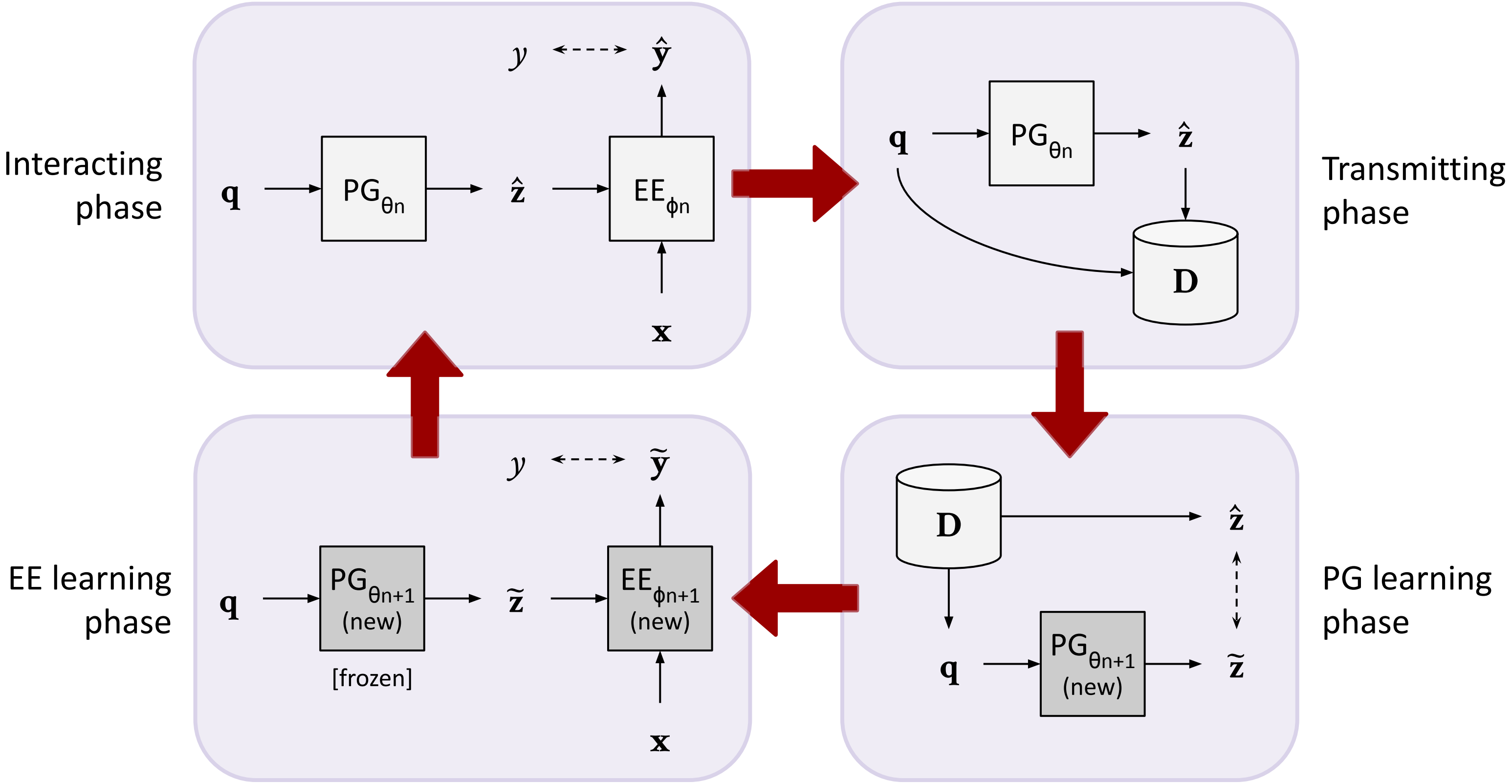
Architecture from "CLOSURE: assessing systematic generalization of CLEVR models" (Bahdanau et al., 2019)

New in this work (details in paper)

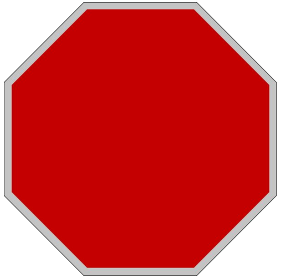
Simulating an inductive bias for structure

- Emergence of the right structure from scratch is still too hard
    - Johnson et al., 2017 needed to pre-train their model with ground-truth programs
- Use a small number of ground-truth programs for supervision
    - Supervision throughout training *simulates* an appropriate inductive bias for IL
    - More data efficient with IL than baselines

Iterated learning for NMNs



Learning bottleneck



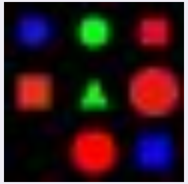
- Limit the length of the learning phases: **early stopping**
- Generally a sweet spot for the number of steps

- Program generator
  - *Too low:* Low confidence in utterances, high variance
  - *Too high:* Overfitting to transmitted data
- Execution engine
  - *Too low:* Gradients are high variance at the start of interacting phase
  - *Too high:* Overfitting to imperfect program generator

SHAPES-SyGeT (**SHAPES Sy**stematic **Ge**neralization **T**est)

Introducing a new split of the SHAPES dataset (Andreas et al., 2016)

- Evaluate systematic generalization
- Splits: Train, Val-IID, Val-OOD
  - Based on separate training and evaluation question templates



Q1 (train): Is a red shape above a green shape? — Is a *COLOR* shape *RELATIVE(1)* a *COLOR* shape?

Q2 (train): Is a *circle* left of below a *square*? — Is a *SHAPE RELATIVE(2)* a *SHAPE*?

Q3 (eval): Is a red shape left of below a green shape? — Is a *COLOR* shape *RELATIVE(2)* a *COLOR* shape?

Download from:
`https://github.com/ankitkv/SHAPES-SyGeT`

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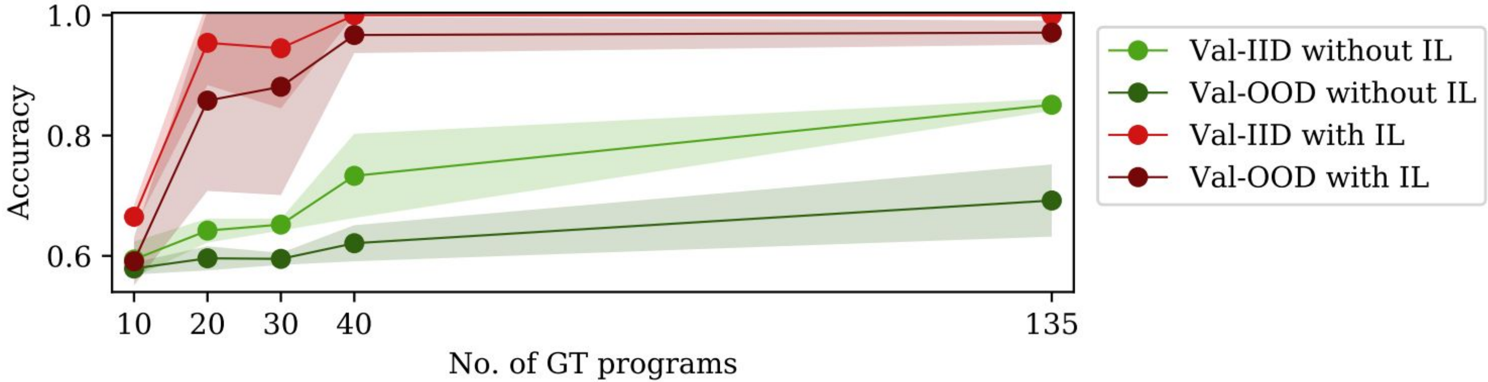
Experiments

Accuracy on SHAPES-SyGeT

Model	Val-IID		Val-OOD	
FiLM	0.720 ± 0.01		$\mathbf{0.609 \pm 0.01}$	
MAC	$\mathbf{0.730 \pm 0.01}$		0.605 ± 0.01	
	#GT 20	**#GT 135**	**#GT 20**	**#GT 135**
Tensor-NMN	0.645 ± 0.01	0.700 ± 0.01	0.616 ± 0.01	0.641 ± 0.03
Tensor-NMN+IL	0.756 ± 0.07	0.763 ± 0.04	0.648 ± 0.02	0.661 ± 0.02
Tensor-FiLM-NMN	0.649 ± 0.02	0.851 ± 0.01	0.605 ± 0.01	0.692 ± 0.06
Tensor-FiLM-NMN+IL	$\mathbf{0.954 \pm 0.07}$	$\mathbf{1.000 \pm 0.00}$	$\mathbf{0.858 \pm 0.15}$	$\mathbf{0.971 \pm 0.02}$

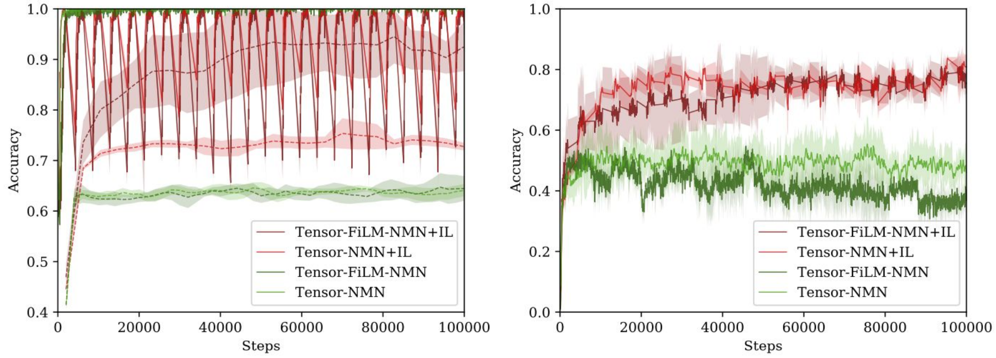
- 20 GT programs = 15%, and 135 GT programs = 100% of training programs
- IL improves generalization in Tensor-NMN and Tensor-FiLM-NMN

SHAPES-SyGeT with varying No. of GT programs



- With 40 GT programs, IL approaches the generalization performance with 135 GT programs
- Do not see the same data efficiency without IL

SHAPES-SyGeT learning curves with 20 GT programs



(a) Task accuracy. Solid lines are training and dashed lines are Val-IID.

(b) Program accuracy.

- All models achieve perfect training accuracy in 5000 steps
- Learning bottleneck encourages consistent improvement in program accuracy
    - Leads to better Val-IID and Val-OOD

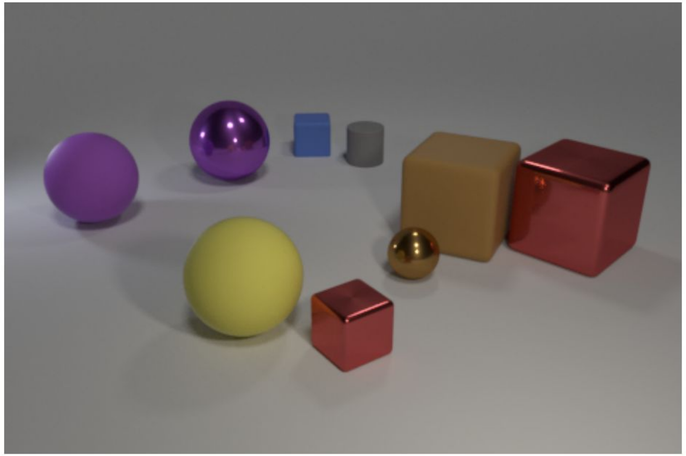
SHAPES-SyGeT example generations

Is a circle above a circle?	
Tensor-NMN :	and shape[circle] scene transform[above] transform[above] shape[circle] scene
Tensor-FiLM-NMN :	and shape[circle] scene transform[above] transform[above] shape[circle] scene
Tensor-FiLM-NMN+IL:	and shape[circle] scene transform[above] shape[circle] scene
Is a blue shape above a square?	
Tensor-NMN :	and color[blue] scene transform[above] transform[above] shape[square] scene
Tensor-FiLM-NMN :	and color[blue] scene transform[above] shape[square] scene
Tensor-FiLM-NMN+IL:	and color[blue] scene transform[above] shape[square] scene
Is a green shape red?	
Tensor-NMN :	and color[green] scene color[red] scene
Tensor-FiLM-NMN :	and color[green] scene color[green] scene
Tensor-FiLM-NMN+IL:	and color[green] color[red] scene
Is a green shape left of below a red shape?	
Tensor-NMN :	and color[green] scene transform[left_of] color[red] scene
Tensor-FiLM-NMN :	and color[green] scene transform[left_of] color[red] scene
Tensor-FiLM-NMN+IL:	and color[green] scene transform[left_of] transform[below] color[red] scene
Is a green shape below above a circle?	
Tensor-NMN :	and color[green] scene transform[below] shape[circle] scene
Tensor-FiLM-NMN :	and color[green] scene transform[above] transform[below] shape[circle] scene
Tensor-FiLM-NMN+IL:	and color[green] scene transform[below] transform[above] shape[circle] scene

Particularly interesting failures to systematically generalize

CLEVR/CLOSURE example

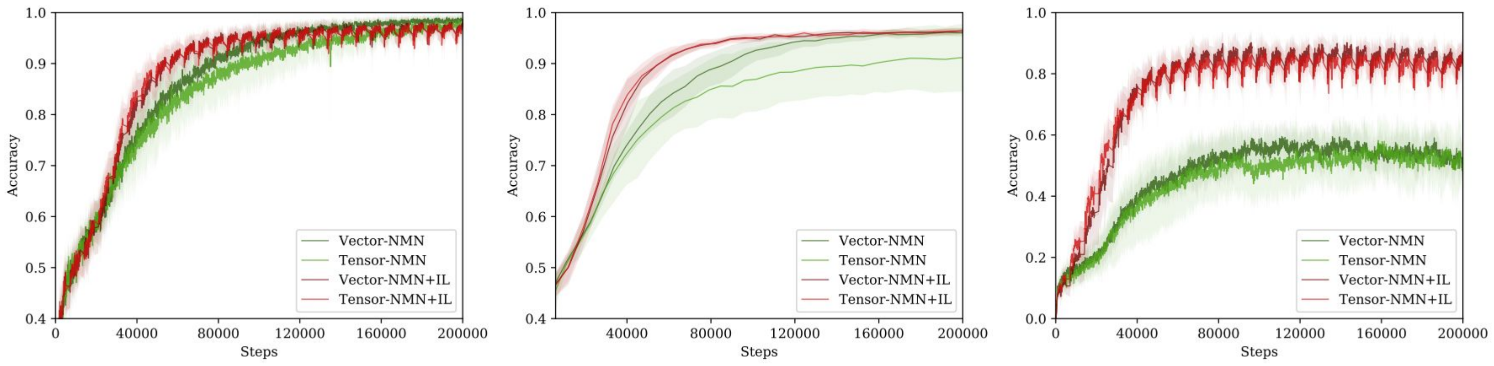
CLEVR (Johnson et al., 2017)
CLOSURE (Bahdanau et al., 2019)



Q1 (CLEVR): There is another cube that is the same size as the brown cube; what is its color?
Q2 (CLEVR): There is a thing that is in front of the yellow thing; does it have the same color as cylinder?
Q3 (CLOSURE): There is another rubber object that is the same size as the gray cylinder; does it have the same color as the tiny shiny block?

(Image from Bahdanau et al., 2019)

CLEVR/CLOSURE learning curves with 100 GT programs



(a) Task training accuracy. (b) Task validation accuracy. (c) Program accuracy.

- Tensor-FiLM-NMN performs slightly worse than Vector-NMN, ignore for simplicity
- All models reach similar training accuracies
- IL leads to significantly higher program accuracy
- The generalization difference is more apparent in the OOD CLOSURE dataset

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Accuracy on CLOSURE categories with 100 GT programs

Evaluation set	Tensor-NMN		Vector-NMN	
	Without IL	With IL	Without IL	With IL
CLEVR-Val	0.912 ± 0.07	$\mathbf{0.964 \pm 0.01}$	0.960 ± 0.01	$\mathbf{0.964 \pm 0.00}$
and_mat_spa	$\mathbf{0.278 \pm 0.17}$	0.264 ± 0.16	$\mathbf{0.400 \pm 0.13}$	0.335 ± 0.18
or_mat	0.327 ± 0.11	$\mathbf{0.481 \pm 0.24}$	0.367 ± 0.11	$\mathbf{0.563 \pm 0.23}$
or_mat_spa	0.286 ± 0.13	$\mathbf{0.405 \pm 0.22}$	0.330 ± 0.11	$\mathbf{0.444 \pm 0.24}$
compare_mat	0.793 ± 0.11	$\mathbf{0.851 \pm 0.17}$	0.660 ± 0.16	$\mathbf{0.873 \pm 0.12}$
compare_mat_spa	0.746 ± 0.13	$\mathbf{0.853 \pm 0.15}$	0.677 ± 0.14	$\mathbf{0.871 \pm 0.12}$
embed_spa_mat	0.824 ± 0.07	$\mathbf{0.947 \pm 0.03}$	0.863 ± 0.07	$\mathbf{0.900 \pm 0.08}$
embed_mat_spa	0.739 ± 0.14	$\mathbf{0.941 \pm 0.02}$	0.894 ± 0.03	$\mathbf{0.936 \pm 0.03}$

- IL improves performance on all but one CLOSURE category
- Tensor-NMN with IL leads to CLEVR accuracy similar to previous works with far fewer programs
  - 18000 for Johnson et al. (2017b), 1000 for Vedantam et al. (2019)

GQA example

GQA (Hudson & Manning, 2019)

(Image from Hudson & Manning, 2019)

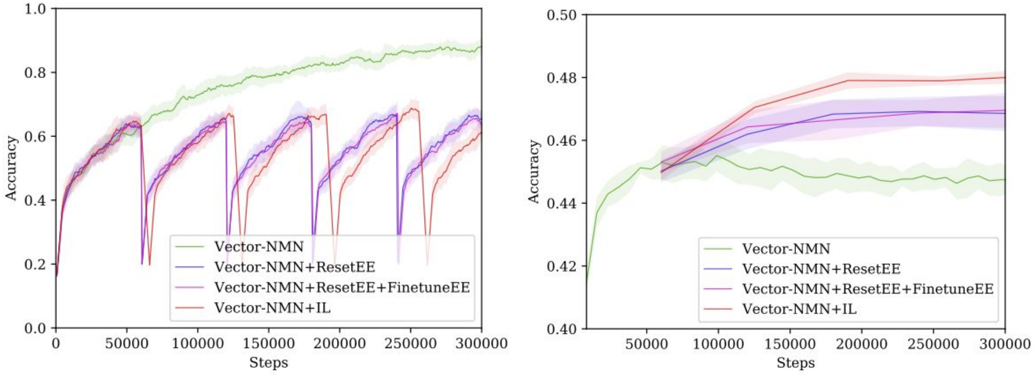
Q1: Is the tray on top of the table black or light brown?
Q2: Is the small table both oval and wooden?
Q3: Is there any fruit to the left of the tray the cup is on top of?

Accuracy on GQA

#GT programs	Model	Accuracy
-	`Vector-NMN` on GT programs	$\mathbf{0.556 \pm 0.002}$
943000	`Vector-NMN`	$\mathbf{0.486 \pm 0.002}$
4000	`Vector-NMN`	0.455 ± 0.006
4000	`Vector-NMN`+ResetEE	0.469 ± 0.007
4000	`Vector-NMN`+ResetEE+FinetuneEE	0.470 ± 0.007
4000	`Vector-NMN`+IL	$\mathbf{0.480 \pm 0.003}$

- Huge program vocabulary, cannot use Tensor-NMN
- Execution engine tends to overfit the training images
  - Stronger baselines: Partial IL: reset the EE while retaining old FiLM embeddings
- Full IL algorithm is necessary for best generalization
  - Approaching accuracy of using all GT programs by using only 0.4%

GQA learning curves with 4000 GT programs



(a) Task training accuracy.

(b) Task validation accuracy.

- ResetEE baselines and IL have similar training curves, but IL has distinctly better generalization
  - Due to better emergent program structure

GQA program accuracies

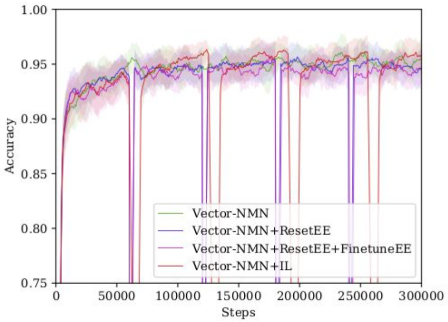
Op: Operation

Subop: Sub-operation

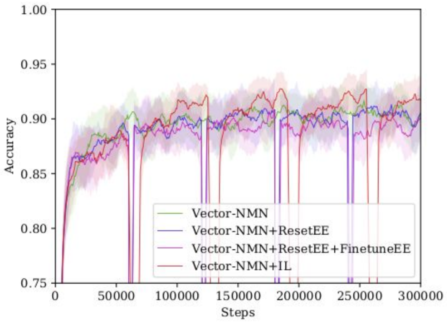
Arg: Argument

ArgNeg: Argument negation

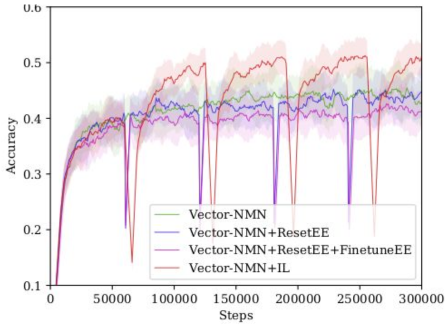
Arity: Number of operands



(a) Op.



(b) Op+Subop.

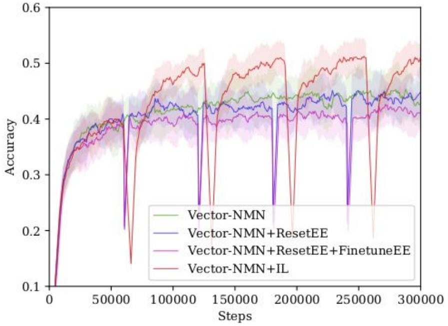


(c) Op+Subop+Arg.

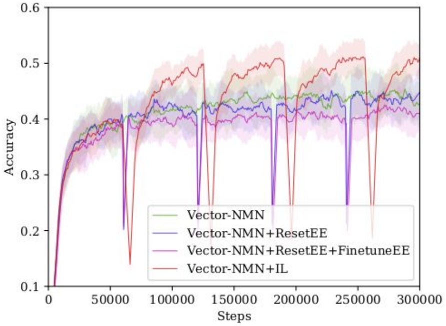
Q: does the lady to the left of the player wear a skirt?

Program:

```
verify.rel(skirt,wearing,o){1}
relate(lady,to the left of,s){1}
select(player){0}
```



(d) Op+Subop+Arg+ArgNeg.



(e) Op+Subop+Arg+ArgNeg+Arity.

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Summarizing

Conclusion

- We demonstrated that IL aids learning of ground-truth program structure
  - SHAPES-SyGeT: toy
  - CLEVR/CLOSURE: intermediate
  - GQA: heavy-duty
- Program generators with correct structure systematically generalize better
- IL deserves to be explored in broad range of machine learning applications

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Let’s discuss!

Full paper

For further questions, reach out at
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