Generalisation in Lifelong RL via Logical Composition

Geraud Nangue Tasse, Steven James, Benjamin Rosman

University of the Witwatersrand

ICLR 2022







Motivation

- In general:
 - Lifelong agents that reuse past skills

Motivation

- In general:
 - Lifelong agents that reuse past skills
- In particular:
 - Are new tasks **expressible** in terms of learned ones?
 - If yes, zero-shot learning?
 - If no, few-shot learning?

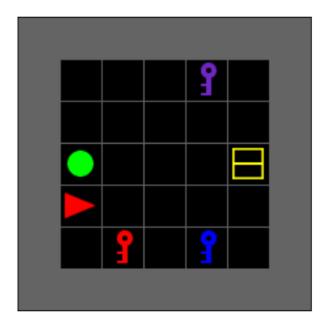
Motivation

- In general:
 - Lifelong agents that reuse past skills
- In particular:
 - Are new tasks expressible in terms of learned ones?
 - If yes, zero-shot learning?
 - If no, few-shot learning?
 - How about lifelong generalisation?

Problem Setting

Pickup-object domain





Goals	9		=	P		=				9		吾			\rightarrow
	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0
	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1
0	1	0	0	1	0	0	1	0	0	1	0	0	1	0	0

Learned

Goals															
(A)	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0
	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1
0	1	0	0	1	0	0	1	0	0	1	0	0	1	0	0



Goals	2		=	P		=	0			9		吾	<u>О</u> Щ		
<u> </u>	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0
	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1
0	1	0	0	1	0	0	1	0	0	1	0	0	1	0	0

SOPGOL

Goals	2		=	P		=	0		=	9		吾	O_III		
	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0
	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1
	1	0	0	1	0	0	1	0	0	1	0	0	1	0	0
\overline{T}	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0

Learned

SOPGOL

Goals	2		Ħ	P		=	0		=	9		暑	0		
•	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0
	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1
	1	0	0	1	0	0	1	0	0	1	0	0	1	0	0
T	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0

SOPGOL

$$\succ T' \coloneqq \neg \blacksquare \land \neg \blacksquare \land \square \land ?$$



Not green and not blue and yellow and key

Goals	2		Ħ	P		=	0		=	9		暑	0		
•	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0
	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1
	1	0	0	1	0	0	1	0	0	1	0	0	1	0	0
T	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0

Learned

SOPGOL

 $\succ T' \coloneqq \neg \blacksquare \land \neg \blacksquare \land \land \ ?$

Not green and not blue and yellow and key

$$Q_{SOP} = \neg Q^*(\blacksquare) \land \neg Q^*(\blacksquare) \land Q^*(\blacksquare) \land Q^*(\P)$$

Goals	2		=	2		=	0		=	9		暑	0		
•	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0
	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1
0	1	0	0	1	0	0	1	0	0	1	0	0	1	0	0
T	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0

1 earnea

SOPGOL

 $\succ T' \coloneqq \neg \blacksquare \land \neg \blacksquare \land \square \land ?$



- ightharpoonup T = T'? Yes!

Goals	2		Ħ	P		=	9		=	9		暑	<u></u>		
•	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0
	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1
0	1	0	0	1	0	0	1	0	0	1	0	0	1	0	0
T	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0

Learned

SOPGOL

Not green and not blue and yellow and key

$$\succ T' \coloneqq \neg \blacksquare \land \neg \blacksquare \land \square \land ?$$

$$\succ T = T'$$
 ? Yes!

Reduces the RL problem to just Supervised learning

Goals	2		=	P		=				P		吾			=
	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0
	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1
©	1	0	0	1	0	0	1	0	0	1	0	0	1	0	0

Pick UP Yellow Boxes

Goals	2		=	9		=	9		=	•		吾	0		
	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0
	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1
(<u>1</u>	1	0	0	1	0	0	1	0	0	1	0	0	1	0	0
T	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1

Learnea

SOPGOL

Goals	2			2		=	0		=	2		8	0		
	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0
	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1
0	1	0	0	1	0	0	1	0	0	1	0	0	1	0	0
	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1

SOPGOL

 $\succ T' \coloneqq \neg \blacksquare \land \neg \blacksquare \land \neg \P$



$$Q_{SOP} = \neg Q^*(\blacksquare) \land \neg Q^*(\blacksquare) \land Q^*(\blacksquare) \land \neg Q^*(\P)$$

Goals	2		=	9		=	9		=	P		8	0		
	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0
	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1
() III	1	0	0	1	0	0	1	0	0	1	0	0	1	0	0
T	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1

Learned

SOPGOL

Not green and not blue and yellow and not key

$$\succ T' \coloneqq \neg \blacksquare \land \neg \blacksquare \land \neg \P$$

$$ightharpoonup T = T'$$
? No!

Goals	2		=	2		=	9		=	2		8	0		=
	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0
	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1
(O)	1	0	0	1	0	0	1	0	0	1	0	0	1	0	0
T	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1

Learned

SOPGOL

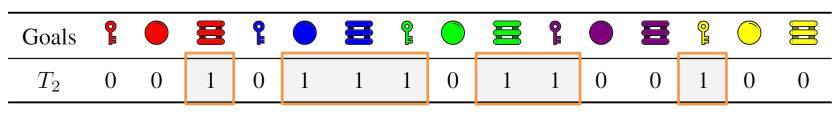
Not green and not blue and yellow and not key

$$\succ T' \coloneqq \neg \blacksquare \land \neg \blacksquare \land \neg \P$$

$$Q_{SOP} = \neg Q^*(\blacksquare) \land \neg Q^*(\blacksquare) \land Q^*(\blacksquare) \land \neg Q^*(\P)$$

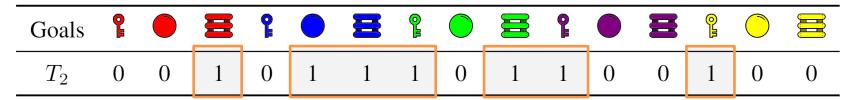
$$ightharpoonup T = T'$$
? No!

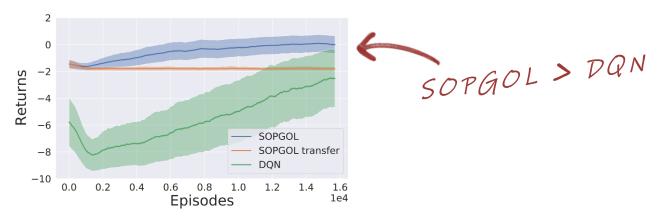
 \triangleright Learn new Q with goal-oriented learning (using Q_{SOP} , to speed up training), then add to library



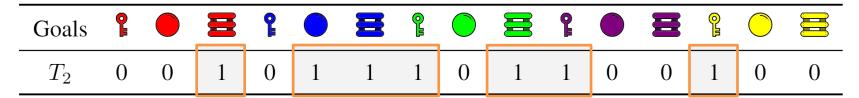
Pick up red/blue/green boxes, or green/purple/yellow keys, or blue balls

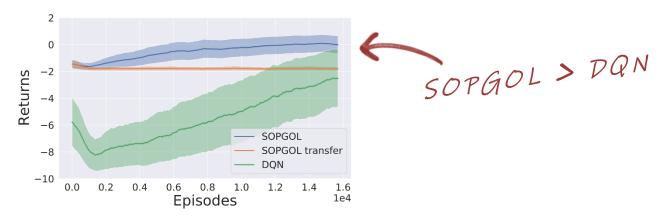
• Pretrained: , , , , , , , ,





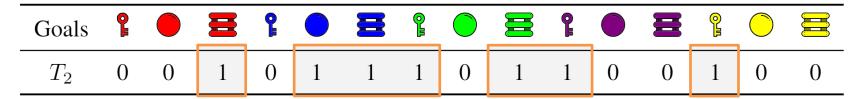
• Pretrained: ____, ___, §

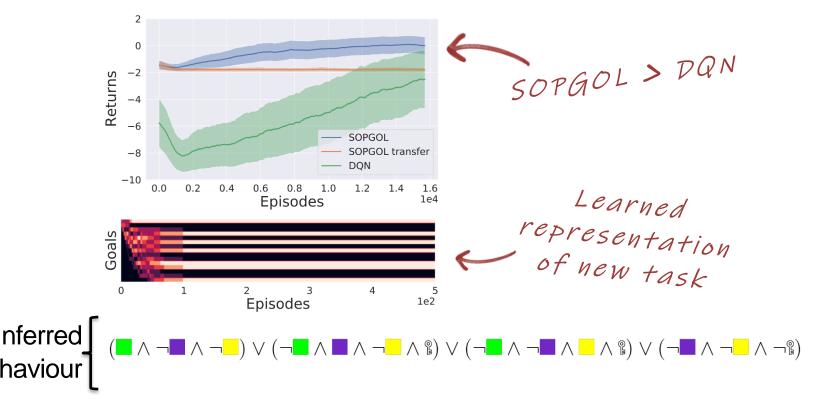






• Pretrained: , , , , , , , ,





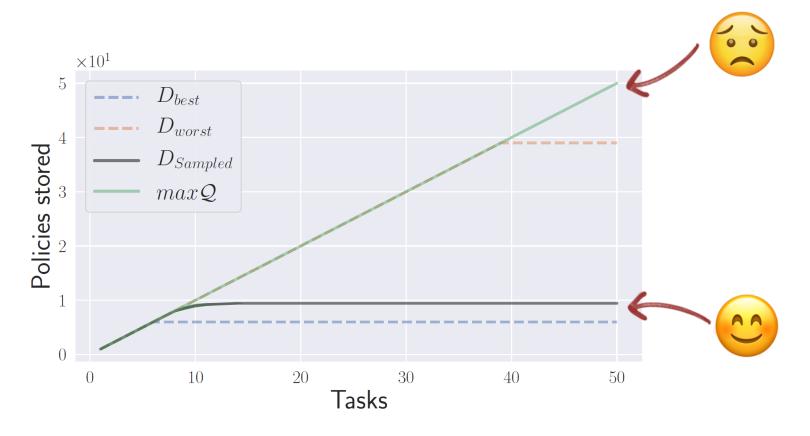
SOPGOL

Theorem: $\log(|goals|) \le \lim_{t \to \infty} (|skills|) \le |goals|$

Note: $|tasks| = 2^{|goals|}$

Generalisation with Lifelong Transfer

• Four-rooms domain: 40 goals, $2^{40} \sim 1$ trillion tasks



Conclusion

- We leverage logical composition for fast transfer between tasks.
- Leads to quick generalisation over any task distribution.
 - we have a logarithmic upper bound on the number of tasks that needs to be learned and stored.
- Leads to both interpretable and sample-efficient lifelong RL.