

# Iterated Learning for Deep Learning

Yuchen Lu

# What is Iterated Learning (IL)?

Iterated learning is the process by which the behavior of the individual is acquired, by observing the behavior of another individual, **who acquired that behavior in the same way.**

It is used to model language evolution, to illustrate the effect of generation transmission on the linguistic structure.

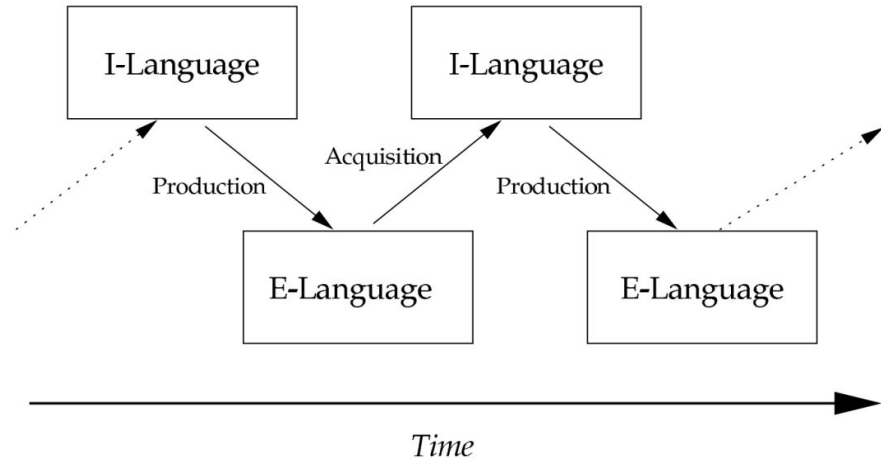
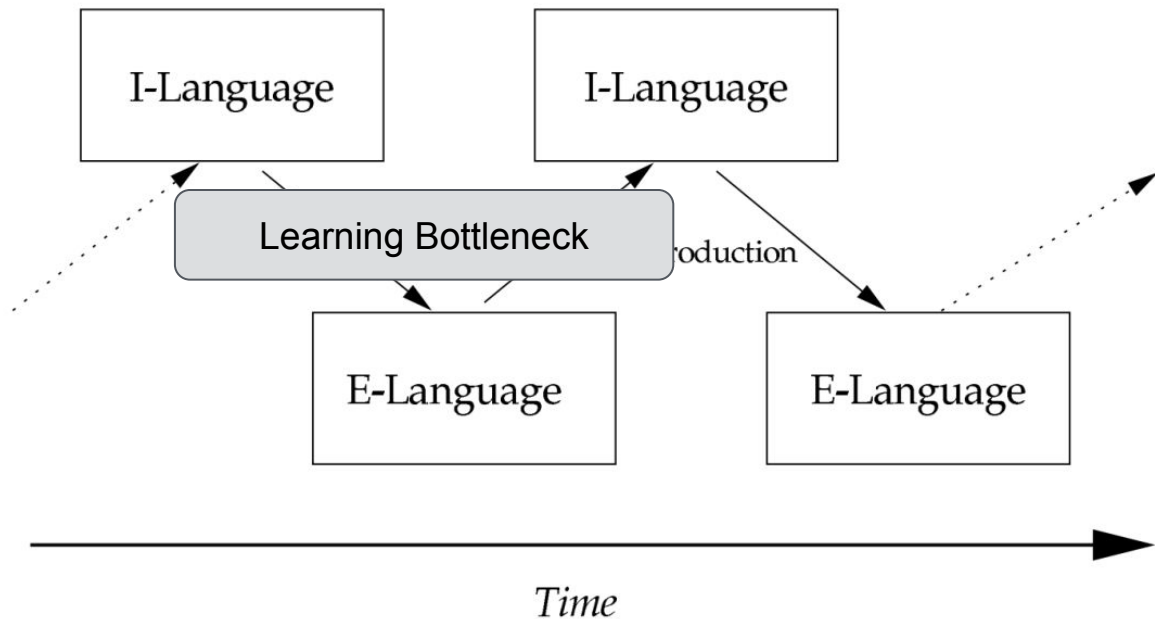


FIGURE 2.1 – Language transmission over time [32]. I-language is the internal language knowledge, while E-language is the external language like utterances.

# Learning Bottleneck, aka *The Poverty of Stimulus*

language learners must attempt to learn an **infinitely expressive linguistic system** on the basis of a relatively **small set of linguistic data**

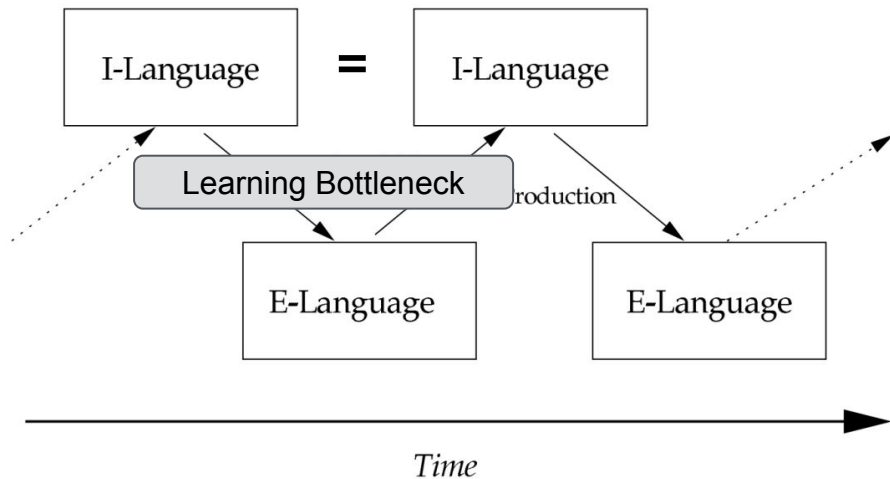


# IL leads to structured language



What can be derived if the I-language converge, meaning I-language of this generation is the same as I-language of previous language

I language should be **efficiently learnable** through limited number of example, and linguistic structure can be exploited to achieve that.



IL Principle: Linguistic structure is the solution found by the cultural evolution, in order for the language to survive the transmission with bottleneck.

# IL leads to structured language

Kirby et al. 2004. Spontaneous Evolution of Linguistic Structure

Define the toy language to be represented by Definite Clause Grammar (DCG).  
Define a grammar induction algorithm. Define a “invention algorithm”. Each transmission only see a subset of meaning-message pairs.

	$a_0$	$a_1$	$a_2$	$a_3$	$a_4$
$b_0$	s	sq	-	pnj	bjmjimsq
$b_1$	n	avvcf	jlimgttzt	pclcfho	kebae
$b_2$	ebhzyuyrl	afeeykokz	-	pyuhu	hwrpg
$b_3$	rqbvtggjac	zrdleab	rxktywr	rbq	rkxpbmx
$b_4$	drnlblwmo	afqjghvu	gnbyq	pquztpi	wf

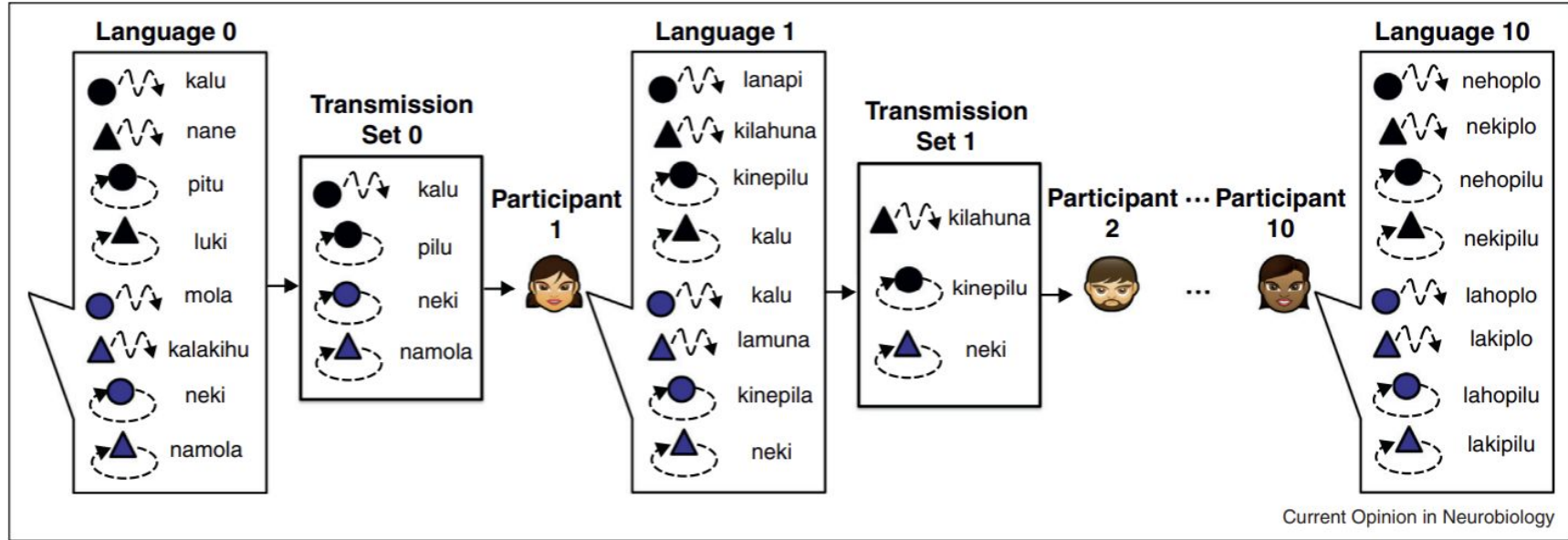
Initial



	$a_0$	$a_1$	$a_2$	$a_3$	$a_4$
$b_0$	wcpalsdqu	asdqu	hnqmxsdqu	gpmhmsdqu	bsdqu
$b_1$	wcpalp	ap	hnqmxp	gpmhmp	bp
$b_2$	wcpalihm	aihm	hnqmxihm	gpmhmihm	bihm
$b_3$	rkxpwcpalmx	rkxppamx	rkxphnqmxmx	rkxpgpmhmmx	rkxpbmx
$b_4$	cswcpalbf	csabf	cshnqmxbf	csgpmhmbf	csbbf

Iteration 30

# IL leads to structured language



Generation 0: Random string

Generation 10: Somewhat compositional.

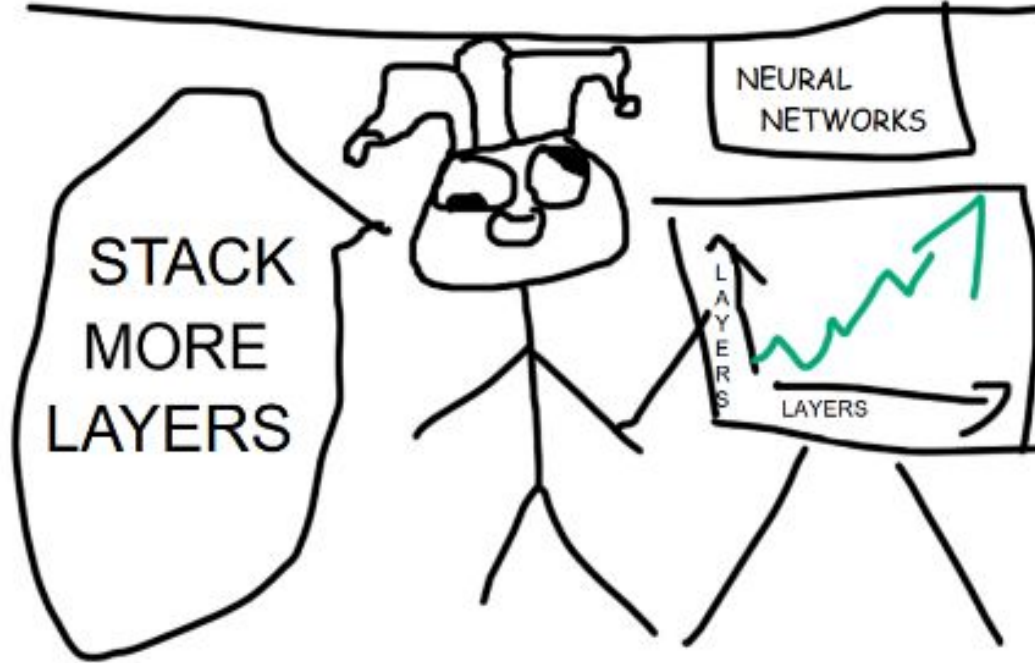
ne- for black, la- for blue

-ho- for circle, -ki- for triangle

-plo for bouncing, -pilu for looping

(Kirby et al. 2008 PNAS)

# Time for some deep neural nets!



# Neural Iterated Learning (Yi et al. ICLR2020)



The very first application of IL is in emergent communication, which is mainly modernizing the classic signalling games with deep neural networks.

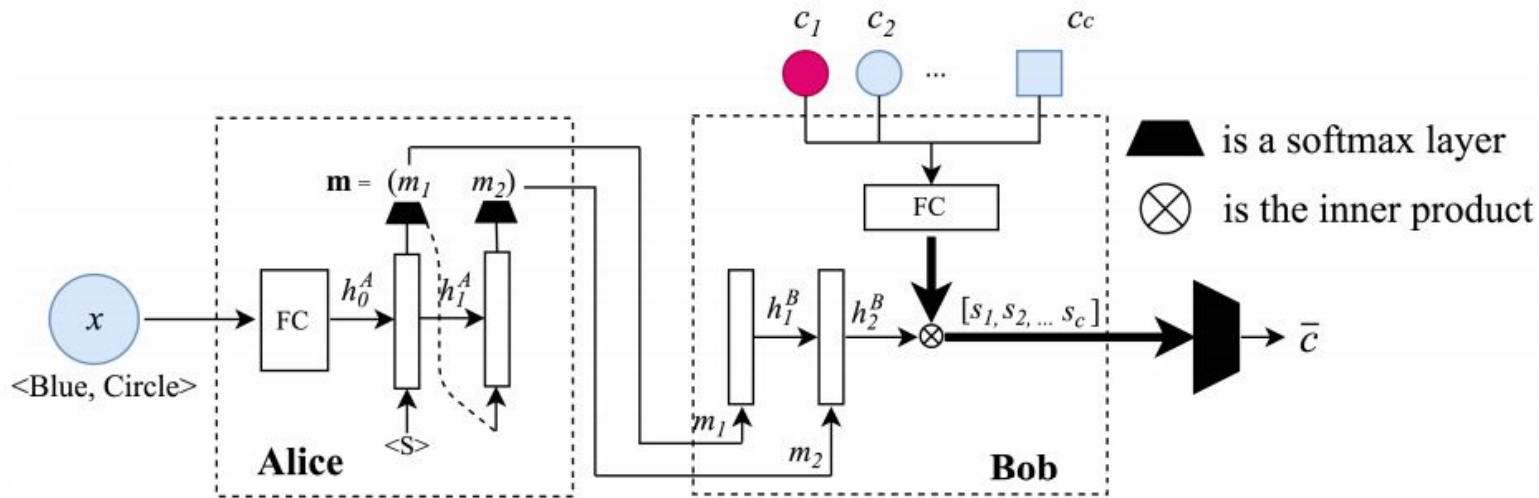


Figure 1: Referential communication game and architectures of the agents.

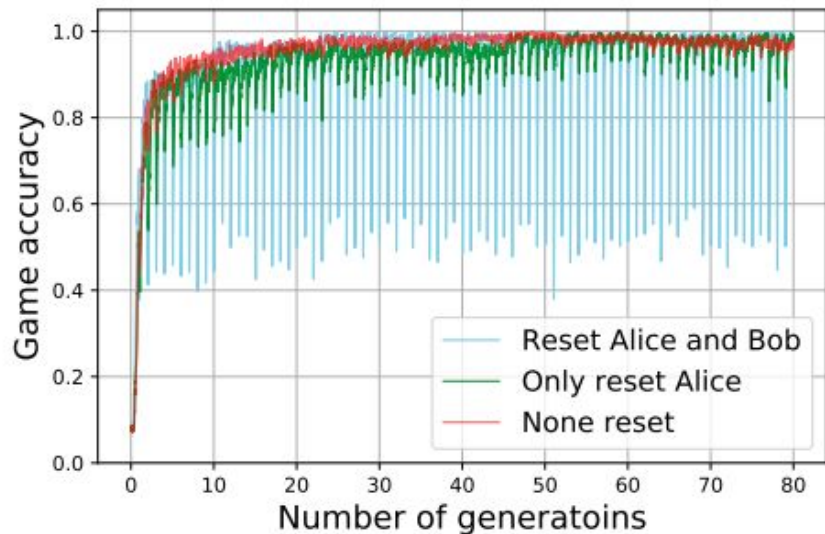


# Neural Iterated Learning (Yi et al. ICLR2020)

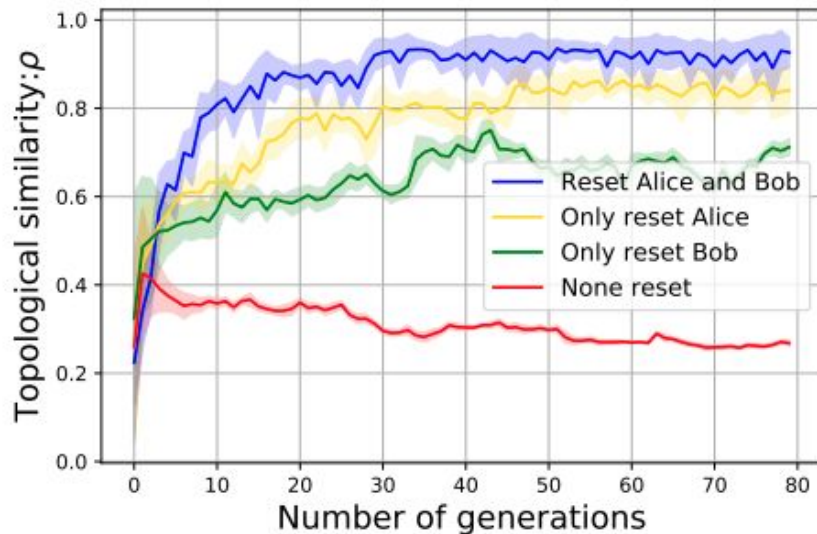


```
Re-initialize Alice and Bob, get  $Alice_i$  and  $Bob_i$ 
// ===== Learning Phase =====
for  $i_a = 1, 2, \dots, I_a$  do
    Randomly sample an example pair from  $D_i$  and use it to update  $Alice_i$  with cross-entropy
    training
end for
for  $i_b = 1, 2, \dots, I_b$  do
     $Alice_i$  generates message based on input objects
     $Bob_i$  receives message and selects the target
     $Bob_i$  updates its parameters if rewarded
end for
// ===== Interacting Phase =====
for  $i_g = 1, 2, \dots, I_g$  do
     $Alice_i$  generates message based on input objects
     $Bob_i$  receives message and selects the target
    BOTH  $Alice_i$  and  $Bob_i$  update parameters if rewarded
end for
// ===== Transmitting Phase =====
for  $i_s = 1, 2, \dots, I_s$  do
    Generate object-message pairs by feeding objects to  $Alice_i$  and save them to data set  $D_{i+1}$ 
end for
```

# Neural Iterated Learning (Yi et al. ICLR2020)



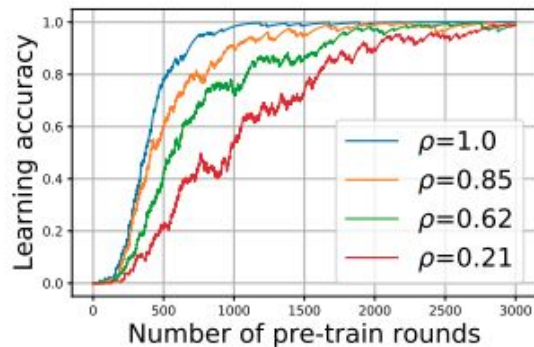
(a) Game performance



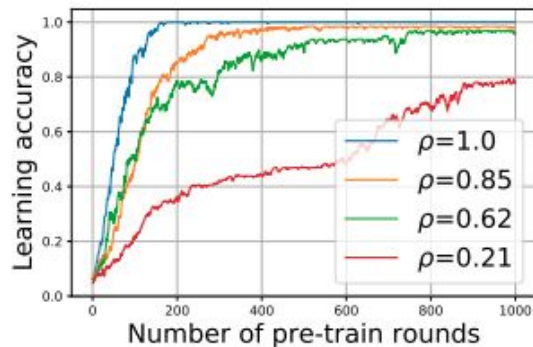
(b) Average  $\rho$  of emergent language

Topographical Similarity: The Spearman Correlation between object distance and message distance. Higher if similar meanings mapped to similar messages.

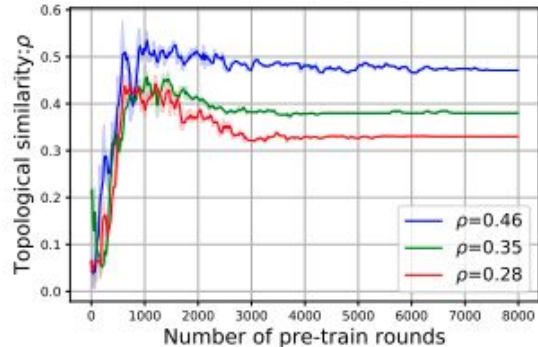
# Neural Iterated Learning (Yi et al. ICLR2020)



(a) Learning accuracy of Alice.



(b) Learning accuracy of Bob.



(c) Alice's  $\rho$

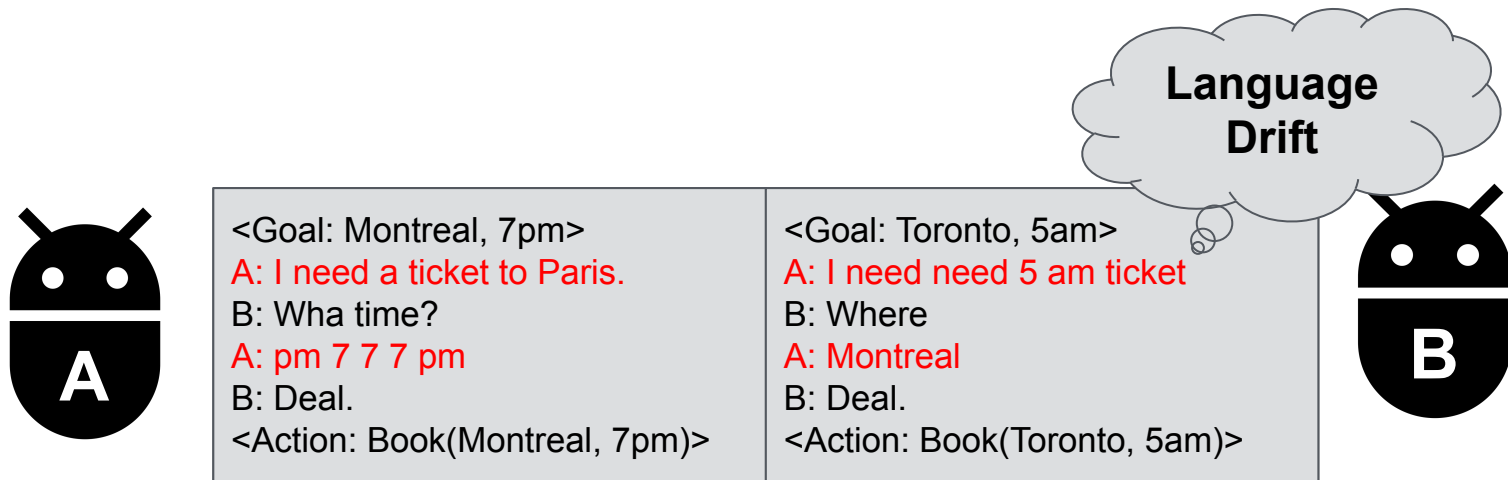
Figure 2: Illustration of the learning speed of Alice and performance improving speed of Bob when pre-training is done with various languages of different topological similarities.

# Countering Language Drift

(Lu et al. ICML2020, Lu et al. EMNLP2020)

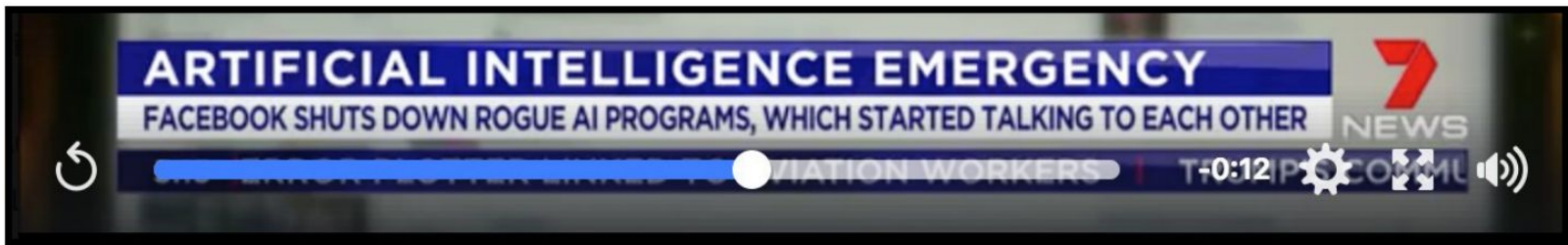


For situated language learning, e.g. goal-oriented dialogue, we have the following pipeline: **Supervised learning** for pretraining, and **finetune through interactions** in a simulator.



□ **Good Task Performance** but **Poor Language**

# Drift happens



Q Popular Latest

*The Atlantic*

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## TECHNOLOGY

### An Artificial Intelligence Developed Its Own Non-Human Language

When Facebook designed chatbots to negotiate with one another, the bots made up their own way of communicating.

ADRIENNE LAFRANCE JUNE 15, 2017



**ROBOSTOP** Facebook shuts off AI experiment after two robots begin speaking in their OWN language only they can understand

Experts have called the incident exciting but also incredibly scary

By James Beal and Andy Jehring  
1st August 2017, 12:03 am | Updated: 2nd August 2017, 4:06 am



NEWS

### Facebook AI project halted after bots invent new language

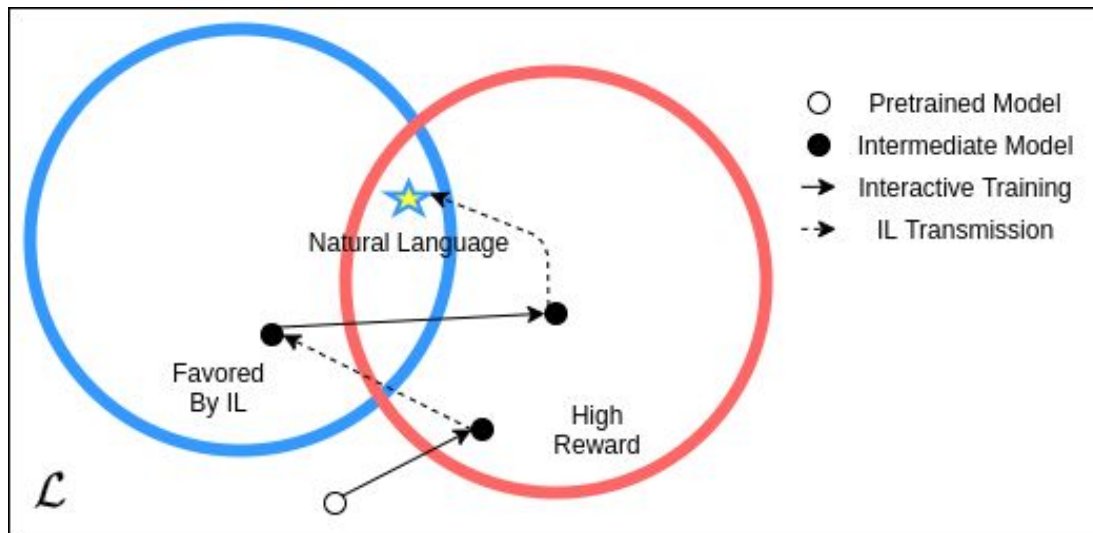
By Malek Murison - August 1, 2017



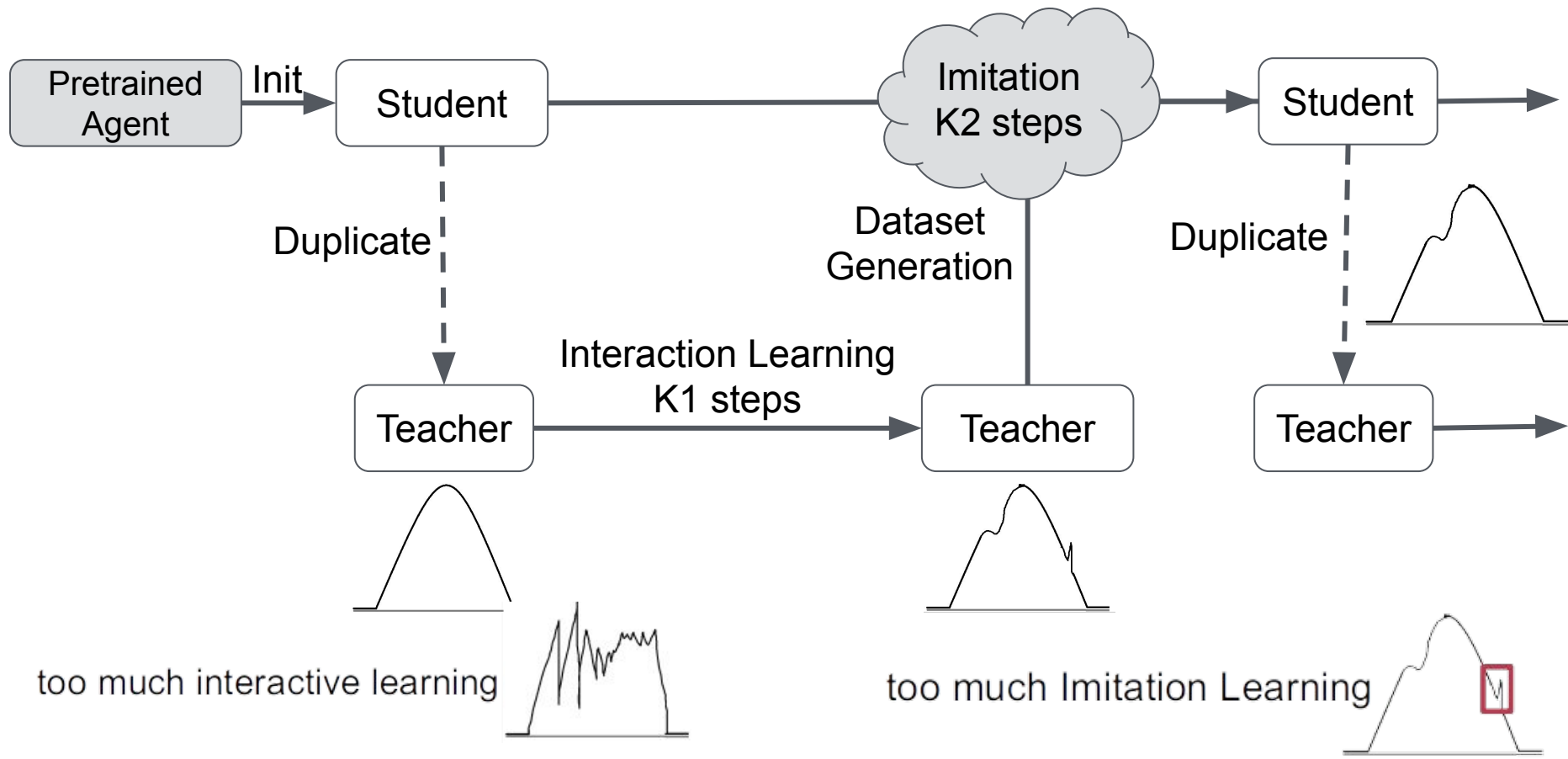
# Iterated Learning to Counter Language Drift

Hypothesis: Language drift might exist in a form of **co-adaptation** and **over-specialization** among pair of agents.

IL Principle: IL favours language with structure. Each transmission with bottleneck would “filter out” the drift part of the language which cannot generalize

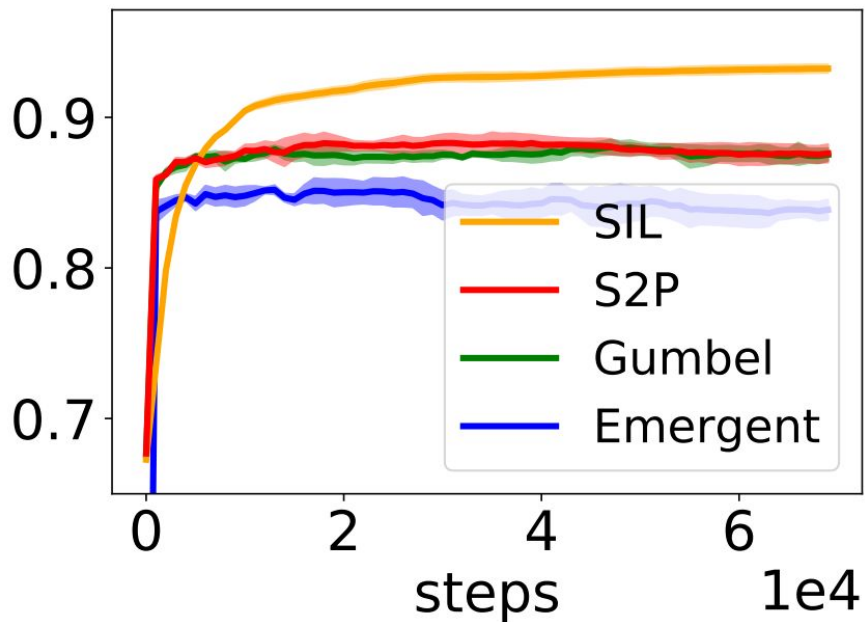


# Seeded Iterated Learning (SIL)

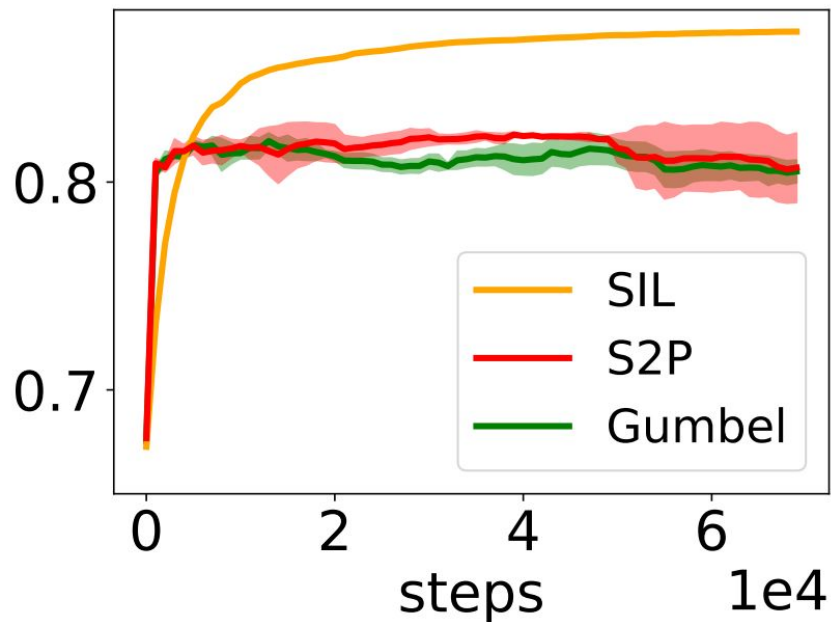


# Lewis Game: Results

X axis is the number of interactive training steps  
Pretrain Task/Language score: 65~70%



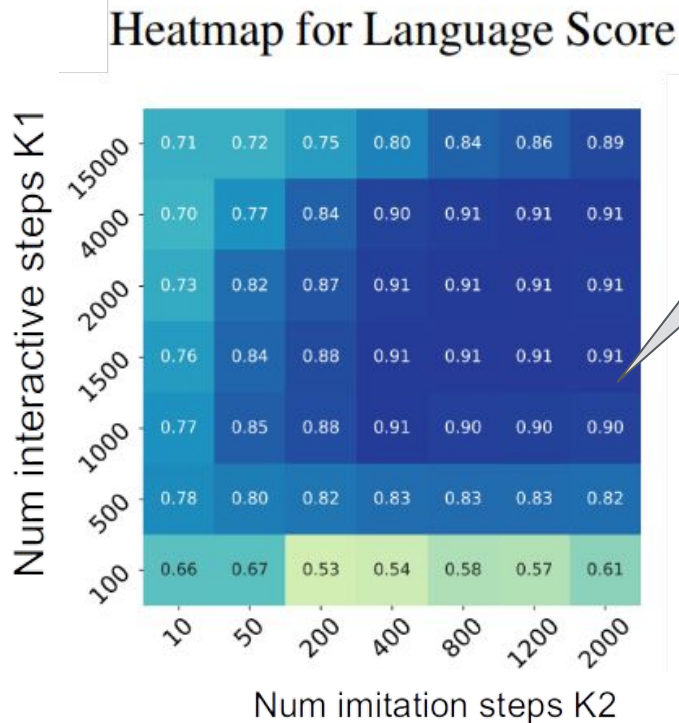
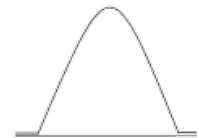
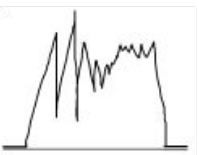
(a) Task Score



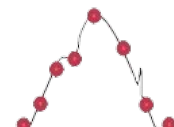
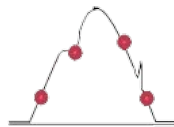
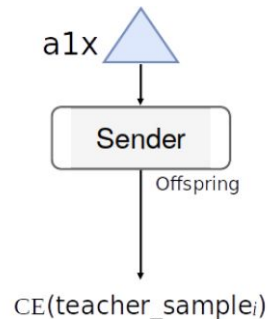
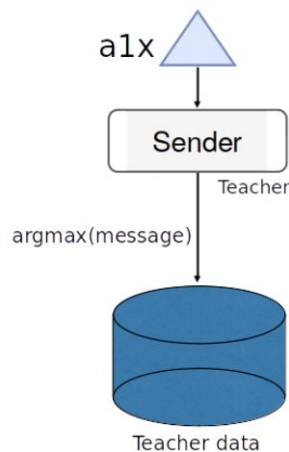
(b) Sender Language Score



# Lewis Game: K1/K2 Heatmap

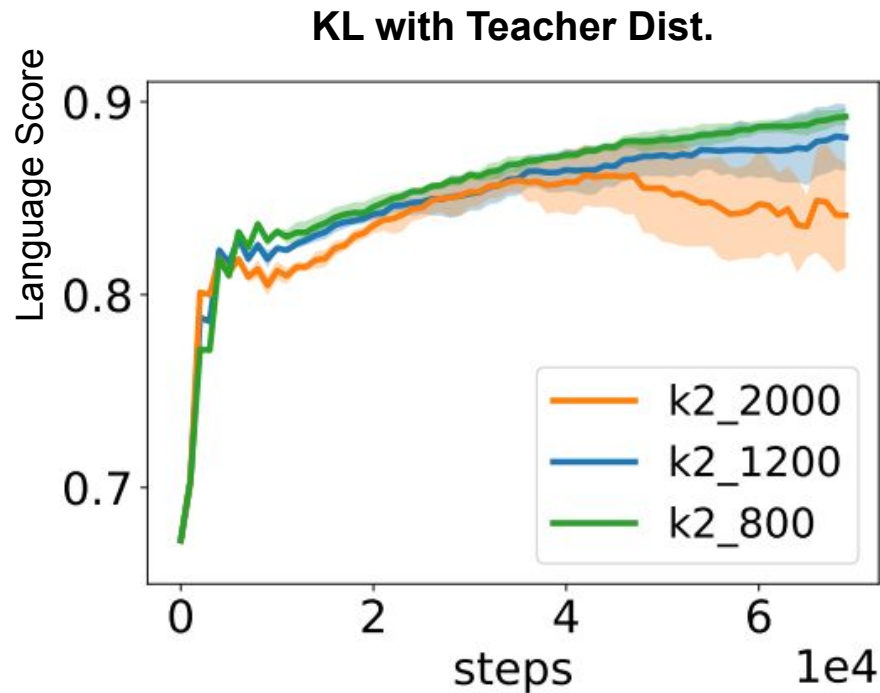
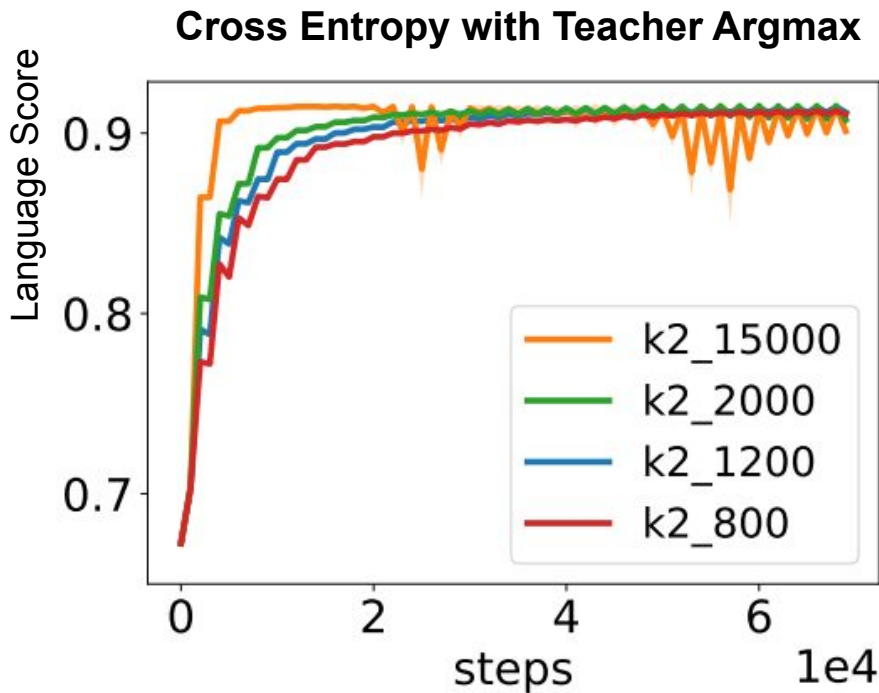


No Overfitting?



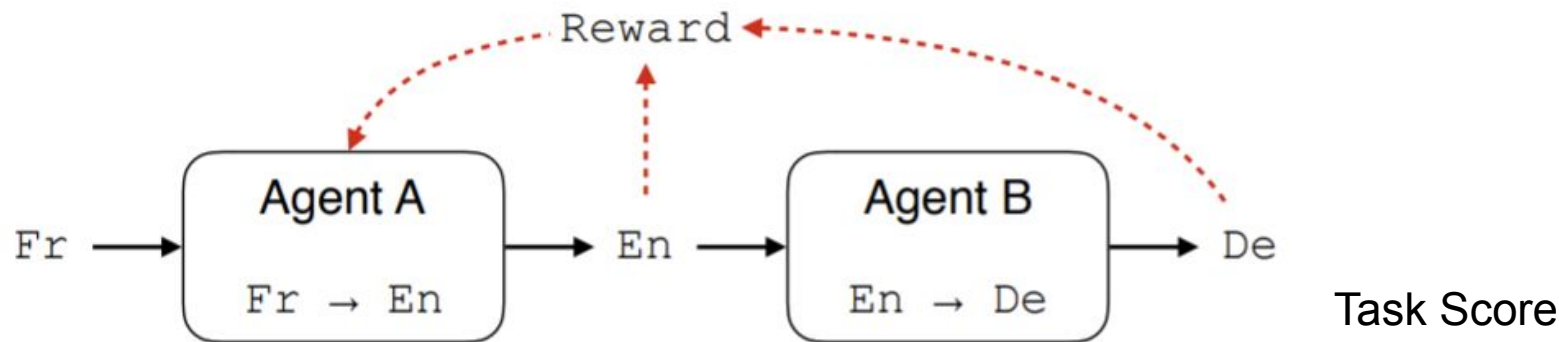
# Lewis Game: Results

Data production is part of the “Learning Bottleneck”



# Translation Game: Setup

Lee et al. EMNLP 2019

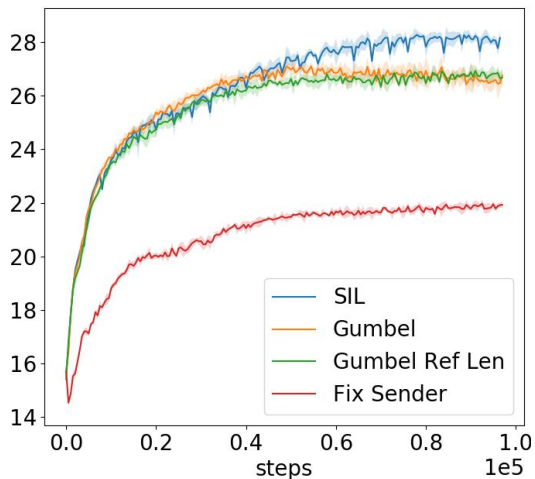


Language Score

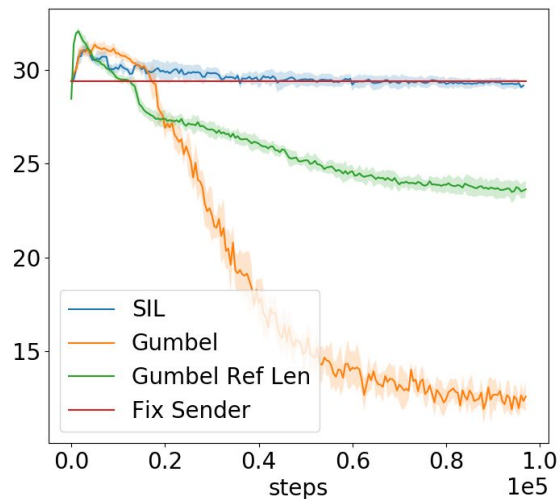
- BLEU EN (English BLEU score)
- English NLL of generated language a pretrained language model.
- R1 (Image retrieval accuracy from sender generated language)
- BLEU DE (German BLEU score)

# Translation Game: Baselines

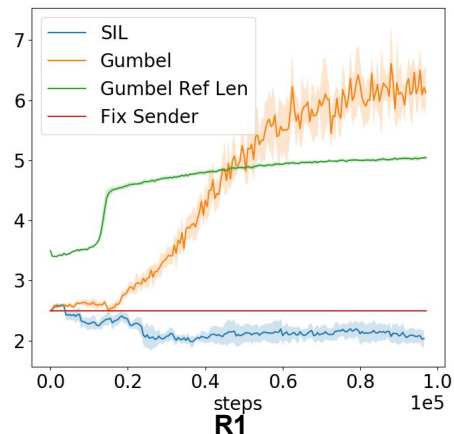
BLEU De



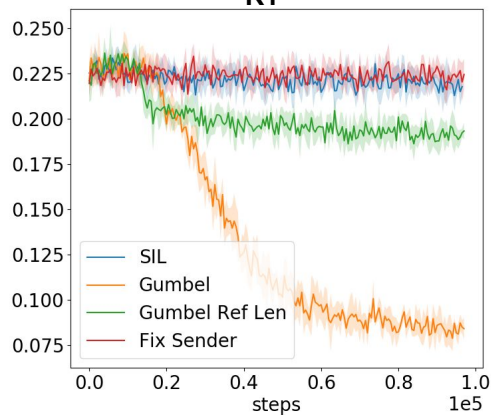
BLEU En



NLL

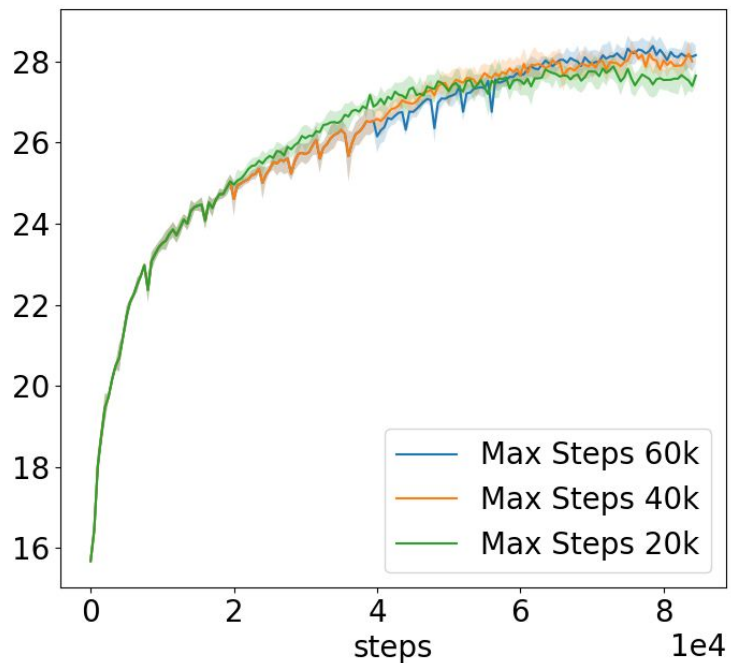


R1

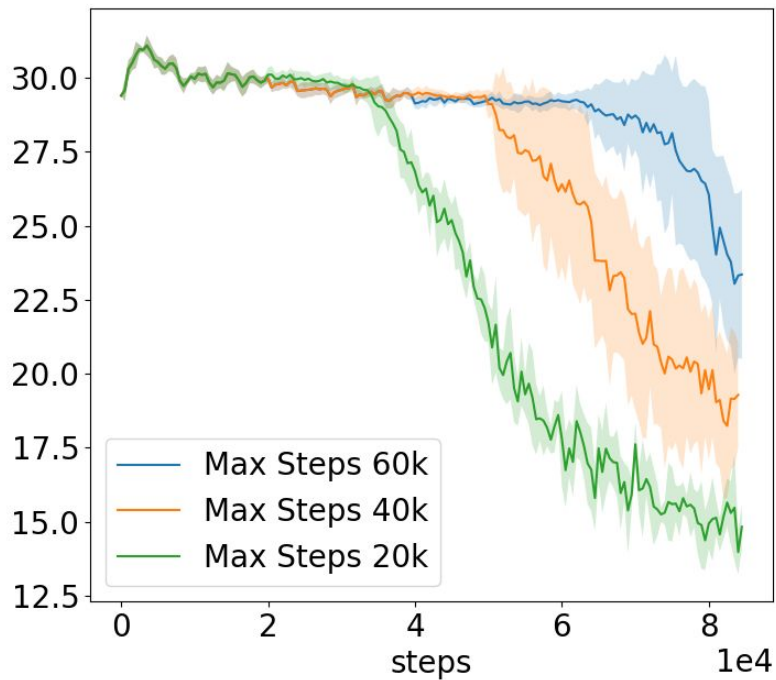


# Translation Game: Effects of SIL

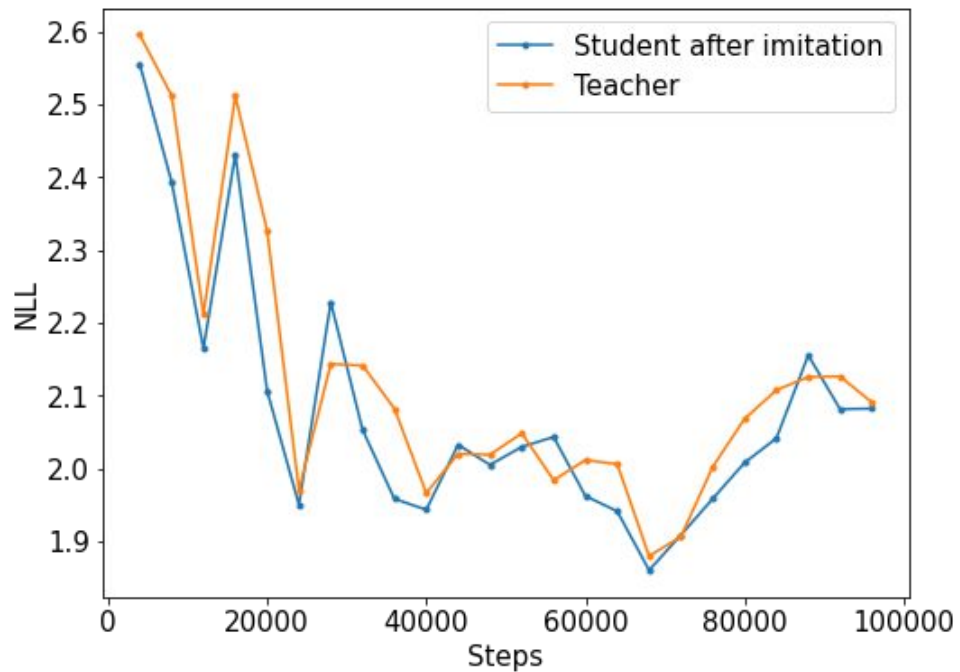
BLEU De



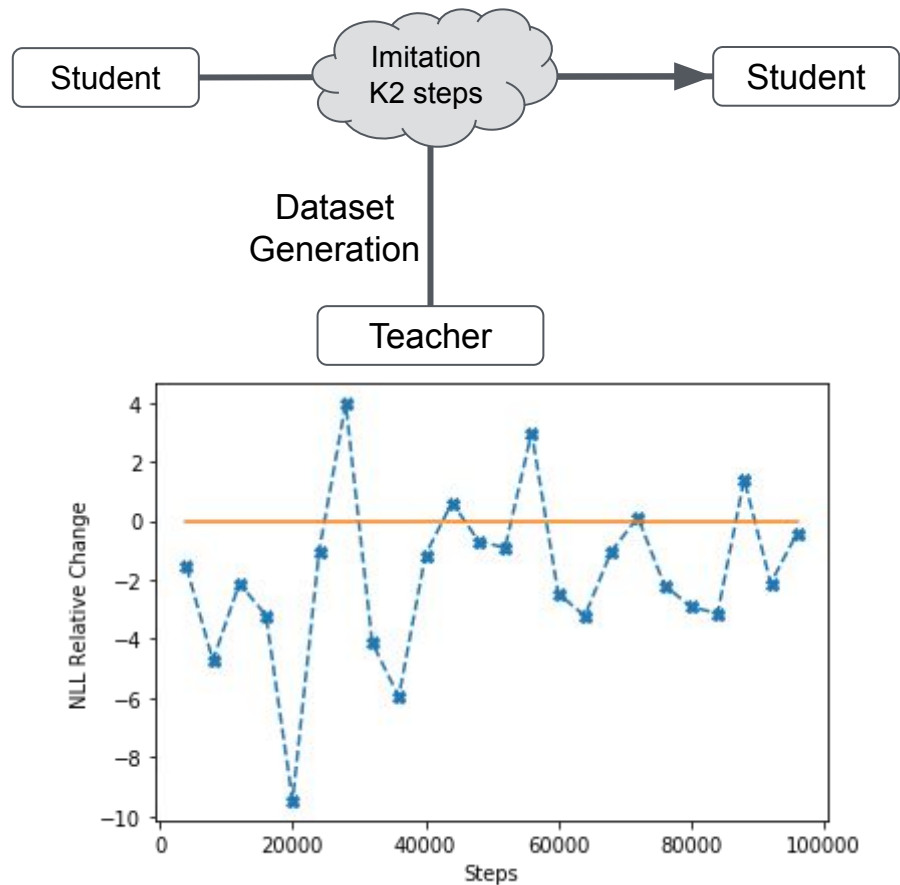
BLEU En



# Effect of Imitation Learning

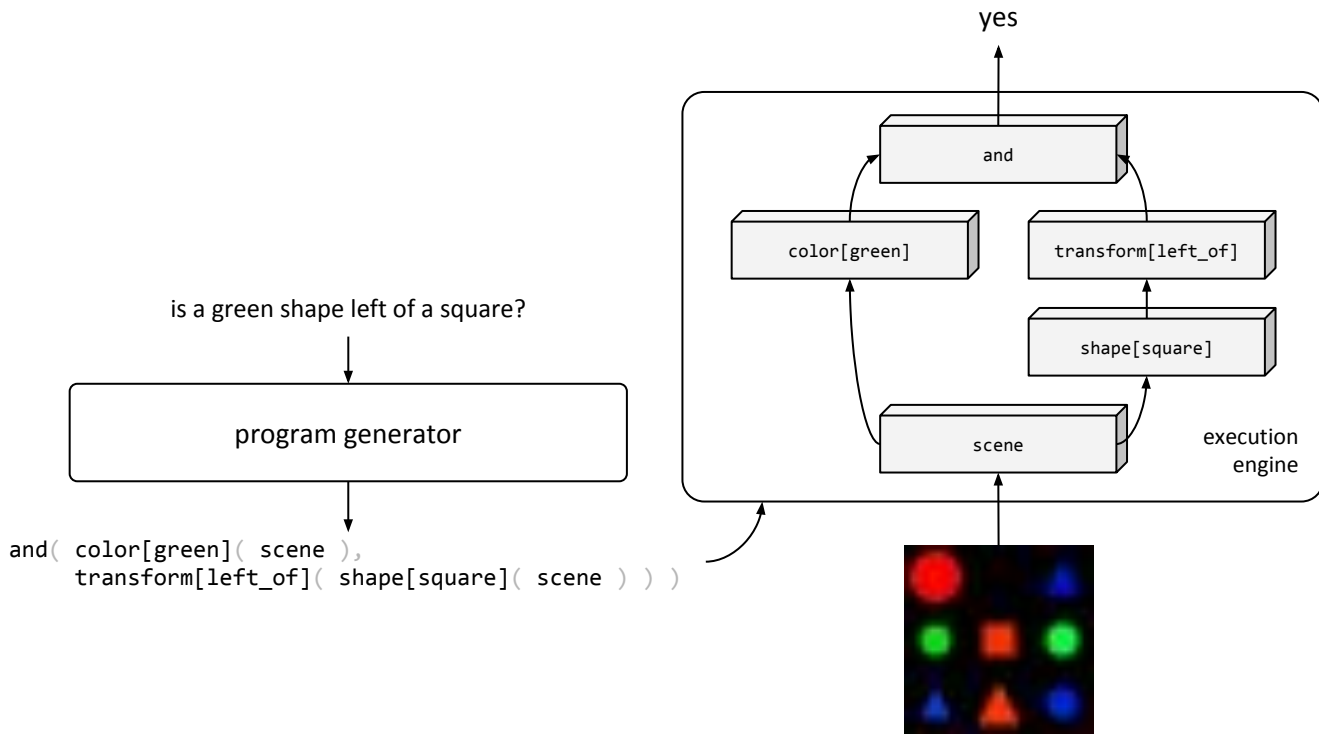


Mostly imitation learning brings the agent more favoured by pretrained language models

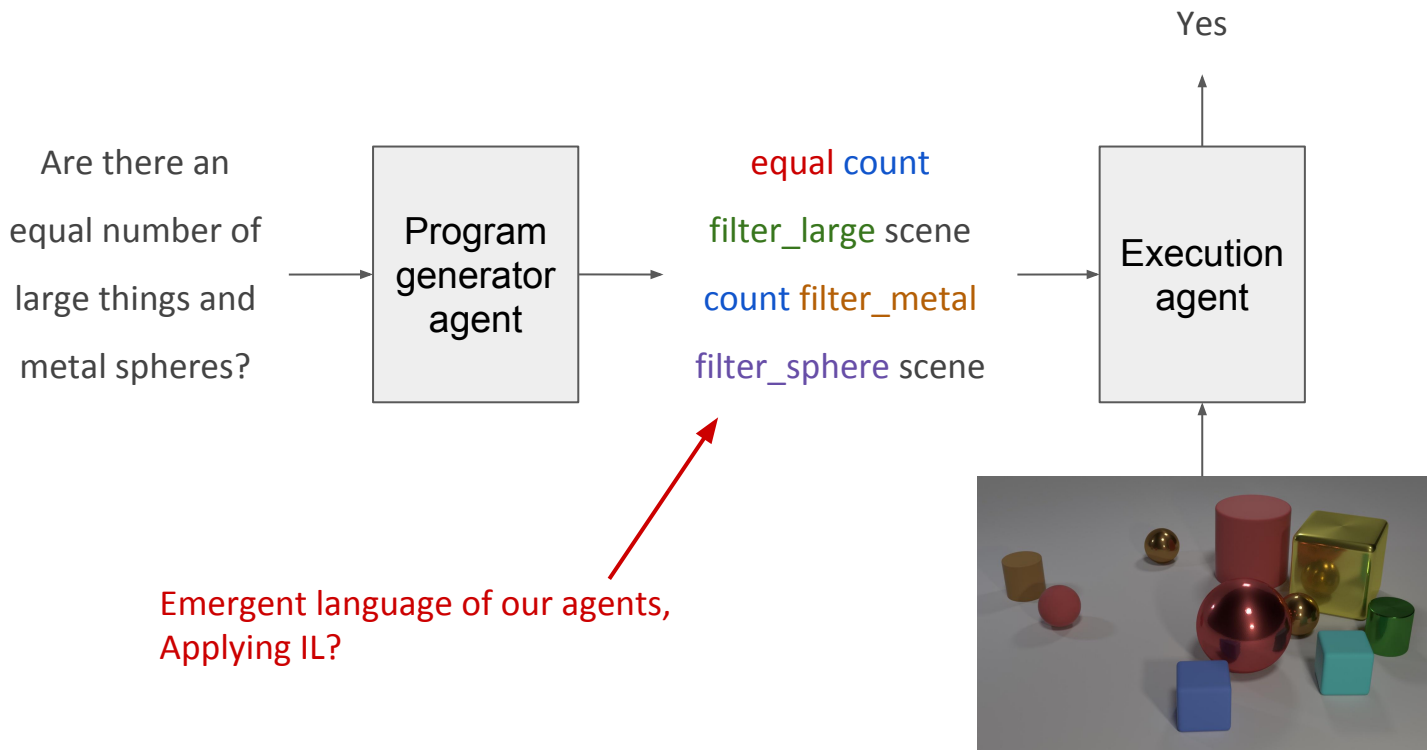


# IL for VQA and Neural Module Network (NMN)

Recent work has proposed to use Neural Module Network (NMN) to achieve systematic generalization in VQA.

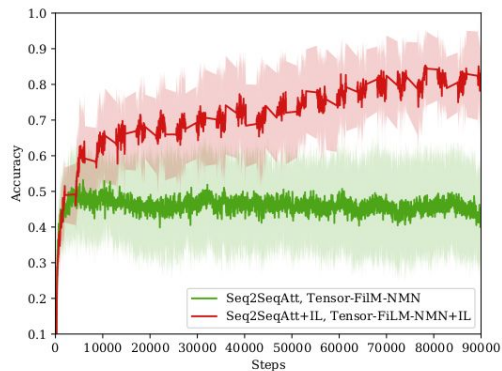


# IL for VQA and Neural Module Network (NMN)

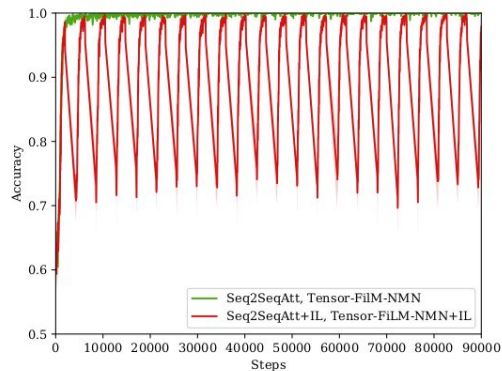




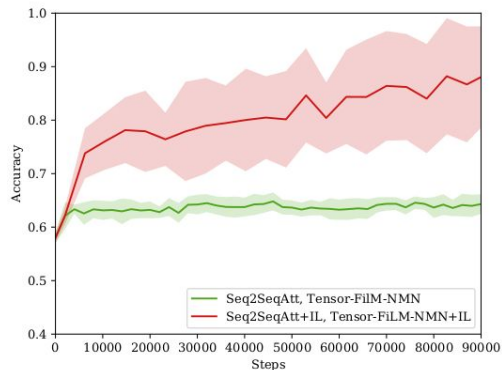
# IL for VQA and Neural Module Network (NMN)



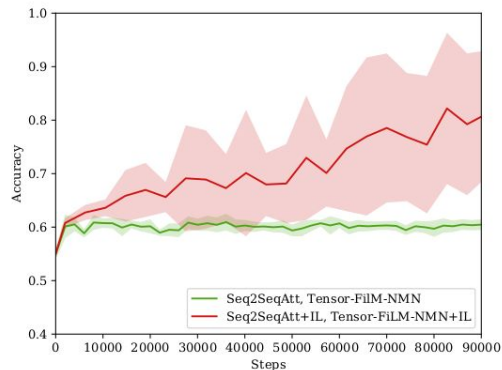
(a) Program accuracy.



(b) Training accuracy.



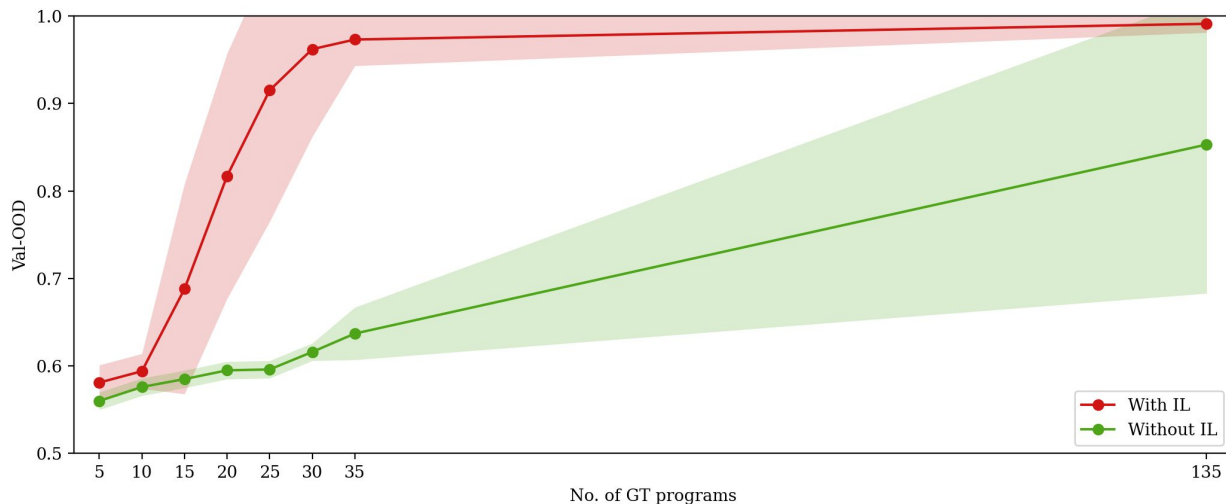
(c) Val-IID accuracy.



(d) Val-OOD accuracy.

- Experiment on a newly proposed benchmark called SHAPES-SyGeT
- Both models achieve perfect training accuracy in 5000 steps
- Learning bottleneck encourages consistent improvement in program accuracy
  - Leads to better Val-IID and Val-OOD

# IL for VQA and Neural Module Network (NMN)



- With 35 GT programs, IL approaches the OOD performance with 135 GT programs
- Do not see the same data efficiency without IL

- Iterated Learning (IL) is proposed as language evolution framework. It states that linguistic structure is the solution of cultural evolution finds to the problem of being efficiently learnable.
- IL has been applied in deep learning, beyond emergent communication and beyond natural language
- More questions: How to explain the success of IL? If IL magnify the learner's bias, does it depend on the model architecture? Can we explain it from the statistical learning theory?
- Can apply it to representation learning? Is it connected to existing practice like self-training?

# Thanks!



“Human children appear preadapted to guess the rules of syntax correctly, precisely because languages evolve so as to embody in their syntax the most frequently guessed patterns. The brain has co-evolved with respect to language, but languages have done most of the adapting.”

-Deacon, T. W. (1997). *The symbolic species*

**Iterated learning for deep learning will be exciting!**