Online Experiments for Language Scientists

Lecture 8: Iterated learning

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Beckner et al (2017)

Beckner, C., Pierrehumbert, J., & Hay, J. (2017). The emergence of linguistic structure in an online iterated learning task. *Journal of Language Evolution*, *2*, 160–176.

An iterated artificial language learning experiment

 Does compositional structure emerge 'for free' from person-to-person transmission?



Clay Beckner (now at Warwick)



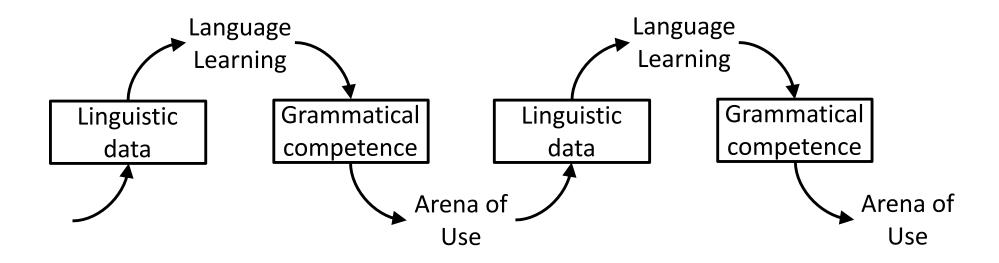
Janet Pierrehumbert (Oxford)



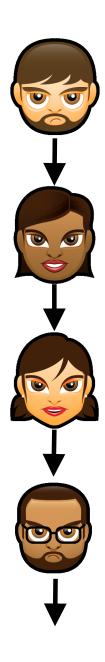
Jen Hay (Canterbury, NZ)

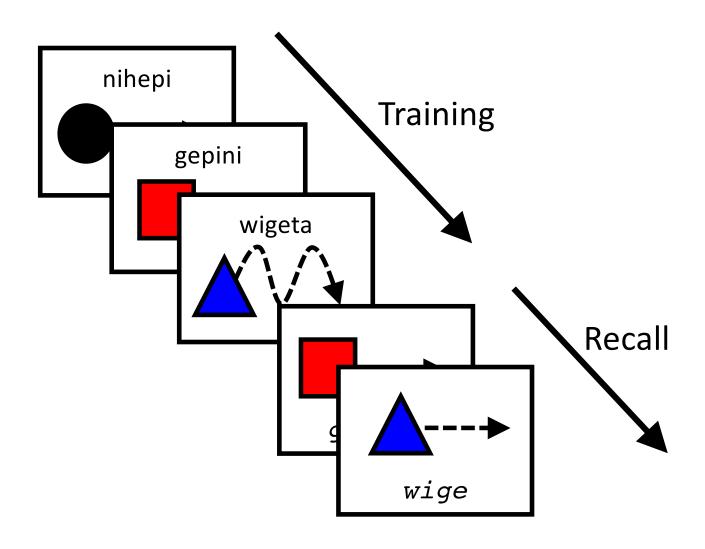
Language is transmitted via repeated **learning** and **use**Language is shaped by these processes

The cycle of learning and use produces structure



Iterated learning





Kirby, S., Cornish, H., & Smith, K. (2008). Cumulative cultural evolution in the laboratory: An experimental approach to the origins of structure in human language. *PNAS*, 105, 10681-10686.

Demo using this week's practical code

An initial holistic (random) language

	wimaku	miniki	gepinini	
	nihepi	wigemi	mahekuki	0
	wikima	nipikuge	hema	Δ
	miwiniku	pinipi	kihemiwi	
	kinimapi	wikuki	kikumi	0
•	miwimi	nipi	wige	Δ
	gepihemi	kunige	miki	
	pikuhemi	kimaki	pimikihe	0
_	mihe	winige	kinimage	Δ

Initial language from chain 4

	wimaku	miniki	gepinini	
	nihepi	wigemi	mahekuki	0
	wikima	nipikuge	hema	Δ
	miwiniku	pinipi	kihemiwi	
	kinimapi	wikuki	kikumi	0
	miwimi	nipi	wige	Δ
	gepihemi	kunige	miki	
	pikuhemi	kimaki	pimikihe	0
_	mihe	winige	kinimage	Δ

Generation 1 language from chain 4

	nige	miniku	poh	
	mip	mpo	miniku	0
	tuge	tuge	weg	Δ
	pemini	kupini	pon	
11/1	kimei	miwn	miheniw	0
• '	poi	mhip	kuwpi	Δ
. •	hepinimi	himini	hipe	
	kuhepi	wige	mie	0
•	pobo	tupim	hipe	Δ

Generation 2 language from chain 4

	nige	tuge	tuge	
	nige	nige	tuge	0
	nige	tuge	mpo	Δ
	nige	tuge	mihenu	
11/4	hepini	miniku	hepini	0
• •	poi	mpo	tupim	Δ
. •	hepini	miniku	tupim	
	hepini	tupim	tupim	0
_	nige	tupim	poi	Δ

Generation 3 language from chain 4

	mihenu	tuge	tuge	
	tuge	tuge	tuge	0
	nige	tuge	tuge	Δ
	miniku	tuge	minihu	
11/4	tuge	tupim	tupim	0
• •	poi	tuge	miniku	Δ
_	mihenu	tupim	tupim	
	tupim	tupim	tupim	0
	poi	tupim	tupim	Δ

Generation 4 language from chain 4

	tuge	tuge	tuge	
	tuge	tuge	tuge	0
		tuge	tuge	Δ
	mihunu	tupim	miniku	
	tupim	tupim	tupim	0
•	poi	miniku	miniku	Δ
. •	tupim	tupim	tupim	
	tupim	tupim	tupim	0
-	poi	tupim	tupim	Δ

Generation 5 language from chain 4

				_
	tuge	tuge	tuge	
	tuge	tuge	tuge	0
	tuge	tuge	tuge	Δ
	minuhu	tupim	tupim	
11/4	tupim	tupim	tupim	0
• •	miniku	tupim	miniku	Δ
_	tupim	tupim	tupim	
	tupim	tupim	tupim	0
	poi	tupim	tupim	Δ

Generation 6 language from chain 4

	tuge	tuge	tuge	
	tuge	tuge	tuge	0
	tuge	tuge	tuge	Δ
	miniku	tupin	tupim	
11/4	miniku	miniku	miniku	0
• •	miniku	tupin	tupin	Δ
. •	poi	tupin	tupim	
	poi	poi	poi	0
	poi	tupin	tupim	Δ

Generation 7 language from chain 4

	tuge	tuge	tuge	
	tuge	tuge	tuge	0
	tuge	tuge	tuge	Δ
	miniku	miniku	tupim	
11/4	miniku	miniku	miniku	0
• '	miniku	tupin	miniku	Δ
. •	poi	poi	tupim	
	poi	poi	poi	0
	poi	tupin	poi	Δ

Generation 8 language from chain 4

	tuge	tuge	tuge	
	tuge	tuge	tuge	0
	tuge	tuge	tuge	Δ
	tupim	tupim	tupim	
11/4	miniku	miniku	miniku	0
• •	tupin	tupin	tupin	Δ
. •	poi	poi	poi	
	poi	poi	poi	0
-	poi	poi	poi	Δ

Generation 9 language from chain 4

	tuge	tuge	tuge	
	tuge	tuge	tuge	0
	tuge	tuge	tuge	Δ
	tupim	tupim	tupim	
11/4	miniku	miniku	miniku	0
• •	tupin	tupin	tupin	Δ
. •	poi	poi	poi	
	poi	poi	poi	0
-	poi	poi	poi	Δ

Generation 10 language from chain 4

	tuge	tuge	tuge	
	tuge	tuge	tuge	0
	tuge	tuge	tuge	Δ
	tupim	tupim	tupim	
11/4	miniku	miniku	miniku	0
•	tupin	tupin	tupin	Δ
. •	poi	poi	poi	
	poi	poi	poi	0
-	poi	poi	poi	Δ

Final language from chain 1 (!)

	nepa	nepa	nepa	
	nepa	nepa	nepa	0
	nepa	nepa	nepa	Δ
	nepa	nepa	nepa	
1	nepa	nepa	nepa	0
	nepa	nepa	nepa	Δ
. •	nepa	nemene	nepa	
	nepa	nepa	nepa	0
_	nepa	nepa	nepa	Δ

The languages become degenerate



Generation 9 language from chain 5 (with homonymy filter)

	ne-re-ki	la-re-ki	renana	
	ne-he-ki	la-ho-ki	re-ne-ki	0
	ne-ke-ki	la-ke-ki	ra-he-ki	Δ
	ne-re-plo	la-ne-plo	replo	
	ne-ho-plo	la-ho-plo	re-ho-plo	0
·	ne-ki-plo	la-ki-plo	ra-ho-plo	Δ
	nepilu	la-ne-pilu	repilu	
	ne-ho-pilu	la-ho-pilu	re-he-pilu	0
_	ne-ki-pilu	la-ki-pilu	ra-ho-pilu	Δ

Beckner et al. (2017)

Reanalysis/gentle roasting of Kirby, Cornish & Smith (2018)

- Our sample size was tiny
- Our statistics were rudimentary
- They find an interesting (?) difference between semantic dimensions

Replication

- Participants recruited from MTurk
- N=240 (2 conditions, 12 chains per condition, 10 participants per chain)
- 22-25 minutes, paid \$3

Measuring structure

```
"the dog chew-ed the bone" – "the dog lick-ed the bone"

Meaning distance = 1 (predicate)

Signal distance = 1 (verb stem)

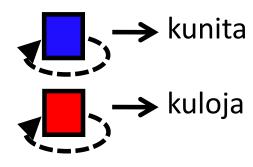
"the dog chew-ed the bone" - "the dog lick-s the bone"
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"the dog chew-ed the bone" - "the dog lick-s the bone" Meaning distance = 2 (predicate, tense) Signal distance = 2 (verb stem, suffix)

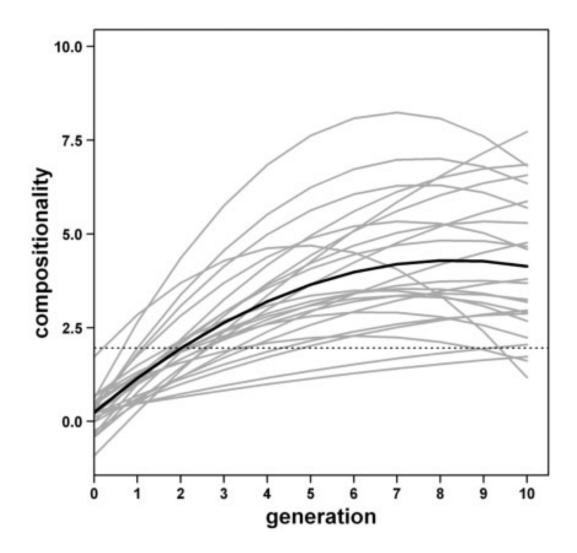
Pairwise meaning and signal distances will be highly correlated in a compositional system: similar meanings map to similar signals (and dissimilar meanings map to dissimilar signals)

Measuring structure

- For every pair of meaning-signal pairs
 - Measure meaning distance (Hamming distance)
 - Measure signal distance (Levenshtein string-edit distance)
 - Correlate these distances
- Evaluate statistical significance of that correlation
 - Randomise label assignments, recalculate measure, repeat 1000 times to give distribution
 - Calculate z-score of veridical correlation



Meaning Distance = 1 Signal distance = 3



	'red'	'green'	'blue'	
'berry'	shen-to	shen-ta	shen-to	'1'
	shen-tra	shen-tro	shen-tra	'2'
	shen-trio	shen-trio	shen-trio	' 3'
'key'	div-tro	div-tro	div-tro	'1'
	dev-tro	dev-tro	dev-etrio	'2'
	dev-stra	div-stra	dev-stra	' 3'
'phone'	lolni-tro	lolni-tro	lolni-to	'1'
	lolne-stra	lolni-tro	lolne-stro	'2'
	lolni-tra	lolni-stra	lolni-stra	' 3'

Beckner et al.'s conclusions

Iterated learning does produce structure

- Our 2008 result replicates with a proper sample size
- The method also works online...
- ... but for this kind of challenging task, MTurk data is noisier?

Time for Q&A/discussion on this week's reading

Next up

Wednesday, 9am: lab on Gather

• Iterated learning, manipulating CSVs and looping trials

Next week: final lecture and lab

• Zipf's Law of Abbreviation, dyadic interaction