



BACKGROUND

Usage-based constructionist approaches

- Language development as interactions between frequency and domain-general learning capacities (e.g., Goldberg, 2019; Tomasello, 2003)
- Q: *how do we appropriately represent developmental trajectories involving clusters of form-function pairings (i.e., constructions)?*

Bayesian-inference-based simulation

- Assumption: human learning involves one's updated beliefs based on previous experience
- Studies focused mostly on English (e.g., Alishahi & Stevenson, 2008; Barak et al., 2016; Perfors et al., 2011)
- Q: *to what extent are the implications of computational simulations generalisable across languages?*

Active transitives & suffixal passives in Korean

- Korean: SOV language with overt case-marking
- Clause-level constructions expressing a transitive event

Active transitive

Canonical	N-NOM	N-ACC	V
Scrambled	N-ACC	N-NOM	V

Suffixal passive

Canonical	N-NOM	N-DAT	V-PSV
Scrambled	N-DAT	N-NOM	V-PSV

- Language-specific properties
- Arguments / case markers can be omitted if they are inferable from the context (Sohn, 1999)

Argument + case-marking omission

Minho-lul cap-ass-ta.
Minho-ACC catch-PST-SE
'Ciwu caught Minho.'

Case marking omission

Ciwu-ka Minho-lul cap-ass-ta.
Ciwu-NOM Minho-ACC catch-PST-SE
'Ciwu caught Minho.'

- Form-function pairings involving case-marking
- Asymmetric degree of association between form and function



Passive morphology

- Rarely attested in input; morphologically irregular; overlap in morphological causatives (Shin, 2020; Sohn, 1999; Yeon, 2015)

RQ

Given language-specific properties in Korean, how a Bayesian learner formulates knowledge about active transitives and suffixal passives?

Abbreviation: ACC = accusative case marker; DAT = dative marker; N = noun; NOM = nominative case marker; PST = past tense marker; SE = sentence ender; V = verb

BAYESIAN SIMULATION

Input composition

- All constructional patterns expressing a transitive event found in caregiver input in CHILDES (MacWhinney, 2000)

Type	Example	Frequency (#)
Canonical active transitive	police-NOM thief-ACC catch	1,757
Scrambled active transitive	thief-ACC police-NOM catch	51
Canonical suffixal passive	thief-NOM police-DAT catch- <i>psv</i>	2
Scrambled suffixal passive	police-DAT thief-NOM catch- <i>psv</i>	1
Canonical active transitive, no ACC	police-NOM thief- ACC catch	268
Canonical active transitive, no NOM	police- NOM thief-ACC catch	19
Scrambled active transitive, no ACC	thief- ACC police-NOM catch	6
Scrambled active transitive, no NOM	thief-ACC police- NOM catch	0
Canonical suffixal passive, no DAT	thief-NOM police- DAT catch- <i>psv</i>	0
Canonical suffixal passive, no NOM	thief- NOM police-DAT catch- <i>psv</i>	0
Scrambled suffixal passive, no DAT	police- DAT thief-NOM catch- <i>psv</i>	0
Scrambled suffixal passive, no NOM	police-DAT thief- NOM catch- <i>psv</i>	0
Active transitive, actor-NOM only	police-NOM catch	935
Active transitive, undergoer-ACC only	thief-ACC catch	1,938
Ditransitive, recipient-DAT only	Lee-DAT send	234
Suffixal passive, undergoer-NOM only	thief-NOM catch- <i>psv</i>	407
Suffixal passive, actor-DAT only	police-DAT catch- <i>psv</i>	13
SUM		5,631

- Schematised pairings of morpho-syntactic and semantic-functional properties; indexing for canonicity

Example of input: canonical active transitive
 Morpho-syntactic layer N_1-i/ka_1 N_2-(l)ul_2 V_3
 Semantic-functional layer Actor_1-NOM_1 Undergoer_2-ACC_2 Action_3
 ※ N and V represent (probabilistically acquired) heuristics of noun and verb, respectively

Model training

- Frequency of constructional patterns in caregiver input
→ initial priors for learning
- Learning algorithm (adapted from Alishahi & Stevenson, 2008)

➢ A new input nCx is classified as an existing construction eCx , ranging over the indices of all the constructions in the model, with the maximum probability given nCx

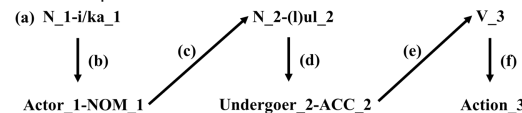
$$\text{Best Construction } (nCx) = \underset{eCx}{\text{argmax}} P(eCx | nCx)$$

➢ Posterior probability is proportional to multiplication of conditional probabilities associated with eCx and the prior of eCx

$$P(eCx | nCx) \propto P(nCx | eCx) * P(eCx)$$

➢ Laplace smoothing to prevent the probability from converging upon zero

- Two types of probability information
- Constructional probability: probabilities of individual patterns
- Transitional probability: conditional probabilities of constructional components within each pattern



Model performance

- Posterior probabilities of constructional patterns at every learning phase (one to 30)
- as a proxy for the degree of clustering for these constructions

RESULTS & DISCUSSION

By-pattern posterior probabilities

- Dominance of several patterns over the others

Type	Caregiver input (#)	Posterior probability per learning		
		1	5	30
Canonical active transitive	1,757	0.454	0.550	0.588
Scrambled active transitive	51	0.005	0.002	< 0.001
Canonical suffixal passive	2	< 0.001	< 0.001	< 0.001
Scrambled suffixal passive	1	< 0.001	< 0.001	< 0.001

※ mirrored distributional nature of child production (cf. Shin, 2020)

Inhibitory effects on the growth of the related patterns

Type	Caregiver input (#)	Posterior probability per learning		
		1	5	30
Canonical active transitive, no ACC	268	0.024	0.008	0.002
Canonical active transitive, no NOM	19	0.002	0.001	< 0.001
Active transitive, actor-NOM only	935	0.083	0.028	0.005
Active transitive, undergoer-ACC only	1,938	0.351	0.355	0.357
Suffixal passive, undergoer-NOM only	407	0.036	0.012	0.002
Suffixal passive, actor-DAT only	13	0.001	< 0.001	< 0.001

※ The other patterns converged upon zero probability immediately after the 1st learning

Inconsistency between simulation and child production

Type	Caregiver input (#)	Child production (#)	Posterior probability (30 th)
Active transitive, actor-NOM only	935	21	0.005
Canonical active transitive, no ACC	268	14	0.002
Suffixal passive, undergoer-NOM only	407	9	0.002

NOM-related patterns

Possible reasons

- Influences of case-marking (i.e., NOM is used exclusively as an indicator of the actor in transitive patterns; cf. Shin, 2020)
- Non-transitive partial utterances (with various noun-marker combinations) not considered in the current simulation
- Lexical items tied to specific constructional patterns in children's utterances

Together, our findings...

- ✓ support the idea that clause-level constructional knowledge grows through an interplay between input properties and domain-general learning capacities
- ✓ adds to cross-linguistic evidence for the effectiveness of Bayesian modelling on representing human learning

REFERENCES

Alishahi, A., & Stevenson, S. (2008). A computational model of early argument structure acquisition. *Cognitive Science*, 32(5), 789-834.
 Barak, L., Goldberg, A. E., & Stevenson, S. (2016). Comparing computational cognitive models of generalization in a language acquisition task. In J. Shi, K. Dun & X. Carreras (Eds.), *Proceedings of the 2016 conference on Empirical Methods in Natural Language Processing* (pp. 96-106). Association for Computational Linguistics.
 Goldberg, A. E. (2019). *Explain me this: Creativity, competition, and the partial productivity of constructions*. Princeton, NJ: Princeton University Press.
 MacWhinney, B. (2000). *The CHILDES project: Tools for analyzing talk* (3rd edition). Mahwah, NJ: Lawrence Erlbaum.
 Perfors, A., Tenenbaum, J. B., & Regier, T. (2011). The learnability of abstract syntactic principles. *Cognition*, 118(3), 306-338.
 Shin, G-H. (2020). Connecting input to comprehension: First language acquisition of active transitives and suffixal passives by Korean-speaking preschool children. Unpublished doctoral dissertation, University of Hawaii at Manoa.
 Sohn, H. M. (1999). *The Korean language*. Cambridge University Press.
 Tomasello, M. (2003). *Constructing a language: A usage-based theory of language acquisition*. Cambridge, MA: Harvard University Press.
 Yeon, J. (2015). Passives. In L. Brown & J. Yeon (Eds.), *The handbook of Korean linguistics* (pp. 116-136). Oxford: John Wiley & Sons.