

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	agent-NOM	theme-ACC	V	
Scrambled	theme-ACC	agent-NOM	V	
Suffixal passive				
Canonical	theme-NOM	agent-DAT	V-PSV	
Scrambled	agent-DAT	theme-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
 Ciwu-ka Minho-lul cap-ass-ta.
 Ciwu-NOM 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?

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-psv	2
Scrambled suffixal passive	police-DAT thief-NOM catch-psv	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-psv	0
Canonical suffixal passive, no NOM	thief-NOM police-DAT catch-psv	0
Scrambled suffixal passive, no DAT	police-DAT thief-NOM catch-psv	0
Scrambled suffixal passive, no NOM	police-DAT thief-NOM catch-psv	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-psv	407
Suffixal passive, actor-DAT only	police-DAT catch-psv	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	Agent_1-NOM_1	Theme_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

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

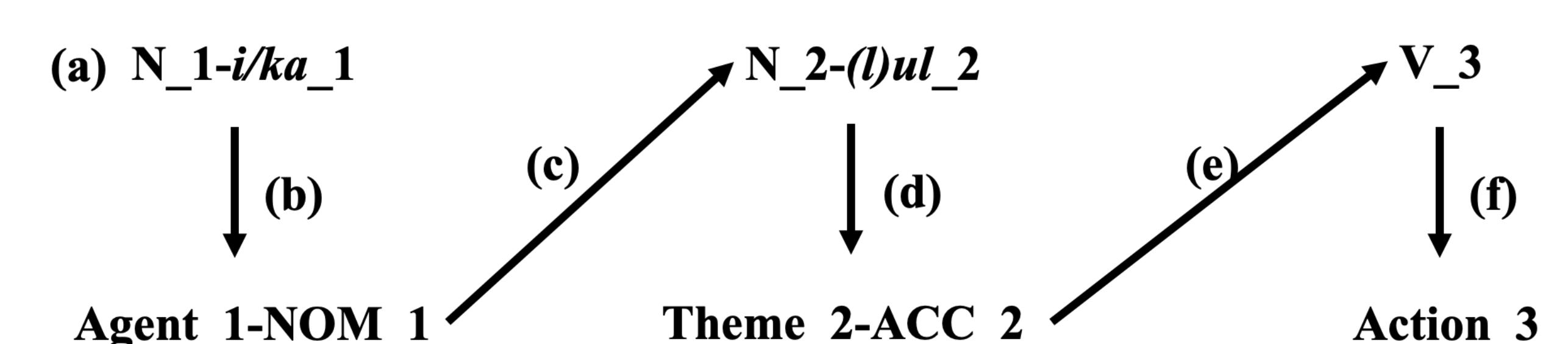
- Posterior probability is proportional to multiplication of conditional probabilities associated with eCx and the prior of eCx

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

- 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
Canonical active transitive	1,757	0.454
Scrambled active transitive	51	0.005
Canonical suffixal passive	2	< 0.001
Scrambled suffixal passive	1	< 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
Canonical active transitive, no ACC	268	0.024
Canonical active transitive, no NOM	19	0.002
Active transitive, actor-NOM only	935	0.083
Active transitive, undergoer-ACC only	1,938	0.351
Suffixal passive, undergoer-NOM only	407	0.036
Suffixal passive, actor-DAT only	13	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

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