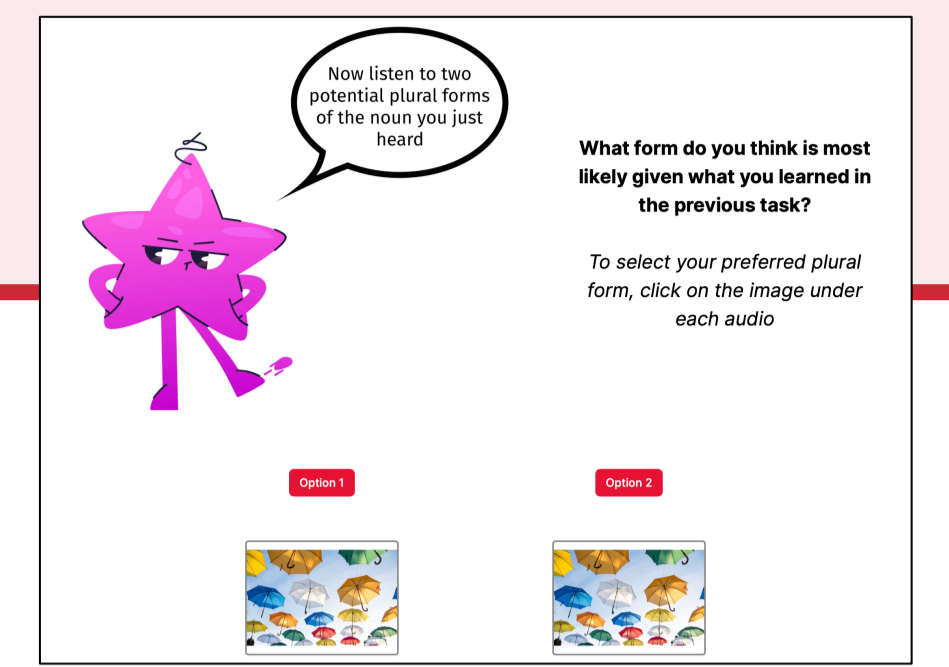




Núria Bosch (nb611@cam.ac.uk) • Bert Vaux (bv230@cam.ac.uk)  
University of Cambridge



## 1 (Some) evaluation metrics in rule induction 2 An Artificial Language Learning Experiment – Plural formation

- **Conservative bias:** stick to the input data (Berwick, 1985; Tenenbaum, 1999)
  - Subset Principle, exemplar-based learning...
- **Simplicity bias:** prefer formally simple(r) rules (Pycha et al., 2003; White, 2013; Durvasula & Litter, 2020).
  - E.g., pick  $\emptyset \rightarrow /r/ / V_{[-hi, -rd, +bk]} \_ V$  over  $\emptyset \rightarrow /r/ / V_{[-hi]} \_ V$  (in r-insertion)
- **Scope (expansion) bias:** prefer rules targeting as many segments as possible (Nie et al., 2019)
  - E.g., like simplicity, BUT also pick  $/o/ \rightarrow [ɔ]$  before  $/r/$ , nasals, coronal obs over  $/o/ \rightarrow [ɔ]$  before  $/r/$  ([F]-simpler)

Substantial work exploring the role of **simplicity and/or conservativeness** in learning:

- **Computational work** (i.a., Gold, 1967; Albright & Hayes, 2002; Carr et al., 2020)
- **Synchronic/diachronic** (i.a., Chomsky, 1957; Fodor & Crain, 1987; Clark & Roberts, 1993)
- **Experimental** (i.a., Pycha et al., 2003; White, 2013; Culbertson & Kirby, 2016)

Role of **scope expansion underexplored**, but recent evidence in diachrony (Nie et al., 2019) and computational models (Sayeed & Vaux, 2023)

**No work on scope expansion/contraction in real-time language learning, however!**

→ **Our contribution:** first attempt at probing **scope biases** with **Artificial Language Learning (ALL)**.

### Research questions

**RQ1:** Which **generalisation biases** do participants exhibit when presented with **sparse input** in an ALL setting?

**RQ2:** Further, do participants exhibit **different generalisation patterns** depending on the **scope of the rule** they are exposed to?

### Participants:

76 native English speakers recruited through Prolific

### Procedure:

Poverty of the Stimulus paradigm (e.g., Wilson 2003)

1. **Familiarization:** CVC pseudo-words with auditory evidence for an alternation in the plural suffix.

/kap/ > /kapwɔk/ BUT /pen/ > /penɔk/

Three conditions manipulating the **SCOPE** of the rule. Each provided **positive evidence** for diphthongization in:

- **Plosives Condition** (intermediate): 40 items – 20 stems (2 stems per C), repeated 2x.
- **Voiced Plosives Condition** (narrow): 32 items – 16 stems (4 stems per C), repeated 2x.
- **Obstruents Condition** (wide): 60 items – 30 stems (3 stems per obstruents, 6 per nasal/approx.), repeated 2x.

- **Negative evidence** (absence of diphthongization) in **nasals** and/or **approximants**.
- **'Control':** 1 phoneme **held out** per natural class.

2. **Evaluation:** quiz measuring learning success in exposed trials.

3. **Testing:** force-choice task with 54 novel stems for all unseen/seen environments.

4. **Debrief:** self-reports of learning strategies ('rule-based' or 'intuition-based')

### Predictions:

- **If biased by conservativeness:** tight fit to input data, little/no overgeneralization.
- **If biased by simplicity:** extraction of rule with maximal formal simplicity (could take multiple forms; [F]-minimization, elsewhere-rule, etc.).
- **If biased by scope:** extraction of rule with most targets (which need not be [F]-simplest rule).

## 3 Results

### Overall patterns:

1. **Overgeneralization of /wɔk/, with no effect of Condition ( $F(2,27) = 2.20, p = .13$ ).**

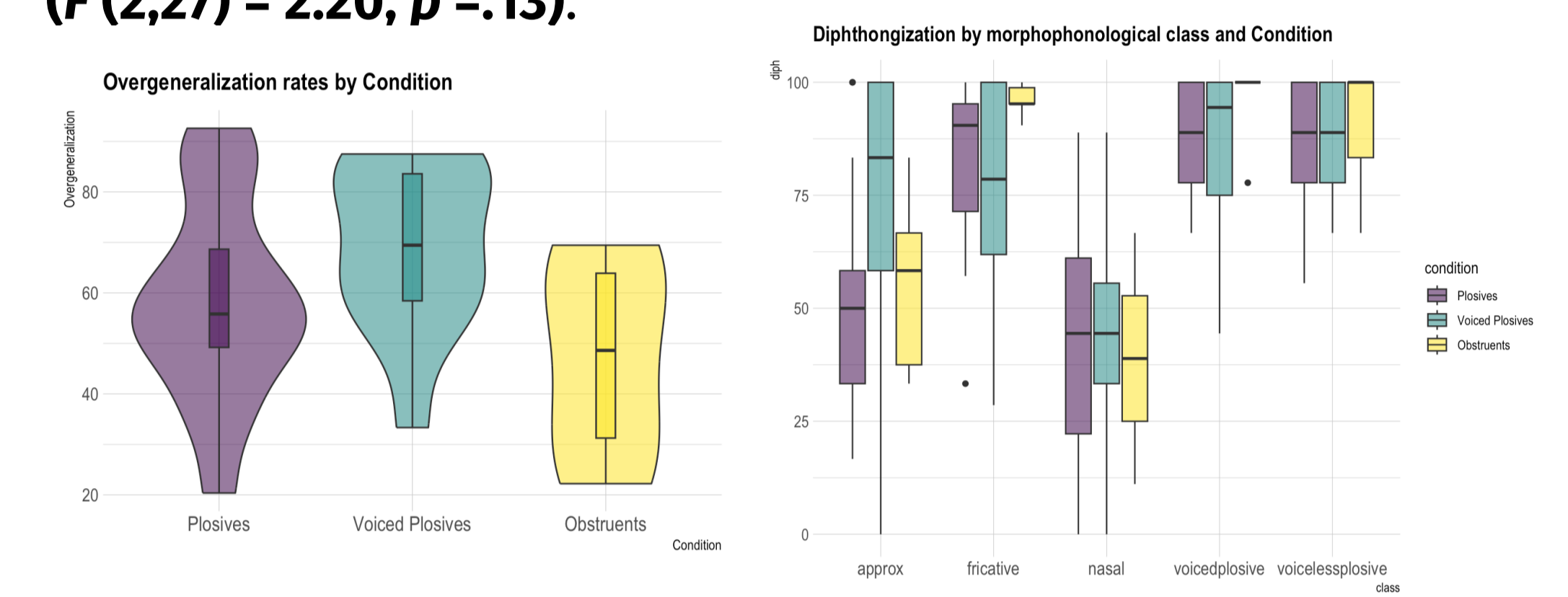


Fig 1.

Fig 2.

- Only **nasals/approximants**, esp. **individual segments in familiarization phase**, were **less likely** to trigger diphthongization, though with substantial variance.
- **All other segments generally triggered diphthongization, incl. held-out segments (e.g., /r/ = 77.78%, /ŋ/ = 75.55%).**
- Mixed effects logistic regression: **all** phonemic contexts **highly associated with diphthongization** at testing ( $p < .001$ ), **bar** nasals-approximants ( $\beta = -0.13, p = 0.610$ ).
  - Segments **outside of training data** much **more likely** to trigger **diphthongization** ( $\beta = 1.08, p < .001$ ).

→ **Upshot: exception-driven learning.** Individual segments (not phonological natural classes) extracted as **exceptions** to an elsewhere rule.

E.g., [PL] → /ɔk/ / /n, m, l/ \_\_\_\_\_  
/wɔk/ ELSEWHERE

### Local patterns:

In a few participants we also observe other hypotheses consistent with the data presented:

- **Scope expansion/simplicity** (2 participants): Voiced Plosives > Plosives
- **Semantically-conditioned generalizations** (9 participants, majority from sparser Condition 2): **animacy-conditioned** rules, based on self-reports, e.g., animals vs objects.
  - **Adults more likely** than children to **induce semantic** over phonological **rules**, especially if learning explicitly (Lidz & Gagliardi, 2014; Brown et al., 2021; Pertsova and Becker, 2021).
    - NB: bias observable *despite explicit directions to ignore any semantic cues*.
- **Possible morphologization** (1 participant): morphologized the nasal /n/ as part of suffix – “plural words end with either ‘wɔk’ or ‘nɔk’”.

### The patterns vs the predictions

- Results consistent with a view where **learners** are **aggressive in generalizing**
  - ✓ simplicity, scope expansion accounts
  - ✗ conservativeness
- Specifically, **exception-driven learning** supports Tolerance Principle’s predictions.
- In principle, **compatible** with a **scope expansion bias**, BUT **data insufficient** to tease it apart from simplicity bias.

## 4 Conclusions and future work

### What we have shown:

- Scope expansion independently attested in diachronic patterns → **Novel experiment** testing the effects of **scope manipulation** in morphophonological generalizations.
- Results support view of learners as **overgeneralizers** in the face of input sparsity, consistent with both simplicity/scope analytic biases.
- Implications for role of type frequency and explicit learning in ALL.

### Questions and future work:

- Better design to tease apart predictions of simplicity vs scope bias.
- Can we design ALL set-ups that minimize the incidence of explicit learning, to more accurately probe learning biases (e.g., more complex task, more learning trials)?
  - Design used plausibly too conducive to exception-driven learning. Can we avoid this?
- Should child participants be favored over adult learners for similar experiments? (see Pertsova & Becker, 2021)

### Acknowledgements

Thanks in particular to Samuel Andersson for help and suggestions; thanks also to Theresa Biberauer for discussion. This work is supported by an Open-Oxford-Cambridge AHRC DTP – St John’s Studentship (UKRI and St John’s College)

## Results (continued)

### 2. Type, not token, frequency conditioned generalizations

- No statistical bias in familiarization data: **balanced token frequency** of diphthongized vs non-diphthongized familiarization items (~50/50%).
- Nonetheless, **type frequency (mostly) determined generalization patterns**, as in Yang’s (2002, *et seq.*) **Tolerance Principle** (see also Schuler et al., 2017; cf. Baayen, 2009).

- Plosives Condition:  $\theta_N = 4.59$  (4 vs 3 types).
- Voiced Plosives Condition:  $\theta_N = 2.89$  (2 vs 2 types).
- Obstruents Condition:  $\theta_N = 4.8$  (9 vs 3 types).

### 3. Predominance of explicit learning: role of learning strategies

- **Rule-based**, explicit-learning strategies (per self-reports) **facilitated learning success**
  - Higher performance in evaluation quiz ( $W = 249, p = .018$ ). **Fig 3.**
  - Higher input-faithfulness in testing ( $W = 199, p = .002$ ). **Fig 4.**
- Introspective self-reports generally well-correlated with implicit/explicit learning (Pertsova & Becker, 2021).
- **HOWEVER: not significantly more likely** to be correlated with **higher overgeneralization rates** ( $t(45) = 0.88$ ). **Fig 5.**
  - Suggests **overgeneralization bias inherent in all participants**, irrespective of self-reported learning strategy.

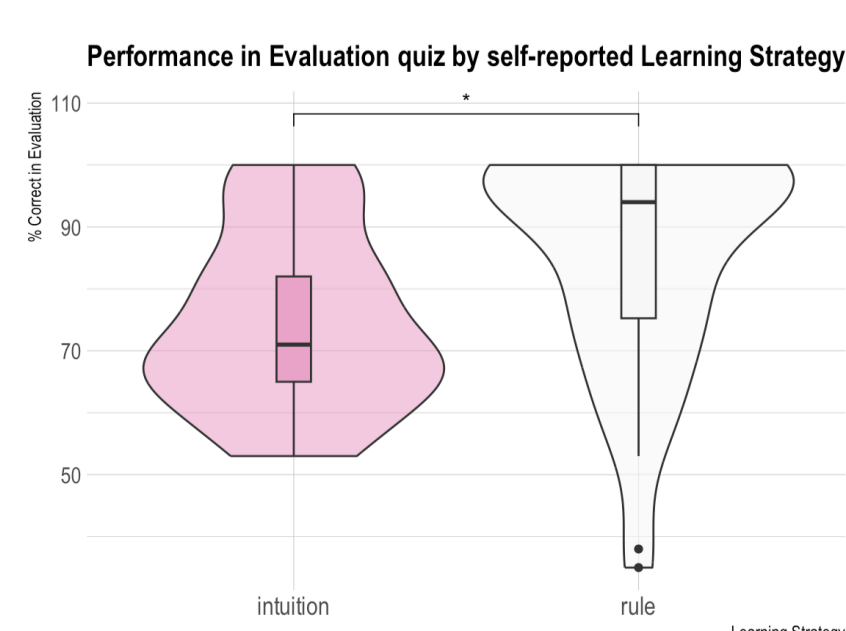


Fig 3.

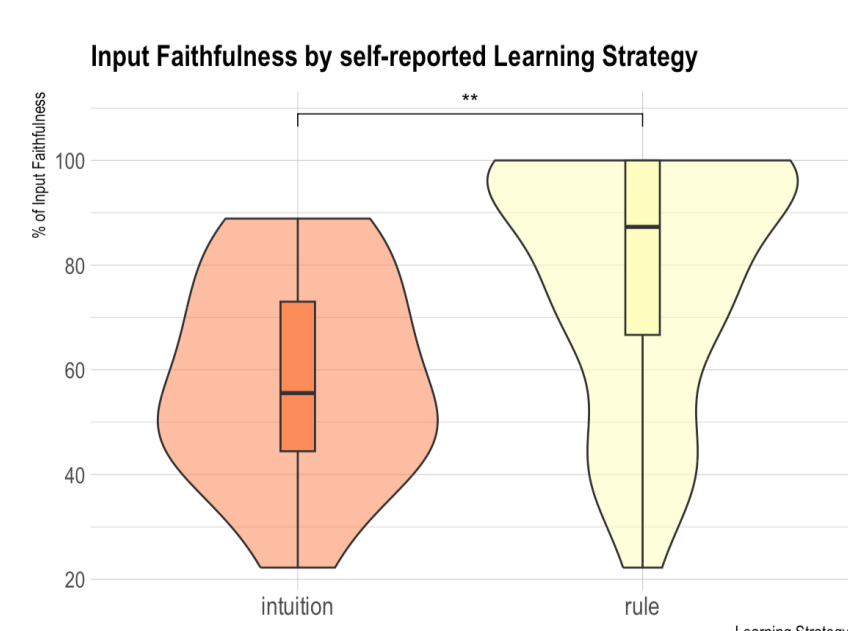


Fig 4.

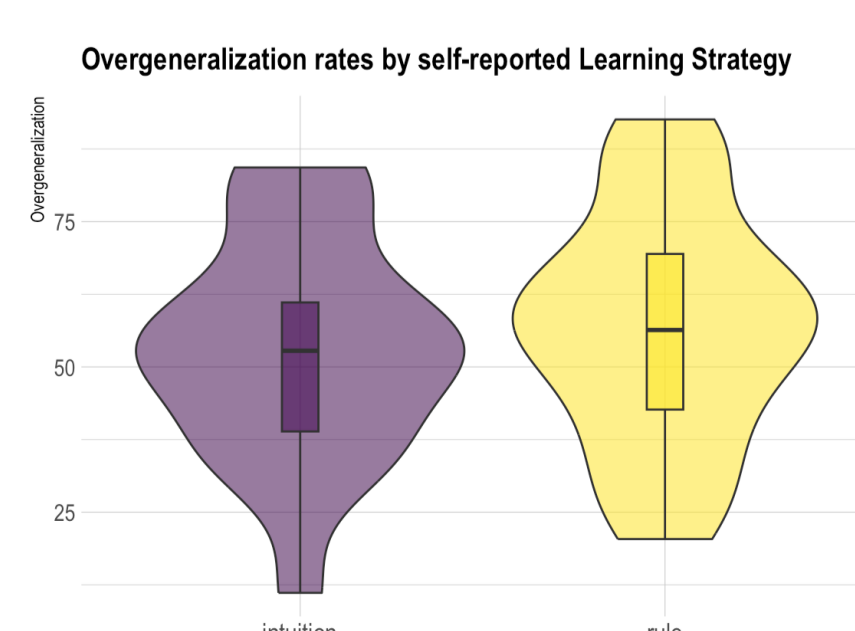


Fig 5.

