Modeling the Acquisition of Phonological Interactions: Biases and Generalization

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Introduction

- There has been extensive theoretical debate on modeling the full range of known phonological process interactions.
  - ➢ Here we focus on *bleeding (B)*, *feeding (F)*, *counterbleeding (CB)*, and *counterfeeding (CF)* interactions.
- We build on recent experimental and computational work (Jarosz 2016, Prickett 2019) to provide novel evidence differentiating theories based on their predictions for learning and generalization.

Background

- Two biases based on diachronic change (Kiparsky 1968, 1971):
  - ➢ *Maximal Utilization (MaxUtil)*: F, CB > B, CF
  - ➢ *Transparency*: B, F > CB, CF
- Jarosz (2016) showed that both biases are predicted by computational learning models and Prickett (2019) found that both affected different aspects of artificial language learning.
- Debates about opacity prominently contrast two dimensions:
  - Parallel (e.g. McCarthy 1999) vs. Serial (e.g. Kiparsky 2000)
  - Productive (e.g. Chomsky 1964) vs. Exceptional (e.g. Sanders 2003)
- We test predictions of four theories spanning these dimensions:

Serial
- ➢ **Stratal OT** (Kiparsky 2000)
- ➢ **HS** (McCarthy 2000) with **SMR** (Jarosz 2014)

Parallel
- ➢ **Two-level constraints**, e.g. *[s]/i/ (McCarthy 1996)
- ➢ **Indexed constraints** (Pater 2010)

Artificial Languages

- Each of the four toy languages we used had two processes:
  - ➢ Palatalization [s] → [ʃ] / _[+High]
  - ➢ Vowel Harmony [-Low] → [αHigh] / [αHigh]C_
- By manipulating the ordering of these processes, as well as the lexicon, we created a unique interaction type in each language:

	B	F		CB	CF
UR	/esi/	/ise/	UR	/esi/	/ise/
Harm.	ese	isi	Pal.	eʃi	-
Pal.	-	iʃi	Harm.	eʃe	isi
SR	[ese]	[iʃi]	SR	[eʃe]	[isi]

Simulations

- We implemented the four theories of interest as probabilistic pairwise ranking grammars and trained them with Expectation Driven Learning (Jarosz 2015).
  - ➢ Learning rate was .05 for all simulations and each model was trained online for 100 passes through the data.
  - ➢ Software (Jarosz, Anderson, Prickett, Lamont, & Nyman 2018): https://github.com/gajajarosz/hidden-structure
- Training data for each language contained 20 words, each belonging to one of four categories. Testing data was always the kind of interacting forms that were absent in training:

	TRAINING				TEST
	Faithful	Palatal.	Harm.	Interact.	Interact.
B	[ase], [ake]	/asi/ → [aʃi]	/ekɪ/ → [ekɛ]	/esi/ → [ese]	/ise/ → ?
F	[ase], [ake]	/asi/ → [aʃi]	/ekɪ/ → [ekɛ]	/ise/ → [iʃi]	/esi/ → ?
CB	[ase], [ake]	/asi/ → [aʃi]	/ekɪ/ → [ekɛ]	/esi/ → [eʃe]	/ise/ → ?
CF	[ase], [ake]	/asi/ → [aʃi]	/ekɪ/ → [ekɛ]	/ise/ → [isi]	/esi/ → ?

- Training data accuracy was assessed after each pass through the data using forced choice tasks (following Prickett 2019):
  - ➢ Palatalization: /asi/ → [aʃi] vs. [asi]
  - ➢ Harmony: /ekɪ/ → [ekɛ] vs. [asi]
  - ➢ Ordering: /esi/ → [ese] vs. [eʃe] *(B/CB) or…* /ise/ → [isi] vs. [iʃi] *(F/CF)*
- Predictions for test data were also collected after each pass.

Predictions: Biases

- As in Prickett (2019), biases were defined using training data accuracy on two types of forms:
  - ➢ *MaxUtil*: Accuracy on palatalization is higher for models trained on F, CB languages than for B, CF languages
  - ➢ *Transparency*: Accuracy on ordering is higher for models trained on B, F languages than CF and CB.
- Results:

	Stratal	HS+SMR	2-Level Const.	Ind. Const.
Max. Util.	✔	✔	✔	✔
Transp.	✔	✔	✗	✗

- In the serial models, the evidence for rankings that correctly map interacting items is more consistent in transparent languages.
- The parallel models lack this asymmetry.

Predictions: Generalization

- We also examined what each model predicted for the test data held out from training. For example, the following table summarizes what the Stratal model acquired for each language.
  - ➢ i.e. which processes are active at each stratum of the grammar for each training condition:

	B	F	CB	CF
Stratum 1	Palatalize & Harmonize	Palatalize & Harmonize	Just Palatalize	Just Palatalize
Stratum 2	Palatalize & Harmonize	Palatalize & Harmonize	Palatalize & Harmonize	Just Harmonize

  - ➢ These grammars correctly capture the mappings present in the training data.
- The table below shows what mappings these grammars predict for the test data URs, which were absent from training:

	B	F	CB	CF
UR	/ise/	/esi/	/ise/	/esi/
Stratum 1	iʃi	ese	-	eʃi
Stratum 2	-	-	iʃi	eʃe
SR	[iʃi]	[ese]	[iʃi]	[eʃe]
Mapping Type	Transp.	Transp.	Transp.	Opaque

  - ➢ Each mapping can be classified as either transparent or opaque based on whether it's B/F or CB/CF, respectively (additionally, mappings can be faithful).
- We applied the same process to the other models:

	Stratal	HS+SMR	2-Lev. Const.	Ind. Const.
B	Transp.	Transp.	Transp.	Transp.
F	Transp.	Transp.	Opaque	Opaque
CB	Transp.	Faithful	Transp.	Opaque
CF	Opaque	Transp.	Opaque	Opaque

  - ➢ This table shows the highest probability outcome predicted by each theory for each condition.

Conclusions

- Links between learning models and phonological theory yield novel predictions that can help resolve longstanding debates.
  - ➢ Biases: predictions about relative learning rates
  - ➢ Generalization: predictions for behavior on unseen data
- Here, predictions differentiate between all four theories.