Revisiting (Im)possible Interactions in Learning Turkish Laryngeal Alternations

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We propose a learning based account of Turkish laryngeal alternations—in which some **(1a)** but not all **(1b)** stem-final voiceless stops alternate with voiced stops (or [k] ~ ∅) when vowel-initial suffixes are attached. [1] found that in a corpus [2], the alternation is predictable by several features of the stem—namely the prosodic size (polysyllabic vs. monosyllabic; simple vs. complex codas), place of articulation, and final vowel quality (backness and height). However, in a wug test [1], adult Turkish speakers generalized based only on the prosodic size and place of articulation, showing little or no sensitivity to the vowel dependency. Because vowel backness/height influencing following consonant laryngeal features has not been reported typologically, [1] proposes that an analytic UG bias rules out this interaction.

We combine the learning algorithms ATP [3] and PLP [4] to propose a learning model for this alternation. ATP constructs morphophonological rules by recursively subdividing words based on their features. This yields a decision tree, with a path to a leaf being a rule; recursion stops when such a rule becomes productive, measured by the Tolerance Principle (TP) [5]. PLP learns phonological rules, beginning around an alternating segment (here the stem-final stop), and expanding attention outward in response to the alternation not being sufficiently predictable, also measured by the TP. We use PLP to extract features for ATP. Thus, ATP has access to prosodic features (MonoSyl, CMPLX), which we assume are already learned, and to features from PLP, but in the order of PLP's window increase: PLP first tracks the alternating stops. Thus, if the alternating nouns can be sufficiently predicted with only the prosodic features and the final stop, then PLP never has a reason to look further, and the model would not generalize based on the final vowels. Critically, the model can track such dependencies should they be necessary; UG need not rule them impossible.

We augmented TELL [2] nouns with frequencies [6] and simulated learners by sampling nouns weighted by frequency. We ran the model on 24 ([1]'s number of participants) size 10K±1K samples and predicted, for each model on each nonce, whether it alternates. We compared the fraction of models that predicted each nonce to alternate to the fraction of participants who did. We also fit two logistic regression models to TELL—one including and one omitting vowel feature predictors—and used these to estimate the probability of each nonce alternating. See **Table 1**. Our model, which allows the possibility of vowels being tracked, achieves comparable correlation to that of the regression model that rules out the possibility of vowel quality influencing the alternation. **Figure 1** provides an example tree. Our model sometimes conditions rules on vowel quality, but such rules are of narrow scope (<1% of nouns) and thus do not contribute substantially to prediction. Thus, our model provides a possible learning based account for human generalization behavior: the lack of sensitivity could be a consequence of the algorithms that construct generalizations, rather than a reflection of an analytical constraint in UG.

(1) (a)	[sɑhi**p**] ~ [sɑhi**b**-im]	‘owner’-POSS	(b)	[to**p**] ~ [to**p**-um]	‘ball’-POSS
	[ɑde**t**] ~ [ɑde**d**-im]	‘amount’-POSS		[hizme**t**] ~ [hizme**t**-im]	‘employment’-POSS
	[gen**t͡ʃ**] ~ [gen**d͡ʒ**-im]	‘youth’-POSS		[hi**t͡ʃ**] ~ [hi**t͡ʃ**-im]	‘worthless one’-POSS
	[byjy**k**] ~ [byjym]	‘big one’-POSS		[il**k**] ~ [il**k**-im]	‘first one’-POSS

Table 1: Model Correlations with [1]’s Wug test results

Model	**Pearson’s *r***	***p*-value**
Our Model	0.83	< 0.001
Regression no Vowels (*alter ~ place*size*)	0.82	< 0.001
Regression with Vowels (*alter ~ place*size+place*back+place*high*)	0.80	< 0.001

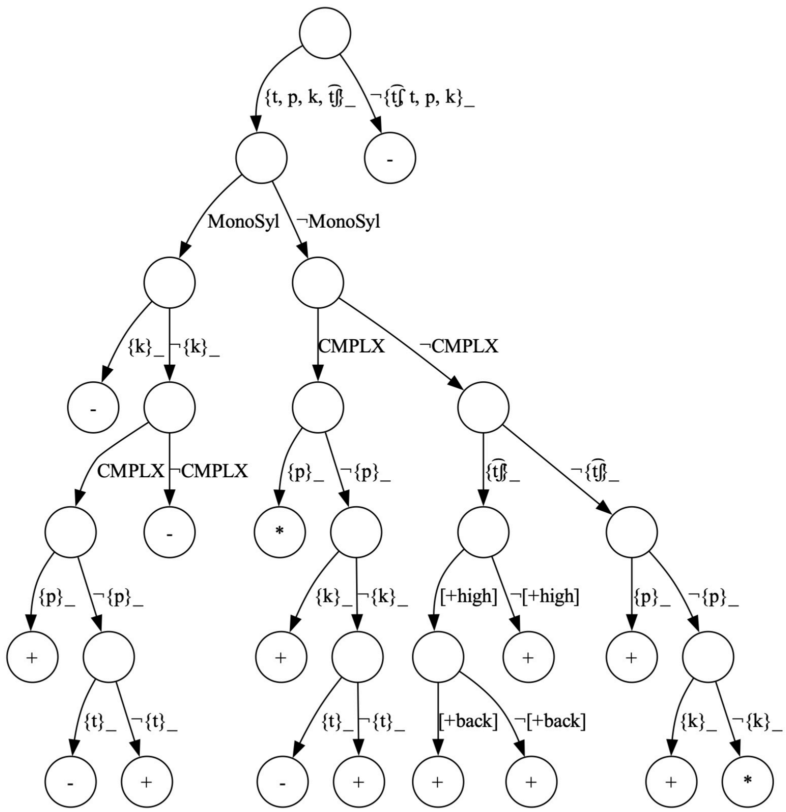

Fig 1: Example learned tree (+/− = +/−alternate; * = not productive)

References

[1] Becker, M., Ketrez, N., & Nevins, A. (2011). The surfeit of the stimulus: Analytic biases filter lexical statistics in Turkish laryngeal alternations. *Language*.
[2] Inkelas, S., Küntay, A., Orgun, O., & Sprouse, R. (2000). Turkish electronic living lexicon (TELL). *Turkic Languages*.
[3] Belth, C., Payne, S., Beser, D., Kodner, J., & Yang, C. (2021). The greedy and recursive search for morphological productivity. *CogSci*.
[4] Belth, C. (In Press). A Learning Based Account of Local Phonological Processes. *Phonology.*
[5] Yang, C. (2016). *The price of linguistic productivity: How children learn to break the rules of language*. MIT press.
[6] Wenzek, G., Lachaux, M. A., Conneau, A., Chaudhary, V., Guzmán, F., Joulin, A., & Grave, E. (2019). CCNet: Extracting high quality monolingual datasets from web crawl data. *LREC.*