Rare Hard-To-Learn Patterns Stably Learned Due To Language-Specific Lexical Frequencies

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Introduction

A major goal of phonological theory is to develop a model that can capture the attested phonological patterns while not vastly over-predicting.

- Constraint based grammars (Optimality Theory[1], Harmonic Grammar[2], etc.) make strong typological predictions through **Factorial Typology**
- Recently, an abundance of work[3] has investigated the hypothesis that learnability affects both categorical and soft typology.

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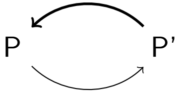
Learnability Filter on Typology

Small asymmetries in learning across one generation can result in large changes to typology over time.[4]

- The *harder* a pattern is to learn, the more likely learners are to accidentally learn a different pattern.
- If one pattern is *mislearned* more frequently than it is *accidentally learned*, it will become less attested across many generations of learning.



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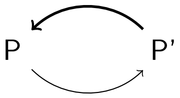

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$$\begin{tikzcd} \mathbf{P} \arrow[r, bend right] & \mathrm{P'} \arrow[l, bend right] \end{tikzcd}$$

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Stability Predictions

Typologically rare patterns are more likely to be mislearned than accidentally learned.

- This suggests that rare patterns are likely to be unstable.
- In O'Hara (2018), I look at initial vs. final asymmetries in stop place of articulation.
- I performed a survey of 77 languages with [k p t] in initial position.
- Finnish is the only language I could find with only [t] in final position.
- Must languages that exhibit rare patterns be unstable?

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	Initial			Final			
No Finals	tV	pV	Vk	✗	✗	✗	27
T-Final	tV	pV	Vk	**Vt**	✗	✗	1
PT-Final	tV	pV	Vk	**Vt**	**Vp**	✗	3
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The Finnish Problem

Finnish exhibits a rare pattern, but is it unstable?

- Finnish has stably shown this [t]-final pattern since at least Agricola (1542 (2014)).
- O'Hara (2018) shows that a [t]-final stage is on the pathway of learnability-conditioned final consonant loss.
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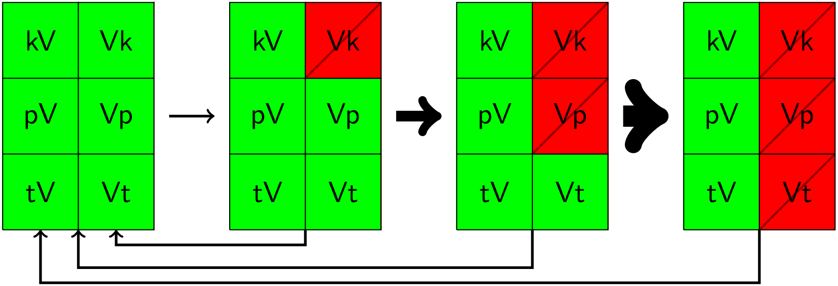

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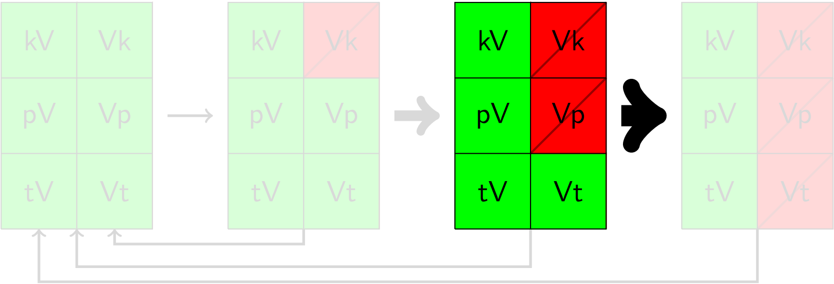

Lexical Factors Condition Stability

The licit phonotactic forms of a language are just one of the ways in which languages can differ.

- Learning is not just affected by whether or not a form exists in the target data
  - But also **how** common that form is in the target data
- Previous work has identified some ways in which the lexicon can interact with learning to shape typology, and affect language change.
  - Staubs (2014); Stanton (2016) show that the low frequency of long words is responsible for underattestation of certain stress patterns
  - Wedel *et al.* (2013) show that the functional load of a contrast affects the likelihood of loss of a contrast: i.e. the more minimal pairs the less common merger is. (Though with no minimal pairs, phoneme frequency may increase the chance of merger)

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Proposal: Lexical Frequencies Condition Stability

CLAIMS

- Finnish is stable due to its lexical frequency
- Language families that have shown different patterns of change have different lexical frequencies.
- The [t]-final pattern is rare because the lexical frequencies that predict the [t]-final pattern are rare.

Generational Model

Generational Learning Model[5]

- Simulated learners using MaxEnt[6] grammars
- Learners are initialized with Markedness constraints high, faith low[7]
- Using the Truncated Perceptron algorithm[8] train a learning agent off of some limited number of forms[9] from a teacher

Pattern $\longrightarrow$ ◯

[5] Following Staubs (2014); Hughto (2018)

[6] Goldwater & Johnson (2003), Hayes (this morning)

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Update Rule

Error-Driven Perceptron Algorithm [10]

- On each iteration, teacher selects an input at random, and produces an output.
- The learner produces an output as well.
- If the learner and teacher differ, raise the weights on the constraints the learner violated, and lower the weights on the constraints the teacher violated.

Example

- Teacher: /tV/-[tV] /pV/-[pV] /kV/-[kV] /Vt/-[Vt] /Vp/-[Vp] /Vk/-[Vk]
- Learner:

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- Learner: /tV/-[V]

	50	50	50	50	50	1		
tV	*K	*KP	*KPT	ONSET	NOCODA	MAX	HARM	PROB
(T) a. tV			-1				-50	.73
(L) b. V				-1		-1	-51	.27

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- Learner: /tV/-[V]

	50	50	49↓	51↑	50	2↑		
tV	*K	*KP	*KPT	ONSET	NOCODA	MAX	HARM	PROB
(T) a. tV			-1↓				-49↑	.98
(L) b. V				-1↑		-1↑	-53↓	.02

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Learning Bias

The Perceptron is a stochastic algorithm.

- Noise emerges in the learning process both from the selection of input forms, and output forms.
- This noise results in mistransmission across generations, which can compound over many generations.
- Patterns/languages differ in the expected speed of learning
- Faster learned patterns will have less noise than slower learned ones.

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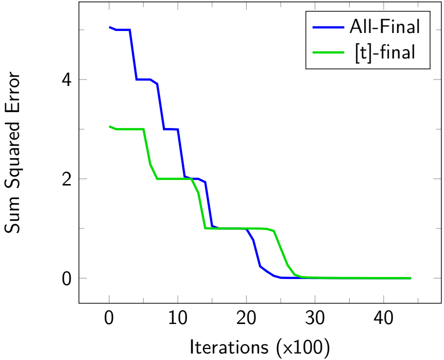
Uniform Baseline

Consider a uniform frequency across the forms

tV	pV	kV	Vt	Vp	Vk
.167	.167	.167	.167	.167	.167

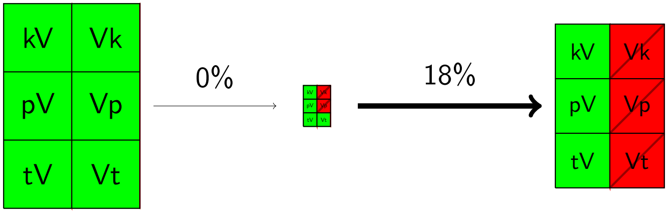
- The All-Final pattern is learned faster than the [t]-final pattern



Uniform Dynamics

[t]-Final pattern ends up being underattested with these dynamics.

- Change rates are percentage of 50 runs of 40 generations of 4600 iterations at .05 learning rate



Finnish

Finnish has much more final [t] than the uniform baseline (nearly 25% of syllables with ANY voiceless stops) have final t.

Forms	tV	pV	kV	Vt	Vp	Vk
Frequency	.107	.096	.142	.115	.0004	.0031
Normalized	.23	.21	.31	.25	.00	.01

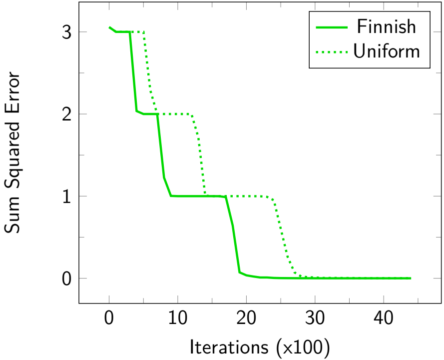
- Finnish frequencies were determined using corpora of 44040 words.[11]

[11] Goldsmith & Riggle (2012)

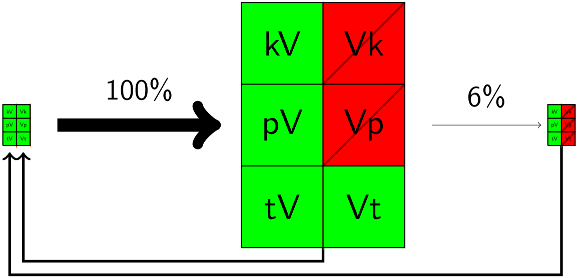
Finnish Simulations

Because /Vt/ is common, the [t]-final pattern is learned much faster than the uniform baseline.

- [t]-final is unlikely to be mislearned, but likely to be accidentally learned.



Finnish Stability



Claim 1

The [t]-final pattern is likely with Finnish frequencies.

Potential New Issues

- It is likely that Finnish stably shows the [t]-final pattern, but how likely was it for Finnish to appear?
- The unmarkedness of coronals makes high frequency of final [t] unsurprising. Why don't other languages with a lot of [Vt] show Finnish's [t]-final pattern?
- If [t]-final can be stable, when would a language lose *all* final stops?
- Three case studies will be used to investigate these issues.

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Finno-Ugric: Estonian

- Estonian is closely related to Finnish and still allows final [k].
- Serve as rough estimate of Proto-Finnish.
- In order to better base this on acquisition, we use available child directed speech corpora [12], with 15,472 unique words.

Forms	tV	pV	kV	Vt	Vp	Vk
Frequency	.0899	.11	.174	.0843	.005	.0187
Normalized	.19	.23	.36	.17	.01	.04

- Estonian has more final [Vk] and less [Vt] than Finnish.

[12] Argus (1998); Kohler (2004); Kutt (2018), a.o.

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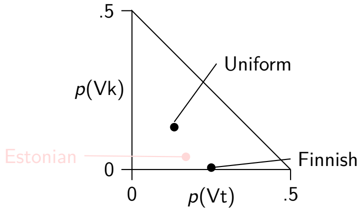

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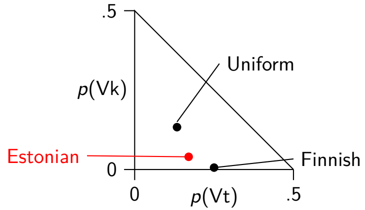

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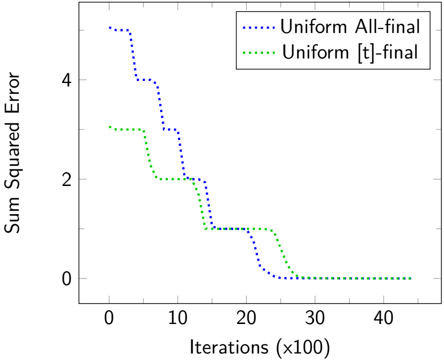

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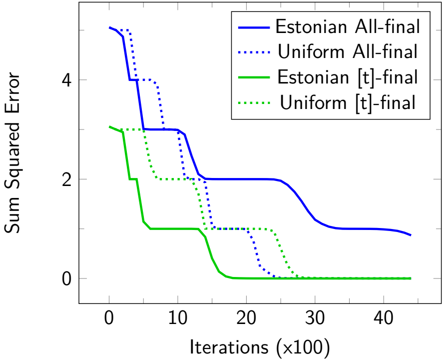
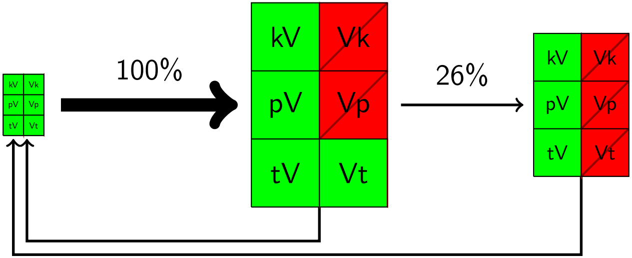


Finno-Ugric Dynamics



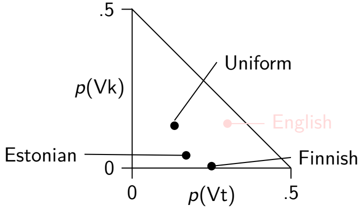
These dynamics predict that the [t]-final pattern is likely in the Finno-Ugric family.

West Germanic: English

English, like Finnish has many coronal-final suffixes.

- But no related languages show [t]-final
- Lexical frequencies of English are found using child directed speech (1321 unique words).[13]

Forms	tV	pV	kV	Vt	Vp	Vk
Frequency	.055	.060	.075	.111	.021	.052
Normalized	.15	.16	.20	.30	.06	.14



[13] Bernstein-Ratner (1987); Brent & Cartwright (1996)

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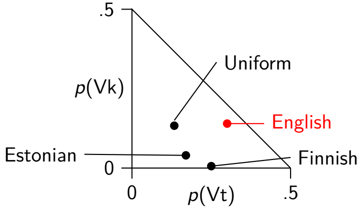

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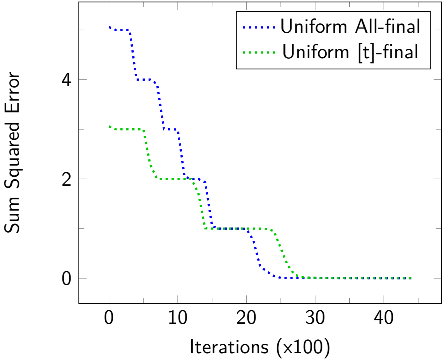
English Simulations

Results of simulations run on English are shown below.

- English learns both simulations faster than the uniform baseline does.



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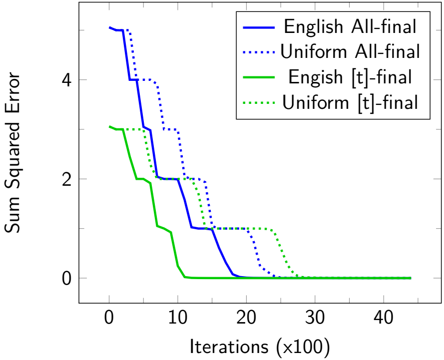
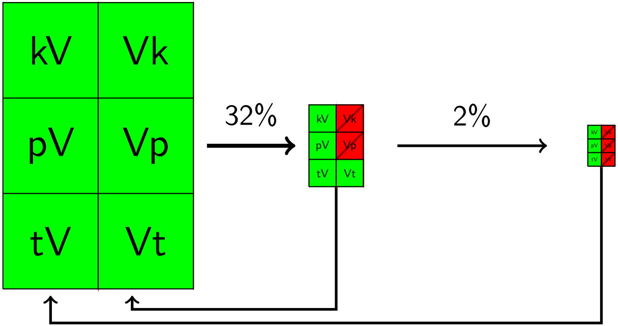


English Dynamics



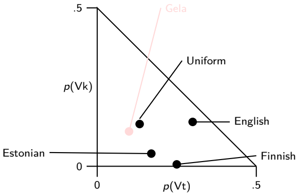
Languages with this sort of profile are more likely to maintain All-Final than Finno-Ugric languages.

Oceanic: Proto-Gela

In the Austronesian family, loss of final consonants has independently occurred at least 14 times.[14]

- Gela (Solomon Islands) has lost all final stops.
- No Oceanic languages exhibit the [t]-final pattern.
- Lexical frequencies of Proto-Gela are found using (720) proto-forms from the Comparative Austronesian Dictionary[15].

Forms	tV	pV	kV	Vt	Vp	Vk
Frequency	.118	.216	.1398	.064	.022	.075
Normalized	.19	.34	.22	.10	.03	.12



[14] Blevins (2004)

[15] Blust & Trussel (2010 (2018))

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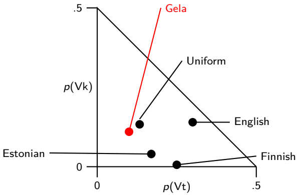

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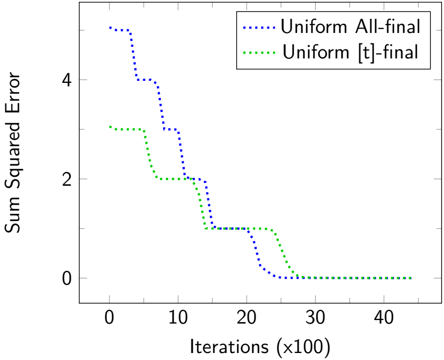
Gela Simulations

- Gela performs worse than baseline on both patterns than uniform baseline



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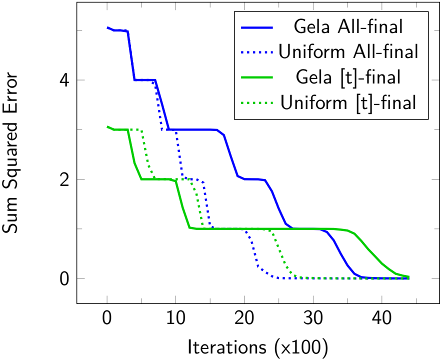
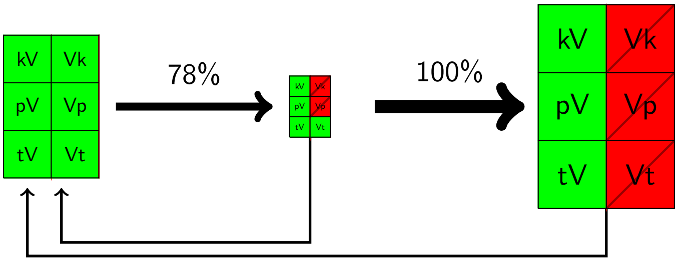


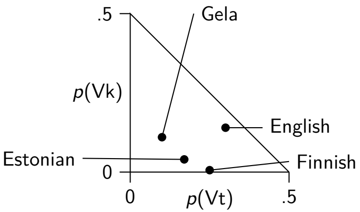
Oceanic Dynamics



It is predicted that Oceanic languages should show All-Final and No-Final patterns, but not [t]-Final.

Interim Summary

We've looked at three language families, and seen that the difference in frequencies predicts a different pattern of stability in each



- Above the blue line, languages maintain the All-Final pattern
- In the bottom left green sector, languages are unstable in All-Final and [t]-Final, so may lose coda stops
- In the red region, All-Final is sufficiently unstable, and [t]-Final is sufficiently stable to predict [t]-Final patterns

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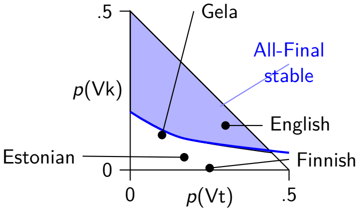

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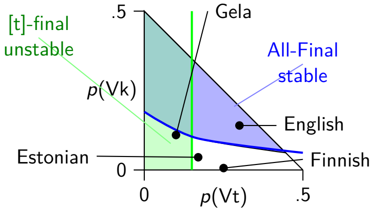

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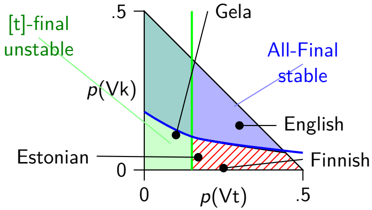

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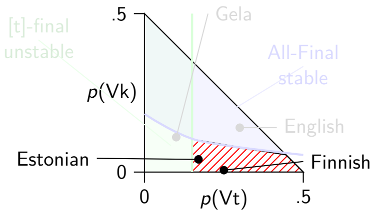

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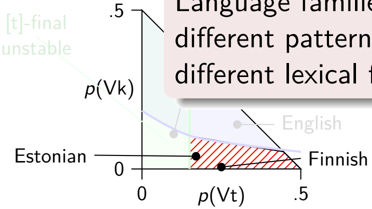

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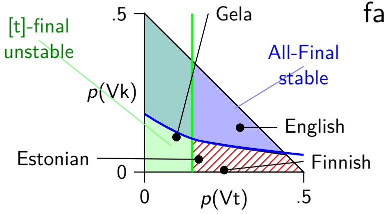
CLAIM 2

Language families that have shown different patterns of change have different lexical frequencies.

But why is [t]-Final rare?

The [t]-final pattern is a likely result for languages with frequencies similar to the Finno-Ugric languages.



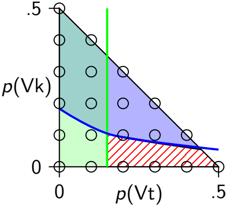
Why do we not see it in other language families?

- The [t]-final pattern is restricted to one small region of the lexical frequency space
- How big is this sector?

How big is [t]-final sector?

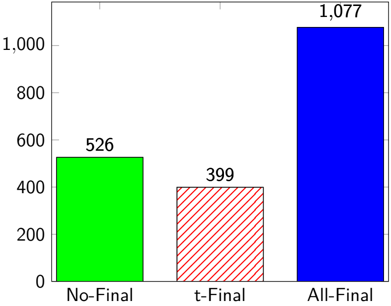
To see how many of the possible frequency profiles predict that [t]-final should be likely and stable, I ran simulations across many frequencies

- For each of the 6 forms, I iterated with a step size of .1 probability, ranging from 0 to 1; while ensuring that the sum of all 6 forms was 1.
  - This resulted in 2002 frequency profiles
  - 5 runs of 2 generations with 360 iterations with a learning rate of .5.



Results

- The [t]-Final stable region is smaller than the other regions.
- This causes [t]-Final to be cross-linguistically rare, even when it can be stable.



CLAIM 3

The [t]-final pattern is rare because the lexical frequencies that predict the [t]-final pattern are rare.

Conclusion

Lexical Frequency greatly conditions the learnability of different patterns.

- Frequency is an important factor to consider when making typological generalizations based on learning.
- Some lexical frequencies can show stability patterns quite at odds with the rest of the frequency space.

Future Questions

- Languages are not likely uniformly distributed across the lexical frequency space, so volume as measured here may not be the best metric
- Lexical Frequency changes as languages evolve. A model integrating both phonotactic and lexicon learning may make further different predictions about how languages are distributed across frequency space.

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