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Accounting for the learnability of saltation in phonological theory: A maximum entropy model with a P-map bias: Supplementary material

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Language, Volume 93, Number 1, March 2017, (Article)

Published by Linguistic Society of America

DOI: <https://doi.org/10.1353/lan.2017.0013>

LANGUAGE
A JOURNAL OF THE LINGUISTIC
SOCIETY OF AMERICA

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ACCOUNTING FOR THE LEARNABILITY OF SALTATION IN PHONOLOGICAL THEORY: A
MAXIMUM ENTROPY MODEL WITH A P-MAP BIAS:
ONLINE SUPPLEMENTARY MATERIALS

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MORE DETAILS ON PRIOR AND POSTLEARNING WEIGHTS. Provided below is a detailed summary of prior and postlearning weights for each of the three models (substantively biased, unbiased, and anti-alternation) in experiment 1 and experiment 2.

EXPERIMENT 1: SUBSTANTIVELY BIASED MODEL. See Table 4 in §5.1 of the main text.

EXPERIMENT 1: UNBIASED MODEL. Table S1 shows the prior and postlearning weights of the unbiased model in experiment 1. Most of the work in this model is done by the markedness constraints alone. Since stops and voiceless obstruents in general never appear as outputs, the weights of the two markedness constraints (*V[-voice]V and *V[-cont]V) increase in both conditions. Moreover, there is little reason for the *MAP constraints to pick up substantial weights because none of the obstruents surface unchanged during training. A few of the *MAP constraints do pick up a small weight; these constraints play a minor role in ruling out alternations not seen during training (e.g. ensuring that [p] → [v], not [p] → [f] or [b]).

CONSTRAINT	PRIOR WEIGHT	POSTLEARNING WEIGHT	
		POTENTIALLY SALTATORY CONDITION	CONTROL CONDITION
*V[-voice]V	0	1.49	1.41
*V[-cont]V	0	1.49	1.72
*MAP(p, v)	0	0	0
*MAP(t, ð)	0	0	0
*MAP(p, b)	0	0.54	0.15
*MAP(t, d)	0	0.54	0.15
*MAP(p, f)	0	0.54	0
*MAP(t, θ)	0	0.54	0
*MAP(b, v)	0	0	0
*MAP(d, ð)	0	0	0
*MAP(f, v)	0	0	0
*MAP(θ, ð)	0	0	0
*MAP(b, f)	0	0	0.56
*MAP(d, θ)	0	0	0.56

TABLE S1. Prior constraint weights and postlearning weights (unbiased model) in the potentially saltatory and control conditions of experiment 1.

EXPERIMENT 1: ANTI-ALTERNATION MODEL. The *MAP constraints in the anti-alternation model each have a prior weight of 2.27 (i.e. the average of the prior weights in the substantively biased model). Table S2 shows how these weights change as a result of training in the two conditions of experiment 1. The general behavior of the weights in this model is similar to those in the substantively biased model. In the potentially saltatory condition, the weights of both markedness constraints increase, while the *MAP constraints penalizing the trained alternations, *MAP(p, v) and *MAP(t, ð), have weights that decrease. The other *MAP constraints have either small modifications to their weights (if they play a minor role in preventing unobserved alternations) or no change in their weights (if they do not affect the outcome at all).

In the control condition, the alternations encountered during training, [b] → [v] and [d] → [ð], result in a substantial increase to the weight of *V[-cont]V and a decrease in the weights of the relevant *MAP constraints, *MAP(b, v) and *MAP(d, ð). The other markedness constraint, *V[-voice]V, receives a modest increase in weight because no voiceless obstruents appear as outputs. The other *MAP constraints have either small increases or no change in their weights, depending on whether they play any role in the outcome.

CONSTRAINT	PRIOR WEIGHT	POSTLEARNING WEIGHT	
		POTENTIALLY	
		SALTATORY CONDITION	CONTROL CONDITION
*V[-voice]V	0	1.62	0.75
*V[-cont]V	0	1.62	2.19
*MAP(p, v)	2.27	1.22	2.27
*MAP(t, ð)	2.27	1.22	2.27
*MAP(p, b)	2.27	2.51	2.32
*MAP(t, d)	2.27	2.51	2.32
*MAP(p, f)	2.27	2.51	2.27
*MAP(t, θ)	2.27	2.51	2.27
*MAP(b, v)	2.27	2.27	0.85
*MAP(d, ð)	2.27	2.27	0.85
*MAP(f, v)	2.27	2.27	2.27
*MAP(θ, ð)	2.27	2.27	2.27
*MAP(b, f)	2.27	2.27	2.60
*MAP(d, θ)	2.27	2.27	2.60

TABLE S2. Prior constraint weights and postlearning weights (anti-alternation model) in the potentially saltatory and control conditions of experiment 1.

EXPERIMENT 2: SUBSTANTIVELY BIASED MODEL. Table S3 shows the prior and postlearning weights for the substantively biased model in experiment 2. In the saltatory condition, the trained alternations ($p \rightarrow v$; $t \rightarrow \delta$) raise the weights of the two markedness constraints, $*V[-\text{voice}]V$ and $*V[-\text{cont}]V$, while reducing the weights of the relevant correspondence constraints, $*MAP(p, v)$ and $*MAP(t, \delta)$. Note that increasing the weight of $*V[-\text{cont}]V$ also supports spirantizing voiced stops. The explicit evidence during training AGAINST spirantizing voiced stops ($b \rightarrow b$; $d \rightarrow d$) bolsters the weights of $*MAP(b, v)$ and $*MAP(d, \delta)$ to protect these voiced stops from changing; however, because the prior weights of these constraints were low due to the high similarity of these pairs of sounds, their weights are not bolstered enough to fully protect the intermediate sounds from changing.

In the control condition, only the markedness constraint $*V[-\text{cont}]V$ receives a substantial boost to its weight due to the trained alternations ($b \rightarrow v$; $d \rightarrow \delta$); $*MAP(b, v)$ and $*MAP(d, \delta)$ both have their weights reduced to zero to permit these alternations. The weights of $*MAP(p, v)$ and $*MAP(t, \delta)$ are increased due to evidence of unchanging voiceless stops during training ($p \rightarrow p$; $t \rightarrow t$). However, because the prior weights of these constraints are already quite high, large increases are not necessary. In this case, the training data and the prior both support the same conclusion: no $[p \sim v]$ alternations and no $[t \sim \delta]$ alternations.

CONSTRAINT	PRIOR WEIGHT	POSTLEARNING WEIGHT	
		SALTATORY CONDITION	CONTROL CONDITION
$*V[-\text{voice}]V$	0	2.45	0.13
$*V[-\text{cont}]V$	0	1.05	1.12
$*MAP(p, v)$	3.65	1.96	3.79
$*MAP(t, \delta)$	3.56	2.01	3.72
$*MAP(p, b)$	2.44	2.94	2.65
$*MAP(t, d)$	2.73	3.16	2.91
$*MAP(p, f)$	1.34	1.74	2.03
$*MAP(t, \theta)$	1.94	2.21	2.45
$*MAP(b, v)$	1.30	2.02	0
$*MAP(d, \delta)$	1.40	2.09	0
$*MAP(f, v)$	2.56	2.56	2.56
$*MAP(\theta, \delta)$	1.91	1.91	1.91
$*MAP(b, f)$	1.96	2.02	2.29
$*MAP(d, \theta)$	2.49	2.53	2.71

TABLE S3. Prior constraint weights and postlearning weights (substantively biased model) in the saltatory and control conditions of experiment 2.

EXPERIMENT 2: UNBIASED MODEL. Table S4 shows the prior and postlearning weights for the unbiased model in experiment 2. In the saltatory condition, the alternations presented during training ($p \rightarrow v$; $t \rightarrow \delta$) raise the weights of the two markedness constraints; $*V[-\text{voice}]V$ is raised substantially, while $*V[-\text{cont}]V$ is raised only a modest amount due to cases of unchanging [b, d] during training. The model instead raises the weights of $*MAP(p, b)$ and $*MAP(t, d)$ to ensure that, for example, [p] is changed all the way to [v] instead of [b]. The weights of $*MAP(b, v)$ and $*MAP(d, \delta)$ are also increased due to unchanging [b, d] during training.

In the control condition, the two markedness constraints and several of the $*MAP$ constraints pick up modest weights. The alternations encountered during training ($b \rightarrow v$; $d \rightarrow \delta$) motivate increasing the weight of $*V[-\text{cont}]V$. However, the cases of unchanging [p, t] during training have the opposite effect; they result in a lower weight for $*V[-\text{cont}]V$. The only way for the model to balance having the trained alternations ($b \rightarrow v$; $d \rightarrow \delta$) and the cases of unchanging [p, t] would be to assign $*V[-\text{cont}]V$ a moderate weight while also assigning $*MAP(p, v)$ and $*MAP(t, \delta)$ very high weights. But because all constraints have a prior weight of zero, this arrangement is not feasible with the distribution of data in the input.

CONSTRAINT	PRIOR WEIGHT	POSTLEARNING WEIGHT	
		SALTATORY CONDITION	CONTROL CONDITION
$*V[-\text{voice}]V$	0	2.01	0.24
$*V[-\text{cont}]V$	0	0.36	0.65
$*MAP(p, v)$	0	0	0.82
$*MAP(t, \delta)$	0	0	0.82
$*MAP(p, b)$	0	1.02	0.87
$*MAP(t, d)$	0	1.02	0.87
$*MAP(p, f)$	0	0.35	0.71
$*MAP(t, \theta)$	0	0.35	0.71
$*MAP(b, v)$	0	0.89	0
$*MAP(d, \delta)$	0	0.89	0
$*MAP(f, v)$	0	0	0
$*MAP(\theta, \delta)$	0	0	0
$*MAP(b, f)$	0	0.23	0.88
$*MAP(d, \theta)$	0	0.23	0.88

TABLE S4. Prior constraint weights and postlearning weights (unbiased model) in the saltatory and control conditions of experiment 2.

EXPERIMENT 2: ANTI-ALTERNATION MODEL. Table S5 shows the prior and postlearning weights for the anti-alternation model in experiment 2. The overall pattern of adjustments to the weights is similar to what was seen for the substantively biased model. In the saltatory condition, the alternations encountered during training ($p \rightarrow v$; $t \rightarrow \delta$) result in increased weights for the markedness constraints, $*V[-\text{voice}]V$ and $*V[-\text{cont}]V$, as well as decreased weights for the relevant $*MAP$ constraints, $*MAP(p, v)$ and $*MAP(t, \delta)$. The cases of unchanging $[b, d]$ in training result in modest increases for $*MAP(b, v)$ and $*MAP(d, \delta)$, as well as a slightly reduced weight for $*V[-\text{cont}]V$ compared to the other markedness constraint.

In the control condition, the weight of $*V[-\text{cont}]V$ is increased due to the alternations encountered during training ($b \rightarrow v$; $d \rightarrow \delta$). These alternation also cause the weights of $*MAP(b, v)$ and $*MAP(d, \delta)$ to be reduced, but not down to zero due to their fairly high prior weight. The cases of unchanging $[p, t]$ result in a modest increase in the weights of $*MAP(p, v)$ and $*MAP(t, \delta)$.

CONSTRAINT	PRIOR WEIGHT	POSTLEARNING WEIGHT	
		SALTATORY CONDITION	CONTROL CONDITION
$*V[-\text{voice}]V$	0	1.90	0
$*V[-\text{cont}]V$	0	1.02	1.31
$*MAP(p, v)$	2.27	1.10	2.70
$*MAP(t, \delta)$	2.27	1.10	2.70
$*MAP(p, b)$	2.27	2.62	2.52
$*MAP(t, d)$	2.27	2.62	2.52
$*MAP(p, f)$	2.27	2.43	2.70
$*MAP(t, \theta)$	2.27	2.43	2.70
$*MAP(b, v)$	2.27	2.68	0.39
$*MAP(d, \delta)$	2.27	2.68	0.39
$*MAP(f, v)$	2.27	2.27	2.27
$*MAP(\theta, \delta)$	2.27	2.27	2.27
$*MAP(b, f)$	2.27	2.36	2.64
$*MAP(d, \theta)$	2.27	2.36	2.64

TABLE S5. Prior constraint weights and postlearning weights (anti-alternation model) in the saltatory and control conditions of experiment 2.