

UCLA

Southern California Annual Meeting on Phonology 2026

Discerning segmental stability using phylogenetic models

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April 11, 2026 · rehanmuh@ucla.edu

Introduction

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Sound change

What we know

- ▶ sound change is often regular
- ▶ conditioned by phonetic environments
- ▶ some changes recur across families

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- ▶ how fast specific segments change
- ▶ how context changes those rates
- ▶ how much variation there is in change across language families

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What we do not know

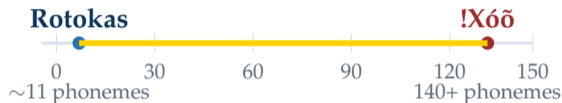
- ▶ how fast specific segments change
- ▶ how context changes those rates
- ▶ how much variation there is in change across language families

We lack a quantitative and principled model for modeling the evolution of segments over time on family trees.

Sources: Maddieson, 1984; Hock, 1991; Labov, 2020; Garrett, 2015

The scale of phonological diversity

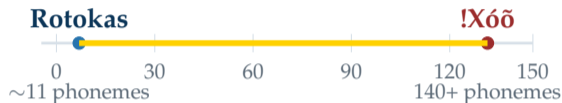
Any rate model must explain both stability and extreme variation in the make-up of phoneme inventories



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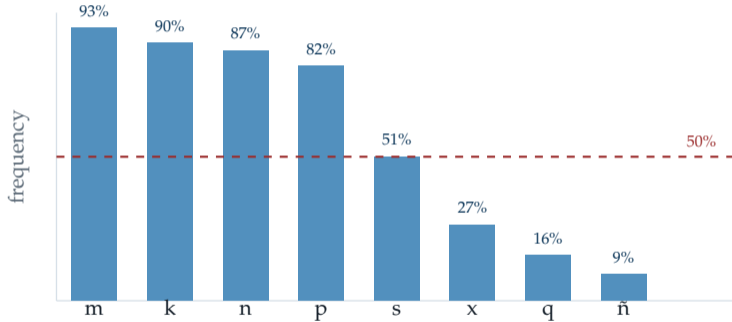


- ▶ inventories vary enormously in size
- ▶ some segments are widespread; others rare and varying in stability

Sources: Maddieson, 1984; Moran and McCloy, 2019; Blasi et al., 2019

Cross-linguistic frequency as a diagnostic for stability

Proportion of PHOIBLE languages containing each segment



Cross-linguistic frequency is a proxy for diachronic stability, but static snapshots might not represent linguistic systems in equilibrium.

Phonetic grounding

Why some changes recur across lineages

Phonetic variation



Listener (mis)parsing



Phonologization

Theoretical Consensus

Change is driven by misperception (Ohala, 1993), leading to recurrent patterns (Blevins, 2004) that are inherently phonetically biased and directional (Garrett and Johnson, 2013).

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Change is driven by misperception (Ohala, 1993), leading to recurrent patterns (Blevins, 2004) that are inherently phonetically biased and directional (Garrett and Johnson, 2013).

Modeling implication

Rates of segmental change must be structured and not arbitrary.

What a probabilistic model should look like

Regularity & pooling

Same local context \Rightarrow same
change parameters across lexical items.

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$*/p/ > [b]$ should look more plausible than $*/p/ > [r]$. Asymmetries should enter the prior.

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Parameter Learnability

Restricted enough that finite cognate data can identify something interpretable.

Previous computational work in this domain

Model / Study	Context	Rate Var.	Naturalness	Insertions	Deletions
Bouchard-Côté et al. (2013)	✓	✓	✗	✓	✓
Hruschka et al. (2015)	✓	✗	✗	✗	✗
Moran et al. (2021)	✗	✓	✗	✗	✗
He et al. (2024)	✓	✗	✗	✓	✓
Cathcart & Wandl (2020)	✓	✓	✓	✗	✗
Auderset (2025)	✗	✓	✗	✗	✗
Desired	✓	✓	✓	✓	✓

None of the former computational models of sound change model all aspects of local segmental change.

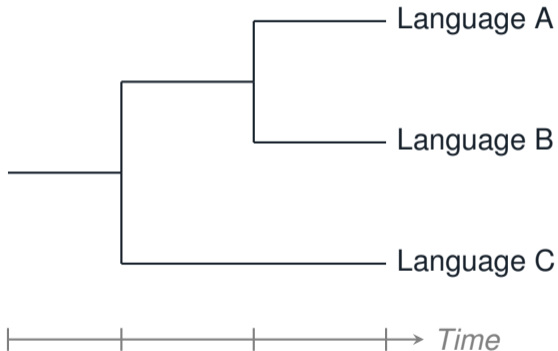
This talk

Goal: Build a probabilistic model that infers *rates of segmental change* while encoding *phonetic similarity, directional biases, local context, and regularity*.

Data

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Input Data 1: Phylogeny

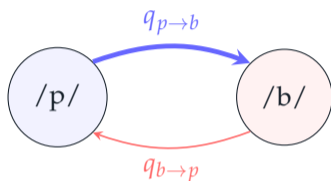


Input Data 2: Aligned Cognates

	Site 2	Site 4
L1	a	e
L2	a	e
L3	a	e

Homologous Column

Input Data 3: Segment Features



[+cons]

[-son]

[-cont]

[-voice]

[-nas]

[+cons]

[-son]

[-cont]

[+voice]

[-nas]

State space and edit types

Illustrative inventory

$\{p, t, k, b, d, g, f, s, h, m, n, l, r, a, i, u, \emptyset\}$

16 segments

1 gap state $_$

1 boundary marker $\#$

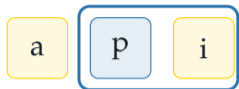
Three transition types

$x > y$ substitution

$\emptyset > y$ insertion

$x > \emptyset$ deletion

Local context as part of the rate structure



target + neighbors = context

- ▶ edge vs. medial position
- ▶ neighboring features from parent states

Feature engineering

PanPhon-style feature vectors as covariates

Representation

Segment $x \rightarrow$ feature vector $\mathbf{f}(x)$

- ▶ **Consonantal:** place, manner, voicing
- ▶ **Vocalic:** height, backness, rounding

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Features as Predictors

Features act as covariates to estimate weight vector \mathbf{w} :

- ▶ **Symmetric:** weights on shared/differing features
- ▶ **Directional:** weights on specific transitions (e.g., $+$ \rightarrow $-$)

Feature Vectors in Practice

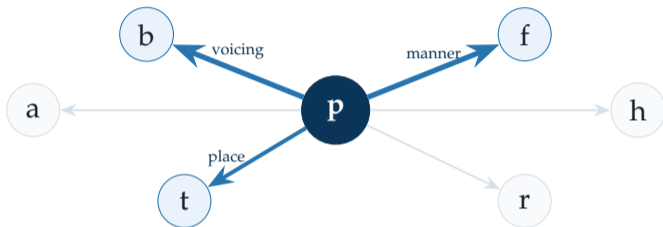
/m/

$$\mathbf{f}(/m/) \in \{1, 0, -1\}^n$$

Covariates and Weights

Feature	Value	Weight
Syllabic (SYL)	-1	w_{syl}
Consonantal (CONS)	1	w_{cons}
Sonorant (SON)	1	w_{son}
Coronal (COR)	-1	w_{cor}
Labial (LAB)	1	w_{lab}
Nasal (NAS)	1	w_{nas}
Voiced (VOI)	1	w_{voi}

Feature distance shapes transition probability



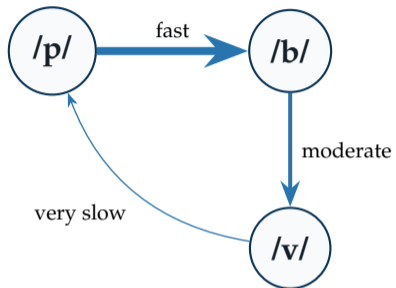
thick = small distance → higher rate

thin = large distance → lower rate

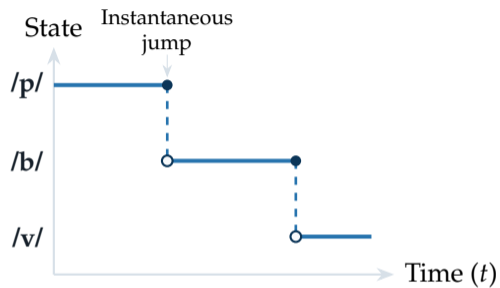
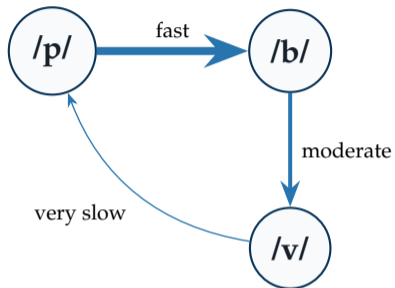
Methods

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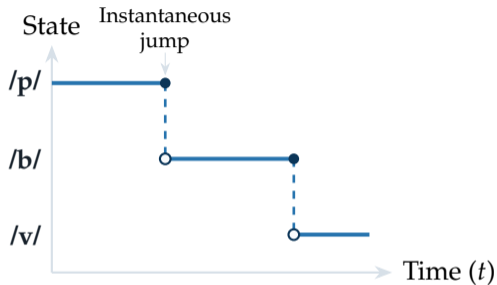
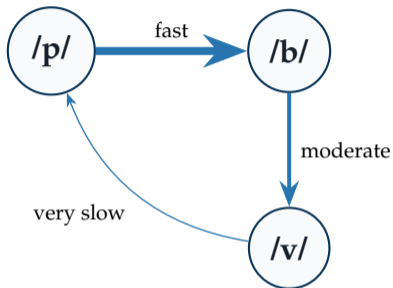
Continuous-Time Markov Chains



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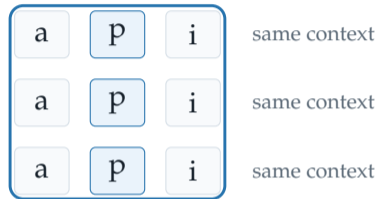


Instantaneous Propensity

- ▶ **Rates (Q):** Innate phonetic biases.
- ▶ **Evolutionary Process:** Continuous time, discrete categories.
- ▶ **Segmental Change:** Instantaneous jumps (e.g., /p/ > /b/).

Regularity encoded in contextual modeling

Same context \Rightarrow same generator



All sites with /p/ between /a/ and /i/ share $Q(a_i)$.

This models Neo-grammarian regularity in probabilistic form.

Strict vs. relaxed clock

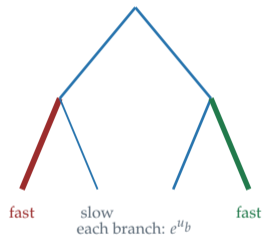
Strict clock



all branches same rate

VS

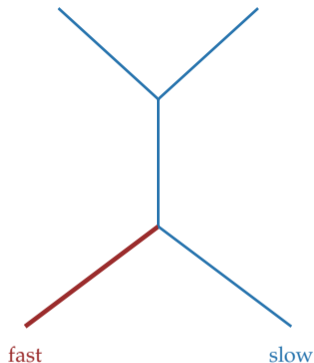
Relaxed clock



Language families routinely violate the strict clock.

Sources: Bromham et al., 2015; Greenhill et al., 2017; Bowerman and Atkinson, 2012

Branch-specific rate heterogeneity



- ▶ multiplicative rate effect e^{u_b} per branch
- ▶ hierarchical shrinkage priors over branch-rate heterogeneity

What determines the rate of change ($x > y$)?

$$Q_{xy}(\mathbf{c}) \propto \pi_y \exp\{\eta_{xy} + \kappa(\mathbf{c}) + u_b\}$$

Phonetic & Structural Drivers

π_y **Stationary frequency**

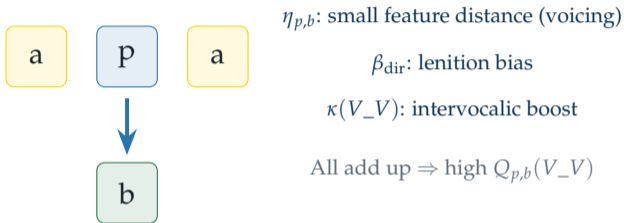
η_{xy} **Similarity & Directionality**
Phonetic similarity and directional biases
(e.g., lenition) encoded via covariates.

Context & Phylogeny

$\kappa(\mathbf{c})$ **Local context**
Effect of surrounding
environment.

u_b **Branch multiplier**
Lineage-specific rate variation.

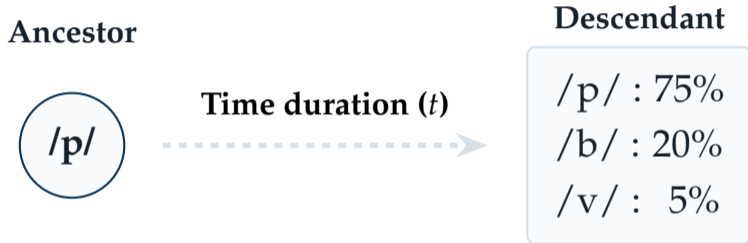
Example: intervocalic lenition



$Q_{p,r}(V_V)$ stays low: no similarity or bias support

Continuous-Time Evolution: Probabilities

The Outcome Over Time ($P(t)$)



Accumulation of Change

- ▶ **Process:** Integrate rates (Q) over time (t).
- ▶ **Result:** A probability distribution over jumps in discrete states.
- ▶ **Impact:** Longer branches = more accumulated change.

Simulation analysis

1. simulate tree and branch lengths

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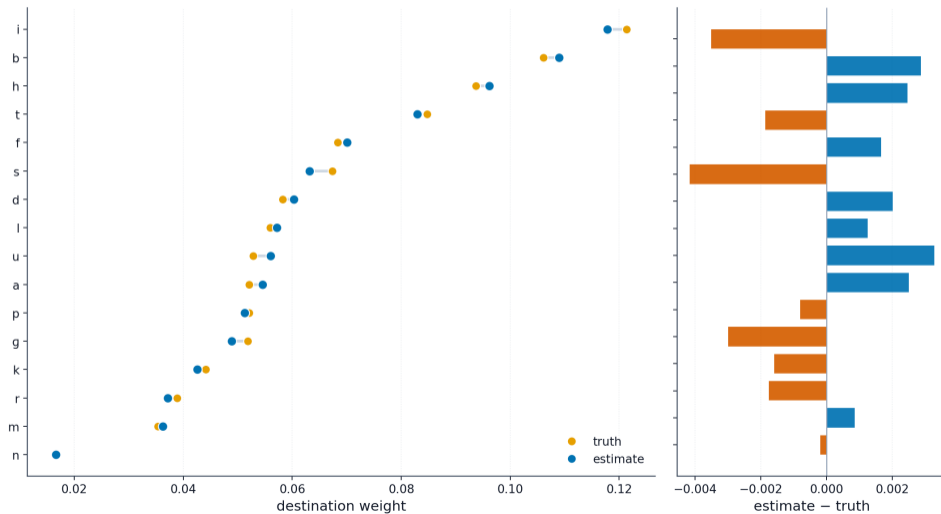
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Inference goal: show that the model developed here can recover parameters defining the probabilistic sound change process *in principle*.

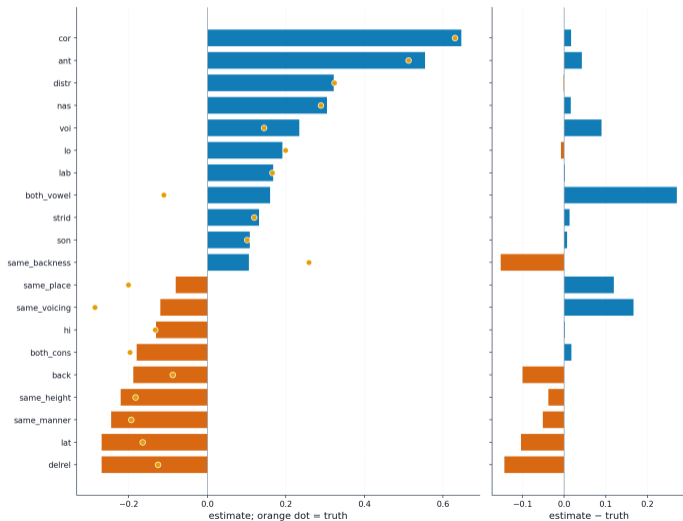
Results

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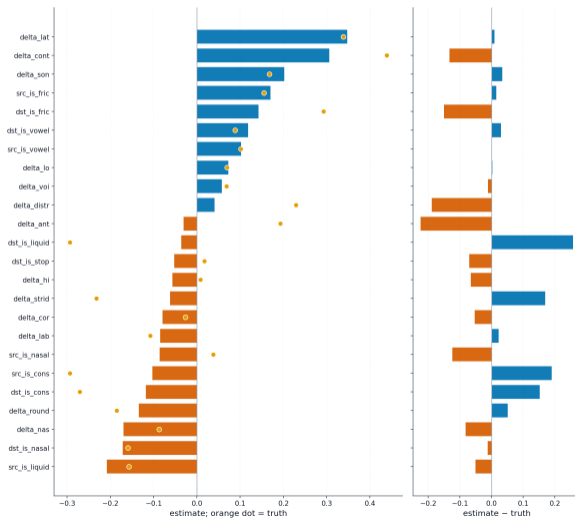
Stationarity probabilities



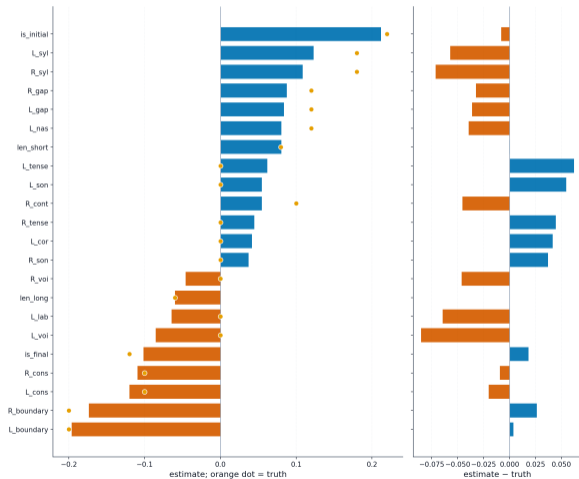
Symmetric coefficients



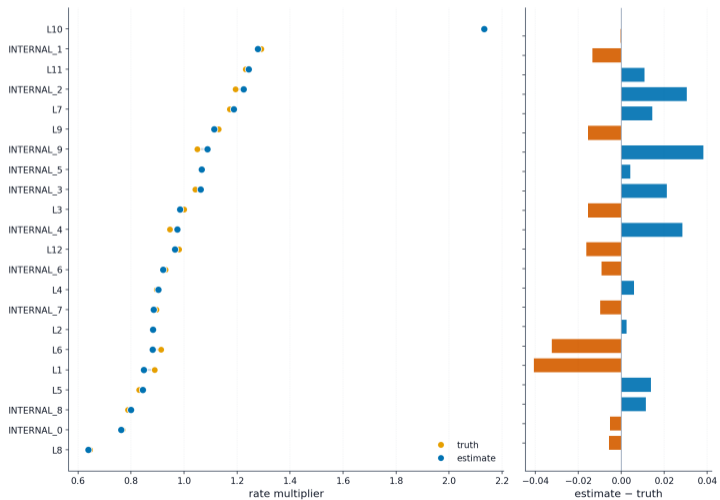
Directional coefficients



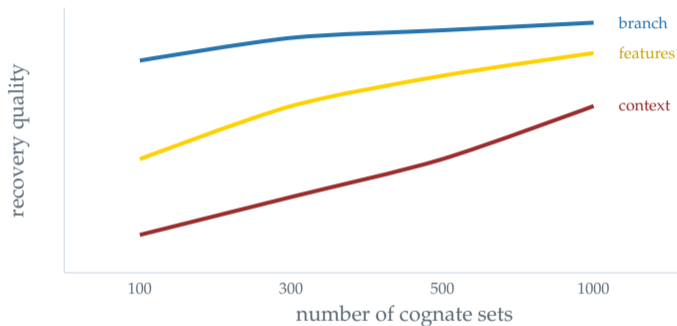
Context coefficients



Branch rate heterogeneity



How identifiability scales with data



Context coefficients benefit most from larger datasets.

Discussion

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Main contributions

1. **Context-sensitive CTMC.** Generator depends on local environment.
2. **Feature-structured rates.** Similarity and directionality taken into account.
3. **Regularity by design.** Shared contexts share transition matrices
4. **Unified indels.** Insertions and deletions via ghost sites.
5. **Branch heterogeneity.** Separate local conditioning from tempo shifts.

Applications

Extending the probabilistic framework

What affects the rate of sound change?

- ▶ **Regularity vs. Diffusion**

Test the validity of the lexical diffusion hypothesis.

- ▶ **Phonetic Grounding**

Check the adequacy of model with phonetic grounding in generating the attested data.

- ▶ **Functional Load**

Regress estimated rates to test for communicative efficiency.

- ▶ **Typological Validation**

Compare inferred rates against databases (PHOIBLE/BDPROTO).

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- ▶ Unified quantitative framework for estimating rates of change while representing sound structure and conditioning environments missing
- ▶ A context-sensitive CTMC with feature-structured rates one plausible step in that direction.
- ▶ Parameter recovery in simulation studies provide a solid footing for future inference

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Thank you

Questions?

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Lexical diffusion

Lexical diffusion

Some changes propagate unevenly through the lexicon; frequency and neighborhood density affect which words change first.

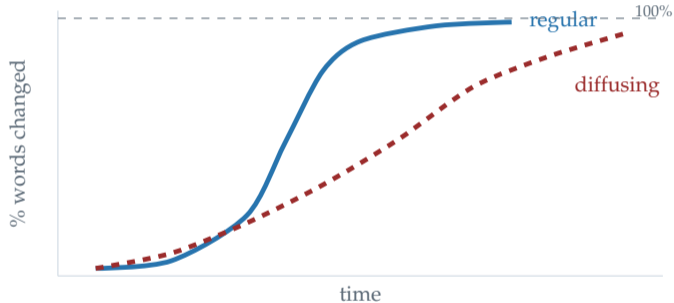
- ▶ Wang (1969): competing changes create residue
- ▶ Bybee (2002): sound change shows usage and frequency effects

A quantitative model should treat regularity as a *testable baseline*, but not enforce it.

Sources: Wang, 1969; Chen and Wang, 1975; Phillips, 1984; Bybee, 2001; Bybee, 2002; Todd et al., 2019

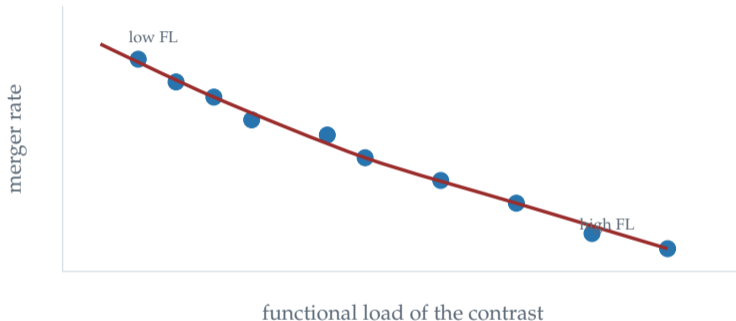
Diffusion dynamics: the S-curve

Both regularity and diffusion predict S-shaped adoption



The empirical question: do lexical items differ in their intrinsic rate of adopting a change?

Functional load as a rate inhibitor



High-FL contrasts resist merger. This is absent from version 1 but is a natural extension.

External and demographic pressures

- ▶ network density shapes diffusion
- ▶ contact and isolation influence the tempo of change
- ▶ anatomical and climatic factors may bias inventories

Actuation problem

Why this change, here, now? A rate model should represent *heterogeneity across branches*.

Sources: Weinreich et al., 1968; Milroy, 1987; Bromham et al., 2015; Greenhill et al., 2017; Dediu and Moisisik, 2019

Defining the Context

Locality, similarity, and phonological domains

1. Strictly Local

Assimilation, lenition, and boundary effects driven by **adjacent** material.

2. Long-Distance

Harmony and correspondence sensitive to **non-local** similarity.

3. Domain-Sensitive

Rules behaving differently inside roots vs. across affixes (**morphological** domains).

Modeling Assumption

The local-context approach taken here is a principled **first approximation**, not a theoretical claim that all phonological structure is strictly local, or should be modeled as such.

Continuous-Time Markov Chains

At a single site

A segment evolves as a continuous-time Markov chain, a probabilistic model for discrete jumps between states.

Sources: Felsenstein, 1981; Bouchard-Côté et al., 2013; Yang, 2006

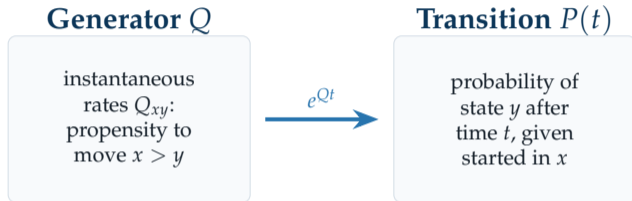
Continuous-Time Markov Chains

The Transition Rate Matrix Q

$$Q = \begin{pmatrix} -\sum_{j \neq 1} q_{1j} & q_{12} & \cdots & q_{1n} \\ q_{21} & -\sum_{j \neq 2} q_{2j} & \cdots & q_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ q_{n1} & q_{n2} & \cdots & -\sum_{j \neq n} q_{nj} \end{pmatrix}$$

- ▶ **Off-diagonal entries** ($q_{ij} \geq 0$): Represent the instantaneous rate of transitioning from state i to state j .
- ▶ **Diagonal entries** ($q_{ii} \leq 0$): Defined such that each row sums to zero.
- ▶ **Transition Probabilities**: Calculated via the matrix exponential $P(t) = e^{Qt}$.

Instantaneous rates of change > probabilities of change



Longer branches \Rightarrow more change

APPENDIX

Mathematical details

A1. Site expansion and root priors

Lexical root prior

$$P(X_r=x \mid \text{lex}) = (1-\varepsilon_{\text{lex}})\pi_x \text{ for } x \in \mathcal{S}_{\text{real}}; \quad \varepsilon_{\text{lex}} \text{ for } x=\emptyset.$$

Ghost root prior

$$P(X_r=x \mid \text{ghost}) = \varepsilon_{\text{ghost}}\pi_x \text{ for } x \in \mathcal{S}_{\text{real}}; \quad 1-\varepsilon_{\text{ghost}} \text{ for } x=\emptyset.$$

A2. Generator matrix

$$Q_{xy} = \exp(\log \mu + \kappa + \eta_{xy}) \pi_y, \quad Q_{xx} = -\sum_{y \neq x} Q_{xy}$$

$$\eta_{xy} = \langle \mathbf{X}_{xy}^{\text{sym}}, \boldsymbol{\beta}_{\text{sym}} \rangle + \langle \mathbf{X}_{xy}^{\text{dir}}, \boldsymbol{\beta}_{\text{dir}} \rangle, \quad \kappa = \langle \mathbf{c}, \boldsymbol{\beta}_{\text{ctx}} \rangle$$

A3. Branch-rate heterogeneity

$$u_b^{\text{raw}} = \tau \lambda_b z_b, \quad z_b \sim \mathcal{N}(0, 1); \quad v_b = u_b^{\text{raw}} - \bar{u}; \quad \tilde{\ell}_b = \ell_b e^{v_b}$$

Centering makes branch effects relative.

A4. Likelihood and pruning

Pattern-compressed likelihood

$$\log p(\mathbf{y} \mid \theta) = \sum_u n_u \log P(\mathbf{y}^{(u)} \mid \theta)$$

Felsenstein recursion

$$L_v(k) = \prod_{c \in \text{children}(v)} \sum_j P_{b_c}(k, j) L_c(j); \quad \text{root: } \sum_k \rho(k) L_{\text{root}}(k).$$

A5. Parallel tempering

Tempered targets $p(\theta | \mathbf{y})^{1/T_m}$; swap acceptance:

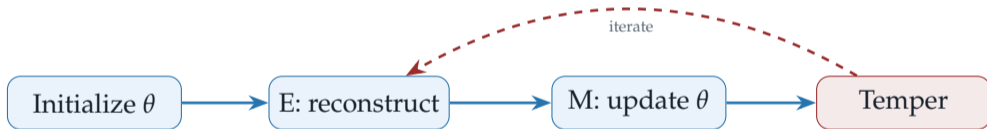
$$\log a_{\text{swap}} = \left(\frac{1}{T_m} - \frac{1}{T_{m+1}} \right) [\log p(\theta_{m+1}) - \log p(\theta_m)]$$

Sources: Geyer, 1991

Inference

Core difficulty

Rates depend on *local context*, but context is determined by *latent ancestral states*.



Sources: Felsenstein, 1981; Bouchard-Côté et al., 2013; Dempster et al., 1977; Geyer, 1991

A6. Stochastic mapping

Set $\omega \geq \max_k(-Q_{kk})$, define $B = I + Q/\omega$. Conditional uniformization samples Poisson event counts and skeleton paths to estimate posterior event histories.

Sources: Huelsenbeck et al., 2003; Nielsen, 2002

A7. Ancestral reconstruction

$$P(X_r=i \mid \mathbf{y}) \propto \rho(i) L_r(i); \quad P(X_c=j \mid X_p=i, \mathbf{y}) \propto P_{ij}^{(g,b)} L_c(j)$$

Simulation design

Tree

20-tip balanced tree; log-normal branch lengths; one fast clade, one slow.

Data

500 cognate sets, 3–8 sites each; 17-state inventory; ground truth mimics known asymmetries.

A8. Regularization

- ▶ Gaussian priors on coefficients to cause shrinkage
- ▶ Half-normal priors on branch scales
- ▶ Structured generator prevents combinatorial explosion

A9. Relation to MaxEnt / Harmonic Grammar

Shared

Weighted structures preserving gradient and restricting hypothesis space.

Different

MaxEnt/HG: output probabilities.
CTMC: transition intensities over time.

Sources: Hayes and Wilson, 2008; Moore-Cantwell, 2016; Shih, 2017; Pater, 2016

A10. Why rates matter for theory

Different theories make different predictions about *where* change should be fast or slow:

- ▶ **Phonetic-bias:** rates highest in articulatorily / perceptually pressured contexts
- ▶ **Analytic-bias:** rates relate to learnability, even with comparable phonetic grounding
- ▶ **Usage-based:** rates relate to frequency and predictability
- ▶ **Grammar-internal:** rates cluster by domain and life-cycle stage

Sources: Blevins, 2004; Moreton, 2008; Garrett and Johnson, 2013; Bybee, 2017; Kiparsky, 2016; Ramsammy, 2015