The Phonological Determinants of Tone in English Loanwords in Mandarin

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Background

- Mandarin tonal adaptation: a famously complex and problematic case
- Mandarin tones:

Tone	High (1)	Rising (2)	Low (3)	Falling (4)
Pinyin	mā	má	mǎ	mà

Background

- Numerous studies have sought to account for tones of English loanwords, but nearly all fail to fully explain considerable variation
- Chang (2020): Tonal assignment mostly non-phonological, based on **lexical tone probabilities**[1, 2]
  - ➢Loanword tones reflect native tone frequencies

[1]Chang 2020, [2]Zheng & Durvasula 2016

Background

- Other studies propose (sometimes conflicting) **phonological determinants**[1, 2, 3, 4, 5]
  - ➢"Stress-to-tone" effects (e.g. initial stressed syllables → high tone)
  - ➢Onset effects: English or Mandarin sonority, voicing, aspiration, etc. favor adaptation with X tone
- Meanwhile, **standard syllables** interfere
  - ➢达 *dá* is the standard character/syllable for English /dɑː/, /dæ/, /dʌ/
  - ➢Standard syllable use a confound in studies of Mandarin tonal adaptation

[1]Zheng & Durvasula 2016, [2]Chang & Bradley 2012, [3]Wu 2006, [4]Mar & Park 2012, [5]Glewwe 2016

Research Question and Data

- Research question: What are the **phonological** determinants, if any, of tonal assignment in English loanwords in Mandarin?
- Corpus study:
  - 2,644 non-epenthetic syllables from dictionary loanwords
- Experiment:
  - 2,182 syllables from native speakers' live adaptations of English nonce words

Analysis

- Analyzed tonal assignment using Maximum Entropy Harmonic Grammar (MaxEnt)[1, 2]
- MaxEnt can:
  - Accommodate multiple competing determinants of tone
  - Model (and thus control for) lexical tone probabilities
  - Control for standard syllable use
  - Handle variation
- MaxEnt models generate predicted tones for loanword syllables, which can be compared to observed tones

[1]Goldwater & Johnson 2003, [2]Hayes & Wilson 2008

Corpus Step 1: Baseline Lexical Model

da-NON-FINAL-STRESSED-VOICED STOP/AFFRICATE ONSET (representing /ˈdæ/, /ˈdɑː/, /ˈdʌ/, etc.)	Observed Counts in the Corpus	Lexical Tone Probs.	*DA1 2.815	*DA2 1.263	*DA3 1.669	*DA4 0	Harmony Scores	Predicted Probs.	Predicted Counts
a. dā	0	0.039	1				2.815	0.039	1
b. dá	12	0.185		1			1.263	0.185	2
c. dǎ	1	0.123			1		1.669	0.123	2
d. dà	0	0.653				1	0	0.653	8

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c. dǎ	1	0.123			1		1.669	0.123	2
d. dà	0	0.653				1	0	0.653	8

- Across all syllables, square of the correlation (r^2) between observed counts and predicted counts = 0.585

Corpus Step 2: Standard Syllables Model

da-NON-FINAL-STRESSED-VOICED STOP/AFFRICATE ONSET (representing /ˈdæ/, /ˈdɑː/, /ˈdʌ/, etc.)	Observed Counts in the Corpus	*DA1 2.815	*DA2 1.263	*DA3 1.669	*DA4 0	DA2 -3.276	Harmony Scores	Predicted Probs.	Predicted Counts
a. dā	0	1					2.815	0.007	0
b. dá	12		1			1	-2.014	0.857	11
c. dǎ	1			1			1.669	0.022	0
d. dà	0				1		0	0.114	2

- DA2 for standard syllable *dá* (达)

Corpus Step 2: Standard Syllables Model

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c. dă	1			1			1.669	0.022	0
d. dà	0				1		0	0.114	2

- Predicted counts vs. observed counts : $r^2 = 0.952$
- Suggests lexical tone probabilities and standard syllable use explain nearly all tonal assignment in corpus

Corpus Step 3: Phonological Model

da-NON-FINAL-STRESSED-VOICED STOP/AFFRICATE ONSET (representing /ˈdæ/, /ˈdɑː/, /ˈdʌ/, etc.)	Observed Counts in the Corpus	*DA1 2.815	*DA2 1.263	*DA3 1.669	*DA4 0	DA2 -3.276	VCD OBS2 -2.425	…	Harmony Scores	Predicted Probs.	Predicted Counts
a. dā	0	1							0.050	0.004	0
b. dá	12		1			1	1		-5.421	0.933	12
c. dǎ	1			1					-0.673	0.008	0
d. dà	0				1				-2.595	0.055	1

- Added 76 phonological constraints like VOICEDOBSTRUENT2

Corpus Step 3: Phonological Model

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b. dá	12		1			1	1		-5.421	0.933	12
c. dǎ	1			1					-0.673	0.008	0
d. dà	0				1				-2.595	0.055	1

- Predicted counts vs. observed counts : $r^2 = 0.967$
- Likelihood ratio test confirms adding phonological constraints significantly improves model's fit

Top Phonological Constraints in Corpus

- Of 76 phonological constraints, three that contributed most to model:

Constraint	Weight	Delta Log Likelihood
VOICEDOBS2	-2.425	134.496
VOICED2	-0.799	40.931
VOICELESS1	-0.857	19.627

- Reveals a voicing effect: mapping from English F0 perturbations to tone

Experiment MaxEnt Analysis

- Step 1: Baseline lexical model
  - $r^2 = 0.574$
- Step 2: Standard syllables model
  - $r^2 = 0.722$
- Step 3: Phonological model
  - $r^2 = 0.837$

Top Phonological Constraints in Experiment

Constraint	Weight	Delta Log Likelihood
UNASP2	-1.084	59.789
INITIAL1	-0.823	47.695
STRESSEDINITIAL1	-1.112	46.635
STRESSEDFINAL4	-0.997	45.552

- Strongest phonological determinants of tone: stress and position
- Mapping from English intonation to tone

Discussion

- Phonological determinants of tone differ between established loanwords and live adaptations
- Different borrowing contexts → different perceptual mappings
- Stress-to-tone adaptation on the rise?[1, 2]
- MaxEnt approach gives most complete analysis of Mandarin tonal adaptation yet and holds promise for other languages

Thank you!

[1]Wang 2020, [2]Ding & Li 2020

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76 Phonological Constraints

- Stressed1-4
- Unstressed1-4
- Nonfinal1-4 (Initial1-4)
- Final1-4
- StressedNonfinal1-4
- UnstressedNonfinal1-4
- StressedFinal1-4
- UnstressedFinal1-4
- Obstruent1-4
- Sonorant1-4
- Voiced1-4
- Voiceless1-4
- Aspirated1-4
- Unaspirated1-4
- MandarinAspirated1-4
- MandarinUnaspirated1-4
- VoicedObstruent1-4
- Voiced&MandarinAspirated1-4
- Tone1-4

Improvement in Corpus Model Predictions

da-NON-FINAL-STRESSED-VOICED STOP/AFFRICATE ONSET (representing /ˈdæ/, /ˈdɑː/, /ˈdʌ/, etc.)	Observed Counts in the Corpus	Predicted Counts (Baseline Lexical)	Predicted Counts (Standard Syllables)	Predicted Counts (Phono-logical)
a. dā	0	1	0	0
b. dá	12	2	11	12
c. dǎ	1	2	0	0
d. dà	0	8	2	1

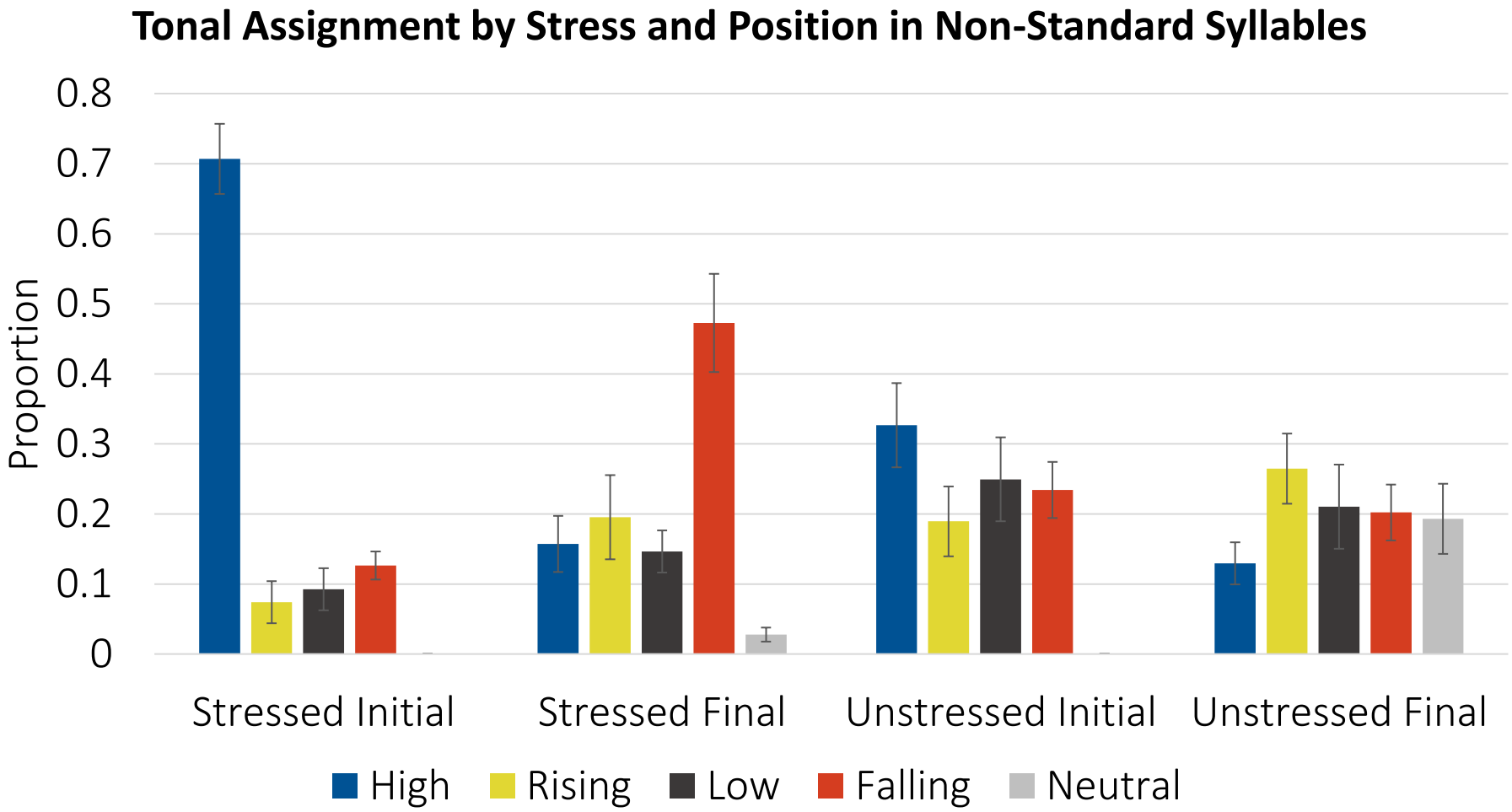
Phonological Constraints of Pruned Phonological Model – Corpus

	Constraint	Weight	Delta Log Likelihood	Predicted Rate: Standard Syllables Model	Predicted Rate: Phonological Model	Observed Rate
1.	VOICEDOBS2	-2.425	134.496	35.7%	44.4%	44.9%
2.	VOICED2	-0.799	40.931	38.3%	40.8%	41.1%
3.	VOICELESS1	-0.857	19.627	39.0%	43.1%	42.4%
4.	MANDUNASP1	-0.973	18.972	40.2%	39.4%	38.5%
5.	UNASP4	-1.085	17.376	18.1%	17.3%	16.3%
6.	OBS3	-0.806	16.959	16.0%	15.5%	15.3%
7.	TONE4	-0.354	16.682	27.0%	27.1%	27.7%
8.	VOICED1	-0.752	14.272	19.3%	18.5%	18.6%
9.	OBS1	-0.577	13.331	38.6%	38.9%	38.3%
10.	VOICELESS4	-0.582	11.964	23.9%	26.4%	27.5%
11.	SON1	-1.078	10.562	9.3%	10.9%	11.3%
12.	MANDUNASP3	-0.975	9.739	11.1%	10.5%	11.0%

Phonological Constraints of Pruned Phonological Model – Corpus

	Constraint	Weight	Delta Log Likelihood	Predicted Rate: Standard Syllables Model	Predicted Rate: Phonological Model	Observed Rate
13.	VOICELESS3	-0.749	9.647	20.0%	20.2%	19.6%
14.	SON4	-0.305	8.734	31.0%	29.3%	30.5%
15.	MANDUNASP4	-0.914	6.960	19.3%	20.8%	20.8%
16.	MANDASP2	-0.957	5.781	22.9%	22.0%	20.8%
17.	VOICED3	-0.561	5.771	16.5%	16.7%	15.6%
18.	STRESSED4	-0.242	5.059	26.0%	25.9%	26.7%
19.	TONE2	-0.184	4.680	28.7%	28.0%	28.4%
20.	STRESSED1	-0.252	3.761	28.8%	30.6%	30.6%
21.	STRESSEDNONFINAL1	-0.211	2.915	29.9%	31.7%	32.4%
22.	FINAL4	-0.260	2.749	27.1%	28.6%	28.9%
23.	SON3	-0.530	1.940	20.0%	21.0%	19.2%

Experiment Results



Phonological Constraints of Pruned Phonological Model – Experiment

	Constraint	Weight	Delta Log Likelihood	Predicted Rate: Standard Syllables Model	Predicted Rate: Phonological Model	Observed Rate
1.	UNASP2	-1.084	59.789	25.6%	29.9%	29.5%
2.	INITIAL1	-0.823	47.695	28.4%	46.6%	45.9%
3.	STRESSEDINITIAL1	-1.112	46.635	30.9%	63.6%	62.2%
4.	STRESSEDFINAL4	-0.997	45.552	23.2%	32.7%	32.4%
5.	UNASP4	-1.003	36.667	23.6%	17.7%	16.1%
6.	VOICEDOBS1	-0.622	30.839	46.3%	48.1%	50.0%
7.	UNSTRESSED3	-0.768	30.527	15.8%	23.5%	23.9%
8.	OBS1	-0.444	30.371	34.8%	39.5%	39.9%
9.	STRESSED1	-0.582	25.073	32.9%	46.9%	46.2%
10.	VOICED3	-0.480	15.370	16.5%	18.3%	19.2%
11.	TONE2	-0.292	13.737	28.8%	27.8%	27.9%
12.	VOICEDOBS3	-0.617	11.685	7.0%	10.5%	11.3%
13.	ASP4	-0.599	9.500	14.7%	14.0%	15.4%
14.	MANDASP2	-0.411	9.087	52.1%	48.4%	48.2%

Phonological Constraints of Pruned Phonological Model – Experiment

	Constraint	Weight	Delta Log Likelihood	Predicted Rate: Standard Syllables Model	Predicted Rate: Phonological Model	Observed Rate
15.	VOICED1	-0.237	7.040	34.5%	38.3%	39.4%
16.	UNSTRESSEDFINAL3	-0.640	6.465	17.1%	25.2%	25.0%
17.	STRESSED2	-0.227	6.167	28.1%	21.7%	22.4%
18.	OBS3	-0.329	6.117	12.1%	13.4%	13.7%
19.	VOICELESS4	-0.343	6.097	21.3%	18.4%	18.7%
20.	MANDUNASP2	-0.354	5.298	18.1%	19.3%	19.5%
21.	ASP3	-0.879	4.625	10.9%	12.2%	11.1%
22.	INITIAL2	-0.179	3.764	29.2%	23.4%	24.0%
23.	UNSTRESSED2	-0.267	3.744	29.7%	34.4%	33.8%
24.	TONE3	-0.198	3.737	16.2%	17.0%	17.4%
25.	SON2	-0.317	3.413	26.1%	26.6%	26.6%
26.	FINAL2	-0.217	2.941	28.4%	32.2%	31.7%
27.	MANDUNASP4	-0.439	2.857	26.4%	20.2%	17.9%
28.	SON4	-0.395	2.266	27.4%	20.6%	20.1%