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Iterated Learning Models of Language Change: A Case Study of Sino-Korean Accent

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Abstract

Iterated learning models of language evolution have typically been used to study the emergence of language, rather than historical language change. We use iterated learning models to investigate historical change in the accent classes of two Korean dialects. Simulations reveal that many of the patterns of historical change can be explained as resulting from successive generations of phonotactic learning. Comparisons between different iterated learning models also suggest that Korean learners' phonotactic generalizations are guided by storage of entire syllable-sized units, and provide evidence that perceptual confusions between different forms substantially impacted historical change. This suggests that in addition to accounting for the evolution of broad general characteristics of language, iterated learning models can also provide insight into more detailed patterns of historical language change.

Keywords: Iterated learning; Language change; Analogical change; Phonotactics; Lexical accent; Korean

1. Introduction

Iterated learning has frequently been used to model the cultural/historical transmission of language from generation to generation (e.g., Brighton, 2002; de Boer, 2000; Kirby, 2001; Kirby & Hurford, 2002; Kirby, Smith, & Brighton, 2004; Oudeyer, 2005; Smith, Kirby, & Brighton, 2003; Wedel, 2012). In iterated learning, an agent observes language data and induces a grammar based on these data. This new language is then used to generate more data, which is passed on to the next generation, and the process is repeated. While this approach has shown considerable utility in agent-based simulations, mathematical models, and

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laboratory experiments (see Kirby, Griffiths, & Smith, 2014 for a review), previous studies have primarily used artificial languages composed of small numbers of items, and have focused on explaining the evolution of broad characteristics of linguistic structure, such as compositionality. There have been few applications of iterated learning systems to detailed patterns of historical change in particular languages over long time spans. As a result, we do not yet know how well iterated learning models capture the way in which languages change once the broad characteristics that are common across all languages, such as compositionality, have already been established.

Historical linguistics is the study of language change. While the most extensively studied area in historical linguistics is *sound change*, which involves exceptionless changes, our focus is on *analogical change*. In analogical change, one word form in a language changes to another form based on generalizations induced from other sets of words. For example, the past tense of English *dive* is in the process of changing from the original *dived* to *dove* under analogy with verbs, such as *drive*: *drove*, *ride*: *rode*. Compared to sound change, analogical change tends to be less regular and its outcome is less predictable, although some explanatory and predictive models of morphological analogical changes have been proposed in the previous literature (Albright, 2002, 2008, 2009; Hare & Elman, 1995; Polinsky & van Everbroeck, 2003).[1]

In this paper, we use iterated learning models to investigate patterns of analogical change. We focus historical accent change in Sino-Korean, the largest word class in the Korean lexicon. Sino-Korean words fall into one of several pitch accent classes, and the assignment of words to these classes has undergone analogical change. We demonstrate that these diachronic changes from Middle Korean (15–16th centuries) to two dialects of contemporary Korean (South Kyengsang and Yanbian) can be accurately captured by iterated learning models in which each generation learns the phonotactics—that is, the probabilistic restrictions on sound patterns—of each pitch accent class. In Simulation 1, we show that phonotactics-based iterated learning models capture overall patterns of analogical change among classes. Specifically, we show that the models capture the high degree of regular correspondence in morphemes that end in –p/l/k, as well as the tendency of morphemes with higher type frequency to exhibit more regular historical correspondence. A baseline model that does not use phonotactic information cannot capture these patterns.

Simulations 2 and 3 use our iterated learning framework to test specific hypotheses about earlier dialects. Simulation 2 asks whether there were early dialectal differences among different varieties of Middle Korean; there is not direct historical evidence for an earlier dialect split, but such an account would be consistent with the historical record. Simulation 3 asks whether perceptual confusions between different accent classes had a substantial role in driving historical change. These aspects of historical dialects are difficult to test empirically, but the iterated learning framework provides a way to test them computationally, by examining their role in shaping the modern dialects. Our work thus provides insight into the factors that influenced historical change in Korean and, more generally, illustrates how iterated learning can be used as a tool for investigating historical change.

The paper is organized as follows. In Section 2, we give background on iterated learning, as well as the accent systems of Middle Korean and the two contemporary Korean dialects,

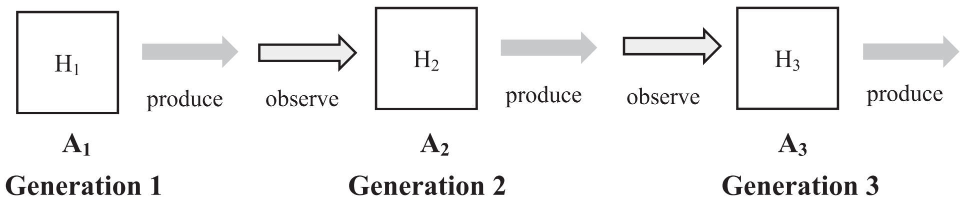

Fig 1. The iterated learning model. $H_{1/2/3}$ indicates hypotheses 1/2/3.

and their historical development. In Section 3, we describe the data used in this paper and the models we constructed. Section 4 reports the results of our iterated learning models with regard to the historical development of Sino-Korean accent. Section 5 discusses these results and concludes.

2. Background

Our approach to modeling the development of Sino-Korean accent draws on insights from two literatures: computational approaches to iterated learning, and empirical data on the historical development of accent systems from Middle Korean to two contemporary Korean dialects. We describe each literature in turn.

2.1. Iterated learning

Agent-based models of iterated learning have been used to study the emergence of language structure (Brighton, 2002; de Boer, 2000; Kirby, 2001; Kirby & Hurford, 2002; Kirby et al., 2004; Oudeyer, 2005; Smith et al., 2003; Wedel, 2012; see Kirby et al., 2014 for a review). In the simplest version of iterated learning models (Fig. 1), each generation has one adult agent and one learner. Based on knowledge of the grammar of a language (Hypothesis 1; H_1), the first agent A_1 produces the output language data for the next generation (A_2) to observe. After observing these data, A_2 induces the relevant generalization(s) and forms another hypothesis (H_2), which results in a new set of output data that is presented to the next generation (A_3). This process is repeated thousands of times in typical simulations. Crucially, when providing input for a learner in the next generation, not all of the information of the language is presented. This learning "bottleneck" (Brighton, 2002; Brighton, Smith, & Kirby, 2005; Kirby, 2002; Smith et al., 2003) plays a pivotal role in motivating language structure to emerge. Agents must use information from the observed data to infer what has never been observed, and this results in pressure for generalization, producing compositional rules.

The findings of studies using agent-based simulations have been supported by mathematical analyses as well (Griffiths & Kalish, 2007; Kirby, Dowman, & Griffiths, 2007; Nowak, Komarova, & Niyogi, 2001; Rafferty, Griffiths, & Klein, 2014; Reali & Griffiths, 2009). For example, Griffiths and Kalish (2007) examine the mathematical properties of iterated learning under the assumption that each learner uses Bayesian inference when learning a language. If each hypothesis h is a language, then $P(h)$ represents a learner's prior bias about what that language is. The learner then updates the probability of each hypothesis h after seeing data d. This posterior probability, $P(h|d)$, is obtained by Bayes' rule:

$$p(h|d) = \frac{P(d|h)\,P(h)}{\sum_{h'} P(d|h')\,p(h')} \tag{1}$$

Griffiths and Kalish show that if learners sample a hypothesis from their posterior distribution, and if this iterated learning process is allowed to continue indefinitely, the distribution over languages in the world should eventually come to approximate learners' prior distributions over languages, predicting a strong relationship between cognitive constraints and linguistic universals.

The predictions of the agent-based and mathematical models have been tested through laboratory experiments (Griffiths, Christian, & Kalish, 2008; Kalish, Griffiths, & Lewandowsky, 2007; Kirby, Cornish, & Smith, 2008; Reali & Griffiths, 2009; Smith, 2009, and others; see Scott-Phillips & Kirby, 2010 for reviews of this approach). For example, Kirby et al. (2008) found that when human participants were trained on an artificial language with a learning bottleneck, the languages transmitted by participants became easier to learn and increasingly structured. These studies primarily addressed questions regarding language *evolution*: why certain characteristics that are often observed across the world's languages evolved from a prior stage in which those characteristics were lacking.

More recently, there has been growing interest in simulating language *change* using iterated learning models. Unlike language evolution, language change is commonly assumed to occur within a relatively fixed space of grammatical parameters, for example, changing from one compositional language to another. Pierrehumbert (2001) and Wedel (2006) simulated sound change as iterated learning of phonetic detail within exemplar models. Boersma and Hamann (2008) showed that the computer simulations of sibilant inventories with constraint-based learners reached to a stable equilibrium within a small number of generations, where the sibilants of the language are optimally dispersed. They also reported that their simulation results mirrored the sound changes of Polish sibilants, which happened in the 13th and 16th centuries. Agent-based simulations with iterated learning were used to investigate the mechanisms behind sound change: possible conditions against reductions in vowel systems (De Boer, 2003), vowel chain shifts ("U.S. Northern Cities Shift," Stanford & Kenny, 2013), /u/-fronting in Standard Southern British (Harrington, Kleber, Reubold, Schiel, & Stevens, 2018), an allophonic distribution of English voiceless stops between word-initial and [s]-initial sequences (Beguš, 2020). Models have also been used to investigate morphosyntactic changes: Hare and Elman (1995) modeled historical developments in the past tense system from Old English to Modern English, and Polinsky and van Everbroeck (2003) modeled the development of the gender system from Latin to Old French. Morgan and Levy (2016) and Morgan (2016) also applied iterated learning to corpus data, modeling ordering preferences observed in binomial expressions, such as "bread and butter." Our study builds on this literature, applying iterated learning to model the historical development of Sino-Korean accent in two contemporary Korean dialects. Specifically, we focus on the role of phonotactics, which concerns restrictions on sound distributions in words, and on perceptual confusability between words, in influencing analogical changes in Korean accent classes. Our models deal with historical change ranging over five centuries, a longer time span than most previous models, and we investigate analogical changes that have been understudied by using iterated learning procedures.

2.2. *Historical development of Korean accent*

The contemporary Korean lexicon is classified into three major categories: native, Sino-Korean, and loanwords (mainly from English). The focus of our iterated learning study is on changes in Sino-Korean accent classes.

Middle Korean (15–16th centuries) had a lexically distinctive pitch accent. This distinctive accent has been lost in the standard dialect of Korean (Seoul Korean), but it is still retained in several contemporary nonstandard dialects.[2] The two dialects we investigate in this paper are South Kyengsang (south-eastern region of South Korea) and Yanbian Korean (north-eastern area of China). In Middle Korean and the two contemporary Korean dialects, nouns are classified based on accent classes. The accent systems themselves are different between Middle Korean and these contemporary dialects, but as a rule, the locus and associated pitch pattern of a Middle Korean word's accent regularly corresponds with the accent of the cognate word in the contemporary dialects. Nevertheless, the distribution of the accents in the lexicons of the two Korean dialects indicates that there was a substantial amount of irregular change that deviated from these regular correspondences. Our goal is to account for these distributional patterns.

We restrict our analysis to two-syllable Sino-Korean nouns (8564 words).[3] Sino-Korean vocabulary is believed to have been borrowed from Middle Chinese around the 9-10th centuries (Ito, 2007; Kōno, 1968). Approximately 70% of Korean words are Sino-Korean (Lee, 2017); thus, they constitute the major part of the lexicon. Two-syllable words are the most typical form of Sino-Korean words. They are composed of two monosyllabic Sino-Korean morphemes: for example, *jak.sok* 約束 "engagement," *pjən.hwa* 變化 "change." Monosyllabic Sino-Korean words are rarely used in Korean, since most Sino-Korean morphemes (monosyllables that correspond with one Chinese character) are bound forms. On the other hand, trisyllabic Sino-Korean words tend to involve additional compound accentuation rules that introduce an additional level of structure and variation. By focusing on disyllabic nouns, we sidestep these complexities while nevertheless incorporating the majority of the Korean lexicon into our analyses.

The remainder of this section describes the pitch accent system of Sino-Korean disyllabic words and traces its adaptation from Middle Chinese to Middle Korean and the historical development from Middle Korean to two Contemporary Korean dialects (South Kyengsang and Yanbian). There are four main aspects of the historical record that play a central role in our simulations. The first is a high degree of regularity between Middle Korean and the contemporary dialects when the coda of a word's initial syllable is –p/l/k. We argue that this high degree of regularity arises because of a nearly exceptionless correlation between those consonants and a particular tone class. This correlation has its roots in Middle Chinese, and so

Table 1
Sino-Korean accent formation rule in Middle Korean

μ_1	μ_2		
	L	H	R
L	LL	LH	
H	HX		
R	RX		

Abbreviation: μ, morpheme.

to understand our simulations, it is important to examine the correspondence between Middle Chinese tone classes and the basic accent system of Middle Korean. The second aspect of the data that we focus on is the relationship between the rate of regular development and a morpheme's type frequency, which we detail below. The third and fourth concern properties of earlier dialects that may have influenced patterns of historical change: an early dialectal split in how high tones behaved phonologically, and the perceptual similarity among accent classes during certain periods of the historical record. To situate and describe these four aspects of the data, we trace the historical record from Middle Chinese through the two Contemporary Korean dialects.

2.2.1. Middle Chinese

Middle Chinese had four tonal classes, which are traditionally labeled Level, Rise, Departing, and Entering.[4] There was a close relationship between these four tonal classes and the coda types: Entering tone syllables ended with an obstruent coda (–p/t/k), whereas other tones ended with a sonorant coda (Hirayama, 1967; Karlgren, 1954). These phonotactic restrictions were passed down to Sino-Korean words in Middle Korean.

2.2.2. Middle Korean

Middle Korean serves as the starting point for our iterated learning simulations. In Middle Korean texts, not only segmentals but also suprasegmentals (pitch accent; H(igh)/R(ise)/L(ow) tones) were recorded; this information provides accurate and consistent phonological details on this stage of the language (Lee & Ramsey, 2011).

Middle Korean had a pitch-accent system (Ramsey, 1978). Each Sino-Korean morpheme had an underlying tone, and Sino-Korean disyllabic nouns, each of which was composed of two monosyllabic morphemes, had four pitch patterns: HX, LH, LL, and RX, where H indicates a high tone, L indicates a low tone, R indicates a pitch rise, and X indicates an unspecified tone whose value as H or L was predictable from the surrounding phrasal context in which the word appeared. The accent pattern of disyllabic Sino-Korean words in Middle Korean depended on the underlying tones of each constituent Sino-Korean morpheme μ, and was determined primarily by the underlying tone of the first syllable (Table 1).

Table 2
Correspondences between Middle Chinese tones and Sino-Korean tones/codas

Middle Chinese Tone	Sino-Korean tones	Sino-Korean codas
Level	L	–Ø/m/n/ŋ
Rise	R/H	
Departing		
Entering	H	–p/l/k

The tones of the individual Sino-Korean morphemes were derived through a regular correspondence with Middle Chinese tones. The four Middle Chinese tones were adapted into Sino-Korean accent as follows ("X > Y" below indicates that "X was adapted as Y"):

Middle Chinese Level tone > Sino-Korean Low

Middle Chinese Rise tone and Departing tone > Sino-Korean Rise or High

Middle Chinese Entering tone > Sino-Korean High.

Restrictions in Middle Chinese between the tone of a syllable and its segmental phonemes—particularly those occupying the syllable coda (the last consonant in a canonical CVC syllable)—were passed on to Sino-Korean when the word was borrowed. As a result, Sino-Korean morphemes that corresponded with the Middle Chinese Level/Rise/Departing tones had codas –Ø/m/n/ŋ, while Sino-Korean morphemes that corresponded with the Middle Chinese Entering tones had codas –p/l/k (Table 2).[5] Thus, if a Sino-Korean morpheme ended with a coda –p/l/k, it always had an H tone in Middle Korean; words whose first morpheme ended in –p/l/k belonged to the Middle Korean HX class with 100% regularity. Morphemes which ended in –Ø/m/n/ŋ were only sometimes assigned to the H class in Middle Korean, meaning that words whose first morphemes ended in –Ø/m/n/ŋ only sometimes belonged to the HX class. For the remainder of the paper, our analyses divide the Middle Korean HX class into two subclasses: EX, which consists of words whose first morphemes had an Entering tone in Middle Chinese, and HX, which consists of words whose first morphemes had a Rise/Departing tone in Middle Chinese.

Although we analyze changes in the EX and HX classes separately throughout the paper, our simulation treats these as a single class within the model, under the assumption that their pitch accents were perceptually identical in Middle Korean.

Middle Korean *native monosyllabic* nouns had two types of H tones: one type alternated to L when it constituted the first member of a compound noun, while the other type did not show such an alternation (Ito, 2013; Kim, 1973; Whitman, 1994). Although it is unclear from the historical record whether Sino-Korean morphemes with an H tone (E/H) also had this distinction and if so, which subclass each Sino-Korean morpheme belonged to, we hypothesize that this distinction may have played a role in the historical development of Sino-Korean accent.

Table 3
Regular correspondences between Middle Korean and contemporary Korean dialects (disyllabic nouns)

Middle Korean	HX	LH	LL	RX
South Kyengsang	HH	HL	LH(L)	LH(H)
Yanbian	HL	LH	LL	HL

2.2.3. *Contemporary Korean dialects*

Our iterated learning simulations examine the emergence of two modern Korean dialects, South Kyengsang and Yanbian Korean, from Middle Korean.

As in Middle Korean, disyllabic nouns of South Kyengsang Korean fall into four accent classes: HH, HL, LH(L), and LH(H), where H indicates a high tone and L indicates a low tone. Accents in parentheses indicate tones that a stem imposes on a following inflectional suffix. The correspondences between the accents of disyllabic nouns in South Kyengsang (both native and Sino-Korean words) and Middle Korean are given in Table 3.[6] In Yanbian, disyllabic nouns appear in one of three possible accent classes—HL, LH, and LL—due to a merger of Middle Korean HX and RX. The regular correspondence between Middle Korean and Yanbian is, nevertheless, straightforward (Table 3). Different surface representations of the accent classes in these two contemporary dialects reflect distinct sound changes that occurred independently.

Our analysis takes the correspondences among accent classes that were created by sound change as given, and focuses on predicting patterns of analogical change over time among words in the different accent classes. That is, we are interested in predicting what proportion of words follow the regular sound correspondences, and what proportion of words show irregular changes between each pair of accent classes. In what follows, we describe the key aspects of these analogical changes that we aim to capture with our iterated learning model. The first two are known characteristics of the data, and our question is whether iterated learning models can capture these properties. The last two are hypothesized characteristics of earlier dialects that are no longer directly observable, but that might have played a role in shaping the observed patterns; we shed light on this by asking whether incorporating these mediating factors improves the models' ability to capture the observed analogical changes.

Overall accent distribution and correspondences with Middle Korean: Although many words appear with the expected accent in South Kyengsang and Yanbian, a substantial proportion show a different accent pattern from the one that would be expected by the regular correspondences. Fig. 2 shows heatmaps of these correspondences.[7] The darkness indicates the proportion of words with a certain accent pattern in each dialect for a specific Middle Korean accent class. The regular correspondences are outlined in black. See Table S1 for the exact numbers and percentages. The irregular correspondences comprise 30% of the Kyengsang lexicon and 37% of the Yanbian lexicon, so there was a substantial amount of analogical change. We discuss below why the regular correspondence from Middle Korean LL to Yanbian LL is not the most frequent one.

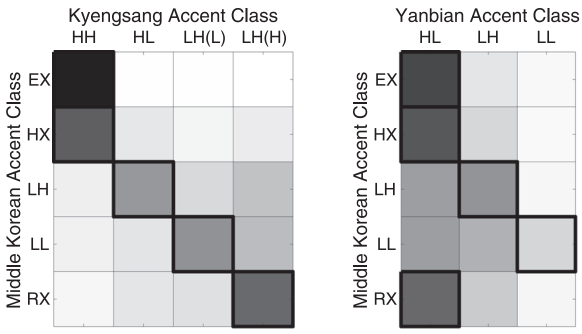

Fig 2. Heatmaps of Middle Korean-contemporary correspondences for Kyengsang (left) and Yanbian (right). Darker colors indicate higher percentages; the boxes with thick outlines are the regular correspondences.

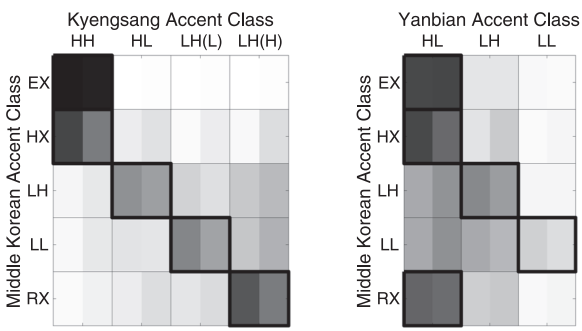

Fig 3. Relationship between type frequency of each Sino-Korean morpheme and historical development. The left half of each square corresponds to high-frequency words, and the right half of each square corresponds to low-frequency words, based on a median split. Darker colors indicate higher percentages; the boxes with thick outlines are the regular correspondences.

Disyllabic Sino-Korean nouns that belonged to the EX subclass in Middle Korean still appear with the expected HH tonal pattern in South Kyengsang very regularly (99%). HX class words other than the EX subtype correspond with the South Kyengsang HH class less regularly (77%). On the other hand, in Yanbian, the Middle Korean EX class shows the highest regularity (86%), but it is not as high as in South Kyengsang.

Type-frequency effect: Historical developments of the Sino-Korean accents appear to be related to individual morphemes' type frequencies. Some morphemes appear in many Sino-Korean words (e.g., *tɛ* 大 "big" as in *tɛ.waŋ* 大王 "great king," *tɛ.kuk* 大國 "big country"), while others are rarely used; they may appear in just one word (e.g., *sin* 訊 "ask" in *sin.mun* 訊問 "questioning"). Fig. 3 subdivides the percentages from Fig. 2 based on a median split of the type frequency of the initial Sino-Korean morphemes (see Table S2 for the exact percentages). In general, the more frequently a Sino-Korean morpheme in the initial syllable appears in disyllabic Sino-Korean words, the more regular the accent patterns are: as a rule, the regularity rates of high-frequency morphemes (the left of each cell of the confusion matrix) are higher than those of low-frequency morphemes (the right of each cell of the confusion matrix). This is indicated by the darker shading on the left half of the cells that represent regular correspondences, and the lighter shading on the left half of many of the others.

It does not make sense to subdivide the data set in the same way based on the final syllable, because for two of the classes (EX/HX and RX), the final syllable did not have a tone specification in Middle Korean; its tone was predictable based on the surrounding context of the word in the text.

Early dialectal differences in high tones: As discussed in 2.2.2, there were two types of H tones in Middle Korean native monosyllabic nouns. Based on the data of the Hamkyeng dialect (spoken in the northeastern region of the Korean peninsula), which is a dialect closely related to Yanbian, this distinction is still retained to some extent, particularly in native compound nouns composed of two monosyllabic words (Ramsey, 1978). The same is true for Yanbian: for example, based on the data obtained through interviews with Yanbian native speakers by the first author, native compound nouns composed of two underlying H tones (H + H) appear with HL 40% versus LH 51%. On the other hand, Kyengsang has almost entirely lost this distinction; traces of this former distinction are only found in certain frozen lexicalized examples (Rah, 1974; Kang, 2017; Kim, 1997; Son, 2017). This difference between the two dialects raises the question of whether there was already a dialectal difference at the stage of Middle Korean. We investigate this hypothesis in Simulation 2, using our iterated learning models to ask questions about earlier dialects that are no longer directly observable.

Analogical changes based on perceptual similarity: Furthermore, several analogical changes appear to stem from ambiguity between similar phonetic realizations. In South Kyengsang, both LH(L) and LH(H) appear as LH in the isolation (citation) form of the noun. Reflecting this neutralization, they tend to be confused with each other when native speakers generate inflected forms.[8] LH(L) tends to change to LH(H) more than LH(H) changes to LH(L), perhaps because LH(H) is a larger class than LH(L): LH(H) 2700 words versus LH(L) 1165 words (Ito, 2014; see also Albright, 2009; Bybee, 1995 regarding attraction to a larger class).

In Kyengsang, another perception-based analogical change probably took place earlier: Middle Korean LH may have changed to LL irregularly. This may have occurred in the process of the leftward accent shift mentioned above (see footnote 6): at some point, LH may have been LF (F = Falling) while LL was LH, thus, they may have been similar LH tones if we analyze LF as LHL; the simple LH tone was probably preferable compared to the more complex LF contour (in Autosegmental Phonology, a falling tone is represented as an HL sequence on a single syllable). Although there is no clear philological evidence for this change, the accent distributions in contemporary South Kyengsang disyllabic nouns suggest that such changes may have occurred historically, as 17% of Middle Korean LH changed to LL (= Kyengsang LH(L)) in Sino-Korean words (Table S1). A similar tendency is observed in disyllabic native words as well (Do, Ito, & Kenstowicz, 2014: 159): 14% of Middle Korean LH changed to LL (= Kyengsang LH(L)), which is the largest exception in the Middle Korean LH class.

Table 4
Summary of factors in the historical development of Sino-Korean accent

Factors	South Kyengsang	Yanbian
Overall accent correspondence	High regularity of Middle Korean EX	
Type frequency	High frequency morphemes tend to be more regular	
Early dialectal differences	Two H tones not clearly retained	Two H tones still retained
Perception-based analogical changes	Confusion between Middle Korean LH and LL (early) Confusion between Middle Korean LL and RX [= Kyengsang LH(L) and LH(H)] (later)	Confusion between Middle Korean LH and LL

Finally, in Yanbian, the citation forms of LH and LL are identical and both appear as LH, and so the LH and LL classes tend to be confused by native speakers. This confusion seems to have led to greater rates of analogical change. LL often changes to LH irregularly, rather than the other way around (LH changes to LL), due to either a type-frequency effect (LH 2154 vs. LL 404) or a culminativity constraint: every word must have a pitch peak (Hayes, 1995).[9]

We refer to these as *perception-based analogical changes*, and describe simulations below that test the role of perceptual similarity in accounting for each of these changes.

Table 4 summarizes the historical tendencies and potential mediating factors that we focus on in modeling the historical development of the South Kyengsang and Yanbian dialects from Middle Korean.

Our goal in this paper is to model the attested historical changes with a relatively small set of simple parameters (rather than involving too many detailed factors) so that we can show the general validity of the iterated learning models in analyzing historical development. See Stanford and Kenny (2013) for relevant discussion.

3. Modeling

In order to capture the historical changes of Sino-Korean accent discussed in 2.3, we constructed four different iterated learning models. In this section, we first introduce the data that were used in our modeling. We then describe the basic designs of our models: three phonotactic models versus a baseline model without phonological information.

3.1. Data

Our simulations used disyllabic Sino-Korean data that were analyzed in previous work on South Kyengsang Korean and Yanbian Korean (Ito, 2008, 2009, 2014). The data reported in

Table 5
The correspondence of the accent of two Kyengsang speakers

S_1/S_2	EX	HH	HL	LH(L)	LH(H)	EX%	HH%	HL%	LH(L)%	LH(H)%
EX	1492	0	6	7	0	99	0	0	0	0
HH	0	420	67	65	57	0	69	11	11	9
HL	7	49	909	97	144	1	4	75	8	12
LH(L)	1	11	38	550	164	0	1	5	72	21
LH(H)	2	36	133	391	1725	0	2	6	17	75

Abbreviation: S_1/S_2, Speaker 1/2.

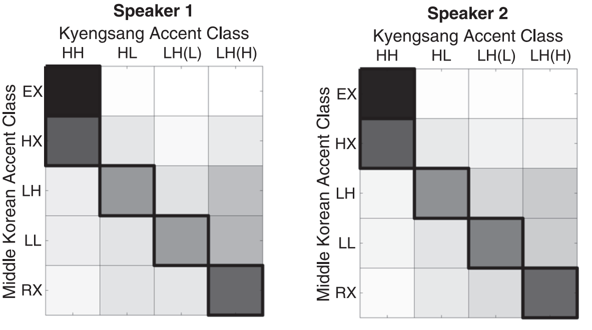

Fig 4. Heatmaps of the historical development of two South Kyengsang speakers. Darker colors indicate higher percentages; the boxes with thick outlines are the regular correspondences.

these studies were collected from one South Kyengsang speaker (born in the 1980s) and one Yanbian speaker (born in the 1970s). In this study, we added another speaker's data (born in the 1980s) for South Kyengsang, which were collected by the first author of this paper.

Table 5 shows the correspondence of the accent classes between the two Kyengsang speakers. That is, it shows the extent to which the accents of the two speakers agree for particular lexical items. In this table, EX indicates the HH class, where the first syllable has a coda –p/l/k. The shaded cells show the cases where the two speakers agreed. For example, there are 1492 words that both speakers reported as EX (agreement), while there are 6 words that speaker 1 reported as EX, while speaker 2 reported as HL (disagreement). Except for the EX class, c. 30% of words varied between the two speakers. There was intraspeaker variation as well. For example, speaker 1 reported variation between LH(L) and LH(H) (= Middle Korean LL and RX) for 5% of the whole corpus. Thus, at the lexical level, the accent patterns did not necessarily agree well between the speakers.

Despite the variance at the lexical level, however, the two Kyengsang speakers showed highly similar patterns in the overall historical development of correspondences between different accent classes. Fig. 4 shows the correspondences between each speaker and Middle Korean (see Table S3 for the exact percentages). Although there are some differences, the general tendencies are similar between the two (correlation coefficient $R = .985$). The same tendency (relatively high variance at the lexical level but consistency in the historical development of the accent patterns) has been reported in the native nouns of two Yanbian speakers

Table 6
Accent distribution of Sino-Korean morphemes in the first generation

Position/accent	H	L	R	Totals
Initial	2406 (197 syl)	3231 (257 syl)	2927 (231 syl)	8564
Final	2969 (199 syl)	2665 (239 syl)	2930 (218 syl)	8564
Totals	5375	5896	5857	17,128

Note. "syl" denotes the number of distinct CVC syllables, such as *ki*, *pon*.

as well (Ito, 2008). Given that we focus in this paper on modeling the percentages of the accent classes in the historical development of these dialects, rather than the accent classes that are specifically assigned to each individual word, we believe these data are sufficiently representative of each dialect, at least for the purposes of this paper. We aggregate data from the two Kyengsang speakers as described in footnote 7.

Each Sino-Korean word in the corpus is composed of two Sino-Korean morphemes. The accent of these morphemes in Middle Korean was provided based on the database of Ito (2007): for example, *piŋ* (L) 氷 "ice," *po* (R) 步 "walk," *puk* (H) 北 "north." For some Sino-Korean morphemes in Middle Korean, the accent was unknown or varied (i.e., multiple accent types were observed). For this study, we used the 8564 Sino-Korean words, where the accent of both morphemes was uniquely designated (no variation) in Middle Korean. The initial accent distribution (generation 1) of the morphemes that composed these disyllabic nouns is shown in Table 6.

The relevant changes took place over five centuries; we modeled a generation as lasting 25 years; thus, we ran each model for 20 iterations.

3.2. Model design

We constructed three iterated learning models, each using a different type of phonotactic learner: the syllable-based model, the MaxEnt model, and the Chinese Restaurant Process (CRP)-MaxEnt model. We compared these to a baseline model that did not implement any phonotactic generalizations when inferring which accent class a word/morpheme belonged to. Comparing the three phonotactic models to each other also allowed us to examine to what extent our results depended on specific hypotheses about how language users make phonotactic generalizations.

Our iterated learning models assumed that in each generation (= Agent A_1, A_2, A_3...), the accents of some Sino-Korean morphemes (not words) were "forgotten." The "remembered" Sino-Korean morphemes were retained in the next generation, whereas the accents of the forgotten morphemes were inferred based on the other words in the vocabulary (= Hypothesis H_1, H_2, H_3...), resulting in a new set of data. This is analogous to an information bottleneck (Brighton, 2002; Brighton et al., 2005; Kirby, 2002; Smith et al., 2003). To decide which Sino-Korean morphemes lose their accent information, we randomly sampled the corpus to construct morpheme sets of various sizes (5–25%) to count as being in the "forgotten" ones. The same morpheme can occur in multiple Sino-Korean disyllabic word types, and each of those instances was treated as independent; thus, for morphemes with high-type frequency, there was a higher probability that at least one instance of that morpheme would be remembered. One, both, or neither of the Sino-Korean morphemes in a disyllabic Sino-Korean word could be forgotten. At each transition between generations, a potentially different set of morphemes was designated as "forgotten," and forgotten morphemes differed across runs and models. Below, we refer to the remembered Sino-Korean morphemes as *training data*.

We run simulations that learn phonotactic regularities based on individual morphemes rather than taking the disyllabic Sino-Korean words as unanalyzed wholes based on evidence that Korean speakers decompose Sino-Korean words into their constituent morphemes. Historically, the Middle Korean vowel /ʌ/ merged to /a/ in word-initial syllable, whereas it merged to /ɨ/ in noninitial syllable in *native* words as in *tʌ.ri* > ***ta**.ri* "bridge," *a.tʌl* > *a.t**ɨ**l* "son" (16–18th centuries, Lee & Ramsey, 2011: 262–263). In Sino-Korean words, however, /ʌ/ did not merge to /ɨ/ even if it appeared in nonword-initial position. It merged to /a/ regardless of its position in the word, as seen in *sʌ.c^{h}on* > *s**a**.c^{h}on* 四寸 "cousin," *son.cʌ* > *son.c**a*** 孫子 "grandson." This suggests that Korean speakers decomposed the Sino-Korean words into their constituent morphemes; if multisyllabic Sino-Korean words were interpreted as unanalyzed wholes, the same merger pattern observed in native words would have been expected.[10]

Based on various segmental sound changes from Middle Korean to contemporary Korean (e.g., consonant clusters > tense, z > Ø, ʌ > a), we divided the training data into two subsets (generations 1–12: "Middle Korean," generations 13–20: "Contemporary Korean"). Although these sound changes occurred at different times (16–18th centuries), we made the simplifying assumption that the first three centuries were like Middle Korean and the following two centuries were like contemporary Korean.

Three phonotactic models computed the posterior probability of Sino-Korean morpheme M belonging to accent class C, based on Bayes' rule:

$$p(C|M) = \frac{p\,(M|C)\,p\,(C)}{\sum_{C'} p\,(M|C')\,p\,(C')} \tag{2}$$

Our models all estimated the prior probability $P(C)$ as the proportion of morphemes in the training data that belonged to accent class C. The method for computing the likelihood of morpheme M belonging to class C, $p(M|C)$, differed across the four models. The syllable-based model takes into account the effects of memorizing specific syllables the agent has seen before, whereas the MaxEnt model utilizes phonotactic constraints that generalize across similar syllables; the CRP-MaxEnt model combines these two properties. The baseline model, on the other hand, does not utilize any phonotactic knowledge and is based solely on the type-frequency of each accent class. The details of each model are as follows.

Syllable-based model: In the syllable-based model, we first counted the frequency of each syllable shape in each accent class in the training data; the frequency count was done separately for the initial and final syllables. We define "syllable shape" as a particular segmental instantiation of the (C)(G)V(G)(C) schema: for example, *pjək*, *c^{h}i*, *kun*. Thus, *kam* and *kan* are different syllable shapes. Since some syllable shapes may not occur in a particular accent class, we added a smoothing number α to these counts. These were then normalized by the total syllable count within the accent class to obtain a probability distribution over syllable shapes for each accent class, as seen in Eq. 3, where N_σ denotes the frequency of syllable σ in the training data from class C. This means that different Sino-Korean morphemes with the same syllable shape have the same likelihood; the same is true for the other phonotactic models as well.[11]

$$\mathrm{p}(\sigma|\mathrm{C}) = \frac{N_\sigma + \alpha}{\sum_{\sigma'} (N_{\sigma'} + \alpha)} \tag{3}$$

MaxEnt model: Phonotactic well-formedness is often described in terms of the relative strength of a set of violable constraints that govern which sound sequences are allowable (Prince & Smolensky, 1993/2004). Harmonic grammar (Legendre, Miyata, & Smolensky, 1990; Smolensky & Legendre, 2006) assigns numerical weights to these constraints that govern how strongly each constraint influences a particular form's degree of well-formedness. Each constraint weight, *w*, is a nonnegative real number, and those weights are multiplied by the number of violations of that constraint that a particular form incurs (each violation is worth –1). The optimal output form for a given lexical item is the one whose sum of weighted violations is closest to zero. For a detailed introduction to phonotactic learning by using weighted constraints, see Pater (2009).

Here, we use MaxEnt grammars (Goldwater & Johnson, 2003; Hayes & Wilson, 2008), a probabilistic variant of Harmonic grammar. In MaxEnt, as in Harmonic grammar, the harmony of a form *x*, *h(x)*, is calculated as:

$$h(x) = \sum_{i=1}^{N} w_i f_i(x), \tag{4}$$

where *w* is a weight and *f* encodes the number of times that *x* violates the constraint. The maxent value of *x*, *P'*(*x*) is calculated by exponentiating the harmony:

$$P'(x) = \exp(h(x)) \tag{5}$$

This is then normalized by the sum of the maxent values of all possible forms to obtain the probability of a particular form *x*:

$$P(x) = \frac{P'(x)}{\sum_{x'} P'(x')} \tag{6}$$

Table 7 gives an example of this probability computation using the example of *s*-stop clusters in English. A constraint banning a voiced stop in this environment (after *s*, represented as *s*__) is weighted more highly than a constraint banning a voiceless stop. Crucially, this results in a higher harmony, and thus a higher probability, for *s*+voiceless stop clusters than for *s*+voiced stop clusters.

Numerical weights for a MaxEnt grammar can be learned based on training data according to the principle of maximum entropy, which seeks weights that most closely match the expected number of occurrences of phonetic sequences to their actual frequency of occurrence in the training data (Goldwater & Johnson, 2003). Hayes and Wilson (2008) addition-

Table 7
Scores, maxent values, and probabilities in MaxEnt grammar

x	*voiced stop/s__ (w = 10)	*voiceless stop/s__ (w = 1)	Harmony (h(x))	MaxEnt value (P'(x))	Probability of x (P(x))
sk		−1	−1	exp (−1) = 0.37	0.37/(0.37+0.00) = 1.00
sg	−1		−10	exp (−10) = 0.00	0.00/(0.37+0.00) = 0.00

ally introduce a heuristic algorithm that can learn the content of the constraints, given the data and a prespecified set of phonological features.

In our simulations, the constraint learning and weighting as well as the calculation of the probability of each lexical item was done using the Maxent2.0 program (written by Colin Wilson), which is an extended version of the UCLA phonotactic learner program (https://linguistics.ucla.edu/people/hayes/Phonotactics/).

Constraint weights were learned separately in each generation based on that generation's training data, and separate sets of weights were learned for initial and final morphemes. In contrast, the constraints themselves were shared across different learners and across initial and final morphemes. We used seven different sets of constraints: three for Middle Korean (1st–12th generations, one for each of the three H/L/R classes), three for contemporary Korean (13th–20th generations, one for each of the three H/L/R classes), and one for Yanbian that aggregated H and R (from the 17th generation reflecting the merger of these two tones; see below). Each set of constraints was learned from the relevant subset of the lexicon (e.g., *[+spread_gl] which bans an aspirated consonant, *[–low] which bans a non-low vowel), and fixed across our simulations. We chose to use different sets of constraints for the different accent classes because this makes it easier to find phonotactic patterns that are different depending on the class (e.g., the relationship between membership in the H class and codas of –p/l/k), rather than finding more general phonotactic restrictions in Sino-Korean morphemes as a whole. The number of constraints was a free parameter of the model, and we explored sets of 20, 50, 100, and 200 constraints.[12]

In our simulations, $p(\sigma|C)$ was calculated as in Eq. 6, where x corresponds to each syllable shape. Still, due to numerical instability, we used smoothing when training the weights for each learner. Because we were unable to add fractional counts, we added one instance of each syllable shape. To ensure that this did not overwhelm the training data from the corpus, we multiplied each of the counts from the corpus by 10. The added data constituted approximately 1.5–3.5% of each training data set. This adjustment improved the calculation of the harmony and the normalizing constant from Eq. 6, which was computed by summing over all possible monosyllables (16,128 for Middle Korean and 32,400 for contemporary Korean).

The Chinese Restaurant Process-MaxEnt model: The CRP-MaxEnt model is a hybrid of the syllable-based model and the MaxEnt model in which syllables are assumed to have been generated by a Dirichlet process (Ferguson, 1973). Rather than restrict novel forms to the finite set of syllables found in the corpus, as the syllable model does, the CRP-MaxEnt model allows a potentially infinite number of forms and uses the MaxEnt model as a base distribution for producing new forms. Based on the log probabilities obtained by using the Maxent2.0 program and the frequency of each syllable in each accent class, the probability of a Sino-Korean syllable given the accent class was calculated as in Eq. 7, for both initial and final syllables, separately.

$$p(\sigma|C) = \frac{N_\sigma}{\sum_{\sigma'} N_{\sigma'} + \alpha} + \frac{\alpha}{\sum_{\sigma'} N_{\sigma'} + \alpha} \cdot p_{MaxEnt}(\sigma|C) \tag{7}$$

In the three phonotactic models, after using Bayesian inference to compute the posterior distribution over accent classes for each of the forgotten Sino-Korean morphemes, a new accent class was sampled from this posterior distribution: forgotten morphemes were assigned a random number between 0 and 1, and their new accent was determined based on the probability of each accent class predicted by the models; for example, if the probabilities of the accent classes H/L/R were 0.2, 0.5, and 0.3, respectively, H was assigned when the random number $r \leq 0.2$, L was assigned when $0.2 < r \leq 0.7$; otherwise, accent class R was assigned.

After resampling all of the forgotten morphemes, the accent of individual Sino-Korean words was determined based on the accent formation rules mentioned above (2.2.2, Table 1).[13]

Baseline model: No phonotactics are used in the baseline model. It uses a constant likelihood for each morpheme across the three accent classes, and thus its assignments of Sino-Korean morphemes to accent classes are based solely on the prior distribution of the accent class in the training data (type frequency).

In Yanbian, we assumed that the merger of Middle Korean HX and RX occurred in generation 17 (four generations—17, 18, 19, and 20—, i.e., 100 years, have this merger). We chose the same time point as the later perception-based analogical change in Kyengsang (discussed in 4.3) for simplicity, but the fact that some older speakers of Yanbian partially retain a long vowel that corresponds with Middle Korean R tone suggests that the merger occurred relatively recently (Ito, 2013).

We conduct three simulations. Simulation 1 examines the ability of iterated learning models that embed a variety of phonotactic learners to capture the basic effects seen in the historical data: the overall accent distribution (in particular the high regularity of the Middle Korean EX class) and the type-frequency effect. For all of the models, we tested five different forgetting rates (0.05, 0.1, 0.15, 0.2, and 0.25). In addition, for the syllable-based and CRP-MaxEnt models, we tested three different smoothing values α (1, 0.1, and 0.01). Table 8 summarizes the parameters of our models. These free parameters are chosen to best fit the historical record in terms of predicting the proportion of forms moving between different accent classes; we tested all of these values and report the best result in this paper.

Simulation 2 investigates the role of the initial state for capturing patterns of historical change, by taking into account the two different H tones (recall Section 2.2.2). Specifically, it explores whether hypothesizing different encodings of the initial state in the first generation

Table 8
Summary of models

Models	Phonotactic information		Bottleneck	Smoothing	# of models
	Phonological constraints (# of constraints)	Syllable memorization	Forgetting rates	α	
Syllable-based	No	Yes		1, 0.1, 0.01	15
MaxEnt	Yes (20, 50, 100, 200)	No	0.05, 0.1, 0.15, 0.2, 0.25	NA	20
CRP-MaxEnt	Yes (20, 50, 100, 200)	Yes		1, 0.1, 0.01	60
Baseline	No	No		NA	5

of the iterated learning models can account for observed differences between the Kyengsang and Yanbian dialects.

Simulation 3 examines the perception-based analogical changes, implementing these as one-directional confusions: Middle Korean LH > LL (not LL > LH) and Middle Korean LL > RX (not RX > LL) in Kyengsang, Middle Korean LL > LH (not LH > LL) in Yanbian.[14]

Model performance was evaluated based on the log likelihood of the correspondences predicted by the model in the last iteration, as seen in Eq. 8. Specifically, if the model predicted that the words that were assigned to class i in Middle Korean had a probability p_{ij} of belonging to class j in the modern dialect, the log likelihood was defined as:

$$L = \sum_{ij} n_{ij} \log p_{ij}, \tag{8}$$

where p_{ij} was a smoothed probability distribution over the accent classes in the modern dialect, computed based on how many words showed each correspondence on the final iteration of iterated learning with smoothing parameter 1; and n_{ij} was the number of word types that actually moved between those two classes according to our corpus. For log likelihood, higher (less negative) numbers are better. We also compute BIC (Bayesian information criterion), an adjusted log likelihood measure that trades off model fit against the number of free parameters in the model, implementing a penalty for more complex models.

4. Simulations

4.1. Simulation 1: Iterated learning as a model of historical change

In Simulation 1, we test three phonotactic models and one baseline model, using a range of parameter values. We are interested in whether there are differences in performance (1)

Table 9
The results of the best models

				All		Kyengsang		Yanbian	
Models	Cons	Rate	α	LL	BIC	LL	BIC	LL	BIC
Syllable-based	NA	0.25	0.1	–12,161.528	24,341.17	–6451.778	12,921.67	–5709.750	11,437.61
MaxEnt	50	0.1	NA	–12,231.141	24,480.39	–6615.067	13,248.24	–5616.074	11,250.26
CRP-MaxEnt	20	0.2	0.1	–12,301.552	24,630.27	–6316.965	12,661.10	–5984.587	11,996.34
Baseline	NA	0.05	NA	–13,449.415	26,907.89	–7695.509	15,400.07	–5753.906	11,516.87

Abbreviations: Cons, number of used constraints; LL, log likelihood; Rate, forgetting rate.

between the three phonotactic models and the baseline model, and (2) among the three phonotactic models, focusing on overall distributional patterns (in particular the high regularity of the Middle Korean EX class) and the type-frequency effect.

4.1.1. Results

Table 9 summarizes the parameters of each model that resulted in the best performance, and gives the resulting log likelihoods. We chose one set of parameters for each model that was the global best across the two dialects.

Overall, the three phonotactic models performed much better than the baseline model, based on the BIC scores. The same is true for Kyengsang. Among the phonotactic models, the CRP-MaxEnt model showed the best performance in Kyengsang.

On the other hand, in Yanbian, two phonotactic models (syllable-based, MaxEnt) showed better performance than the baseline, whereas the CRP-MaxEnt model was the worst. This is mainly because the latter predicted that correspondences between the Middle Korean EX class and the Yanbian HL class would be more regular than they actually are: 99% versus actual 86% (see Fig. 5 and Table S4). Near-deterministic model predictions have particularly high impact on likelihood scores when they do not match the data. We examine why such a difference was observed between the two dialects in Simulation 2.

The best baseline was obtained when the forgetting rate was smallest (0.05). This is because the smaller forgetting rate made it possible to retain the original accent more; the regular correspondences resulted in better predictions compared to the completely random accent assignment to the “forgotten” morphemes.

General patterns: Fig. 5 shows the predicted accent correspondences by our four models along with the actual correspondences between Middle Korean and South Kyengsang (top)/Yanbian (bottom). The shading reflects a transition matrix from Middle Korean to the modern dialects, normalized across all the words that come from a particular class in Middle Korean. See Table S4 for the exact percentages.

In Kyengsang, the high regularity of the Middle Korean EX class was relatively well captured in the three phonotactic models: 89–99% of the Middle Korean EX class was predicted to belong to the expected HH class in Kyengsang versus only 53% by the baseline model. Fig. 6 (a) shows how regular correspondence rates with Middle Korean accent changed over all generations in Kyengsang, which was predicted by the

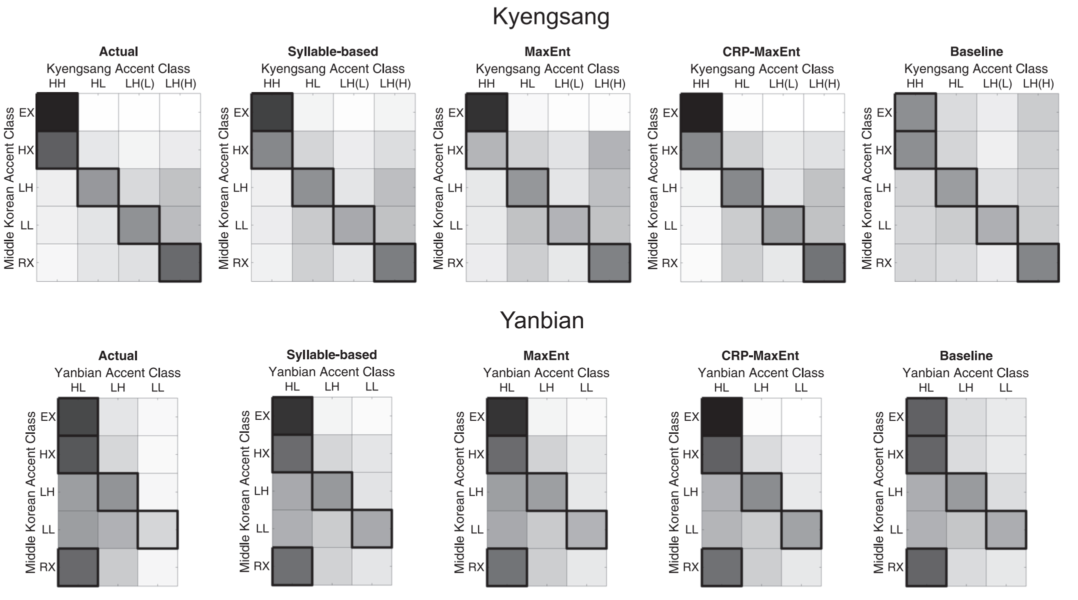

Fig 5. Heatmaps showing the correspondence between the Middle Korean accent and the Kyengsang (top)/Yanbian (bottom) accent predicted by four models as well as the actual correspondence. Darker colors indicate higher percentages; the boxes with thick outlines are the regular correspondences.

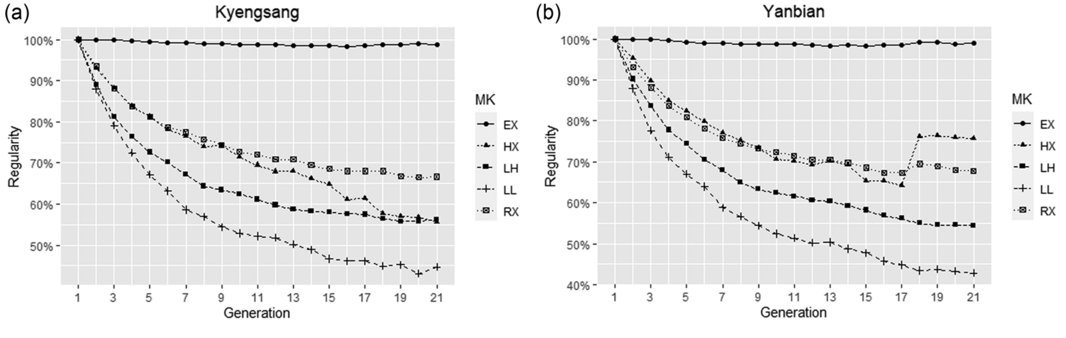

Fig 6. Regularity rates in each generation predicted by the CRP-MaxEnt model. Abbreviation: MK, Middle Korean accent class.

CRP-MaxEnt model (20 constraints, forgetting rate = 0.2, $\alpha = 0.1$). As can be seen, the regularity rate of the Middle Korean EX class was stable throughout the generations. It is considered that the strong correlation between an H tone and codas –p/l/k was captured based on particular syllable shapes (CVp/l/k) or some relevant phonotactic constraints (e.g., *[–word-boundary][+approximant] which bans syllable-final /l/, *[–sonorant][+word boundary] which bans syllable-final obstruents).[15]

In Yanbian, the accent distributions were qualitatively well captured in all models: Middle Korean EX showed the highest regularity, followed by HX/RX, then LH/LL. The regularity of Middle Korean LL is relatively high in the predictions of all models compared to the actual data (35–43% vs. actual 18%). This is probably due to the perception-based analogical change from LL to LH in Yanbian, which was not taken into account in Simulation 1. We explore the importance of this factor in Simulation 3 by incorporating perception-based analogical changes into our iterated learning model. Fig. 6 (b) shows the trajectories of the regular correspondence rates with Middle Korean accent that changed over all generations in Yanbian, which was again predicted by the CRP-MaxEnt model (20 constraints, forgetting rate = 0.2, $\alpha = 0.1$). As in Kyengsang, the regularity rate of the Middle Korean EX class was stable throughout the generations. On the other hand, the regularity of the Middle Korean HX class went up in generation 18, reflecting the assumed accent merger of HX and RX in this dialect.

Although the general tendencies were well-predicted by our phonotactic models, the predictions did not necessarily agree with the actual accent classes of each individual word. In order to examine this point further, we computed the percentage of agreement on individual words' accent classes between two runs of the same model. As seen in Table 10, two runs of the same models using exactly the same parameters showed relatively low agreement on predictions for specific lexical items in most classes, although the predicted distributions themselves were more or less the same between the two runs. Analogical changes are by nature irregular, in that they do not always produce the same result. Our results suggest that the direction of analogical change as a whole does not critically depend on particular lexical items, and more or less the same development can emerge based on the general phonotactic information as well as the frequency factor, which is discussed below.

Frequency effects: Fig. 7 subdivides the confusion matrices from Fig. 5 based on the type frequency of the initial Sino-Korean morphemes. See Table S5 for the exact percentages.

In Kyengsang, the type-frequency effect observed in the actual development (i.e., except for the EX class, the words with a high-type frequency Sino-Korean morpheme tend to be more regular in their development than the words with a low-type frequency morpheme) was reflected in all three phonotactic models: across all accent classes, the regular correspondence rate was higher for morphemes with high-type frequency, compared to morphemes with low-type frequency (even for EX in the syllable-based model). As mentioned above (3.2), this is probably because high-frequency morphemes have more instances in the training data. On the other hand, low-frequency morphemes do not have many instances in the training data and so have lower phonotactic support for preserving their original accent class, leading to the accent changes. The type-frequency effect was not clearly observed in the baseline model.

The same is true for Yanbian. The type-frequency effect was captured in all three phonotactic models, with the exception of the HX class in the MaxEnt model.

4.1.2. Discussion

In Simulation 1, the phonotactic models were all much better than the baseline model in Kyengsang. In particular, the CRP-MaxEnt model showed the best performance (lowest BIC score) among the phonotactic models. The type-frequency effect of Sino-Korean morphemes was also reflected in all three phonotactic models, but not in the baseline models. This suggests that phonotactic models can capture the attested diachronic accent changes in

Table 10
Correspondences of two runs

Kyengsang

Syllable-based

Run1/2	EX%	HH%	HL%	LH(L)%	LH(H)%
EX	91	0	4	2	3
HH	0	47	19	9	25
HL	3	8	52	9	27
LH(L)	2	7	27	38	26
LH(H)	2	5	25	11	58

MaxEnt

Run1/2	EX%	HH%	HL%	LH(L)%	LH(H)%
EX	92	0	4	2	2
HH	0	24	28	13	35
HL	2	10	41	13	34
LH(L)	2	11	26	26	35
LH(H)	1	11	23	10	54

CRP-MaxEnt

Run1/2	EX%	HH%	HL%	LH(L)%	LH(H)%
EX	99	0	1	0	0
HH	0	54	25	9	12
HL	0	5	52	11	31
LH(L)	0	6	23	42	28
LH(H)	0	2	20	9	68

Baseline

Run1/2	EX%	HH%	HL%	LH(L)%	LH(H)%
EX	57	0	14	7	21
HH	0	28	26	13	33
HL	8	18	30	14	30
LH(L)	8	16	28	23	25
LH(H)	8	16	21	12	42

Yanbian

Syllable-based

Run1/2	EX%	HL%	LH%	LL%
EX	96	0	3	2
HL	0	65	24	11
LH	4	35	50	12
LL	3	36	24	37

MaxEnt

Run1/2	EX%	HL%	LH%	LL%
EX	97	0	2	1
HL	0	64	25	11
LH	4	44	41	11
LL	3	42	28	26

CRP-MaxEnt

Run1/2	EX%	HL%	LH%	LL%
EX	100	0	0	0
HL	0	66	23	11
LH	1	36	52	12
LL	0	32	23	45

Baseline

Run1/2	EX%	HL%	LH%	LL%
EX	76	0	16	9
HL	0	63	25	12
LH	10	45	30	16
LL	10	45	25	20

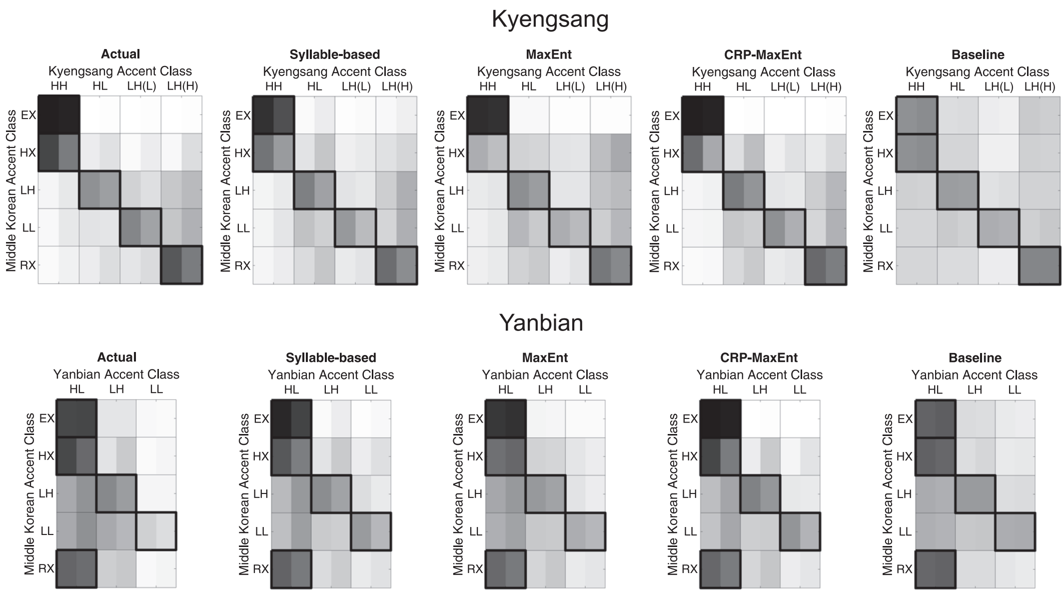

Fig 7. Type frequency of each Sino-Korean morpheme and historical development in Kyengsang (top)/Yanbian (bottom). The left half of each square corresponds to high-frequency words, and the right half of each square corresponds to low-frequency words. Darker colors indicate higher percentages; the boxes with thick outlines are the regular correspondences.

Kyengsang quite accurately, at least compared to the baseline model. Although there was considerable variability between runs in the particular morphemes that underwent analogical change, this variability likely reflects processes in language change that are relatively random, as discussed in 3.1: even between two Kyengsang speakers, there is substantial variability in how particular words are assigned to the accent classes. In both modeling and data, however, the broad patterns among different accent classes are relatively constant despite the word-level variability.

As for Yanbian, two models (syllable-based and MaxEnt) showed relatively better performance than the other two (CRP-MaxEnt and baseline), although the type-frequency effect was predicted well by the three phonotactic models compared to the baseline model in Yanbian as well.

The lower fit of the CRP-MaxEnt model is mainly due to the predicted highly regular correspondence between the Middle Korean EX class and the Yanbian HL class. This may have been due to incorrect assumptions about the distribution of accent classes in early generations, a factor which is related to two different underlying H tones. Simulation 2 addresses this possibility.

4.2. *Simulation 2: Testing an early dialect split*

In Kyengsang, the CRP-MaxEnt model showed the best performance, whereas the CRP-MaxEnt model was the worst in Yanbian. This striking difference between the two dialects is mainly because the CRP-MaxEnt model predicted too high a regular correspondence of

Table 11
Results of the best models in Yanbian KS (Kyengsang) and YB (Yanbian)

					All		Kyengsang		Yanbian	
Models	KS	YB	Cons	Rate	α	LL	BIC	LL	BIC	LL	BIC
Syllable-based	100	90	NA	0.15	0.1	–11,974.799	23,967.71	–6354.625	12,727.36	–5620.174	11,258.46
MaxEnt	100	90	50	0.05	NA	–12,052.318	24,122.75	–6384.116	12,786.34	–5668.202	11,354.51
CRP-MaxEnt	100	90	20	0.25	0.1	–11,887.253	23,801.67	–6305.764	12,638.69	–5581.489	11,190.14
Baseline	100	100	NA	0.05	NA	–13,449.415	26,907.89	–7695.509	15,400.07	–5753.906	11,516.87

Note. 100 means that the E/H class in the initial syllable appears with an H tone at the rate of 100%, while 90 means 90%.

Middle Korean EX to Yanbian HL (predicted 99% regular correspondence vs. actual 86%). However, the poor performance of the CRP-MaxEnt model in Yanbian depended on specific assumptions that may have been inaccurate.

As discussed in 2.2.2 and 2.2.3, there were two types of H tones in Middle Korean native monosyllabic nouns (one type may have alternated to L when it constituted the first member of a compound noun, while the other type did not show such an alternation; Ito, 2013; Kim, 1973; Whitman, 1994); this distinction is still to some extent retained in Yanbian/Hamkyeng, whereas it was not clearly retained in Kyengsang (Kang, 2017; Kim, 1997; Rah, 1974; Ramsey, 1978; Son, 2017). Although there is no record of which Sino-Korean morphemes with an H tone (E/H) belonged to the alternating type in Middle Korean, it is likely that some of the E/H class morphemes that we assumed to be in the H tone class in the ancestor of Yanbian actually appeared as L in the initial syllable of Sino-Korean disyllabic words. Based on these considerations, we suggest that although both Kyengsang and Yanbian/Hamkyeng originate from the same protolanguage, they had already become two different dialects in this respect at the stage of Middle Korean.

Given this, we made a modified data set for the beginning stage (generation 1) in which the E/H class in the initial syllable did not appear with an H tone at the rate of 100%: only 90% had an H tone, while the remaining 10% had an L tone (randomly selected).[16] In order to test the above hypothesis (i.e., that Kyengsang had lost the distinction of the two different underlying H tones, while Yanbian had not), we ran the simulation by using this modified file with both Kyengsang and Yanbian, and explored which combination showed the best performance. As a whole, four different combinations were tested: both Kyengsang and Yanbian 100%, Kyengsang 100% / Yanbian 90%, Kyengsang 90% / Yanbian 100%, both Kyengsang and Yanbian 90%.

4.2.1. Results

Table 11 shows the results of each model with the best performance. Among all models, the three phonotactic models showed best performance when Kyengsang had the 100% H data set, while Yanbian had the 90% H data set. In particular, the performance of the CRP-MaxEnt model in Yanbian improved dramatically. Based on these results, the three phonotactic models of Yanbian are now equally good compared to the baseline model. On the other hand, the baseline model showed the best performance when both Kyengsang and Yanbian had the 100% H data. However, given that the baseline model was the worst model in both dialects on the basis of the BIC scores, we can conclude that Kyengsang 100% / Yanbian 90% was the best combination overall.[17]

4.2.2. Discussion

In Simulation 2, we varied the initial starting state between the 100% H data set and the 90% H data set in the two dialects. In all phonotactic models, the Kyengsang 100% / Yanbian 90% combination showed the best performance, which significantly improved the fit relative to forcing them to have the same starting state.

This supports our hypothesis of two different starting points for Kyengsang and Yanbian, and the difference in the historical development of Sino-Korean accent between the two dialects can be explained by assuming the existence/absence of the distinction between the two types of H tones, in parallel with the native compound nouns. In other words, the poor performance of Yanbian obtained in Simulation 1 (in particular the CRP-MaxEnt model) may have been due to an incorrect assumption concerning the starting point.

4.3. Simulation 3: Perception-based analogical changes

Simulation 3 explores the effect of perceptual confusion between different accent classes that are pronounced the same way. There are two such cases in the development of the South Kyengsang dialect from Middle Korean. The most recent case of this phenomenon is that LH(L) and LH(H) are often confused by South Kyengsang speakers due to having the same isolation (citation) form LH. In Sino-Korean words, LH(L) tends to change to LH(H), rather than the opposite, based on the larger size of the LH(H) accent class in this lexical class (disyllabic Sino-Korean words). This analogical change probably started to occur when Middle Korean RX changed to LH(H) in South Kyengsang. Although we do not have data to determine exactly when this change started, we assume in our simulations that it occurred in the 17th generation (approximately one century ago). The fact that Middle Korean RX corresponds with H:H (double-H tone with a long vowel) in the North Kyengsang dialect, which has a similar accent system as South Kyengsang, suggests that the South Kyengsang change to LH(H) does not go back very far in the history of the language.

Based on the accent distribution in South Kyengsang, we also assume that an analogical change from Middle Korean LH to Middle Korean LL occurred until the 16th generation. As discussed in 2.2.3, these two accent classes probably were perceptually similar at some stage of the language. We do not consider this analogical change for the Yanbian dialect since this change is assumed to be correlated to the leftward accent shift, which only occurred in the historical development of Kyengsang.

To test whether incorporating these perceptual confusions into the model will improve the model's fit to the historical data, we added two analogical changes (from Middle Korean LH to LL in the 1st–16th generations; and from Middle Korean LL to RX [= from South Kyengsang LH(L) to LH(H)] in the 17th–20th generations) to each Kyengsang model with the best performance as discussed in 4.2 (the 100% H data set). We tested rates of perceptual confusion ranging from 0.01 to 0.05, in steps of 0.01. Since we constructed three types of models with perception-based analogical changes (only early analogical changes [1st–16th generations], only later analogical changes [17th–20th generations], both analogical changes [1st–20th generations]), the total number of models was 5 * 3 = 15 of each type. For each model, we chose the parameter values that gave the highest log likelihood for predicting patterns of historical change.

We conducted a similar analysis in Yanbian (the 90% H data set for three phonotactic models and the 100% H data set for the baseline model). Many words in the LL class irregularly changed to LH in Yanbian based on their identical LH isolation (citation) form. We took into account this perception-based analogical change in each model from the 17th generation and compared their performance with the simpler models. We varied the rate of analogical change from 0.1 to 0.3 (changing by 0.05). We chose larger values for Yanbian, since Middle Korean LH changed to Middle Korean LL in Kyengsang 17% of the time, while the frequency of change from LL to LH in Yanbian is 36%. Thus, we need the bigger rates for the Yanbian change.

4.3.1. Results

Table 12 (top) summarizes the results of the models with perception-based analogical changes in Kyengsang. Based on the log likelihood, the best model among them was where the two perception-based analogical changes (1st–16th generations; 17th–20th generations) were taken into account with all models except for the CRP-MaxEnt model. There was no model that showed the best performance when only the second perception-based analogical change (17th–20th generations) was included. We conducted a likelihood ratio test to compare the models, which tests whether the model fit improves beyond the overfitting that would be predicted to arise by chance when using a more complex model. The models with the first perception-based analogical change (1st–16th generations) were compared with those without perception-based analogical changes, whereas the models with both perception-based analogical changes (1st–20th generations) were compared with those with only the first change. The three models with two perception-based analogical changes were significantly different from the models with one analogical change. In the CRP-MaxEnt model, on the other hand, adding the second perception-based analogical change (17th–20th generations) did not improve the model. But on the whole, adding the analogical changes in the simple model improved model performance. This suggests that the current accent distribution in South Kyengsang has been affected by at least the analogical change that occurred in the 1st–16th generations.

As seen in Table 12 (bottom), for all model types in Yanbian, the ones with a perception-based analogical change showed better performance than the simpler model without it. This also supports the claim that a perception-based change contributed to the accent distribution of current Yanbian. Fig. 8 shows the predicted accent correspondences by our four models, including the perception-based analogical changes, along with the actual correspondences between Middle Korean and South Kyengsang (top)/Yanbian (bottom). See Table S6 for the exact percentages.

Table 12
Results of the models with analogical changes

Kyengsang: Under the "Gen(eration)" column, "1–16" indicates the first analogical change, "1–20" both analogical changes.

Model	Gen	A_rate	LL	LR test (lambda, p)	BIC
Syllable-based	1–16	0.02	–6208.895	291.46, < .001	12,444.96
	1–20	0.02	–6203.318	11.15, < .001	12,442.86
MaxEnt	1–16	0.03	–6268.505	231.22, < .001	12,564.18
	1–20	0.03	–6243.449	50.11, < .001	12,523.12
CRP-MaxEnt	1–16	0.05	–6183.614	244.3, < .001	12,403.45
	1–20	0.05	–6199.723	–32.22, 0.5	12,444.72
Baseline	1–16	0.01	–7571.915	247.19, < .001	15,161.94
	1–20	0.04	–7514.628	114.57, < .001	15,056.42

Yanbian:

Model	A_rate	LL	LR test (lambda, p)	BIC
Syllable-based	0.15	–5442.802	354.74, < .001	10,912.77
MaxEnt	0.2	–5499.583	337.24, < .001	11,026.33
CRP-MaxEnt	0.2	–5416.268	330.44, < .001	10,868.76
Baseline	0.25	–5451.427	604.96, < .001	10,920.96

Note. The parameters for each model (Cons = number of used constraints; Rate = forgetting rate) are: syllable-based (Rate = 0.15, $\alpha = 0.1$), MaxEnt (Cons = 50, Rate = 0.05), CRP-MaxEnt (Cons = 20, Rate = 0.25, $\alpha = 0.1$), and baseline (Rate = 0.05). Kyengsang (all models) and Yanbian (baseline model) based on the 100% H data set and Yanbian (phonotactic models) based on the 90% H data set.

Abbreviations: A_rate, the best rate of the analogical changes; LL, log-likelihood; LR test, likelihood ratio test compared with the corresponding model without an analogical change (df = 1).

4.3.2. Discussion

In all model types, we obtained significant improvement by adding perception-based analogical changes. This suggests that these changes contributed to the accent distributions in both dialects.

4.4. Comparison among the phonotactic models

The above simulations show a clear advantage for the phonotactic models over the baseline model in capturing the historical development of Korean accent classes. In this section, we compare the three phonotactic models qualitatively and evaluate which model is most appropriate to capture the historical development of Sino-Korean accent. The phonotactic models differ along two main axes. The first is whether they retain knowledge of entire syllables (syllable-based and CRP-MaxEnt), or simply evaluate syllables based on the extent to which those syllables conform with a set of abstract phonotactic constraints (MaxEnt). The second is whether they have abstract phonotactic constraints that allow generalization across syllables (MaxEnt and CRP-MaxEnt), or do not (syllable-based).

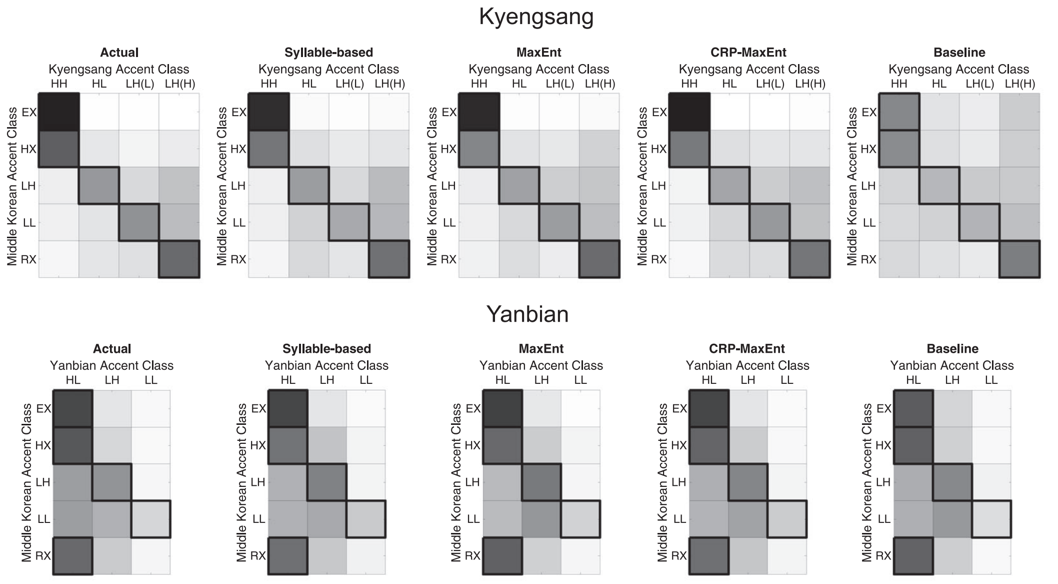

Fig 8. The correspondence between the Middle Korean accent and the Kyengsang (top)/Yanbian (bottom) accent predicted by four models in Simulation 3, as well as the actual correspondence. Darker colors indicate higher percentages; the boxes with thick outlines are the regular correspondences.

The role of syllables: Among the three phonotactic models, the performance of the MaxEnt model was the lowest in both dialects based on the BIC scores in Tables 11 and 12. The syllable-based and CRP-MaxEnt models memorized particular syllables and could reuse them for new lexical items, whereas the MaxEnt model assumed syllable shapes to have been sampled independently each time from the phonotactic grammar.

Most syllable shapes were originally biased to a particular tonal type in Middle Korean. In the Middle Korean data set that we used as the initial state in these simulations, 59% of the syllable shapes appeared with only one tone; 64% of the syllable shapes appeared with just one tone more than 90% of the time, and 72% of the syllable shapes appeared with just one tone more than 80% of the time. Our modeling results suggest that this consistency is higher than would be predicted if syllable shapes were sampled independently from the grammar. The fact that taking syllable shapes into account is useful for accurately modeling Sino-Korean accent changes is unsurprising: Sino-Korean words are composed of Sino-Korean morphemes, which are always monosyllabic. These results are also in line with previous work that has argued for the importance of precomputing and storing larger units of linguistic structure (O'Donnell, 2015).

The importance of a MaxEnt base distribution: Based on the BIC scores in Table 11, the scores were slightly lower for the CRP-MaxEnt model than the syllable-based model (the same is true for Table 12 when we compare the best results in each model in Kyengsang).

This means that the CRP-MaxEnt model shows an advantage, relative to the syllable-based model, in capturing historical changes of Sino-Korean accent. In particular, the difference between the syllable-based model and the CRP-MaxEnt model is observed in the irregular correspondences of the Middle Korean EX class. First, in the syllable-based model, the predicted regularity of the Middle Korean EX class is 89% (Fig. 5 and Table S4) / 95% Fig. 8 and Table S6), whereas it is 99% (Figs. 5 and 8, Tables S4 and S6) in the CRP-MaxEnt model, which is closer to the near-perfect regularity of the actual development (99%).

The predicted irregular development also shows the different tendencies between the two models. As seen in Fig. 5 and Table S4, in the syllable-based model, the RX class (= Kyengsang LH(H)) was assigned irregularly to 5% of words, whereas this ratio in the CRP-MaxEnt models was essentially zero. Although this irregular development (Middle Korean EX > Kyengsang LH(H)) was predicted to be lower in Fig. 8 and Table S6 (2%), the same discrepancy was observed in the 17th generation of Yanbian, which is the last generation that retained the distinction between Middle Korean HX and RX given our assumptions: comparing the predictions made by the syllable-based model (forgetting rate $= 0.15$, $\alpha = 0.1$, 90% H data set) and the MaxEnt-CRP model (20 constraints, forgetting rate $= 0.25$, $\alpha = 0.1$, 90% H data set), the former predicted that 3% of the Middle Korean EX words irregularly changed to RX, while the latter predicted a change of 0%. The predictions by the syllable-based model are problematic given the fact that such a change is in general not observed in contemporary Korean dialects, including standard Seoul Korean.[18]

The reason the syllable-based model gets this wrong is because the relevant initial syllable shapes from the E class (= the H class with a coda-p/l/k) were equally unlikely to occur in the L and R classes, making the likelihoods of the E class syllables in those classes simply dependent on the smoothing parameter. On the other hand, in the CRP-MaxEnt model, the base distribution leads the model to retain the E class syllable shapes with a high tone strongly. Thus, while both the syllable-based and CRP-MaxEnt models predicted quite accurate accent distributions, the former model predicted unattested patterns. Given this and the fact that the CRP-MaxEnt model showed the best performance based on the BIC scores, the CRP-MaxEnt model appears to be the most appropriate model to capture the historical development of Sino-Korean in both Kyengsang and Yanbian.

4.5. Alternative model structures

So far, we have shown that the phonotactic models with iterated learning are useful in explaining the historical development of Sino-Korean accent. In this section, we briefly report how alternative model structures worked in comparison with our iterated learning models. We examine two different approaches: noniterative learning and morpheme-based learning.

Noniterative learning: In all of our models, we assumed 20 generations of learners, based on the fact that the textual materials we deal with date from around five centuries ago. In order to measure the impact of the iterated learning aspect of our paradigm, we ran our models for

Table 13
Results of the noniterative learning models using the best forgetting rate

				All		Kyengsang		Yanbian	
Models	Cons	Rate	α	LL	BIC	LL	BIC	LL	BIC
Syllable-based	NA	0.8	0.1	–12,224.420	24,466.95	–6398.830	12,815.77	–5825.590	11,669.29
MaxEnt	50	0.7	NA	–12,212.626	24,443.36	–6535.835	13,089.78	–5676.791	11,371.69
CRP-MaxEnt	20	0.9	0.1	–12,034.694	24,096.55	–6338.840	12,704.85	–5695.854	11,418.87
Baseline	NA	0.5	NA	–13,119.752	26,248.56	–7248.825	14,506.71	–5870.927	11,750.91

Abbreviations: Cons, number of used constraints; LL, log likelihood; Rate, forgetting rate.

just one iteration, and reoptimized the forgetting rate for this setting.[19] We tested five different forgetting rates (0.5, 0.6, 0.7, 0.8, and 0.9). Table 13 shows the best results. The log likelihood/BIC scores in Table 13 are more or less equivalent to the results of Table 9, consistent with an interpretation the forgetting rate controls the speed with which the chain converges, rather than changing what it eventually converges to. This type of noniterative learning is not a viable model of historical change, however, in that it assumes a sudden accent change only in one generation with an unrealistically high forgetting rate. Moreover, a noniterated model cannot easily incorporate factors that influence historical change at specific time points, such as the intermediate time point of the R-H merger in Yanbian and the perceptual confusions that were the focus of Simulation 3.

Morpheme-based learning: Another alternative approach is to introduce morpheme-level differences into our models. In our models discussed so far, we did not take into account the identity of each morpheme. If a model forgot one instance of a morpheme, the pitch class of that instance needed to be reconstructed based on the phonotactic grammar, without knowing which other instances of the same syllable shape were actually instances of the same morpheme. This may have been the reason why memorizing syllables appeared to be so important in the phonotactic models. To investigate this further, we conducted a simulation in which we assumed the models knew the identity of each morpheme and treated different instances of that morpheme in the same way. “Forgotten” morphemes were sampled in the same way as in previous simulations, but morphemes whose accent class was “remembered” in at least one word were automatically recovered correctly, without needing to be reconstructed from any phonotactic grammar. This was done for the initial and final syllables separately. In addition, when an accent was assigned probabilistically to a morpheme whose pitch accent had previously been forgotten, all instances of the morpheme were assigned the same accent, rather than being sampled independently from each other. We again needed a much higher forgetting rate (0.5–0.9) to obtain good performance (Table 14). Using these best-fitting forgetting rates, overall log likelihoods were in a comparable range to Simulation 1. However, in addition to using implausible parameter values, the morpheme-based model also makes incorrect predictions: it predicts that some morphemes would be 100% regular, while other morphemes would be 100% irregular in their historical development, due to the assumption that the same morphemes always have the same underlying accent. In the actual historical development, the

Table 14
Results of the morpheme-based models using the best forgetting rate

				All		Kyengsang		Yanbian	
Models	Cons	Rate	α	LL	BIC	LL	BIC	LL	BIC
Syllable-based	NA	0.8	0.1	–12,536.445	25,091.00	–6925.154	13,868.42	–5611.291	11,240.69
MaxEnt	50	0.8	NA	–12,146.301	24,310.71	–6573.779	13,165.67	–5572.522	11,163.15
CRP-MaxEnt	20	0.8	0.1	–12,295.288	24,617.74	–6528.547	13,084.26	–5766.741	11,560.65
Baseline	NA	0.7	NA	–12,966.372	25,941.80	–7174.757	14,358.57	–5791.615	11,592.29

Abbreviations: Cons, number of used constraints; LL, log likelihood; Rate, forgetting rate.

regular development rate was more varied. Some morphemes (in particular the E-class morphemes) showed 100% regular development, while for other morphemes, only 80%, 60%, 20%, and so on of the instances of that morpheme underwent regular development. The strict morpheme-based model is unable to predict this type of variable pattern of change.

Our simulation does not completely rule out a role for morpheme identity. For example, there might be soft, violable constraints that prefer instances of a morpheme to have the same pitch accent. Based on word recognition experiments on disyllabic Sino-Korean words, Yi and Yi (1999), Yi, Jung, and Bae (2007), and Yi (2009) show that the processing of Sino-Korean words is modulated by interactions between the morphological level and the orthographic level (individual syllables), which are assumed to exist separately from the lexical level (disyllabic Sino-Korean words) in the mental lexicon. Given this as well as previous studies that analyze phonological similarities between morphologically related words (Benua, 1995; Burzio, 1996; Kenstowicz, 1996; Kraska, 1995; McCarthy, 1995), it would be worthwhile to pursue the role of both morphemes as well as syllables in more detail in the historical development of Sino-Korean words. While we do not explore the full range of possible morphological constraints here, disentangling the role of syllable identity from that of morpheme identity in shaping the historical change of Sino-Korean accent remains an important task for future research.

5. General discussion

In both descriptive and generative studies about Korean accent so far, the regular correspondences between Middle Korean and contemporary dialects as well as some conditionings/tendencies observed in the historical development have been clarified (Do et al., 2014; Fukui, 2003, 2013; He, 1955; Ito, 2008, 2013, 2014; Ramsey, 1978, and others). Still, these traditional approaches have limitations in that it is difficult to test how the historical development was affected by various factors, such as phonotactics, frequency, and so on. In this paper, we showed that iterated learning models could capture central aspects of the historical development of Sino-Korean accent from Middle Korean into two contemporary Korean dialects: South Kyengsang and Yanbian. We used three different strategies for computing and generalizing phonological regularities within each accent class, and found that all three predicted patterns of historical change better than the baseline models. These results indicate that the historical development of Sino-Korean accent can be characterized by repeated reconstruction of accents for some proportion of the lexicon based on phonological knowledge in each generation, which accumulated over the past five centuries as the language was passed from generation to generation. More broadly, whereas iterated learning models had previously focused on the evolution of abstract characteristics of language or (ongoing) sound changes/morphosyntactic changes, ours is among the first models to show that it can account for detailed patterns of language change based on long-term attested data—specifically, analogical changes, which are less regular and predictable than sound changes.

All three phonotactic models reproduced a type-frequency effect, whereas the baseline model did not. The fit between model and data means that the tendency of morphemes with lower type frequencies to change accent class more frequently than those with higher type frequencies can arise from straightforward statistical learning principles: having more instances of a morpheme (syllable) in the training data for an accent class raises the probability that words containing the same morpheme (syllable) will be assigned to that class, creating stability across generations of learners.

We also showed how iterated learning models can be useful in testing hypotheses concerning the state of the past language based on analogical change, similar to other work that has done so based on sound change (Bouchard-Côté, Hall, Griffiths, & Klein, 2013). We hypothesized that Kyengsang and Yanbian had different grammars at the starting point of our models based on some attested data in Middle Korean as well as the compound accent patterns in contemporary Kyengsang and Yanbian/Hamkyeng. This modification improved the fits of our three phonotactic models, thus indirectly supporting the validity of our hypothesis about the earlier state of the language. Given that for many languages historical records are not always available in sufficient quantity, our results suggest that iterated leaning models can be used as a supplementary tool for reconstructing the earlier state of a language.

Furthermore, iterated learning models can diagnose which factors are critical in shaping the patterns of language change. The superior performance of the CRP-MaxEnt model, which includes both constraint-based encoding of phonotactic knowledge and storage of larger units at a syllable level, suggests that learners may use both of these strategies—rather than just one, as in the MaxEnt and syllable-based models—when generalizing phonological forms. This improvement in performance was not simply due to its being a more complex model, as evidenced by the improvement in BIC, which penalizes models that have extra free parameters. Our simulations also showed that perceptual confusions are likely to have played a substantial role in shaping the analogical changes in Korean accent class, as incorporating perception-based analogical changes significantly improved their match with empirical data. The results of likelihood ratio tests indicated that this improvement went beyond what would have been expected by simply increasing model complexity. Previous literature has implicated perceptual confusions in other types of language change, such as loanword adaptations (Peperkamp, 2005; Peperkamp & Dupoux, 2003), and our results provide computational evidence of their importance in analogical change.

Our iterated learning models captured the general tendency and the directionality of accent class changes in the Korean lexicon, but could not replicate the specific changes at the individual word level. It is not clear whether we should expect a model of historical change to be able to capture this level of lexical detail. There was considerable variability among runs of the same model in our simulations, and there is considerable variability among speakers as well: the two Kyengsang speakers whose data we modeled did not always agree in their accent assignments. Thus, there may have been a good deal of randomness in creating the attested patterns of analogical change. In addition, language change can involve other factors that were not incorporated into our models, such as token frequencies of each word and sociolinguistic factors that can affect the behavior of individual words. It is probably possible to find better fits if we added more factors into our models. However, our goal in this paper is to show that iterated learning can replicate the attested historical development quite accurately based on a relatively simple set of factors (cf. Stanford & Kenny, 2013). Our results support the general validity of using iterated learning models in this way.

The close correspondence between these iterated learning models and actual patterns of historical change in Korean suggests that the same bottleneck effect that has been posited with respect to language evolution may also play a role in explaining language change. This raises a number of interesting questions regarding how language acquisition and processing might play a role in instantiating that bottleneck. The most straightforward analogue of the forgotten morphemes in our simulation might be a failure to hear certain forms clearly in the input, or a failure to encode the relevant forms in memory during learning, but there are also other mechanisms that would likely lead to similar patterns. For example, experiments have shown that accessibility of a form during language production can lead to overextension of that form in a way that may be a factor in language change (Harmon & Kapatsinsky, 2017). The extent to which these different acquisition and production processes can create the type of bottleneck that is assumed in many iterated learning models remains an interesting question for future research.

In sum, we have shown that iterated leaning models can be useful in the study of analogical change: they can reproduce attested patterns of change, diagnose the existence of unseen factors, such as perceptual confusion, and test hypotheses of language reconstruction. Iterated leaning also enables us to explain the divergence of languages or dialects by introducing language- or dialect-specific factors, such as different grammars (e.g., phoneme inventory, feature specification, accent system, and phonological rules), as well as grammar-independent factors (e.g., token-frequency and perceptual confusion). Finally, in the most general sense, our study illustrates how formal models of language learning and generalization can be used to predict patterns of linguistic change in a mutually reinforcing and beneficial way (Lightfoot, 1999).

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Notes

1 For more general information on sound change and analogical change, see Campbell (2004), Crowley and Bowern (2010), Millar and Trask (2015), Ringe and Eska (2013).
2 For more general discussion on Korean pitch accent, see Ito and Kenstowicz (2017).
3 We do not investigate native words and loanwords in this paper for the following reasons. First, there are relatively few native simplex words whose accents are attested in Middle Korean: 508 monosyllabic nouns and 775 disyllabic nouns (Ito, 2013). Second, although native simplex nouns have the same set of accent classes as Sino-Korean nouns, the phonotactic patterns associated with those accent classes are different, as are the default accent classes. This means that we would need to take word classes into account to model the historical development of both native and Sino-Korean words, a task which is outside the scope of this paper. As for loanwords, they are mostly recent borrowings, and hence, there is no attestation of their accent in Middle Korean.
4 The tones of the Middle Chinese morphemes have been reconstructed based on the contemporary Chinese dialects as well as rime dictionaries and other information (see Baxter & Sagart, 2014 and other studies).
5 The Middle Chinese coronal coda –t was adapted as –l in Sino-Korean (Kōno, 1968).
6 The accent change from Middle Korean to South Kyengsang has been explained as a leftward chain shift (Kenstowicz, Cho, & Kim, 2007). Middle Korean LL, which was actually LL(H) as a rule, retracted the H tone on the suffix to the stem-final syllable, thus changing from LL to LH; the suffix that lost its accent was assigned a default L tone and the word became LH(L). Original Middle Korean LH, being pushed by the innovating LH derived from retraction, changed to HL. In the absence of any syllable on the left, Middle Korean HX spread its initial H tone to the right and became a double-H tone (HH). Finally, Middle Korean RX decomposed the initial Rise to LH and its H tone moved to the second syllable; this H tone also spread to the following syllable (in this case to the following suffix), leading to LH(H).
7 The Kyengsang data are aggregated from two speakers. When the accent of the two speakers did not agree or the same speaker reported multiple accents, we divided 1 by the number of variants, so that each word corresponds with a count of 1. For example, if two accent patterns were reported for one word, then each accent was assigned 0.5. The Yanbian data are from one speaker, but the observed variation for this speaker was dealt with in the same way as for Kyengsang. See 3.1 for discussion as to why our data from this small number of speakers can be treated as representative of these dialects.

8 This is related to paradigm leveling, which introduces systematic phonological similarities between morphologically related words. See Kenstowicz (1996) for the relevant discussion.

9 A culminativity constraint predicts that LL changes to HL as well, and in fact 46% of the Middle Korean LL class irregularly changed to Yanbian HL (Table S1). However, given that the Middle Korean LH class also changed to Yanbian HL frequently (45%, Table S1), it is unclear whether the change from Middle Korean LL to Yanbian HL is due to the culminativity constraint or to the general type frequency effect. Note that HL is the largest class in Yanbian Sino-Korean words (66% based on Table S1).

10 Yi and Bae (2009) pointed out that in Korean, the correspondence between the syllable and the morpheme varied according to the word type. Native words have less homophony, and many morphemes are composed of two or more syllables; whereas, Sino-Korean words are composed of monosyllabic morphemes, and the same syllable shape can represent multiple morphemes. They reported that native and Sino-Korean words behaved differently in morphological priming experiments, reflecting these differences (as discussed in Section 4.5). In addition, previous studies have shown different phonological patterns between native and Sino-Korean words. For example, Zuraw (2011) showed that compound tensification mainly appeared in native words and it was much less frequent in Sino-Korean words. Ito (2008, 2014) demonstrated that the accent development patterns from Middle Korean were distinct between native and Sino-Korean words in both South Kyengsang and Yanbian Korean. Park (2020) showed that native and Sino-Korean words resulted in a simulated phonotactic learner acquiring different phonotactic grammars, and that they contributed to the results of well-formedness judgment experiments independently.

11 Thus, our models depend on not only the fact that the same Sino-Korean morpheme may appear multiple times in different Sino-Korean words, but also on the fact that there are many homophones (different morphemes that have the same syllable shape) in Sino-Korean: c. 95% of Sino-Korean morphemes in our corpus have homophones. The mean number of homophones is 9.6; for example, *ak* 鰐, 惡, 齷, 樂. An alternative model that takes into account the morpheme differences is discussed in 4.5.

12 Other than a default "word-boundary" feature implemented by Maxent2.0 automatically, we used 19 features and three projections (default, consonant, and vowel/glide). Projections were used to find the constraints that work within the designated category, such as constraints against two consonants in $\underline{\text{C}}\text{V}\underline{\text{C}}$. For all projections, we set the maximum constraint length (the number of features used in one constraint) as 4. The feature files and the constraint files are given as Supplementary Materials.

13 For simplicity, we assumed the accent of Sino-Korean words in Kyengsang had the leftward accent shift after the "original" accent class was determined in the way just described. For example, when both morphemes had the underlying L tone, the accent of the resultant Sino-Korean word was LL based on the accent formation rules. In the case of Kyengsang, we assumed that the expected LL accent appeared with LH(L) due to the leftward accent shift. This treatment was not included in the models themselves; this is basically just an issue of labeling accent classes.

14 If a learner were rationally resolving perceptual confusions—that is, assigning words to classes according to the type frequency of those classes—then the overall type frequencies of the classes would be expected to remain constant. The historical record suggests an additional bias toward assigning these words to the more frequent class; in order to reduce the number of free parameters, we assumed this bias to be at 100% (= only one-directional change) and simply manipulated the proportion of words whose accent was perceptually confused.

15 The same phonotactic restrictions can be expressed in different ways by the Maxent2.0 program. Thus, for example, the ban against syllable-final obstruents was represented by *[–word boundary][–sonorant] in a different constraint set.

16 In Middle Korean, monosyllabic native nouns that alternated from H to L in compounds tended to be very basic words, such as *nun* "eye," *pal* "foot," *os* "clothing." The ratio of the alternating H in Sino-Korean morphemes should have been relatively low given that most of them are bound forms.

17 Kim (1997: Section 7) distinguishes two different tone systems for compounds in the North Kyengsang dialect: the compound tone system and the phrasal tone system. The former corresponds with the alternating type under our definition. He claims that the compound tone system is lexically listed based on three reasons: (1) compounds which show the compound tone system are limited in length; (2) they are not productive; and (3) they are semantically less transparent. He also reports that all non-native compounds except for one type (= native + Sino-Korean compounds) exhibit the phrasal tone system, which supports our hypothesis of the Kyengsang 100% H data set.

18 In traditional Seoul Korean, the Middle Korean R tone corresponds with a long vowel, whereas Middle Korean L/H tones correspond with a short vowel.

19 We did not include the Yanbian accent merger of the underlying R tone to H and assumed that the merger occurred after learning was complete. Thus, the Yanbian and Kyengsang simulations were identical; only the calculations of log likelihood and BIC were different between the two dialects.

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Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Table S1. Middle Korean (MK)-contemporary Korean correspondences

Table S2. Relationship between type frequency of each Sino-Korean morpheme and historical development

Table S3. Historical development of two South Kyengsang speakers

Table S4. The correspondence between the Middle Korean (MK) accent and the Kyengsang (KS)/Yanbian (YB) accent predicted by four models in Simulation 1, as well as the actual correspondence

Table S5. Type frequency of each Sino-Korean morpheme and historical development in Kyengsang/Yanbian in Simulation 1

Table S6. The correspondence between the Middle Korean (MK) accent and the Kyengsang (KS)/Yanbian (YB) accent predicted by four models in Simulation 3, as well as the actual correspondence