




## A constraint-based approach to acquisition of word-final consonant clusters in Turkish children

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### Abstract

The current study provides a constraint-based analysis of L1 word-final consonant cluster acquisition in Turkish child language, based on the data originally presented by Topbas and Kopkalli-Yavuz (2008). The present analysis was done using [r]+obstruent consonant cluster acquisition. A comparison of Gradual Learning Algorithm (GLA) under Optimality Theory (OT) as opposed to Harmonic Grammar (HG) is made to see under which model GLA functions more efficiently and reaches the target adult form faster. This convergence was simulated using the simulation feature of *Praat* (Boersma & Weenik, 2012). Since child language is unmarked at the initial state, faithfulness constraints have been assigned lower ranking values than markedness constraints. The noise was set to 2.0 and the plasticity to 0.1. The findings of the simulations show that GLA is more compatible with Noisy HG in showing convergence properties with the target adult output forms. In other words, the number of trials HG-GLA needed to reach the winning/optimal form was fewer than it was for OT-GLA.

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*Keywords:* First language acquisition; Gradual Learning Algorithm; Noisy Harmonic Grammar; sonorants; stochastic Optimality Theory; Turkish; word-final consonant clusters

## 1. Introduction

With the introduction of Optimality Theory (OT; Prince & Smolensky, 1993) many investigators were attracted by the clarity and efficiency of violable constraints in explaining language acquisition, and specifically, the acquisition of syllable structure, among many other linguistic phenomena. Numerous studies have looked at the acquisition of consonant clusters in children either cross-sectionally (Barlow, 2005; Ohala, 1999) or developmentally (Lleó & Prinz, 1996). A majority of the previous research has primarily focused on the acquisition of onset clusters (Barlow, 2005; Ohala 1995; Pater and Barlow, 2002; Smit, 1993) while relatively fewer studies have considered acquisition patterns for coda clusters (Levelt et al., 2000; Lleó & Prinz, 1996).

This idea that cluster simplifications of children are not random has long been established in the literature. It has further been shown that consonant cluster simplifications are related with neither the mere ordering of sounds nor the specific place or manner of articulation alone since several factors in

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isolation might hardly explain the intricate structure of simplification patterns across languages. Rather, those patterns are dependent upon a combination of factors which can be precisely put as “sonority effects” (Ohala, 1999). Additionally, despite the vast amount of evidence in support of “sonority effects” in cluster acquisition, there is need for more cross-linguistic research to better evaluate the role of sonority and other factors effective in the acquisition of coda clusters (Demuth, 2011). Hence, languages which have been relatively less investigated are potentially more helpful in shedding light on the applicability of sonority notion. Turkish, an Altaic language, constitutes a good testing ground for this as the language has not been exhaustively researched in the subject matter. Moreover, the fact that Turkish has an allegedly tri-moraic structure (Topbas & Kopkalli Yavuz, 1999; also see Inkelas & Orgun, 1992) makes it an even more interesting case in testing sonority in word-final clusters.

Despite their relatively recent history, constraint-based approaches have been proven to be effective in explaining linguistic phenomena, especially in phonology. They are particularly helpful in accounting for child phonologies where markedness constraints are higher ranked than they are in adult languages. Previous studies (Demuth, 2008; Gnanadesikan, 1995; Fikkert, 1994; Pater, 1997) have shown that children’s productions in early stages of language learning are not “randomly generated articulatory objects”, rather, they are “word-like units that are prosodically constrained” (Demuth, 2011, pp. 17-18). It has been proposed that the lexical representation of children’s output forms differs from adult languages, and that children cannot produce certain segments because they cannot perceive them (Kisparisky & Menn, 1977). However, such claims have been counter-evidenced in recent years by attributing this difficulty of production to initial-state rankings of markedness and faithfulness constraints.

The purpose of this paper, therefore, is to present an analysis of the word-final consonant cluster simplification methods of Turkish children within a constrained-based framework by implementing Gradual Learning Algorithm under Noisy Harmonic Grammar and stochastic Optimality Theory. Following the presentation of the original data used, the effects of universal and language-specific factors that influence the acquisition process are discussed in the light of previous cross-linguistic research that pinpoints tendencies and strategies for coda cluster simplification. Finally, an overview of the relevant constraint-based models and approaches are presented along with the preliminary findings from the computational implementations of data.

## *1.1. Literature review*

### *1.1.1. Factors affecting the development of word-final consonant clusters: universal constraints*

Previously, a vast array of studies on children’s acquisition of consonant clusters have shown that the variation in child phonology is guided by both language universals and language specific constraints. Cross-linguistically, following the Sonority Sequencing Principle (SSP) (Clements, 1990), deletion of segments has been shown to be a common practice in the acquisition of consonant clusters. (McLeod et al., 2001; Smit, 1993) Simply put, the notion of sonority can be broadly described as the relative loudness of a sound (Ladefoged, 1975) which is determined by measurements of acoustic intensity (Blevins, 1995), and consequently, this varying degree of loudness affects the order of particular sounds that are allowed in clusters. Languages have been reported to follow some form of “sonority scale/hierarchy” (Blevins, 1995; Clements, 1990; Selkirk, 1984).



“compensatory lengthening could be related to the mora-timing” (p. 112). In order to make his claim tenable, he resorts to both acoustic analyses and violable constraints ranking within an OT framework. Demuth (2011), however, points out that findings in English do not support Ohala’s findings and states that it is understandable given the moraic-structure and the status of subliminal forms in Japanese. Similar to Japanese, codas in Turkish also have moraic status, and this makes them an interesting area of research to test previous claims. The following section will briefly review the moraic syllable structure in Turkish and related phenomenon.

### 1.1.2. Factors affecting the development of word-final consonant clusters: language-specific constraints

The syllabic structure of Standard Turkish, spoken in mainland Turkey, shows the following prosodic characteristics relevant to the analysis in this paper:

(2) Syllable structure of Turkish (Inkelas & Orgun 1992, 1995; Kopkalli-Yavuz 2003)

- a. Syllables are minimally and maximally bimoraic
- b. Coda consonants contribute to the projection of mora

Thus, CVC syllables bear two moras while CVCC syllables are claimed to have three moras (Inkelas & Orgun, 1993). This is, therefore, against the syllable characteristics of Turkish (2a), which is called the maximality condition. According to Macken’s (1990) analysis of CVCC syllable structure based on maximality, final consonants are “extrametrical” because only a single mora can be assigned after the nucleus (Inkelas & Orgun, 1993). However, this is not supported in Turkish as those consonants become a part of the onset when they are followed by a vocalic suffix (Topbas & Kopkalli-Yavuz, 2008). Inkelas and Orgun (1995) also show that the final consonant in an onset cluster does bear a mora but it is “invisible” unless a vocalic suffix follows it. Therefore, when there is a sonorant sound in a word-final cluster, it also bears a mora because in cases of loss of the sonorant, compensatory lengthening is observed (Gess, 2011; Hayes, 1989). The potential syllable structures are illustrated below as claimed by Hall (2000) and Macken (1990) for other languages.

(3) Potential analyses of trimoraic syllable structures of the word ‘Turk’

(a)		(b)
μ   μ   μ		μ   μ
[t y   r c]	vs.	[t y   r ] c
(Hall 2000)		(Macken 1990)

In the present study, analysis by Hall (3a) is adopted, because in the data when there is a loss in consonant clusters, sonorant segments rather than the obstruents get deleted (r, l, and n; contrary to what SSP would predict). More interestingly, in cases where these sonorants are deleted, the deletion process is accompanied by vowel lengthening in the majority of cases. In the sections to follow, two different constraint-based approaches to data analysis are discussed.

### 1.1.3. A Constraint-Based Analysis of Learning Path: Two Approaches to Data Analysis

In constraint-based approaches, learning has been accounted for through different learning algorithms. In addressing the issue of learnability in OT, Tesar and Smolensky (1993) were the first with their model called Constraint Demotion Algorithm (CDA). According to this model, learners rank the constraints to be learned based on the input they receive and similarly, they can deduce information about the constraints based on the surface forms. This model in its initial form only

considers “non-varying” languages with a “totally ranked hierarchy”, but the convergence of the initial grammar with the optimal one is guaranteed (Boersma & Pater, 2008). To include “varying languages” in the analyses, an error-driven stochastic OT model of learning which is also called Gradual Learning Algorithm (GLA) was developed (Boersma 1997; Boersma & Hayes, 2001; also see Boersma & van Leussen, 2017). GLA under stochastic OT (OT-GLA) grammar claims that children learn rankings of constraints with numerical values on a continuous scale and evaluate the candidates based on random variation which can be calculated based on probability distributions rather than purely ranking them (Boersma & Pater, 2008).

Despite being able to learn variation, OT-GLA has also been shown to have failed to converge with the optimal grammar (Pater, 2008). Considering its failure to converge in some instances, Boersma and Pater (2008) used the noise evaluation feature of OT-GLA and aimed to develop a learning model which is guaranteed to converge like human language acquisition while at the same time allowing for variation. In order to do this, they adopted Gradual Learning Algorithm under the Harmonic Grammar (HG; Legendre, Miyata & Smolensky, 1990), which is described as an adaptation of stochastic OT (Pater, 2008). The basic idea in GLA is that grammar is continuously adjusting itself by sorting the constraints and ranking them on a numeric scale based on their stochastic values (Boersma, 1998; Pater, 2008). In the next sections, OT-GLA and HG-GLA used in the analysis are elaborated.

#### *1.1.3.1. Gradual Learning Algorithm under the Noisy Harmonic Grammar (HG-GLA)*

In Harmonic Grammar (HG), the grammaticality is defined with the harmony function by giving weights to constraints rather than ranking them in an ordinal fashion (Boersma, 1997, 1998; Boersma and Hayes, 2001). Giving weights to constraints demonstrates what kind of roles the other candidates have in determining the winning candidate. This is especially helpful when investigating the intermediate stages of learning.

In the noisy form of HG, which is called the Noisy Harmonic Grammar, there is a noise function which refers to the perturbation of weighted values through computer simulations (Boersma & Pater, 2007). In GLA, noise brings about an overlap of constraint ranking values. As mentioned earlier, in HG the values which “rank” the constraints are calculated as the sum of a candidate’s weighted constraint scores. This is also known as “gang effects” in the literature (Boersma, 1997, 1998; Pater, 2007). According to the description of overlapping constraint weights in Noisy HG, the more constraint weights of two constraints approach each other, the higher the noise overlap will be, and this, in turn, will result in an increased probability of reversal of overlapping constraints (Boersma & Hayes, 2001). Therefore, each time there is a mismatch between the input and the target output, the weights assigned to constraints are adjusted until the maximally harmonic (=optimal) output is reached. This helps to evaluate the loser candidates’ role in the final output forms (Reynolds, 2011).

#### *1.1.3.2. Gradual Learning Algorithm under stochastic OT (OT-GLA)*

GLA can also be paired with Stochastic OT (Boersma and Hayes, 2001), which differs from traditional Optimality Theory in a number of ways. As Jarosz puts it, “[it] is a probabilistic extension of [traditional] OT’s constraint rankings” (p. 587). Stochastic OT, in conjunction with GLA, has been claimed to successfully simulate the child language acquisition stages (Boersma & Levelt, 2000). In contrast to traditional OT, in stochastic OT, constraints are ranked along a continuous scale. This continuity feature has an influence on the evaluation of candidates. One criticism of traditional OT was that it ranks constraints based on a strict domination system, which does not allow tracking of learning. To get around this problem, Stochastic OT assigns numbers along a continuous scale with no strict rankings analogous to weights in Noisy HG.

Although Stochastic OT and Noisy Harmonic Grammar models may share a lot of features, the difference between Stochastic OT and Noisy HG lies in the ranking parameters of the output. Jarosz (2010) explains the differences between two models as follows:

[Noisy] HG defines a probability distribution over weightings of constraints in the same way that Stochastic OT defines a probability distribution over rankings. This variation in weights/rankings determines the probability with which different output structures are selected as optimal. In sum, while the stochastic component in noisy HG resides in the weightings themselves being noisy, the stochastic component in [Harmonic Grammar] models exists at the level of candidate output structures directly. (p. 590)

Further in her work, Jarosz (2010) also makes a comparison of OT-GLA and HG-GLA models using three different languages and corpus data. Reporting her results from computational simulations with no specific reference to constraint-based tableaux, she concludes that OT-GLA and HG-GLA are similar in their description of learning path. On the other hand, Reynolds (2011) does not agree with Jarosz by claiming that OT-GLA is more successful than HG-GLA because it is capable of accounting for the intermediate stages of learning. No agreement up to date has been reached in the relative effectiveness of different probabilistic approaches to constraint-based grammars, and this is not surprising given the relatively short history of the models. The present study aims to compare these two models using computer simulations in word-final consonant cluster acquisition in Turkish.

## *1.2. Research questions*

In order to provide a constraint-based analysis of L1 word-final consonant cluster acquisition in Turkish child language, the present study aims to answer the following questions using L1 data originally presented by Topbas and Kopkalli (2008):

1. Between Gradual Learning Algorithm under Stochastic Optimality Theory and Noisy Harmonic Grammar, which of the two constraint-based approaches may better account for the developmental stages of convergence in L1 Turkish children's word-final consonant cluster acquisition data?
2. How do computational implementations of acquisition data provide evidence to support the faster convergence of one over the other constraint-based approach?

## **2. Method**

### *2.1. Sample data used in the simulations*

Turkish does not have onset clusters in words of native origin, and the range of coda clusters is also limited. Among them, as a wide range of coda clusters are formed using the sonorant+obstruent sequences, it crucial to understand their production by children. However, it should be noted that previous research tends to exclude the syllables containing [l] and [r] sounds in their analyses as these sounds already pose a difficulty for children until later stages in acquisition (Ohala, 1999). Despite the controversial status of liquids, Topbas and Kopkalli-Yavuz (2008) maintain that Turkish data might help better understand the acquisition tendencies by children paving the way for a closer analysis of sonorants cross-linguistically.

In their study, 350 typically-developing children (2;0-5;11) were examined longitudinally and cross-sectionally. Children were divided into four age groups providing us with the developmental pattern of Turkish children in coda cluster acquisition. They produced six types of sonorant+obstruent

clusters, one of which [r]+obstruent coda cluster as in the word Turk [tyrc]. The findings of the study overall reveal that successful productions of C1 and C2 in clusters increased with age, and the percentage of C1 deletion was higher than C2 deletion. Moreover, C1 deletion was accompanied by the lengthening of the vowel preceding the deleted consonant, and this tendency increased with age. The present study used these findings regarding the actual productions of clusters by children, and attempted to show under which constraint-based model these results may be better accounted for. The analyses were limited to the [r]+obstruent word-final consonant cluster type.

## 2.2. Instrument

In an attempt to test how effective OT-GLA and HG-GLA may be in describing acquisition of word-final consonant clusters in L1 Turkish, computer simulations were created using freely-available, *Praat* program (Boersma & Weenik, 2012). *Praat* adjusts rankings of different candidates to reach the input form provided using GEN and CON functions of a grammar. It also allows the simulation of noise function mentioned earlier in addition to plasticity. In constraint-based theories, one crucial aspect allowing us to show simulations of child language acquisition is “plasticity”, which is found both in stochastic OT and the Noisy Harmonic Grammar. By definition, it is “the numerical quantity by which the algorithm adjusts the constraints’ ranking values at any given time” (Boersma & Hayes, 2001, p. 52). It tells us the amount of wiggle room a constraint has for movement as the learning takes place, i.e., if plasticity is set higher, this allows a weighted constraint to move more freely, which in turn enables the constraint to reach the target form faster than in the latter case. With the help of these features in *Praat*, it is possible to mimic the gradual learning process of child language development.

## 2.3. Data Analysis

The constraints necessary to account for Turkish child language word-final [r]+obstruent cluster acquisition are listed in (4): Faithfulness constraints militate against loss of moras as well coda segments in the syllable while markedness constraint bans complex codas as well as certain “r” sounds due to its marked nature across languages.

### (4) Constraints relevant for word-final CC acquisition

#### MARKEDNESS

\*COMPLEXCODA (\*CC): Complex codas are banned

\*R (seg): Avoid [r]

#### FAITHFULNESS

MAX ( $\mu$ ): Input moras must be preserved in the output

MAXCODA: Input coda consonants must be parsed

### (5) Ranking Values assigned to each constraint at the initial-state

*COMPLEXCODA	100
*R	100
*MAX ( $\mu$ )	90
*MAXCODA	90

As shown previously, markedness constraints dominate faithfulness constraints at the initial stages of learning phonologies (Gnanadesikan, 1995). In other words, the child learner starts out with more unmarked outputs to satisfy the higher-ranked markedness constraints, and in later stages, faithfulness constraints are promoted in the hierarchy. Following previous literature (Boersma & Levelt, 2000) which assigns lower values to faithfulness constraints, and higher values to markedness constraints, in the present study, initially 100 and 90 ranking/weighting values were assigned to markedness and faithfulness constraints, respectively. The general assumption is that the farther apart the values assigned are, the more it is difficult for the rankings/weightings to reach the target output.

### 3. Results

Learning was implemented in HG-GLA and OT-GLA using 2.0 noise/standard deviations and 0.1 plasticity. The following tableau shows the simulation of initial state weighting for the [r]+obstruent sequence<sup>†</sup>:

**Tableau 1<sup>‡</sup>.** The initial-state grammar for word ‘Turk’ under HG-GLA

Weights	100	100	90	90	$\sum$
Turk	*COMPLEX CODA	*R	MAX ( $\mu$ )	MAXCODA	$H$
Turk	(-1)	(-1)			-200
• Tu:k				(-1)	-90
Tuk			(-1)	(-1)	-180

After 10.000 trials using GLA under Noisy Harmonic Grammar, the following rankings were reached (Tableau 2). While the markedness constraints are highly ranked in the initial state (Tableau 1), they are demoted in the final state as shown in Tableau 2 raising the faithfulness constraints (F>M) reaching more adult-like output forms.

**Tableau 2.** The end-state grammar for word ‘Turk’ under HG-GLA

Weights	128.315	87.294	62.190	58.236	$\sum$
Turk	MAXCODA	MAX ( $\mu$ )	*R	*COMPLEX CODA	$H$
☞ Turk			(-1)	(-1)	-120.426
ku:k	(-1)				-128.315
Kuk		(-1)		(-1)	-145.530

When we set “the decision strategy” to OT-GLA for the same input ([r]+obstruent), the structure of the output tableaux change, but essentially the initial ranking of constraints do not. We already have the rankings of initial state-grammar in Tableau 1; however, since the presentation of tableaux differs, the initial state is also provided below in Tableau 3:

<sup>†</sup> The symbol • indicates the non-optimal output—i.e. preferred in the learning path

<sup>‡</sup> Evaluation tables in OT are called tableaux.



**Tableau 3.** The initial state grammar for word ‘Turk’ under OT-GLA

Turk	*COMPLEX CODA	*R	MAX ( $\mu$ )	MAXCODA
Turk	*!	*		
☞ Tu:k				*
Tuk			*!	*

There is no difference (except for the structure) between Tableau 1 and 3 with respect to the initial ranking values of constraint rankings. One difference is that Tableau 4 does not allow us to tap into the competition of constraints during the learning process. The following rankings in Tableau 4 were obtained after 12.0000 trials:

**Tableau 4.** The end-state grammar for word ‘Turk’ using OT-GLA

Turk	MAXCODA	MAX ( $\mu$ )	*COMPLEX CODA	*R
☞ Turk			*	*
Tu:k	*!			
Tuk		*!	*	

This suggests us that the number of trials required for a grammar to converge under OT-GLA is more than it is under HG-GLA. However, more simulations with a wider range input forms are required to make stronger claims.

#### 4. Conclusions

In this study, a comparison of two constraint-ranking approaches were applied in order to account for how Turkish children preserve the moraic structure of the word by lengthening the preceding vowel following an “r-drop” in pronouncing the word “Turk”. Preliminary findings of the simulations demonstrate that “[r]+obstruent” acquisition grammar by Turkish children converges with the adult target form faster in the HG-GLA than in OT-GLA. This means that having a probability distribution over the weightings rather than over the rankings of the constraints works better in explaining the process. However, the number of trials required to reach the winning/optimal candidate are so close that it prevents us from making stronger claims about either of them.

Therefore, a finer investigation of several interacting factors is required. First, the data under investigation here comprise of only one type of word-final consonant clusters, so other types of sound sequences should also be investigated to be able to test the claims and make generalizations about the development of sonorant+obstruent sound sequences in children. A finer-grained analysis of intermediate stages is also needed to understand the true nature of the developmental stages. This will also allow us to use the mean scores of substitution strategies such as vowel lengthening and deletion observed in each stage. Additionally, the results obtained through computer simulations, and the reported percentages could be compared to see how much they predict each other. A follow-up study taking the listed limitations into consideration would shed more light on our understanding of coda clusters in Turkish.

Explaining the nature of acquisition by giving probability distributions to weightings and rankings is important because it could help better understand the developmental stages of grammatical systems in language acquisition. This approach is not limited to phonology, but rather used in other areas of linguistics (e.g., morphosyntax). The output of such approaches may also yield fruitful for the clinical world in their attempts to diagnose abnormal individual variation or disorders in L1 speech development in children. Following the findings of such simulations or constraint-rankings, language-specific phonological tasks to assess normal speech development might be developed. Similar implications may be applied to second language acquisition, especially in identifying non-target-like productions of L2 by creating probability simulations to show the constraints that make learners unable to reach the target form. Information gained through such studies might also be used to inform L2 learners about their own L2 acquisition stages and help them better understand the “hows” and “whys” of certain outputs in their interlanguage. Once supported by empirical findings, such knowledge could also encourage L2 teachers and curriculum designers to approach L2 teaching practices in a more profound way.

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## Türk çocuklarında sözcük sonu demetçik daralması edinimine kısıtlar teorisi yaklaşımı

### Öz

Bu çalışmada ilk olarak Topbaş ve Kopkalli-Yavuz (2008) tarafından sunulan ana dili Türkçe olan çocuklardaki demetçik daralması edinimi (acquisition of word-final consonant clusters) verileri Kısıtlar Teorisi yaklaşımı çerçevesinde incelenmiştir. Mevcut analiz, sadece '[r]+duraklamalı ünsüz' ses grubunu kapsayan demetçik daralması edinimi verileri kullanarak yapılmıştır. Aşamalı Öğrenme Algoritmasının (Gradual Learning Algorithm-GLA), Harmonik Dilbilgisi ve Uygunluk Teorisi (Optimality Theory) yaklaşımlarıyla incelemek ve bu şekilde GLA'nın hangi model altında iyi açıklandığını görmek amaçlanmıştır. Bu yakınsama, Praat simülasyon özelliğini kullanarak simüle edilmiştir (Boersma & Weenik, 2012). Ana dilde çocuk dili belirli (marked) olmadığından, sadakat (faithfulness) kısıtlamalarına belirlilik (markedness) kısıtlamalarından daha düşük sıralı değerler atanmıştır (1). Gürültü 2.0'a ayarlanmış ve plastisite başlangıçta 0.1'e ayarlanmıştır. Simülasyonların bulguları, Kademeli Öğrenme Algoritmasının, yetişkin hedef kullanımı ile OT-GLA'nın yaptığı gibi yakınsama özelliklerini göstermede Gürültülü HG'ye (bkz. Tablo 2) daha uyumlu olduğu yönündedir (bkz. Tablo 3). Başka bir deyişle, HG-GLA'nın kazanan/optimal forma ulaşmak için gereken deneme sayısı OT-GLA için gerekli olandan daha az olduğu görülmüştür.

*Anahtar sözcükler:* Ana dil edinimi; Demetçik daralması; Gürültülü Harmonik Dilbilgisi; Kademeli Öğrenme Algoritması; Stokastik Uyumluluk Teorisi; Titreşimli sesler; Türkçe

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