

# Artificial sound change: Language change and deep convolutional neural networks in iterative learning

Gašper Beguš  
University of California, Berkeley  
*begus@berkeley.edu*

## Abstract

This paper proposes a framework for modeling sound change that combines deep convolutional neural networks and iterative learning. Acquisition and transmission of speech across generations is modeled by training generations of Generative Adversarial Networks on unannotated raw speech data. The paper argues that several properties of sound change emerge from the proposed architecture. Generative Adversarial Networks (Goodfellow et al., 2014; Donahue et al., 2019) are uniquely appropriate for modeling language change because the networks are trained on raw unsupervised acoustic data, contain no language-specific devices and, as argued in Beguš (2020b), encode phonetic and phonological representations in their latent space and generate innovative data that are linguistically highly informative. Four generations of Generative Adversarial Networks were trained on an allophonic distribution in English where voiceless stops are aspirated word-initially before stressed vowels except if preceded by [s]. The first generation of networks is trained on the relevant sequences in human speech from the TIMIT database. The subsequent generations are not trained on TIMIT, but on generated outputs from the previous generation and thus start learning from each other in an iterative learning task. The initial allophonic distribution is progressively being lost with each generation, likely due to pressures from the global distribution of aspiration in the training data that resembles phonological pressures in natural language. The networks show signs of a gradual shift in phonetic targets characteristic of a gradual phonetic sound change. At endpoints, the networks' outputs superficially resemble a phonological change — rule loss — driven by imperfect learning. The model features signs of stability, one of the more challenging aspects of computational models of sound change. The results suggest that the proposed Generative Adversarial models of phonetic and phonological acquisition have the potential to yield new insights into the long-standing question of how to model language change.

**keywords:** artificial intelligence, deep convolutional neural networks, generative adversarial networks, speech, phonetic learning, phonological learning, historical linguistics, sound change

## 1 Introduction

Sound change is one of the most widely studied phenomena of human language and behavior in general (Hansson, 2008; Garrett, 2015). It has long been established that languages change constantly on all levels: phonetic, phonological, morphological, syntactic, and semantic. For example, Modern French developed from (Vulgar) Latin. The two languages differ in phonemic inventories and their phonetic realizations, morphology, word order, and in individual words meanings. Language change on the phonetic/phonological level (i.e. sound change) is arguably the most systematic and well-studied. Despite the relatively long history of scientific inquiry into the topic (Paul, 1880), many open questions remain regarding the causes of sound change and language change in general. Even

its definition is problematic, as Garrett (2015) notes: “[d]espite its ubiquity, there is no generally accepted definition of sound change.”

The primary source of uncertainty in what causes sound change is that sound change is usually observed as a completed event, where only the endpoints are accessible to researchers: the initial stage A of a language with some phonemic inventory and its distribution and the end stage B with the completed sound change. For example, Latin [k] surfaces as [s] in French when it appears before front vowels: Latin [ke:ra] > French [sir] (for a recent treatment, see Tifrit and Voeltzel 2016). Based on comparative evidence and general typology of sound change, we can reconstruct that this change proceeded through an intermediate stage where [k] developed to [ts] first and only later to [s], but often direct evidence for such stages are lacking. The study of sound change is additionally complicated by the fact that in many cases, stage A is only reconstructed and not directly attested. Even if attested, stage A is rarely accessible to researchers in other form than in written records that are less informative and reliable than recordings: to be sure, no acoustic data exist for the Latin word [ke:ra].

From a global viewpoint that concerns primarily the outcomes of sound changes, typology and directionality of sound change are well-studied and understood. For example, we know which types of sound changes are possible, which sound changes are more frequent than others (Kümmel, 2007), and which sound changes are unattested or even impossible (Honeybone, 2016; Beguš, 2018b). Furthermore, frequencies of sound changes can also be quantified (Bell, 1970, 1971; Cathcart, 2015; Beguš, 2018a). What is less well understood, however, is what exactly causes language to change and how changes spread across the speech community. The exact mechanisms of sound change are difficult to study directly because observing sound changes in progress is a challenging task: with the exception of rare cases (e.g. van de Velde et al. 1996), we lack long-term acoustic data of segments that change with generations of speakers.

Several factors have been identified that contribute to sound change, such as variation caused by articulatory tendencies, motor control, perception of sounds, language acquisition and learnability, word frequency, contact between languages, and social factors (Garrett and Johnson, 2013; Garrett, 2015; Bybee, 2017). Empirical evidence exists for many of these proposals, yet because sound change has not been studied in progress, it is difficult to establish which factors cause sound change and how they interact. Particularly complex is the discussion on whether sound change is primarily driven by (i) language-specific grammatical, (ii) domain-general cognitive mechanisms (such as learnability), or (iii) is sound change emergent from articulatory and perceptual tendencies in transmission of language over generations of speakers.

If grammatical constraints or cognitive mechanisms in general disfavor a particular phonological process, learners might not acquire it and over generations the process would be lost. The learning dispreference can be grammatical, i.e. language-specific (domain-specific) or part of general cognitive mechanisms (Kapatsinski, 2018), i.e. domain-general. For example, it is possible that some phonological processes are difficult to learn for only domain-specific linguistic reasons. One such case would be final voicing (where voiced stops such as [b, d, g] devoice to [p, t, k] word-finally, e.g. /pad/ → [pat]). Final voicing is predicted to be marked and dispreferred by the grammar (Kiparsky, 2006, 2008), yet there is no general cognitive (non-phonetic) reason for final voicing to be any more difficult to learn than its counterpart final devoicing. On the other hand, behavioral experiments show that featurally more complex processes are more difficult to learn than less complex processes (Moreton and Pater, 2012), which is directly explainable with domain-general cognitive mechanisms (Moreton et al., 2017). For example, infants learn to restrict [b, d, g] to the syllable-final position, but fail to learn to restrict [b, t, g] to the same position: the latter group requires at least one feature more to be described and is therefore more complex (Saffran and Thiessen, 2003).

In addition to the domain-general cognitive and domain-specific grammatical influences, sound change is traditionally viewed as being driven by *phonetic* factors: articulatory and perceptual biases that operate in transmission of language in space and time (Garrett and Johnson, 2013). Sound changes that are common across world’s languages usually have clear and well-understood phonetic motivations (Ohala, 1981; Blevins, 2004; Hansson, 2008; Garrett and Johnson, 2013). Human articulatory forces and perceptual biases operate in speech production and perception. Furthermore, phonetic data is highly variable and variation often operates directionally. For example, voiceless stops between vowels (e.g. [apa]) and after nasals (e.g. [ampa]) have more voicing into closure than in other positions (Davidson, 2016). High airflow and nasal leakage that operate in these positions promote gradually higher degrees of voicing. When these tendencies change from being automatic (not controlled by speakers) to non-automatic (actively controlled by speakers), we get a sound change that introduces a phonological rule. The process is described as phonologization (Hyman, 1976, 2013). Since strong phonetic forces (precursors) lead to common sound changes, it is reasonable to assume phonetic forces cause sound change.<sup>1</sup>

## 1.1 Prior work

Due to the lack of direct empirical evidence on how exactly sound changes arises, computational simulations have been used as substitutes to distinguish between different proposals. Several computational models have been proposed that simulate agents (speakers) learning some linguistic input and interacting with other agents. Typically, over the course of generations of such agent-based learning, a change in some phonetic feature occurs which replicates sound change in progress (Baker, 2008). For example, peripheral vowels [a], [i], and [u] reduce to a central vowel [ə] when agents with a bias for reduction interact in an iterative learning task (de Boer, 2003). By comparing computational models with properties of sound change that are empirically observed, we can evaluate models and the degree to which they approximate reality. If the model matches observed behavior in sound change, it can be argued that the assumed architecture of the model is responsible for the match, which means that the relevant mechanisms likely influence the actual sound change.

One of the prominent frameworks in computational simulations of sound change is the exemplar theory model (Johnson, 1997; Pierrehumbert, 2001; Wedel, 2006; Kirby and Sonderegger, 2015; Duran et al., 2017) which assumes speakers store some perceived phonetic information (such as targets for vowel formants F 1–F4) as “remembered tokens” or exemplars. Phonetic categories consist of a set of such exemplars, grouped by “similarity across any salient dimension” (Wedel, 2006). Categories are updated with each new token and each new production samples from this distribution, creating a range of possible values within the exemplar, which thus introduces phonetic variation in speech production. Several agent-based simulations of sound change have been proposed in which agents interact and learn from each other some abstract and extracted phonetic representation (de Boer, 2003; Kirby and Sonderegger, 2015).

The existing computational simulations of sound change require strong assumptions about learnability and a high level of abstraction of phonetic features. First, the models need to assume a simplified representation of learning: agents are already assumed to be able to learn and store

---

<sup>1</sup> Additionally, sound change is an umbrella term for several distinct processes, which further complicates the study behind mechanisms of sound change. Each of these interrelated processes (e.g. gradual phonetic vs. analogical vs contact-induced change) is likely influenced by different factors. The most well-studied change is the gradual phonetic change of the Neogrammarian type that affect some phonetic property in speech of a given community of speakers (Garrett and Johnson, 2013). This type of change is considered to be influenced primarily by articulatory and perceptual forces and less by speaker’s phonological knowledge, although arguments have been made arguing that phonology affects the gradual phonetic change too (Fruehwald, 2016).

phonetic features and values. Second, the models are not trained on raw acoustic inputs, but on items that only tangentially represent linguistic reality<sup>2</sup> or are extracted and reduced forms of the phonetic signal. For example, learning of vowels is usually modeled with absolute values of formats F1–F4. When an agent observes or learns a vowel, it stores the representation reduced to the four dimensions. Occasionally, noise and bias are added, but the learning in the model is still highly abstracted and does not closely resemble acquisition in language learning infants or even speech perception in adults. Recently, more elaborate models operate with some extracted phonetic features, but the dimensions that the agents learn are still highly abstracted; for example, absolute formant values (Wedel, 2006; Kirby and Sonderegger, 2015; Stevens et al., 2019). Hearing language-acquiring children need to learn articulatory targets for vowels and other sounds from raw acoustic inputs and not from already extracted simplified dimensions.

Neural network architectures have long influenced computational models of language. The majority of neural network approaches to modeling language data operate on a morphological or syntactic levels with fewer applications in phonetics and phonology. Nevertheless, neural networks have been widely used to model phonetic learning both in the earlier works (McClelland and Elman, 1986; Gaskell et al., 1995; Plaut and Kello, 1999; Kello and Plaut, 2003) as well as more recently with autoencoder and other deep learning architectures (Räsänen et al., 2016; Elof et al., 2019; Shain and Elsner, 2019).

Populations of neural networks have also been used to model language change in the earlier development of neural network research (for an overview, see Baker 2008). For example, Hare and Elman (1995) models morphological change with populations of neural networks. Training is stopped early in the model to simulate imperfect learning. After generations of networks, the first of which is trained on Old English data (whereby subsequent generations start learning from each other), the morphological system becomes more regular, reflective of Modern English (Hare and Elman, 1995; Baker, 2008). Likewise Livingstone (2002) trains fully connected two-layer neural networks to model emergence of dialects. However, these models require highly abstracted representations, are not trained on raw acoustic data, and are not fully generative in the sense that the networks would output innovative data. To the author’s knowledge, none of the proposals within the deep neural network framework model sound change in an iterative learning setting trained on raw speech.

## 1.2 Goals

This paper models language change with deep convolutional neural networks within the Generative Adversarial Networks framework (Goodfellow et al., 2014) that are trained on raw acoustic inputs. Beguš (2020b) argues that acquisition of phonetics and phonology can be modeled as a dependency between latent space and generated data in the GAN framework and proposes a technique to identify the network’s internal learning representations that are phonetically and phonologically meaningful. To model sound change, we introduce GANs to the iterative learning paradigm: agents in the model are individual Generative Adversarial Networks (as implemented for audio data in Donahue et al. 2019 based on Deep Convolutional Generative Adversarial Networks by Radford et al. 2015), which learn to output acoustic data that resembles speech of the raw acoustic data they are trained on.

The following iterated learning architecture is proposed: the initial input for the first generation of neural networks (a single GAN) are sequences of sounds from the TIMIT database (Garofolo et al., 1993). The network is trained on this input and after some number of epochs, generates data that closely resemble the input speech. The next generation of networks is trained on the

---

<sup>2</sup>Earlier simulations operated with fully abstract symbols, such as  $p$  and  $q$  that represent two variants in Nettle (1999).

generated data from the previous generation. This is iterated as long as the networks output data that can be modeled with the standard acoustic methodology for speech data. This iteration between generations of networks superficially simulates the transmission of speech between actual language learners providing the opportunity to study sound change in progress through a process that mirrors real language learning and transmission.

We test the development of an allophonic distribution based on English primary data. In English, stops [ $p^h$ ,  $t^h$ ,  $k^h$ ] are generally aspirated — produced with a long VOT or puff of air — before stressed vowels in absolute word-initial position (when no other consonant precedes the stop) and unaspirated [p, t, k] if an [s] precedes (Lisker, 1984; Iverson and Salmons, 1995; Vaux, 2002; Vaux and Samuels, 2005; Davis and Cho, 2006; Ahmed et al., 2020), e.g. ['pit] ‘pit’ and ['spit] ‘spit’). English L1 learners thus need to acquire long VOT (aspiration) and shorten it if an [s] precedes. Regardless of how we formalize this process (in symbolic rewrite rules as in Chomsky and Halle 1968 or connectionist constraints in Prince and Smolensky 1993/2004), the learner needs to acquire a conditional distribution: short VOT if [s] precedes, otherwise long VOT. If the acquisition is imperfect, the learner fails to shorten the VOT in the [s]-condition and extends the unmarked *elsewhere* variant — long VOT — into the more restricted [s]-condition. This stage is confirmed by language acquisition research: children acquiring English as L1 produce longer VOT and occasionally very long VOT durations in the s-condition compared to the adult population (Bond and Wilson, 1980; Bond, 1981; McLeod et al., 1996), likely because they fail to acquire the distribution perfectly. Similarly, patients with speech impairments produce long VOT in the [s]-condition because they fail to apply the phonological rule (Buchwald and Miozzo, 2012).

By training generations of GANs on a minimal allophonic distribution, we test which predictions of language change can emerge in deep convolutional neural networks. First, we test whether GANs that learn from each other can output linguistically analyzable data. We illustrate that acoustic phonetic analysis of both the duration (Section 3.2) and spectral properties (Section 3.3) can be performed on the generated outputs and that such an analysis yields informative results. Second, we test whether generations of GANs are able to represent properties of the data with the same frequencies as in the original training distributions (Section 3.1). For example, we analyze how well the less frequent #sTV sequences are represented relative to TIMIT. As already mentioned, both language-learning children and convolutional neural networks show evidence of imperfect learning of the aspiration rule in English — they occasionally fail to apply the rule. We test the effects of such imperfect learning on outputs of deep convolutional networks in iterative learning tasks. In other words, can failure to fully acquire a rule accumulate in the loss of a rule? Imperfect acquisition predicts that the more general #TV condition will remain unchanged, while the restricted #sTV condition will undergo loss of a distribution. We argue that appearance of such a loss indeed emerges in GANs trained iteratively and that gradual shifts of phonetic targets underlie the loss of a distribution (Section 4).

The advantage of the proposed model is that the networks are fully generative and unsupervised: they need to learn speech data from noise in the latent space based on raw acoustic inputs in the training data, replicating the conditions of infant language acquisition. The model does not require any level of abstraction; the only data manipulation that the models require is slicing acoustic inputs into sequences of sounds. No assumptions about learning are necessary and no language-specific features are assumed in the model.

Additionally, neural networks in the GAN architecture do not access the training data directly: they need to learn to output data from noise. Beguš (2020b) argues that GANs produce innovative outputs that are structured, highly informative, and consistent with linguistic behavior in language acquisition, speech impairments, and speech errors. Beguš (2020b) also argues that the networks learn to use the random space as an approximation to phonetic and phonological features. Several

parallels between phonetic and phonological learning in language-acquiring children and neural networks are thus observed. This paper tests whether similarities emerge also when Generative Adversarial Networks learn from each others in an iterative learning architecture.

The proposed experiment also has implications for the discussion on distinguishing different influences on sound change. While the proposed model does not include any articulatory or perceptual phonetic forces, diverging from modeling reality, it is in fact a desirable property for computational tests of different hypothesis about sound change. A model without articulatory information can provide evidence for changes that do not require articulatory bias, thus controlling for one factor in the set of possible influences on sound change. The Generative Adversarial Neural network architecture also lacks any domain-specific linguistic elements. This means that the proposed model can test which properties of sound change can be derived with domain-general cognitive mechanisms in absence of language-specific or articulatory phonetic influences. Combining iterative learning with deep convolutional networks trained on raw audio data is also part of a broader goal to test which properties of language and language acquisition can be derived with deep convolutional networks in the GAN setting.

## 2 Materials

### 2.1 Background: Generative Adversarial Phonology

The GAN architecture first proposed by Goodfellow et al. (2014) involves two networks, a Generator network ( $G$ ) and a Discriminator network ( $D$ ). The Generator is trained to map latent random variables ( $z$ ) to data, while the Discriminator is trained on distinguishing real data ( $x$ ) from generated data ( $\hat{x}$ ). The Generator is trained to maximize the Discriminator’s error rate, and the Discriminator is trained to minimize its own error rate. This minimax training results in a Generator network that outputs data that are increasingly difficult to distinguish from real data.

Radford et al. (2015) introduce deep convolutional networks to the GAN architecture (DCGAN). The DCGAN model has recently been transformed from modeling two-dimensional visual data to one-dimensional time-series audio data in a proposal called WaveGAN (used in this experiment) by Donahue et al. (2019). The architecture includes the Generator network as a five-layer deep convolutional network that takes as its input 100 latent  $z$ -variables distributed uniformly on the interval  $z_{1-100} \sim \mathcal{U}(-1, 1)$  and outputs 16,384 data points that constitute over 1 s of audio file (sampled at 16 kHz). The Discriminator similarly takes as an input 16,384 data points of either generated ( $G(x)$ ) or real ( $x$ ) data and estimates Wasserstein distance according to the proposal in Arjovsky et al. (2017). For a detailed description of the hyperparameters, see Radford et al. (2015); Donahue et al. (2019).

Beguš (2020b) argues that deep convolutional networks in the GAN setting learn to encode phonetic and phonological representations in the latent space. The network is trained on the same allophonic distribution as in this paper (using the same data), but only for one generation. Beguš (2020b) showed that the network can successfully learn a simple allophonic distribution, such as the English aspiration distribution ( $[\text{p}^{\text{h}}\text{i}\text{t}] \sim [\text{s}\text{p}\text{i}\text{t}]$ ). The advantage of modeling speech acquisition with GANs is that the networks not only replicate data, but generate innovative outputs. The innovative outputs are highly informative and linguistically interpretable. For example, the Generator learns to recombine phonetic units into unobserved novel combinations that can be analyzed as linguistically valid. A model trained on #TV and #sTV sequences (such as  $[\text{t}^{\text{h}}\text{æ}]$  and  $[\text{s}\text{t}\text{æ}]$ ) can output #TTV or #sV sequences that were not part of the training data (Beguš, 2020b). Similarly, in a model architecture for lexical learning fiwGAN (proposed in Beguš 2020a), the Generator outputs *start*  $[\text{s}\text{t}\text{a}\text{rt}]$ , although  $[\text{s}\text{t}\text{a}\text{rt}]$  was not part of training data: the network is only trained on *dark*, *suit*

	Steps	Epochs	Training data	Source of data
<b>Gen1</b>	12,255	717	5,463	TIMIT
<b>Gen2</b>	12,239	687	5,700	Gen1
<b>Gen3</b>	12,249	687	5,700	Gen2
<b>Gen4</b>	12,246	687	5,700	Gen3

Table 1: Generations of trained networks, their training steps, number of data points in training

and six other unrelated words.

The Generator also learns to use a subset of latent variables to represent approximates of phonological concepts such as presence of [s]. Beguš (2020b) proposes a technique to identify latent variables that correspond to some phonetic or phonologically meaningful representation and argues that the relationship between the variables and presence of the representation in the output is near linear. By manipulating individual variables to values well outside the training interval (Beguš, 2020b), we can actively force presence or absence of a segment such as [s] in the output. Interpolating a single variable results in gradual increase or decrease of frication noise of [s] (Beguš, 2020b). While manipulating internal representations of the trained networks is highly informative for probing tasks, no variables are manipulated in the iterative learning experiments presented here — the objective of the paper is to test what types of changes emerge in an iterative learning setting without any active manipulations to the networks.

## 2.2 Model

The computational experiment is performed on a model in Donahue et al. (2019) called WaveGAN, which is an implementation of the DCGAN architecture (Radford et al., 2015) for audio data with few modifications. Figure 1 illustrates the training procedure. The first network (Gen1) is trained on data from the TIMIT database (Garofolo et al., 1993). The training data consists of 4,930 sequences with the structure #TV and 533 sequences with the structure #sTV (5,463 total). The training is stopped after 12,255 steps. At this point, 5,700 outputs are generated from Gen1. No manipulations are performed on the latent space. These 5,700 data points constitute the training data for the second network: Gen2. Gen2 is thus trained exclusively on the generated outputs of the first network, Gen1. After 12,239 steps, the training is stopped, at which point the Generator network outputs 5,700 data points that are fed to the next network. Altogether four generations of networks were thus trained (Gen1, Gen2, Gen3, Gen4). All networks are trained on approximately equivalent number of training steps and data points. Because the training is stopped at a relatively small number of training steps, noise arises with each generation of networks to induce imperfect learning. For this reason, we only trained four generations. Table 1 lists training steps and details about data points of the four networks. The networks were trained at an approximate pace of 25 steps per 300 s on an NVIDIA Tesla M10 GPU unit.

## 2.3 Data

The data used for training in the first generation (Gen1) are sliced from the TIMIT database (Gen0). (Garofolo et al., 1993). TIMIT is one of the largest hand-annotated corpora currently available that involves spoken language in a controlled environment with a high level of audio quality. The database includes 10 sentences per each of the 630 speakers (total 6,300 sentence) from 8 dialectal groups, which provides a relatively diversified corpus. For the purpose of training the networks on an allophonic distribution, sequences with the structure #TV and #sTV were

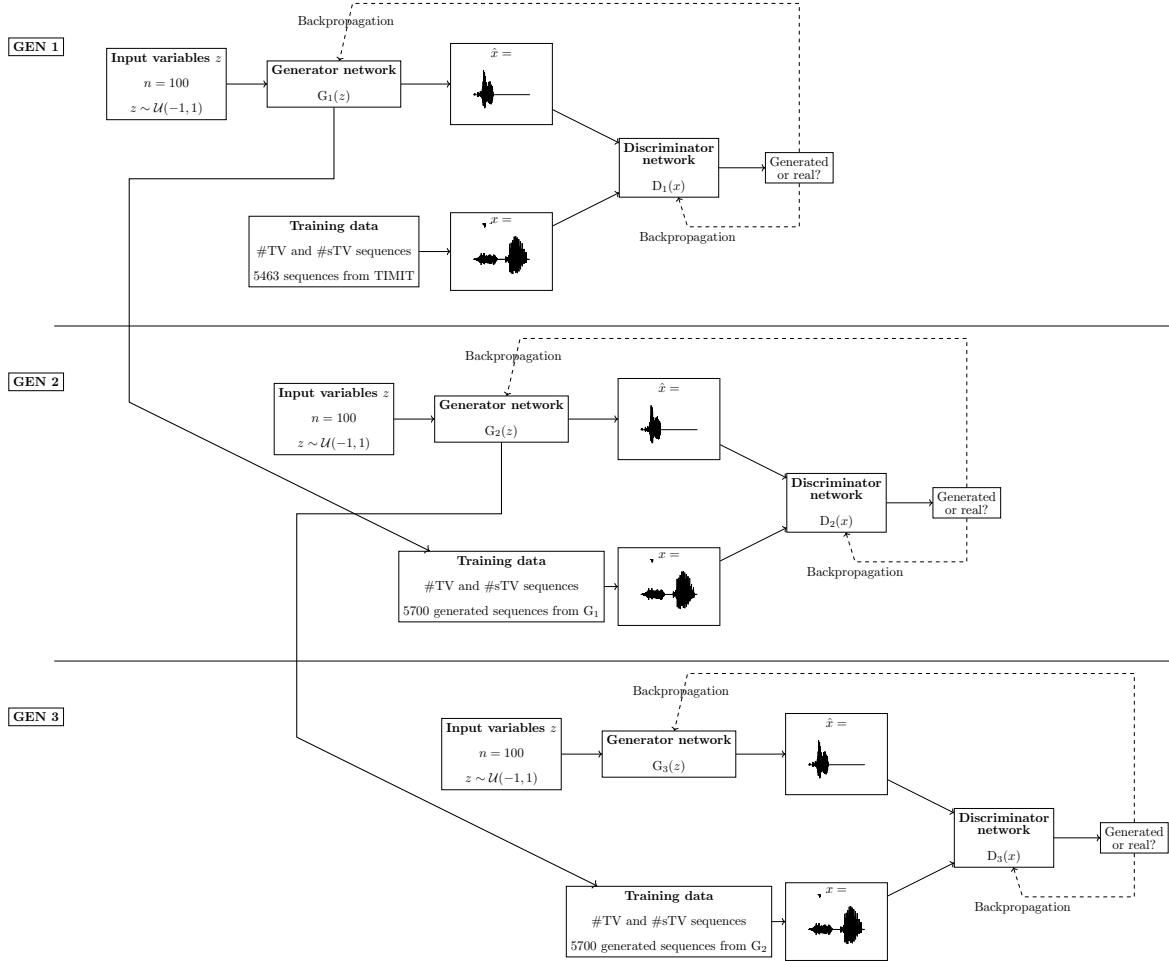


Figure 1: A diagram of generations of Generative Adversarial Networks as trained in this paper (each network is trained on the proposal in Donahue et al. 2019). Gen 4 is omitted from the figure.

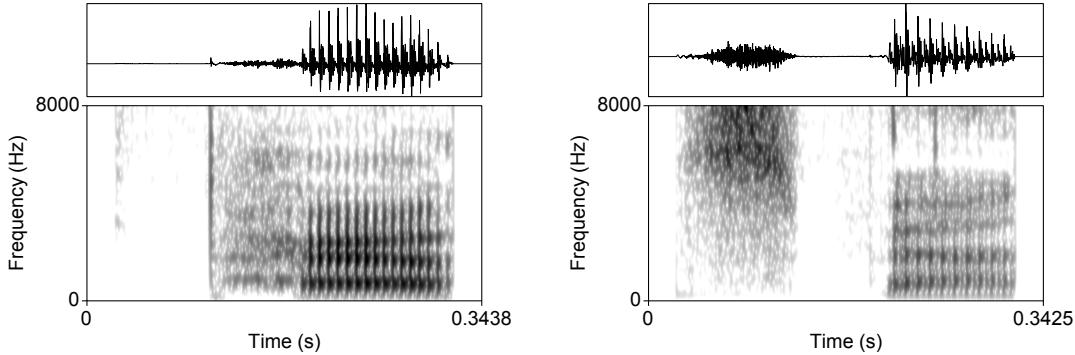


Figure 2: Waveforms and spectrograms (0–8,000 Hz) of a typical #TV and a #sTV sequence ([ $p^h\text{æ}$ ] and [spæ]) from the TIMIT database used for training. The networks are trained on waveforms exclusively: spectrograms are given here only for illustration. Waveforms are additionally padded with silence until they reach 16,384 datapoints.

sliced from the database.<sup>3</sup> In other words, the networks are trained on TIMIT sequences of a voiceless stop /p, t, k/ (represented by T) at the beginning of a word (represented by #), followed by a vowel (represented by V)<sup>4</sup> and optionally preceded by a sibilant fricative [s] (represented by s). The training data are limited to vowels and do not include any other segments after the vowel in order to control for unwanted effects of other potential conditional distributions (Beguš, 2020b). Vowels are distributed approximately equally across the two conditions: #TV and #sTV.

The sequences are raw acoustic waveform files, sampled at 16 kHz and fed to the model (which pads them with silence into exactly 16,384 data points that constitute the waveform). The training data are raw waveform files and include no segmentation or any other information. The only supervision in the model is the fact that data is sliced into sequences of the structure #TV and #sTV. Figure 2 illustrates two typical training sequences sliced from TIMIT, one for each of the two conditions.

### 3 Results

#### 3.1 Proportion of #sTV sequences

To analyze learning of the allophonic distribution across generations in deep neural networks, we first generate 2,000 outputs from the Generator network for each of the four generations of networks (8,000 outputs total) and test how the proportion of #sTV sequences changes with each generation.

The TIMIT training data for Gen1 contains altogether 5,463 sequences, 533 of which are of the #sTV structure. In other words, 9.76% of the initial training data are #sTV sequences. This ratio appears slightly lower in the next generations, but not substantially so. Of the 2,000 outputs examined per each generation, the number of #sTV sequences range from 119 to 157 (or 5.95% to 7.85% see Table 2).

To test whether the differences in the proportion of #sTV sequences across the four generations

<sup>3</sup>The data and the first network (Gen1) are the same as in Beguš (2020b).

<sup>4</sup>TIMIT uses the ARPABET convention. The following vowels are included in the analysis (in ARPABET and IPA transcriptions): aa = a, ae = æ, ah = ʌ, ao = ɔ, aw = ɑʊ, ax = ə, ax-h = ə̄, axr = ə̄̄, ay = aɪ, eh = ɛ, er = ɜ̄, ey = eɪ, ih = ɪ, ix = i, oy = oɪ, uh = u, uw = u, ux = ū.

	All sequences	#sTV	#TV	%of #sTV	#TV annotated
(TIMIT) <b>Gen0</b>	5,463	533	4,930	9.76%	4,930
<b>Gen1</b>	2,000	151	1,849	7.55%	157
<b>Gen2</b>	2,000	153	1,847	7.65%	157
<b>Gen3</b>	2,000	157	1,843	7.85%	157
<b>Gen4</b>	2,000	119	1,881	5.95%	157

Table 2: Counts of analyzed data and proportion of #sTV in the output data across the generations. Gen0 represents the TIMIT database.

and the TIMIT initial training data are significantly different, we fit the counts of #sTV and #TV sequences from Table 2 to a negative binomial regression model. The dependent variable is the count of the sequences; the independent variables are GENERATIONS (treatment-coded with Gen1 as the reference level) and STRUCTURE (#sTV vs. #TV, treatment-coded with #TV as reference) with the interaction.<sup>5</sup>

Overall, the proportion of #sTV sequences in the output is significantly smaller in the first generation (Gen1) compared to the training data from TIMIT (Gen0) ( $\beta = 0.28, z = 2.84, p = 0.005$ ) and slightly smaller in Gen 4 than in Gen1 ( $\beta = -0.26, z = -1.98, p = 0.048$ ). The differences between Gen1 and Gen2 and Gen3 are not significant (full model in Table 3). Figure 3 illustrates the distribution (estimates are from a logistic regression model). It appears that the proportion of the #sTV sequences compared to the #TV sequences is relatively stable across the generations of networks.

	Estimate	Std. Error	z value	Pr(> z )
(Intercept) = Gen1, #TV	7.5224	0.0259	290.4652	< 0.0001
Gen0	0.9807	0.0317	30.9598	< 0.0001
Gen2	-0.0011	0.0366	-0.0295	0.9764
Gen3	-0.0033	0.0366	-0.0887	0.9293
Gen4	0.0172	0.0365	0.4701	0.6383
#sTV	-2.5051	0.0862	-29.0761	< 0.0001
Gen0:#sTV	0.2805	0.0988	2.8395	0.0045
Gen2:#sTV	0.0142	0.1215	0.1172	0.9067
Gen3:#sTV	0.0422	0.1208	0.3494	0.7268
Gen4:#sTV	-0.2553	0.1289	-1.9806	0.0476

Table 3: Coefficients of a negative binomial regression model of counts of #sTV sequences in the generated data across the four generations and the TIMIT database (Gen0).

### 3.2 VOT duration

To evaluate how learning of the allophonic distribution changes with each generation, we compare VOT durations in #TV and #sTV sequences across the four generations and TIMIT. The author annotated all #sTV sequences in the 8000 generated outputs (4 generations  $\times$  2000) and a number of #TV sequences that equaled the highest number of #sTV sequences in the outputs per genera-

<sup>5</sup>The regression is performed with the *gam()* function in *mgcv* (Wood, 2011) in R statistical software (R Core Team, 2018).

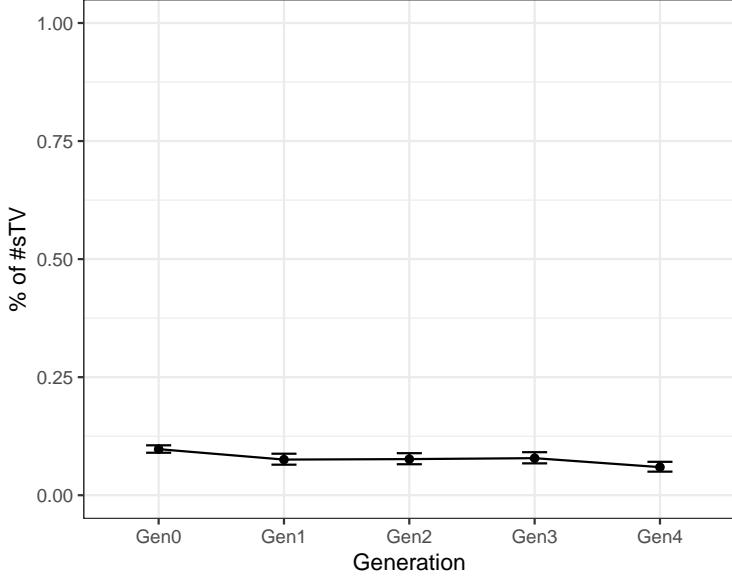


Figure 3: Proportion of  $\#sTV$  sequences in the output across generations of trained network when data is fitted to a linear logistic regression model (not a negative binomial model). Gen0 represents the proportion in the TIMIT database on which the first generation (Gen1) is trained.

tion, i.e. 157.<sup>6</sup> Measurements of VOT durations in the TIMIT database used for training the first generation, are taken from the 5,463 TIMIT-internal hand-annotations.

Identifying  $\#sTV$  sequences and especially boundaries between aspiration duration and closure/onset of the vowel in the generated outputs is a challenging task. Since automatic speech tagging systems are still underperforming trained human phoneticians even for acoustically cleaner and less ambiguous data, human annotation is necessary for data annotations for the current levels of audio quality in the generated data. The author manually inspected all 8,000 data points. In order to keep annotation criteria constant across the generations, the entire dataset (8,000 outputs) were inspected four times.

The generated outputs are not recordings of actual human speech, which is why finding boundaries between the release of the following stop and onset of the vowel is particularly challenging. Two example waveforms and spectrograms with annotations are given in Figure 4. The main criteria for phonetic annotation were consistency across generations and finding acoustic equivalents of closure, stop release, aspiration noise, and vowel onset. Borderline cases analyzed as either  $\#sTV$  (and therefore included in the analysis) or  $\#sV/\#TV$  (and therefore excluded) were decided based on consistency of criteria across generations. Guidelines for data annotations as described in Ladefoged (2003) were used.<sup>7</sup>

The main question of the present experiment is whether the difference in aspiration between the two conditions changes significantly across generations of deep convolutional neural networks. While the most prominent phonetic correlate of aspiration is VOT duration and spectral properties of burst and aspiration noise (Klatt, 1975; Hussain and Mielke, 2020), the duration of aspiration

<sup>6</sup>The annotated  $\#TV$  sequences for VOT duration measurements were chosen from the beginning of the 2,000 generated data samples in order to represent the durations of  $\#TV$  sequences consistently across the generations and to reduce selection bias.

<sup>7</sup>Generated data and annotations are available here: [https://osf.io/5kbef/?view\\_only=b5fddd6fffcfa4a538e658bb99c02ab89](https://osf.io/5kbef/?view_only=b5fddd6fffcfa4a538e658bb99c02ab89).

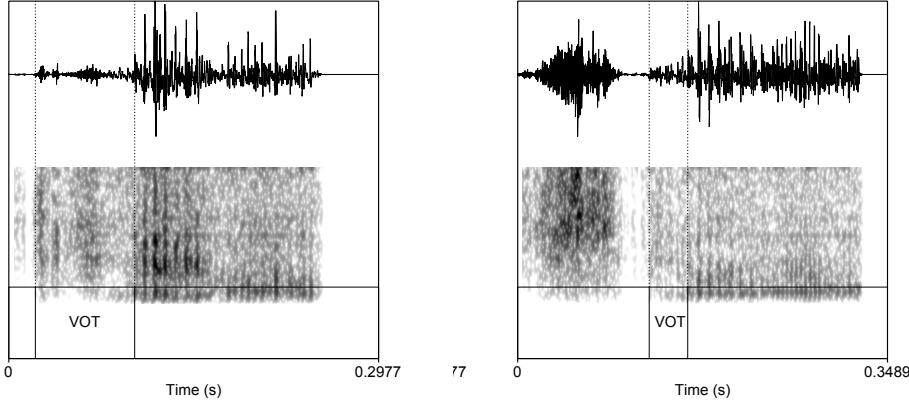


Figure 4: Waveforms and spectrograms (0-8000 Hz) of two generated outputs from Gen4 with corresponding annotations.

(VOT) is influenced by many other phonetic factors (such as place of articulation or vowel quality). However, in the Generated data, even VOT durations, which are phonetically prominent, are occasionally challenging to annotate. Vowel quality and place of articulation are very difficult to reliably analyze. For this reason, we analyze VOT durations and the spectral properties of the aspiration noise (Section 3.3). To control for other influences, we analyze duration and spectral properties in the #sTV condition *relative to* the #TV condition. Given that we do not expect distributional differences in other phonetic parameters across the generations, the results should not be substantially impacted by other phonetic features. Additionally, the spectral analysis of frication noise in Section 3.3 suggests that no substantial changes in spectral properties occur across the four generations.

The raw data suggest that the difference in VOT durations between the two conditions, #TV and #sTV, becomes increasingly smaller with every generation of trained Generative Adversarial Networks and that this smaller difference results primarily from VOT in the #sTV sequences gradually becoming longer. Table 4 gives raw means of VOT durations across the generations; Figure 5 illustrates the distribution. While it appears that the average duration of VOT in the #TV condition does not change substantially across the generations, VOT duration in the #sTV condition substantially lengthens: it reaches 43.31ms in Gen4 (compared to 25.36ms in TIMIT).

	VOT in ms			
	#TV		#sTV	
	Mean	SD	Mean	SD
Gen0	59.33	20.97	25.36	8.76
Gen1	61.83	24.76	38.85	18.44
Gen2	58.42	22.44	40.40	19.74
Gen3	58.88	24.52	42.56	20.63
Gen4	62.41	26.36	43.31	18.30

Table 4: Means of VOT durations in ms with standard deviation across the two conditions (#TV and #sTV) four generations (Gen1–4) and TIMIT (Gen0).

The data distribution in the first generation of networks, Gen1, suggest that the network does

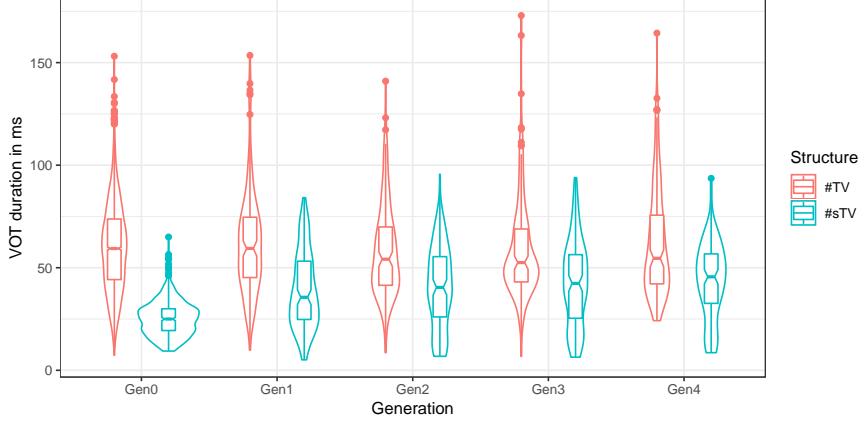


Figure 5: Violin and boxplot of VOT duration in ms across the four generations of trained networks and TIMIT.

learn the conditional distribution, but imperfectly so, as the network outputs data in which the VOT duration in the <#sTV> condition is longer than any VOT duration in this condition in the training data (see also Beguš 2020b). Figure 6 illustrates two outputs of Gen1 with short VOTs (20.2 ms in the left and 27.1 ms in the right sequence) and two outputs in which the VOTs are longer than any in the training data (82.4 ms in the left and 84.2 ms in the right).

By Gen4, outputs with short VOT become exceedingly rare, while outputs with long VOT, longer than in the TIMIT training data from Gen0, become very frequent. Figure 7 illustrates this distribution with two examples of <#sTV> sequences. The VOT duration at this point is long and the closure is almost entirely absent from the output.

To test the significance of the difference in VOT durations across different generations, the data is fit to a Gamma regression model with log link (in R Core Team 2018).<sup>8</sup> The dependent variable is duration of VOT in ms. The model has two predictors: STRUCTURE (treatment-coded with <#sTV> as the reference level) and GENERATION (treatment-coded with Gen1 as the reference level) and an interaction between the two predictors. The AIC value of the model with the interaction is higher compared to the model without the interaction ( $-33142$  vs.  $-32760$ ), which is why the interaction and the two predictors are kept in the final model.

The model reveals several distributions in the data that are relevant to the questions posed by this paper. First, the model suggests that the difference in VOT duration between the <#TV> and <#sTV> conditions are significant for Gen1:  $\beta = -0.465$ ,  $z = -11.03$ ,  $p < 0.0001$ . In other words, the network learns to output shorter VOT in Gen1 in the <#sTV> condition compared to the <#TV> condition, which means that the network learns the conditional distribution of VOT duration (see also Beguš 2020b).

While the network learns to output shorer VOT in the <#sTV> condition, the learning is imperfect. This is suggested by the interaction term STRUCTURE:GENERATION which is a significant predictor (AIC =  $-33011$  vs.  $-32764$ ). Crucially, the difference in VOT duration between the two conditions (<#TV> and <#sTV>) is significantly greater in the TIMIT database compared to Gen1 (trained on TIMIT):  $\beta = -0.385$ ,  $z = -8.44$ ,  $p < 0.0001$ . Similarly, this difference is significantly greater in Gen1 compared to Gen3:  $\beta = 0.14$ ,  $z = 2.36$ ,  $p = 0.018$  (for other coefficients, see Table 5). These results suggest that the Generator learns the allophonic distribution imperfectly with each generation. The difference in VOT duration between the two conditions is substantially and

<sup>8</sup>Gamma regression provides a better fit than an inverse Gaussian model (AIC =  $-33010.92$  vs.  $-31925.08$ ).

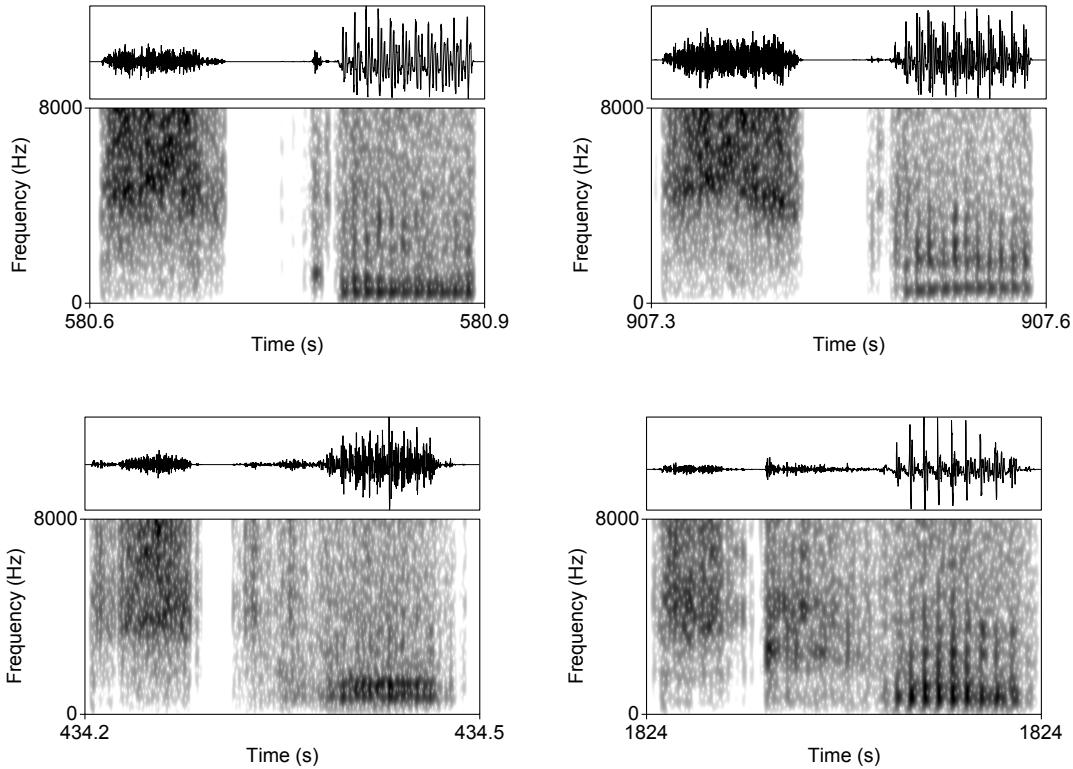


Figure 6: Waveforms and spectrograms (0–8,000 Hz) of four #sTV sequences from Gen1, two with short VOT (upper row) and two with long VOT (lower row). The generator only outputs waveforms, spectrograms are provided only for the analysis.

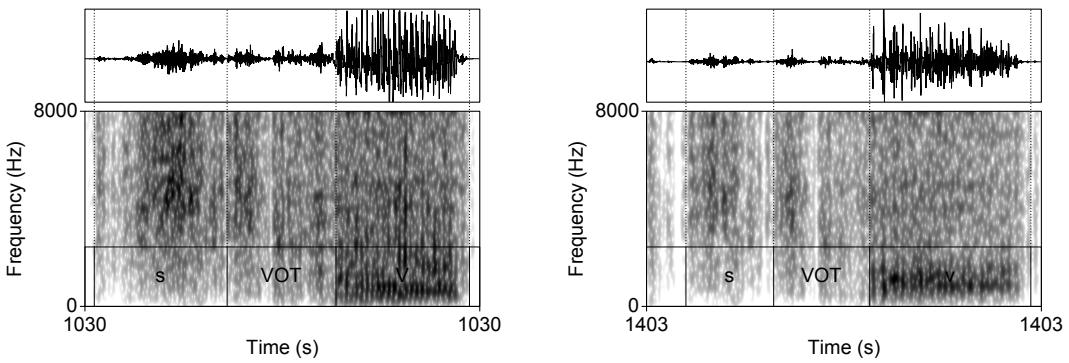


Figure 7: Waveforms and spectrograms (0–8,000 Hz) of two #sTV sequences with typically long VOTs from Gen4. The network outputs only waveforms: spectrograms and annotations are given here for analysis.

significantly smaller in the first generation (Gen1) compared to human training data (TIMIT), but this difference gets even smaller when further generations learn from each other. In other words, the iterative learning results in increasingly smaller distinction in VOT duration between the #TV and #sTV conditions.

The absolute VOT durations in the #sTV condition are significantly longer in the first generation trained on TIMIT (Gen1) compared to TIMIT (Gen0) and significantly longer in the third and fourth generations that are trained on outputs of previous GAN networks (Gen3 and Gen4) compared to the first (Gen1). The differences between Gen1 and Gen3/Gen4 are smaller compared to the difference between Gen0 and Gen1:  $\beta = 0.091, z = 2.17, p = 0.030$  for Gen3, and  $\beta = 0.109, z = 2.40, p = 0.016$  for Gen4. In other words, there is a trend for the difference in VOT duration between the #TV and #sTV sequences to become smaller with each generation and especially for VOT in the #sTV condition to become longer. Figure 8 shows a clear pattern: while the VOT duration in the #TV condition remains relatively constant across the generations, the VOT duration in the #sTV condition rises steadily with each generation.

Not only are the VOT durations of #TV relatively stable across generations, they also do not differ from the original distribution in the training data (TIMIT). Post-hoc tests of the difference in the absolute VOT duration in the #TV condition across the four generations suggest that VOT remains stable across generations. None of the pairwise comparisons between Gen0 (TIMIT), Gen1, Gen 2 and Gen3 and Gen4 are significant (see Table 6). This suggests that the first generation of the Generator networks (as well as the subsequent generations) learn the VOT durations in the #TV condition from the training data relatively faithfully and that this duration remains stable in subsequent generations (unlike in the #sTV condition).

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)=Gen1,#sTV	-3.248	0.030	-107.95	0.0000
#TV	0.465	0.042	11.03	0.0000
Gen0	-0.426	0.034	-12.39	0.0000
Gen2	0.039	0.042	0.92	0.3567
Gen3	0.091	0.042	2.17	0.0304
Gen4	0.109	0.045	2.40	0.0164
#TV:Gen0	0.385	0.046	8.44	0.0000
#TV:Gen2	-0.096	0.059	-1.61	0.1073
#TV:Gen3	-0.140	0.059	-2.36	0.0182
#TV:Gen4	-0.099	0.062	-1.61	0.1065

Table 5: Coefficients of the Gamma regression model.

Even more informative for modeling sound change are density plots of VOT durations in the #sTV condition in Figure 9. They reveal a clear trend, not only in overall duration, but that the peak VOT distribution is gradually increasing with each generation. VOT in the TIMIT database (Gen0) is substantially shorter than in all other generations. The highest density of Gen1 remains around the peak of TIMIT Gen0, while the distribution has substantially longer right tail with several data points in which the VOT is longer than any VOT duration in the training data. This suggests that the distribution in Gen1 is learned, but imperfectly. The next generations (Gen2, Gen3, and Gen4) show a gradual shift of the peak of the distribution towards longer VOT and additionally a trend towards a bimodal distribution. In all three generations, the outputs appear to have the majority distribution in what would be considered a long VOT that increasingly shifts towards even longer values. At the same time, the outputs also feature a lower peak around the

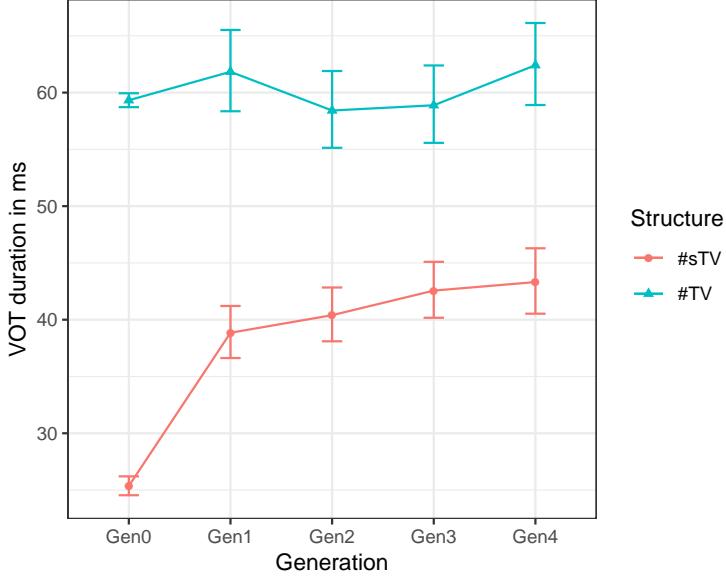


Figure 8: Predicted values based on the Gamma regression model in Table 5.

original shorter VOT duration (closer to the TIMIT database). This sub-peak appears smaller in Gen4 compared to Gen3. In the <#TV condition, the peaks are relatively stable across the four generations and TIMIT.

### 3.3 Spectral properties

As already mentioned, spectral properties of aspiration noise can differ across aspirated and unaspirated stops (Hussain and Mielke, 2020). To test whether the change of VOT durations also entails changes of spectral properties of aspiration, we perform spectral analyses of the VOT duration. We are primarily interested whether spectral properties change significantly across the four generations of iteratively trained networks when duration of the VOT is controlled for.

To test the stability of the aspiration’s spectral properties across the four generations of neural networks, we perform spectral analysis of the aspiration noise measured at 10 intervals (from 10% to 100%. of the duration). All 1,208 analyzed VOT durations (Table 2) across the four generations were thus analyzed for a total of 12,080 observations. For each annotated period of aspiration in the <#TV and <#sTV condition, we analyze Center of Gravity (COG), Standard Deviation, Skew, and Kurtosis of power spectra with 750-8,000 Hz filter (100Hz smoothing) using script by Rentz (2017) in Praat (Boersma and Weenink, 2015). Four generalized additive mixed effects models were fit for each of the four measured spectral properties (using the *mgcv* package; Wood 2011; Sóskuthy 2017). The models include STRUCTURE as a parametric term (reference <#sTV vs. <#TV) and thin-plate difference smooths for PERCENT of VOT duration (10–100% in 10% increments), absolute DURATION (full VOT duration in seconds), and GENERATION of neural networks (1-4, limited to 4 knots) and all two-way tensor product interactions. The model also includes random smooths for each trajectory (1,208 total).

In addition to the change of VOT duration, the tensor product interaction between DURATION of VOT and GENERATION is the most informative test for the question of whether spectral properties significantly change across the four generations. Figure 10 plots the four spectral properties over the four generations and the various durations of VOT at 10% and 50% of VOT duration. All

Contrast	Ratio	SE	df	z.ratio	p.value
STRUCTURE = #TV					
gen1 / gen0	1.0422	0.0312	Inf	1.381	0.6402
gen1 / gen2	1.0584	0.0442	Inf	1.360	0.6537
gen1 / gen3	1.0501	0.0438	Inf	1.171	0.7680
gen1 / gen4	0.9907	0.0413	Inf	-0.223	0.9994
gen0 / gen2	1.0155	0.0304	Inf	0.512	0.9862
gen0 / gen3	1.0075	0.0302	Inf	0.250	0.9991
gen0 / gen4	0.9506	0.0285	Inf	-1.692	0.4391
gen2 / gen3	0.9922	0.0414	Inf	-0.189	0.9997
gen2 / gen4	0.9361	0.0391	Inf	-1.583	0.5084
gen3 / gen4	0.9435	0.0394	Inf	-1.394	0.6313

Table 6: Post-hoc comparison of VOT duration in the #TV condition across the generations with Tukey adjustment based on the Gamma regression model.

estimates of the four models are given in Tables 7, 8, 9, 10. None of the estimates for the tensor product interaction DURATION:GENERATION in the #sTV condition are significant in the four models that measure COG, Skew, Kurtosis, and SD. The plots illustrate relatively constant values of the spectral values across the four generations. In other words, for the same levels of DURATION, spectral properties do not change substantially across the iteratively trained generations of neural networks.

## 4 Discussion

Training deep convolutional networks in the GAN architecture in iterative learning tasks reveal several superficial similarities between language change and changes in acoustic outputs of the deep convolutional networks. First, the networks show relative stability in the proportion of #TV and #sTV sequences that they output. Human subjects extend frequencies of phonological properties of the lexicon to novel test items in behavioral experiments (Hayes and Londe, 2006; Zymet, 2018). This phenomenon is usually called *frequency matching*. In Hungarian, for example, some roots can take a dative morpheme with the back vowel [-nök], while others roots take the same morpheme, but containing a front vowel [-nɛk]. In a subclass of nouns, [-nök] appears in 7.8% cases in Hungarian lexicon. When speakers are asked to choose between [-nök] and [-nɛk] in novel unobserved words that resemble the actual class of nouns in which [-nök] appears in 7.8% cases, they closely match this frequency: they choose [-nök] in 6.3% of outputs in a behavioral experiment (Hayes and Londe, 2006).

Traces of such behavior are observed in our model: the proportion of [s]-initial sequences in the Generator’s outputs is relatively stable across the four generations. This means that the network’s output distribution closely matches training data. While the first network (Gen1) outputs slightly fewer #sTV sequences compared to their representation in the TIMIT training data, two subsequent generations (Gen2 and Gen3) do not diverge significantly in proportions of #sTV sequences from their training data (see Figure 3). The proportion is slightly, but significantly lower in Gen4, but 5.95% of sequences still contain an [s]. The networks are thus relatively successful in matching frequencies of the training data in the generated outputs, especially considering the fact that we do not train the individual generations to convergence, but stop training after relatively few steps. While this result might seem trivial, it is conceivable that the considerably less frequent #sTV

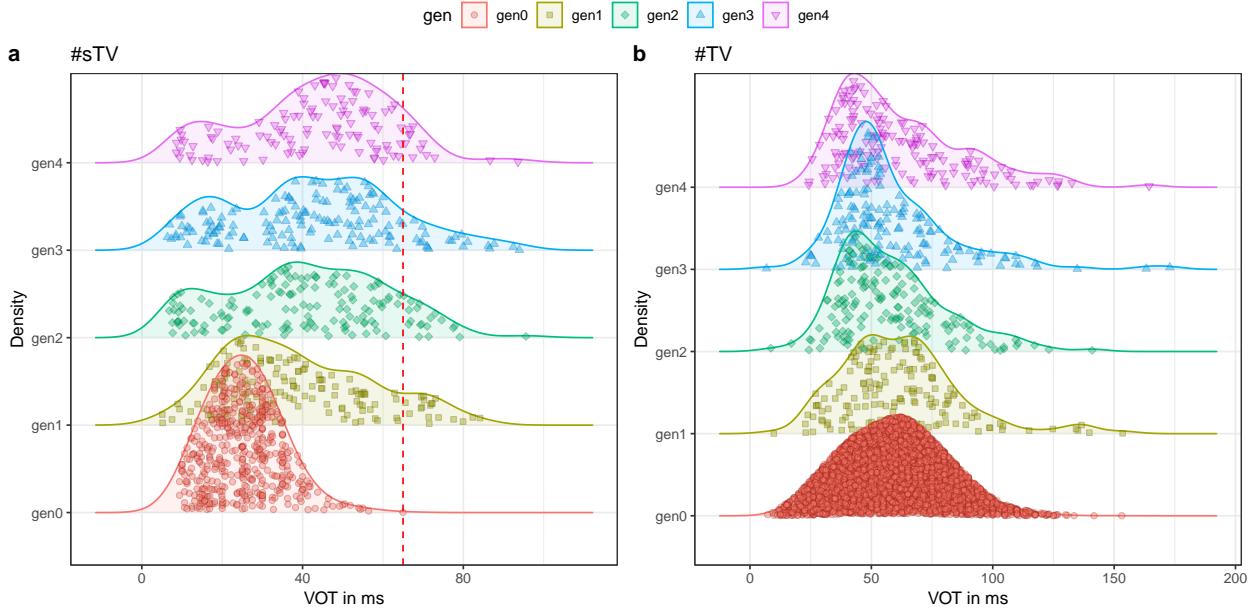


Figure 9: Density plots with data points of VOT duration in the #sTV (a) and #TV (b) conditions across the four generations and TIMIT (Gen0). The red dashed line indicates the longest VOT duration in the #sTV condition in the training data (TIMIT).

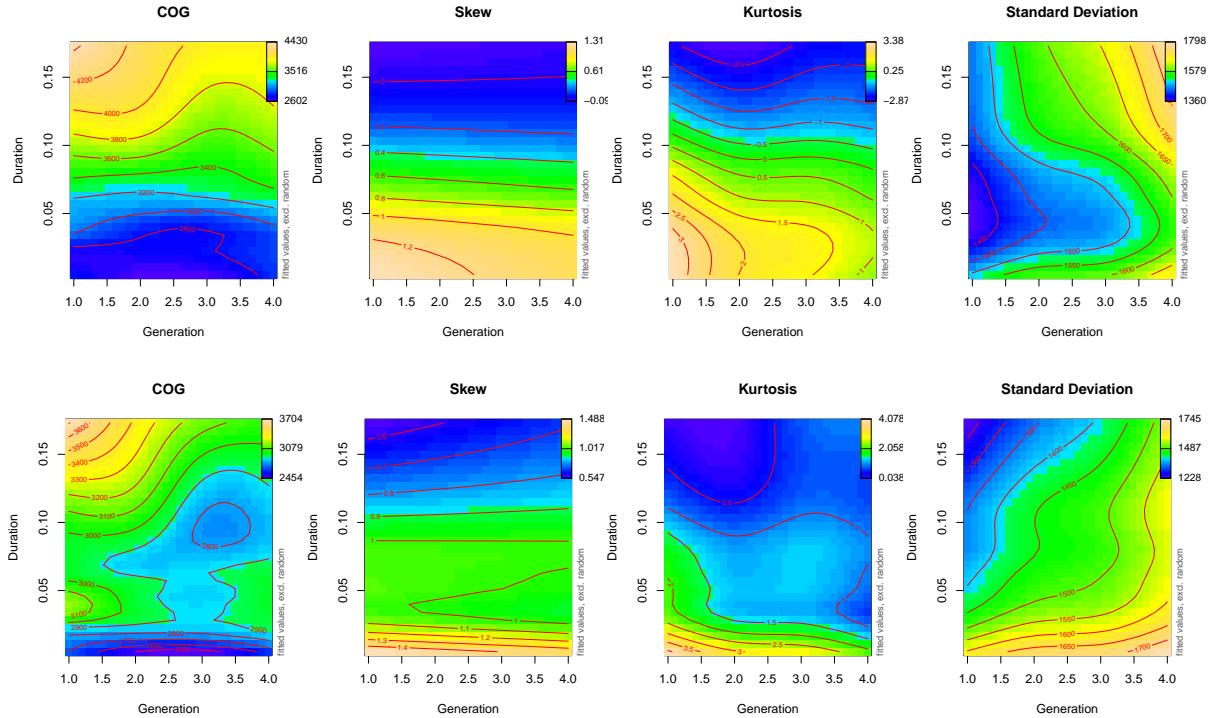


Figure 10: Plots of nonlinear interactions between GENERATION and DURATION of VOT for the four dependent variables, COG, Skew, Kurtosis, and Standard deviation at 10% of VOT duration (upper row) and 50% of VOT duration (lower row).

sequences would be lost earlier with generations of networks — parallel to the loss of the durational distribution of VOT (see below).

The networks also learn to output data that resembles speech and learn the conditional allophonic distribution in English — deaspiration after [s] ([<sup>h</sup>pɪt] ~ [spɪt]). In the first generation (Gen1) trained on TIMIT, the difference in VOT duration between the #TV and #sTV sequences is significant (see also Beguš 2020b). The distribution peak of VOT durations in the #sTV condition is in the first generation well-aligned with the original TIMIT distribution (Figure 9). Nevertheless, the distribution has a substantially longer right tail and the mean duration of VOT in Gen1 is significantly longer than in TIMIT, as suggested by the Gamma regression model in Table 5.

By Gen4, long VOT durations become so frequent that the distribution might be considered as not featuring the allophonic distribution at all. Plots of VOT distributions across generations (Figure 9) show that the distribution peaks gradually moves towards long VOT with each generation. While VOT is still shorter in the #sTV compared to the #TV condition in Gen4, the peak of VOT distribution is sufficiently long that most phonological analyses would likely analyze such a distribution as not involving an allophonic process. The slightly shorter VOT duration would likely be ascribed to the fact that the stop T is part of a consonant cluster (sT) and therefore automatically shorter. While VOT durations get increasingly longer with each generation, VOT durations in the more frequent #TV condition remain stable and do not change significantly.

The generated outputs thus resemble both a phonetic gradual sound change and a phonological change — loss of a phonological rule. Peak distribution of VOT durations in the experiment gradually changes with each generation. This can be analyzed as superficially parallel to shifts in articulatory targets in a gradual phonetic sound change in natural language. The endpoint result, on the other hand, can be analyzed as a phonological rule loss. Rule loss in phonology (Kiparsky, 1965; Bermúdez-Otero and Hogg, 2003) is a process whereby a language at stage A features a phonological rule and loses that rule at stage B. When a distribution becomes automatic and does not require active control of the speakers, it is assumed that a process is part of an automatic phonetic distribution and not part of phonological computation. It is difficult to assess how actively the Generator controls VOT durations in Gen4, but it is likely the case that most linguistic analyses would treat such a minor difference in VOT duration as part of a phonetic rather than phonological shortening. So at least superficially, a phonological rule loss emerges in the deep convolutional neural networks trained in iterative learning tasks: TIMIT (Gen0) features an allophonic rule of deaspiration of [s]-initial sequences, while at the stage of Gen3 or Gen4, such rule is likely lost.

The reason why the VOT duration in the [s]-condition gets gradually longer with imperfect learning whereas VOT durations in the #TV sequences remain stable is parallel to phonological pressures in natural language. In our training data, #TV sequences are significantly more frequent than #sTV sequences: 4,930 vs. 533. This distribution actually reflects English lexicon: all sequences of the shape #TV and #sTV were sliced from TIMIT for the training data, but because #TV is substantially more frequent in English lexicon, it is also more represented in TIMIT. The more frequent sequence in the training data is thus #TV and therefore long VOT is the more general, less restricted variant (or in linguistic terms the “unmarked” elsewhere variant; see also Figure 5). This difference in training distributions affects the acquisition of shorter VOT durations in the #sTV condition both in natural language acquisition as well as in deep convolutional networks trained in iterative learning tasks. However, while the property of the data — the lower frequency of one condition — is a linguistic property, the fact that imperfect learning in iterative tasks results in an apparent loss of a distribution is not linguistic (domain-specific) because the models that undergo learning have no pre-assumed linguistic information.

The acquisition of VOT durations in human language learners undergoes several stages: first, VOT durations in voiceless stops are shorter than in adult targets in the #TV condition, because

long VOTs are more difficult to acquire (Gilbert, 1977; Macken and Barton, 1980; Lowenstein and Nittrouer, 2008; Yang, 2018). Later, however, children produce long VOTs in #TV sequences and in some cases even longer VOTs compared to the adult targets (Macken and Barton, 1980). The development of VOT durations in the #sTV condition is even more intriguing. Crucially, children output substantially longer VOT durations compared to adult language in the #sTV condition (Bond and Wilson, 1980) despite the fact that long VOTs are generally more difficult to acquire (Gilbert, 1977; Lowenstein and Nittrouer, 2008; Yang, 2018). In other words, children extend the long VOTs in the #TV condition to the #sTV condition and then need to acquire the shortening of VOT in the #sTV condition. In fact, they often fail to shorten VOTs in the #sTV condition which results in long VOTs in #sTV sequences (Bond and Wilson, 1980). Just like in training data, #sTV sequences are less frequent, which is likely the reason for the unexpected long VOTs in the #sTV condition during acquisition.

Both deep convolutional networks and language-acquiring children thus need to acquire the shortening of VOT in the more limited and less frequent [s]-condition. Failure to do so results in a long VOT duration in the #sTV sequences. Imperfect learning that results in long VOT in the #sTV sequences is attested in both language-acquiring children, as suggested by Bond and Wilson (1980), and deep convolutional networks, as suggested by the computational simulations in this paper. Imperfect acquisition over time can accumulate in gradual shifts in phonetic targets (Baker, 2008) which, at the endpoints, results in a phonological rule loss. Peaks of distributions of VOT duration in the four generations gradually move from short towards long VOT, and the end-result contains predominantly long VOT durations in the #sTV conditions. Imperfect acquisition in the GAN networks is catalyzed by the fact that we train the networks for a relatively few training steps (less than 13,000). The magnitude of imperfect acquisition is likely smaller in language-acquiring children. This is likely the reason for why appearance of rule loss emerges only after four generations of deep convolutional Generator networks in our model, but substantially more speakers are usually needed for emergence of sound change. With less imperfect learning, the deep convolutional networks would likely take longer to achieve the same effect. The principle behind the change nevertheless remains even if the acquisition is less imperfect than in our computational model.

In addition to measuring VOT durations, we performed spectral analyses of aspiration noise that included COG, SD, skew, and kurtosis measured at every 10% of aspiration duration. The results of non-linear regression models suggest that for equal VOT durations, spectral properties of frication noise do not change significantly across the generation. In other words, when VOT duration is controlled for, the aspiration noise does not change significantly, which suggests that lengthening of the VOT is the primary change operating in the four generations of deep convolutional networks.

The author is unaware of any English varieties where such a rule loss would occur in this particular allophonic distribution. Other parallels, however, have been recorded in the literature on sound change in progress. For example, vowels in American English are nasalized before nasal stops. In a word like *pen* ['p<sup>h</sup>ɛn], the vowel /ɛ/ is often produced with nasalization ([ɛ]), although this distribution is allophonic rather than contrastive (parallel to our allophonic rule of deaspiration). This nasalization results from coarticulation of nasalization: the gesture that causes nasality (raising of the velum) onsets early during the production of the vowel in anticipation of the nasal target of the following nasal stop. Like in our training data, the nasal variant of the vowel (e.g. [ɛ]) is less frequent and more contextually limited compared to the oral vowel (e.g. [ɛ]). In some varieties, in fact, a sound change in progress has been reported, whereby nasalization coarticulation gets progressively shorter with generations of speakers (Zellou and Tamminga, 2014; Tamminga and Zellou, 2015) (Zellou and Tamminga 2014 also report a reversal of sound change). In other words, the targets for nasalization during the vowels onset gradually later with younger generations of

speakers, which results in an oral [ɛ] rather than nasal [ɛ̄] in words like ['p<sup>h</sup>ɛn]. While this change is hypothesized to be driven by social factors (Tamminga and Zellou, 2015), it is just as likely that phonological pressures in the form of the oral vowels being the more common variant play a role in the initiation of the change.

## 5 Conclusion

The framework presented in this paper has several advantages for modeling language change. The networks are trained on raw acoustic inputs with no levels of abstraction or pre-extracted features. Deep convolutional network in the GAN framework need to learn to produce data from random noise and they never fully replicate the data, but produce innovative linguistically interpretable data. This means their output data are not replicates, but innovative original outputs. As argued elsewhere (Beguš, 2020b,a), the innovative outputs of the Generator are highly informative and often replicate stages in language acquisition. In this paper we additionally argue that the innovative outputs can result in phonetic and phonological changes when trained in iterative learning tasks.

The current model contains no articulatory information. While this is generally unideal, because human speech acquisition is highly influenced by articulators, it allows us to model language change as if only cognition-general mechanisms were involved in language acquisition and production. The results from the computational experiment suggest that both gradual change of targets that resembles phonetic change as well as phonological rule loss can emerge when deep convolutional networks are trained in iterative learning tasks without any articulatory information and without language-specific parameters in the model. In future work, we should be able to compare results of the articulation-free model with models containing articulatory information to get a better understanding of which properties of sound change can be derived from domain-general cognitive mechanisms and which properties of sound change require articulatory forces.

The current paper offers an initial step in a broader goal of modeling language’s cultural evolution based on generations of deep convolutional networks trained on raw speech. Far more complex interactions between agents can be conceived in future work. For example, GANs can be set to communicate with and learn from each other in interactive ways already during the training. Further modeling of this kind should shed light onto one of the most widely studied but still poorly understood phenomenon in language — sound change.

## Acknowledgements

This research was funded by a grant to new faculty at the University of Washington and the University of California, Berkeley. I would like to thank Sameer Arshad for slicing data from the TIMIT database.

## References

- Ahmed, S., Andersson, S., Vaux, B., 2020. English phonology and morphology. In: Aarts, B., Hinrichs, L., McMahon, A. (Eds.), *Handbook of English Linguistics*. Wiley.
- URL <https://www.wiley.com/en-gb/The+Handbook+of+English+Linguistics,+2nd+Edition-p-9781119540564>
- Arjovsky, M., Chintala, S., Bottou, L., 06–11 Aug 2017. Wasserstein generative adversarial networks. In: Precup, D., Teh, Y. W. (Eds.), *Proceedings of the 34th International Conference on Machine Learning*. Vol. 70 of *Proceedings of Machine Learning Research*. PMLR, International Convention Centre, Sydney, Australia, pp. 214–223.
- URL <http://proceedings.mlr.press/v70/arjovsky17a.html>
- Baker, A., 2008. Computational approaches to the study of language change. *Language and Linguistics Compass* 2 (2), 289–307.
- URL <https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1749-818X.2008.00054.x>
- Beguš, G., 2018a. Bootstrapping sound changes, submitted ms., University of Washington.
- URL [ling.auf.net/lingbuzz/004299](http://ling.auf.net/lingbuzz/004299)
- Beguš, G., 2018b. Post-nasal devoicing and the blurring process. *Journal of Linguistics*, 1–65.
- Beguš, G., 2020a. Ciwgan and fiwgan: Encoding information in acoustic data to model lexical learning with generative adversarial networks.
- Beguš, G., 2020b. Generative adversarial phonology: Modeling unsupervised phonetic and phonological learning with neural networks. *Frontiers in Artificial Intelligence* 3, 44.
- URL <https://www.frontiersin.org/article/10.3389/frai.2020.00044>
- Bell, A., 1970. A state-process approach to syllability and syllabic structure. Ph.D. thesis, Stanford University.
- Bell, A., 1971. Some patterns of the occurrence and formation of syllabic structure. *Working Papers on Language Universals* 6, 23–138.
- Bermúdez-Otero, R., Hogg, R. M., 2003. The actuation problem in optimality theory. In: Holt, D. E. (Ed.), *Optimality Theory and Language Change*. Springer Netherlands, Dordrecht, pp. 91–119.
- URL [https://doi.org/10.1007/978-94-010-0195-3\\_4](https://doi.org/10.1007/978-94-010-0195-3_4)
- Blevins, J., 2004. *Evolutionary Phonology*. Cambridge University Press, Cambridge.
- Boersma, P., Weenink, D., 2015. Praat: doing phonetics by computer [computer program]. version 5.4.06. Retrieved 21 February 2015 from <http://www.praat.org/>.
- Bond, Z. S., 1981. A note concerning /s/ plus stop clusters in the speech of language-delayed children. *Applied Psycholinguistics* 2 (1), 55–63.
- Bond, Z. S., Wilson, H. F., 1980. /s/ plus stop clusters in children's speech. *Phonetica* 37 (3), 149–158.
- URL <https://www.karger.com/DOI/10.1159/000259988>
- Buchwald, A., Miozzo, M., 2012. Phonological and motor errors in individuals with acquired sound production impairment. *Journal of Speech, Language, and Hearing Research* 55 (5), S1573–S1586.
- URL <https://pubs.asha.org/doi/abs/10.1044/1092-4388%282012/11-0200%29>
- Bybee, J., 2017. Grammatical and lexical factors in sound change: A usage-based approach. *Language Variation and Change* 29 (3), 273–300.

- Cathcart, C. A., 2015. A probabilistic model of Evolutionary Phonology. In: Bui, T., ldiz, D. O. (Eds.), Proceedings of the Forty-Fifth Annual Meeting of the North East Linguistic Society. GLSA, Amherst, MA, pp. 145–150, volume 1.
- Chomsky, N., Halle, M., 1968. The Sound Pattern of English. Harper & Row, New York.
- Davidson, L., 2016. Variability in the implementation of voicing in American English obstruents. *Journal of Phonetics* 54, 35–50.
- Davis, S., Cho, M.-H., 2006. The distribution of aspirated stops and /h/ in American English and Korean: an alignment approach with typological implications. *Linguistic* 41 (4), 607–652.
- de Boer, B., 2003. Conditions for stable vowel systems in a population. In: Banzhaf, W., Ziegler, J., Christaller, T., Dittrich, P., Kim, J. T. (Eds.), *Advances in Artificial Life*. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 415–424.
- Donahue, C., McAuley, J. J., Puckette, M. S., 2019. Adversarial audio synthesis. In: 7th International Conference on Learning Representations, ICLR 2019, New Orleans, LA, USA, May 6-9, 2019. OpenReview.net, pp. 1–16.  
URL <https://openreview.net/forum?id=ByMVTsR5KQ>
- Duran, D., Bruni, J., Dogil, G., Roux, J., 2017. The social life of setswana ejectives. In: Proc. Interspeech 2017. pp. 3787–3791.  
URL <http://dx.doi.org/10.21437/Interspeech.2017-922>
- Eloff, R., Nortje, A., van Niekerk, B., Govender, A., Nortje, L., Pretorius, A., Biljon, E., van der Westhuizen, E., Staden, L., Kamper, H., 09 2019. Unsupervised acoustic unit discovery for speech synthesis using discrete latent-variable neural networks. In: Proc. Interspeech 2019. pp. 1103–1107.
- Fruehwald, J., 2016. The early influence of phonology on a phonetic change. *Language* 92 (2), 376–410.
- Garofolo, J. S., Lamel, L., M Fisher, W., Fiscus, J., S. Pallett, D., L. Dahlgren, N., Zue, V., 11 1993. Timit acoustic-phonetic continuous speech corpus. Linguistic Data Consortium.
- Garrett, A., 2015. Sound change. In: Bowern, C., Evans, B. (Eds.), *The Routledge Handbook of Historical Linguistics*. Routledge, New York, pp. 227–248.
- Garrett, A., Johnson, K., 2013. Phonetic bias in sound change. In: Yu, A. C. L. (Ed.), *Origins of Sound Change: Approaches to Phonologization*. Oxford University Press, Oxford, pp. 51–97.
- Gaskell, M., Hare, M., Marslen-Wilson, W. D., 1995. A connectionist model of phonological representation in speech perception. *Cognitive Science* 19 (4), 407 – 439.  
URL <http://www.sciencedirect.com/science/article/pii/0364021395900071>
- Gilbert, J. H. V., 1977. A voice onset time analysis of apical stop production in 3-year-olds. *Journal of Child Language* 4 (1), 103–110.
- Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., Bengio, Y., 2014. Generative adversarial nets. In: Ghahramani, Z., Welling, M., Cortes, C., Lawrence, N. D., Weinberger, K. Q. (Eds.), *Advances in Neural Information Processing Systems 27*. Curran Associates, Inc., pp. 2672–2680.  
URL <http://papers.nips.cc/paper/5423-generative-adversarial-nets.pdf>
- Hansson, G., 2008. Diachronic explanations of sound patterns. *Language and Linguistics Compass* 2, 859–893.
- Hare, M., Elman, J. L., 1995. Learning and morphological change. *Cognition* 56 (1), 61 – 98.  
URL <http://www.sciencedirect.com/science/article/pii/0010027794006555>

- Hayes, B., Londe, Z. C., 2006. Stochastic phonological knowledge: the case of hungarian vowel harmony. *Phonology* 23 (1), 59–104.
- Honeybone, P., 2016. Are there impossible changes?  $\theta > f$  but  $f \not> \theta$ . *Papers in Historical Phonology* 1, 316–358.
- Hussain, Q., Mielke, J., 2020. An acoustic and articulatory study of laryngeal and place contrasts of kalasha (indo-aryan, dardic). *The Journal of the Acoustical Society of America* 147 (4), 2873–2890.  
URL <https://doi.org/10.1121/10.0000999>
- Hyman, L. M., 1976. Phonologization. In: Julland, A. (Ed.), *Linguistic studies presented to Joseph H. Greenberg*. Anna Libri, Saratoga, CA, pp. 407–418.
- Hyman, L. M., 2013. Enlarging the scope of phonologization. In: Yu, A. C. L. (Ed.), *Origins of Sound Change: Approaches to Phonologization*. Oxford University Press, Oxford, pp. 3–28.
- Iverson, G. K., Salmons, J. C., 1995. Aspiration and laryngeal representation in germanic. *Phonology* 12 (3), 369–396.  
URL <http://www.jstor.org/stable/4420084>
- Johnson, K., 1997. Speech perception without speaker normalization: An exemplar model. In: *Talker variability in speech processing*. Academic Press, San Diego, CA, pp. 145–165.
- Kapatsinski, V., 2018. *Changing Minds Changing Tools: From Learning Theory to Language Acquisition to Language Change*. MIT Press, Cambridge.
- Kello, C., Plaut, D., 04 2003. The interplay of perception and production in phonological development: Beginnings of a connectionist model trained on real speech. In: Solé, M. J., Recasens, D., Romero, J. (Eds.), *5th International Congress of Phonetic Sciences*, Barcelona, Spain, August 3-9, 2003. pp. 297–300.  
URL <http://www.internationalphoneticassociation.org/icphs/icphs2003>
- Kiparsky, P., 1965. Phonological change. Ph.D. thesis, Massachusetts Institute of Technology.
- Kiparsky, P., 2006. Amphichronic program vs. Evolutionary Phonology. *Theoretical Linguistics* 32 (2), 217–236.
- Kiparsky, P., 2008. Universals constrain change, change results in typological generalizations. In: Good, J. (Ed.), *Linguistic universals and language change*. Oxford University Press, Oxford, pp. 23–53.
- Kirby, J., Sonderegger, M., Jul. 2015. Bias and population structure in the actuation of sound change. arXiv e-prints, arXiv:1507.04420.
- Klatt, D. H., 1975. Voice onset time, frication, and aspiration in word-initial consonant clusters. *Journal of Speech and Hearing Research* 18 (4), 686–706.  
URL <https://pubs.asha.org/doi/abs/10.1044/jshr.1804.686>
- Kümmel, M., 2007. *Konsonantenwandel*. Reichert, Wiesbaden.
- Ladefoged, P., 2003. *Phonetic Data Analysis: An Introduction to Fieldwork and Instrumental Techniques*. Blackwell, Malden, MA.
- Lisker, L., 1984. How is the aspiration of english /p, t, k/ "predictable"? *Language and Speech* 27 (4), 391–394.  
URL <https://doi.org/10.1177/002383098402700409>
- Livingstone, D., 2002. The evolution of dialect diversity. In: Cangelosi, A., Parisi, D. (Eds.), *Simulating the Evolution of Language*. Springer London, London, pp. 99–117.  
URL [https://doi.org/10.1007/978-1-4471-0663-0\\_5](https://doi.org/10.1007/978-1-4471-0663-0_5)

- Lowenstein, J. H., Nittrouer, S., 2008. Patterns of acquisition of native voice onset time in english-learning children. *The Journal of the Acoustical Society of America* 124 (2), 1180–1191.  
URL <https://doi.org/10.1121/1.2945118>
- Macken, M. A., Barton, D., 1980. The acquisition of the voicing contrast in English: a study of voice onset time in word-initial stop consonants. *Journal of Child Language* 7 (1), 41–74.
- McClelland, J. L., Elman, J. L., 1986. The trace model of speech perception. *Cognitive Psychology* 18 (1), 1 – 86.  
URL <http://www.sciencedirect.com/science/article/pii/0010028586900150>
- McLeod, S., van Doorn, J., Reed, V., 1996. Homonyms and cluster reduction in the normal development of children's speech. In: Proceedings of the Sixth Australian International Conference on Speech Science & Technology. pp. 331–336.
- Moreton, E., Pater, J., 2012. Structure and substance in artificial-phonology learning. Part II, Substance. *Language and Linguistics Compass* 6 (11), 702–718.
- Moreton, E., Pater, J., Pertsova, K., 2017. Phonological concept learning. *Cognitive Science* 41 (1), 4–69.  
URL <https://onlinelibrary.wiley.com/doi/abs/10.1111/cogs.12319>
- Nettle, D., 1999. Using social impact theory to simulate language change. *Lingua* 108 (2), 95 – 117.  
URL <http://www.sciencedirect.com/science/article/pii/S0024384198000461>
- Ohala, J. J., 1981. The listener as a source of sound change. In: Masek, C. S., Hendrick, R. A., Miller, M. F. (Eds.), Papers from the Parasession on Language and Behavior. Chicago Linguistic Society, Chicago, pp. 178–203.
- Paul, H., 1880. *Principien der Sprachgeschichte*. Max Niemeyer, Halle.
- Pierrehumbert, J., 2001. Exemplar dynamics: Word frequency, lenition, and contrast. In: Bybee, J. L., Hooper, P. J. (Eds.), Frequency Effects and the Emergence of Lexical Structure. John Benjamins, Amsterdam, pp. 137–157.
- Plaut, D. C., Kello, C. T., 1999. The emergence of phonology from the interplay of speech comprehension and production: A distributed connectionist approach. In: MacWhinney, B. (Ed.), The emergence of language. Lawrence Erlbaum Associates Publishers, Mahwah, NJ, US, pp. 381–415.
- Prince, A., Smolensky, P., 1993/2004. Optimality Theory: Constraint Interaction in Generative Grammar. Blackwell, Malden, MA, first published in Tech. Rep. 2, Rutgers University Center for Cognitive Science.
- R Core Team, 2018. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria.  
URL <https://www.R-project.org/>
- Radford, A., Metz, L., Chintala, S., 2015. Unsupervised representation learning with deep convolutional generative adversarial networks. arXiv preprint arXiv:1511.06434.
- Räsänen, O., Nagamine, T., Mesgarani, N., 08 2016. Analyzing distributional learning of phonemic categories in unsupervised deep neural networks. CogSci ... Annual Conference of the Cognitive Science Society. Cognitive Science Society (U.S.). Conference 2016, 1757–1762.  
URL <https://pubmed.ncbi.nlm.nih.gov/29359204>
- Rentz, B., 2017. spectral\_moments.praat. praat script.  
URL [https://github.com/rentzb/praat-scripts/blob/master/spectral\\_moments.praat](https://github.com/rentzb/praat-scripts/blob/master/spectral_moments.praat)
- Saffran, J. R., Thiessen, E. D., 2003. Pattern induction by infant language learners. *Developmental psychology* 39 (3), 484–494.

- Shain, C., Elsner, M., Jun. 2019. Measuring the perceptual availability of phonological features during language acquisition using unsupervised binary stochastic autoencoders. In: Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers). Association for Computational Linguistics, Minneapolis, Minnesota, pp. 69–85.  
 URL <https://www.aclweb.org/anthology/N19-1007>
- Sóskuthy, M., Mar 2017. Generalised additive mixed models for dynamic analysis in linguistics: a practical introduction. arXiv e-prints, arXiv:1703.05339.
- Stevens, M., Harrington, J., Schiel, F., 2019. Associating the origin and spread of sound change using agent-based modelling applied to /s/-retraction in english. *Glossa: A Journal of General Linguistics* 4 (1), 8.
- Tamminga, M., Zellou, G., 08 2015. Cross-dialectal differences in nasal coarticulation in american english. Proceedings of the 18th International Congress of Phonetic Sciences (ICPhS XVIII, Glasgow), 0745.
- Tifrit, A., Voeltzel, L., 2016. All rules precede all syntagmatic natural processes? *Glossa: A Journal of General Linguistics* 1 (10).
- van de Velde, H., Gerritsen, M., van Hout, R., 1996. The devoicing of fricatives in standard dutch: A real-time study based on radio recordings. *Language Variation and Change* 8 (2), 149–175.
- Vaux, B., 2002. Aspiration in English, ms., Harvard University. Accessed on June 27, 2019.  
 URL [https://www.academia.edu/300605/Aspiration\\_In\\_English](https://www.academia.edu/300605/Aspiration_In_English)
- Vaux, B., Samuels, B., 2005. Laryngeal markedness and aspiration. *Phonology* 22 (3), 395–436.
- Wedel, A., 2006. Exemplar models, evolution and language change. *The Linguistic Review* 23 (3), 247–274.  
 URL <https://www.degruyter.com/view/j/tlir.2006.23.issue-3/tlr.2006.010/tlr.2006.010.xml>
- Wood, S. N., 2011. Fast stable restricted maximum likelihood and marginal likelihood estimation of semi-parametric generalized linear models. *Journal of the Royal Statistical Society (B)* 73 (1), 3–36.
- Yang, J., 2018. Development of stop consonants in three- to six-year-old mandarin-speaking children. *Journal of Child Language* 45 (5), 1091–1115.
- Zellou, G., Tamminga, M., 2014. Nasal coarticulation changes over time in philadelphia english. *Journal of Phonetics* 47, 18 – 35.  
 URL <http://www.sciencedirect.com/science/article/pii/S0095447014000734>
- Zymet, J., 2018. Lexical propensities in phonology: corpus and experimental evidence, grammar, and learning. Ph.D. thesis, University of California, Los Angeles.

## A Appendix

A. parametric coefficients	Estimate	Std. Error	t-value	p-value
(Intercept) = #sTV	2851.0891	21.9554	129.8580	< 0.0001
#TV	110.3979	29.9005	3.6922	0.0002
B. smooth terms	edf	Ref.df	F-value	p-value
s(GENERATION) = #sTV	2.5277	2.5652	8.0885	0.0006
s(GENERATION):#TV	1.0006	1.0007	2.4167	0.1201
s(PERCENT) = #sTV	4.1403	5.0016	58.7212	< 0.0001
s(PERCENT):#TV	5.6734	6.7431	21.2203	< 0.0001
s(DURATION) = #sTV	3.0980	3.1985	13.7967	< 0.0001
s(DURATION):#TV	4.1206	4.2611	2.2167	0.0624
ti(PERCENT,GENERATION) = #sTV	5.6734	7.3919	1.3457	0.2180
ti(PERCENT,GENERATION):#TV	9.5814	12.3519	1.7253	0.0563
ti(DURATION,GENERATION) = #sTV	10.3210	10.8199	1.7353	0.0767
ti(DURATION,GENERATION):#TV	1.0038	1.0042	0.1402	0.7096
ti(DURATION,PERCENT) = #sTV	11.3020	12.4611	8.9140	< 0.0001
ti(DURATION,PERCENT):#TV	5.8098	6.8613	4.9689	< 0.0001
s(PERCENT,TRAJECTORY,bs = "fs",m=1)	3166.1177	10864.0000	1.2998	< 0.0001

Table 7: Estimates of the generalized additive mixed effects model with COG as the dependent variable. The model includes the parametric term STRUCTURE (treatment-coded with #sTV as the reference level) and thin plate smooths for absolute DURATION, PERCENT of VOT duration, and GENERATION, limited to 4 knots and random smooths for each trajectory. The model includes all two-way tensor product interactions.

A. parametric coefficients	Estimate	Std. Error	t-value	p-value
(Intercept) = #sTV	1.0995	0.0222	49.6085	< 0.0001
#TV	-0.0753	0.0300	-2.5134	0.0120
B. smooth terms	edf	Ref.df	F-value	p-value
s(GENERATION)= #sTV	1.0001	1.0001	0.7932	0.3732
s(GENERATION):#TV	1.0000	1.0000	0.2621	0.6087
s(PERCENT) = #sTV	3.5668	4.3585	45.4869	< 0.0001
s(PERCENT):#TV	4.0558	4.9625	19.2470	< 0.0001
s(DURATION) = #sTV	3.3745	3.5492	11.0218	< 0.0001
s(DURATION):#TV	3.0015	3.1647	0.7124	0.5352
ti(PERCENT,GENERATION) = #sTV	1.0001	1.0001	3.8582	0.0495
ti(PERCENT,GENERATION):#TV	4.8661	6.3659	2.4462	0.0264
ti(DURATION,GENERATION) = #sTV	1.0001	1.0001	0.4104	0.5218
ti(DURATION,GENERATION):#TV	1.0002	1.0002	0.0277	0.8679
ti(DURATION,PERCENT) = #sTV	11.8866	13.3683	10.9157	< 0.0001
ti(DURATION,PERCENT):#TV	4.0359	5.0538	1.4901	0.1627
s(PERCENT,TRAJECTORY,bs = "fs",m=1)	2364.7832	10864.0000	0.6582	< 0.0001

Table 8: Estimates of the generalized additive mixed effects model with Skew as the dependent variable. The model includes the parametric term STRUCTURE (treatment-coded with #sTV as the reference level) and thin plate smooths for absolute DURATION, PERCENT of VOT duration, and GENERATION, limited to 4 knots and random smooths for each trajectory. The model includes all two-way tensor product interactions.

A. parametric coefficients	Estimate	Std. Error	t-value	p-value
(Intercept) = #sTV	1.7897	0.0804	22.2580	< 0.0001
#TV	0.1426	0.1057	1.3487	0.1775
B. smooth terms	edf	Ref.df	F-value	p-value
s(GENERATION)= #sTV	2.7896	2.8498	9.8579	< 0.0001
s(GENERATION):#TV	1.7272	1.8634	0.7376	0.4462
s(PERCENT)= #sTV	4.5849	5.6104	10.9902	< 0.0001
s(PERCENT):#TV	1.6770	2.0465	19.0525	< 0.0001
s(DURATION)= #sTV	4.1470	4.5475	7.7653	< 0.0001
s(DURATION):#TV	1.0000	1.0000	0.7506	0.3863
ti(PERCENT,GENERATION)= #sTV	1.9587	2.2062	6.0669	0.0017
ti(PERCENT,GENERATION):#TV	1.0002	1.0004	5.5611	0.0184
ti(DURATION,GENERATION)= #sTV	1.0004	1.0005	2.5465	0.1106
ti(DURATION,GENERATION):#TV	1.0002	1.0003	0.3882	0.5333
ti(DURATION,PERCENT)= #sTV	11.7809	13.5848	11.1060	< 0.0001
ti(DURATION,PERCENT):#TV	1.7229	1.9216	0.4682	0.5861
s(PERCENT,TRAJECTORY,bs = "fs",m=1)	1543.5132	10864.0000	0.2827	< 0.0001

Table 9: Estimates of the generalized additive mixed effects model with Kurtosis as the dependent variable. The model includes the parametric term STRUCTURE (treatment-coded with #sTV as the reference level) and thin plate smooths for absolute DURATION, PERCENT of VOT duration, and GENERATION, limited to 4 knots and random smooths for each trajectory. The model includes all two-way tensor product interactions.

A. parametric coefficients	Estimate	Std. Error	t-value	p-value
(Intercept) = #sTV	1506.5772	5.3036	284.0665	< 0.0001
#TV	-58.5769	6.9805	-8.3915	< 0.0001
B. smooth terms	edf	Ref.df	F-value	p-value
s(GENERATION)= #sTV	2.9165	2.9493	54.3544	< 0.0001
s(GENERATION):#TV	1.9670	2.1560	10.5145	< 0.0001
s(PERCENT) = #sTV	6.5730	7.6910	9.5337	< 0.0001
s(PERCENT):#TV	3.4464	4.2477	5.0991	0.0003
s(DURATION)= #sTV	5.1565	5.7368	24.4827	< 0.0001
s(DURATION):#TV	1.0003	1.0004	5.2345	0.0222
ti(PERCENT,GENERATION)= #sTV	14.1105	17.9717	2.6478	0.0002
ti(PERCENT,GENERATION):#TV	1.3648	1.5431	1.4046	0.1664
ti(DURATION,GENERATION)= #sTV	1.0005	1.0007	1.9439	0.1634
ti(DURATION,GENERATION):#TV	2.0627	2.3099	1.1559	0.4356
ti(DURATION,PERCENT)= #sTV	6.4038	8.2036	6.0598	< 0.0001
ti(DURATION,PERCENT):#TV	1.9721	2.2224	1.1459	0.3054
s(PERCENT,TRAJECTORY,bs = “fs”,m=1)	1226.7901	10864.0000	0.1875	< 0.0001

Table 10: Estimates of the generalized additive mixed effects model with SD as the dependent variable. The model includes the parametric term STRUCTURE (treatment-coded with #sTV as the reference level) and thin plate smooths for absolute DURATION, PERCENT of VOT duration, and GENERATION, limited to 4 knots and random smooths for each trajectory. The model includes all two-way tensor product interactions.