Understanding change through stability: a computational study of sound change actuation

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Abstract

Many approaches to sound change attempt to derive common patterns of sound change from universal pressures, such as physiological and psychoacoustic constraints on speech. Accounts of this type face the following problem: it is not clear why universal pressures only lead to changes in some languages, but not in others. This issue is part of the so-called actuation problem. The question of sound change actuation is usually addressed by referring to social factors and individual differences that may inhibit or encourage the spread of a sound change in a community. While this paper acknowledges the importance of such explanations, it argues that some aspects of sound change actuation can also be approached by looking at structural factors that are typically associated with the initiation of sound change. I use computational simulations to investigate the evolution of sound systems under multiple pressures. The simulated sound systems evolve towards stable states in adaptive landscapes defined partly by universal pressures (e.g. phonetic biases and contrast maintenance) and partly by language-specific factors (e.g. the relative frequency of specific phonetic environments). The former create common pathways of change, while the latter lead to cross-linguistic variation. As it will be shown, this approach can account both for stability and change. The simulations also demonstrate how language-specific factors can be used to make predictions about the stable states towards which sound systems converge.

Keywords: sound change; actuation problem; phonetic bias; contrast maintenance; computational simulation

1. Introduction

The main goal of this paper is to contribute to our understanding of how sound changes are constrained, and, specifically, why a given change may be more likely to take place in certain languages and varieties than in others. This issue is often referred to as the *actuation problem* (Weinreich et al., 1968; Baker et al. 2011). Many accounts of sound change identify two hurdles that need to be overcome for a sound change to take place. First, some speakers need to produce speech that deviates from the conventional speech targets of their community. Their innovative speech patterns then need to spread to a substantial number of other speakers within their speech community. These steps are usually referred to as the *initiation* and the *spread* of sound change (cf. Milroy and Milroy, 1985:347–348; Ohala, 1993:268; Janda and Joseph, 2003:17–18; Stevens and Harrington, 2014:4). When talking about constraints on sound change, the notions of initiation and spread are often used in rather different ways. Approaches to sound change that focus on initiation (e.g. Ohala, 1981, 1993; Blevins, 2004; Pierrehumbert, 2001) typically look at how universal properties of speech production and perception constrain sound change. One important finding that has emerged from these approaches is that cross-linguistically common sound changes can almost always be traced to universal phonetic biases (Blevins, 2004:8–10). Research on the spread of sound change (Weinreich et al., 1968; Milroy, 1992; Labov, 2001) tends to have a different orientation: while it also incorporates some cross-linguistic elements, it puts a stronger emphasis on social patterns that are specific to the community under investigation. These patterns are seen as the main determinants of the paths along which innovations spread in a community. For instance, Labov's (1963) classic study of the English variety spoken on Martha's Vineyard established that the degree of centralisation of /ay/ and /aw/ (an ongoing sound change on the island) correlated strongly with speakers' attitudes towards life on the island, as well as a range of other factors including age, gender and occupation. This differential focus on cross-linguistic *versus* language-specific patterns has led some researchers to posit that studies looking at sound change initiation should not concern themselves with the actuation puzzle, since it can only be solved by looking at the spread of sound change (e.g. Ohala, 1993:268).

The view of sound change presented in this paper fully acknowledges the crucial role of social factors and population dynamics in the actuation of sound change. However, I will argue that factors traditionally associated with the initiation of sound change should also form an important part of research into the actuation problem. These include articulatory and perceptual pressures (e.g. Paul, 1880; Ohala 1981; Blevins, 2004; Garrett and Johnson, 2013), a tendency towards the maintenance of lexical contrasts (e.g. Martinet, 1952; Campbell, 1975; Antilla, 1989; Labov, 1994; Wedel, 2006), innate learning biases (e.g. Chomsky and Halle 1968; Saffran, 2002; Moreton, 2008) and a range of other factors. In this paper, I refer to these as *universal pressures* on sound change, since they follow from general properties of human cognition and the human speech apparatus. It has been argued that such pressures cannot provide insight into the actuation problem precisely because of their universality: how could they account for cross-linguistic differences if they are present in every speaker (see e.g. Weinreich et al., 1968:111–112)? According to this argument, accounts of sound change actuation based on universal pressures cannot explain 'why language fails to change' (Weinreich et al., 1968:112). I will show that this problem arises only when we look at sound changes in a vacuum, that is, changes to a single sound category under the influence of a single universal pressure. When we consider sound systems affected by multiple interacting pressures, we get more varied and realistic predictions, which can help us understand certain types of cross-linguistic differences.

To illustrate the problems outlined above, consider the two universal pressures that are the focus of this paper: *phonetic biases* and *contrast maintenance*. Phonetic biases are physiological and psychoacoustic constraints on speech. Contrast maintenance refers to a tendency for contrastive sound categories to remain well separated in phonetic space. Many scholars view these pressures as having ontologically different effects acting in opposite directions. Thus, phonetic biases are claimed to *enable* sound change by creating the variation that serves as its source (see e.g. Ohala, 1981, 1989; Labov, 1994; Blevins, 2004), while contrast maintenance *inhibits* sound change when it would endanger phonological oppositions (see e.g. Campbell, 1975; Antilla, 1989; Blevins and Wedel, 2009). While the precise effects of these two universal pressures may be somewhat more complicated (e.g. contrast maintenance itself may act as an active force that creates more contrastive variants, instead of simply inhibiting ongoing changes), it is clear that they can interact with each other. However, the details of this interaction remain unclear. How can we predict which pressure gains the upper hand in a particular language, leading to a particular type of change (or the absence of change)? This is a clear manifestation of the actuation problem referred to above.

This paper will suggest that the actuation problem and the interaction between different universal pressures on sound change are closely related. If we understand how the competition among opposing pressures is resolved, we also gain at least a partial answer to the question of why certain changes can go ahead while others are inhibited. I will argue that the interaction among universal pressures is not simply either-or. Their relative strengths in a given sound system are determined by language-specific factors. For instance, the effects of phonetic biases and contrast maintenance are mediated by lexical factors such as *functional load* and the relative frequency with which a specific category occurs in a biasing environment (henceforth *bias proportion*; these factors and their roles in sound change will be discussed in more detail below). We can view these language-specific factors as the context in which universal pressures apply. Sometimes, this context will be highly conducive for a given pressure, leading to a strong and visible effect. Other times, this context will not provide many opportunities for the universal pressure to apply, and it will not produce a strong effect. Since these factors are dependent upon specific properties of a given language at a given time, I refer to them as *contingent factors*.

As it will be shown, universal pressures and contingent factors define complex adaptive landscapes, which determine the possible pathways followed by sound systems during their evolution. If a particular sound system lies in an unstable part of the adaptive landscape, it will tend to move away from it. Conversely, if it is located in a stable part of the adaptive landscape, it will remain there. Since the shape of this adaptive landscape is determined partly by universal pressures, certain stable states will be cross-linguistically more frequent than others. However, cross-linguistic variation in contingent factors will dilute the strength of these universal tendencies.

An important part of the argument summarised above is the claim that the predictions made on the basis of universal pressures and contingent factors are primarily about the properties of stable sound systems, and only indirectly about the probability of sound change itself. Although this may seem like a subtle difference, it has far-reaching consequences. First, an account that predicts stable states clearly avoids the overprediction problem stated by Weinreich et al. (1968) and Baker et al. (2013): universal pressures on sound change do not always lead to change, since the systems seek equilibria defined by multiple competing pressures. Once such an equilibrium has been found, the system will tend to stay there even if it is suboptimal with respect to some of the pressures (e.g. they satisfy one phonetic bias but not a different one). Second, the predictions of these models relate to sound systems at specific points in time and their testing does not necessarily require longitudinal data. This makes it much easier to evaluate their validity. Third, stable states allow us to investigate the interactions among multiple pressures in a straightforward manner, which is more difficult to do in a model looking at the likelihood of changes.

This paper uses computer simulations to show how the argument summarised above derives from a popular model of sound change relying on plausible assumptions about speech production and perception (Pierrehumbert, 2001; Wedel, 2006; Stanford and Kenny, 2013; Garrett and Johnson, 2013). The simulations will be used clarify the roles of universal pressures and contingent factors in sound change and illustrate the notions of adaptive landscapes and stable states in the context of sound systems. Moreover, they exemplify the predictions that this type of model generates. In order to make the discussion easier to follow, the simulations are based on a specific phenomenon: the fronting of /u/ in the context of coronal consonants (cf. Harrington et al. 2008, 2011). However, it is important to emphasise that the goal of these simulations is not to investigate a particular phenomenon, but to make the main argument of the paper more concrete. Wedel (2011:135) describes this type of simulation as ‘an existence proof that a given structure can arise through interactions between some defined set of system properties, and/or […] a supporting illustration for verbal or analytic arguments.' Therefore, in the discussion of the simulation results, the main focus will be on the broad dynamics of the simulated systems. I do not test the empirical validity of the specific predictions of the model with respect to /u/-fronting (although I believe a research programme focusing on these predictions would certainly be worth pursuing).

The main argument of the paper is delivered as follows. In Section 2, I provide an overview of existing approaches to sound change and the actuation problem, a brief summary of computational approaches to sound change and some justification for the main assumptions of the model of speech production and perception used in the simulations. Then, I present a technical description of the modelling architecture used in this paper (Section 3). Section 4 describes the results of three different sets of simulations: one focusing on the effects of phonetic biases, another one focusing on contrast maintenance, and the last one looking at the interaction between these two pressures. As it will be shown, all of these simulations lead to stable states. In Section 5, I discuss the implications of these findings. I also show that while the model predicts stable states, this does not mean that sound change will never occur again once a stable state has been reached. In other words, addressing the overprediction issue referred above does not necessarily create an underprediction issue. Finally, Section 6 presents the conclusions of the paper.

2. Background

2.1 Sound change and the actuation problem

This section provides a brief overview of previous research on sound change and the actuation problem. In the first half of this overview, I focus on approaches which seek to link sound change to one specific type of universal pressure, namely phonetic biases. In the second half, I look at recent attempts to reconcile these approaches with the actuation problem. This review of the literature (based partly on Stevens and

Harrington, 2014) will help to clarify where the current approach differs from previous ones and where its main contributions lie.

For the purposes of the following discussion, I adopt the following three-step breakdown of sound change based on Lindblom et al. (1995:16), which is slightly more detailed than the two-step breakdown discussed in the introduction (i.e. initiation *vs.* spread):

(1) a. generation of innovative variants;
  b. (possibly erroneous) transmission of variants from one speaker to another;
  c. spread of the variant across the speech community.

This scheme is adopted purely for convenience. As it will be shown, different approaches to sound change and the actuation problem emphasise different parts of (1). Therefore, the steps in (1) can be used to compare these approaches in a single conceptual framework even when their underlying assumptions are very different. I do not mean to suggest that an empirically adequate model of sound change necessarily has to distinguish between or account for all these steps.

Since the approaches discussed in this section all rely heavily on the notion of phonetic biases, it will be useful to provide a definition. In this paper, the term *phonetic bias* is used to refer to low-level, universal properties of speech production and perception. One example is vowel undershoot: speakers often fail to reach the phonetic target for vowels in prosodically weak positions (e.g. in unstressed syllables; cf. Lindblom, 1963; Szeredi, 2010), resulting in slightly less peripheral productions. This tendency arguably originates in simple physical properties of the articulators (such as their speed), which have little to do with the speakers' intentions or learnt phonetic patterns (which is not to say that the resulting patterns do not have learnt aspects). Since such physical properties are typically shared by most humans (perhaps with small variations), the effects of vowel undershoot are universally observable, although these effects may often be very small (Gendrot and Adda-Decker, 2007). Other examples of universal phonetic biases include aerodynamic constraints, various patterns of coarticulation and many more examples of phonetic ‘weakening’ or ‘lenition’ (see Garrett and Johnson, 2013 for a comprehesive discussion of phonetic biases).

The model of sound change originally proposed by Ohala (1981, 1989, 1993) and further developed by Blevins (2004, 2006) focuses explicitly on steps (1a–b) to the exclusion of step (1c) (see e.g. Ohala, 1993:238; Blevins, 2004:19). The starting point for this model is the observation that speech variation due to phonetic biases (cf. step (1a)) is a ubiquitous property of human languages, but such variation in itself does not constitute sound change. This is because (i) this type of variation is unintentional on the part of the speakers, and therefore arguably not learnt and (ii) listeners can typically compensate for the influence of phonetic biases in their perception (Ohala, 1993:244–245). For instance, the acoustic quality of the sound [s] may shift towards [ʃ] when followed by a rounded [u]. However, listeners can compensate for this effect by shifting their perceptual boundaries between [s] and [ʃ] and successfully recognise the intended sound as [s] (Mann and Repp, 1980). In Ohala’s and Blevins’ models, this compensation may occasionally fail to take place (or it may overapply), leading to ‘mini sound changes’ (Ohala, 1993:243). This corresponds to step (1b). Mini sound changes can, in turn, be transformed into real sound changes if an innovative variant that comes by through misperception spreads across the community (1c). According to Ohala (1993:244), ‘it is probably a rare thing for one speaker’s innovative pronunciation to spread via imitation to sizable numbers of other speakers’, which explains why mini sound changes rarely lead to community-wide sound changes. Thus, although this model focuses on steps (1a) and (1b), it invokes step (1c) to explain why only a small set of universal pressures lead to sound changes in a given language.

Lindblom et al. (1995) propose a slightly different model of sound change, which incorporates all three of the steps shown in (1). According to Lindblom (1990), speakers can manipulate the phonetic characteristics of their utterances to achieve different degrees of hypo and hyperarticulation, which can result in a wide range of surface variants. For instance, hypoarticulated speech will contain more centralised vowel realisations, while hyperarticulated speech will contain more peripheral vowel realisations. As this example shows, phonetic biases in production play a central role in this account as well as in Ohala's. This type of variation corresponds to step (1a). Lindblom et al. (1995) argue that listeners are typically in the 'what'-mode of perception, focusing on the contents of the speaker's utterances and abstracting away from the effects of shifts along the hypo and hyperarticulation continuum (potentially using mechanisms that are similar to the ones invoked by Ohala and Blevins). However, listeners may occasionally shift their mode of perception to the 'how'-mode, allowing them to store 'raw' phonetic material without controlling for contextual variation. In such a scenario, the innovative form may be transmitted from one speaker to another, which corresponds to step (1b). As these innovative forms are transmitted across speakers, they submit them to 'Articulatory, Perceptual, Social and Systemic Evaluation'; this evaluation (similarly to variation in speech production) is also 'structured, by and large, along the H&H dimension' (Lindblom et al., 1995:19–20). Lindblom and colleagues argue that a change may fail to spread across the community (step (1c)) if it results in perceptually more 'confusable' or articulatorily more challenging forms (Lindblom et al., 1995:20). This means that the speaker can affect the outcome of a possible sound change both at steps (1a) and (1c).

By allowing hyperarticulation as well as hypoarticulation as possible outcomes of variation in speech production, Lindblom et al.'s (1995) model can account for phenomena such as fortition and contrast maintenance, whose sources are less clear in Ohala's and Blevins' models (but see Blevins, 2004:285–291 for a contrast-based account of chain shifts). Lindblom et al. (1995:24) also argue that speakers strive towards 'a balance between intelligibility and articulatory energetics' both in producing and repeating innovative forms, which means that they acknowledge the role of competing pressures in sound change. However, they do not provide an account of how this competition is resolved. Moreover, they also do not clarify under what circumstances listeners will shift to the 'how'-mode of perception (see below for a more nuanced approach to this question by Garrett and Johnson, 2013), and it is not clear when a sound change can be kept in check by 'Articulatory, Perceptual, Social and Systemic Evaluation' by members of the speech community. Therefore, similar to Ohala and Blevins, Lindblom et al. (1995) do not provide a model-internal mechanism that could explain why universal pressures only lead to changes in some languages.

Usage-based models of sound change (Pierrehumbert, 2001; Bybee, 2002; Phillips, 2006; Silverman, 2006, 2012; Wedel, 2006) also tend to focus on steps (1a) and (1b), although they are capable of accounting for some aspects of (1c) as well (see e.g. Foulkes and Docherty, 2006; Docherty and Foulkes, 2014). The models outlined in the previous paragraphs represent phonetic variation at a relatively abstract level, and conceptualise sound change as the replacement of one categorical variant with a different one. To give an example, Ohala (1981) illustrates his misperception-based approach to sound change by suggesting that a string of sounds originally 'intended' as /ut/ by the speaker may be realised with a vowel that is closer to [y] (as a result of coarticulation between the vowel and the consonant; Ohala, 1981:183–184). The listener may then reconstruct the target vowel as /y/, leading to a mini sound change. In fact, Ohala (1993) argues that "[i]n most cases the 'before' and 'after' states [in a mini sound change] could be contrasting sounds or sound sequences in some human language" (Ohala, 1993:266). In contrast, usage-based models often deal with variation at a more fine-grained level, typically modelling phonetically gradual changes that proceed in small increments (e.g. Pierrehumbert, 2001). Therefore, there is a sense in which the models described in the previous paragraphs and usage-based models can be viewed as complementary: the former can provide a clear account of changes such as /k^w/ > /p/, which are 'articulatorily discontinuous' (Hansson 2008:863), while the latter can account for phonetically gradual changes. Note, however, that this complementarity is rarely exploited or even acknowledged in research within these different frameworks.

There are two crucial assumptions about production, perception and learning that are typically shared by usage-based accounts of sound change (e.g. Bybee, 2001; Pierrehumbert, 2001): (i) category representations include probabilistic knowledge of fine phonetic variation and (ii) speakers continue to update these representations on the basis of their linguistic experience throughout their lifetime. Models of sound change incorporating these assumptions along with phonetic biases can implement an important mechanism called the *production-perception feedback* *loop* (Pierrehumbert, 2001). This mechanism can account for the gradual incorporation of the effects of automatic low-level phonetic biases into category representations. The basic idea is as follows. Phonetic targets are chosen on the basis of the speakers' learnt probabilistic category representations. Due to the effects of phonetic biases, these targets are not implemented entirely faithfully: for instance, vowel undershoot may shift a phonetic target [a] towards a less peripheral [ɐ] realisation in unstressed syllables. The generation of these potentially biased variants corresponds to step (1a). The output tokens are fed back into the speakers' and the listeners' category representations (1b). If a given phonetic bias applies more or less consistently to tokens from a specific category, these slightly modified tokens will keep 'nudging' the overall category representation towards the location specified by the phonetic bias, potentially resulting in large-scale shifts over time. For instance, a category originally realised as [a] may gradually shift towards [ɐ] or even [ə] in unstressed syllables as the distorted variants created by vowel undershoot keep being added to its representation. Importantly, usage-based models are similar to the other models described above in that they do not typically identify the circumstances under which this process of change through positive feedback could be inhibited, although Blevins and Wedel (2009) do suggest that contrast maintenance may play such an inhibiting role in certain cases.

In sum, the models reviewed above provide crucial insight into the way universal pressures such as phonetic biases may lead to sound change, but they cannot answer the question of why universal pressures do not affect all languages in the same way. Ohala (1993:268) explicitly states that such questions are of little relevance to research directed at the phonetic bases of sound change, and suggests that researchers in this area should restrict their attention to steps (1a) and (1b). However, Baker et al. (2011) have recently pointed out that this restriction does not work in practice: while models of sound change do not necessarily have to be able to predict exactly when and where a change will occur, they have to be able to account for both stability and change.

Stevens and Harrington's (2014) overview of the recent literature on sound change and the actuation problem indicates that these problems have received increased attention over the last few years (see also the papers in Yu, 2013a). At least two recent papers have attempted to reconcile phonetically-based accounts of sound change with the actuation problem (Baker et al., 2011; Garrett and Johnson, 2013). As Stevens and Harrington (2014:5) point out, these papers rely on social, articulatory and perceptual differences between individuals to account for stability and change within the same model. Baker et al. (2011) argue that sound change is dependent on the presence of inter-individual variation in the magnitude of phonetic patterns such as coarticulation. In their account, innovative variants are only transmitted between individuals if (i) the new variant is substantially different from the listener's own production (e.g. it shows noticeably more coarticulation) and (ii) the listener views the speaker as socially influential. This has the following implication for sound change: 'the ability of phonetically motivated coarticulation to lead to sound change depends on the chance alignment of extreme coarticulation with extreme [social] influence' (Baker et al., 2011:351). They argue that such 'chance alignments' are rare, which results in a situation where stability is the norm, and changes only take place occasionally (but see Yu, 2013b for a suggestion that such alignments are not entirely random due to robust correlations between cognitive processing styles and social traits). Garrett and Johnson (2013) present a different account, which is based on the idea that there are certain circumstances under which speakers may be more likely to operate in the 'how'-mode of perception (cf. above), therefore failing to compensate for the effects of contextual biases. In their account, this is more likely to occur when a listener communicates with individuals who belong to a specific group that the listener wishes to identify with. In such situations, the listener 'may […] notice variants when they are produced by the target group even though they disregard those same variants when produced by other speakers' (Garrett and Johnson, 2013: 94). These variants – originally due to phonetic biases – may gain social significance to the listener, who will then employ them as target productions in their own speech, thus contributing to the actuation of sound change.

Both of these papers share an important feature: they propose that the transmission of innovative variants (1b) can only take place under certain circumstances, which are at least partly determined by social factors. Since the transmission of variants is typically blocked, innovations can rarely spread across the speech community (1c). Thus, Baker et al. (2011) and Garrett and Johnson (2013) avoid the actuation problem by proposing a tighter link between steps (1b) and (1c).

The account presented in this paper takes a different approach to the actuation problem, relying mainly on steps (1a) and (1b). Instead of looking at the effects of a single universal pressure on isolated sound categories, I investigate the interaction of multiple pressures in a sound system, and assume that the effects of phonetic biases and contrast maintenance may be attenuated or intensified by language-specific factors. Therefore, different languages and language varieties may be affected differently by the same universal pressures. These predicted differences are not categorical: it is not simply the case that an innovative variant arises in one variety but not in another. Instead, the predicted cross-linguistic variation is phonetically gradient. Despite clear differences in focus, the account presented here is by no means incompatible with the alternative accounts summarised above. The current paper focuses mainly on how cross-linguistic (and cross-dialectal) differences impact steps (1a) and (1b), while other approaches to the actuation problem look at how individual differences impact steps (1b) and (1c). Ultimately, we need answers to both of these questions in order to gain a better understanding of sound change actuation, and bringing these two different approaches closer to each other is an important task for future research.

2.2 Computational simulations in the study of sound change

This paper uses computational simulations to explore possible patterns of interaction between phonetic biases and contrast maintenance in small artificial sound systems. This is done by modelling repeated rounds of production and perception by a single agent (the decision to use a single agent will be explained in more detail in the next section). These simulations allow us to examine the evolutionary dynamics of a sound system based on a set of simple assumptions about speech production and perception, and they illustrate the types of predictions that we can derive from this model. Although it is possible that these goals could also be achieved through thought-experiments, computational simulations provide a more principled mapping between the model and its predictions. This is necessary in the case of complex systems, since they can often develop in unexpected ways, and are usually not tractable using simple verbal argumentation. Although we will see that the dynamics of the systems investigated in this paper are simple and easy to interpret, there is no *a priori* guarantee that a complex system will show such principled behaviour (cf. Wedel, 2011:136). Therefore, simulations are a useful tool even for relatively simple model systems. Note that in certain cases, analytical models may provide a computationally less intensive and therefore more flexible alternative to computational simulations (see e.g. Kirby and Sonderegger 2013). This paper does not explore this alternative methodology: the simulation-based approach is computationally feasible and – at least in the current case – sufficient to fully explore the model under investigation.

There is a wide range of studies which approach sound change and the evolution of sound systems through computational simulations (e.g. de Boer, 2001; Pierrehumbert, 2001; Oudeyer, 2006; Ettlinger, 2007; Boersma and Hamann, 2008; Wedel, 2006; Garrett and Johnson, 2013; Kirby, 2013; Stanford and Kenny, 2013). In the rest of this section, I present a brief overview of other simulation-based studies of sound change, focusing on accounts that are close to the present one in terms of their focus and general structure. These studies all share a few basic properties. They simulate the behaviour of artificial agents who repeatedly produce and perceive sound categories over a long time period. Large-scale changes emerge from the accumulation of the effects of relatively weak pressures over many iterations. The main differences among these models lie in the way they implement these properties and in the specific questions they attempt to answer through simulations.

Pierrehumbert (2001) and Wedel (2006) present computational simulations which explore the implications of the production-perception feedback loop described in the previous section. The models in these papers rely on a minimal version of the production-perception feedback loop, with a single 'soliloquising' agent who serves both as the speaker and the listener. Following Goldinger (1996) and Johnson (1997), Pierrehumbert (2001) and Wedel (2006) propose exemplar-based models of production and perception. That is, they model category representations as exemplar clouds, which contain phonetically detailed memory traces of previously experienced stimuli (examples of specific sounds in specific words). These exemplar clouds are updated continuously, with more recent exemplars playing a more influential role in production and perception due to a process of decaying memory activation for stored exemplars. Production targets are generated by sampling from this exemplar cloud, and category identification proceeds by comparing incoming stimuli to stored exemplars from different categories. As explained in the previous section, this type of model can account for the transformation of weak but consistent biases into robust changes through repeated iterations of the production-perception feedback loop (Pierrehumbert, 2001). In addition, it can also model the tendency for contrastive categories to remain separate by assuming that tokens that are phonetically ambiguous to the listener (e.g. a production of the word *bat* that happens to be phonetically intermediate between *bat* and *bet*) have a lower probability of being added to the listener's exemplar cloud than unambiguous tokens (Wedel, 2006; Blevins and Wedel, 2009). Since the simulations in this paper are based on a similar model, these ideas are discussed in more detail in the next section.

Kirby (2013) proposes a similar agent-based model of sound change, which shows how the loss of contrast along one cue dimension (e.g. VOT) can lead to the enhancement of contrast along a different cue dimension (e.g. f_0). Kirby's model assumes that speakers have a preference towards enhancing contrasts along cue dimensions that are more informative than others. This model therefore makes the following prediction: if a previously informative cue loses its informativity due to external pressures (such as phonetic biases), the next most informative cue will be enhanced and take over as the main exponent of the contrast. This prediction is borne out in a recent change in Seoul Korean, where a stop contrast that was originally cued by VOT is now mainly cued by f_0 (Kirby, 2013). Kirby's account is closely related to the current one in that it explicitly stresses the importance of looking at both contrast-related forces (in this case, cue enhancement) and phonetic biases. This paper takes this approach even further by looking at more fine-grained patterns of interaction between these two pressures.

The models presented by Stanford and Kenny (2013) and Garrett and Johnson (2013) are also based on exemplar-based storage and a feedback loop between production and perception. However, these models make stronger assumptions about the effects of social structure on speech interactions between individuals. As explained previously, Garrett and Johnson (2013) show that groups of speakers may phonologise weak phonetic biases differentially depending on whether their members attribute social-indexical value to biased variants. Stanford and Kenny (2013) explore a model where agents move around in a simulated world. The interactions between agents are based on proximity. Moreover, they occasionally add and remove agents (simulating birth and death), and their world includes two separate population centres (corresponding to two different cities). They show that this model can replicate findings about differences between the cross-generational transmission of chain shifts *versus* the diffusion of chain shifts from one city to another (cf. Labov 2007).

2.3 The current approach

The simulations presented in this paper are built on the same set of basic assumptions as the models summarised in the previous section. They implement the production-perception feedback loop by modelling the evolution of sound categories in an agent who repeatedly produces and perceives examples of those categories. Like the usage-based approach described in section 2.1 and the models reviewed in section 2.2, the current model relies on two crucial assumptions about production and perception:

(i) speakers can store phonetic details in their category representations, and
(ii) they are capable of modifying these representations on the basis of their linguistic experience throughout their lifetime.

The first assumption is well-supported by a range of observations in the literature. Pierrehumbert (1999) and Hawkins (2003) show that fine phonetic details are used both in production and in perception, and argue that the ubiquity of fine-grained cross-linguistic variation in the realisation of phonetic categories is clear evidence for the presence of phonetic detail in category representations. Similarly, studies of perceptual compensation have shown that speakers possess detailed knowledge of patterns of phonetic realisation in different contexts (e.g. Mann and Repp, 1980; Beddor et al., 2002). Following Kirby (2013), the current model opts for parametric probability distributions as a tool for representing phonetically detailed knowledge of category realisations. This type of representation is closely related to prototype models of category representation (Posner and Keele, 1968). There is no *a priori* reason why this type of framework should produce substantially different evolutionary dynamics from one that assumes exemplar-based category representations. As Ashby and Alfonso-Reese (1995) demonstrate, the main difference between prototype and exemplar models of categorisation is that the former use parametric probability density functions to approximate categorisation behaviour, while the latter use non-parametric probability density functions for the same purpose. Sóskuthy (2013) shows that simulated sound systems change in the same way regardless of the type of category representation as long as these representations are phonetically detailed. This should also be evident from the presentation of the simulation results in section 4 of this paper, which are qualitatively similar to the exemplar-based simulations in Pierrehumbert (2001) and Wedel (2006).

The assumption that speakers can change their category representations throughout their lifetime also receives ample support from the literature. For instance, Evans and Iverson (2007) found that Northern English students exposed to Southern English speech at university exhibit gradient shifts in the realisations of certain vowels over a period of two years. A related study by Sancier and Fowler (1997) shows that a native speaker of Brazilian Portuguese studying in the United States exhibits gradient shifts in the voice onset time (VOT) of fortis consonants as a function of exposure to Brazilian Portuguese and American English. Finally, a series of studies by Harrington and colleagues (Harrington et al., 2000; Harrington 2006, 2007) demonstrates long-term changes in the phonetic realisations of certain vowels in the speech of Queen Elizabeth II.

The current model borrows an additional assumption from Wedel (2006) and Blevins and Wedel (2009): that phonetically ambiguous words are underrepresented in the production-perception feedback loop. This assumption leads to contrast maintenance at the level of sound categories. Models of sound change based on the production-perception feedback loop provide a natural way of linking word-level ambiguity-avoidance to phoneme-level contrast maintenance. Wedel, Kaplan and Jackson (2013:184) state that in models of this type, 'any mechanism in production or perception favoring phonetically more contrastive tokens of minimal pair members promotes greater phonetic distinction between the phonemes defining that minimal pair across the lexicon.' The literature discusses at least two different mechanisms which might have such effects. One of these is rooted in perception, and the other one in production. As for the former, Labov (1994), Guy (2003), Wedel (2006) and Blevins and Wedel (2009) argue that ambiguous tokens of specific categories can be lost through simple misperception if the listener fails to feed them back into their category representations, or if they feed them back into the wrong category representation. The production-based explanation suggests that speakers actively choose less ambiguous realisations, especially when the production of ambiguous tokens would lead to a significant loss of information (e.g. Lindblom, 1990; Aylett and Turk, 2006; Jurafsky et al., 2001). There is currently no compelling evidence that favours either approach. This paper will focus on the perception-based account, since it has already been implemented in previous simulation-based papers (e.g. Wedel, 2006). This choice does not crucially affect the dynamics of the systems investigated in the following sections.

Although the current approach shares the basic assumptions of previous computational models, the way these assumptions are put to use differs substantially from most previous work. In this paper, the focus is not on the presence or absence of sound changes, but on the limiting behaviour of (potentially) changing sound systems (this is similar to the approach taken by Kirby and Sonderegger, 2013). As it will be shown, the sound systems modelled here all share qualitatively similar patterns of limiting behaviour: convergence towards stable states. Section 4 will present an overview of several thousand simulation runs, which illustrate these stable states and show that their positions are strongly affected by variations in contingent factors such as bias proportion and functional load. The systematic exploration of the parameter space of the model along with a focus on its limiting behaviour is a unique feature of the present paper.

Given the prominent roles of bias proportion and functional load in the current model, it will be useful to provide a brief overview of these contingent factors. Let us start with bias proportion. Many phonetic biases can be viewed as contextual effects: they only apply to tokens of a given category in the appropriate phonetic environment. Bias proportion refers to the frequency with which a category finds itself in a biasing environment. Some authors (including Bybee, 2002 and Harrington et al., 2008, 2011) argue that contextual effects can cause category-wide shifts, and suggest that this is especially likely when the category has high bias proportion. This happens because categories with high bias proportion offer more opportunities for the bias to apply, and the effects of the bias accrue faster in their representations. Harrington et al. (2008) suggest that the fact that English dialects are so prone to undergo /u/-fronting may be due to high bias proportion: according to frequency counts from the CELEX lexical database (Baayen et al., 1993), English /u/ is preceded by coronal and palatal consonants around 70% of the time (Harrington 2007).

Functional load is a contingent factor related to the phenomenon of contrast maintenance. In this paper, functional load is defined as the relative importance of a phonemic contrast in distinguishing pairs of lexical items. Many authors argue that contrasts with high functional load (e.g. a large number of minimal and/or near-minimal pairs) are less likely to be lost than contrasts with low functional load (see e.g. Martinet, 1952; Blevins and Wedel, 2009; Wedel, Kaplan and Jackson, 2013; Wedel, Jackson and Kaplan, 2013). This is a straightforward prediction of models based on the production-perception feedback loop: sound categories with a large number of minimal (or near-minimal) pairs offer more opportunities for lexical ambiguities to arise, leading to more misperception. This results in a stronger pressure for contrast maintenance. Wedel, Kaplan and Jackson (2013) and Wedel, Jackson and Kaplan (2013) present empirical evidence for this claim using cross-linguistic corpus data. They show that historical mergers between phoneme pairs tend to be associated with low functional load relative to cases where no mergers have taken place.

There is one final assumption in the current model that should be discussed before we begin looking at the specifics of the simulations in the next section: the use of a single agent. This is an obvious simplification, since real speech events typically (though not always) involve multiple participants. The reason for this simplification (also used by Pierrehumbert, 2001 and Wedel, 2006) is mostly practical. Simulations with a single agent are computationally less intensive and more tractable than multi-agent simulations. The question is, of course, whether this simplification changes the evolutionary dynamics of the simulated sound systems. In the current case, the answer is no. As long as we assume that all agents behave in the same way in production and perception, adding further agents to the simulations does not change the final outcomes. Sóskuthy (2013:115–120) demonstrates this by showing that single-agent simulations implemented in the same way as the simulations in the current paper produce exactly the same outcomes as simulations with six interacting agents. This is because (i) the update of category representations based on perceived stimuli guarantees that all agents will have approximately the same category representations (assuming that all pairs of agents interact at the same rate) and (ii) if multiple agents share the same category representations, these representations will be affected in exactly the same way by production/perception events.

The goal of this simplification is not to downplay the importance of individual differences. In the real world, individuals differ with respect to their physical, psychological and social attributes, and this can potentially lead to more complicated evolutionary dynamics than the type shown in the simulations below (see Stevens & Harrington, 2014 for an overview). Indeed, Stanford and Kenny (2013) and Garrett and Johnson (2013) demonstrate how added assumptions about individual differences can lead to inhibited changes and imperfect diffusion from one dialect to another. The current simulations aim to provide a better understanding of the dynamics of the production-perception feedback loop at a more abstract level and to show that different languages and varieties may be affected differently by universal pressures even in the absence of individual social and cognitive differences. It is an important goal for future research to show how the addition of more complex population dynamics can alter the behaviour of this simple model. The results presented in this paper will serve as a useful baseline for such investigations.

3. Methods

3.1 Simulating the production-perception feedback loop

The simulations presented in this paper are all built around the notion of the production-perception feedback loop. They model the behaviour of a single agent who produces a range of category realisations, which are then fed back into their representations. This loop is repeated many times in the course of a single simulation to allow for the effects of phonetic biases and contrast maintenance to accumulate in category representations

Figure 1 provides a schematic illustration of the production-perception feedback loop.

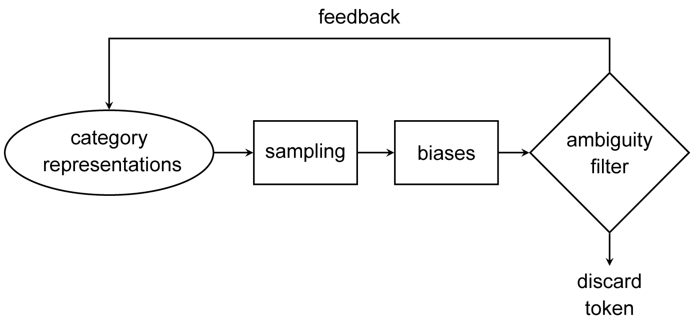

Figure 1: *The production-perception feedback loop.*

The diagram divides the feedback loop into several smaller steps, which correspond to various stages of speech production and perception. The loop starts with *category representations*, which are used to generate production targets through a simple *sampling* mechanism. These production targets are then displaced through the application of phonetic *biases*. The *ambiguity filter* represents the mechanism for lexical contrast maintenance described in Section 2.3: phonetically ambiguous tokens are occasionally discarded, which means that they have less influence on category representations. This only happens rarely in the model used in this paper (this is controlled by the functional load parameter *r* described below). If the token successfully passes the ambiguity filter, it is *fed back* into category representations, and the loop starts over again.

Category representations are modelled as normal distributions defined over continuous phonetic dimensions. For reasons of simplicity, only a single phonetic dimension is used in the simulations presented in this paper. Since the simulations are structured around the phenomenon of /u/-fronting, this dimension corresponds roughly to vowel backness. A normal distribution can be defined exhaustively using two parameters: the mean and the standard deviation (or variance). To illustrate, Figure 2 shows a normal distribution calculated on the basis of F2 measurements for 25 tokens of the vowel [u] from American English (Hillenbrand et al., 1995).

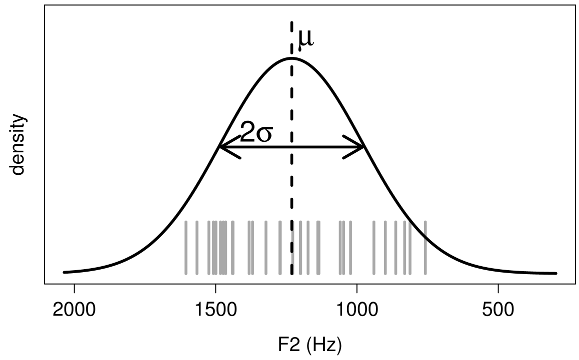

Figure 2: 25 *tokens of the vowel* [u] *from American English* (*grey lines*)*, the corresponding normal distribution* (*the black curve*)*, and its mean and standard deviation.*

Normal distributions can be used to calculate production targets through *sampling* (the second step in Figure 1): choosing a random point along the phonetic dimension represented by the *x*-axis with a probability proportionate to the value of the probability density function around that point. The current implementation of the production-perception feedback loop follows previous approaches (e.g. Pierrehumbert, 2001; Wedel, 2006) in adding a small amount of noise to production targets. This is analogous to production error, whereby a production target is not realised faithfully due to imperfections in the articulatory apparatus (cf. Feldman et al., 2009). Although production error may seem like an optional component in this model, its absence would lead to highly unrealistic patterns of behaviour. Without this error term, it would be theoretically possible for agents to realise categories without any variation (e.g. consistently producing a vowel with the same formant values), or to base contrasts between sound categories on arbitrarily small phonetic differences (e.g. consistently distinguishing two vowel categories by a single Hertz along the F2 dimension). The absence of such patterns in natural languages is a strong argument for modelling production with an error term.

Phonetic biases are implemented as point-like attractors in phonetic space, which affect tokens in specific environments. I will illustrate this using the example of /u/-fronting in coronal and palatal contexts. The source of this effect is a fronting of the tongue body during the articulation of /u/ under the influence of the neighbouring coronal and palatal consonants, which yields a raised F2 (Harrington et al., 2011:122). In other words, the coronal/palatal constriction creates a target location and the tongue body is displaced towards this point in articulatory space during the articulation of the vowel. Note that the vowel does not have to reach this target either in articulatory or in acoustic space – in fact, the extent of the displacement may be rather small. Moreover, since this movement is target-oriented, the size of the displacement will be even smaller when a given production is already close to the attractor (otherwise the biased production might end up ‘overshooting’ the bias attractor).

The behaviour described above can be formalised using a logistic function:

$$\mathrm{bias}_i(x) = x + s_i\left(\frac{1}{1+\exp\left(\frac{x-b_i}{d}\right)} - 0.5\right) \qquad (1)$$

where x is a real number representing the production target, s_i is a parameter that determines the strength of bias *i*, b_i is the location of the bias attractor and d is a scaling factor (set to 1 in all the simulations in this paper). Figure 3 illustrates the size and the direction of the displacement caused by a phonetic bias as a function of where the original production target is in phonetic space ($b_i = 0$ and $s_i = 0.01$).

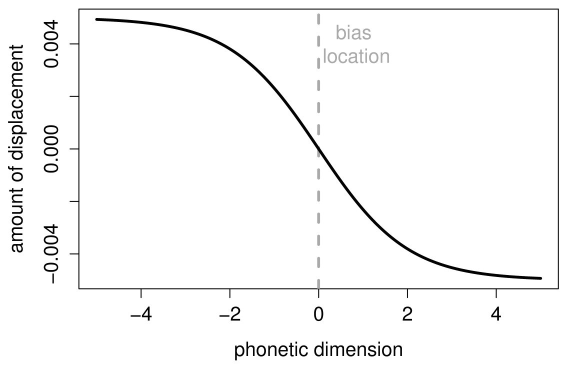

Figure 3: *The size and the direction of the displacement caused by a phonetic bias as a function of position along a given dimension. Parameter settings*: $b_i = 0$, $s_i = 0.01$, $d = 1$.

When a production target has a value that is lower than b_i, the function in Figure 3 increments it by a small amount. When the production target has a value that is higher than b_i, the sign of the function changes, which means that it now decrements the original value. Note also that the size of the displacement increases as we move away from the bias attractor, but the logistic function imposes an upper limit on this increase.

The simulations in the next section include a further parameter that relates to phonetic biases: *bias proportion*. Bias proportion is the relative frequency with which production targets from a given category are exposed to a specific phonetic bias. Therefore, bias proportion can take on values between 0 (the category is never affected by the bias) and 1 (it is always affected by the bias).

The ambiguity filter is a specific way of implementing contrast maintenance, originally proposed by Wedel (2006). As shown in Figure 1, this filter has two potential outcomes: the production is either (i) fed back into the appropriate category representation or (ii) it is discarded. The choice between these two outcomes depends on how ambiguous the production is to the listener, or, in other words, how likely it is to be misperceived. Highly ambiguous forms have a relatively high probability of being discarded, while unambiguous forms are likely to be kept. Assuming that the correct category label for stimulus x is c_i, the probability of misperception is given by the following formula:

$$p(\neg c_i \mid x) = 1 - \frac{p(x \mid c_i)}{\sum_{j=1}^{n} p(x \mid c_j)} \qquad (2),$$

where n is the overall number of categories, and $p(x \mid c)$ is the probability density function associated with category c (in this case, a normal distribution). This formula derives straightforwardly from Bayes' theorem, assuming that all category labels have the same prior probability. It is closely analogous to the categorisation formulae used in exemplar and prototype-based frameworks (cf. Ashby and Alfonso-Reese, 1995).

The misperception probabilities given by this formula vary as follows. Let us assume that there are two categories, a fully back /u/ and a fully front /i/ (for expository convenience, I treat the distinction between front unrounded and back rounded vowels as a single continuum and refer to it simply as backness). The correct category label for stimulus x is /u/. If x is located in a part of the vowel space typically associated with /u/, but not /i/ (high-back), the probability of misperception will be low. If it is intermediate between /u/ and /i/, the probability of misperception will be higher. Finally, if it is located in a part of the vowel space typically associated with /i/, but not /u/ (high-front), the probability of misperception will be very high.

The probabilities above are weighted by a further factor, which is a proxy for *functional load* in the current model. If functional load is low, even ambiguous productions will have a high probability of being kept, reflecting the fact that misperception is less likely to take place if lexical competition is limited. Conversely, if functional load is high, even unambiguous productions may be discarded due to a high degree of lexical competition. In the current model, functional load is implemented as a parameter with values between 0 and 1. The full formula for the ambiguity filter (including functional load, *r*) is given below:

$$p(\text{discard } x \mid x, c_i) = rp(\neg c_i \mid x) \qquad (3),$$

where $p(\text{discard } x \mid x, c_i)$ is the probability of discarding token x from category c_i.

The final step in the production-perception feedback loop shown in Figure 1 is feedback: updating the appropriate category representation as a function of the incoming stimulus. The current model represents categories in the form of normal distributions, which are defined by their means and standard deviations. Therefore, category update consists in shifting these parameters to accommodate the incoming stimulus. The mean will always shift towards the stimulus, while the standard deviation will either increase or decrease depending on how far the stimulus is from the mean. The following formulae are used to update the mean and the standard deviation:

$$\mu_{n+1} = \frac{k\mu_n + x}{k+1} \qquad (4)$$

$$\sigma_{n+1}^2 = \frac{(k-1)\,\sigma_n^2 + k\,(\mu_n - \mu_{n+1}) + (x - \mu_{n+1})^2}{k} \qquad (5)$$

These formulae are weighted variants of the unbiased estimators of the population mean and variance, where previous experience with the category (represented by μ_n and σ_n^2) has weight *k* in calculating the new parameter estimates μ_{n+1} and σ_{n+1}^2, while the new stimulus has weight 1. In other words, the parameter *k* in these formulae is inversely proportional to the degree to which a single stimulus can shift the parameters of the category representation. I will refer to *k* as the constant of update.

3.2 The simulation setup

Each of the simulations contain two categories, defined over a single continuous phonetic dimension. I will refer to this phonetic dimension as *backness*, which is an abstract measure of horizontal tongue position, with higher values representing a higher degree of backness. The categories will be labelled /i/ and /u/. Note that these labels are used for convenience: the exact identity of the phonetic parameters modelled in the simulations has no bearing on the main results (e.g. using a VOT contrast between stops would give very similar overall dynamics). Backness is defined as a closed interval between [0,1]; tokens that fall outside this interval are simply shifted back to the boundaries (i.e. 0 or 1). This boundedness introduces an additional bias into the simulations: since extreme productions are not fed back into category representations, there is a weak pressure for the categories to move towards the centre of phonetic space (in this case, the value 0.5).

In order to ensure that the final outcomes are not a function of specific starting values for the categories, the initial category means are generated randomly. The centre of the category /u/ can take on any value between [0.2,0.9], while the centre of the category /i/ is constrained to take on values between [0.1, μ_u – 0.1]. This means that /i/ always starts with a realisation that is more front than /u/. The initial standard deviation is the same for both categories: 0.07 (this is a reasonable value for vowels defined over a single dimension of backness with a unit length).

Both categories are exposed to the same universal fronting bias, with a bias attractor at 0.4 (corresponding to the relatively – but not completely – front F2 locus of coronals). The strength of this bias is set to 0.015, which means that the maximum absolute displacement for a production target is less than 0.01. This corresponds to a weak bias, whose effects can only be seen after a large number of iterations. The bias proportion values are not identical for the two categories: bias proportion is fixed at 0.07 for /i/ (i.e. /i/ is exposed to the bias 7% of the time), while it is varied systematically between [0,1] for /u/. This corresponds to the type of variation in contingent factors that is often be observed cross-linguistically (e.g. the relative frequency of /u/ in coronal/palatal environments differs from language to language; the bias proportion of /i/ is kept constant in order to examine the effect of varying just one factor).

The value of the parameter corresponding to functional load (i.e. *r* in (3)) is varied between [0,0.05]. Although this may seem like a very narrow range, given that *r* can potentially take on much higher values too, we will see that a value of 0.05 already results in a high degree of contrast maintenance. There is also some reason to assume that higher values of *r* may be unrealistic. One way of conceptualising *r* is as the rate of 'catastrophic' misperceptions, where the listener fails to reconstruct the intended form (cf. Wedel, 2006; Sóskuthy, 2013). It is unlikely that this happens very often: in many cases, the form will be recoverable from the context. Given that we do not have sufficient information about misperception in natural speech to reliably estimate the value *r*, a conservative estimate is preferable.

There are two further parameters in the simulation: the value of *k* (cf. (4), (5)), which determines the relative influence of incoming stimuli, and the number of iterations. The value of *k* is 2,000 in all the simulations, which means that a single stimulus will only have a very small effect on the overall category representation. Each simulation is run for 4 million iterations. Such a large number of iterations is necessary to ensure that the simulated systems can settle into stable states.

A single simulation round consists of the steps shown in Figure 1, performed separately for each of the two categories. In each round, the simulated agent first generates a production target for one of the categories and then applies the fronting bias to this category. At this point, the agent may proceed in two different ways. If the token is ambiguous between the two categories, there is a small chance (0–5%) that they may discard it (cf. section 3). Otherwise, they simply feed it back into their category representation for the target category. This is repeated for the other category as well. This means that each category is produced 4 million times in each of the simulations. This could be translated into real speech interactions as 'a single speaker in a community producing two phonemes 4 million times,' although such interpretations are not particularly useful in the current case, given the abstract focus of the simulations. This procedure was implemented in R, a programming language for statistical computing (R Core Team, 2014). In order to facilitate the replication of the experiments reported below, the code has been attached as supplementary material.

The values of bias proportion and functional load are varied systematically in an effort to explore the parameter space of the model. There are 11 possible equally spaced values for each parameter: for bias proportion, the lowest value is 0 and the highest value 1; for functional load, the lowest value is 0 and the highest value 0.05. Each combination of parameter values is represented by 25 different simulations, giving an overall 3025 different simulation runs.

Table 1 provides a summary of the parameter values used in the simulations.

PARAMETER	FORMULA	VALUE
Initial category mean for /u/	μ_u, (4)	[0.2,0.9]
Initial category mean for /i/	μ_i, (4)	[0.1,μ_u – 0.1]
Initial category SD for /u/ and /i/	σ, (5)	0.07
Variance inflation	v	0.001
Bias attractor	b_i, (1)	0.4
Bias strength	s_i, (1)	0.015
Bias proportion for /u/	–	[0,1]
Bias proportion for /i/	–	0.07
Scaling factor for bias	d, (1)	1
Functional load	r, (3)	[0,0.05]
Weight of existing parameter values	k, (4–5)	2,000
Number of iterations	–	4,000,000

Table 1: *A summary of the parameter values used in the simulations. The first column shows the name of the parameter, the second one links the parameter to the relevant formula in Section* 3.1*, and the third column shows the value.*

4. Results

The results of the simulations will be presented in three parts. Section 4.1 summarises the results of simulations which only show the effects of phonetic biases, but not contrast maintenance (i.e. functional load is set to 0). Section 4.2 then discusses simulations which show the effect of contrast maintenance, but not phonetic biases (i.e. bias proportion is set to 0). Finally, Section 4.3 presents the rest of the simulation results, which illustrate how contrast maintenance and phonetic biases interact with each other in determining the outcomes of the simulations.

4.1 The effects of phonetic biases

Let us first discuss those simulations where contrast maintenance plays no role (i.e. simulations where the value of the functional load parameter is 0). Overall, there are 275 such simulations: 25 for each value of bias proportion between [0,1]. In order to get a sense of how the category means evolve in these simulations, let us first focus on a subset of the data with extreme bias proportion values (0.1 and 0.9). Figure 4 shows how the representations of /u/ and /i/ change as a function of time by plotting the category means against the number of iterations. The top row represents simulations with a bias proportion value of 0.1, and the bottom row simulations with a bias proportion value of 0.9. In the first two columns, each line represents the evolution of a given category (/u/ or /i/) in a single simulation run. The third column shows how the overall range of category means changes over time by plotting 95% confidence intervals based on the trajectories in the first two columns. It is useful to recall that /i/ is always initialised with a backness value which is at least 0.1 units lower than the initial value of /u/ in the same simulation. This is the reason why the /i/ trajectories have a consistently lower starting point than the /u/ trajectories.

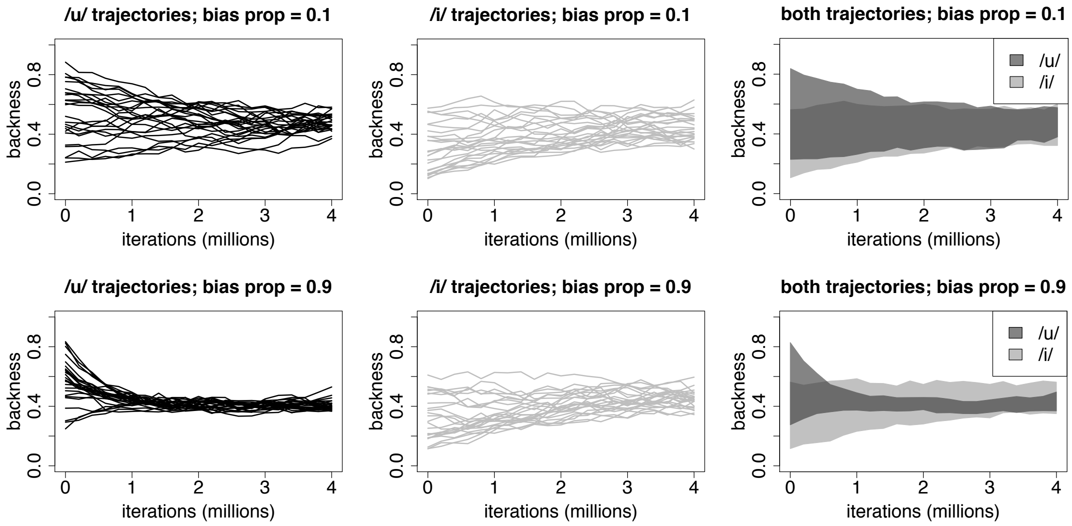

Figure 4: *The individual trajectories of the category means for* /u/ (*first column*) *and* /i/ (*second column*), *and* 95% *confidence intervals for the two sets of trajectories* (*third column*). *The top row indicates all simulations with a bias proportion value of* 0.1, *and the bottom row all simulations with a bias proportion value of* 0.9.

The simulated trajectories show a number of clear trends. First of all, both /u/ and /i/ seem to be moving towards a similar (though not identical) range of final values between 0.4–0.5. This is, of course, what we expect based on the structure of the simulations: the phonetic bias pulls both categories towards the value 0.4, while the boundedness of phonetic space exerts a weak pressure on both categories to move towards the central value of 0.5. Second, once the category means reach this range, they settle into a stable state and do not show any further systematic changes. This is particularly clear in the graph in the lower left corner, which shows the evolution of /u/ when the value of bias proportion is set to 0.9. The category means move rapidly towards the area between the bias attractor and the centre of phonetic space during the first 1 million iterations. All subsequent changes can be interpreted as random fluctuations within a limited region.

At this point, it will be useful to introduce the notion of *adaptive landscapes*, which will make it easier to present the results of the simulations in a systematic way. The adaptive landscape is a powerful visual metaphor originally proposed in the field of evolutionary biology (Wright 1932). Adaptive landscapes in evolutionary biology can be visualised as topographical maps, where latitude and longitude represent a range of different possible traits, and altitude represents the fitness of the traits. Fitness simply stands for reproductive success: a trait with low fitness will quickly die out in a population, while a trait with high fitness will likely survive for many generations. Due to natural selection, populations converge towards peaks in the adaptive landscape and tend not to descend to lower altitudes once they have reached a peak (often resulting in stable sub-optimal solutions).

Adaptive landscapes can also be used to describe the evolution of the simulated sound systems discussed in this paper. Figure 5 shows a kernel density estimate of the distribution of the category means for /u/ after 4 million iterations for all simulations where the value of bias proportion is 0.9 (cf. the panel in the lower left corner of Figure 4).

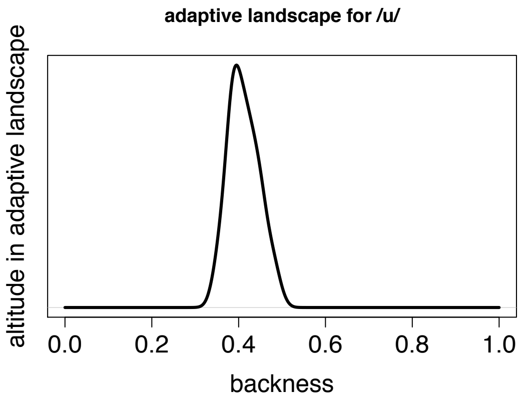

Figure 5: *The distribution of final category means for* /u/ *when bias proportion* = 0.9 *and functional load* = 0*. Loosely speaking, this distribution can be interpreted as an snapshot of the adaptive landscape for /u/.*

As has been noted above, this distribution represents a stable state: although the initial category means have a uniform distribution between [0.2,0.9], by the end of the simulation they all converge towards a narrow range of values (determined by the location of the phonetic bias and the boundedness of phonetic space), and stay within that range. In other words, categories within this range are reproduced faithfully in later iterations, while categories outside this range are not. If we limit our attention to the category means (despite the fact that the adaptive landscape may include other properties as well, such as category standard deviations), this diagram can be interpreted as a snapshot of the adaptive landscape for this particular type of simulation. The category means evolve towards the peak over many iterations. Importantly, the shape of the adaptive landscape is a function of the parameters that serve as the input to the simulations.

Let us now see how variations in bias proportion affect the adaptive landscape for the category means of /u/ and /i/. Figure 6 shows how the distribution of category means at the end of the simulations varies as a function of bias proportion.

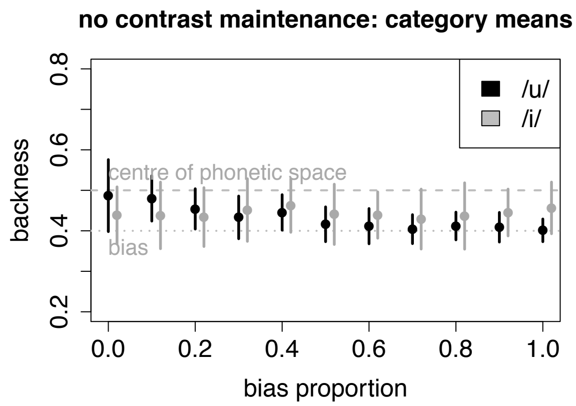

Figure 6: *The final category means for* /u/ (*black*) *and* /i/ (*grey*) *as a function of bias proportion*. *The dots represent averages, and the vertical lines standard deviations*. *The dotted horizontal line shows the location of the bias attractor, and the dashed horizontal line the centre of phonetic space*.

An inspection of the values for /i/ shows that the bias proportion of /u/ has no systematic effect on the position of /i/. The small fluctuations in the distribution of category means are due to chance. This is not a surprising result: the two categories are completely independent of each other in these simulations, which means that the adaptive landscape for /i/ is not affected by changes in the bias proportion of /u/. However, the adaptive landscape for /u/ does change. At low values of bias proportion, the peak is close to 0.5, and the range of possible values is relatively wide. This is because the fronting bias has very little influence on the category, and the stable state for the category is determined mainly by the weak bias towards central values resulting from the boundedness of phonetic space. As we move towards higher bias proportion values, the peak shifts closer to the location of the bias attractor, and the range of possible values becomes much narrower, reflecting the increased influence of the fronting bias.

4.2 The effects of contrast maintenance

To show how contrast maintenance affects the simulated sound systems, I will now present the results from those simulations where phonetic biases only had a minimal effect on the sound categories. The value of bias proportion for /u/ is fixed at 0.1 for all the simulations discussed in this section (0.1 was chosen in order to ensure that the two categories have comparable bias proportion values). Figure 7 illustrates the evolution of category means over time for simulations with extreme values for functional load (0.005 and 0.045). The figure is structured in the same way as Figure 4.

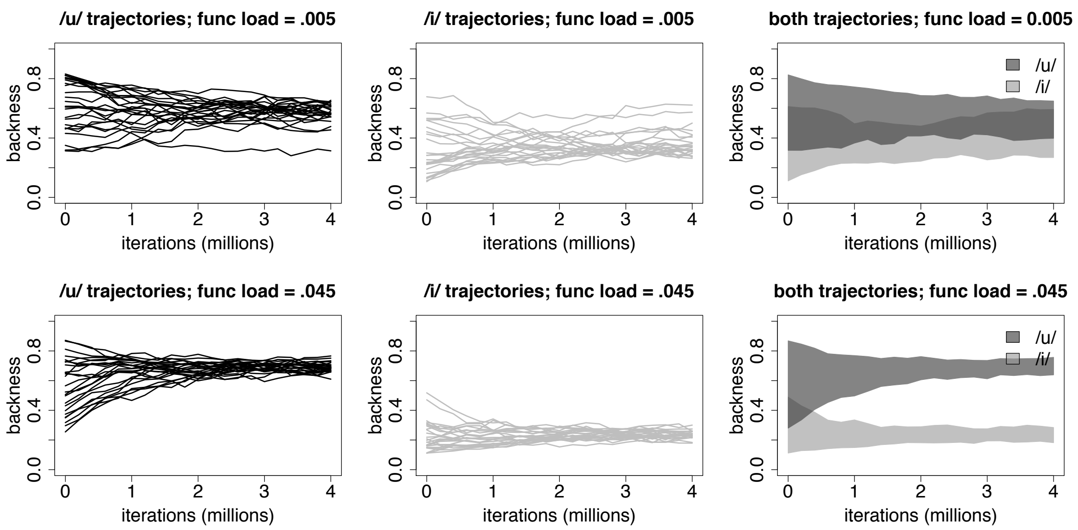

Figure 7: *The individual trajectories of the category means for* /u/ (*first column*) *and* /i/ (*second column*), *and* 95% *confidence intervals for the two sets of trajectories* (*third column*). *The top row indicates all simulations with a functional load of* 0.005, *and the bottom row all simulations with a functional load of* 0.045.

The top row shows a moderate amount of separation between the category means. It is useful to compare these graphs to the ones in the top row of Figure 4, which shows simulations with the same bias proportion values, but with a functional load of 0. The final ranges for /u/ and /i/ are clearly further apart for the current simulation setup than they are for the one illustrated in Figure 4. This indicates that even a contrast with very low functional load can exert a relatively strong influence on the category means. Looking at the simulations with a functional load of 0.045, the separation between the category means becomes much sharper: /i/ and /u/ converge towards clearly distinct ranges of values. Increasing functional load leads to a higher degree of contrast maintenance.

Figure 8 shows the category means at the end of the simulations.

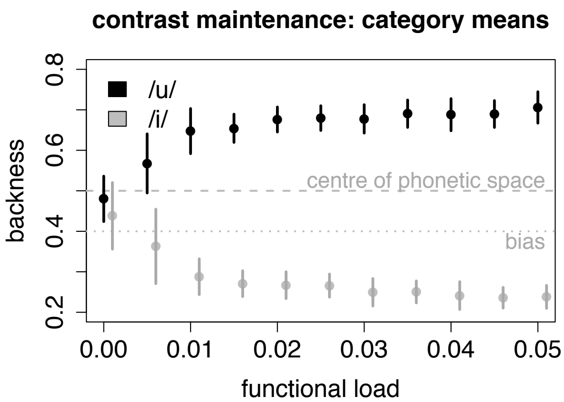

Figure 8: *The final category means for* /u/ (*black*) *and* /i/ (*grey*) *as a function of functional load. The dots represent averages, and the vertical lines standard deviations. The dotted horizontal line shows the location of the bias attractor, and the dashed horizontal line the centre of phonetic space.*

The effect of functional load is even clearer in this graph: while the final category means are relatively close at low values of functional load, at higher values they move far apart, and the range of possible values also becomes somewhat narrower for both /u/ and /i/. Note also that the relationship between contrast maintenance and functional load is non-linear: initially, even a small increase in functional load leads to a large increase in contrast maintenance, but at higher values of functional load the degree of contrast maintenance becomes fixed and does not seem to grow any further.

As the value of functional load increases, there is an important qualitative shift in the behaviour of the simulations. At very low values of functional load, there is hardly any contrast maintenance, which means that the two categories evolve independently of each other. In such simulations, each of the categories moves in its own adaptive landscape. However, as the effects of contrast maintenance become stronger, the categories lose their independence, and start evolving together as a system. As a result, it makes more sense to talk about an adaptive landscape for the sound system, as opposed to separate adaptive landscapes for individual categories. The peak in this landscape is a combination of category means that are sufficiently far apart, and which also satisfy other pressures (in this case, the pressure to move towards central values, which results from the boundedness of phonetic space).

4.3 The combined effects of phonetic biases and contrast maintenance

Sections 4.1 and 4.2 focused on the separate contributions of phonetic biases and contrast maintenance. The current section looks at how these two different forces interact with each other in determining the outcomes of the simulations. The previous sections have already established that the main contribution of phonetic biases and contrast maintenance is in determining the location of the peaks in the adaptive landscape which the sound systems converge towards. Therefore, this section focuses on the final outcomes of the simulations after 4 million iterations. To give a full picture of how phonetic biases and contrast maintenance interact with each other, I provide a summary of the final outcomes of all 3025 simulations (including the ones discussed in sections 4.1 and 4.2).

Figure 9 shows the average final category means (left-hand panel: /u/; right-hand panel: /i/) for each set of 25 simulations representing a given combination of bias proportion and functional load.

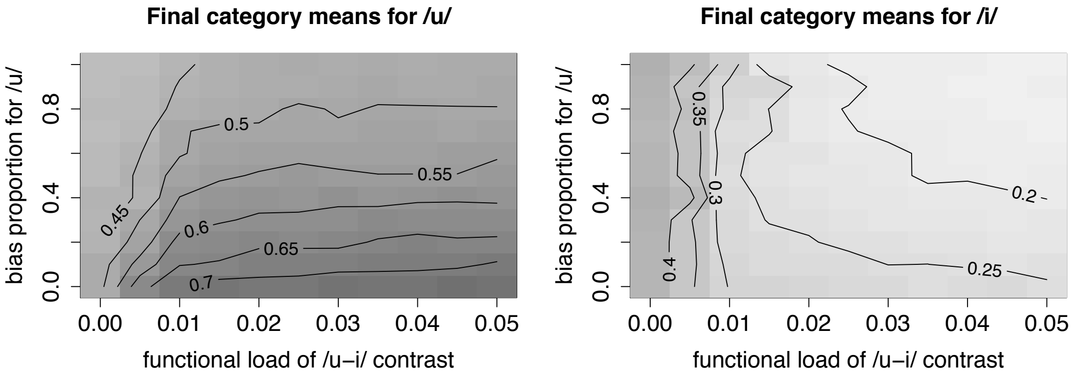

Figure 9: *The final category means for* /u/ (*left*) *and* /i/ (*right*) *as a function of functional load and bias proportion*. *The shading represents the absolute average backness of the category means* (*darker rectangles stand for the more back values*). *The numbers on the contour lines show specific backness values.*

Functional load and bias proportion for /u/ are plotted along the *x* and *y* axes, respectively. The average backness values are represented by the lightness of the small rectangles: darker rectangles stand for more back realisations, while lighter ones for more front realisations. The shading is comparable across the two diagrams, that is, the same shade of grey represents the same backness value in both of them. Contour lines have been added to make the graphs easier to interpret. Note that although the final means for the two categories are shown in two separate panels, these panels represent different aspects of the *same* adaptive landscape, as the stable states for /u/ and /i/ are not independent of each other.

Let us first look at the left-hand panel, which represents /u/. The fronting bias and contrast maintenance clearly act against each other. When bias proportion is high and functional load is low, the category mean for /u/ approaches the bias attractor, with values close to 0.4. Conversely, when the bias proportion is low and the functional load is high, the realisation of /u/ remains confined to more back values (i.e. 0.65–0.7) to allow more space for /i/. At intermediate values of bias proportion and functional load, we see a continuous range of compromises between these extremes, which are determined by the relative strengths of the two forces. For instance, a bias proportion of 0.4 combined with a functional load of 0.01 yields a category mean of roughly 0.55 for /u/. It should be noted that the contour lines become horizontal once functional load rises above 0.02. This is because further increases in functional load have little influence on contrast maintenance beyond this point (cf. Section 4.2), while bias proportion continues to have the same more or less linear effect on the category mean for /u/.

The category /i/ is affected in a slightly different way. Variations in the functional load of the contrast have similar effects on both categories: as functional load increases, they shift further away from each other. This is clearly evident in the panel on the right, where we see that increasing functional load has a fronting effect on the category mean for /i/. This occurs because /i/ is repelled away from /u/, which occupies the back half of the continuum. However, variations in the bias proportion parameter for /u/ can only have indirect effects on /i/. At lower values of functional load, the two categories evolve independently of each other (cf. section 4.2), and therefore varying the bias proportion for /u/ has no effect on /i/ at all. However, as functional load increases, the bias proportion for /u/ begins to have a strong influence on the location of the centre of /i/, with higher bias proportion values yielding more front realisations of /i/. This is because the high bias proportion of /u/ draws this category closer to the bias attractor at 0.4, and /i/ is forced to move towards more extreme front values in order to satisfy contrast maintenance.

Crucially, all the observations presented above can be interpreted as statements about the adaptive landscape for this simple sound system. The optimal combination of category means (that is, the peak in the adaptive landscape) is determined by the values of bias proportion and functional load. Each of the simulated systems show convergence towards the peak in the adaptive landscape over a long time period. Once they reach this peak, they do not stray far from it.

Below is a summary of the main findings of Sections 4.1–4.3. These findings will serve as the basis of the discussion in the next section.

1. The simulated sound systems converge towards stable states in the adaptive landscape regardless of the specific parameter values.
2. The locations of these stable states are determined by bias proportion and functional load:
    a. Increasing *bias proportion* draws the stable state for a specific category closer to the bias attractor.
    b. Increasing *functional load* strengthens the interdependence between the categories, and forces the stable states further apart.
3. Intermediate values of bias proportion and functional load result in systems representing various compromises between phonetic biases and contrast maintenance.

5. Discussion

In order to clarify where the main contribution of this study lies, it is important to point out where the findings reported above overlap with previous observations in the literature. Pierrehumbert's (2001) simulations demonstrate that the effects of weak biases can be magnified through the production-perception feedback loop, yielding gradual but robust changes. The fact that the categories in the current simulations converge gradually towards the bias attractor is simply a different aspect of the same phenomenon. Bybee (2002) shows that the rate at which a given lexical category undergoes a reductive sound change varies as a function of its exposure to contexts favouring the change. The effect of bias proportion reported in the previous section is closely related to this finding. Wedel (2006) and Blevins and Wedel (2009) show that local selection pressures favouring non-ambiguous tokens can lead to contrast maintenance at the level of word forms and sound categories. The mechanism used to implement contrast maintenance in this study is taken from Wedel (2006). Thus, it is not surprising to find that the categories in the current simulations stay distinct at higher values of functional load.

The main finding of this paper is that predictions relating to pressures on sound change are not simply about the *absence* or *presence* of change: they are about the peaks in the adaptive landscape towards which sound systems converge. The simulations presented in the previous section all show the same type of asymptotic behaviour: convergence towards a stable state. In some of the simulations, the categories are initialised with values that already satisfy the pressures on the sound system, and simply stay close to these initial values. In other simulations, the categories are initialised with values that do not satisfy the pressures on the sound system, and undergo an initial period of change before they reach a stable state. But regardless of what happens at the beginning of the simulation, the final outcome is always the same: the categories settle into an equilibrium and do not undergo any further systematic changes. The influence of factors such as bias proportion and functional load cannot simply be described in terms of categorical labels such as actuation *versus* blocking. For instance, it is not the case that beyond a certain level of functional load changes that would bring /u/ and /i/ closer to each other are categorically blocked. Instead, bias proportion and functional load act together to shape the adaptive landscape and determine the configuration in which the simulated sound systems become stable.

The simulation results also demonstrate how universal pressures and contingent factors interact with each other (see Section 1 for a definition of these two types of conditioners of sound change). As it has been explained above, gradient variations in contingent factors such as bias proportion and contrast maintenance yield gradient changes in the stable states for /u/ and /i/. Although the range of possible stable states is fairly wide, it is by no means unconstrained: universal pressures such as phonetic biases and contrast maintenance impose limits on the set of possible final outcomes and serve as the basis of statistical universals. While a specific phonetic bias may not be able to have a strong influence on a given sound system (e.g. due to low bias proportion or high functional load), its effects will still be seen in many other systems. Since pressures on sound change such as phonetic biases are universal, they will exert the same influence on the adaptive landscapes of all sound systems, even if this influence is mediated by contingent factors. This means that – in a statistical sense – we will likely encounter more languages satisfying a given pressure than we should expect if cross-linguistic distributions arose purely by chance.

Importantly, the approach to sound change outlined above avoids the version of the actuation problem described in Section 1. Why is it the case that specific phonetic biases are not phonologised in all languages, and contrast maintenance does not always block mergers? If these pressures are universal, should we not expect every language to succumb to them sooner or later (cf. Baker et al., 2011)? These questions only make sense if we focus narrowly on the effects of isolated phonetic biases on individual categories, that is, if we study sound change in a vacuum. When we look at the interaction of several different factors in a complex system, it becomes clear that no single system could possibly satistfy all universal pressures at the same time, given that many of these pressures act in opposite directions. All universal pressures have an influence on the adaptive landscapes navigated by sound systems, but the strength of their influence will vary substantially across different languages as a function of contingent factors and simple chance. As a result, the same universal pressures will affect different languages in different ways.

At this point, a different issue arises: the simulations in the previous section suggest that sound systems should not show robust changes once they have settled into a stable state. However, although temporary stasis is possible, the sound systems of natural languages never stop changing completely. Therefore, it may appear that this account 'underapplies' by 'failing to predict cases where change occurs' (Baker et al. 2011:349). This apparent problem results from the fact that we have viewed the adaptive landscape as a static, unchanging entity so far. However, the adaptive landscape itself can undergo changes. Contingent factors are dependent on external factors such as lexical distributions, which can themselves change. For instance, if there is a rise in the frequency of morphemes where a given category occurs in a biasing environment, the bias proportion of the category will also increase. When the factors that form the basis of the adaptive landscape undergo changes, the location of the peaks in the landscape will be affected as well. As a result, a sound system that had previously reached a stable state may find itself in an unstable region of the adaptive landscape, which will lead to sound change (see

Wedel, 2009 for further examples of how changes at one linguistic level can lead to changes at other levels). To put it more simply, sound changes are predicted to occur when the factors that determine the adaptive landscape undergo substantial changes. This approach to sound change can therefore account both for stability and change.

As it has been noted in the introduction, the main strength of this framework lies in its ability to generate testable predictions. The type of simulation presented above can be used to derive predictions about stable configurations for sound systems at different settings for contingent factors. The contingent factors mentioned above (bias proportion and functional load) can be estimated directly from corpora by looking at lexical frequency distributions (e.g. functional load can be estimated through minimal pair counts; cf. Wedel, Jackson and Kaplan, 2013; Wedel, Kaplan and Jackson, 2013). Therefore, it is possible to generate predictions for the locations of sound categories in a specific language by running simulations where the input parameters are taken from corpus data. These predictions can then be matched to actual acoustic measures from the language. To give an example, the simulation results in Section 4.3 can be checked against F2 measurements and corpus estimates for bias proportion and functional load from languages like English, Japanese, Spanish, where there are only two high vowels. An important advantage of this approach is that it allows us to test assumptions about the mechanisms underlying sound change without requiring longitudinal data.

It is, of course, possible that we find that the results of such an experiment do not match the predictions from the simulations. This would be a strong indication that at least some of the specific assumptions of the simulations are wrong. For instance, it is possible that the implementation of the fronting bias described above is unrealistic. The simulations presented above are relatively simple in terms of their make-up: they do not include a mechanism for merger and they say nothing about social factors, frequency effects and a range of other factors. Many of these would be possible to implement in some form in the framework described here, and, as shown in section 2, such extensions have been explored in the modelling literature. For instance, Kirby's (2013) model involves contrast along multiple dimensions and a mechanism of contrast enhancement, and shows how a contrast that is weakened along one cue dimension can be enhanced along a different dimension under a pressure to maintain phonemic oppositions. Garrett and Johnson (2013) add individual differences to their model, and demonstrate that an enhanced architecture of this type can tackle both stability and change. The simulations in Stanford and Kenny (2013) incorporate complex social and spatial dynamics, and are therefore capable of replicating differences between diffusion and transmission. Importantly, however, these models do not seem to differ substantially from the current one in terms of the nature of their predictions. The simulated sound systems appear to evolve towards stable states (even if these stable states are not the same for different subpopulations), and the locations of the stable states vary as a function of contingent factors (e.g. social structure in the case of Garrett and Johnson, 2013 and Stanford and Kenny, 2013). This is precisely where the main strength of the approach described in the present paper lies: it makes it possible to compare a range of different models in a unified setting.

Another way in which the current simulation framework could be extended is by looking at more complex sound systems. The simulations in this paper only include two categories. One important question for future research is whether the results about stable states generalise to more complex systems with multiple sound categories and perhaps additional sources of pressures. The results presented by Sóskuthy (2013) are promising in this respect, as they show that sound systems with 3, 5 or 7 sound categories evolving in a two-dimensional space show qualitatively very similar dynamics to the ones described in this paper. These simulated sound systems also converge towards stable states, although the structure of the adaptive landscape is more complicated, with several distinct peaks that the systems can settle on. Other related simulations of complex sound systems by de Boer (2001) and Oudeyer (2006) also show relatively stable outcomes.

Let us briefly review the main implications of this account for research on sound change. Consider the following quote from Weinreich et al. (1968:137):

> ‘[…] it seems to us unlikely that the actuation problem will readily yield to

> purely structural investigations, and we expect that their contribution will be confined to the task of stating limitations and elucidating – in part – the mechanism of language change. Solutions to the actuation problem must be expected from other directions.'

The current approach shows that it is possible address certain aspects of the actuation problem by looking at structural aspects of language, although it acknowledges that a full account of sound change actuation will need to take both the initiation and the spread of sound change into account. A key suggestion of this paper is that different languages and language varieties may converge towards different stable states as a function of differences in contingent factors such as bias proportion and functional load. It is therefore a crucial task for future research to determine the extent of cross-linguistic variation in such factors, and to establish the degree to which this variation can be used to make valid predictions about sound systems. However, it is equally clear that such variation alone will not account for all cross-linguistic differences. For instance, Weinreich et al. (1968:136–137) report that a four-way contrast among high vowels in Yiddish (*ĭ*, *ŭ*, *ī*, *ū*) has been subject to neutralisation in a range of Yiddish varieties, but the specific patterns of neutralisation differ from dialect to dialect (e.g. {*ĭ*, *ŭ*} > *ĭ* and {*ī*, *ū*} > *ī* in Southern Yiddish; {*ĭ*, *ī*} > *i* and {*ŭ*, *ū*} > *u* in North Eastern Yiddis; and {*ĭ*, *ŭ*, *ī*, *ū*} > *i* in the Yiddish variety spoken in North Central Poland and the Northern Ukraine). Since these varieties are closely related, it is unlikely that they are very different in terms of contingent factors such as *functional load* and *bias proportion* (although this is an empirical question that should be evaluated based on data from these varieties). Therefore, these factors alone may not be enough to explain the observed differences. In such cases, a combination of the current account with accounts based on the spread of sound change may provide a more comprehensive explanation. Perhaps Yiddish high vowels (as opposed to high vowels in other languages) are susceptible to mergers due to low functional load and/or high bias proportion, and the different partially and fully merged systems are all possible stable states. The selection of a specific stable state from the available options may then be determined by social factors typically associated with the spread of sound change. I hope that future research will help to turn such admittedly speculative accounts into more principled explanations by studying the interaction between structural and social factors in sound change. The notions of stable states and adaptive landscapes may well prove to be useful tools in this undertaking.

6. Conclusion

The main goal of this paper was to address certain aspects of sound change actuation by looking at structural factors traditionally associated with the initiation of sound change. This was done by exploring the behaviour of sound systems evolving under multiple pressures through a production-perception feedback loop using computer simulations. The simulated sound systems showed the same general behaviour insofar as they all moved towards stable states in an adaptive landscape. It was shown that the shape of this adaptive landscape is determined by the interaction between universal pressures which are the same in all languages and contingent factors which vary cross-linguistically. In the specific case investigated here, I demonstrated that the final position of /u/ and /i/ along the dimension of backness varies as a function of bias proportion and functional load in the simulated systems. The approach exemplified by these simulations can account both for stability and change: the simulated systems become stable once they reach a peak in the adaptive landscape, but further changes may result if the factors that determine the adaptive landscape (e.g. bias proportion and functional load) undergo changes themselves. I also argued that this simulation framework can be used to generate substantive predictions about sound change and the shape of sound systems, which can be matched against corpus data and acoustic measurements. Moreover, the simulation architecture can be extended in various ways without changing the general nature of these predictions, which allows researchers to evaluate the importance of different factors in sound change.

Acknowledgements

This work is based partly on my PhD thesis completed at the University of Edinburgh. I am greatly indebted to my former supervisors, Patrick Honeybone, James Kirby and Simon Kirby, and my examiners, Jen Hay and Julian Bradfield. I would also like to thank Paul Foulkes, Péter Rácz and Andy Wedel for their helpful comments on an earlier draft. This paper benefitted hugely from the detailed and thoughtful comments provided by three anonymous reviewers.

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