Formal models of Structure Building in Music, Language and Animal Song

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Abstract

Human language, music and a variety of animal vocalisations constitute ways of sonic communication that exhibit remarkable structural complexity. While the complexities of language and possible parallels in animal communication have been discussed intensively, reflections on the complexity of music and animal song, and their comparisons are underrepresented. In some ways, music and animal songs are more comparable to each other than to language, as propositional semantics cannot be used as an indicator of communicative success or well-formedness, and notions of grammaticality are less easily defined. This review brings together accounts of the principles of structure building in language, music and animal song, relating them to the corresponding models in formal language theory, with a special focus on evaluating the benefits of using the Chomsky hierarchy (CH). We further discuss common misunderstandings and shortcomings concerning the CH, as well as extensions or augmentations of it that address some of these issues, and suggest ways to move beyond.

1 Introduction

Human language, music and the complex vocal sequences of animal songs constitute ways of sonic communication that evolved a remarkable degree of structural complexity, for which - extensive research notwithstanding - completely satisfactory explanatory and descriptive models have yet to be found. Formal models of structure have been most commonly proposed in the field of natural language, often building on the foundational work of Shannon and Chomsky in the 1940s and 1950s [Shannon 1948, Chomsky 1956]. Research in mathematical and computational linguistics has resulted in extensive knowledge of the formal properties of such models, as well as of their fit to phenomena in natural languages. Such formal methods have been much less prevalent in modelling music and animal song. Research using formal models of sequential structure has often focused on comparing the structure of human language to that of learned animal songs,
focusing particularly on songbirds, but also whales and bats (e.g., Doupe and Kuhl 1999, Bolhuis et al. 2010, Hurford 2009, Knoernschild 2014). Such comparisons addressed aspects of phonology (e.g., Yip 2006, Spierings and ten Cate 2014) and syntax (e.g., Berwick et al. 2011, ten Cate et al. 2013, Markowitz et al. 2013, Sasahara et al. 2012), aiming to identify both species-specific principles of structure building and cross-species principles underlying the sequential organisation of complex communication sounds. In such comparisons there has been a big focus on the role of ‘recursion’ as a core mechanism of the language faculty in the narrow sense (Hauser et al. 2002) and its uniqueness to both humans and human language.

However, although recursion and the potential uniqueness of other features of language are important topics, it is certainly not the only relevant topic for comparative studies (see also Waldenberger 2006, Fitch 2006, Rothenberg et al. 2014). Structurally and functionally, music, language and animal song not only share certain aspects but also have important differences. A three-way comparison between language, music and animal songs and the techniques that are used to model and explain them, has the potential to benefit research in all three domains, by highlighting shared and unique mechanisms as well as hidden assumptions in current research paradigms.

In this chapter we present an overview of research considering structure building and sequence generation in language, music and animal song. Our starting point is the work of Shannon and Chomsky from the 1940s and 1950s, which has been prominent in establishing a tradition of research in formal models of structure in natural language. We discuss issues concerning building blocks, Shannon’s \( n \)-gram models and the Chomsky hierarchy (CH), as well as the limitations of both frameworks in relation to empirical observations from the biological and cognitive sciences. We then proceed with discussing ways of addressing these limitations, including extending the CH with more fine-grained classes, the addition of probabilities and meaning representations to symbolic grammars, and replacing abstract symbols with numerical vectors.

At the end of the chapter, we reflect on what type of conclusions can be drawn from comparing and using these models and what impact this may have for future research.

2 Building blocks and sequential structure

Models for sequence generation highly depend on the choice of atomic units of the sequence. Before considering models of structure building, we may first want to identify what the elementary building blocks are that sequences - be it in language, music or animal vocalisations - are built up from. This, however, turns out to be much more complicated than we might naively expect.

2.1 Elementary units of models of language

One of the classical universal ‘design features’ of human language is duality of patterning (Holden 2004), which refers to the fact that all languages show evidence of at least two combinatorial systems: one where meaningless units of sounds are combined into words and morphemes, and one where those meaningful morphemes and words are further combined into words, phrases, sentences and discourse. Although the two systems are not independent and arguably should not be considered this way, in this chapter we pragmatically focus mainly on the second combinatorial system that combines already meaningful units into larger pieces, because this is the target of the most heavily studied models of structure building in natural language. Later in the chapter (in Section 10) we briefly consider the interplay between the two systems.

But even when restricting ourselves to meaning-carrying units, it turns out to be far from trivial to identify phoneme, morpheme, syllable or word boundaries based on cues in the observable signal (i.e. a spectogram) alone (Liberman et al. 1967). The choice of elementary units of models for structure in language is therefore usually not based on features of the acoustic information but, rather, on semantic information accessible through introspection. Most commonly, models considering structure in language are defined over words.
2.2 Building blocks of animal song

Like language, animal songs combine units of sound into larger units in a hierarchical way, but the comparability of the building blocks and the nature of the hierarchical structure in language, music and animal song is not at all straightforward. In particular, there are no clear analogues for words, phrases or even sentences in animal song (Besson et al., 2011; Scharff and Petri, 2011), and regardless of the approach taken to establish the smallest unit of the sequence (in bird song commonly referred to with the term ‘note’ or ‘element’) making decisions that are somewhat arbitrary seems unavoidable. A common way of identifying units in animal songs is to study their spectrogram and delineate units based on acoustic properties such as silent gaps (e.g., Isaac and Marler, 1963; Marler and Pickert, 1984; Adam et al., 2013; Fehér et al., 2009) or changes in the acoustic signal (e.g., Clark and Feo, 2008; Payne and McVay, 1971). Additionally, evidence about perception and production of different acoustic structures is often used to motivate a particular choice of building blocks (e.g., Tierney et al., 2011; Cynx, 1990; Franz and Goller, 2002; Amador and Margoliash, 2013). Strikingly, choices regarding building blocks might also be made by studying patterns of recombination and co-occurrence (Podos et al., 1992; ten Cate et al., 2013), an observation that illustrates the interdependence of the choice of building blocks and models for structure building, an issue that we revisit in Section 10. For a detailed review of the different methods used to identify units in animal vocalisations, we refer to (Kershenbaum et al., 2014).

2.3 Basic elements in music

In music - aside from the lack of a (compositional) semantic interpretation - the complexity of the musical surface (i.e. an interplay of different features like rhythm, metric, melody and harmony), leaves an even larger spectrum of possible choices for building blocks. Models can be defined not only over notes or chords, but also intervals and durations of notes, or other more complex features could be used as elementary units of the sequence. Traditionally, much of the discussion of structure in music has focused on Western classical music and has built on building blocks of melody, voice-leading (e.g., Tymoczko, 2006; Callender et al., 2008; Quinn and Mayromatis, 2011), outer voices (e.g., Aldwell, 2011), harmony (Winograd, 1968; Rohrmeier, 2007, 2011), combinations of harmony and voice-leading (Kassler, 1986; Aldwell, 2011; Neuwirth and Rohrmeier, 2015), or complex feature combinations derived from monophonic melody (Conklin and Witten, 1995; Pearce, 2005) and harmony (Whorley et al., 2013; Rohrmeier and Graepel, 2012).

The choice of building blocks is thus a difficult issue in all three domains we consider, and any choice will have important consequences for the models of structure that can be defined over these building blocks. The fact that choices regarding the ‘units of comparison’ may strongly affect the conclusions that can be drawn is frequently overlooked in the literature comparing birdsong, music and language. Nevertheless, it is often best to make pragmatic decisions about the building blocks in order to move on; as it turns out, some of the questions about building blocks can be addressed only after having considered models of structure (at which point applying model selection, a topic we revisit later, can help to revisit choices about the building blocks).

3 Shannon’s n-grams

In the slipstream of his major work on information theory, Shannon (1948) introduced n-gram models as a simple model of sequential structure in language. n-grams define the probability of generating the next symbol in a sequence in terms of the previous (n-1) symbols generated. When n=2, the probability of generating the next word depends only on what the current word is, and the n-gram model - called a ‘bigram’ model in this case - simply models transition probabilities. n-gram models are equivalent to (n-1)th-order Markov models over the same alphabet.

1 Although many of these aspects also occur in speech (cf. prosody), the structural aspect of human language appears to be easier to isolate.
3.1 Probability estimation

$n$-gram probabilities can be estimated from a corpus using maximum likelihood estimation (or relative frequency estimation) (Jurafsky and Martin, 2000). In theory, the bigger the value of $n$, the better one can predict the next word in a sentence, but in practice no natural language corpus is large enough to estimate the probabilities of events in the long ziplian tail of the probability distribution with relative frequency estimation.\footnote{This is an even bigger problem when trying to model bird song, where datasets are generally small and in many cases the number of possible transition probabilities - despite the comparably small number of elementary units - vastly exceeds the...} When human language is modelled, this problem is usually addressed by decreasing the prob-
ability of the counted n-grams and reassigning the resulting probability mass to unseen events, a process
called smoothing or discounting (Weikum, 2002). Smoothed n-gram models have long been the state of the
art for assigning probabilities to natural language sentences, and though better performing language models
(in terms of modelling the likelihood of corpora of sentences, e.g., Schwenk and Gauvain, 2003 Republic
and Mikolov, 2012) have been developed now, n-gram models are still heavily used in many engineering
applications in speech recognition and machine translation, due to their convenience and efficiency.

3.2 n-gram models of birdsong

n-gram models (often simple bigrams) have also been frequently applied to bird song (Isaac and Marler, 1963;
Chatfield and Lemon, 1970; Catchpole and Slater, 1995; Okanoya, 2004; Briefer et al., 2009; Markowitz et al.
2013; Samotskaya et al., 2016) and music (Ames, 1989; Pearce and Wiggins, 2012). For many bird species,
bigrams in fact seem to give a very adequate description of the sequential structure. Chatfield and Lemon
(1970) studied the song of the cardinal and reported that a 3-gram (trigram) model modeled song data
only marginally better than a bigram model, measured by the likelihood of the data under each of these
models. There is a single, small data set used for extracting n-grams and measuring likelihood, which makes
drawing firm conclusions from this classic analysis difficult. More recent work with birds that were exposed
to artificially constructed songs as they were raised suggests that transitional probabilities between adjacent
elements are the most important factor in the organisation of the songs also in zebra finches and Bengalese
finches (Lipkind et al., 2013), although many other examples of bird song also require more models (ten Cate
et al. 2013; ten Cate and Okanoya, 2012; Katahira et al., 2011, 2013).

3.3 n-gram models for music

In music, numerous variants of n-gram models have been used, to model musical expectancy (Narmour
1992; Schellenberg, 1997, 1996; Krumhansl, 1995; Eerola, 2003), but also to account for the perception of
tonality and key (which has been argued to be governed by pitch distributions that correspond to a unigram
model (Krumhansl, 2004; Krumhansl and Kessler, 1982) and to describe melody and harmony (Conklin and
Witten, 1995; Ponsford et al., 1999; Reis, 1999; Pearce, 2005; Rohrmeier, 2006; Rohrmeier and Graepel, 2012
Whorley et al., 2013). In particular, in the domain of harmony, Piston's table of common root progressions
(Piston, 1948) and Rameau's theory (of the basse fondamentale) (Rameau, 1717) may be argued to give
the structure of a first-order Markov model (a bigram model) of the root notes of chords (Hedges and Rohrmeier
2011; Temperley, 2004). In analogy with the findings in bird song research, several music modelling studies
find trigrams optimal with respect to modelling melodic structure (Pearce and Wiggins, 2004) or harmonic
structure (Rohrmeier and Graepel, 2012), although here too, the size of the datasets used is too small to
draw firm conclusions.

In choosing the optimal value of n, some additional aspects that play a role are usually not considered
in language and animal song. For instance, because of the interaction of melody with metrical structure,
not all surface symbols have the same salience when forming a sequence, which could be an argument to
in the face of data sparsity - prefer a 4-gram model over a 3-gram model to model music with a three-beat
metrical structure, as a 3-gram necessarily cannot capture the fact that the first beat of a bar is, in harmonic
terms, more musically salient than the other two (Ponsford et al., 1999). More generally, the interaction
between different single-stream features in music forms a challenge for n-gram models, an aspect that is not
as inescapable when modelling language and animal song (but see Ullrich et al., 2016) for an interesting,
multi-stream pattern in zebra finch vocalisations and dance). One model that addresses this problem by
combining n-gram models over different features and combined feature-spaces was proposed in Conklin and
Witten (1995).

number of examples in the entire set of empirical data.
The classical Chomsky hierarchy

Shannon’s $n$-grams are simple and useful descriptions of some aspects of local sequential structure in animal communication, music and language. It is however often argued that they are unable to model certain key structural aspects of natural language. In theoretical linguistics, $n$-grams, no matter how large their $n$, were famously dismissed as useful models of syntactic structure in natural language in the foundational work of Noam Chomsky from the 1950s ([Chomsky](1956)). In his work, Chomsky argued against incorporating probabilities into language models; in his view, the core issues for linguists concern the symbolic, syntactic structure of language. He proposed an idealisation of natural language where a language is conceived of as a potentially infinite set of sentences, and a sentence is simply a sequence of words (or morphemes). By systematically analyzing the ways in which such sets of sequences of words could be generated, Chomsky discovered a hierarchy of increasingly powerful grammars, relevant for both linguistics and computer science, that has later been named the ‘Chomsky Hierarchy’ (CH).

4.1 Four classes of grammars and languages

In its classical formulation, the CH distinguishes four classes of grammars and their corresponding languages: regular languages, context-free languages, context-sensitive languages, and recursively enumerable languages. Each class contains an infinite number of sets, and is strictly contained in all classes that are higher up in the hierarchy: every regular language is also context-free, every context-free language is also context-sensitive, and every context-sensitive language is recursively enumerable. When probabilities are stripped off, ($n$-grams correspond to a proper subset of the regular languages.

4.2 The Chomsky hierarchy and cognitive science

For cognitive science, the relevance of the hierarchy comes from the fact that the four classes can be defined by the kinds of rules that generate structures as well as by the kind of computations needed to parse the sets of sequences in the class (the corresponding formal automaton). Informally, regular languages are the sets of sequences that can be characterised by a “flowchart” description, which corresponds to a finite-state automaton or FSA. Regular languages can be straightforwardly processed (and generated) from left to right in an incremental fashion. Crucially, when generating or parsing the next word in a sentence of a regular language, we only needs to know where we currently are on the flowchart, not how we got there (for an example see Figure 5).

At all higher levels of the CH, some sort of memory is needed by the corresponding formal automaton that recognises or generates the language. The next level up in the classical CH are context-free languages (CFL’s), generated by context-free grammars (CFG’s), equivalent to so-called push-down automata, that employ a simple memory in the form of a stack. CFG’s consist of (context-free) rewrite rules that specify which symbols (representing a category of words or other building blocks, or categories of phrases) can be rewritten to which list of symbols. Chomsky observed that natural language syntax allows for nesting of clauses (center embedding), and argued that finite-state automata are incapable of accounting for such phenomena. In contrast, context-free grammars can express multiple forms of nesting as well as forms of counting elements in a sequence. An example of such nesting, and a context-free grammar that can describe it, is given in Figure 2.

4.3 Using the Chomsky hierarchy to model music

The success of the CH in linguistics and computer science and Chomsky’s demonstration that natural language syntax is beyond the power of finite-state automata has influenced many researchers to examine the formal structures underlying animal song and music (though there is no comprehensive comparison of models in either domain in terms of the CH yet). In music, there appears to be evidence for a number of nontrivial structure building operations at work that invite an analysis in terms of the CH or related frameworks.
The sentences *The song the bird sang was beautiful* and *The song the bird the linguists observed sang was beautiful* are examples of sentences with center embedding in English. The latter sentence can be derived from the start symbol S by subsequently applying rules 1, 2a, 2b, 3, 2a, 2c, 2a, 2d, 4c, 4b, 4a. (Note that traditionally, the analysis of the sentence contains a so called trace connecting the VP to its subject; left out here for clarity).

(1) S \rightarrow NP VP  
(2a) NP \rightarrow NP SBAR  
(2b) NP \rightarrow the song  
(2c) NP \rightarrow the bird  
(2d) NP \rightarrow the linguists  
(3) SBAR \rightarrow NP VP  
(4a) VP \rightarrow was beautiful  
(4b) VP \rightarrow sang  
(4c) VP \rightarrow observed

![Diagram of center embedding in English](image)

While more cross-cultural research is necessary, key structural operations that we can already identify include repetition and variation (Margulis, 2014), element-to-element implication (e.g. note-note, chord-chord) (Narmour, 1992; Huron, 2007), hierarchical organisation and tree structure, and nested dependencies and insertions (e.g., Widdess et al., 1981; Jackendoff and Lerdahl, 2006). Most of these operations are more naturally expressed using CFGs than with FSAs, and indeed a rich tradition that emphasises hierarchical structure, categories and, particularly, recursive insertion and embedding exists to characterise Western tonal music (Winograd, 1968; Keller, 1978; Kassler, 1986; Narmour, 1992; Steedman, 1983, 1996; Haas et al., 2009; Rohrmeier, 2007, 2011; Granroth-Wilding and Steedman, 2014; Neuwirth and Rohrmeier, 2015).

However, music unlike language, does not convey propositional semantics. The function of the proposed hierarchical structures therefore cannot be the communication of a hierarchical, compositional semantics (Slevc and Patel, 2011), and one cannot appeal to semantics or binary grammaticality judgments to make the formal argument that language is trans-finite-state. Rather, a common thread in research about structure in music is that at any point in a musical sequence listeners are computing expectations about how the sequence will continue, regarding timing details and classes of pitches or other building blocks (Huron, 2007; Rohrmeier and Koelsch, 2012). Composers can play with these expectations: meet expectations, violate them, or even put them on hold. In this play with expectations lie both the explanation for the existence of nested context-free structure in music and the way to make a more-or-less formal argument to place music on the CH. This is because the fact that an event may be prolonged (i.e. extended through another event; an idea originating with Schenker, 1935) and events may be prepared or implied by other events, creates the possibility of having multiple and recursive preparations. Employing an event as a new tonal center (musical modulation) could be formally interpreted as an instance of recursive context-free embedding of a new diatonic space into an overarching one (somewhat analogous to a relative clause in language) (Rohrmeier).
2007, 2011 Hofstadter [1986], which provides a motivation of the context-freeness of music through complex patterns of musical tension (Lerdahl and Krumhansl 2007; Lehne et al. 2013). Figure 3 shows an example of a syntactic analysis of the harmonic structure of a Bach chorale that illustrates an instance of recursive center-embedding in the context of modulation.

Figure 3: Analysis of Bach’s chorale “Ermuntre Dich, mein schwacher Geist” according to the GSM proposed by Rohrmeier (Rohrmeier 2011). The analysis illustrates hierarchical organisation of tonal harmony in terms of piece (piece), functional regions (TR, DR, SR), scale-degree (roman numerals) and surface representations (chord symbols). The analysis further exhibits an instance of recursive center-embedding in the context of modulation in tonal harmony. The transitions involving $TR_{key}=\psi(x, y_{key})$ denote a change of key such that a new tonic region (TR) is instantiated from an overarching tonal context of the tonal function $x$ in the key $y_{key}$.

Although the fact that composers include higher-level structure in their pieces is uncontroversial, whether listeners are actually sensitive to such structures in day-to-day listening is a debated topic (Heffner and Slevc 2015; Koelsch et al. 2013; Farbood et al. 2015). An alternative potential explanation for the existence of hierarchical structure in music could be found in the notation system and tradition of formal teaching and writing, a factor that may even be relevant for complexity differences in written and spoken languages in communities that may differ with respect to their formal education (Zengel 1962). However, there are also analytical findings that suggest that principles of hierarchical organisation may be found in classical North Indian music (Widdess et al. 1981) that is based on a tradition of extensive oral teaching. More cross-cultural research on other cultures and structures in more informal and improvised music is required before conclusions may be drawn concerning structural complexity and cross-cultural comparisons.
4.4 The complexity of animal vocalisations

In animal vocalisations, there is little evidence that non-human structures or communicative abilities (in either production or in reception) exceed finite-state complexity. However, a number of studies have examined abilities to learn trans-finite-state structures (e.g., Fitch and Hauser, 2004; Lipkind et al., 2013; Chen et al., 2015, 2016). Claims have been made - and refuted - that songbirds are able to learn such instances of context-free-structures (see Gentner et al., 2006; Abe and Watanabe, 2011); and respective responses (van Heijningen et al., 2009; ten Cate, 2014; Zuidema, 2013a; Beckers et al., 2012; Corballis, 2007). Hence further targeted research with respect to trans-finite-stateness of animal song is required to shed light on this question. By contrast, a number of studies argues for implicit acquisition of context-free structure (and even (mildly) context-sensitive structure in humans in abstract stimulus materials from language and music (Jiang et al., 2012; Oddén et al., 2012; Rohrmeier et al., 2012; Rohrmeier and Cross, 2008; Li et al., 2013; Rohrmeier and Rebuschat, 2012; Kuhn and Dienes, 2005).

5 Practical limitations of the Chomsky hierarchy

It has turned out to be difficult to empirically decide where to place language, music and animal song on the CH, due to a number of different but related issues. One of the more easily addressable problems concerns the finegrainedness of the levels of the CH. It was observed in many studies that (plain) n-grams are inadequate models of the structure of the vocalisations of several bird species on both the syllable and phrase (e.g., Markowitz et al., 2013; Jin and Kozhevnikov, 2011; Okanoya, 2004; Katahira et al., 2011) and song (Todt and Hultsch, 1996; Slater, 1983) level. Although n-gram models seem to suffice for modelling songs of for instance mistle thrushes (Isaac and Marler, 1963; Chattfield and Lemon, 1970) and zebra finches (Zann, 1996), richer models are needed to characterise the vocalisations of Bengalese finches (e.g., Katahira et al., 2011, 2013), blackbirds (Todt, 1975; ten Cate et al., 2013) and other birds singing complex songs (see Kershbaun et al., 2014; ten Cate and Okanoya, 2012) for a review). However, this difference in complexity is not captured by the CH, as the complexer models proposed (e.g., hidden Markov models, Rabiner and Juang, 1986) are still finite-state models that fall into the lowest complexity class of the CH: regular languages.

A similar issue occurs on higher levels of the hierarchy, when one tries to establish the formal complexity of natural languages such as English. It was noticed already in the 1980’s that some natural languages seem to display structures that are not adequately modeled by CFG’s (Sieber, 1985; Huybregts, 1984; Culy, 1985). However, the class of context-sensitive languages - one level up in the hierarchy - subsumes a much larger set of complex generalisations, many of which are never observed in natural language.

5.1 Adding extra classes

Both issues can be addressed by extending the CH with more classes. Rogers and colleagues (Jäger and Rogers, 2012) do so on the smallest level of the hierarchy, describing a hierarchy of sub-regular languages that contains the set of strictly local (SL) languages, which constitute the non-probabilistic counterpart of n-gram models. In the 1990’s, Joshi et al. (1991) pointed out that a number of linguistic formalisms (e.g. tree-adjoining grammars (Levy, 1975) or combinatorial categorial grammars (Steedman, 2000)) proposed to address the apparent inadequacy of CFG’s to model natural language, are formally equivalent with respect to the class of languages they are describing. These languages, collectively referred to as mildly context-sensitive languages (MCSSL’s, Joshi, 1985), can be roughly characterised by the fact that they are a proper superset of context-free languages, can be parsed in polynomial time, capture only certain kinds of dependencies and have constant growth property (Joshi et al., 1991).
Importantly, the CH concerns a theoretical construct that organizes types of structures according to different forms of rewrite rules and has, being a theory of formal languages in conjunction with idealized formal automata, little immediate connection with cognitive motivations or constraints (such as limited memory). The fact that it defines a set of languages that happen to be organized in mutual superset relations and are well explored in terms of formal automata that produce them does not motivate its reification in terms of mental processes, cognitive constraints or neural correlates. Although the CH has been inspired research in terms of a framework that allowed for the comparison of different models and formal negative arguments against the plausibility of certain formal languages or corresponding computational mechanisms, it does not constitute an inescapable a priori point of reference for all kinds of models of structure building or processing. Such forms of formal comparison and proofs should inspire future modelling endeavours, yet better forms of structural or cognitive models may involve distinctions orthogonal to the CH and may rather be designed and evaluated in the light of modelling data and its inherent structure as well as possible.

What are some different aspects that new models of structure building and corresponding cognitive models should take into account? In order to model the complexity of ecological real-world structures, they should be able to deal with graded syntactic acceptability [116] and sequence probability, they should be grounded in considerations of descriptive parsimony, in links to semantics and form-meaning interactions, and they should not only account for production and perception, but also consider learnability and computational complexity (e.g. memory requirements, and accounting for limited memory in biological systems). Finally, formal models should be required to make predictions for empirical structures based on which they may be distinguished on an empirical basis.

One main topic in theoretical linguistics, orthogonal to the finer classifications within the CH, concerns the distinction between 'weak generative capacity' and 'strong generative capacity' that are relevant for debates in music and animal research. There are divergent definitions of these terms. Briefly, they concern the difference whether we can focus on just classes of sets of sequences (i.e. regarding models just by the surface sequences they model: 'weak generative capacity'), or need to look at classes of structural analyses that different models can generate (i.e. regarding models in terms of the hidden underlying structure they assume to model sequences: 'strong generative capacity').

This is relevant, for instance, for distinguishing issue (2) long-distance dependencies, from (3) context-freeness, recursively enumerable context-sensitive mildly context-sensitive context-free regular/finite-state strictly locally testable finite languages

Figure 4: The extended Chomsky hierarchy.
5.2 Empirically establishing the complexity of different languages

Orthogonal to this granularity problem, is the more difficult problem of empirically evaluating membership of a class on the (extended) CH. The mere fact that a set of sequences can be built by a grammar from a certain class does not constitute a valid form of argument to place the system in question at the level on the (extended) CH. This is because a system lower in the hierarchy can approximate a system higher in the hierarchy with arbitrary precision by simply listing instances. For instance, Markov models are successfully used to describe some statistical features of corpora of music, (e.g., Tymoczko and Meeës, 2003; De Clercq and Temperley, 2011; Rohrmeier and Cross, 2008; Huron, 2007), but crucially, this fact does not imply that a Markov model is also the best model. The best model might be a context-free model that involves a single rule that captures a generalisation not captured by many specific nodes in the HMM.

To drive home this point further, consider again the example of center embedding described in Section 4. Note that arbitrarily deep center embeddings do not occur in practice (and even center embeddings of very limited depth are rarely observed and are shown to be incomprehensible for most humans; see e.g., Miller and Isard, 1964; Stolz, 1967). In any real world data, there is thus always only a finite (and, in fact, relative small) number of center embeddings; this finite set is easily modelled with an FSA that contains a different state for each depth. A finite-state account, however, loses a generalisation: different states lead to the same types of sequences, and we suddenly have a strict upperbound on the depth of possible embeddings.

A similar issue arises when long-distance dependencies are used to prove the inadequacy of finite-state models. For instance, when a bird sings songs of the structure $AB^nC$ and $DB^nE$, a long-distance dependency between $A$ and $C$ and between $D$ and $E$ can be observed, but the songs can be easily modeled with FSAs (see Figure 5) by just assuming two different (hidden) states from which the Bs are generated: one for the condition starting with $A$ and ending with $C$, and one for the other. This explains why some efforts to empirically demonstrate the context-freeness of bird song or music may not be convincing from a formal language theory perspective if they are based on just demonstrating a long-distance dependency. However, a long-distance dependency does have consequences for the underlying model that can be assumed in terms of its strong generative capacity (i.e., the set of structures it can generate) and compressive power: in the example shown in Figure 5, we were forced to duplicate the state responsible for generating $B$, in fact we require $2m$ states (where $m$ is the number of non-local dependency pairs, such as $A \ldots C$ or $D \ldots E$, that need to be encoded). Therefore, if there are multiple (finite), potentially nested non-local dependencies, the number of required states grows exponentially, which is arguably unsatisfactory when considering strong generative capacity arguments (see also the comparable argument regarding the implicit acquisition of such structures in Rohrmeier et al., 2012, 2014). If the intervening material in a long-distance dependency is very variable, even if not technically unbounded, considerations of parsimony, strong-generative capacity, elegant structure-driven compression and considerations of efficiency provide strong reasons to prefer a model other than the minimally required class in the CH, or a different type of model altogether.

5.3 Learnability

A third type of problem concerns the learnability of certain types of structures from examples, and the complexity of the inference process that this requires. A common paradigm to probe the type of generalisations made by humans and other species is to generate a sequence of sentences from an underlying grammar and study how well test subjects learn them in an artificial grammar learning (AGL) experiment (Reber, 1967; Pothos, 2007). Such experiments show robustly, for instance, that humans are able to distinguish grammatical from ungrammatical sentences generated by a CFG without having very explicit knowledge of the ‘rules’ they are using to make this distinction (Fitch et al., 2012). Many examples of AGL experiments with birds (not even necessarily songbirds; see e.g., Herbranson and Shimp, 2008, for an AGL study with pigeons) and other animals (such as rats or monkeys, Murphy et al., 2008; Wilson et al., 2013, respectively) can be found in the literature.

The results of AGL experiments remain difficult to interpret, as the inference procedures (and their complexity) to learn even relatively simple structures from examples are not well understood. Reviews of the ample number of AGL studies with both humans and non-human animals, as well as more formal accounts
Figure 5: A finite-state automaton and a context-free grammar generating a repertoire consisting of two sequences: \( AB^n C \) and \( DB^n E \) (with \( n \geq 0 \)). Note that the finite-state automaton is redundant in comparison with the CFG in the way that it contains multiple instances of the same structure \( B^n \).

of their interpretability can be found in (Fitch et al., 2012; ten Cate, 2016) and (Fitch and Friederici, 2012; Pothos, 2007), respectively.

5.4 Relating the Chomsky hierarchy to cognitive and neural mechanisms

Another class of arguments to move beyond the confines of the CH comes from considering its relation with cognition. Historically, the CH is a theoretical construct that organises types of structures according to different forms of rewrite rules, and it has little immediate connection with cognitive motivations or constraints (such as limited memory). Although it has been extensively used in cognitive debates on human and animal cognitive capacities, the CH may be quite fundamentally unsuitable for informing cognitive or structural models that capture frequent structures in language, music and animal song. This may be a surprising claim, given the long and proud history of the Chomsky hierarchy, the fact that its classes are organised in mutual superset relations and the fact that the top level contains all recursively enumerable languages: everything has its place on the Chomsky hierarchy. However, all the mathematical sophistication of the classes on the CH does not motivate their reification in terms of mental processes, cognitive constraints or neural correlates. A metaphor might help drive this point home. All squares on a chess-board can be reached by a knight in a finite number of steps. We can therefore compute the distance between two fields in terms of the number of moves a knight needs. This metric is universal in some sense (it applies to any two squares), but in general it is unhelpful, because its primitive operation (the knight’s jump) is not representative for other chess pieces. Similarly, the CH’s metric of complexity is universal, but its usefulness is restricted by the primitive operations (rewrite operations) it assumes.

A well-known issue that further illustrates this point is the fact that repetition, repetition under a modification (such as musical transposition), and cross-serial dependencies constitute types of structures that require quite complex rewrite rules (see also the example of context-sensitive rewrite rules expressing cross-serial dependencies in Rohrmeier et al., 2014), where such phenomena, in contrast, are frequent forms of form-building in music and animal song. Mechanisms that can recognise and generate context-free languages are not limited to rewrite rules or even phrasal constituents (consider e.g. dependency grammars Tesnière, 1966 that describe the structure of a string in terms of binary connections between its elements), and the mismatch between the simplicity of repetitive structures and the high CH class it is mapped onto might be one of many motivations to consider different types of models.
Other motivations to move beyond the confinements of the CH lie in the modelling of real-world structures that undermine some of the assumptions of the CH. Generally, the observation that music involves not only multiple parallel streams of voices, but also correlated streams of different features and complex timing, constitutes a theme that receives considerable attention in the domain of music cognition, but it does not easily match with the principles that underlie the CH, which is based on modelling a single sequence of words. Similarly, one can argue that the CH is incapable of dealing with several essential features and characteristics of language, such as the fact that language is primarily used to convey messages with a complex semantic structure and the gradedness of syntactic acceptability (Aarts 2004; Sorace and Keller 2005).

In summary, the CH does not constitute an inescapable a priori point of reference for all kinds of models of structure building or processing, but it has inspired research in terms of a framework that allowed the comparison of different models and formal negative arguments against the plausibility of certain formal languages or corresponding computational mechanisms. Such formal comparison and proofs should inspire future modelling endeavours, yet better forms of structural or cognitive models may involve distinctions orthogonal to the CH and may be designed and evaluated in the light of modelling data and its inherent structure as well as possible.

6 Moving towards different types of models

Considering the challenges we have mentioned, what are some different aspects that new models of structure building and corresponding cognitive models should take into account? In the slew of possible desiderata for new models, we observe two categories of requirements that such models should address.

6.1 Modelling observed data

The first category regards the suitability of models to deal with the complexity of actual real-world structures, which includes being able to deal with graded syntactic acceptability, but also handling semantics and form-meaning interactions. One main aspect that is particularly relevant is the notion of grammaticality or wellformedness. The CH relies quite strongly on this notion for establishing and testing symbolic rules, but the idea that grammaticality is a strictly binary concept is problematic in the light of real-world data. Even if the underlying system would prescribe so in theory, models should be able to account for the fact that in practice grammaticality is graded rather than binary (e.g., Abney 1996). In the case of music, it is not clear whether ungrammatical or irregular structures are clear-cut or distinguished in agreement by non-expert or expert subjects. This problem is even more prominent in the domain of animal songs, where introspection cannot be used to assess the grammaticality of sequences or the salience of proposed structures, and research can typically be based only on so-called positive data, examples conforming with the proposed rules. It is significantly more difficult to establish the validity and extension of rules in absence of negative data - i.e. where humans or animals explicitly reject a malformed sequence - which is hard to obtain in case of animal research.

6.2 Evaluation and comparison

A second category of requirements concerns the evaluation and comparison of different models. As we have pointed out, the CH is not particularly useful for selecting or even distinguishing models based on empirical data, as it provides no means to quantify the fit of a certain model with observed data. To overcome this problem, new models should include some mechanism that allows the modeller to evaluate which model better describes experimental data, for instance by evaluating the agreement of their complexity judgments with empirical findings from the sentence processing literature (e.g., Engelmann and Vasishth 2009; Vasishth). Related to this, due to the fact that our knowledge of possible rules in language is largely implicit, it is not always easy to even to agree on the structural analysis of a sentence. Even when the formalism used for analysis is fixed, trained linguists are not always in agreement on which tree exactly should be assigned to a certain sentence, see e.g. Berzak et al. (2016); Skut et al. (1999).
et al., 2010; Gibson and Thomas, 1999), their assessment of the likelihood of observed or made-up sequences, or by evaluating their predictive power. The last method of evaluating models seems particularly suitable for music, where empirical data are often focused around the expectations listeners are computing about how the sequence will continue. Further considerations to prefer one model over another could be grounded in descriptive parsimony or minimum description length (Mavromatis, 2009).

In the remainder of this chapter, we discuss three important extensions of the CH that address some of the previously mention issues.

7 Dealing with noisy data: adding probabilities

An important way to build better models of cognition and deal with issues from both above mentioned categories comes from reintroducing the probabilities that Chomsky abandoned along with his rejection of finite-state models. A hierarchy of probabilistic grammars can be defined that is analogous to the classical (and extended) CH and exhibits the same expressive power. We already mentioned that augmenting the automata generating SL languages yields n-gram models, whereas the probabilistic counterpart of an FSA is a hidden Markov model (HMMs). Similarly, CFGs and CSGs can be straightforwardly extended to probabilistic CFGs (PCFGs) and probabilistic CSGs (PCSG’s), respectively.

Adding probabilities to the grammars defined in the CH addresses many of the issues mentioned above. Probabilistic models can deal with syntactic gradience by comparing the likelihood of observing particular sentences, songs or musical structures (although accounting for human graded grammaticality judgments is not easy, see e.g., Lau et al., 2015). Furthermore, they lend themselves well to information-theoretic methodologies such as model comparison, compression or minimum description length (Grünwald, 2007; Mackay, 2003). Probabilities allow us to quantify degrees of fit, and thus select models in a Bayesian model comparison paradigm by selecting the model with the posterior probability given the data and prior beliefs or requirements. In addition, probabilistic models permit defining a probability distribution over possible next words, notes or chords in a sequence, which matches well with many experimental data about sentence and music processing.

The use of probabilistic models is widespread in both music, language and animal song. Aside from the previously mention n-gram models, frequently applied in all three domains, more expressive probabilistic models have also been widely used. Pearce’s IDyOM model - an extension of the multiple feature n-gram models proposed by Conklin and Witten - has been shown to be successful in the domains of both music and language (Pearce and Wiggins, 2012). Recent modelling approaches generalised the notion of modelling parallel feature streams into dynamic Bayesian networks that combine the advantages of HMMs with modelling feature streams (Murphy, 2002; Rohrmeier and Graepel, 2012; Raczyã…nski et al., 2013; Paiement, 2008).

In general, HMMs - which assume that the observed state is generated by a sequence of underlying (hidden) states that emit surface symbols according to a given probability distribution (for a comprehensive tutorial see Rabiner, 1989) - have been used extensively to model sequences in music (e.g., Rohrmeier and Graepel, 2012; Mavromatis, 2005; Raphael and Stoddard, 2004) and animal song (e.g., Katahira et al., 2011; Jin and Kozhevnikov, 2011). HMMs are also frequently practiced in modelling human language, although their application is usually limited to tasks regarding more shallow aspects of structure, such as part-of-speech tagging (e.g., Brants, 2000) or speech recognition (e.g., Rabiner and Juang, 1993; Juang and Rabiner, 1991). For modelling structural aspects of natural language, researchers usually resort to probabilistic models higher up the hierarchy, such as PCFG’s (e.g., Petrov and Klein, 2007), lexicalised tree-adjoining Grammars (Levy, 1975) or Combinatory Categorial Grammars (Steedman, 2000).

8 Dealing with meaning: adding semantics

One crucial aspect of human language of language that does not play a role in the CH is semantics. Chomsky’s original work stressed the independence of syntax from semantics, but that does not mean that semantics
is not important for claims about human uniqueness or structure building operations in language, even for linguists working within a ‘Chomskian’ paradigm. Berwick et al. (2011), for instance, uses the point that bird song crucially lacks underlying semantic representations to argue against the usefulness of bird song as a comparable model system for human language. Their argument is that in natural language the transfinite-state structure is not some idiosyncratic feature of the word streams we produce, but something that plays a key role in mediating between thought (the conceptual-intentional system in Chomsky’s terms) and sound (the articulatory-perceptual system). Note that while the relevance of the interlinkedness of thought and sound in language is an important point, we are not sure on which evidence Berwick et al. (2011) ground their statement that birds song lacks semantic representations.

8.1 Transducers

Crucially, the conceptual-intentional system is also a hierarchical, combinatorial system (most often modeled using some variety of symbolic logic, most famously the system of Montague 1970). From that perspective, grammars from the (extended) CH describe only one half of the system; a full description of natural language would involve a transducer that maps meanings to forms and vice versa (e.g., Jurafsky and Martin 2000, Zuidema 2013b). For instance, finite-state grammars can be turned into finite-state transducers, and context-free grammars into synchronous context-free grammars. All of the classes of grammars in the CH, have a corresponding class of transducers (see Knight and Graehl 2005, for an overview). Depending on the type of interaction we allow between syntax and semantics, there might or might not be consequences for the set of grammatical sentences that a grammar allows if we extend the grammar with semantics. In any case, the extension is relevant for assessing the adequacy of the combined model - e.g. we can ask whether a particular grammar supports the required semantic analysis - as well as for determining the likelihood of sentences and alternative analyses of a sentence.

8.2 Semantics in music

Whether we need transducers to model structure building in animal songs and music is a question that remains to be answered. There have been debates about forms of musical meaning and its neurocognitive correlates. A large number of researchers in the field agree that music may feature simple forms of associative meaning and connotations as well as illocutionary forms of expression, but lacks kinds of more complex forms of combinatorial semantics (see the discussion of Koelsch 2011; Slevc and Patel 2011; Fitch and Gingras 2011; Davies 2011; Reich 2011). However, it is possible to conceive of complex forms of musical tension that involve nested patterns of expectancy and prolongation as an abstract secondary structure, and motivate syntactic structures at least in Western tonal music, and in analogy would require characterising a transducer mapping syntactic structure and corresponding structures of musical tension in future research.

8.3 Semantics in animal song

Similarly, there have been debates about the semantic content of animal communication. There are a few reported cases of potential compositional semantics in animal communication (Arnold and Zuberbühler 2012), but these concern sequences of only two elements and thus do not come close to needing the expressiveness of finite-state or more complex transducers. For all animal vocalisations that have non-trivial structure, such as the songs of nightingales (Weiss et al. 2014), blackbirds (Todt 1975, ten Cate et al. 2013), pied butcherbirds (Taylor and Lestel 2011) or humpback whales (Payne and McVay 1971; Payne and Payne 1985), it is commonly assumed that no combinatorial semantics underlies it. However, it is important to note that the ubiquitous claim that animal songs do not have combinatorial, semantic content is actually based on few to no experimental data. As long as the necessary experiments are not designed and performed, the absence of evidence of semantic content should not be taken as evidence of absence.

If animal songs do indeed lack semanticity they would be more analogous to human music than to human language. The analogy to music would then not primarily be based on the surface similarity to music on the level of the communicative medium (use of pitch, timbre, rhythm or dynamics), but on functional
considerations such as that they do not constitute a medium to convey types of (propositional) semantics or simpler forms of meaning, but are instances of comparably free play with form and displays of creativity (Wiggins et al., 2015).

8.4 A music-language continuum?

Does this view on music-animal song analogies have any relevance for the study of language? There are reasons to argue it does, because music and human language may be regarded as constituting a continuum of forms of communication that is distinguished in terms of specificity of meaning (Brown, 2001; Cross and Woodruff, 2010). Consider, for instance, several forms of language that may be considered closer to a ‘musical use’ in terms of their use pitch, rhythm, meter, and semantics, such as motherese, prayers, mantras, poetry, and nursery rhymes, as well as perhaps forms of the utterance “huh” (see Dingemanse et al., 2014).

Animal vocalisations may be motivated by forms of meaning (that are not necessarily comparable with combinatorial semantics), such as expressing aggression or submission, warning of predators, group cohesion, or they may constitute free play of form for display of creativity, for instance (but not necessarily), in the context of reproduction. Given that structure and structure building moving from the language end to the music end is less constrained by semantic forms, more richness of structural play and creativity is expected to occur on the musical side (Wiggins et al., 2015).

9 Dealing with gradations: adding continuous-valued variables

An entirely different approach to modelling natural language - parallel to the symbolic one employed by the Chomsky hierarchy - is one where the symbols and categories of the CH are replaced by vectors and the rules are projections in a vector space (implicitly) defined in matrix vector algebra. Thus, instead of having a rule ‘X \rightarrow Y Z’, where X, Y and Z are symbolic objects (such as a ‘prepositional phrase’ (PP) in linguistics, or a motif in a zebra finch song), we treat X, Y and Z as n-dimensional vectors of numbers (which can be binary, integer, rational or real numbers; for example \([0, 1, 0, \ldots]\) or \([0.453, 0.333, -0.211, \ldots]\)) and ‘\(→\)’ becomes an operation on vectors that describes how the vector for Z can be computed given the vectors for X and Y. Vector grammars offer a natural way to model similarity between words and phrases, which can be defined as their distance in the vector space. Consequently, as one can compute how close a vector is to its prototypical version, vector grammars can straightforwardly deal with noisy data, and exhibit a gradual decrease of performance when inputs become longer or noisier, both properties that are attractive for cognitive models of language.

9.1 Vector grammars and connectionism

Vector grammars bear a close relation to connectionist neural network models of linguistic structure that were introduced in the 1990s (Elman, 1990; Pollack, 1990). After being practically abandoned as models of linguistic structure for over a decade, neural networks are experiencing a new wave of excitement in computational linguistics, following some successes with learning such grammars from data for practical natural language processing tasks, such as next word prediction (Mikolov et al., 2010), sentiment analysis (Scher et al., 2010; Ferradji, 2008; Le and Zuidema, 2014), generating paraphrases (Le and Mikolov, 2014; Iyyer et al., 2014) and machine translation (Bahdanau et al., 2014). As they can straightforwardly deal with phenomena that are continuous in nature (such as loudness, pitch variation or beat) as well as conveniently handle multiple streams at the same time, vector grammars or neural networks - although not frequently applied in this field - also seem very suitable to model music (see Cherla et al., 2015; Spiliopoulou and Storkey, 2011) for some examples of recent work in which neural network models are used to model aspects of music.

Whether neural network models are fundamentally up to the task of modelling structure in language and what they can teach us about the nature of mental processes and representations (if anything at all) has been the topic of a longstanding (heated) debate (some influential papers are Fodor and Pylyshyn, 1988; Pollack, 1990).
1990; Rumelhart and McClelland, 1986; Pinker and Mehler, 1990). Whichever side one favors in this debate, it seems undoubtedly true that the successes of neural networks in performing natural language processing tasks are difficult to interpret and that the underlying mechanisms are difficult to characterise in terms of the structure building operations familiar from the CH tradition. Part of this difficulty comes from the fact that neural network models are typically trained on approximating a particular input-output relation (‘end-to-end’) and do not explicitly model structure. Although one might argue that many end-to-end tasks require (implicit) knowledge about the underlying structure of language, it is not obvious what this structural knowledge actually entails. Analysing the internal dynamics to interpret how solutions are encoded in the vector space is notoriously hard for networks that have more than a couple nodes and the resulting systems - a few exceptions aside (e.g., Karpathy et al., 2015) - often remain black boxes. Furthermore, finding the right vectors and operations that encode a certain task is a complicated task; the research focus is therefore typically more on finding optimisation techniques to more effectively search through the tremendous space of possibilities than on interpretation (e.g., Zeiler, 2012; Kingma and Ba, 2015; Hochreiter and Schmidhuber, 1997; Chung et al., 2015).

9.2 The expressivity of vector grammars

The focus or difficulties in the field aside, however, one can observe that the expressivity of connectionist models reduces the need for more complex architectures (such as MCSG’s), as vector grammars are computationally much more expressive than symbolic systems with similar architectures. For instance, Rodriguez (2001) demonstrated that a simple recurrent network (or SRN, on an architectural level similar to an FSA) can implement the counter language $a^nb^n$, a prime example of a context-free language (see Figure 6). Theoretically, one can prove that an SRN with a non-linear activation function is a Turing complete system that can implement any arbitrary input-output mapping (Siegelmann and Sontag, 1995). Although it is not well understood what this means in practice - we lack methods to find the parameters to do so, appropriate techniques to understand potential solutions and arguably even suitable input-output pairs - the theoretical possibility nevertheless calls into question the a priori plausibility of the hypothesis that context-freeness is uniquely human. Rodriguez’s results demonstrate a continuum between finite-state and (at least some) context-free languages, which cast doubt on the validity of the focus on architectural constraints on structure building operations that dominates the CH. As such, while much theoretical work exploring their expressive power is still necessary, vector grammars provide another motivation to move on to probabilistic, non-symbolic models that go beyond the constraints of the CH.

10 Discussion

We have discussed different formal models of syntactic structure building, building blocks and functional motivations of structure in language, music and bird song. We aimed to lay a common ground for future formal and empirical research addressing questions about the cognitive mechanisms underlying structure in each of these domains, and about commonalities as well as differences between music and language, and between species. This chapter can thus be seen as a long-overdue effort to bring theoretical approaches in music and animal vocalisation into common terms that can be compared with approaches established in formal and computational linguistics, complementing the literature responding to Hauser, Chomsky and Fitch’s provocative hypothesis concerning the ‘exceptional’ role of the human cognitive/communicative abilities.

Our journey through the computational models of structure building - from Shannons n-grams, via the CH to vector grammars and models beyond the CH - has uncovered many useful models for how sequences of sound might be generated and processed. We arrived at a discussion of recent models that add probabilities, semantics and graded categories to classical formal grammars. Graded category models, which we called vector grammars, link formal grammar and neural network approaches and add the power to deal with structures that are inherently continuous. An important finding using such vector grammars is that one relatively simple architecture can predict sequences of different complexity in the CH and therefore have the
Figure 6: (a) A simple recurrent network (SRN), equivalent to the one proposed by [Elman, 1990]. The network receives a sequence of inputs (in this case “a a a b b b”) and outputs whether this is a grammatical sequence (+/−). The arrows represent so called “weight matrices” that define the projections in the vector space used to compute the new vector activations from the previous ones. NB: traditionally the SRN does not classify whether sequences belong to a certain language, but predicts at every point in the sequence its next element (including the ‘end of string’ marker). Whether a sequence is grammatical can then be evaluated by checking if the network predicted the right symbol at every point in the sequence where this was actually possible (thus, in the case of $a^n b^n$, predicting correctly the end of the string, as well as all the $b$’s but the first one). (b) The same network, but unfolded over time. On an architectural level, the SRN is similar to an FSA.
potential to undermine assumptions concerning categorically different cognitive capacities between human and animal forms of communication (Horton, 1993; Hauser et al., 2002).

Perhaps the most important lesson we can draw from comparing models for structure building, is that the chosen level of description determines much about the type of conclusions that can be drawn, and that there is no single ‘true’ level of description: the choice of model should therefore depend strongly on the question under investigation. This is true within a certain paradigm (such as the choice of basic building blocks, or the level of comparison) and between paradigms. Most comparative research to structure building compares words in language with notes in music and animal song, and sentences to songs. But this ignores the potential structure in bouts of songs. If songs were in fact to be compared with words rather than sentences, such models would be comparing the bird’s phonology with human syntax (Yip, 2006).

Moreover, the choice of model determines which aspects of structure building we are comparing across domains. What should be considered in this case is not which model is better in itself, but which model is better for a certain purpose. For instance, fully symbolic models from the CH provide a useful perspective for the comparison of different theoretical approaches and predictions concerning properties of sets of sequences, but at the same time, they might not necessarily tell us much about the cognitive mechanisms that underlie learning, processing or generating such sets of sequences. This means that even if we can show that animal song and human language are of a different complexity class in the CH, we cannot automatically assume that there is a qualitative difference in the cognitive capacities of humans and non-human animals, as demonstrated by the relatively simple neural network architectures that can predict sequences of different complexity in the CH.

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