

Tool-assisted induction of subregular languages and mappings

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Abstract of the Dissertation

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The last decade was very fruitful in the field of subregular research. New classes of subregular languages and mappings were uncovered for modeling natural language phenomena, and new learning algorithms were developed for these classes. The subregular approach has been successfully applied to phonotactics (Heinz, 2010a), rewrite processes in phonology and morphology (Chandlee, 2014), and even syntactic constraints over tree structures (Graf, 2018b). However, the rapid pace of the theoretical research has not been matched when it comes to engineering considerations. Many of the proposed learning algorithms have not been implemented yet, and as a result, their performance on concrete data sets is not known.

In my dissertation, I implement and experiment with some of the learners available for subregular languages and mappings. I test these learners on data that is modeled after linguistic phenomena such as word-final devoicing and

various types of harmony systems. The code for these evaluations is available as part of my Python package *SigmaPie*  (Aksënova, 2020b).

The findings of my thesis allow linguists and formal language theorists to assess possible applications of subregular techniques and approaches, in particular typology, cognitive science, and natural language processing.

*There is a single light of science, and
to brighten it anywhere is to brighten it everywhere.*


— Isaac Asimov

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Chapter 1

Introduction

The availability of tools greatly impacts the future of ideas. Charles Babbage was the first to conceptualize the design of a computer in 1837, however, he could not implement it because the required funding and technologies needed for the production of his *Analytical Engine* were not yet available. Only in 1941, technological progress allowed for the first general-purpose computer named Z3 to be assembled. Furthermore, it was the development of the X-ray crystallography technique that allowed Rosalind Franklin to take a picture of the crystallized fibers in 1952 that ultimately led to the discovery of DNA sequencing. Frequently, the development of tools for a certain scientific area is an essential catalyst for progress.

In my dissertation, I implement and experiment with some of the algorithms available for the formal classes of *subregular languages and mappings* that recently proved themselves to be extremely useful for modeling natural language dependencies. Namely, I discuss the results of the automatic extraction of subregular grammars from data exhibiting various linguistic patterns, such as word-final devoicing, harmony systems of different types, and others. The code behind the inference algorithms is available as a part of my package *SigmaPie*  (Aksënova, 2020b). This package is open source, implemented in Python 3, and

available via `pip`. *SigmaPie* allows linguists and formal language theorists to assess possible applications of subregular ideas in the areas of typology, cognitive linguistics, and natural language processing. This package is flexible and can be used to explore a variety of research questions. It provides researchers who are interested in subregular complexity and learning with a sandbox where they can play with new ideas in a hands-on fashion.

This thesis is meant to be a starting point for scientists who wish to incorporate *SigmaPie* into their research. It discusses the theoretical foundations of subregular linguistics and it shows how *SigmaPie* can be used to experimentally test theoretical claims. Both the discussion and the experiments consider only string representations, rather than autosegmental or tree-based ones. That does not mean that the subregular view, or its implementation via *SigmaPie*, cannot be extended to handle these richer types of structures. Strings provide an accessible starting point for subregular work, they are not its intended endpoint. Similarly, *SigmaPie* is a sandbox rather than a finished product — its active use in research will greatly shape *SigmaPie* and push it in whatever direction turns out to be most fertile and productive.

1.1 Subregular linguistics and learning

Formal tools help to generalize natural language patterns and study them independently of linguistic theories, therefore allowing researchers to focus on one of the core questions of linguistics: *what is the complexity of natural language?* Although this question is not yet answered, we already know to some extent the complexity of the restrictions that phonotactics and morphotactics impose on the surface forms of their objects. We have also come closer closer to understanding what types of changes are involved in phonological and morphological processes. **Formal language theory** provides a perspective on modeling natural language

dependencies. Under this perspective, a formal language is a possibly infinite set of words satisfying some set of rules. *Subregular languages* have weak generative capacity, and therefore cannot express some types of dependencies, but their power is enough for phonology and morphology.

The subregular perspective has a goal of identifying weak subclasses of languages and mappings that are sufficiently powerful for natural language dependencies. Subregular languages are a good fit for phonotactics and morphotactics, while subregular mappings provide a convenient way to describe phonological and morphological phenomena. These languages and mappings are subclasses of finite-state automata and transducers that are sub-divided from regular languages since the 1970s (McNaughton and Papert, 1971). Although they are not novel for the field of formal language theory, they made their way to linguistics much later (Heinz, 2010a, 2011). The subregular approach is a fruitful and promising research direction, see Section 1.2 and Background for formal definitions and further information.

However, in natural language processing (NLP), little attention is paid to the vast body of linguistic research on the types of dependencies that occur in language. Moreover, it is not even clear how to incorporate this linguistic knowledge into currently used NLP models. Neural networks, which are widely employed nowadays in NLP, learn patterns in an uninterpretable fashion; as a result they do not furnish a way for linguists to look inside those networks and understand *how* and *what exactly* was learned. On the contrary, *subregular* learning algorithms (which I will call “subregular learners” from here on) are fully transparent and interpretable.

Subregular learning algorithms guarantee the interpretability of the way the grammar was discovered, as well as the interpretability of the grammar per se. In other words, it is always *possible to look inside the algorithm*. Observing the behavior of the algorithm and studying its properties is necessary for understanding which

configurations in the training data help to discover the pattern. If we are dealing with natural language data, transparent learning algorithms might help to explore the way humans learn languages, to the extent that useful parallels can be drawn between the two. Interestingly, the discussed classes of subregular languages are learnable just from positive data, without any need for negative data.

In the field of formal languages, theoretical achievements are not always followed by their practical applications. As a result, a frequent situation arises where a learning algorithm is proposed in the literature but is not implemented. Although it is important to prove theorems about the convergence of such algorithms, it is also important to subject them to empirical testing. As of now, not a lot of such algorithms are implemented, and even fewer of them are employed in practice. Sometimes, as Gildea and Jurafsky (1996) show in their paper, the grammatical inference algorithms need to be modified and *linguistically “biased”* to work with raw language data. The last few decades brought us a lot of new knowledge about the complexity of human language patterns, and the majority of this knowledge is still waiting to be incorporated into these algorithms.

The *SigmaPie* package implements subregular learners that efficiently extract grammars after observing a finite number of well-formed strings of the target language. This package also implements sample generators, scanners, and some other tools. The generation of a data sample of the required complexity is needed during the design of artificial learning experiments. Scanners and re-writers verify the well-formedness of strings regarding some grammar or modify the input according to a specified set of rules. Additionally, the toolkit provides functions such as changing the polarity of the grammar or removing uninformative elements from the grammar. The subregular perspective is transparent and interpretable, but so far it lacked tools that help to leverage this transparency. Such a toolkit would be especially useful to linguists working on modeling natural language dependencies.

1.2 Linguistic motivation behind the subregular approach

What is the minimum generative capacity of the grammar that is capable of encoding human language-like patterns? In other words, what types of dependencies must that grammar take into account? Answering these questions might furnish powerful insights into human cognition. The first step must be uncovering what *types* of patterns do human languages exhibit.

To describe and generalize phenomena observed in natural languages, we need to build their computational or mathematical models. Formal languages provide a way to do this. Their object can be any structured object formed from a finite collection of discrete elements, where those objects can be strings, trees, or graphs. In this thesis, however, I will only focus on string representations.

Subregular modeling provides two perspectives: modeling well-formedness conditions as languages, and modeling transformations as mappings. A **well-formedness condition** can be encoded as a language, or a potentially infinite collection of strings satisfying that condition. For example, in Russian, voiced obstruents become voiceless at the end of the word. It results in words such as *lo[b]* being excluded from the collection of well-formed Russian strings, whereas their voiceless counterparts such as *lo[p]* ‘forehead’ are grammatical. Suppose that every word has a dedicated marker \times at the end of the word. Then the ban against voiced obstruents at the end of the word can be encoded as a grammar that rules out all cases where a voiced obstruent is followed by that marker: *b \times* , *g \times* , *d \times* , etc.

In contrast, a **transformation** can be formalized as a collection of pairs of strings, where those strings represent the states “before” and “after” the rule application. In other words, those pairs demonstrate the underlying representations and the corresponding surface forms. From this perspective, Russian word-final devoicing

can be viewed as a collection of pairs, where the final obstruent of the first string can be either voiced or voiceless, but it is always voiceless in the second one: ($lo[b]$, $lo[p]$) ‘forehead’, ($lu[g]$, $lu[k]$) ‘meadow’, ($lu[k]$, $lu[k]$) ‘onion’, etc. The corresponding grammar then looks at every symbol of the underlying representation and rewrites it as is, unless that symbol is the word-final voiced obstruent: then it is substituted by its voiceless counterpart. In such a way, subregular models can capture well-formedness conditions, and encode the mapping of underlying representations to the corresponding surface forms.

In the domain of string languages, *regular languages and mappings* provide a reasonable upper bound for phonology and morphology (Johnson, 1972; Koskenniemi, 1983; Kaplan and Kay, 1994; Beesley and Karttunen, 2003). The class of regular languages, however, can be further subdivided into a nested hierarchy of weaker *subregular* languages. Closer research of phonological and morphological patterns shows that in fact, these patterns do not require the whole power of regular languages. Several subregular classes express well-formedness conditions imposed by phonotactics and morphotactics (Heinz et al., 2011; Aksënova et al., 2016; Heinz, 2018). Subregular — namely, *subsequential* — mappings describe a multitude of morphological and phonological processes (Chandlee, 2017; Chandlee and Heinz, 2018). Subregular grammars found their applications even in the areas of syntax and semantics. (De Santo et al., 2017; Graf and Shafiei, 2019; Graf, 2019). In this thesis, I focus on modeling phonological dependencies of different kinds.

Nowadays, researchers work on many aspects of subregular languages. There has been significant progress in the understanding of their underlying mathematical structures (Fu et al., 2011; Heinz and Rogers, 2013). Multiple papers show how different linguistic phenomena can be accounted for in terms of subregular models (Heinz et al., 2011; Heinz and Lai, 2013; Chandlee, 2014; Aksënova et al., 2016; Dolatian and Heinz, 2018; Graf, 2019; Karakaş, 2020). The

approach was extended to trees and now can express such complicated dependencies as c-command or case assignment as well (Graf and Shafiei, 2019; Vu et al., 2019). The works cited above are all very recent. To help accelerate this currently growing direction of research, I implemented a package that provides the subregular functionality and explored *practical* capabilities of those algorithms.

1.3 Main insights and structure of the dissertation

Different subregular learners capture different types of natural language dependencies. While these distinct learning algorithms all rest on a sound theoretical foundation, it is unknown how well the theorems about the correctness of those learners carry over to real-world performance. This thesis demonstrates how this open issue can be explored with the help of *SigmaPie*. I design multiple artificial learning experiments and score the subregular learners on datasets exhibiting patterns such as local assimilations, multiple long-distant harmonies of different types, some typologically unattested patterns, and others. The datasets range from artificial automatically generated samples to real-language datasets such as German, Finnish, and Turkish wordlists. While the artificially generated datasets explore if a pattern is learnable in general, the raw data shows what issues the learners have when faced with the raw natural language data. Every target pattern is approached from two perspectives: as a well-formedness condition on the surface forms, and as a transformational rule changing values of some elements.

Specific findings I show that indeed, subregular learners perform as theoretically expected, and extract grammars of the corresponding complexity from generated datasets. It confirms that they can model different natural language dependencies, including but not limited to local dependencies, different

long-distance harmonies, and even segmental patterns. Importantly, some of these learners were able to perform well on such complex tasks as learning of a long-distance dependency from raw data.

Relevance for linguistics Subregular languages and mappings indeed model a wide variety of natural language patterns. Subregular learning algorithms efficiently learn languages and mappings from positive data. Setting up the learning pipeline itself is not complicated, and I thoroughly discuss the way I did it in my thesis. Such *SigmaPie*-based learning experiments provide a way to test ideas on artificial and natural language datasets.

While chapters 3 and 4 explore subregular modeling from a practical point of view, **Chapter 2. Background** gives a theoretical perspective on subregular languages and mappings. I discuss the modeling capacities of subregular grammars and transformations by capturing attested natural language patterns such as word-final devoicing, unbounded tone plateauing, and several different types of harmonies. Namely, the reviewed formal classes are strictly local, strictly piecewise, tier-based strictly local, and multi-tier strictly local languages; and subsequential transformations. Additionally, in that chapter, I also discuss the problem of inferring grammars from data, and list the useful properties shared by the subregular learners.

In **Chapter 3. Learning languages**, I target modeling well-formedness conditions. Namely, I employ four subregular language classes that express generalizations, including local and long-distance processes such as attested and unattested harmony systems with and without blockers, word-final devoicing, and even suprasegmental patterns. A training sample is a list of well-formed strings that does not include words that violate the target generalization. So, for example, for a target pattern of vowel harmony, the training dataset is a sample of harmonic words. The conducted experiments confirmed the learning

expectations for the artificial datasets, showing how different linguistic patterns are captured by subregular models. However, the performance of the learners on raw natural language data was worse, and in some cases, a more powerful model was required to capture a pattern of lower complexity. In that chapter, I also outline the architectures of the learners originally introduced in (Heinz, 2010b; Jardine and McMullin, 2017; McMullin et al., 2019).

Chapter 4. Learning mappings is concerned with modeling transformations changing the underlying representations into the corresponding surface forms. According to Chandlee (2014), many of phonological and morphological dependencies belong to the class of subsequential mapping. Thus, I give an overview of a subsequential learner OSTIA (Oncina et al., 1993; de la Higuera, 2010), and use it to extract generalizations from datasets exhibiting different linguistic dependencies. In this case, patterns are represented as pairs of strings. So, for example, if a pair demonstrates a vowel harmony, then the first string shows the underlying, or underspecified, representation, while the vowels in the second word are fully specified and harmonic. The learner was able to model a variety of local and long-distance dependencies but struggled to capture a blocking effect. Additionally, that chapter discusses other algorithms that learn mappings and can be employed for similar tasks in the future.

Finally, **Chapter 5. Conclusion** summarizes the obtained results and proposes directions for future research. Figure 1.1 gives an overview of the flow of this thesis, starting from the theory of modeling well-formedness conditions and transformations, and then followed by a part discussing the applications and the accomplished learning experiments. The *SigmaPie* package was used in the experiments reported in Chapters 3 and 4. Its code is available via Python package manager pip and is listed in Appendix A. The correctness of the code was assessed via a series of unit tests, provided in Appendix B.

This dissertation shows how learning experiments can be conducted using

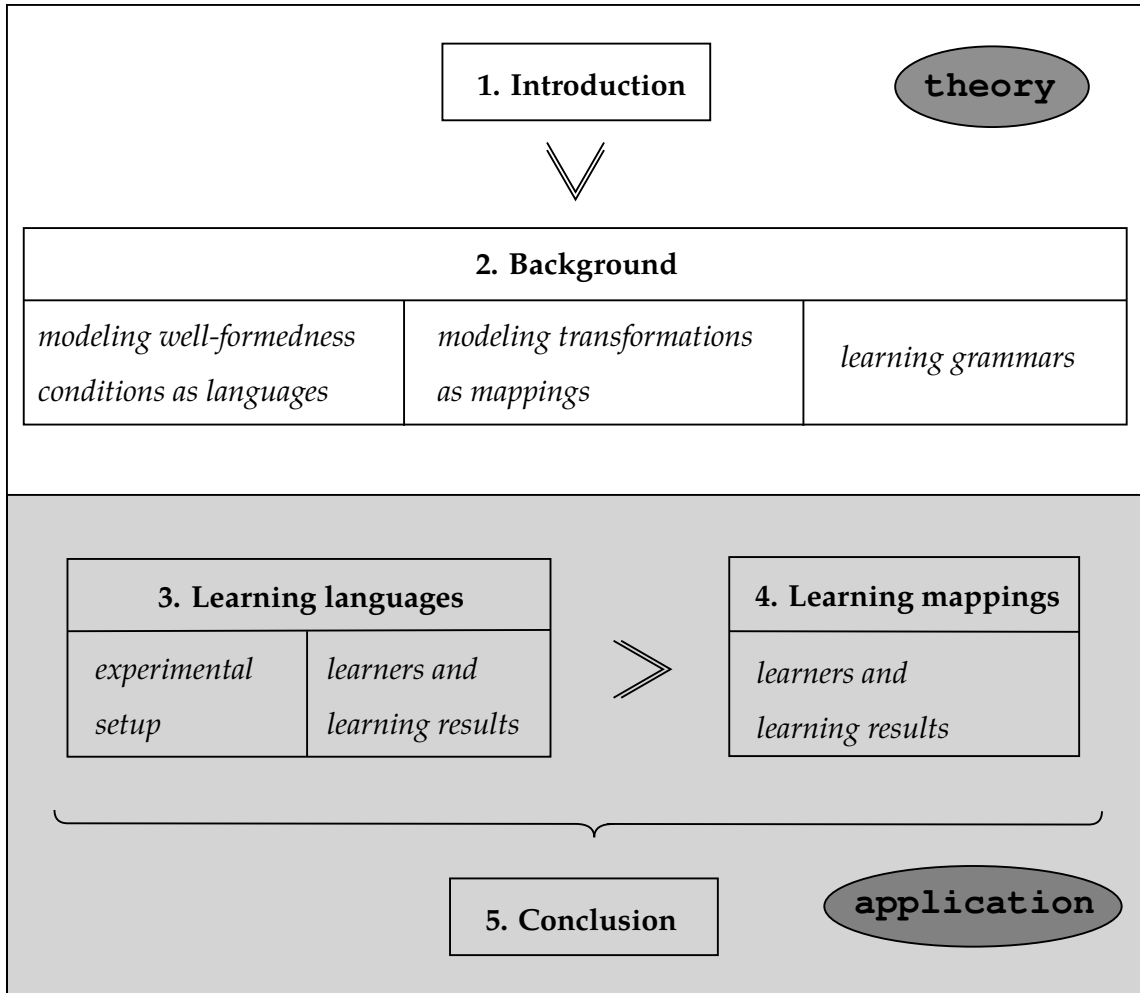


Figure 1.1: Flow of chapters of this dissertation: Introduction, Background, Learning languages, Learning mappings, and Conclusion.

subregular learners from *SigmaPie* package and discusses the results of those experiments. This package contains functionality that allows linguists to model linguistic phenomena and test those models, manually and automatically.

Chapter 2

Background

Linguistic rules capture two types of generalizations: **well-formedness conditions**, i.e. the requirements for a word to be well-formed, and **transformations**, i.e. the rules of re-computing the given underlying representation into the corresponding surface form. The former restrict the word's form itself, such as “two vowels should never be adjacent to each other”, while the latter describe the change, such as “insert [j] in-between two adjacent vowels”. For example, transformations map the Russian word that is orthographically represented as *dlinnoshee* ‘long-necked’ into its pronunciation *dlinnosh[eje]*, and the well-formedness conditions ensure that the pronunciation *dlinnosh[eee]* is not allowed since it contains two vowels adjacent to each other.

Grammars describe how to build well-formed words from the elements of the **alphabet**. A **language** of the grammar is a potentially infinite collection of all well-formed strings of that grammar. Thus in a formal sense, it simply refers to a collection of words, or **strings**. **Transformations** are functions from the input language, i.e. a collection of “underlying representations”, onto the output language, or a collection of “surface forms”.

In this chapter, I discuss *subregular grammars* (Section 2.1) and *subsequential functions* (Section 2.2) as they seem to be a good fit for natural language

dependencies (Heinz, 2011; Heinz et al., 2011; Gainor et al., 2012; Heinz and Lai, 2013; Aks nova et al., 2016; Graf, 2017a; Chandlee and Heinz, 2018, i.a.). In the two following chapters, I show the results of the *automatic extraction* of subregular grammars and subsequential functions given the learning framework defined in Section 2.3.

2.1 Modeling well-formedness conditions

To model well-formedness conditions means to find a way to discriminate between well-formed and ill-formed words of a language. In other words, it implies finding a grammar that only builds well-formed strings, and that can recognize which strings are ill-formed. For example, given the alphabet of vowels and consonants, a grammar can prohibit vowel hiatus by penalizing adjacent vowels.¹

Subregular grammars provide an interpretable and succinct way to encode such rules. These grammars are very weak and restricted, however, they are sufficiently powerful for natural language. Interestingly, the subregular nature of linguistic generalizations allows us to explain the absence of some theoretically possible yet typologically unattested patterns (Gainor et al., 2012); I come back to the issue of typology in Section 2.1.2. Also, this approach gives insights into human cognition since there is evidence that only some subregular language classes are learnable (Lai, 2015). As it follows from the name itself, subregular grammars are a subset of the regular ones, and therefore let us first establish the regular nature of natural language patterns.

¹Strictly speaking, grammars do not recognize if a string is well-formed, but rather provide a finite specification of the language. Instead, a recognizer judges the well-formedness of strings. However, for the sake of simplicity and conciseness, I do not separate these two notions in my dissertation.

2.1.1 Regular nature of natural language patterns

Consider a pattern of Russian compounding, where a morpheme $-o$ ² is located in-between compounding stems. For example, the stems *vod(-a)*³ ‘water’ and *voz* ‘carrier’ can be combined to obtain a complex word *vod-o-voz* ‘water carrier’. If the compound is composed of multiple stems, the marker is added in-between every one of them: *vod-o-voz-o-voz* ‘carrier of water carriers’.

This pattern can be viewed as a language of well-formed sequences of stems and compounding affixes. Strings such as *stem*, *stem-o-stem*, *stem-o-stem-o-stem* belong to the target language, but *stem-stem* and *stem-o* do not. This can be rephrased a rule “a well-formed form cannot start or end with a compounding marker, and within a word, two markers or two stems should not be adjacent to each other”. Generalizations like this can be conveniently expressed as finite state automata.

A **finite state automaton** (FSA) is a type of an abstract machine that is defined by a finite list of states and the transitions between those states (Lawson, 2003). In the case of string-based automata, these transitions are annotated with characters. An automaton reads a string of characters (the input string), and every new character changes the current state. Some of the states are **initial**, meaning that the first character of the input string can be read from those states. **Final**, or *accepting* states are the ones that indicate that the string is accepted. The input string is accepted by an automaton when the first character of that string can be read from the initial state, and this string is a path from the initial state to the final one.

Consider the automaton in Figure 2.1. The numbered circles represent states, and the arrows are the transitions between those states. States are usually referred to as q , therefore the states of that machine are q_0 , q_1 and q_2 . The initial state is represented with an incoming “start” arc. The state q_1 is marked with a double

²This marker is also sometimes realized as $-e$.

³ $-a$ is a suffix marking nominative case, singular form for some nominal classes.

circle, meaning that it is final.

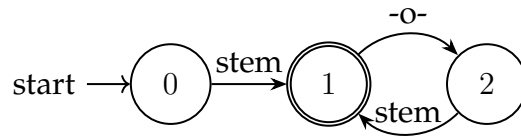


Figure 2.1: FSA for Russian compounding.

A language of an FSA is a potentially infinite set of strings, every member of which can be recognized by that automaton. For example, in Figure 2.1, the only possible transition from the initial state q_0 reads a stem and moves the machine to q_1 . The state q_1 is the accepting state, and any string that brings the automaton to the accepting state is well-formed with respect to the rules encoded in the automaton. A single stem is therefore considered well-formed. A compounding marker *-o-* moves the machine from the state q_1 to q_2 . But q_2 is not final, so strings cannot be accepted if they end up in that state: the compounding marker cannot be the final element of the word. The machine then necessarily returns to the state q_1 , therefore accepting *stem-o-stem*. If more markers and stems follow, it takes the loop $q_1 \rightarrow q_2 \rightarrow q_1$ again. The complexity of the language recognized by an FSA is not more than **regular**.

Regular languages are a specific type of **formal languages**, which in turn are (potentially infinite) collections of strings produced according to the rules of some grammar. Different language classes can be recognized by different automata, similarly to the way a finite state automaton was used before to encode a regular language of Russian compounding. These automata can also be referred to as *abstract machines*, a more general name for theoretically possible computers encoding the rules of those languages. These machines, and therefore languages corresponding to them, can be ordered with respect to the complexity of the dependencies that they encode. The first version of such a hierarchy was introduced in Chomsky (1956) and is therefore known as **the Chomsky hierarchy**.

Nowadays, we usually use an extended version of the hierarchy that includes mildly context-sensitive and finite language classes, see Figure 2.2, and Jäger and Rogers (2012) for a more detailed survey).

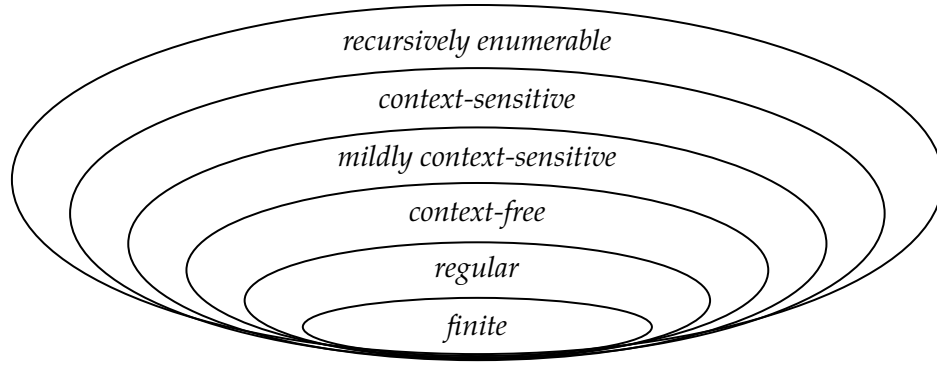


Figure 2.2: The extended Chomsky hierarchy from (Jäger and Rogers, 2012).

This hierarchy represents nested classes of formal languages aligned with respect to their expressive complexity. On the very top of the hierarchy, there are **recursively enumerable** languages. Those are the languages that can be physically computed, i.e. realized by a computer in the universe⁴ (Chomsky, 1956). An example of such a language contains all polynomial equations with integer coefficients that have a solution in the integers (Goldberg, 2018). Although such a language exists, there is no method of deterministically predicting if an equation has such a solution. Below, there are **context-sensitive** languages that recognize non-linear⁵ patterns, such as the language of primes (Hartmanis and Shank, 1968). There are subclasses of context-sensitive languages which are a better fit for natural language syntax, such as **mildly context-sensitive** languages. They are a good fit for syntactic dependencies as they handle cross-serial

⁴The current definition is based on the physical Church-Turing thesis (Church, 1936; Turing, 1937b,a).

⁵The non-linearity refers to the growth of the number of a : every following number is *much* larger than the previous. For example, patterns such as a^{2^n} , where n is greater than 0, are non-linear.

dependencies such as some cases of copying; see (Huybregts, 1984; Joshi, 1985; Shieber, 1985; Kallmeyer, 2010) discussing syntax, and (Culy, 1985) about a context-sensitive pattern in morphology. The machine corresponding to **context-free** languages uses a stack of a potentially infinite size: in such a way, it recognizes patterns such as $a^n b^n$, “*have as many a as b*” (Hopcroft et al., 2006). **Regular** languages are limited to the dependencies that can be recognized by an FSA (Hopcroft et al., 2006). It is commonly assumed that morphology and phonology are regular (Johnson, 1972; Kaplan and Kay, 1994; Beesley and Karttunen, 2003; Roark and Sproat, 2007), and I will come back to this topic in the following paragraphs. Finally, at the very bottom of the hierarchy, one can see a class of **finite** languages that refer to a finite number of strings. Classes that are more complex than mildly context-sensitive dependencies are rarely discussed in connection with natural languages: they are too powerful.

Finite-state models correspond to regular languages, and were introduced in 1940s by McCulloch and Pitts (1943). Chomsky (1956), however, theorized that this type of modeling does not seem to be suitable for natural languages, although in the following years his arguments were shown to be inconclusive, and the question about the regular nature of linguistic dependencies was reopened again. Also, there was a significant number of applications of finite-state machines to language-related tasks, such as text search (Thompson, 1968), machine translation (Oncina et al., 1994; Knight and Al-Onaizan, 1998; Bangalore and Riccardi, 2002), speech recognition (Caseiro, 2003; Mohri et al., 2002, 2008), semantic parsing (Jones et al., 2011, 2012), and others. The restrictiveness of finite-state models is frequently used to balance the robustness of neural networks. For example, a neural FST-based pronunciation learning model was designed by Bruguier et al. (2017). Additionally, Roark et al. (2019) use a neural network guided by a regular grammar to assign pronunciations to words. At the same time, linguists and computer scientists started to employ regular languages and finite-state models as

a tool to research the complexities of patterns in human languages, see Hulden (2014) discussing the main milestones.

The regular nature of phonology was examined several decades ago by (Johnson, 1972; Kaplan and Kay, 1981, 1994). Importantly, Kaplan and Kay (1994) show that all SPE-style transformational rules (Chomsky and Halle, 1968), can be represented as finite-state machines. Since all attested phonological patterns can be modeled as SPE-style rules, and since SPE-style rules are regular, the complexity of regular languages is a good upper bound for phonological dependencies. In the same paper, they also presented a set of modeling tools and used them to capture patterns such as nasal assimilation and epenthesis.

Koskenniemi (1983), and later Beesley and Karttunen (2003) show that finite-state machinery is sufficient for encoding morphological dependencies as well. Even the non-concatenative morphology can be modeled in such a way (Kay, 1987; Beesley, 1996; Kiraz, 1996). For more examples of applications of finite-state methods in linguistics, see (Gildea and Jurafsky, 1996; Roche and Schabes, 1997; Hetherington, 2001; Jurafsky and Martin, 2009). Although regular languages are a good fit for linguistic patterns, research shows that the full power of regular languages is not necessary, and *subregular* languages that are discussed further provide a tighter fit for phonology and morphology.

2.1.2 Subregular languages and their linguistic importance

The class of regular languages can be subdivided into a nested hierarchy of *subregular* classes — **subregular hierarchy**. “Parent” classes properly subsume their “children” classes, and thus the former are more powerful than the latter. The “sibling” relation implies that the classes are not known to subsume each other. Some of the classes of the subregular hierarchy are presented below in Figure 2.3.

Figure 2.3 shows some of the subregular classes, namely the ones that are

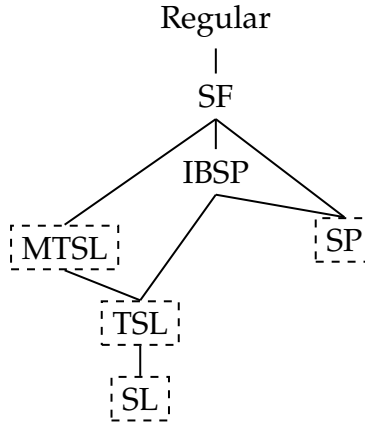


Figure 2.3: Some of the classes of the subregular hierarchy; the subregular classes discussed further in this chapter and in Chapter 3 are boxed.

crucially important for modeling linguistic dependencies, and therefore extensively used in this dissertation. Those are strictly local (SL), strictly piecewise (SP), tier-based strictly local (TSL) and multi-tier strictly local (MTSL) languages. The crucial difference between these languages is in the types of dependencies they can capture, see Table 2.1. The combined functionality of those classes covers local dependencies and long-distance dependencies with or without a blocker.

Language	Dependencies it can handle
<i>SL</i>	only local dependencies
<i>SP</i>	long-distance dependencies without blocking (any number thereof)
<i>TSL</i>	long-distance dependencies with blocking
<i>MTSL</i>	multiple long-distance dependencies with blocking

Table 2.1: Types of dependencies captured by some of the subregular classes.

Subregular languages are encoded by *subregular grammars*. These subregular grammars operate by blocking some types of substrings or subsequences in

well-formed strings of their languages. A **substring** is a consecutive part of the string. For example, *ab*, *aba*, and *abacd* are substrings of the string *abacd*, whereas *aa* and *bcd* are not, because these symbols are not adjacent in the string *abacd*. **Subsequences** can be seen as a non-consecutive counterpart of substrings. A string *u* is a subsequence of *w* if all elements of *u* can be found in *w*, and the order of those elements is preserved. Continuing the previous example, both *aa* and *bcd* are indeed subsequences of *abacd*. Importantly, the elements of substrings and subsequences cannot violate the order in which the elements appeared in the original string: *ca* is neither a substring nor a subsequence of the string *abacd*. Subregular grammars are always defined for some particular locality, so a 2-local grammar operates with substrings or subsequences of the length 2. Substrings and subsequences will be formally defined in the next two subsections (Definition 2.1.1 in Section 2.1.3, and Definition 2.1.4 in Section 2.1.4; see also (Elzinga et al., 2008; Rogers et al., 2010; Fu et al., 2011, a.o.)).

While *positive grammars* list all allowed substructures of their languages, the *negative* ones list the substructures that must not be encountered in well-formed strings of their languages. Moreover, for the subregular classes discussed in this thesis, these grammars are equivalent: for every negative grammar, it is possible to construct a positive grammar that generates the same language, and vice versa.

The example grammars discussed above are negative grammars, so they prohibit certain substructures in well-formed strings of their languages. **Strictly local** (SL) grammars filter strings that violate some local dependency in the string, i.e. contain ill-formed *substrings* (Heinz, 2010b). For example, a language *ab, abab, ababab, etc.* contains any possible string of *a* and *b* that does not contain the substrings *aa* and *bb*. **Tier-based strictly local** (TSL) grammars project a potentially smaller string from the input string by using a tier alphabet. These grammars evaluate the relatively local dependencies among the elements of the *tier alphabet*, whereas all other symbols are “transparent” for the grammar (Heinz

et al., 2011). For example, if the tier contains *a* and *b* and the string is *bccacbc*, the *tier image* of that string is *bab*. If a TSL constraints are *ba* or *ab*, the string *bccacbc* will be ruled out, since its tier image contains the illicit bigrams. **Multi-tier strictly local** (MTSL) grammars can have more than just a single tier, and, therefore, multiple tier images are evaluated with respect to multiple local grammars (De Santo and Graf, 2019). **Strictly piecewise** (SP) grammars restrict certain *subsequences* in well-formed strings of their languages (Rogers et al., 2010; Heinz, 2010a). For example, if a subsequence *xx* is prohibited, a string *xaax* is ruled out. In such a way, SL, SP, TSL and MTSL grammars model a wide range of local and long-distant dependencies (Heinz, 2011; Heinz et al., 2011; Heinz and Lai, 2013; Aksënova et al., 2016; Chandlee and Heinz, 2018).

There are other subregular classes not listed here such as star free (SF), interval-based strictly piecewise (IBSP), input-output tier-based strictly local (IO-TSL) and its subclasses, piecewise testable (PT), etc., but they are out of scope of this dissertation (Lawson, 2003; Graf, 2018a). Additionally, I will only discuss grammars working with strings, but this approach is currently extended to other representations as well (Chandlee et al., 2019; Chandlee and Jardine, 2019).

The classes SL, TSL, MTSL, and SP jointly span a wide-ranging array of phonological phenomena. SL can handle all phenomena that are locally bounded, e.g. word-final devoicing or intervocalic voicing. It can also handle phenomena that are unbounded but proceed in locally bounded steps, for instance some types of vowel harmony where two harmonic vowels are never separated by more than two segments. Truly unbounded phenomena, on the other hand, require SP, TSL, or MTSL. SP can handle multiple long-distance phenomena at the same time, but only if they do not involve any blocking effects. An example of that is unbounded tone plateauing, where no low tone may occur within an interval spanned by two high tones, no matter how far apart those two tones are. For long-distance phenomena with blocking, one has to use TSL, but TSL is not as capable as SP

when it comes to enforcing multiple long-distance dependencies in parallel. This shortcoming is remedied by TSL’s extension MTSL. Neither TSL nor MTSL can handle unbounded tone plateauing, though, as will be explained in detail in Sec. 2.1.5. While, the next few subsections will greatly expand on this overview, it should already be apparent that these subregular classes do indeed cover a lot of empirical ground.

The **strong subregular hypothesis** interprets the large empirical coverage of these few subclasses as a general indication that natural language phonology and phonotactics are much more restricted than previously believed — in particular, the class of regular languages is too generous an upper bound and subregular classes provide a better fit for phonology (Heinz, 2010a). In line with phonotactics, Aksënova et al. (2016) shows that subregular languages are a good fit for morphotactic dependencies. The well-formedness conditions imposed on languages of generalized and monomorphemic quantifiers are also subregular. There are likewise applications of subregular grammars to syntax (Graf, 2017c; De Santo et al., 2017; Vu et al., 2019). These findings suggest that subregularity play an important role across many distinct language models, thereby bolstering the strong subregular hypothesis.

In the rest of the chapter, I focus on SL, SP, TSL and MTSL languages and grammars, and provide linguistically-motivated examples of those. Additionally, I define these classes mathematically and describe the corresponding classes of finite-state automata. Later, in chapter 3, I will model those and some other dependencies, and show how their subregular grammars can be learned from real data. Table 2.2 summarizes patterns that are discussed further and subregular classes to which they belong.

SL	SP	TSL	MTSL
<i>word-final devoicing and obstruent voicing assimilation</i>			
✓	×	✓	✓
<i>unbounded tone plateauing</i>			
×	✓	×	×
<i>sibilant harmony in voicing and anteriority, no blockers</i>			
×	✓	✓	✓
<i>vowel harmony in ATR, nasalized vowels are blockers</i>			
×	×	✓	✓
<i>vowel harmony in ATR and rounding, some vowels are blockers for rounding</i>			
×	×	✓	✓
<i>sibilant harmony in voicing and anteriority, voiceless obstruents are blockers for voicing</i>			
×	×	×	✓

Table 2.2: Subregular patterns attested in natural languages and discussed in sections 2.1.3-6.

2.1.3 Local restrictions as SL languages

The subregular class of strictly local (SL) languages captures local dependencies, and many restrictions in phonology have a purely local nature (Rogers and Pullum, 2011). Indeed, most of the patterns of phonological assimilation affect adjacent segments. In what follows, I exemplify SL languages using several purely local phenomena, and then formally introduce them using the notion of k -factor and the property of suffix substitution closure (Rogers et al., 2013).

Intuitive definition

In what follows, the SL languages are demonstrated through two local phenomena happening in Russian: one of them prohibits voiced obstruents in the

word-final position, and another one enforces adjacent obstruents to agree in voicing. Additionally, I show the interaction between these two patterns.

Russian obstruent assimilation and word-final devoicing The examples (1-2) below show that the consonant of the preposition *iz* ‘from’ agrees in voicing with the obstruent of the following word.⁶

(1) i[z B]erlina ‘from Berlin’

(2) i[s P]ragi ‘from Prague’

Additionally, in Russian, as well as in other languages such as German, there is a word-final devoicing that prohibits the appearance of a voiced obstruent in a word-final position (Brockhaus, 1995; Padgett, 2002). For example, *lug* ‘field’ is realized as *lu[k]*. In this case, the same cluster of obstruents might appear voiceless word-finally, and voiced in other positions of the word, see the pairs of examples in (3-4) and (5-6).

(3) mo[sk] ‘brain’ ~ (4) mo[zg]i ‘brains’

(5) dro[st] ‘thrush’ ~ (6) dro[zd]y ‘thrushes’

These two generalizations can be captured in a *strictly local* way, namely, by prohibiting illicit substrings. Assume that the inventory of obstruents is $\{z, s, b, p, g, k\}$, where z, b , and g are voiced, and s, p and k are voiceless. It is never possible to see two (or more) disagreeing obstruents adjacent to each other, i.e. the target SL grammar needs to prohibit zs, zp, zk, sz, sb, sg , etc.

To target voiced obstruents at the end of the word, the grammar needs to be able to differentiate between the word-final and other positions. For this reason, strings are usually annotated with the markers \times and \times denoting the beginning and the end of the string (Rogers and Pullum, 2011). Then, the SL grammar capturing word-final devoicing needs to rule out $z\times, g\times$, and $b\times$.

Figure 2.4 shows how the SL grammar outlined above evaluates the

⁶I do not discuss exceptions to this rule, such as the well-formedness of the cluster [sv].

\times m o s k \times \times m o z g \times
 \times m o z k \times \times m o s g \times

Figure 2.4: Evaluation of strings *mozg*, *mozk*, *mosg* and *mosk* by an SL grammar capturing obstruent cluster assimilation and word-final devoicing.

pronunciations *mozg*, *mozk*, *mosg* and *mosk*. The string *mozg* has its obstruents agree in voicing, but the final obstruent is voiced, and therefore ruled out by the restriction $g\times$. The final obstruent in *mozk* is voiceless, but now the cluster disagrees and therefore ruled out by zk . In *mosg*, both violations are present. Finally, the form *mosk* contains no violations, and indeed, this is the correct pronunciation of the corresponding Russian word.

The illicit substrings such as $g\times$ and zk are the *restrictions* defined by the grammar. A set of restrictions R of a negative grammar lists all substrings that *cannot* be found in well-formed strings of the language. An *alphabet* of the language, usually denoted as Σ , includes the list of symbols the language uses. In this case, Σ includes all Russian phonemes. Finally, every grammar defines its *locality*, namely, the size of the longest string prohibited by that grammar; it is usually referred to as k (McNaughton and Papert, 1971; Rogers and Pullum, 2011). In the case of the SL grammar capturing Russian well-formedness conditions, all the prohibited strings are of length 2 ($k = 2$); such substrings are also called *bigrams* or *2-factors*. The Russian SL grammar is then strictly 2-local, or SL-2. These three components – the alphabet Σ , the set of restriction R , and the locality window k – define SL grammars, see Grammar 2.3.

SL grammars disallow the appearance of the banned clusters such as gs or zk , however, they do not induce the change of the ill-formed segments. The perspective of changing one form into another is examined in the Section 2.2 discussing modeling transformations. SL models are useful in modeling the

SL grammar Russian obstruent voicing assimilation and word-final devoicing

$$\Sigma = \{a, b, v, g, d \dots z, s, p, k \dots \varepsilon, {}^j u, {}^j a\}$$

$$R = \langle zs, zp, zk, sz, sb, sg \dots z\bowtie, g\bowtie, b\bowtie, d\bowtie \rangle$$

$$k = 2$$

Grammar 2.3: SL-2 grammar for Russian obstruent voicing assimilation and word-final devoicing.

well-formedness conditions arising from word-final devoicing, intervocalic voicing, consonant cluster assimilation, and other local phenomena. However, SL models cannot model long-distance dependencies.

Tuareg sibilant harmony Long-distance dependency affects segments that can be located far from each other. For instance, in Tuareg (Berber), sibilants regressively agree in voicing and anteriority (Hansson, 2010b). In the examples below, a causative prefix agrees with the sibilant in the root (8-11) but is realized as *s-* if no other sibilant is present (7). This is an instance of long-distance agreement, and therefore it can happen across an arbitrary number of intervening elements.

(7) *s-əlməd* ‘CAUS-learn’

(8) *s-əq:usət* ‘CAUS-inherit’

(9) *z-əntəz* ‘CAUS-extract’

(10) *ʃ-əm:əfən* ‘CAUS-be.overwhelmed’

(11) *ʒ-ək:uʒət* ‘CAUS-saw’

SL grammars capture only local generalizations, but, for example, in (9), there are 4 elements separating the agreeing sibilants. It would imply that the required locality of the SL grammar is at least 6 to accommodate the two sibilants and everything in-between them. However, this would not be enough for other cases since there is no upper bound on the number of the intervening segments

in-between two agreeing sibilants. As a result, the power of SL grammars is not enough to capture patterns such as Tuareg sibilant harmony.

Playing devil’s advocate, though, one may object that in practice there is such a thing as a longest word due a variety of reasons, e.g. performance limitations or limited morphological productivity. If the longest word has at most n segments, then no phonological phenomenon can involve more than n segments, making in SL- n . But there are multiple problems with this position. First of all, it ignores the widely assumed distinction between competence and performance. Second, it assumes that phonology is limited to a single phonological word, which isn’t the case either. At least some phenomena apply across phonological word boundaries, so it is not enough to assume a fixed upper bound on the length of phonological words — one has to assume a fixed upper bound on the length of phonological dependencies. Finally, and most importantly, this position ignores succinctness. The number of possible n -grams grows exponentially with n : assuming an inventory of 10 distinct sounds, there are $10^2 = 100$ distinct bigrams, $10^3 = 1,000$ trigrams, $10^4 = 10,000$ 4-grams, and so on. The size of an SL grammar explodes as we extend to handle increasingly non-local phenomena. And this also poses a challenge for learnability because larger SL-grammars require more evidence to infer from the training data (a space of 100 options is more easily explored than one of 10,000 options). So even if long-distance phenomena might indeed be limited to some fixed upper bound, this bound is so high for natural languages that an SL grammar simply cannot describe these long-distance phenomena in a succinct and elegant manner that supports efficient learning.

Formal definition

SL grammars define languages by listing substrings that cannot appear in well-formed words of those languages. These substrings are often referred to as k -factors, in order to be distinguished from the more NLP-oriented use of the

term n -gram, that frequently implies the use of probabilistic models (Rogers and Pullum, 2011; Rogers et al., 2013). Further in this section, I follow De Santo and Graf (2019) in their algebraic definition of this class.

While Σ , as previously in this section, denotes the alphabet, Σ^k is a k -long word that uses symbols of that alphabet. Σ^* generalizes Σ^k , it employs the *Kleene star* (Kleene, 1956) to define a word of any length, including length 0, i.e. the empty string ε . A length of the string w is denoted as $|w|$.

Definition 2.1.1 (k -factors)

A string u is a k -factor, or a substring of a string w iff $\exists x, y \in \Sigma^*$ such that $w = xuy$ and $|u| = k$. The function F_k maps words to the set of k -factors within them:

$$F_k(w) = \{u : u \text{ is a } k\text{-factor of } w \text{ if } |w| \geq k, \text{ else } u = w\}$$

For example, the 2-factors of the word abc are $\{ab, bc\}$. Strictly k -local grammars list the k -factors that cannot be used in the well-formed strings of their languages, i.e. they can be viewed as collections of illicit k -factors. Markers $\bowtie \notin \Sigma$ and $\bowtie \notin \Sigma$ are used in the same way as previously in Section 2.1.3: they are edge markers marking the beginning and the end of the string.

Definition 2.1.2 (SL languages and grammars)

A language L is strictly k -local (SL_k) iff there exists a finite set $S \subseteq F_k(\bowtie^{k-1}\Sigma^*\bowtie^{k-1})$ such that

$$L = \{w \in \Sigma^* : F_k(\bowtie^{k-1}w\bowtie^{k-1}) \cap S = \emptyset\}.$$

We call S a strictly k -local grammar, and use $L(S)$ to indicate the language recognized by S . A language L is strictly local iff it is SL_k for some $k \in \mathbb{N}$.

Consider a language described by a regular expression $(ab)^*$. Its language includes strings such as $\varepsilon, ab, abab, ababab$, etc. A negative SL-2 grammar that describes this language is $S = \{\bowtie b, a\bowtie, aa, bb\}$. Indeed, the well-formed strings of that language cannot start with b , end with a , and have two a or two b adjacent to

each other. Importantly, a language is strictly k -local if it satisfies k -local *suffix substitution closure* (Rogers and Pullum, 2011).

Definition 2.1.3 (Suffix substitution closure)

For any $k \geq 1$, a language L satisfies k -local suffix substitution closure iff for all strings u_1, v_1, u_2, v_2 , for any string x of length $k - 1$ if both $u_1 \cdot x \cdot v_1 \in L$ and $u_2 \cdot x \cdot v_2 \in L$, then $u_1 \cdot x \cdot v_2 \in L$.

For instance, a language $(ab)^*$ is SL-2, and it satisfies suffix substitution closure. Both strings ab and $ababab$ contain the 1-local substring a , and it correctly predicts that the string $abab$ is also in the language. However, a language a^*ba^* is not SL. It is not SL-2 since the closure of the strings aba and baa contains $baba$, and it is not in the language. It is not SL-3, because the closure of $aaba$ and $baaa$ contains the illicit form $baaba$; and so on. The language a^*ba^* is not closed under the suffix substitution, and therefore it is not SL.

Apart from the algebraic perspective, strictly local languages can be characterized in automata-theoretic terms. Rogers and Pullum (2011) describe SL languages as those that can be recognized by FSAs scanning a k -symbol window across the input string, and failing on strings that contain factors prohibited by the corresponding grammar. In such an SL- k automaton, states represent the $k - 1$ -local suffix of the input string read immediately before now, and the transitions from the states encode symbols that can follow. If a transition cannot be taken, or if the final activated state is not accepting, the input string is rejected. When a string is well-formed, there is a path through the automaton that starts in the initial state and ends in the final one.

States of SL-automata encode the previous substring of the input string. So, for example, in SL-2 automaton the states differentiate depending on the symbol that was observed

2.1.4 Long distance restrictions as SP languages

While SL grammars can only capture local dependencies, strictly piecewise (SP) grammars generalize exclusively long-distance patterns: SL grammars prohibit sequences of adjacent segments within words, while SP grammars do not have the requirement of adjacency. An SP restriction prohibits a certain *order* of elements (Rogers et al., 2010; Fu et al., 2011). While an SL restriction VV prohibits two vowels adjacent to each other thus avoiding hiatus, the same SP restriction means that nowhere in the string can there be a vowel followed by another vowel. The language of such an SP grammar would only include words with no more than a single V .

Intuitive definition

In this section, I demonstrate how SP grammars can capture patterns of sibilant harmony and unbounded tone plateauing. SP grammars encode restrictions on the order of elements, and thus cannot differentiate between disharmonic stems and grammatical words exhibiting a blocking effect.

Tuareg sibilant harmony Coming back to the pattern of Tuareg sibilant harmony exemplified before in (7-11), it can be modeled with an SP grammar by prohibiting subsequences of disagreeing sibilants. The bigrams sz and ʃ_3 are prohibited because their elements disagree in voicing, $\text{ʃ}s$ and z_3 disagree in anteriority, etc. In total, this grammar contains 12 restrictions R that are listed in Grammar 2.4.

Such an SP grammar has an alphabet that includes all Tuareg phonemes, and its list of restrictions includes all pairs of sibilants disagreeing in voicing or anteriority. The locality of such grammar is 2. Figure 2.5 shows that there are no violations in the word $z\acute{a}nt\acute{a}z$: indeed, no substructure of that string is prohibited. However, the word $z\acute{a}nt\acute{a}_3$ is ruled out because the subsequence z_3 is ill-formed.

SP grammar Tuareg sibilant harmony in voicing and anteriority

$$\Sigma = \{s, ʒ, z, ʃ, ə, d, l, m, t \dots\}$$

$$R = \langle sz, sʃ, sʒ, zs, ʃs, ʒs, zʃ, zʒ, ʃz, zʃ, zʒ, ʃz, ʃz, ʃz \rangle$$

$$k = 2$$

Grammar 2.4: SP-2 grammar for Tuareg sibilant harmony in voicing and anteriority.

z ə n t ə z z ə n t ə ʒ



Figure 2.5: Evaluation of strings *zəntəz* and *zəntəʒ* by an SP grammar capturing sibilant harmony in voicing and anteriority.

Imdlawn Tashlhiyt sibilant harmony Now, consider a language closely related to Tuareg, namely, Imdlawn Tashlhiyt (Berber), in which affixal sibilants also regressively harmonize with the stem in voicing and anteriority (Hansson, 2010b; McMullin, 2016). The difference is that in Imdlawn Tashlhiyt, the spreading of the voicing feature can be blocked by any intervening voiceless obstruent. At the same time, similarly to Tuareg, the anteriority harmony exhibits no blocking effect. Consider the data from (Elmedlaoui, 1995; Hansson, 2010a) in (12-18), where the causative prefix *s-* illustrates the harmonic pattern.

- (12) s:-uga ‘CAUS-evacuate’
- (13) s-as:twā ‘CAUS-settle’
- (14) ʃ-fiaʃr ‘CAUS-be.full.of.straw’
- (15) z-bruz:a ‘CAUS-crumble’
- (16) ʒ-m:ʒdawl ‘CAUS-stumble’
- (17) s-mχazaj ‘CAUS-loathe.each.other’
- (18) ʃ-quʒ:i ‘CAUS-be.dislocated’

In (12), there are no sibilants in the root, so the prefix is realized as *s-*. Examples

(13-16) show that as previously, the causative affix agrees with the stem sibilant in voicing and anteriority. However, the voicing harmony can be blocked, and it is exemplified in (17) and (18). In (17), the sibilants are both anterior, but χ is stopping the regressive spreading of [+voice], so the prefix is realized as voiceless. Similarly, in (18), both sibilants are non-anterior, but the voicing spreading is also blocked, this time by q .

In Imdlawn Tashlhiyt, voiceless obstruents are *blockers* for the voicing harmony, and this prevents SP grammars from being able to model the generalization. The rules of the harmony are the same as before, therefore all restrictions discussed earlier in Grammar 2.5 are still valid. However, there is no way to express a blocking effect in an SP grammar. An SP restriction is a restriction on the precedence of one segment by another, and therefore the presence of the bigram sz is necessary to rule out disharmonic words such as *saz:twa*. But the same restriction will necessarily rule out grammatical words such as *sm χ azaj*: it will simply “miss” the blocker, see Figure 2.6.

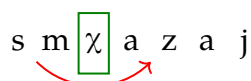


Figure 2.6: SP grammar incorrectly rules out Imdlawn Tashlhiyt word *sm χ azaj*.

Increasing the size of the substrings to 3 will not solve the problem with the blocking effect either. An SP grammar that finds the word *sm χ azaj* correct will inevitably accept all subsequences of that word. As a result, it would incorrectly predict the well-formedness of the word *smzaj*, where s and z disagree in voicing without the presence of a blocker.

Unbounded tone plateauing The ability of SP grammars to see substructures independently of other elements of the string gives them the power to encode *unbounded tone plateauing* (UTP), as attested in Luganda (Niger-Congo). In that

language, low tones are realized as high if they are surrounded by high tones (Hyman and Katamba, 2010). This makes it impossible for a well-formed word in Luganda to have low tones surrounded by high tones, see the data in (19) cited by (Hyman, 2011; Jardine, 2016a). Accented vowels indicate high tones, and other vowels are low.

- (19) bikópo byaa-walúsiimbi → bikópó byáá-wálúsiimbi
‘the cups of Walusimbi’

Using the letters H and L to indicate high and low tones, we can express the generalization as “never have one or more L in-between two H ”. This allows for strings such as HHL and $LLLHHHL$, but prohibits ones such as $HHLLLHH$. Due to the long-distant nature of SP grammars, a 3-local SP grammar can capture UTP by ruling out words that contain a subsequence HLH , see Figure 2.7.

L L H H L L H H L L L H


Figure 2.7: SP grammar captures the UTP pattern.

SP grammar Luganda unbounded tone plateauing
 $\Sigma = \{H, L\}$
 $R = \langle HLH \rangle$
 $k = 3$

Grammar 2.5: SP-3 grammar for Luganda unbounded tone plateauing.

Strictly piecewise grammars capture one or more long-distance phenomena that do not exhibit blocking effects. They prohibit subsequences of strings, therefore ruling out all words that contain the illicit substructure. For example, the restriction zs means that nowhere in the string, z can be followed by s . However, blocking effects cannot be captured via an SP grammar, because the

grammar is not sensitive to the presence of the blockers that make the banned substructure acceptable. A pattern where a substring $s \dots z$ is prohibited, but $s \dots k \dots z$ is allowed is not SP: ruling out the former one would rule out the latter one as well. Blockers do not change the presence of an illicit subsequence. Purely short-distant restrictions such as the word-final devoicing also cannot be expressed by an SP grammar: the restriction $b \times$ prohibits *any* string containing b , because \times always follows b in a word annotated with the word-final marker \times .

Formal definition

An SP grammar is defined as a list of subsequences prohibited in well-formed strings of its language. Further, I define the notion of the subsequence and the SP languages formally following Rogers et al. (2010), and then provide an alternative definition in automata-theoretic terms.

Definition 2.1.4 (Subsequences)

A string v is a subsequence of w , $v \sqsubseteq w$, if v is an empty string, or if $v = \sigma_1 \sigma_2 \dots \sigma_n$, and there is a collection of substrings $x_1, \dots, x_n \in \Sigma^$, such that those substrings can be placed between the elements of v thus obtaining $w = w_0 \sigma_1 w_1 \dots \sigma_n w_n$.*

Then all k -long subsequences $P_k(w)$ of a word $w \in \Sigma^$ can be computed as*

$$P_k(w) = \{v \in \Sigma^k : v \sqsubseteq w\}$$

Similarly, $P_{\leq k}(w)$ lists all subsequences of $w \in \Sigma^$ of the length up to k .*

$$P_{\leq k}(w) = \{v \in \Sigma^{\leq k} : v \sqsubseteq w\}$$

For example, consider a string $w = abcd$. Then $P_3(w) = \{abc, abd, acd\}$, and $P_{\leq 3}(w) = P_3(w) \cup \{\varepsilon, a, b, c, d, ab, ac, ad, bc, bd, cd\}$, where ε is the empty string.

Definition 2.1.5 (SP languages and grammars)

A language is SP- k if there exists a set of subsequences $S \subseteq \Sigma^k$ such that

$$L(\mathcal{G}) = \{w \in \Sigma^* : P_{\leq k}(w) \subseteq P_{\leq k}(S)\}.$$

The exact reason why SP grammars cannot capture the blocking effect is their *closure under subsequence*; see (Rogers et al., 2010) for other properties of SP languages and grammars.

Definition 2.1.6 (Subsequence closure)

Given a word $w \in L$, all strings v that are subsequences of w , $v \sqsubseteq w$, also belong to the language L .

Alternatively, an SP language can be defined as a deterministic finite automaton (DFA) of a particular shape. Such a machine is a quintuple $\mathcal{M} = \langle Q, \Sigma, q_0, \delta, F \rangle$, where Q is a finite set of states, Σ is the alphabet, q_0 is the unique initial state, δ is the transition function, and F is the set of accepting states. The following properties are true for the automata recognizing SP languages. All states of \mathcal{M} are accepting, i.e. $F = Q$. If q_2 is reachable from q_1 and if there is no transition reading $\sigma \in \Sigma$ from q_1 , there will be no transition reading σ from q_2 (missing edges propagate down). All cycles are self-edges. If such a machine accepts a string $w \cdot v \cdot u : w, v, u \in \Sigma^*$, it necessarily accepts a string $w \cdot u$. This dependency, however, is not true in the other direction: if such a DFA accepts $w \cdot u$, there could be $v \in \Sigma^*$ such that $w \cdot v \cdot u$ is not an acceptable input sequence. A DFA with these properties accepts only SP languages.

2.1.5 Long-distant dependencies with blocking as TSL languages

Earlier, I showed that SL and SP grammars cannot capture long-distance harmonies with a blocking effect. SL grammars can only express local generalizations, and SP restrictions target certain subsequences and therefore are not sensitive to the presence of blockers. Tier-based strictly local (TSL) grammars

capture long-distance dependencies by *making them local* over the tier (Heinz et al., 2011).

Intuitive definition

I demonstrate the capacities of TSL grammars using the examples of vowel harmony in Karajá (ATR harmony with nasalized blockers) and Buryat (ATR and rounding harmony without blockers).

Karajá vowel harmony Consider vowel harmony in Karajá (Macro-Jê), where a tense vowel spreads the advanced tongue root (ATR) feature leftwards. It makes it impossible to have a lax vowel followed by a tense one. This spreading can be blocked by intervening nasalized vowels; they are opaque for this harmony (Ribeiro, 2002).

(20)	woku	[woku]	‘inside’
(21)	dɔɾɛ	[dɔɾɛ]	‘parrot’
(22)	budɛ	[budɛ]	‘little, few’
(23)	brɔɾɛdĩ	[broɾɛnĩ]	‘cow (<i>lit.</i> deer-similar.to)’
(24)	dɔɾɛ de	[dorede]	‘parrot’s wing’
(25)	rakɔhɔdɛkõre	[rakɔhɔdɛkõre]	‘He/she didn’t hit it.’
(26)	ɾɛbõre	[ɾɛmõre]	‘I caught (it).’

The data in (20-26) exemplifies the rule of harmony and is discussed in more detail in Ribeiro (2002). Note, that the harmony is reflected in the transcriptions and not in the orthography of the language. Stems in Karajá can contain tense (20) or lax (21) vowels, and the lax vowels can only follow the tense ones (22). A tense vowel starts its harmonic domain and spreads the [+ATR] feature regressively (23-24). However, nasalized vowels such as *õ* and *ĩ* are opaque for this spreading: they do not enforce the agreement of the vowel thus allowing lax vowels to precede the nasal ones, even if a tense vowel follows it (25-26).

A TSL grammar is defined for a *tier alphabet* T that includes all segments that are relevant for the long-distance dependency. All vowels are relevant for the harmony, i.e. they are either undergoers (lax vowels), or blockers (nasalized vowels), or start the harmonic domain (tense vowels). Therefore in this case, the tier alphabet contains all vowels, $T = \{\varepsilon, o, e, u, \text{ɔ}, \tilde{o}, \tilde{a}, a, \dots\}$. A *tier image* of the string is a representation of that string where only the elements of T are preserved. For example, the tier image of *rakɔhɔɖɛkõre* is *aɔɔɛõe*. Finally, the set of restrictions R is defined for the tier representations of the string. In other words, the prohibited elements are the substrings that must not be observed in the tier representations of well-formed words of the language.

To construct the tier grammar for the Karajá vowel harmony, one needs to prohibit all combinations of a lax vowel followed by a tense one, i.e. $\varepsilon e, \varepsilon o, \text{ɔ} o, \text{ɔ} u$, etc. The presence of the nasalized vowels on the tier allows for sequences such as $\varepsilon \dots \tilde{a} \dots e$, where the opaque element blocks spreading of the ATR feature. Indeed, in such cases, the lax vowel ε and the tense e are not tier adjacent because of the intervening \tilde{a} . This makes TSL grammars a good fit for many harmonic patterns, even if they exhibit blocking effects.

$$\begin{aligned}
\text{TSL grammar} \quad & \text{Karajá vowel harmony in ATR} \\
\Sigma = & \{\varepsilon, \tilde{o}, \tilde{a}, o, e, u, \text{ɔ}, a, \tilde{a}, \tilde{o} \dots b, d, r \dots\} \\
T = & \{\varepsilon, \tilde{o}, \tilde{a}, o, e, u, \text{ɔ}, a, \tilde{a}, \tilde{o} \dots\} \\
R = & \langle \varepsilon e, \varepsilon o, \text{ɔ} o, \text{ɔ} u, \varepsilon u \dots \rangle \\
k = & 2
\end{aligned}$$

Grammar 2.6: TSL-2 grammar for Karajá vowel harmony in ATR.

See Figure 2.8 for the visualization of how the TSL grammar evaluates strings. The word *budɛ* is well-formed, since the tense vowel is not preceded by any lax vowels, however, *bɛdu* contains the violation εu and therefore is ruled out. In *rɛbõre*, there is a lax vowel followed by a tense one, but there is a blocker \tilde{a} in-between them,

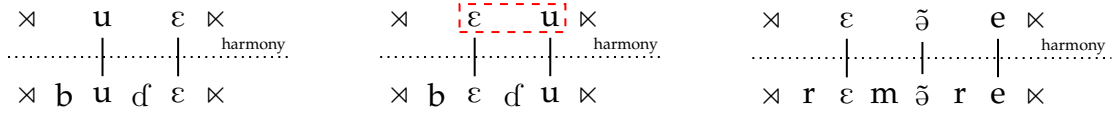


Figure 2.8: Evaluation of strings *budε*, *bεdu* and *rebõre* by a TSL grammar capturing Karajá vowel harmony in ATR.

and its presence on the tier breaks the locality between ε and e therefore allowing such a configuration.

Buryat vowel harmony Now, let us consider a type of vowel harmony in Buryat (Mongolian) that spreads both ATR and rounding features. All vowels within a word must agree in ATR. Consecutive non-high vowels agree in rounding unless there is an intervening high vowel that blocks this assimilation (Poppe, 1960). The set of transparent items is the same for both agreements: it includes /i/ and all consonants (van der Hulst and Smith, 1987; Skribnik, 2003; Svantesson et al., 2005).

- (27) ɔr-ɔ:d 'enter-PERF'
- (28) ɔr-ʊ:l-a:d 'enter-CAUS-PERF'
- (29) to:r-o:d 'wander-PERF'
- (30) to:r-u:l-e:d 'wander-CAUS-PERF'
- (31) mɔrin-ɔ: 'horse-POSS'
- (32) o:rin-go: 'group-POSS'

Examples (27-32) illustrate the harmony using causative and perfective suffixes. The causative suffix *-ʊ:l* (*-u:l*) has its vowel specified as high, therefore it agrees with the stem only in ATR. A non-high vowel of the perfective affix *-a:d* (*-ɔ:d*, *-e:d*, *-o:d*) agrees with the preceding segment in ATR and, if that segment is non-high, in rounding. In (27), the non-high perfective affix agrees with the non-high root vowel in ATR and rounding: both vowels are lax and rounded. But adding the high causative affix in-between them, as in (28), results in the blocking of the labial spreading: the perfective affix no longer agrees with the stem in rounding, because

they are separated from each other by the intervening high vowel. Examples (29-30) show the same effect for the tense roots, and (31-32) demonstrate the transparency of the vowel /i/.

All vowels except /i/ harmonize, and therefore in this case, $T = \{a, e, \text{ɔ}, o, u, \text{ʊ}\}$. For example, the tier image of *to:ru:le:d* is *oue*.⁷ To create a list of tier restrictions, we need to understand what sequences of harmonizing vowels need to be ruled out. First, such a TSL grammar includes all bigrams where vowels disagree in tense because the tense harmony cannot be blocked by anything. It rules out 18 tier restrictions of the type $[\alpha\text{tense}][-\alpha\text{tense}]$, i.e. $\text{ɔ}o, o\text{ɔ}, \text{ʊ}u, u\text{ʊ}$, etc. Then, we enforce the agreement of tier-adjacent non-high vowels by prohibiting bigrams such as $[-\text{high}, \alpha\text{round}][-\text{high}, -\alpha\text{round}]$. It rules out 8 combinations such as $\text{ɔ}a, a\text{ɔ}, eo$, and others. Finally, we block rounded vowels from following high vowel, i.e. $[+\text{high}][-\text{high}, +\text{round}]$. That results in prohibiting $\text{ʊ}\text{ɔ}, uo, u\text{ɔ}$, and $\text{ʊ}o$. In such a way, we encode Buryat vowel harmony in ATR and rounding using a TSL grammar in 2.7.

TSL grammar Buryat vowel harmony in ATR and rounding

$$\begin{aligned}\Sigma &= \{a, b, t, o, \text{ɔ}, e, d, l, \dots\} \\ T &= \{a, e, \text{ɔ}, o, u, \text{ʊ}\} \\ R &= \langle \text{ɔ}o, o\text{ɔ}, \text{ʊ}u, u\text{ʊ} \dots \text{ɔ}a, a\text{ɔ}, eo, oe, ao \dots \text{ʊ}\text{ɔ}, uo, u\text{ɔ}, \text{ʊ}o \rangle \\ k &= 2\end{aligned}$$

Grammar 2.7: TSL-2 grammar for Buryat vowel harmony in ATR and rounding.

Figure 2.9 shows that the tier images of *to:ro:d* and *to:ru:le:d* are *oo* and *oue*, respectively. These tiers are well-formed: both words are tense, and in both cases, the second vowel inherits its rounding feature from the first non-high vowel, however, its value cannot be passed from a high vowel to a non-high one. The word *to:re:d* is illicit since its tier image *oe* is prohibited: vowels must agree with

⁷The length of vowels is ignored since it is not relevant for the rules of the harmony.

the preceding non-high vowel in rounding. The form *to:ru:lɔ:s* is also ruled out, since its tier *ouɔ* contains the prohibited bigram *uɔ*, since *ɔ* cannot inherit its rounding value from the preceding high vowel *u*, and they also disagree in ATR. In such a way, TSL grammar captures a pattern where a certain set of elements exhibits a long-distance dependency.

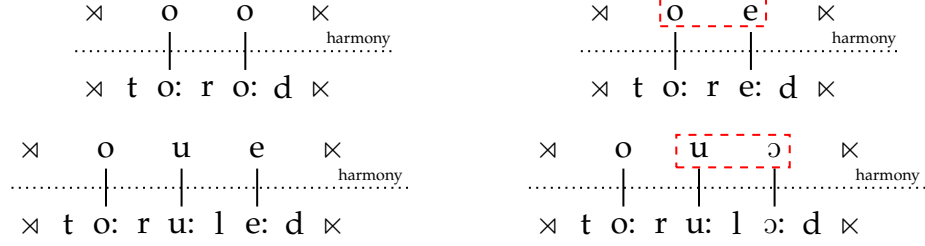


Figure 2.9: Evaluation of strings *to:ro:d*, *to:ru:le:d*, *to:re:d* and *to:ru:lɔ:s* by a TSL grammar capturing Buryat vowel harmony in ATR and rounding.

Apart from the long-distant patterns, TSL grammars can easily capture local dependencies since they are a proper extension of SL languages, as defined in Section 2.1.2. If a purely local dependency such as obstruent word-final devoicing or obstruent cluster voicing assimilation is expressed via a TSL grammar, its tier alphabet *T* will be the same as Σ .

As of the patterns discussed above, the Tuareg sibilant harmony in voicing and anteriority can also be described by a TSL grammar. In this case, the tier includes all sibilants. However, a similar harmony of Imdlawn Tashlhiyt, where only the voicing assimilation can be blocked by voiced obstruents, is not TSL. The anteriority harmony cannot be blocked, and the appearance of the voiced obstruents on the tier would break the locality relation between the sibilants. The absence of the voiceless obstruents on the tier, however, makes it impossible to model the blocking of the voicing harmony. This creates two sets of items involved in a long-distance dependency: sibilants that are relevant for the anteriority harmony, and both sibilants and voiceless obstruents that are involved

in the voicing harmony. It would thus require two tiers to capture the Imdlawn Tashlhiyt pattern; see McMullin (2016) and Aks nova and Deshmukh (2018) for the discussion of harmonies in more than a single feature, and tier properties of those harmonies.

Similarly, it is impossible to express a UTP generalization “no low tones in-between high tones” using a TSL grammar. Both L and H tones are important for the pattern, but including them both on the tier would make it impossible to notice the HLH configuration: the presence of the additional Ls, such as in *HHLLLLLLH*, makes the dependency non-local.

To sum up, TSL languages capture long-distance dependencies that can potentially include blocking or licensing effects. However, several long-distant assimilations cannot be expressed by a single TSL grammar if they affect different sets of segments.

Formal definition

TSL languages are a proper extension of the SL ones, but the k -local constraints are imposed on the *tier* symbols $T \subseteq \Sigma$. De Santo and Graf (2019) define tier-locality using the notion of the *erasing function* E , also called the *projection function*. Its purpose is to delete all symbols that are not included in the tier alphabet T . Given some string $\sigma \in \Sigma$, the erasing function E_T maps σ to itself if $\sigma \in T$ and to ε otherwise. In such a way, under the erasing function, a tier image of a word $w = \sigma_0 \dots \sigma_n$ is obtained by substituting non-tier elements $\sigma \notin T$ by ε .

Definition 2.1.7 (TSL languages and grammars)

A language L is tier-based strictly k -local (TSL- k) iff there exists a tier $T \subseteq \Sigma$ and a finite set $S \subseteq F_k(\bowtie^{k-1} T^* \bowtie^{k-1})$ such that

$$L = \{w \in \Sigma^* : F_k(\bowtie^{k-1} E_T(w) \bowtie^{k-1}) \cap S = \emptyset\}$$

Additionally, S the set of forbidden k -factors on tier T , and $\langle T, S \rangle$ is a TSL- k grammar.

De Santo and Graf (2019) show that a language L is TSL iff it is strictly k -local on tier T for some $T \subseteq \Sigma$ and $k \in \mathbb{N}$. Indeed, SL properties such as suffix substitution closure (see the definitions in 2.1.3) can be generalized, as was done by Lambert and Rogers (2020). For example, a language $x^*a^*x^*b^*x^*$ is not SL since it is not closed under suffix substitution. However, if only a and b are included in the tier alphabet, it becomes TSL-2, with the shape of the tier restricted to a^*b^* .

In their paper, Lambert and Rogers (2020) show how to construct a DFA for a given TSL grammar. Namely, they start by encoding every allowed TSL- k factor in its own automaton, uniting all the automata obtained this way, and then adding loops reading non-tier symbols to every state. In such a way, a TSL-representing DFA is a DFA expressing the local restrictions on the tier symbols, and looping on the non-tier ones.

2.1.6 Multiple long-distant dependencies with blocking as MTSL languages

Multi-tier strictly local (MTSL) grammars are conjunction of several TSL grammars. A language of an MTSL grammar is the intersection of languages of multiple TSL grammars (De Santo and Graf, 2019). An MTSL grammar lists k tier alphabets $T_1 \dots T_k$, and for every tier alphabet T_i , there is a corresponding set of restrictions R_i . A string is well-formed with respect to a given MTSL grammar if it is well-formed on every tier.

Intuitive definition

Imdlawn Tashlhiyt sibilant harmony exhibits a blocking effect for only one feature out of two that are spreading (voicing and anteriority). In this subsection, I show that this pattern is MTSL.

Imdlawn Tashlhiyt Consider the regressive sibilant harmony in Imdlawn Tashlhiyt discussed earlier in 2.1.4. Sibilants in that language agree in voicing and anteriority. For example, in *zbruz:a* ‘CAUS-crumble’, both sibilants are voiced and anterior, and in *sas:twa* ‘CAUS-settle’, they are voiceless and anterior, in *ʃfiaʃr* ‘CAUS-be.full.of.straw’, they are voiceless and non-anterior. However, while the anteriority harmony cannot be blocked by anything, the voicing harmony can be blocked by intervening voiceless obstruents such as χ , k or q , resulting in the well-formedness of words such as *smʃazaj* ‘CAUS-loathe.each.other’.

This pattern is not SL, SP or TSL. It is not SL since it involves a long-distance dependency. An SP grammar cannot capture it, either, because it cannot model blockers. A TSL grammar is not a good fit either: both sibilants and voiceless obstruents need to be present on the tier to express the voicing harmony; however, the presence of non-sibilants on the tier breaks the tier locality required to model the anteriority assimilation. More than a single tier is required to model this generalization.

The power of MTSL grammars allows projecting multiple tiers, and this helps to model the Imdlawn Tashlhiyt pattern. Sibilants and voiceless obstruents are projected on one tier, let us call it T_{voice} , whereas only sibilants are visible on the second tier T_{ant} . The tier capturing the voicing harmony restricts all combinations of sibilants disagreeing in voicing (sz , zs , $ʃz$, $zʃ$), and also voiced sibilants followed by voiceless obstruents (zk , zf , $z\chi$, etc.). On the tier of anteriority, the combinations of sibilants of different anteriority are not allowed ($sʃ$, $zʃ$, $ʃs$, etc.). The obtained grammar is summarized in 2.8.

This MTSL grammar correctly models the generalization behind the Imdlawn Tashlhiyt pattern. Ill-formed strings such as *ʒbruz:a* are illicit because the tier of the anteriority harmony contains a prohibited bigram $ʒz$. The combinations of sibilants that agree in voicing are allowed on that tier, and it is the case in well-formed words such as *smʃazaj*, where $ʃ$ blocks the voicing agreement. Voiced sibilants cannot

MTSL grammar Imdlawn Tashlhiyt sibilant harmony in voicing and anteriority

$$\begin{aligned}\Sigma &= \{a, b, m, u, g, r, s, z, \text{ʃ}, \text{ʒ}, h, k, f, \chi, q, \dots\} \\ T_{ant} &= \{s, z, \text{ʃ}, \text{ʒ}\} \\ R_{ant} &= \{s\text{ʃ}, z\text{ʃ}, \text{ʃ}s, \text{ʃ}z, s\text{ʒ}, z\text{ʒ}, \text{ʒ}s, \text{ʒ}z\} \\ T_{voice} &= \{s, z, \text{ʃ}, \text{ʒ}, h, k, f, \chi, q\} \\ R_{voice} &= \{sz, zs, \text{ʃ}\text{ʒ}, \text{ʒ}\text{ʃ}, zh, zk, zf, z\chi, zq, \text{ʒ}h, \text{ʒ}k, \text{ʒ}f, \text{ʒ}\chi, \text{ʒ}q\} \\ k &= 2\end{aligned}$$

Grammar 2.8: MTSL-2 grammar for Imdlawn Tashlhiyt sibilant harmony in voicing and anteriority.

precede voiceless obstruents, so forms such as *zmʃazaj* are ruled out on the tier of voicing by the restriction *zʃ*. Figure 2.10 visualizes the discussed examples.

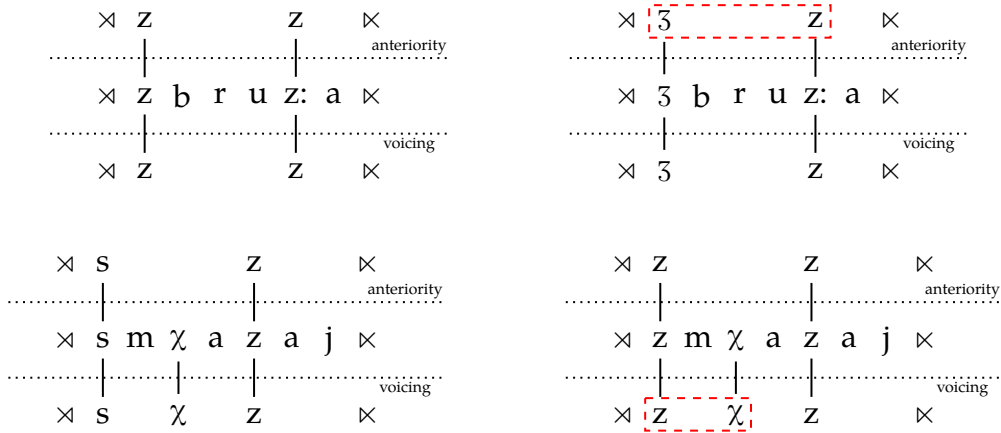


Figure 2.10: Evaluation of strings *zbruz:a*, *ʒbruz:a*, *smʃazaj* and *zmʃazaj* by a MTSL grammar capturing Imdlawn Tashlhiyt sibilant harmony in voicing and anteriority.

MTSL grammars model several agreements within the same language, even when they target different sets of segments. Interestingly, those sets are either in the set-subset relation, or are disjoint, but never only partially overlap. Imdlawn Tashlhiyt discussed in this section is an example of a harmony where the tier

alphabets are in the set-subset relation. In Bukusu (Bantu), vowels agree in height along with the assimilation of nasals in height, therefore exemplifying the case of the disjoint tier alphabets (Odden, 1994; Elmedlaoui, 1995; Hansson, 2010a). Aksënova and Deshmukh (2018) summarize this restriction and propose its possible explanation.

Formal definition

The language at the intersection of several TSL grammars can be viewed as a single grammar projecting multiple tiers, i.e. a multi-TSL, or MTSL grammar (De Santo and Graf, 2019).

Definition 2.1.8 (MTSL languages)

An n -tier strictly k -local (n -MTSL _{k}) language L is the intersection of n distinct TSL- k languages ($k, n \in \mathbb{N}$).

Since the language of an MTSL grammar is the intersection of several TSL languages, one can imagine a construction of the corresponding DFA by intersecting several DFAs representing those TSL languages. According to Lambert and Rogers (2020), it is possible to create DFAs for any languages definable by Boolean combinations of SL, SP, and TSL automata. Consequently, it includes MTSL languages.

2.1.7 Unattested patterns

Interestingly, none of the subregular language classes mentioned above express such theoretically possible but unattested patterns as first-last harmony, where the first vowel of the word needs to harmonize with the last one, and some others (Lai, 2015; Avcu, 2018).

First-last harmony In a prosodic word, the first vocalic segment harmonizes with the last one.

Majority harmony In a prosodic word, if a majority of vowels are underlyingly fronted, all vowels acquire the fronting feature; otherwise, they all become back.

Sour grapes harmony In a prosodic word, features A and B are spreading. However, if some of the spreadings are blocked, no spreading applies.

While the typological explorations of harmony systems suggest that this is due to the computational limitations (Heinz and Lai, 2013), there could be other reasons as well. For example, there is a possibility that such systems cannot evolve naturally in human languages (Blevins, 2004). More research is needed to understand the nature of the restrictions on natural language patterns, but the results supporting the strong subregular hypothesis suggest that all attested patterns in phonology can be captured by means of subregular languages.

Of course, the accessible typological data is limited, and therefore it is difficult to verify some of the subregular predictions. However, relying on the available knowledge is necessary to build the initial conceptions about the system of rules behind natural languages. Only after the initial assumptions are made, they can be improved, and, ultimately, lead to discoveries.

2.1.8 Models of well-formedness conditions: summary

Subregular grammars describe well-formedness conditions imposed on words in natural languages. In this section, I focused on SL, SP, TSL, and MTSL grammars since they capture a vast majority of phonological patterns. SL grammars capture only local phenomena, therefore they are a good fit for word-final devoicing and obstruent cluster voicing assimilation. SP grammars generalize long-distance dependencies by prohibiting certain orders of elements, thus they are a good fit for harmonies without blockers and unbounded tone plateauing. Only a certain subset of elements of the alphabet is projected on a tier by TSL grammars, therefore they capture a long-distance dependencies locally by ignoring irrelevant segments. This allows them to model a harmony that can potentially involve

blockers. Finally, MTSL grammars project several tiers, and this helps to represent several independent yet simultaneous harmonies. Neither of these 4 classes is powerful enough to encode such theoretically possible yet typologically unattested patterns as first-last harmony, as Section 2.1.7 shows. In such a way, these subregular grammars can capture most of the dependencies imposed by phonological well-formedness conditions.

Some known natural language patterns, however, require powers of different subregular language classes. Among them, there is a pattern of Sanskrit /n/-retroflexion and Yaka harmony triggered by local conditions (Walker, 2000; McMullin, 2016; Karakaş, 2020). IO-TSL and IBSP subregular language classes can model those cases (Graf, 2017b, 2018a).

Later, in chapter 3 of this dissertation, I discuss several subregular patterns and show how the corresponding grammars can be learned from the real data.

2.2 Modeling transformations

The previous section explored modeling of natural language well-formedness conditions using subregular languages. Here, I discuss formalizing and modeling *transformations*, or rewrite rules, that apply to underlying representations and yield corresponding surface forms. Namely, I demonstrate that subsequential finite-state *transducers* can be employed to model transformations, and discuss their sub-types. Subsequential mappings are a subclass of the rational mappings, which in turn are a limited kind of regular functions, which entails that subsequential functions are subregular, too.

2.2.1 Formalizing transformations

Let us start with a concrete example of a rewrite rule in natural language phonology, and how it can be expressed with finite-state machinery. Earlier in

Section 2.1.5, I discussed Buryat progressive vowel harmony in ATR and rounding. Vowels agree in these two features, while consonants and /i/ are transparent. While all harmonizing vowels are undergoers for the ATR agreement, high vowels *ʊ* and *u* block the spreading of the rounding feature, thus prohibiting the appearance of *ɔ* and *o*. So, for example, all vowels in a word *to:r-u:l-e:d* ‘wander-CAUS-PERF’ are tense, and the high vowel *u* blocks spreading of the rounding feature. In *to:r-o:d* ‘wander-PERF’, all vowels are low, and therefore they agree in rounding as well. Values of non-initial vowels only depend on their height and the value of the previous vowel.

Now, consider this harmony as a set of pairs exemplifying the mapping from the underlying representations (UR) to the surface forms (SF), see the data in (33-38).

UR	→	SF	
(33) ɔr-L:d	→	ɔr-ɔ:d	‘enter-PERF’
(34) ɔr-H:l-L:d	→	ɔr-ʊ:l-a:d	‘enter-CAUS-PERF’
(35) to:r-L:d	→	to:r-o:d	‘wander-PERF’
(36) to:r-H:l-L:d	→	to:r-u:l-e:d	‘wander-CAUS-PERF’
(37) mɔrin-L:	→	mɔrin-ɔ:	‘horse-POSS’
(38) o:rin-gL:	→	o:rin-go:	‘group-POSS’

A UR of the initial vowel is fully specified, whereas all non-initial vowels are only specified for the height, and therefore are denoted as **Low** or **High**. To obtain the SFs, all *L* and *H* of the URs need to be substituted starting from the leftmost one. The rules of this substitution are listed below.

$$L = \left\{ \begin{array}{l} \text{‘} \mathfrak{c} \text{’ if the previous harmonizing vowel is ‘} \mathfrak{c} \text{’} \\ \text{‘} \mathfrak{a} \text{’ if the previous harmonizing vowel is ‘} \mathfrak{a} \text{’ or ‘} \mathfrak{u} \text{’} \\ \text{‘} \mathfrak{o} \text{’ if the previous harmonizing vowel is ‘} \mathfrak{o} \text{’} \\ \text{‘} \mathfrak{e} \text{’ if the previous harmonizing vowel is ‘} \mathfrak{e} \text{’ or ‘} \mathfrak{u} \text{’} \end{array} \right\}$$

$$H = \begin{cases} \text{'}\mathfrak{u}\text{' if the previous harmonizing vowel is '}\mathfrak{o}\text{' , '}\mathfrak{a}\text{' or '}\mathfrak{u}\text{' } \\ \text{'}\mathfrak{u}\text{' if the previous harmonizing vowel is '}\mathfrak{o}\text{' , '}\mathfrak{e}\text{' or '}\mathfrak{u}\text{' } \end{cases}$$

In order to express this process in formal terms, we can build on the notion of finite-state automata (FSAs) we encountered in Section 2.1.1. FSAs are defined via a finite number of states and transitions between them. Those transitions are annotated with symbols, and strings are read by following the corresponding transitions. If such transitions exist and the last portion of the string brings the machine to the final state, the string is *accepted*, i.e. considered well-formed with respect to the rules encoded by the FSA. Otherwise, the string is *rejected*. In such a way, an FSA reads a string and evaluates its well-formedness.

The transitions of the FSA have the following shape: $q_a \xrightarrow{b} q_b$. Such a transition indicates that if the FSA is in state q_a and encounters a b , it switches into the state q_b . The core difference of a **finite-state transducer** (FST) is that it *writes* an output string while reading the input string (Schützenberger, 1961). Transitions of the FST indicate what portion of the input is read, and what is added to the output string, also called the *translation*. For example, the transition $q_a \xrightarrow{b:x} q_b$ means “to go from q_a to q_b , read b and write x ”. Consider a simple example of an FST in Figure 2.11. While FSAs are functions mapping *strings to boolean values*, FSTs map *strings to strings*.

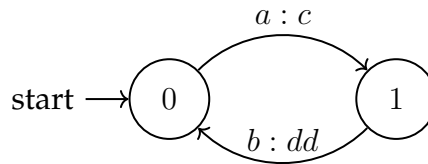


Figure 2.11: An example of the FST.

A transducer in Figure 2.11 accepts strings that start with a and alternate a and b . Every time a is read, c is written, and every time b is read, dd is written. It translates aba as $cddc$, and $abab$ as $cddcdd$. Figure 2.11 does not indicate whether a state is final. This is because I will focus exclusively on **rational** transducers, in which all states

are final.

We can construct an FST mapping Buryat URs to the corresponding SFs, as depicted in Figure 2.12. For simplicity, N represents all elements that are not involved in the harmony – consonants and the transparent vowel /i/. Such a transducer has 5 states, with q_0 being the initial state. Every state has a loop $N:N$ on it, which means that the irrelevant symbols for the harmony are left as is and do not move the machine to another state. The notation $N:N$ is a shorthand for many different loops of the form $x : x, y : y, z : z$, etc. where the symbols on the transitions are irrelevant for the process the FST encodes. If the initial vowel is e or u , it moves the machine to state q_1 , and all the following low and high vowels are rewritten as e and u , respectively. If the initial vowel is o , state q_2 is activated, so all the following low vowels agree in tense and rounding, and therefore are realized as o . However, reading a high vowel u moves the machine to q_1 thus blocking the rounding spreading. States q_3 and q_4 similarly encode the rounding harmony for lax stems. In such a way, the transducer in Figure 2.12 takes a Buryat UR as input and returns the corresponding SF as output, where the underspecified segments H and L are rewritten with respect to the rules of the harmony.

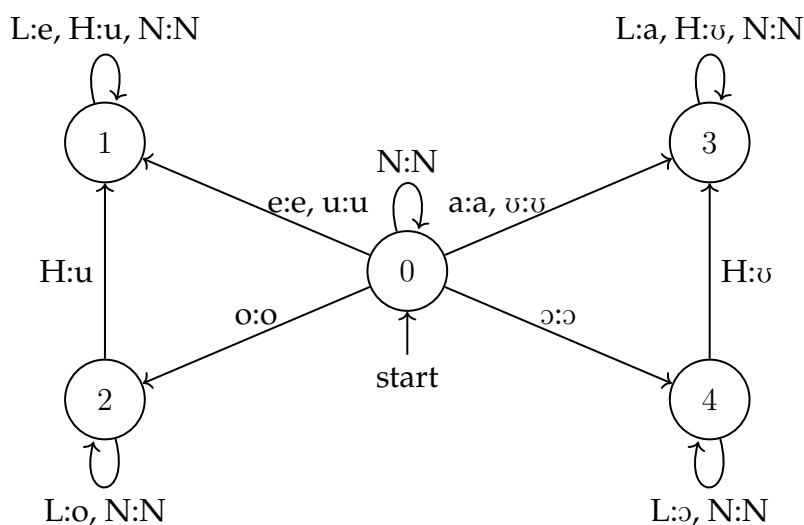


Figure 2.12: Transducer for Buryat vowel harmony.

For example, assume that the word *ɔrLd* is given as input. The initial *ɔ* brings the machine to the state q_4 , and *r* is rewritten as *r* because of the loop annotated with $N:N$. The following *L* is now specified: the reflexive loop on the state q_4 changes its value to *ɔ*. Finally, *d* is left without modifications. The FST in 2.12 rewrites that input form as *ɔrɔd* and it is indeed the expected output, see the example (33). Alternatively, consider the UR *torHILd*. The initial vowel *o* brings the machine to the state q_2 , meaning that all the consecutive vowels will be tense. The following underspecified vowel is high, so it is rewritten as *u*. Reading that high vowel moves the FST to q_1 . The spreading of the rounding feature is blocked, and given that the following vowel is low, it is realized as *e*. This results in the translation *toruled*, and the example (36) confirms it. In such a way, FSTs model phonological processes that change URs to the corresponding SFs.

2.2.2 Subsequential mappings

As we saw in Section 2.1.1, well-formedness conditions in phonology are overwhelmingly regular, and the same seems to hold for phonological mappings (Johnson, 1972; Koskeniemi, 1983; Kaplan and Kay, 1994). A mapping is regular iff it can be represented by a (not necessarily rational) FST, as we did with Buryat vowel harmony in Figure 2.12.

Similar to the results discussed in the previous sections, recent research shows that phonological mappings also do not require the full power of regular languages. Instead, subsequential mappings, and in particular the very limited subtypes of input strictly local and output strictly local transformations were shown to be a good fit for natural language phonological and morphological processes (Chandlee, 2014; Chandlee and Heinz, 2018); they will be further discussed in Section 2.2.4. Therefore, here, as well as in Chapter 4, I focus on **subsequential transducers** as a formal model of rewrite rules in language.

Note that there is also a closely related class of sequential mappings, and the

terminology in the literature is unfortunately not consistent. Traditionally, sequential mappings are a subclass of the subsequential mappings. More recently, it has been argued that this terminology is confusing, and the terms should be switched: the superclass should be called “sequential” rather than “subsequential”, and the subclass should be called “subsequential” instead of “sequential”. This has made it very difficult to discern which class an author is referring to with these terms. Following Roche and Schabes (1997) and de la Higuera (2010), I adopt the modern terminology where the subsequential mappings are a subclass of the sequential mappings. A **sequential FST** reads symbols of the input string one by one. Crucially, for every input symbol, there is at most one transition outgoing from any state of such FST that reads that symbol. Apart from inheriting properties of the sequential class, a **subsequential** machine also implements a *state outputting function* that allows for the final portion of the translation to be generated at the end of the parse, depending on the state in which the FST stopped after reading the last input symbol. So, for example, the transducer in Figure 2.12 is sequential, but not subsequential, since the states do not have the state outputting function implemented. Since all sequential machines are rational, all of their states are accepting.

In Section 2.1.3, I described the pattern of word-final devoicing in Russian, where voiced obstruents are realized as voiceless at the end of the word. For example, *lob* ‘forehead’ is pronounced as *lo[p]*, and *lʲod* ‘ice’ as *lʲo[t]*. For simplicity, assume that all voiced obstruents are encoded as *B*, all voiceless ones are *P*, and other segments that are not relevant for the process of word-final devoicing as *N*. The main rule of the target transducer is then to re-write all word-final *B*s as *P*s. Here, I am using a simplified alphabet for the sake of simplicity of the pattern representation. However, further, in Section 3.4, I will show that the choice of alphabet has an effect on what constraints are learned from the data. In such a way, Figure 2.13 shows a subsequential FST for Russian

word-final devoicing. This FST takes advantage of the subsequential property of having the state outputting function that appends P to the end of the word if the reading of the input string was completed in the state q_1 .

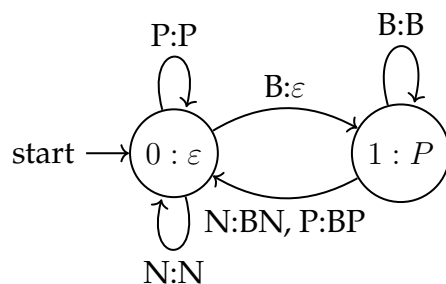


Figure 2.13: Subsequential FST for word-final devoicing.

Consider how the transducer in Figure 2.13 rewrites the Russian word *pedagog* ‘pedagogue’. This word corresponds to the sequence $PNBNNBNB$ according to the simplified representation outlined above. The FST reads symbols of that sequence one by one starting from the initial state q_0 . At first, it reads P and N and outputs the same symbols. The following B leads to the state q_1 , and that B is written together with the following N when the machine moves back to the state q_0 . It was delaying the output of B to make sure that only the word-final B is rewritten as P . Finally, when the FST reads the final B , it outputs P instead by the state output of q_1 , because it is the final activated state. The translation of $PNBNNBNB$ is $PNBNNBNP$, that corresponds to correctly rewriting *pedagog* as *pedago[k]* since $[k]$ is the voiceless counterpart of $[g]$.

Chandlee (2014), and later Chandlee and Heinz (2018) show that the majority of phonological processes can be modeled in similar ways. Chandlee (2017) later extends these results to morphology and models different types of affixation, word boundary processes and some types of reduplication. Other patterns that are shown to be subregular include metathesis, epenthesis, flapping, deletion, harmonies, and many others (Chandlee, 2014). Even some suprasegmental processes, such as stress, seem to exhibit subregular properties (Rogers, 2018). For

a survey of vowel harmonies and their computational complexities, see (Gainor et al., 2012). However, generalizations beyond some processes seem to require more complexity than subregular mechanisms can provide (Dolatian and Heinz, 2018).

Similarly, although subsequential mappings fit a large portion of natural language patterns, there are phonological processes that are not subsequential. For example, bidirectional feature spreadings cannot be captured by a subsequential machine because the latter ones can read a string either left-to-right or right-to-left: it cannot pass the value in *both* directions. Even though this pattern intuitively seems to be pretty simple, two runs of a transducer are required to capture it (Heinz and Lai, 2013). As another example, a transducer applying the rules of UTP to the underlying tonal representations is not subsequential either (see Sections 2.1.4 and 4.1.3): for a sequence of low tones to become high, it needs triggers on both sides. Such mappings, however, are still regular, namely, they are weakly deterministic and circumambient (Heinz and Lai, 2013; Jardine, 2016a; Lamont et al., 2019).

Although it is not clear so far if subregularity is indeed a hard upper bound on the complexity of natural language dependencies, it provides several very valuable perspectives such as a wide empirical coverage, as well as desirable learning properties (see Section 2.3). Patterns from as simple as word-final devoicing (Sections 2.1.3 and 2.2.2) to as complex as the interaction of local and long-distance dependencies (see Samala pattern in De Santo and Graf (2019)). While subregular languages describe a variety of typologically attested patterns and phenomena, they also predict the impossibility of patterns that are, in fact, unattested. So, for example, subregular languages that seem to be the best fit for linguistic patterns cannot handle first-last harmony that enforces the agreement of the first and the last vowels within a word (Heinz and Lai, 2013). Neither can it account for the sour grapes harmony spreads a harmonizing feature only if a

blocker is not present, see Section 2.1.7 for other examples.

As of the outliers, it is important to know the *principal* factors that do not allow them to be captured by subregular means. Importantly, the linguistic analysis also plays role in the overall computational complexity of the pattern: see, for example, a Noon pattern discussed in Moradi et al. (2019) that falls in different complexity categories when analyzed under different morphological paradigms. Although the tight upper bound of phonological and morphological dependencies still needs to be determined, the subregular perspective can be viewed as a beam highlighting the area of the hierarchy of formal languages that certainly needs attention due to its interesting properties and predictions.

Playing devil’s advocate, one might argue that the perspective given by the subregular approach can in the future turn out to be incorrect. Indeed, that can be the case, however, history shows that the ideas that are not exactly correct but insightful still can be a valuable trigger of scientific progress. For example, in physics, there were many atomic models (Dalton’s, Thomson’s, Bohr’s a.o.) that were insightful, but not always right. Although those theories are now deprecated, they were important steps towards the discovery of the Schrödinger’s model in 1926 that is still widely accepted nowadays. Even if the subregular hypothesis will turn out to be too weak for natural language dependencies, subregular models provide valuable insights into typology and cognition (Heinz and Lai, 2013; Luo, 2017), and even human cognitive system (Rogers and Pullum, 2011; Lai, 2015; Avcu, 2018).

2.2.3 Left and right subsequential mappings

Subsequential transducers are a good fit for local and long-distance phonological processes such as intervocalic voicing, word-final devoicing, assimilations, harmonies, and many others. In all the examples discussed so far (Buryat vowel harmony in Section 2.2.1 and Russian word-final devoicing in Section 2.2.2), the

transducer reads the underlying representation left-to-right, correctly capturing the progressive feature spreading. Such transducers are **left subsequential**, in contrast to **right subsequential** FSTs that read the input string right-to-left.

Whereas a left subsequential transducer captures progressive harmonies, it fails to generalize regressive ones. In the latter, the *last* harmonizing segment contains the information about the feature value that needs to be spread. For example, in Tuareg, sibilants regressively assimilate in voicing and anteriority; see Section 2.1.3 for details. The data below repeats the SFs presented in (7-11), together with the URs, where /S/ represents the underspecified sibilant.

- (39) S-əlməd → s-əlməd 'CAUS-learn'
- (40) S-əq:usə → s-əq:usət 'CAUS-inherit'
- (41) S-əntəz → z-əntəz 'CAUS-extract'
- (42) S-əm:əfən → ʃ-əm:əfən 'CAUS-be.overwhelmed'
- (43) S-ək:uʒət → ʒ-ək:uʒət 'CAUS-saw'

The right subsequential FST in Figure 2.14 implements the regressive Tuareg sibilant harmony. For simplicity, *N* refers to any segment that is not a sibilant. Every state has a loop reading *N* and writing the same *N*, therefore non-sibilants are not affected by the harmony in any way. Additionally, the loop on the state q_0 rewrites *S* as *s*, because an underspecified sibilant is realized as /s/ if there is no other sibilant to its right. For example, in (39), there is no sibilant in the root, and therefore the causative prefix is realized as /s/. In other cases (40-43), /S/ agrees with the root sibilant in voicing and anteriority. For example, in (43), the third segment from the end is ʒ that moves the FST to the state q_4 , and all following underspecified sibilants are rewritten as ʒ.

Although indeed the majority of harmony processes are either left-subsequential or right-subsequential, bidirectional harmonies require more computational power (Heinz and Lai, 2013). For example, in Maasai, a dominant harmony enforces the spreading of root's ATR features to both prefixes and

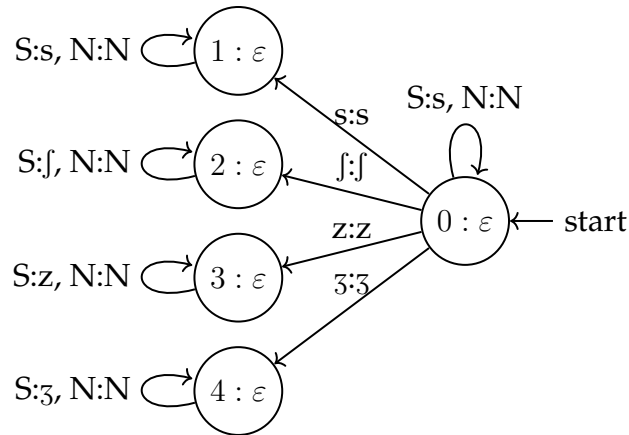


Figure 2.14: Right subsequential FST for Tuareg regressive sibilant harmony.

suffixes (Rose and Walker, 2011). Even though for a linguist such a pattern would not seem complicated, it requires a two-way FST to be represented. The first left-to-right run of such an FST does not affect the value of the prefix vowels, but rather spreads the root ATR specification onto the suffixes. Now, when the ATR value is known, the second right-to-left run returns to the beginning of a word, assigning that value to the prefix vowels. Additionally, the way a pattern is encoded highly affects its computational complexity. Apart from the string representations, there are subregular perspectives on autosegmental tiers and features, and new insights can come from that direction of research as well (Chandlee et al., 2019; Chandlee and Jardine, 2019).

2.2.4 ISL and OSL mappings

In this section, I look at two different ways transformational rules can be applied to the underlying representations. Thus, instead of discussing linguistic patterns, I focus on the *manner of the rule application*. Although this section is not crucial for understanding the following chapters, its goal is to provide a reader with an integral perspective on the subregular modeling of transformational rules and well-formedness conditions.

For example, consider an SPE-style rule $a \rightarrow b/a - a$ from (Chandlee, 2014). There are two ways it can be applied. Given the UR *aaaaa*, the simultaneous application of this rule to all positions yields the SF *abbba*. However, if this rule was applied step-by-step, the obtained SF would be *ababa*, since the change of the second *a* to *b* makes the context of the third *a* incompatible with the one specified by the transformation. To reflect this difference, Chandlee (2014) introduces smaller subclasses of subsequential mappings: *input strictly local* (ISL) and *output strictly local* (OSL) ones. The ISL functions encode simultaneous rule application of strictly local functions, while the OSL ones reflect the iterative one. Figure 2.15 shows the relationship among left/right subsequential, ISL and OSL functions in a simplified way; see Chandlee et al. (2014, 2015) for proofs and details.

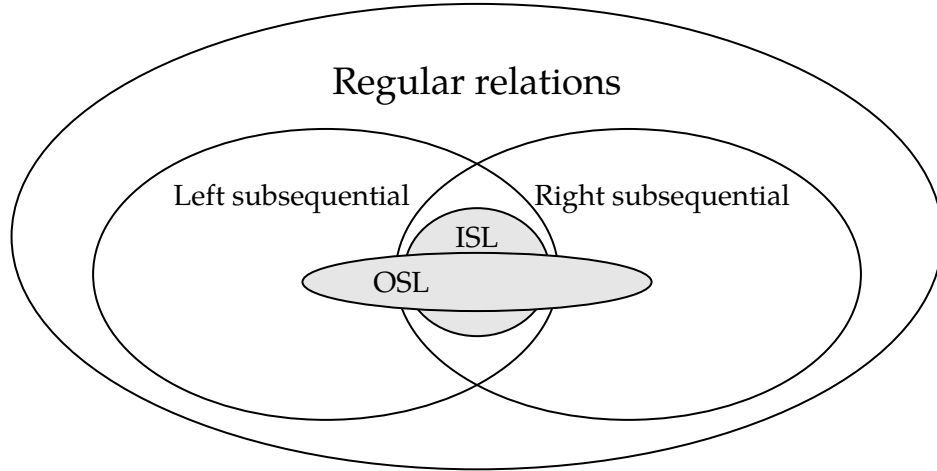


Figure 2.15: Relationship among left subsequential, right subsequential, OSL, and ISL functions; adapted and simplified from (Chandlee, 2014).

Chandlee et al. (2014) define both ISL and OSL mappings using the notion of **tails**. Tails show the dependency between the possible continuations of input strings, and portions of the output contributed by those continuations. Formally, tails are defined as $tails(x) = \{(y, v) : f(x \cdot y) = u \cdot v \text{ and } u = lcp(f(x \cdot \Sigma^*))\}$, where f is the function mapping the input strings to the corresponding outputs, \cdot is the

concatenation operator, and lcp is the longest common prefix. For example, the longest common prefix of abc and $abde$ is ab , since it is the longest prefix shared by those two strings. A slightly extended notation introduced below changes that definition to $tails(\vec{x}) = \{(y, v) : f(\vec{x} \cdot y) = u \cdot v \text{ and } u = lcp(f(\vec{x} \cdot \Sigma^*))\}$.

Assume that Σ and Γ are (possibly different) alphabets used to represent the strings before and after application of some rule. Additionally, strings \vec{x} and y belong to Σ^* , and u and v belong to Γ^* , i.e. these strings consist only of symbols included in Σ^* or Γ^* , respectively. A tail of the prefix \vec{x} is a list of all pairs (y, v) , where y is a possible continuation of the input prefix \vec{x} , i.e. $\vec{x} \cdot y$ is the input string. The corresponding to $\vec{x} \cdot y$ output string is $u \cdot v$, where u is the longest prefix shared by all outputs corresponding to inputs starting with \vec{x} .

As an example, let us find a list of tails of the input prefix $\overrightarrow{\times aa}$ in the mapping M . Note, that only the input strings are annotated with the edges \times and \times .

$$M = (\times aa \times, aa), (\times aaa \times, aba), (\times aaaa \times, abba), (\times aaaaa \times, abbba), \\ (\times aaaaaa \times, abbbbba), (\times aaaaaaa \times, abbbbbbba) \dots$$

All input strings of that mapping start with $\overrightarrow{\times aa}$. The longest common prefix of the corresponding output strings is a : for example, the second symbol is different in aa and aba . Below, I mark the selected input prefix $\overrightarrow{\times aa}$ and the longest common prefix a .

$$M_{marked} = (\overrightarrow{\times aa} \times, a), (\overrightarrow{\times aa} a \times, a), (\overrightarrow{\times aa} aa \times, abba), (\overrightarrow{\times aa} aaa \times, abbba) \dots$$

The list of tails of $\overrightarrow{\times aa}$ can be computed by removing $\overrightarrow{\times aa}$ and a from the input and output strings of M_{marked} , respectively.

$$tails(\overrightarrow{\times aa}) = (\times, a), (a \times, ba), (aa \times, bba), (aaa \times, bbba) \dots$$

The obtained list of tails implies that after observing $\overrightarrow{\times aa}$, the input continuation \times introduces a to the translation, $a \times$ contributes ba , and so on. Further in this subsection, I show how the notion of tails is used to define ISL and OSL mappings (Chandlee, 2014; Chandlee et al., 2014, 2015).

Input strictly local mappings

The k -ISL functions encode simultaneous rule application, i.e. when a transformational rule applied to all positions at the same time. In mapping M , for example, a is substituted by b if it is surrounded by a in the input string. It creates pairs such as $(aaaaa, abbba)$: three internal a are changed to b since their context in the input string is the same as specified by the rule $a \rightarrow b/a _ a$.

Chandlee et al. (2014) define an ISL mapping as follows. If two input strings u_1 and u_2 share the same $k - 1$ -local suffix, their set of tails is identical as well.

$$\text{suff}^{k-1}(u_1) = \text{suff}^{k-1}(u_2) \Rightarrow \text{tails}(u_1) = \text{tails}(u_2)$$

If the mapping M is indeed ISL, the set of tails is the same for all strings ending with the same $k - 1$ local prefix. Let us assume that $k = 3$, since the rule targets an item in the context of two other elements. Input strings $\times aa \times$ and $\times aaa \times$ both have the 2-local suffix $a \times$, and that definition states that their sets of tails must be identical as well. To confirm this, let us compare tails of $\times aa$ and $\times aaa$.

$$\begin{aligned} \text{tails}(\overrightarrow{\times aa}) &= (\overrightarrow{\times aa} \times, aa), (\overrightarrow{\times aa} a \times, aba), (\overrightarrow{\times aa} aa \times, abba) \dots = \\ &(\times, a), (a \times, ba), (aa \times, bba) \dots \end{aligned}$$

$$\begin{aligned} \text{tails}(\overrightarrow{\times aaa}) &= (\overrightarrow{\times aaa} \times, aba), (\overrightarrow{\times aaa} a \times, abba), (\overrightarrow{\times aaa} aa \times, abbbba) \dots = \\ &(\times, a), (a \times, ba), (aa \times, bba) \dots \end{aligned}$$

Their tails are indeed the same, and it confirms that the *simultaneous application* of the rule $a \rightarrow b/a _ a$ is an *ISL* function. The corresponding transducer encodes a 3-local window reading the input string. Knowledge of the previous 2 input symbols informs the transducer about the next action regarding the following symbol that it reads. Figure 2.16 demonstrates these steps.

Input:	× a a a a a ×
Output 1:	×
Input:	× a a a a a ×
Output 2:	× a
Input:	× a a a a a ×
Output 3:	× a b
Input:	× a a a a a ×
Output 4:	× a b b
Input:	× a a a a a ×
Output 5:	× a b b b
Input:	× a a a a a ×
Output 6:	× a b b b a
Input:	× a a a a a ×
Output 7:	× a b b b a ×

Figure 2.16: ISL application of the rule $a \rightarrow b/a _ a$ to $aaaaa$.

Output strictly local mappings

Now, let us consider the iterative application of the same rule $a \rightarrow b/a _ a$. In this case, every time the rule is applied, it changes the form that the same rule produced earlier, and therefore $aaaaa$ is changed to $ababa$. This type of transformation can be visualized as a 3-local window moving through the input string and rewriting the middle item if the contexts match. The steps below show the application of the rule;

the underlined segments are the contexts, and the boxed items show how the target element was changed. The list of pairs in M' shows the corresponding mapping.

$$\times \boxed{a:a} \underline{aaaa} \times \rightarrow \times \underline{a} \boxed{a:b} \underline{aaa} \times \rightarrow \times \underline{ab} \boxed{a:a} \underline{aa} \times \rightarrow \times \underline{aba} \boxed{a:b} \underline{a} \times \rightarrow \times \underline{abab} \boxed{a:a} \underline{\times}$$

$$M' = (\times aa \times, aa), (\times aaa \times, aba), (\times aaaa \times, abaa), (\times aaaaa \times, ababa), \\ (\times aaaaaa \times, ababaa), (\times aaaaaaa \times, abababa) \dots$$

Chandlee et al. (2015) shows that such mappings are k -OSL since the previous application of this rule affects the following one. Their definition of OSL mappings is below, where the function f , as previously, maps its argument (input string) to the corresponding output. For a mapping to be OSL, the following needs to be true: if two output strings share the same $k - 1$ -local suffix, the tails of the corresponding input strings are the same.

$$suff^{k-1}(f(u_1)) = suff^{k-1}(f(u_2)) \Rightarrow tails(u_1) = tails(u_2)$$

That would imply that in the mapping M' , tails of $\overrightarrow{\times aaa}$ and $\overrightarrow{\times aaaaa}$ are the same because the translations of $\times aaa \times$ and $\times aaaaa \times$ share the same $k - 1$ -local suffix ba (those translations are aba and $ababa$, respectively).

$$tails(\overrightarrow{\times aaa}) = (\overrightarrow{\times aaa} \times, \mathbf{aba}), (\overrightarrow{\times aaa} a \times, \mathbf{abaa}), (\overrightarrow{\times aaa} aa \times, \mathbf{ababa}) \dots = \\ (\times, \varepsilon), (a \times, a), (aa \times, ba) \dots$$

$$tails(\overrightarrow{\times aaaaa}) = \\ (\overrightarrow{\times aaaaa} \times, \mathbf{ababa}), (\overrightarrow{\times aaaaa} a \times, \mathbf{ababaa}), (\overrightarrow{\times aaaaa} aa \times, \mathbf{abababa}) \dots = \\ (\times, \varepsilon), (a \times, a), (aa \times, ba) \dots$$

<i>Input 1:</i>	× a a a a a ×
<i>Output 1:</i>	×
<i>Input 2:</i>	× a a a a a ×
<i>Output 2:</i>	× a
<i>Input 3:</i>	× a a a a a ×
<i>Output 3:</i>	× a b
<i>Input 4:</i>	× a a a a a ×
<i>Output 4:</i>	× a b a
<i>Input 5:</i>	× a a a a a ×
<i>Output 5:</i>	× a b a b
<i>Input 6:</i>	× a a a a a ×
<i>Output 6:</i>	× a b a b a
<i>Input 7:</i>	× a a a a a ×
<i>Output 7:</i>	× a b a b a ×

Figure 2.17: OSL application of the rule $a \rightarrow b/a _ a$ to $aaaaa$.

Indeed, since their tails are the same, this shows that the mapping is OSL. The corresponding transducer encodes a 3-local window that keeps track of the last 2 output symbols. Based on those symbols and the current symbol it decides how that current symbol is changed. The iterative rule application is demonstrated in Figure 2.17.

To sum up, k -ISL and k -OSL mappings encode dependencies affecting k -local windows. ISL functions apply a rule simultaneously to all the positions of the input string, whereas the OSL functions apply a rule step-by-step. While in the former case, the changes are independent from each other, the latter uses information about the previous change to inform the following one. Chandlee (2014) argues that linguistic strictly local processes are ISL or OSL, and demonstrates it using a variety of linguistic examples such as Greek fricative

deletion, English flapping, and others (Joseph and Philippaki-Warbuton, 1987).

2.2.5 Models of transformations: summary

FSTs encode regular mappings that are well-known to be a good fit for natural language phonology and morphology (Johnson, 1972; Kaplan and Kay, 1994; Beesley and Karttunen, 2003). However, a particular class of functions, namely, *subsequential*, includes the major part of natural language patterns. Transducers implementing subsequential mappings read the symbols of the underlying representations one by one and output the corresponding surface forms. This allows one to model a wide variety of local and long-distance dependencies such as word-final devoicing and vowel harmony. For the discussion of predictions and outcomes of subregular and subsequential modeling, see Section 2.2.2.

It should be noted that some attested phonological processes are not subsequential. Among them, there are circumambient pattern of unbounded tonal plateauing and reduplication requiring the power of two-way FSTs (Jardine, 2016a; Dolatian and Heinz, 2018). Those patterns, however, are beyond the scope of this dissertation.

In Chapter 4, I discuss results of tool-assisted learning experiments targeting various phonological processes such as tone plateauing, local processes, and different types of harmony systems with and without blockers.

2.3 Learning grammars from data

Previous sections showed that subregular grammars can model natural language dependencies. However, all the previously presented grammars were constructed manually. In this section, I discuss the possibility of building those models *automatically*. It not only allows the researchers to avoid the burden of manual grammar construction, but also gives us insights into the mechanisms helping to

discover those patterns.

Grammatical inference is a sub-field of machine learning that is concerned with the extraction of grammars from data. As Colin de la Higuera formulates in his book “Grammatical Inference” (2010), this field lies at the intersection of linguistics, inductive analysis, and pattern recognition. *Linguistics*, and computational linguistics, in particular, brings the core idea of the existence of a *formal grammar*, or a set of rules defining a *language*. *Language learning* can then be viewed as a process of discovering a language’s grammar by the learner. The field of *inductive inference* aims at a problem of inferring the underlying grammar that consistently predicts what is grammatical and what is not after observing a set of elements of the language, where those elements can be strings, trees, or other structured objects. Finally, *pattern recognition* describes the best model and its properties that would explain the data; it *analyzes* the pattern.

If the task is to model a language, then the goal is to find a grammar that describes that language. If the grammar is not known *a priori*, it might be possible to *learn* its rules by observing and exploring the language. **Grammatical inference algorithms** require a finite sample of data representing the target language as input, and return a grammar hypothesis as output. Often, such algorithms need only **positive data**, or, in other words, a collection of well-formed structures of the target language. However, some algorithms require **negative data** as well — in this case, a list of ill-formed words needs to be available. That grammar solves a **membership problem** for that language, or, in other words, it correctly predicts for any given string if that string belongs to the target language, see Figure 2.18. If instead a mapping needs to be learned, grammatical inference algorithms require a sufficient sample of the input-output pairs as input and construct a transducer that generalizes that mapping.

The learning algorithms for SL, SP, TSL and MTSL languages, and also the algorithm inferring subsequential mappings, will be discussed in details in

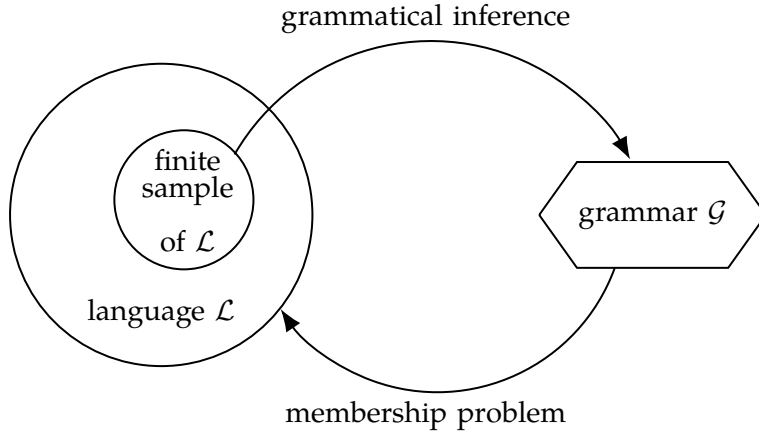



Figure 2.18: Relationship between a language \mathcal{L} and a grammar \mathcal{G} .

Chapters 3 and 4. These algorithms share several common properties: they all require only positive data to find the grammar, they are fully interpretable, and work in polynomial time and data. In what follows, I explain these properties. Indeed, *learning only from the positive data* is the desired characteristic, since human learners do not have access to what is not possible in their languages: a finite sample of well-formed examples is sufficient for extracting the pattern. (Chomsky, 1986). Only some of the subregular languages have this property: the full class of regular languages cannot be learned from positive data. *Interpretability* of an algorithm means that both the learning process and the outcome are transparent: it is possible to trace how the learner came to a certain conclusion, and explain the obtained results. These learners extract grammars in *polynomial time*, so they can be computed in practice. (The running time of polynomial algorithms is n^c , where n is the size of the training sample, and c is some constant (Sipser, 2013).) Finally, *learning in the limit* guarantees that after a finite number of errors, the learner will start making only correct predictions (Gold, 1967).

As a part of my dissertation, I implemented the *SigmaPie* package  for working with subregular languages and mappings. It provides learners for SL, TSL, MTSL, SP languages and subsequential mappings (Aks nova, 2020b). In

Chapter 3, I explore how well those subregular learners extract *well-formedness conditions* from artificial automatically generated datasets exhibiting human language-like patterns such as one or more harmonies with or without blockers, word-final devoicing, tone plateauing, and others. The training sample for those experiments is a collection of words well-formed according to one of those generalizations. Later in Chapter 4, I explore modeling of *processes* similar to the ones listed above. In this case, the training sample contains pairs of underlying representations and the corresponding surface forms. In such a way, I model processes and well-formedness conditions using tools implemented as a part of *SigmaPie*.

2.4 Aspects of practical applications

There were several successful applications of grammatical inference algorithms in the previous decades. For example, Alexander Clark won the Tenjinno competition in 2006 by using a modified version of OSTIA, a subsequential learner discussed further in Chapter 4 (Oncina et al., 1993; Clark, 2006). Also, Chandlee et al. (2012) explore the integration of FSA-based grammatical inference techniques into robotic planning.

However, the subregular learners are *structural* and not probabilistic, and therefore frequently, the absence of some particular configuration in the training sample results in the algorithm failing to learn simple patterns. For instance, Gildea and Jurafsky (1996) show that a corpus of English pronunciations is not enough for OSTIA to generalize a rule of English flapping.

Indeed, the results of my Chapters 3 and 4 confirm that local restrictions and gaps in the natural language data obscure the extraction of some dependencies. This is why I mostly focused on learning *sub-phenomena* instead of the complex interactions of local and long-distance dependencies found in natural language

data. Alternatively, capturing different aspects of the data can be done by combining forces of different learners (Heinz, 2010a; Heinz and Idsardi, 2013). For example, a language can exhibit tone plateauing (SP) together with a long-distance harmony with blocking (TSL). To learn this pattern, the SP and TSL learning algorithms can be run in parallel, and the intersection of the obtained languages yields the target language. However, future research is needed to understand if transformations can be combined in a way that would preserve properties such as subsequentiality.

There are other directions of research that could improve the performance of subregular learners. For example, implementing linguistic notions such as features can help to see the behavior of elements as groups instead of individual segments. The initial results on integrating features and natural classes are available in (Strother-Garcia et al., 2016; Chandlee et al., 2019). Some prior knowledge about the shape of the data can be encoded into the learners using methods that help to systematically exclude certain possible configurations from consideration, as it was shown by Wellman and Henrion (1993). Also, adding probabilities to the learning algorithms allows abandoning the “black and white” structural approach incapable of modeling such probabilistic phenomena as harmony fading or the occurrence of disharmonic words. Heinz and Rogers (2010); Shibata and Heinz (2019) explore the probabilistic subregular models, and Heinz and Koirala (2010); Vu et al. (2018) add together features and probabilities.

This chapter is setting the scene for the automatic modeling of well-formedness conditions and transformational rules using subregular methods. I introduced the main subclasses of subregular languages and mappings and showed how different typologically diverse linguistic patterns can be captured using subregular means. It is also worth noticing that subregular classes that seem to be the best fit for linguistic dependencies are also efficiently

learnable from positive data. Moreover, the outcomes of those learning algorithms, as well as the steps of the learning process, are fully interpretable and transparent. While it requires additional research to understand if subregular languages and mappings provide a tight upper bound on the computational complexity of natural language dependencies, the subregular approach provides valuable perspectives on modeling linguistic phenomena, as discussed in Sections 2.1.2 and 2.2.2. In Chapters 3 and 4, I explore the automatic modeling of linguistic phenomena using subregular learners.

Chapter 3

Learning languages

Previously, I showed that different phonological and morphological phenomena can be modeled as subregular languages. In this chapter, I demonstrate the automatic extraction of subregular languages from linguistic data. To do so, I employ four subregular language classes that express generalizations, including local and long-distance dependencies such as attested and unattested harmony systems with and without blockers, word-final devoicing, and even suprasegmental patterns.



Indeed, local patterns can be expressed with strictly local (SL) grammars and long-distance phenomena with strictly piecewise (SP) grammars. If a long-distance pattern uses blockers (e.g., opaque vowels in vowel harmony), then we use tier-based strictly local (TSL) grammars. If the language exhibits multiple long-distance phenomena, then we may also need multi-tier strictly local (MTSL) grammars. This perspective on morphotactics and phonotactics also rules out typologically unattested patterns such as first-last harmony, majority harmony, or embedded circumfixation.

In what follows, I discuss algorithms which extract SL, SP, TSL and MTSL grammars from the data. Apart from the training sample, these algorithms require knowing the class of the target grammar, and the locality window of that

grammar, i.e. the length of substructures with which it operates. In other words, we need to know the formal complexity of the target language in order to learn it efficiently using subregular learning algorithms. Given a sufficient and representative training sample and proper specifications of the target grammar, the subregular learners discover the pattern in polynomial time and data.

I start by introducing the datasets that I will use throughout the chapter to perform the learning experiments. These datasets vary from automatically generated artificial languages to real wordlists exemplifying attested linguistic dependencies, such as word-final devoicing in German, vowel harmony in Turkish, and others. I then use these datasets as training samples for the subregular learners, discuss the obtained grammars, and automatically evaluate the predictions of those grammars based on the well-formedness of the strings they generate. At the end of the chapter, I provide a table that summarizes the results of the learning experiments.

The exemplified learners work exclusively with *string representations*. These algorithms focus on structural properties; they are limited to non-probabilistic algorithms which evaluate the well-formedness of input strings. As of now, I have not implemented statistical versions of these algorithms, or algorithms which work with non-string-based representations.

The subregular learners, scanners and sample generators are available as a module of my Python package *SigmaPie*  (Aksënova, 2020b). The code of the toolkit is provided in Appendix A. It is also available on GitHub, as well as the code behind the implementations of the further discussed learning experiments  (Aksënova, 2020d).

3.1 The experimental setup

I use both artificial and natural languages to explore the performance of the SL, SP, TSL and MTSL learners. The artificial languages imitate concrete natural language phenomena. The learning of these artificial languages shows us if the extraction of those patterns is possible *conceptually*, whereas the performance of those algorithms on the natural language datasets shows us what is currently possible *in practice*. Due to the transparency and interpretability of the subregular learners, we can always see the path the learner took to extract the target grammar. If the learning experiment was unsuccessful, we can always look inside those algorithms and see what obstructed the convergence.

3.1.1 Experimental pipeline




The **experimental pipeline** involved 3 steps: learning, generation, and evaluation. **Learning** included automatic extraction of subregular grammars from the given training samples. I then used those extracted grammars to **generate** samples of strings. Finally, during the **evaluation** step, I computed the percentage of the strings from the automatically generated datasets that are well-formed with respect to the target grammars.

Regardless of what can be considered a general practice, I am *not* testing the performance of the grammars on the held out parts of the training sample. That approach would not let us to detect the cases in which the learner “overgeneralized” the pattern. For example, some learning experiments resulted in the learner incorrectly converging on the empty negative grammar: such a learner simply assumed that “anything goes”. Trivially, it will score 100% on all the held-out data. Only by looking at the predictions of the grammar it is possible to see if the learner generalized the language of the training sample.

The results showing the performance of the subregular models are presented

in 3.6. Only negative grammars were employed for the experiments due to the succinctness of their grammars.


3.1.2 Natural languages

The real data used for the experiments comes from German, Finnish and Turkish. The German dataset is a wordlist for wordgames posted by enz  (Enzenberger, 2019). The Finnish data is taken from a collection of wordlists scraped by douglasbuzatto  (Buzatto, 2016). The collection of Turkish words was uploaded by Harrison et al. (2004) as a part of his project *The Vowel Harmony Calculator* . Due to the non-probabilistic nature of the algorithms, I removed the data items that violate the target generalizations, such as disharmonic stems. This is necessary to evaluate the structural properties of the learners. In the future, the availability of the probabilistic subregular learners will allow to process disharmonic stems as well.

The target patterns exemplified by natural language datasets involved three levels of abstraction. The *raw representations* contained the strings from the wordlists; it allows us to explore the problems that the learner faces when it is given realistic data. The *masked representation* is more abstract and involved substituting all the symbols in the original data that are not relevant for the target pattern by a single symbol of choice. It allows the learner to focus on the generalization since all the “irrelevant” material is masked. It lets us explore if there is enough information in the simplified strings of the language to notice the pattern behind the behavior of the dependent elements. For example, if Turkish vowel harmony was explored under this perspective, all consonants were masked as *x*. Finally, the *abstract representation* represented the pattern with the highest degree of generality, therefore compelling the learner to discover only the “core” part of the generalization. This allows us to carefully examine the learning process: the levels of abstraction help remove the “concreteness” of the natural

language dependencies and focus on the general properties of the target patterns.

3.1.3 Artificial languages

I used 5 artificial language generators for the experiments in this and the following chapters. Their code is available on GitHub  (Aks nova, 2020d). In all of these generators, the number of strings (the default value is 10) and the length of those strings (the default value is also 10) can be defined a priori.

The **Simple Harmony Generator** encodes and generates samples demonstrating long-distance dependencies such as vowel harmony and consonant harmony. The generator lets us define several harmonic classes, where a *harmonic class* is a collection of elements that cannot co-occur within the same well-formed word of the language. For example, if there are two harmonic classes $A = \{a, o\}$ and $B = \{b, p\}$, the well-formed words of this language can use at most 1 element of these class, unless a blocker intervenes. These classes A and B define strings such as *apappa*, *oppooo*, *bbaab*, and so on; but the ones such as *abbobb* cannot be produced by this generator. The blockers are defined as $\{f:a, s:p\}$, meaning that the occurrence of f in the string allows only a to be seen after itself. Other elements of a 's harmonic class are now prohibited, e.g., f blocks any subsequent o . Additionally, b is prohibited after an s . This generator now produces words such as *ababbsappp* and *obbofbasaapp*. Transparent elements can be expressed as single-item harmonic classes, such as $X = \{x\}$; it lets x be freely inserted in different parts of any string. Additionally, the minimal and maximal length of every harmonic class is also parametrized (the default values are $\text{min} = 1$ and $\text{max} = 3$), as well as the emission probability of every blocker (the default probability is $p(s) = p(f) = 0.2$).

The **Fake Turkish Generator** is much more specialized in comparison to the generator outlined above. It produces sequences of vowels that are well-formed with respect to the rules of Turkish vowel harmony, with all the consonants

simplified to a single symbol. Like that, it produces harmonic sequences such as *öxüüxeei* and *oaıxxxıı*. The “choice” of the consonant, as well as the minimal and maximal lengths of vowel and consonant clusters, can be specified in the generator. The Turkish dataset cannot be defined by the Simple Harmony Generator because the same set of segments participates in two types of harmonies (backness and rounding), and some of the vowels that are undergoers for the backness harmony serve as blockers for the rounding one.

The **Word-Final Devoicing Generator** simply produces a set of strings that follow the rule of the word-final devoicing. For this, we define a list of voiced and voiceless segments, as well as the alphabet of the language. By default, the voiced and voiceless segments are $\{b\}$ and $\{p\}$ respectively, and the alphabet of the language is $\{a, b, p\}$. For example, this generator produces strings such as *apabaa* and *abbap*, but never the ones such as *paab*.

The **UTP Generator** produces strings of low (*L*) and high (*H*) tones that are well-formed concerning the unbounded tonal plateauing (UTP) generalization in Luganda. This generalization prohibits a low tone from appearing in a string if surrounded by high tones. For example, it produces strings such as *LLHH* and *LHHHL*, but is incapable of generating the ones such as *HHLHH* and *HLLLLH*.

The **First-Last Harmony Generator** generates a language with first-last harmony. The language enforces agreement between the first and the last elements within the string. A list of agreeing elements needs to be specified (the default value is $\{a, o\}$), as well as the list of all other elements that can appear in the well-formed strings of this language ($\{a, o, x\}$ is the default). Strings such as *axoxoxa* and *ooaxo* are then grammatical, but *axaxxo* or *oaa* are not. Importantly, harmonic systems of this type are unattested in natural languages.¹

¹First-last harmony can be unattested due to several different reasons. It might be impossible for such a pattern to naturally occur from language changes, or it can simply be not learnable by humans. Lai (2015) discusses the differences between the attested and unattested harmony patterns.


These generators were employed to produce data that was then fed to the SL, SP, TSL and MTSL learners. The next subsection provides the detailed description of the datasets used as training samples during the subregular experiments.

3.1.4 Target patterns

The learning experiments in this chapter target typologically widespread linguistic patterns such as word-final devoicing, tone plateauing and harmonic systems of different kinds. Here, I explain how I obtained the artificial training samples for every one of these patterns. For German, Finnish and Turkish natural language datasets, I also discuss the preprocessing steps that I did to get the data in the shape appropriate for the experiments.

Pattern 1: word-final devoicing

The phenomenon of word-final devoicing is attested in languages such as Russian and German. It prohibits underlyingly voiced obstruents from being pronounced voiced at the end of the word. In German, word-final /b/, /d/, and /g/ are realized as [p], [t], and [k] (Brockhaus, 1995). For example, the word for ‘children’ is *Kinder*, but its singular form is pronounced as *Kin[t]*, i.e. the underlyingly voiced segment is realized as voiceless at the end of the word.

For this experiment, I used a German wordlist  (Enzenberger, 2019), its masked version, and an abstract representation of this pattern. During the masking step, all irrelevant segments were simply represented as *a*, and the abstract representation of this pattern only included 3 types of elements: voiced obstruents (*b*), voiceless obstruents (*p*), and others (*a*).

Raw representation This wordlist in its original form contains 685,618 words written in German orthography. However, German orthography does not reflect the process of the word-final devoicing and therefore the preprocessing of this

corpus was necessary. It included two steps: incorporating the effect of the word-final devoicing and filtering words that contain non-German symbols. Firstly, I substituted every occurrence of the word-final /g/, /b/ and /d/ by their voiceless counterparts /k/, /p/, and /t/, respectively. In total, there were 1,599 words that end with /b/ (0.2% of the total number of words); 15,294 words that end with /d/ (2.2%); and 17,098 words with a word-final /g/ (2.4%). This step resulted in words such as *Kind* being changed to *Kint*, *Rad* to *Rat*, etc. Secondly, I excluded all strings that use letters that do not belong to the German alphabet, such as *złoty*, *château*, and some others. After those words were excluded, the size of the German wordlist became 685,147 words.

```
1 print(german_wfd)
2 # ['hochjagende', 'zugebliebener', 'verbricht', 'besuchszimmer', '
   beschneien', ...]
```

Masked representation The next step was to simplify German wordlist. Namely, for the phenomenon of the word-final devoicing, segments other than $\{b, p, g, k, d, t\}$ are not important, and therefore all of them can be simply masked as *a*. The rules of the masking are summarized in Table 3.1. Since none of the words were deleted during this step, the size of that sample was the same as before: 685,147 words.

$$\begin{aligned} b, g, d &\leftarrow b, g, d \\ p, k, t &\leftarrow p, k, t \\ a &\leftarrow a, \ddot{a}, c, e, f, h, i, j, l, m, n, o, \ddot{o}, q, r, s, u, \ddot{u}, v, w, x, y, z, \text{ß} \end{aligned}$$

Table 3.1: German: *raw* \rightarrow *masked* representation.

```
1 print(german_wfd_masked)
2 # ['aakaabaaaa', 'aakaabaaak', 'aakaa', 'aakat', 'aaa', ...']
```

Abstract representation Finally, the pattern can be simplified even further to only three classes of elements: voiced obstruents, voiceless obstruents, and items that are irrelevant for the word-final devoicing. Let us then refer to these classes as *b*, *p* and *a*, respectively. The rules of this simplification for the German alphabet are presented in Table 3.2.

<i>b</i>	←	<i>b, g, d</i>
<i>p</i>	←	<i>p, k, t</i>
<i>a</i>	←	<i>a, ä, c, e, f, h, i, j, l, m, n, o, ö, q, r, s, u, ü, v, w, x, y, z, ß</i>


Table 3.2: German: *raw* → *abstract* representation.

To generate such a pattern, I used the word-final devoicing generator previously discussed in Section 3.1.3. Like this, I obtained a sample of 1,000 strings that represent the target pattern abstractly. The length of every word of this sample is 10 symbols.

```
1 toy_wfd = generate_wfd(n = 1000)
2 print(toy_wfd)
3 # ['aaabbpbbbp', 'pbapbapapa', 'apabaappap', 'bbbbaabbbp', '
   pbbpabppap', ...]
```

Pattern 2: a single vowel harmony without blocking

The next targeted phenomenon was a simple case of a vowel harmony that does not exhibit a blocking effect. In Finnish, vowels can be sub-divided into 3 categories: front (*ä, ö, y*), back (*a, o, u*) and neutral (*e, i*). Vowels within a word must agree with respect to their fronting or backness features, and the initial vowel controls the spreading (Rose and Walker, 2011). The neutral vowels are transparent regarding the harmonic process, and therefore they can occur in both types of words. For example, a word *puisto* ‘park’ contains back and neutral vowels, whereas *ikäntyvien* ‘older’ contains front and neutral ones.

For this experiment, I used a Finnish wordlist  (Buzatto, 2016), its masked version, and a simplified abstract representation of this pattern. The masked representation of the Finnish sample included masking all elements transparent for the harmony as x , and the alphabet of the abstract pattern only included 3 elements: vowels of one harmonic class (a), vowels of another harmonic class (o), and transparent elements (x).

Raw representation Originally, the Finnish wordlist contained 287,699 words. Three preprocessing steps were necessary: removing the words with non-Finnish letters from the sample, filtering the disharmonic words, and making changes to the representation of some letters. Firstly, I eliminated words that contain symbols that are not included in the Finnish alphabet, such as digits and punctuations. I also removed words such as *långsamt* ‘slowly’, that are in fact Swedish and therefore use the Swedish letter *å* represented as } in this dataset. The behavior of such words is not clear regarding Finnish vowel harmony. A total of 331 such words were removed from the dataset (0.1% of all words). Then, I substituted { and | that stand in this wordlist for *ä* and *ö*, respectively, by their more legible counterparts *A* and *O*. Finally, I filtered the disharmonic stems such as *etukäteen* ‘in advance’ and *juhlapäivä* ‘holiday’, there were 36,563 of such words in total (12,7%). 250,805 words remained after the preprocessing steps were completed.

```
1 print(finnish_harmony)
2 # ['mathilden', 'lisAnimen', 'macmillanin', 'urquhartin', '
   ilmeneviksi', ...]
```

Masked representation Next, I created a dataset where every segment transparent for the Finnish vowel harmony was masked. The vowels {*ä*, *ö*, *y*, *a*, *o*, *u*} were left intact, whereas the other elements were rewritten as x , see the Table 3.3. The obtained dataset also contains 250,805 words.

```
1 print(finnish_harmony_simplified)
```

$$\begin{aligned} \text{ä, ö, y} &\leftarrow \text{ä, ö, y} \\ \text{a, o, u} &\leftarrow \text{a, o, u} \\ \text{x} &\leftarrow \text{b, c, d, e, f, g, h, i, j, k, l, m, n, p, q, r, s, t, v, w, x, z} \end{aligned}$$

Table 3.3: Finnish: *raw* \rightarrow *masked* representation.

```
2 # ['xaxxixxex', 'xixAxixex', 'xaxxixxaxix', 'uxxuxaxxix', 'ixxexexixxi', ...]
```

Abstract representation Lastly, I simplified the pattern even more by generalizing the harmonic and transparent elements of Finnish to three classes: *a* for the class of front vowels, *o* for the class of back vowels ², and *x* for all other elements that make this dependency long-distant, see Table 3.4.

$$\begin{aligned} \text{a} &\leftarrow \text{ä, ö, y} \\ \text{o} &\leftarrow \text{a, o, u} \\ \text{x} &\leftarrow \text{b, c, d, e, f, g, h, i, j, k, l, m, n, p, q, r, s, t, v, w, x, z} \end{aligned}$$

Table 3.4: Finnish: *raw* \rightarrow *abstract* representation.

To generate artificial data, I used the harmonic generator discussed in Section 3.1.3. I defined a single harmonic class $A = \{a, o\}$ with $X = \{x\}$ representing the transparent elements. Any word was able to contain *x*, however, *a* and *o* could not co-occur within the same word. I generated a sample of 1,000 words that were well-formed regarding the rules of this simplified vowel harmony.

```
1 generator = Harmony({("a", "o"): "A", ("x"): "X"})
2 toy_vhnb = generator.generate_words(n = 1000)
3 print(toy_vhnb)
```

²*a* and *o* are both back vowels, this is just an abstraction to keep the alphabet as simple as possible.

```
4 # ['oxxxooxxxx', 'ooxxxooxxo', 'aaxxxaaxxx', 'oxxxoxxxo', '
    xxxaaxxaxx', ...]
```

Pattern 3: a single vowel harmony with blocking

The previous example concerns the case when there is a single vowel harmony that does not exhibit a blocking effect. However, blocking is a frequent phenomenon in harmonic systems. Consider Assamese, where vowels regressively harmonize in the advanced tongue root (ATR) feature (Mahanta, 2007). In the word *pɔlɔx* ‘silt’ all vowels are lax, however, when the tense suffix *-uwe* is applied to that stem, all the vowels become tense: *poloxuwe* ‘fertile land’. Nasals, as well as some other segments, block this long-distance spreading. In *zɔmɔni* ‘humorous’, lax vowels precede the nasal *n*, whereas the tense one follows it. Unfortunately, I found no available dataset exhibiting a harmony of this type. However, patterns of this type are widespread among the languages of the world, so in this experiment, I model the blocking effect.

Abstract representation In the harmonic system without blockers, there were 3 classes of elements: undergoers expressing one value of the harmonic feature (*a*), undergoers expressing the other value (*o*), and segments irrelevant for the harmony (*x*) that are present in the abstract representation just to make the dependency long-distant. Now, let us model *blockers* that enforce some particular value of the harmonic feature further in the string. Continuing the previous example, let us introduce a blocker *f* that only allows for *a* to be seen after itself thus allowing for well-formed sequences such as *ooxoxofxaxa* and *aaxaxaffaaa*.

Strings representing this pattern are automatically produced by the harmonic generator. Its setup is similar to the one discussed in the previous experiment, but also includes the definition of the blocker *f* that prohibits *o* after itself, i.e. only *a* can be seen further in the string. The blocker together with the value that it

a	←	[+ α] vowels
o	←	[− α] vowels
x	←	transparent elements
f	←	blockers enforcing [+ α] specification

Table 3.5: A harmony in [α] exhibiting blocking effect; *abstract* representation.

licenses must be provided to the generator as the parameter blocker. In this case, this parameter is set to $\{f:a\}$. I generated 1,000 strings that follow the target pattern.

```

1 generator = Harmony({("a", "o"):"A", ("x"):"X"}, blockers = {"f":"a"
    })
2 toy_vhwb = generator.generate_words(n = 1000)
3 print(toy_vhwb)
4 # ['oxxxooxxx', 'xxooxfaaax', 'aaxxxaaxxx', 'ofxxafxxaa', '
    aafaaaxaaf', ...]
```

Pattern 4: several vowel harmonies without blocking

In some languages, harmonic systems involve the spreading of more than one feature. For example, in Kirghiz, vowels agree in fronting and rounding (Nanaev, 1950; Kaun, 1995). All vowels within a word can be of 4 types: back and unrounded (*kiz-da* ‘girl-LOC’), back and rounded (*ot-to* ‘fire-LOC’), fronted and unrounded (*kim-de* ‘who-LOC’), and fronted and rounded (*üj-dö* ‘house-LOC’). Modeling this type of harmony involves increasing the inventory of the harmonic class: now there are 4 options of feature specifications that are available for vowels within words.

Abstract representation To have an abstract picture of this pattern, let us assume that we are dealing with the long-distant vowel agreement in features [α] and [β].

Then it is possible to generalize $[-\alpha, -\beta]$ vowels as a , $[-\alpha, +\beta]$ ones as e , $[+\alpha, -\beta]$ ones as o , and, finally, $[+\alpha, +\beta]$ vowels as u . I will again use x as a transparent element. This abstract harmony will enforce all vowels within the same word to agree in both features $[\alpha]$ and $[\beta]$: as the result, only one element out of the set $\{a, e, o, u\}$ can appear in the well-formed words of such language.

a	←	$[-\alpha, -\beta]$ vowels
e	←	$[-\alpha, +\beta]$ vowels
o	←	$[+\alpha, -\beta]$ vowels
u	←	$[+\alpha, +\beta]$ vowels
x	←	transparent elements

Table 3.6: A harmony in $[\alpha]$ and $[\beta]$; *abstract* representation.


Such a harmonic pattern can be encoded by extending the harmonic class of the generator: now, instead of two elements, it includes four. 1, 000 strings of such language were generated.

```

1 generator = Harmony({("a", "o", "e", "u"): "A", ("x"): "X"})
2 toy_mhnb = generator.generate_words(n = 1000)
3 print(toy_mhnb)
4 # ['xuuxxxuuu', 'xxeeexeee', 'xxxaaxxaa', 'xooxooxox', ...]
```

Pattern 5: several vowel harmonies with blocking

In this experiment, I target another type of a harmonic system spreading several features, but in this case, it also involves the blocking effect. For example, in Turkish, vowel harmony enforces vowels to agree in backness and rounding. For backness, all vowels within a word need to agree in this feature. However for roundness, only high vowels acquire the rounding value of the previous vowel; therefore, the non-high vowels are always realized unrounded in the non-initial syllables (Levi, 2001; Krämer, 2003). For example, the word *son-lar-uun* ‘end-PL-GEN’ exemplifies

that a non-high vowel from the plural suffix cannot acquire a rounding feature from the previous vowel, and therefore cannot further transmit it to the following high vowel. However, in *son-un* ‘end-GEN’, the high vowel is realized rounded because it is preceded by a rounded vowel. In both words, all vowels agree in backness. In such a system, non-high vowels have a double nature: they are undergoers for the backness harmony, however, they are blockers for the rounding one. Thus to test the performance of subregular models with this complex type of harmonic system, I will be using the Turkish wordlist  (Harrison et al., 2004).

I start by preprocessing the Turkish corpus by eliminating the words that contain non-Turkish characters and filtering the disharmonic stems. Then I generalize the pattern by masking all the consonants since they are irrelevant for the harmonic pattern³. Finally, I generate an artificial dataset exhibiting Turkish harmony.

Raw representation The wordlist that I use contains 23,501 lexemes. However, it also required several preprocessing steps. Firstly, I eliminated all words that used non-Turkish characters and nonce-words, such as *bungalow* and *lx*; there were 890 of such words (3.8% of total words). Secondly, I removed the stems that violate the rules for backness and rounding harmony (such as *koreografi* and *kümülatif*). Since Turkish vowel harmony is frequently violated (Pöchtrager, 2010)⁴, there were 10,545 such words (44.9%). After those forms were eliminated, the corpus contained 14,434 Turkish harmonizing words.

```
1 print(turkish_harmony)
2 # ['som', 'lafazan', 'konuk', 'kekti', 'lafzan', ...]
```

³I ignore the cases when stem-final palatalized λ starts its backness harmony domain

⁴It is hard to imagine a better name for a paper about Turkish disharmony than Pöchtrager’s *Does Turkish diss harmony?*

Masked representation At the next step, I masked all the symbols that are not relevant to the Turkish harmony. Namely, all the consonants are transparent, and therefore were substituted as x , whereas the vowels $\{a, e, o, \ddot{o}, u, \ddot{u}, i, \ddot{i}\}$ were left intact, see Table 3.7. The obtained dataset contains 14,434 words as well.

$$\begin{aligned} a, e, o, \ddot{o}, u, \ddot{u}, i, \ddot{i} &\leftarrow a, e, o, \ddot{o}, u, \ddot{u}, i, \ddot{i} \\ x &\leftarrow \text{ç, ğ, ş, b, c, d, f, g, h, j, k, l, m, n, p, r, s, t, v, y, z} \end{aligned}$$

Table 3.7: Turkish: *raw* \rightarrow *masked* & *abstract* representations.

```
1 print(turkish_harmony_simplified)
2 # ['xixxix', 'xuxx', 'xaaxa', 'xexxe', 'xaxIx', ...]
```

Abstract representation The vowel inventory of Turkish cannot be further simplified: all 3 features – backness, rounding, and height – are important for the choice of the following vowel, and this yields exactly $2^3 = 8$ vowels. However, it is highly likely that the Turkish data contains “accidental” gaps: some subregular learners require to observe all symbols of the alphabet adjacent to each other to make a decision, but this is rarely the case with natural language data.

I implemented a generator of fake Turkish, that imitates Turkish vowel sequences and uses x as a transparent element. In this way, it is possible to be sure that given enough data, the learner will always observe all the combinations of elements that it needs. In this case, 1,000 strings were not enough since the alphabet of the artificial language is larger in comparison to the previous cases, and the generalization is more complex, therefore I used a wordlist of 15,000 fake Turkish words.

```
1 print(toy_mhwb)
2 # ['xx0exxix', 'xxUUxUUx', 'exxiixee', 'iiexxxex', 'xuuxxuux', ...]
```

Pattern 6: vowel harmony and consonant harmony without blocking

There are also typologically attested cases where there are several independent harmonies within the same language. For instance, in several Bantu languages (Kikongo, Kiyaka, Bukusu a.o.), a vowel harmony co-occurs with long-distance consonant assimilation. As a case study, consider Bukusu, where vowels agree in height, and /l/ assimilates to /r/ if it is preceded by /r/ within the same word (Odden, 1994; Hansson, 2010a). This can be demonstrated by a causative affix that includes both a high vowel and a liquid. As a result, the affix /il/ can be realized in four different ways: *il*, *ir*, *el*, and *er*. In *teex-el* ‘cook-APPL’, the affixal vowel is low due to the low vowel in the stem, and the liquid surfaces as /l/; the version of this affix with a high vowel is *lim-il* ‘cultivate-APPL’. However, if the rhotic liquid precedes the affix, it is realized with /r/: *reeb-er* ‘ask-APPL’ and *rum-ir* ‘send-APPL’. To model this pattern, we need to imitate two harmonies: one affects vowels, and another one targets the consonants.

Abstract representation The abstract representation of such harmonic pattern exhibits two harmonic classes, one of them includes vowels $\{a, o\}$, and another one includes consonants $\{b, p\}$, see Table 3.8. This language then allows for the words such as *poppooo* and *aaabba*, but not for the ones such as *babboo* or *opobp*. As previously, there are no transparent elements because vowels make the consonant harmony long-distant, and vice versa.

a	←	$[-\alpha]$ vowels
o	←	$[+\alpha]$ vowels
b	←	$[-\beta]$ consonants
p	←	$[+\beta]$ consonants

Table 3.8: A harmony in $[\alpha]$ and a harmony in $[\beta]$; *abstract* representation.

We can encode this pattern by increasing the number of harmonic classes. Now, the harmonic class $A = \{a, o\}$ represents vowel harmony, and $B = \{b, p\}$ depicts the consonant one. Given these specifications, I generated a sample of 1,000 words of such abstract harmonic language.

```
1 generator = Harmony({("a", "o"): "A", ("b", "p"): "B"})
2 toy_dhnb = generator.generate_words(n = 1000)
3 print(toy_dhnb)
4 # ['bbbaaabbbaa', 'bboobobooob', 'pppooppopp', 'appaaappaa', ...]
```

Pattern 7: vowel harmony and consonant harmony with blocking

We can also imagine a harmony that affects vowels and consonants, and additionally exhibits a blocking effect. Although such a pattern, to the best of my knowledge, is unattested, it is a typologically plausible one.

Abstract representation Let us build on the harmonic system discussed before, and add one modification to it: now, the consonant harmony can be blocked. The blocker is then represented as t , and it prohibits b to be seen after itself. This blocker will not affect the simultaneous vowel harmony in any way, see Table 3.9. Words such as *abbabab*, *abataapap* and *oobobtoop* are well-formed regarding the rules of this harmony, but *ababtab* or *obbotppaap* are not.

- a $\leftarrow [-\alpha]$ vowels
- o $\leftarrow [+ \alpha]$ vowels
- b $\leftarrow [-\beta]$ consonants
- p $\leftarrow [+ \beta]$ consonants
- t \leftarrow blocks spreading of $[-\beta]$

Table 3.9: A harmony in $[\alpha]$ and a harmony in $[\beta]$ with blockers; *abstract representation*.

Again, it is possible to employ the harmonic generator to generate this language. The setup is similar to the one discussed in the previous subsection, with the blocker $\{t:p\}$ introduced as well. The generated dataset contains 1,000 strings of this language.

```
1 generator = Harmony({("a", "o"):"A", ("b", "p"):"B"}, blockers = {"t": "p"})
2 toy_dhwb = generator.generate_words(n = 1000)
3 print(toy_dhwb)
4 # ['pppoootopt', 'obbbtpooot', 'aabbbaatat', 'pppaapappp', '
   bbbtpppaap', ...]
```

Pattern 8: unbounded tone plateauing

Next, I will target the phenomenon of *unbounded tone plateauing* (UTP). This pattern is observed in some Niger-Congo languages such as Luganda, where all low tones (L) are realized as high (H) if they are surrounded by high tones. For example, tonal sequences such as *LLHH*, *HHLLL* and *LLHL* are well-formed, whereas the ones such as *HLLLH* are not (Hyman, 2011; Jardine, 2016a). The learner would then need to induce that after observing a high tone followed by a low tone, the appearance of another high tone is impossible.

Abstract representation Such a pattern required implementing a separate generator. The output of that generator is a sample of well-formed sequences of high and low tones in languages such as Luganda. For the subregular experiment, I used a wordlist of 1,000 such sequences.

```
1 toy_utp = generate_utp_strings(n = 1000)
2 print(toy_utp)
3 # ['HHHHH', 'LHLL', 'LHHHH', 'LHHHH', 'HHHHH', ...]
```

Pattern 9: first-last harmony

The final challenge for the subregular learners is the one they shall *not* meet: learning a language that is neither SL, nor SP, TSL or MTSL. As an example of one, I will be using the *first-last harmony* pattern discussed by Lai (2015). The artificial pattern of the first-last harmony requires that the first element of the word to agree with the last one, therefore considering words such as *aaooxoxoa* and *oxoaxo* well-formed, and rejecting ones such as *oxxoa*. This language requires a generator that handles more complicated dependencies than SL, SP, TSL, and MTSL grammars can express, and therefore learners for those classes are expected to fail to generalize patterns such as first-last harmony.

Abstract representation I used another generator to obtain a sample of this unattested language. Its alphabet included symbols *a*, *o*, and *x*, and the generalization was simplified to *words can either start and end with a, or with o, but cannot have the initial and final symbols different*. A first-last harmony generator produced a sample of 5,000 strings that I used to show that subregular learners indeed cannot capture this pattern.

```
1 first_last_data = first_last_words(n = 5000)
2 print(first_last_data)
3 # ['axoaxaxaa', 'aaxaaxxxoa', 'ooaxaoaooo', 'axxoaxaaaa', '
   oxaoaxxxao', ...]
```

Expected results

In this section, I discuss the 9 types of patterns that I modeled using automatically learned subregular grammars. This list exhausts the options for the modeling possibilities by SP, SL, TSL and MTSL grammars: every one of those phenomena can be represented by a different combination of those four subregular classes. For example, word-final devoicing can be modeled by SL, TSL, and MTSL

Target patterns	SP	SL	TSL	MTSL
<i>word-final devoicing</i>	✗	👍	👍	👍
<i>a single vowel harmony without blocking</i>	👍	✗	👍	👍
<i>a single vowel harmony with blocking</i>	✗	✗	👍	👍
<i>several vowel harmonies without blocking</i>	👍	✗	👍	👍
<i>several vowel harmonies with blocking</i>	✗	✗	👍	👍
<i>vowel harmony and consonant harmony without blocking</i>	👍	✗	✗	👍
<i>vowel harmony and consonant harmony with blocking</i>	✗	✗	✗	👍
<i>unbounded tone plateauing</i>	👍	✗	✗	✗
<i>first-last harmony</i>	✗	✗	✗	✗

Table 3.10: The expected results of the language learning experiments.

grammars; a single vowel harmony without blocking can be expressed via SP, TSL, and MTSL grammars; tone plateauing can only be generalized as SP, first-last harmony cannot be modeled by either of them, etc. The list of patterns and the corresponding grammars can be found in Table 3.10.

3.2 Strictly local models

Strictly local grammars express local generalizations by listing substrings that *cannot* be present in well-formed words of their languages. In linguistics, they are employed to model local dependencies such as intervocalic voicing, consonant cluster assimilation, or others. In this section, I show that the SL inference algorithm is capable of automatically extracting the pattern of word-final devoicing from the German dataset. SL grammars cannot handle long-distance dependencies, and therefore their performance on harmonic datasets is extremely poor.

3.2.1 SL learning algorithm

The **intuition** behind the learning algorithm is that it simply assumes that every k -gram that was not observed in the training sample is prohibited. The alphabet of the SL grammar and its locality window need to be defined a priori. As a pre-processing step, all words of the training sample are annotated with the start- and end-markers \bowtie and \bowtie ; this allows to distinguish word-initial and word-final positions from any other position in the string.⁵ The learner records all k -grams that are attested in the input data, therefore, constructing the *positive* SL grammar. The *negative* SL grammar then lists all the unattested k -grams. For example, if the alphabet is $\{a, b\}$, the locality of the grammar is 2, and the observed bigrams are $P = \{\bowtie a, a \bowtie, ab, ba\}$, the negative 2-local SL grammar is $R = \{\bowtie \bowtie, \bowtie b, b \bowtie, aa, bb\}$.

The **pseudocode** of the k -SL learner can be found below. I is the training sample, i.e. it contains the collection of the well-formed strings of the language. $|w|$ refers to the length of the word w , $w[i]$ targets the i th character of the string w , and \cdot is a concatenation operator.

Algorithm 1 Extracts G_{SL_k} from I

```

 $G \leftarrow \emptyset$ 
for  $w$  in  $I$  do
   $w \leftarrow \bowtie \cdot w \cdot \bowtie$ 
  if  $|w| \geq k$  then
    for  $i$  in  $k \dots |w|$  do
       $G \leftarrow G \cup \{w[i-k] \dots w[i]\}$ 
    end for
  end if
end for

```

This algorithm extracts a positive grammar from the data. The equivalent

⁵Grammars can be represented as 3 sets: a set of n -grams that can occur word-initially, a set of n -grams that can appear word-internally, and a set of n -grams that can be word-final (Heinz, 2010a).

negative grammar is then obtained by simply subtracting the set of allowed k -grams from a list of all possible k -grams that can be built from the grammar's alphabet Σ . The positive SL grammar and its equivalent negative SL grammar recognize the same language: $L(NEG_G_{SL_k}) = L(\Sigma^k \cap POS_G_{SL_k})$, where Σ^k refers to all k -long strings that can be generated based on the elements of Σ .

3.2.2 Successful experiments

Strictly local grammars are capable of expressing local dependencies, and therefore the only experiment in which the SL learner performed very well (100%) was for word-final devoicing. The runners-up were some cases of artificially generated datasets of simple vowel harmonies (83 ~ 89%) and tone plateauing (85%), but these numbers are unsurprising given that the alphabets of those grammars are very small and the generated strings are usually not very long; hence, the chance of “guessing” a grammatical word is significant. The decent performance of the SL grammars on artificial harmonic datasets comes from the shape of the generated data itself, giving insight into the additional parameters that need to be controlled for in the subsequent experiments. The performance of the SL learners is extremely bad (30 ~ 70%) on more complex cases of harmonic systems, especially the ones that involve several harmonies.

Experiment 1: word-final devoicing This experiment involved testing the learner using three types of training samples: artificially generated, masked German, and raw German data. Since the pattern has a local nature, the performance of the learner in all of these cases was 100%.

```
1 sl = SL(polar = "n")
2 sl.data = toy_wfd
3 sl.extract_alphabet()
4 sl.learn()
```


The first line initializes a negative SL grammar `s1`. The locality of the grammar is not specified, and therefore by default it is set to 2. Then, the artificial dataset for word-final devoicing `toy_wfd` is passed into the data attribute of the class `s1`. To avoid the burden of listing the elements of the alphabet manually, I am using the function `extract_alphabet` that does it automatically. Finally, the last line invokes the learning algorithm.

```
1 print(s1.alphabet)
2 # ['a', 'b', 'p']
3 print(s1.grammar)
4 # [('b', '<'), ('>', '<')]
```

The automatically extracted alphabet is $\Sigma = \{a, b, p\}$, and the set of unattested bigrams is $R = \{b\bowtie, \bowtie\bowtie\}$. The learner indeed saw that it is impossible to have a voiced obstruent b in a word-final position. Additionally, it did not observe an empty string in the training sample, and therefore assumed that it needs to be ruled out as well.

```
1 sample = s1.generate_sample(n = 1000)
2 print(sample)
3 # ['pbpababa', 'apaapa', 'ap', 'bbp', 'bbbabpbbp', ...]
```

After the grammar was extracted, I generated a sample of well-formed strings with respect to the rules of the learned grammar using the function `generate_sample`. The parameter `n` indicates the number of words that need to be generated.

```
1 evaluate_wfd_words(sample)
2 # Percentage of well-formed words: 100%.
```

Then I used an evaluative function `evaluate_wfd_words` to compute the percentage of words generated by `s1` that comply with the rule of the word-final devoicing. Indeed, none of the generated words violated the target pattern. Notice how it was possible to “look inside” the algorithm and explore the exact generalizations that it made due to the *interpretability* of the subregular grammars.

Pattern	<i>word-final devoicing</i>
Type of data	artificial data
Example of data	aaabbbpbbbp, pbapbapapa, apabaappap, bbbbaabbbp, ...
Learned 2-SL grammar	$b\bowtie, \bowtie\bowtie$
Generated sample	pbpababa, apaapa, ap, bbp, bbbabpbbp, ...
Evaluation	<code>evaluate_wfd_words(sample)</code>
Score	100%

Table 3.11: SL learning of the word-final devoicing; abstract representation.

I used a similar setup for all of the consequent experiments in what follows. From now on, for a more succinct representation, I will represent the experimental setup as a table.

Now, let us explore the performance of the SL learner using the masked German dataset. From the corpus of masked German words, the SL grammar again extracted the correct rules: none of the voiced obstruents /b/, /d/, and /g/ can appear at the end of the well-formed words. As before, all of the words generated by this grammar are well-formed.

Pattern	<i>word-final devoicing</i>
Type of data	masked German data
Example of data	aakaabaaaa, aakaabaaak, aakaa, aakat, aaa, ...
Learned 2-SL grammar	$b\bowtie, d\bowtie, g\bowtie, \bowtie\bowtie$
Generated sample	btddta, gpttk, batktbtgbktbba, gatdkbgkgdp, ...
Evaluation	<code>evaluate_wfd_words(sample)</code>
Score	100%

Table 3.12: SL learning of the word-final devoicing; masked representation.

This learner was also able to extract the correct rule from the German dataset. But in this case, the size of the learned grammar was very large: 109 bigrams. In other words, 109 bigrams are unattested in the German wordlist. Indeed, among others, the learner extracted the bigrams representing the word-final devoicing, namely $*b_{\times}$, $*g_{\times}$, and $*k_{\times}$. Apart from the target grammar, the learner induced lots of other unattested restrictions such as $*cj$, $*d\beta$, $*\ddot{a}\ddot{a}$, $*\ddot{u}z$ and so on.

Pattern	<i>word-final devoicing</i>
Type of data	raw German data
Example of data	hochjagende, zugebliebener, verbricht, besuchszimmer, ...
Learned 2-SL grammar	b_{\times} , cj , cv , cw , cx , ...
Generated sample	piüüdki z_{\times} fhr, nzjbpcbö p_{\times} fbniabga...
Evaluation	<code>evaluate_wfd_words(sample)</code>
Score	100%

Table 3.13: SL learning of the word-final devoicing; raw representation.

We could also explore the dataset generated by the learned grammar. It includes words such as *piüüdki z_{\times} fhr* and *nzjbpcbö p_{\times} fbniabga*. We can increase the locality of the grammar, and learn the prohibited trigrams. The 3-SL grammar generates words such as *känckhacix* and *flaw*. Finally, the 4-local grammar generates words that look more “German”, such as *Eipotfeigsucktbohnt* and *luxmetie*. What is the most important for the current experiment, is that all of the words generated by this grammar follow the rule of the word-final devoicing. We can conclude that SL grammars are capable of learning this pattern even when facing raw data as the training sample.

3.2.3 Unsuccessful experiments

All conducted experiments show that SL grammars were only able to successfully extract the pattern of word-final devoicing. In this subsection, I list the results of the experiments that showed negative results and numerically evaluate the learning outcomes.

Experiment 2: a single vowel harmony without blocking SL grammars are only suited to model local dependencies, and therefore the SL learner is not expected to generalize a long-distant pattern like vowel harmony. Given an artificial dataset, the grammar indeed learned that vowels *a* and *o* cannot be adjacent to each other *locally*, so it is never the case in the strings generated by the extracted grammar. But it does not see a problem with disagreeing vowels at a distance from each other. Therefore in the output of the generator, we see ungrammatical strings such as *xoxaxxxxaa* and *oxaa*. The performance of the SL model on this task is 83%, mostly due to the learned local generalization and the fact that the majority of the generated strings are pretty short.

Pattern	<i>one vowel harmony, no blockers</i>
Type of data	artificial data
Example of data	oxxxooxxxx, oxxxooxxo, aaxxxaaxxx, oxxxoxxxo, ...
Learned 2-SL grammar	ao, oa, ××
Generated sample	<i>xoxaxxxxaa</i> , oo, <i>oxaa</i> , x, xo, ...
Evaluation	harmonic_evaluator(sample, single_harmony_no_blockers)
Score	83%

Table 3.14: SL learning of a single harmony without blockers; abstract representation.

The grammar performed worse on the masked Finnish corpus, because only 72% of the generated words were grammatical. As before, it succeeded in learning

the local version of the restriction. However, it could not generalize it thus predicting the well-formedness of words such as *aooooooooxäyyöö*. An SL grammar trained on the raw Finnish data performed much worse: only 41% words that were predicted to be well-formed by this grammar, were, in fact, well-formed. I omit the table with those results.

Pattern	<i>one vowel harmony, no blockers</i>
Type of data	masked Finnish data
Example of data	xaxxixxex, xixäxixex, xaxxixxaxix, uxxuxaxxix, ...
Learned 2-SL grammar	äa, äo, äu, öa, öo, ...
Generated sample	yxy, yö, uuuux, oaa, aooooooooxäyyöö , ...
Evaluation	<code>harmonic_evaluator(sample, front_harmony)</code>
Score	72%

Table 3.15: SL learning of a single harmony without blockers; masked representation.

Experiment 3: a single vowel harmony with blocking Adding a blocker to the vowel harmony pattern resulted, as previously, in the learner capturing the local generalization, but failing to generalize it to the long-distant pattern. The performance of the model is 89%. But again, this is mostly due to the small size of the alphabet and the short average length of the generated strings; thus, this increased the chances of getting a harmonizing word simply by chance.

Experiment 4: several vowel harmonies without blocking Similarly to the cases before, when challenged with several vowel harmonies without a blocking effect, the SL learner only captured the local version of the generalization. But in this case, the performance of the learner is worse than with the previously discussed artificial

Pattern	<i>one vowel harmony with blockers</i>
Type of data	artificial data
Example of data	oxxxooxxxx, xxooxfaaax, aaxxxaaxxx, ofxxafxxaa, ...
Learned 2-SL grammar	ao, fo, oa, ××
Generated sample	x, fafafxfa, axooxo , ox, x, ...
Evaluation	harmonic_evaluator(sample, single_harmony_with_blockers)
Score	89%

Table 3.16: SL learning of a single harmony with blockers; abstract representation.

grammars: indeed, there are now 4 choices of vowels instead of 2, and only one of them can be chosen and used throughout the word. It is now harder to get the harmonizing words “by chance”, and therefore such a model has a performance of only 69%.

Pattern	<i>several vowel harmonies, no blockers</i>
Type of data	artificial data
Example of data	xuuuuxxxuuu, xxxeeexeee, xxxaaxxxaa, xoooxooxox, ...
Learned 2-SL grammar	ae, ao, ua, ue, uo, ...
Generated sample	xaaaa, u, oxuuxeexux , a, aaxxxu, ...
Evaluation	harmonic_evaluator(sample, double_harmony)
Score	69%

Table 3.17: SL learning of several vowel harmonies without blockers; abstract representation.

Experiment 5: several vowel harmonies with blocking Expectedly, SL grammars performed even worse when trying to learn a pattern of several long-distance assimilation among vowels, where some of these assimilations exhibit blocking effect. The learner predicted the correct backness harmony in

67% of the words, and the rounding harmony was correct in 70%. However, overall, only 59% of the words predicted by the grammar were, in fact, grammatical with respect to the rules of the Turkish harmonic system.

Pattern	<i>several vowel harmonies with blockers</i>
Type of data	artificial data
Example of data	xxöexxix, xxüüxüüx, exxiixee, iiexxxex, xuuxxuüu, ...
Learned 2-SL grammar	ıö, üü, ie, ii, io, ...
Generated sample	öxi, oaxüüee , ıaıa, uaıaaax, ü, ...
Evaluation	harmonic_evaluator(sample, backness_and_rounding)
Score	59% overall (67% backness only, 70% rounding only)

Table 3.18: SL learning of several harmonies with blockers; abstract representation.

When given a masked Turkish dataset as input, the accuracy of the learner increased to 70%. In the future, I would be interested in understanding why the learner performs on masked Turkish words better than on the artificially generated language. Only 30% of the predicted words were grammatical when trained on the actual Turkish data.

Experiment 6: vowel harmony and consonant harmony without blocking This experiment tests the SL learner on data showcasing two harmonies that affect different sets of segments. The learner is not successful since the elements participating in one harmony make the other harmony non-local, and vice versa. As a result, it predicts the generated words correctly only in 64% of the cases.

Experiment 7: vowel harmony and consonant harmony with blocking The performance of the SL learner on the dataset exhibiting vowel and consonant harmonies with blocking effect is not different from the one before: only 64% of the words generated by the grammar are well-formed.

Pattern	<i>vowel and consonant harmonies, no blockers</i>
Type of data	artificial data
Example of data	bbbaaabbbaa, bbooboboob, pppoopppop, appaaappaa, ...
Learned 2-SL grammar	ao, oa, bp, pb, $\times \times$
Generated sample	b, p, ppp, poobap, obbboboopp, ...
Evaluation	harmonic_evaluator(sample, double_harmony_no_blockers)
Score	64%

Table 3.19: SL learning of vowel and consonant harmonies without blockers; abstract representation.

Pattern	<i>vowel and consonant harmonies with blockers</i>
Type of data	artificial data
Example of data	pppoootopt, obbbtpooot, aabbbaatat, pppaapppp, ...
Learned 2-SL grammar	ao, oa, bp, pb, tb, $\times \times$
Generated sample	p, oobobbbaattapapot, a, aa, ota, ...
Evaluation	harmonic_evaluator(sample, double_harmony_with_blockers)
Score	64%

Table 3.20: SL learning of vowel and consonant harmonies with blockers; abstract representation.

Experiment 8: unbounded tone plateauing The phenomenon of UTP prohibits the occurrence of low tones in-between high tones. Because this process looks at minimally 3 segments at any time, I use a window of $k = 3$. However, it does not learn this pattern. Indeed, it learns it locally, but as before, it does not induce its long-distant nature. The performance of the generator is 85%, but it is mostly due to frequently occurring short words and a small alphabet that contains only two elements.

Pattern	<i>unbounded tone plateauing</i>
Type of data	artificial data
Example of data	HHHHH, LHLL, LHHHH, LHHHH, HHHHH, ...
Learned 3-SL grammar	HLH
Generated sample	HHHLLH, LLHL, LHLLH, HL, LHH, ...
Evaluation	evaluate_utp_strings(sample)
Score	85%

Table 3.21: SL learning of unbounded tone plateauing; abstract representation.

Experiment 9: first-last harmony As expected, the SL learner fails to generalize the pattern of the first-last harmony. Apart from this pattern not being SL/TSL/MTSL, it involves a long-distance dependency between the beginning and the end of the word. The sole long-distance nature makes this phenomenon already impossible to model with SL grammars. The learner only induces that x cannot be the first or the last symbol in the well-formed strings of that language because all well-formed strings start and end with either a or o . The performance of such model is 51%.

Pattern	<i>first-last harmony</i>
Type of data	artificial data
Example of data	axoaaxaxaa, aaxaaxxxoa, ooaxaoaooo, axxoaxaaaa, ...
Learned 2-SL grammar	$\times x, x \times$
Generated sample	oxa, aaoaxxooaoaoa, ooo, oxxo, oao, a, ooa, ...
Evaluation	evaluate_first_last_words(sample)
Score	51%

Table 3.22: SL learning of first-last harmony; abstract representation.

3.2.4 SL experiments: interim summary

The nature of SL models is to capture local generalizations. As a result, the only challenge that SL grammars successfully passed was learning *word-final devoicing* that can be rephrased as “do not have voiced obstruents /b/, /d/ and /g/ at the end of the word”. This experiment involved learning the pattern from 3 different representations of data: artificially generated sample, simplified German data, and the raw German wordlist. SL succeeded in generalizing this local pattern from all three representations, scoring 100% on every one of them.

The rest of the experiments included different versions of long-distant harmonies or other non-local patterns such as unbounded tone plateauing, and unattested pattern of the first-last harmony. Needless to say, the SL learner is not suited for those types of patterns, and therefore its average score was relatively low. Section 3.6 shows the chart of the performance of SL models in comparison to the results obtained by other subregular learners.

3.3 Strictly piecewise models

The previous section shows that SL grammars are not capable of modeling long-distance dependencies such as tone plateauing and vowel harmonies of different types. SP grammars, on the contrary, are not able to model local generalizations. They prohibit *subsequences* and not *substrings*: if a bigram *ab* is prohibited, it means that *a* cannot be followed by *b* anywhere further in the string. For example, an SL language prohibiting *ab* will rule out a word *baaabb* but will consider *acccb* grammatical. However, an SP language with the same bigram listed in its grammar will rule out both words: in both of them, *a* is followed by *b*. Therefore, in linguistics, SP models are used to model long-distance dependencies that do not exhibit a blocking effect, such as some cases of harmonies and unbounded tone plateauing.

3.3.1 SP learning algorithm

The **intuition** behind the SP learner is similar to the one behind the SL induction algorithm. But instead of recording all the attested substrings, the SP learner memorizes all the subsequences that were observed in the training sample. In such a way, it constructs a hypothesis of a positive grammar describing the input data. If a negative grammar needs to be constructed instead, it generates all possible k -local subsequences based on the given alphabet and then removes from that set the ones that were attested in the training data. Read more about such learners in (Heinz, 2010a).

The **pseudocode** of the k -SP learner is given below. It iteratively expands a set of k -long subsequences P based on the word w contained in the training sample.

Algorithm 2 Extracts G_{SP_k} from w

Require: $|w| \geq k$

$P \leftarrow \{w[0] \dots w[k-1]\}$

$C \leftarrow \emptyset$

for s in $\{w[k] \dots w[|w|]\}$ **do**

for p in P **do**

for i in $\{0 \dots k-1\}$ **do**

$sq \leftarrow \{p[0] \dots p[i-1]\} \cup \{p[i+1] \dots p[|p|]\} \cup \{s\}$

$C \leftarrow C \cup \{sq\}$

end for

end for

$P \leftarrow P \cup C$

$C \leftarrow \emptyset$

end for

return P

3.3.2 Successful experiments

The experiments in which the SP learner performed exceptionally well were the ones that included long-distance dependencies that cannot be blocked by anything. Those were some of the harmonic systems and the pattern of unbounded tone plateauing. However, in cases where the dependency was local or a blocking effect was involved, the learner failed to capture the pattern. As a result, the SP learner did not model the patterns of the word-final devoicing, and even the simplest cases of harmonic systems that included a blocker.

Experiment 2: a single vowel harmony without blocking The SP learner performed extremely well when challenged with the task of learning a single vowel harmony pattern without a blocker. For this experiment, I used 3 different datasets: automatically generated words imitating the harmonic pattern, masked Finnish words, and the raw Finnish data. On all these datasets, the output of the SP models consisted exclusively of well-formed words therefore scoring 100%.

When faced with the abstract representation of the pattern, the SP learner extracted the grammar $\{ao, oa\}$ that can be interpreted as *after a occurred in the string, o cannot be seen, and vice versa*. This is exactly the correct generalization, and therefore the output of the generator contained only well-formed words: *axxaax*, *xooxoo*, and so on. The accuracy of such a model is 100%.

Not much changed when the learner was challenged with the masked Finnish dataset: it observed that front vowels are never followed by back vowels in Finnish words and vice versa. As a consequence, it extracted all the combinations of the type $[\alpha\text{front}][-\alpha\text{front}]$: *äa*, *äo*, *äu*, and others. Even with the larger vowel vocabulary, the performance of such a learner was still 100%.

Finally, even when the learner was given raw Finnish data, it saw the same pattern of fronting harmony. Apart from the rules of the harmony it also extracted the irrelevant subsequences that were never observed in the training

Pattern	<i>one vowel harmony, no blockers</i>
Type of data	artificial data
Example of data	oxxxoxxxxx, oxxxoxxxo, aaxxxaaxxx, oxxxoxxxo, ...
Learned 2-SP grammar	ao, oa
Generated sample	axxaax, aa, oo, oxxxox, oxxxo, xooxoo, 'xaxa, ...
Evaluation	harmonic_evaluator(sample, single_harmony_no_blockers)
Score	100%

Table 3.23: SP learning of a single harmony without blockers; abstract representation.

Pattern	<i>one vowel harmony, no blockers</i>
Type of data	masked Finnish data
Example of data	xaxxixxex, xixäxixex, xaxxixxaxix, uxxuxaxxix, ...
Learned 2-SP grammar	äa, äo, äu, öa, öo, öu, ...
Generated sample	ua, xouuaxu, ooa, axu, äyxxä, a, ää ...
Evaluation	harmonic_evaluator(sample, front_harmony)
Score	100%

Table 3.24: SP learning of a single harmony without blockers; masked representation.

sample such as *äw* or *wq*. All of the words generated with the obtained grammar were grammatical regarding the rules of Finnish vowel harmony.

Experiment 4: several vowel harmonies without blocking The SP learner correctly constructed a grammar for an artificial language where vowels harmonize for two features, therefore creating 4 choices of vowels: $[-\alpha, -\beta]$, $[-\alpha, +\beta]$, $[+\alpha, -\beta]$, and $[+\alpha, +\beta]$. The obtained SP grammar that represents this pattern is *au*, *ae*, *ao*, *ua*, etc. 100% of the words generated by the learner are

Pattern	<i>one vowel harmony, no blockers</i>
Type of data	raw Finnish data
Example of data	mathilden, lisänimen, macmillanin, urquhartin, ...
Learned 2-SP grammar	äq, äu, äw, öa, öo, vq, ...
Generated sample	cykqäkpjprpbhftä, yesxöven, hägvgs, dtvza, ...
Evaluation	harmonic_evaluator(sample, front_harmony)
Score	100%

Table 3.25: SP learning of a single harmony without blockers; raw representation.

harmonic and well-formed.

Pattern	<i>several vowel harmonies, no blockers</i>
Type of data	artificial data
Example of data	xuuuxxxuuu, xxxeeexeee, xxxaaxxxaa, xoooxooxox, ...
Learned 2-SP grammar	ae, ao, ua, ue, uo, ...
Generated sample	'a', 'ooxooo', 'ooo', 'oxoxoo', 'exexee', ...
Evaluation	harmonic_evaluator(sample, double_harmony)
Score	100%

Table 3.26: SP learning of several vowel harmonies without blockers; abstract representation.

Experiment 6: several vowel harmonies without blocking The learner also successfully learned the pattern involving two independent spreadings, such as consonant harmony for $[\alpha]$ and vowel harmony for $[\beta]$. It inferred the exactly correct rules: don't have consonants disagree (pb , bp) and don't have vowels disagree (ao , oa). Again, the performance of the learner is 100%.

Pattern	<i>vowel and consonant harmonies, no blockers</i>
Type of data	artificial data
Example of data	bbbaaabbbaa, bbooboboob, pppoopppop, appaaappaa, ...
Learned 2-SP grammar	ao, oa, bp, pb, $\times \times$
Generated sample	pp, bobbabb, pppapp, ppa, ...
Evaluation	harmonic_evaluator(sample, double_harmony_no_blockers)
Score	100%

Table 3.27: SP learning of vowel and consonant harmonies without blockers; abstract representation.

Experiment 8: unbounded tone plateauing The learner also succeeded in learning the UTP pattern. Notice, that this requires examining three elements, since the low tones (*L*) are prohibited if they are *in-between* two high tones (*H*). SP generalization *HLH* exactly describes this pattern and correctly rules out strings such as *HHHLLLLHH* that contain the illicit subsequence.

Pattern	<i>unbounded tone plateauing</i>
Type of data	artificial data
Example of data	HHHHH, LHHLL, LHHHH, LHHHH, HHHHH, ...
Learned 3-SP grammar	HLH, $\times \times \times$, $\times \times \times$, ...
Generated sample	HHHLL, LLL, LHHH, HH, LLLHHLLL ...
Evaluation	evaluate_utp_strings(sample)
Score	100%

Table 3.28: SP learning of unbounded tone plateauing; abstract representation.

3.3.3 Unsuccessful experiments

SP models failed to learn other patterns such as word-final devoicing and all cases of harmonies with a blocking effect. Strictly local generalizations, as well as the notion of a blocker, cannot be expressed in a strictly piecewise way. Also, as expected, the algorithm failed to learn first-last harmony.

Experiment 1: word-final devoicing The phenomenon of word-final devoicing cannot be expressed via SP grammars. More generally, the core notion of word-initial and word-final markers is not relevant for SP. For example, prohibiting the subsequence $b\bowtie$ would rule out any word in which b is present since if the words are annotated with the end markers, then any word containing b contains $b\bowtie$ as a subsequence. The extracted grammar is empty, and given that the grammar is negative, it translates to the generalization *anything goes*. The learner fails to acquire the pattern and produces well-formed strings only in 68% of the cases.

Pattern	<i>word-final devoicing</i>
Type of data	artificial data
Example of data	aaabbbbbb, pbapbapapa, apabaappap, bbbbaabbbp, ...
Learned 2-SP grammar	\emptyset
Generated sample	bapaaab, bpbpababa, pppabbbpba, bpaaap, pb, ...
Evaluation	evaluate_wfd_words(sample)
Score	68%

Table 3.29: SP learning of the word-final devoicing; abstract representation.

Experiment 3: a single vowel harmony with blocking Strictly piecewise constraints target subsequences at *any distance* from each other within a word. Therefore, if an SP grammar prohibits *oa*, it will simply miss a blocker that could license such configurations. Under the perspective of such an SP grammar, both

strings *ooxoxaa* and *xxooxfaaax* contain *oa*, and therefore need to be ruled out. However, if given a dataset of harmony with a blocker that includes words such as *xxooxfaaax*, the learner assumes that the sequence *oa* is observed and, in fact, possible. Since *ao* is not prohibited, words such as *ooaa* are generated by the learned grammar. SP grammars, therefore, cannot express blockers, so the performance of the learner on this artificial dataset is 84%.

Pattern	<i>one vowel harmony with blockers</i>
Type of data	artificial data
Example of data	oxxxooxxxx, xxooxfaaax, aaxxxaaxxx, ofxxafxxaa, ...
Learned 2-SP grammar	ao, fo
Generated sample	fafa, oa , x, ooaa , aafxxfxaxafxxxxfaxfax ...
Evaluation	harmonic_evaluator(sample, single_harmony_with_blockers)
Score	84%

Table 3.30: SP learning of a single harmony with blockers; abstract representation.

Experiment 5: several vowel harmonies with blocking As shown before, SP grammars cannot model a blocking effect. Therefore they do not perform well even on the artificial dataset exhibiting Turkish harmony, where non-high vowels serve as blockers for the rounding harmony. The fronting harmony cannot be blocked by anything, and therefore fronting harmony can in fact be modeled in a strictly piecewise way. However, the violations of the rounding harmony cause the accuracy of the predictions of the grammar to not be higher than 76%.

Since the SP learner fails on the artificial dataset, its performance is also far from ideal on the masked and raw Turkish data. Interestingly, however, it performed the best (89%) on the raw Turkish data, while scoring 76% percent on the masked corpus. This case is similar to German, where the SP model performed badly on the artificial and masked corpora (68% and 58%, correspondingly), but was able to achieve the accuracy of 89% on the raw data.

Pattern	<i>several vowel harmonies with blockers</i>
Type of data	artificial data
Example of data	xxöexxix, xxüüxüüx, exxiixee, iiexxxex, xuuxxuüu, ...
Learned 2-SP grammar	iö, iü, ie, ii, io, ...
Generated sample	ux, e, axi, ixxxix, uax, oxi , ai, ...
Evaluation	harmonic_evaluator(sample, backness_and_rounding)
Score	76% overall (100% backness only, 76% rounding only)

Table 3.31: SP learning of several harmonies with blockers; abstract representation.

Experiment 7: vowel harmony and consonant harmony with blocking This dataset included blockers as well, therefore making it impossible to model the target generalization using an SP grammar. This double harmonic pattern included two types of assimilations: vowel and consonantal. The vowel harmony cannot be blocked by anything, and therefore SP grammars model it well. However, the consonant harmony included a blocker. Thus, the SP grammar cannot model the consonant harmony since it predicts such ungrammatical strings as *bptottpttptp*. The overall accuracy of the model is 83%.

Pattern	<i>vowel and consonant harmonies with blockers</i>
Type of data	artificial data
Example of data	pppoootopt, obbbtpooot, aabbbaatat, pppaapappp, ...
Learned 2-SP grammar	ao, oa, pb, tb
Generated sample	bptottpttptp, ppp, obtp, o, bttoop, babpapp , ...
Evaluation	harmonic_evaluator(sample, double_harmony_with_blockers)
Score	83%

Table 3.32: SP learning of vowel and consonant harmonies with blockers; abstract representation.

Experiment 9: first-last harmony SP grammars cannot capture the pattern of first-last harmony. The learner extracts an empty grammar, so it allows for any sequence of x , a and o : clearly, it does not enforce the first and the last vowels to match. In fact, as the German final devoicing experiments show, SP grammars cannot distinguish between word-internal and word-final/initial positions. Only 32% of the strings predicted by the learned grammar were grammatical with respect to the rules of the first-last harmony.

Pattern	<i>first-last harmony</i>
Type of data	artificial data
Example of data	axoaaxaxaa, aaxaaxxxoa, ooaxaoaooo, axxoaxaaaa, ...
Learned 2-SP grammar	\emptyset
Generated sample	oxa, aaaaaxxooaoaoa, ooo, oxxo, oao, a, ooa, ...
Evaluation	<code>evaluate_first_last_words(sample)</code>
Score	32%

Table 3.33: SP learning of first-last harmony; abstract representation.

3.3.4 SP experiments: interim summary

The nature of strictly piecewise grammars allows them to capture long-distant generalizations. The SP learner thus performs incredibly well (100%) on challenges such as single and multiple long-distance harmonies without blockers, and also on the pattern of unbounded tone plateauing.

However, the effect of blocking cannot be expressed in an SP way since as soon as the learner observes the disagreeing elements across the blocker, it assumes that those elements can disagree in general. Both word-final devoicing and first-last harmony patterns rely on the notion of being word-initial or word-final, and they cannot be represented with a SP perspective: an SP constraint $x \bowtie$ would simply rule

out all strings where x is present. The long-distant nature of the SP generalizations makes it impossible for them to capture local generalizations.

3.4 Tier-based strictly local models

Previous sections discussed strictly local and strictly piecewise languages. The first ones were *only* able to model local dependencies, whereas the latter ones *only* expressed the long-distance ones, without the ability to be sensitive to intervening material. As a result, none of these two classes were able to handle long-distance harmonies with blockers. The subregular class of tier-based strictly local grammars has a way of representing long-distance constraints locally. TSL grammars project some characters of a string on a *tier* therefore making elements from that set local, and ignoring the elements that are not included in that set. For example, a grammar with tier symbols a and b and the restriction ab rules out words such as *acccbb*: its *tier image* is *abb*, and it is ill-formed since it contains the prohibited substring ab . In this way, we get another perspective on modeling long-distance dependencies.

3.4.1 TSL learning algorithm

To learn a TSL grammar, simply extracting factors from the data is not sufficient. The goal is to uncover the *tier alphabet*, or a set of elements exhibiting a long-distance dependency. Currently, the most powerful learner for the TSL class is *kTSLIA* designed by Jardine and McMullin (2017).⁶ **Intuitively**, it initially assumes that every symbol of the alphabet (Σ) is also a member of a tier alphabet (T), and then looks for evidence if it can remove that symbol from T . For an item to be removed from T , it needs to satisfy two conditions. First, it can be freely removed from anywhere; and second, it needs to be able to be inserted

⁶Its earlier versions were presented in (Jardine, 2016b) and (Jardine and Heinz, 2016).

everywhere. This algorithm is interpretable, and learns the k -TSL class of languages in polynomial time and data for any value of k .

Algorithm 3 Extracts G_{TSL_k} from I

Require: a finite input sample $I \in \Sigma^*$, a positive integer k

$L \leftarrow \text{ngram}(I, k - 1)$

$N \leftarrow \text{ngram}(I, k)$

$M \leftarrow \text{ngram}(I, k + 1)$

$T \leftarrow \Sigma$

for x in T **do**

if $\forall uv \in L, u xv \in N$ and $\forall u xv \in M, uv \in N$ **then**

$T \leftarrow T \cap \{x\}$

end if

end for

$R \leftarrow T^k \cap \{\text{tier}(s) : s \in I\}$

return T, R

The **pseudocode** of this algorithm uses two auxiliary functions – ngrams and tier, where $\text{ngrams}(I, k)$ extracts all k -local substrings from the given set of strings I , and $\text{tier}(s)$ creates a tier representation of a string s . So, for example, if the string is $s = cabcba$ and the tier is $T = \{a, b\}$, $\text{tier}(s)$ evaluates to aba . Σ^k stands for all k -grams that can be build using the elements of Σ . This algorithm starts by assuming that every member of Σ needs to be included in T . Then for every symbol x , it explores all $(k-1)$ -grams of the observed data sample and tries to insert x in all positions of those $(k-1)$ -grams: like this, it yields a set of k -grams, let us call it A . It also explores all $(k+1)$ -grams containing x and removes x from those therefore yielding another set of k -grams, let's call it B . If the sets A and B are subsets of k -grams found in the input sample, the symbol x is removed from the tier alphabet because its behavior is not crucial for the target language. Finally, it constructs a list of restricted bigrams R by collecting n -grams that were *not*

observed in tier images of the training sample.

3.4.2 Successful experiments

TSL grammars can learn patterns in which a set of items exhibits some local or long-distant dependency. However, when several different long-distant dependencies are affecting different sets of elements, such as the independent vowel and consonant harmonies, the power of TSL grammars is not enough.

Experiment 1: word-final devoicing TSL grammars are a superset of the SL ones, and therefore it is following from the subregular hierarchy itself that TSL grammars can express patterns that are expressible using the SL ones. I represent tiers as tuples of the form $(a, b, p)_T$ followed by a list of restrictions that are imposed on that tier.

Pattern	<i>word-final devoicing</i>
Type of data	artificial data
Example of data	aaabbbppbbp, pbapbapapa, apabaappap, bbbbaabbbp, ...
Learned 2-TSL grammar	$(a, b, p)_T$: $b \times, \times \times$
Generated sample	bppaapbaabp, aabbbabbbp, abbpaba, a, babpp ...
Evaluation	<code>evaluate_wfd_words(sample)</code>
Score	100%

Table 3.34: TSL learning of the word-final devoicing; abstract representation.

The performance of the TSL learner remained 100% on the dataset of masked and raw German data as well, therefore I am only presenting the results of the latter experiment. In these cases, the TSL learner learned the tier that is the same as the alphabet of the language, thus simply learning the SL grammar.

Pattern	<i>word-final devoicing</i>
Type of data	raw German data
Example of data	hochjagende, zugebliebener, verbricht, besuchszimmer, ...
Learned 2-TSL grammar	$(a, b, c, d, e, f, \dots)_T$: $b\bowtie, cj, cv, cw, cx, \dots$
Generated sample	mlqftorjoiäxäzmölnmt, nlca, uoüßmakoöräzum...
Evaluation	<code>evaluate_wfd_words(sample)</code>
Score	100%

Table 3.35: TSL learning of the word-final devoicing; raw representation.

Experiment 2: a single vowel harmony without blocking The TSL learner extracted a grammar describing a single harmony pattern without blocking from two datasets: the masked version of Finnish harmony, and the abstract representation of Finnish. On both representations, it performed superbly: 100%.

The abstract representation is based on an artificial language dataset. When this is given as the input, the learner extracted the tier $T = \{a, o\}$. Notice, that it correctly excluded x from the tier. Based on the set of unigrams of the data $\{a, o, x, \bowtie, \bowtie\}$, it constructed a list of bigrams $\{xa, ax, ox, xo, xx, \bowtie x, x\bowtie\}$, and all these bigrams appeared in the input sample. Then, it tried to remove x from all observed 3-grams, and again, the obtained list of bigrams was found in the input data. Therefore, x was considered not a tier element. This TSL grammar rules out ungrammatical strings such as *axaxxxxxoo*, since the tier image of that string is *aaoo*: the bigram that is seen on the tier image.

The learner also extracted the TSL grammar from masked Finnish data: it also conjectured that x is not a tier element. On a tier of all vowels, that grammar prohibited all combinations of vowels that disagree in backness.

However, it failed to learn the rule of the Finnish vowel harmony from a raw data: only 42% of the words that that grammar generated, were, in fact, well-formed regarding the rules of Finnish vowel harmony. The majority of the Finnish letters,

Pattern	<i>one vowel harmony, no blockers</i>
Type of data	artificial data
Example of data	oxxxoxxxxx, oxxxoxxxo, aaxxxaaxxx, oxxxoxxxo, ...
Learned 2-TSL grammar	$(a, o)_T$: ao, oa, $\times \times$
Generated sample	xaxxxaxx, xxoxxxx, xxaxax, xxox, xxxoxox, ...
Evaluation	harmonic_evaluator(sample, single_harmony_no_blockers)
Score	100%

Table 3.36: TSL learning of a single harmony without blockers; abstract representation.

Pattern	<i>one vowel harmony, no blockers</i>
Type of data	masked Finnish data
Example of data	xaxxixxex, xixäxixex, xaxxixxaxix, uxxuxaxxix, ...
Learned 2-TSL grammar	$(a, o, u, \text{ä}, \text{ö}, y)_T$: äa, äo, äu, öa, öo, ...
Generated sample	xyyäxyxyxäxx, öxöäxyxx, yäxyxyxäxx, ...
Evaluation	harmonic_evaluator(sample, front_harmony)
Score	100%

Table 3.37: TSL learning of a single harmony without blockers; masked representation.

for the exception of l and n , were unable to be freely inserted into any $n - 1$ -gram, or deleted from any $n + 1$ -gram of the data, and therefore they were not excluded from the tier alphabet.

Experiment 3: a single vowel harmony with blocking Among the learners discussed so far, the TSL learner was the only one that was able to learn the rules of a single vowel harmony with blocking effect. In doing so, it achieved the accuracy of 100%. The learned grammar correctly excluded x from the tier, and noticed that the blocker f is crucial for this language. It prohibited disagreeing

Pattern	<i>one vowel harmony, no blockers</i>
Type of data	raw Finnish data
Example of data	mathilden, lisänimen, macmillanin, urquhartin, ...
Learned 2-TSL grammar	$(a, b, c, d, e, f, g, \dots)_T$: äq, äu, äw, öa, öo, ...
Generated sample	nololdlnölllyn, tlnynlppl, leldznnleln ...
Evaluation	harmonic_evaluator(sample, front_harmony)
Score	42%

Table 3.38: TSL learning of a single harmony without blockers; raw representation.

vowels adjacent on the tier; and if a blocker intervenes, the following vowel must not be *o*. Thus this grammar correctly rules out words such as *ooxxfxxo* and *ooxxxxa* since tiers of these strings contain the prohibited bigrams *fo* and *oa*, correspondingly, see Figure 3.1.

Pattern	<i>one vowel harmony with blockers</i>
Type of data	artificial data
Example of data	ooxxooxxxx, xxooxfaaax, aaxxxaaxxx, ofxxafxxaa, ...
Learned 2-TSL grammar	$(a, f, o)_T$: ao, fo, oa
Generated sample	xxoxfx, xxa, xxxoxoxfxaxafx, xxaxaxxx, ...
Evaluation	harmonic_evaluator(sample, single_harmony_with_blockers)
Score	100%

Table 3.39: TSL learning of a single harmony with blockers; abstract representation.

Experiment 4: several vowel harmonies without blocking The learner induced that the “consonant” *x* is not relevant for the vowel harmony system, and it also learned that on the tier of vowels, no disagreeing vowels can appear next to each other. This learning outcome is therefore similar to the one of the second experiment, but with 4 harmonic classes inferred instead of 2. This TSL grammar

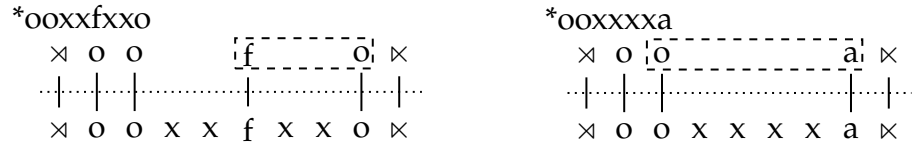


Figure 3.1: The extracted TSL grammar evaluating strings (Experiment 3)

only generates words that are well-formed with respect to the rules of the vowel harmony thus scoring 100% accuracy.

Pattern	<i>several vowel harmonies, no blockers</i>
Type of data	artificial data
Example of data	xuuuxxxuuu, xxxeeexeee, xxxaaxxxaa, xooxxooxox, ...
Learned 2-TSL grammar	$(a, e, o, u)_T$: ae, ao, ua, ue, uo, ...
Generated sample	xxxaxaxax, xexxxexx, xxuxx, oxoxxox, ...
Evaluation	harmonic_evaluator(sample, double_harmony)
Score	100%

Table 3.40: TSL learning of several vowel harmonies without blockers; abstract representation.

Experiment 5: several vowel harmonies with blocking The TSL learner correctly built a model for a Turkish-style harmonic system. One tier is, indeed, able to capture both spreadings at the same time. Given the tier consisting of all the vowels, the backness harmony can be expressed by a set of constraints of the type $[\alpha\text{front}][-\alpha\text{front}]$ ($\ddot{u}u$, $u\ddot{u}$, ae , ea , $\ddot{u}a$, ...), and the rounding harmony that is blocked by non-high vowels is generalized as restrictions of the shape $[\alpha\text{round}][-\text{high}, +\text{round}]$ (oo , uo , eo , ...) and $[\alpha\text{round}][-\alpha\text{round}, +\text{high}]$ ($\ddot{o}i$, oi , au , ...). The performance of such model is 100%.

This result is theoretically expected since, in this pattern, there are two vowel

Pattern	<i>several vowel harmonies with blockers</i>
Type of data	artificial data
Example of data	xxöexxix, xxüüxüüx, exxiixee, iiexxxex, xuuxxuuiu, ...
Learned 2-TSL grammar	$(i, ö, ü, a, e, i, o, u)_T$: iö, iü, ie, ii, io, ...
Generated sample	xxöxxexx, xixxx, axixxx, xaxxaxx, ...
Evaluation	harmonic_evaluator(sample, backness_and_rounding)
Score	100% overall (100% backness only, 100% rounding only)

Table 3.41: TSL learning of several harmonies with blockers; abstract representation.

harmonies happening at the same and affecting the same set of segments. If we take two TSL grammars G_1 and G_2 that have the same tier alphabet but different sets of prohibited n -grams, taking a union of the prohibited n -grams would yield us another TSL grammar G_3 . Importantly, G_3 generates a language that is the intersection of the languages of G_1 and G_2 . To re-iterate this in more linguistic terms, *two harmonies can fit on the same tier if the same sets of elements are involved in them.*

However, the learner did not perform well on the masked Turkish data. It failed to remove x from the tier since it did not observe $öü$ and ou adjacent to each other, even though they are well-formed regarding the harmonic rules. Its hypothesis, therefore, was not different from the one postulated by the SL grammar, and the accuracy of the model is 67%.

The artificial dataset freely allowed vowel hiatus. Harmonic vowels could be adjacent, such as in *xxouxx*. However, Turkish has gaps in what pairs of harmonic vowels can be adjacent in vowel hiatus. Consequently, the performance of the TSL learner on the raw Turkish data was even worse, namely, 30%.

Pattern	<i>several vowel harmonies with blockers</i>
Type of data	masked Turkish data
Example of data	xixxix, xuxx, xaaxa, xexxe, xaxix, ...
Learned 2-TSL grammar	$(i, \ddot{o}, \ddot{u}, a, e, i, o, u, x)_T$: i \ddot{o} , i \ddot{u} , ie, ii, io, ...
Generated sample	uux \ddot{u} ix, \ddot{u} , iaaxeix, xiiix \ddot{u} e, ...
Evaluation	harmonic_evaluator(sample, backness_and_rounding)
Score	67% overall (74% backness only, 74% rounding only)

Table 3.42: TSL learning of several harmonies with blockers; masked representation.

3.4.3 Unsuccessful experiments

TSL grammars can model patterns when a single set of elements is involved in a long-distance dependency. However, if there is more than one long-distant process affecting different sets of elements, such as independent vowel and consonant harmonies, one tier is not enough.

Experiment 6: vowel harmony and consonant harmony without blocking It is impossible to model independent vowel and consonant harmonies using TSL grammars. Vowels and consonants are involved in different long-distant phenomena, and therefore neither of them can be removed from the tier. However, the presence of consonants does not allow us to represent vowels in a tier-based local fashion, and vice versa. Therefore, neither vowel nor consonant harmony can be enforced: only 74% of the words generated by such grammar are well-formed. This model is the same as its SL counterpart.

Experiment 7: vowel harmony and consonant harmony with blocking Since TSL grammars failed to model the previous pattern with the independent vowel and consonant harmonies, they also fail to learn a similar pattern with a blocking

Pattern	<i>vowel and consonant harmonies, no blockers</i>
Type of data	artificial data
Example of data	bbbbaabbbaa, bbooboboob, pppoopppop, appaaappaa, ...
Learned 2-TSL grammar	$(a, b, o, p)_T$: ao, oa, bp, pb
Generated sample	apapoopop, oppoobbbooppob, abab, baaaap, ...
Evaluation	harmonic_evaluator(sample, double_harmony_no_blockers)
Score	74%

Table 3.43: TSL learning of vowel and consonant harmonies w/o blockers; abstract representation.

effect. Thus the performance of the TSL grammar, in this case, is again similar to its SL counterpart: 69%.

Pattern	<i>vowel and consonant harmonies with blockers</i>
Type of data	artificial data
Example of data	pppoootopt, obbbtpooot, aabbbaatat, pppaapapp, ...
Learned 2-TSL grammar	$(a, b, o, p, t)_T$: ao, oa, bp, pb, tb
Generated sample	ptopaba, btopttpt, a, pppa, ob, ...
Evaluation	harmonic_evaluator(sample, double_harmony_with_blockers)
Score	69%

Table 3.44: TSL learning of vowel and consonant harmonies with blockers; abstract representation.

Experiment 8: unbounded tone plateauing There is no choice of a tier alphabet that would allow a TSL grammar to capture the *no H...L...H* generalization. If *H* and *L* are both present on the tier, such TSL grammar behaves like the SL one. Otherwise either *H* or *L* needs to be omitted from the tier, but both of them are crucially important for the generalization. Hence the pattern of UTP is neither SL

nor TSL. The learned grammar performs with the accuracy of 90% exclusively due to a small alphabet and the majority of the generated strings being short.

Pattern	<i>unbounded tone plateauing</i>
Type of data	artificial data
Example of data	HHHHH, LHHLL, LHHHH, LHHHH, HHHHH, ...
Learned 3-TSL grammar	$(H, L)_T$: HLH
Generated sample	HHHLLH, HLL, HHHLLHHLLHHLLHHLL, LLLH, ...
Evaluation	<code>evaluate_utp_strings(sample)</code>
Score	90%

Table 3.45: TSL learning of unbounded tone plateauing; abstract representation.

Experiment 9: first-last harmony As expected, the TSL learner cannot learn the unattested pattern of the first-last harmony. In fact, the obtained grammar is the same as the one proposed by the SL learner, and therefore it makes exactly the same types of mistakes.

Pattern	<i>first-last harmony</i>
Type of data	artificial data
Example of data	axoaaxaxaa, aaxaaxxxoa, ooaxaoaooo, axxoaxaaaa, ...
Learned 2-TSL grammar	$(a, o, x)_T$: $\bowtie x, x \bowtie$
Generated sample	aaoxaxxoxao, aaxaooxa, axooaao, oxxo, ...
Evaluation	<code>evaluate_first_last_words(sample)</code>
Score	50%

Table 3.46: TSL learning of first-last harmony; abstract representation.

3.4.4 TSL experiments: interim summary

A TSL learner, if given a representative sample of data, extracts a *tier alphabet* that represents a set of elements involved in a long-distance dependency. If every item of that set is also involved in another dependency, it can capture such cases as well, as it did in case of the abstract pattern of Turkish harmony. Overall, TSL learner succeeded in building a grammar for every pattern that exhibited either a local dependency or a long-distance dependency among a single set of elements if given a representative sample.

However, if there is more than a single set of items involved in different long-distance dependencies, this cannot be modeled by TSL grammars. Therefore TSL learner failed on a challenge that included learning separate vowel and consonant harmonies: for those cases, one tier is not enough.

3.5 Multi-tier strictly local models

Previous two sections explore two different perspectives on modeling long-distance dependencies. Strictly piecewise grammars prohibit subsequences elements of which can be *arbitrarily far* from each other. SP models thus handle cases of multiple long-distance dependencies; however, none of them can include blockers. Also, SP models can *only* model long-distance dependencies: they cannot handle locally bounded patterns. TSL grammars can encode local patterns and also blocking effects; however, they are limited to a *single* set of items involved in a long-distance dependency. Hence they cannot encode such cases as independent vowel and consonant harmonies within the same language. In this section, I explore the performance of multi-tier strictly local (MTSL) models: namely, models that employ several TSL grammars at the same time.

3.5.1 MTSL learning algorithm

The subregular class of MTSL grammars is a proper extension of TSL. However, the k TSLIA algorithm introduced earlier cannot be simply extended from a single tier to multiple ones since its initial assumption is that *all members of Σ* belong to a tier alphabet: it implicitly assumes the existence of just a single tier.

Together with Kevin McMullin and Aniello De Santo, we developed the MTSL learning algorithm *MTSL2IA* (McMullin et al., 2019). While there are several approaches to learning SL, SP, and TSL languages, MTSL2IA is the first published algorithm that tackles the problem of extracting MTSL grammars. It relies on the assumption that we can first detect all the prohibited k -grams, and then learn a tier for every one of them. Thus, we learn *a tier for every negative bigram* of the MTSL grammar. Currently, this algorithm only works with 2-local restrictions, and the work of extending it to k is ongoing.

Crucially, the MTSL2IA algorithm relies on the notion of a *path* denoted as $\langle \rho_1, X, \rho_2 \rangle$. It can be thought of as a subsequence $(\rho_1 \dots \rho_2)$ accompanied by a set of symbols X that occurred in-between ρ_1 and ρ_2 in the training sample. For example, the following paths can be extracted from a string *abac*: $\langle a, \{\}, b \rangle$, $\langle a, \{b\}, a \rangle$, $\langle a, \{b, a\}, c \rangle$, $\langle b, \{\}, a \rangle$, $\langle b, \{a\}, c \rangle$, and $\langle b, \{\}, c \rangle$.

Intuitively, this algorithm works as follows. At first, it detects a list of bigrams B that is unattested in the training sample I . Then it loops over all elements of B , and for every bigram $\rho_1 \rho_2 \in B$, it assumes that the tier for that bigram is Σ . Afterwards it collects a set of all paths of the form $\langle \rho_1, X, \rho_2 \rangle$, and finds all symbols $\sigma \in \Sigma$ that can be removed from X so that the newly obtained path $\langle \rho_1, X \setminus \{\sigma\}, \rho_2 \rangle$ is still attested in the list of paths of I . It then removes such σ from a tier associated with $\rho_1 \rho_2$. After all members of B were processed, the algorithm outputs a grammar G that is a collection of all unattested bigrams with the tiers corresponding to those bigrams; see the **pseudocode** above. Similarly to the learners discussed in the previous subsections, MTSL2IA learns the grammar

Algorithm 4 Extracts G_{MTSL_2} from I

Require: a finite input sample $I \in \Sigma^*$

$B \leftarrow \Sigma^2 \cap \text{ngram}(I, 2)$

$i \leftarrow 1$

for $\rho_1\rho_2 \in B$ **do**

$R_i \leftarrow \rho_1\rho_2$

$T_i \leftarrow \Sigma$

for $\sigma \in \Sigma \cap \{\rho_1, \rho_2\}$ **do**

if $\forall \langle \rho_1, X, \rho_2 \rangle \in \text{path}(I)$ s.t. $\sigma \in X, \langle \rho_1, X - \{\sigma\}, \rho_2 \rangle \in \text{path}(I)$ **then**

$T_i \leftarrow T_i - \{\sigma\}$

end if

end for

$G_i \leftarrow \langle T_i, R_i \rangle$

$i \leftarrow i + 1$

end for

$G \leftarrow G_1 \wedge G_2 \dots G_{|B|-1} \wedge G_{|B|}$

return G

from a positive sample in polynomial time and data (McMullin et al., 2019).

Example Imagine having a dataset that exhibits long-distance sibilant assimilation between ʃ and s unless blocked by f . Additionally, it also has vowel harmony affecting a and o . This dataset includes the following strings: *saasa*, *ʃaʃaa*, *sooos*, *oʃoʃo*, *ʃoʃos*, *ʃafas*, *sofoʃ*, *safaʃ*, *sʃʃ*, *sʃʃ*, and so on. Of course, strings violating the rules of sibilant (such as *ʃaaʃas* or *soʃooa*) or vowel (*aʃoo*, *sosoa*) harmony are not included in the training sample. As soon as the sample is given as input to the learner, the learner notices the absence of bigrams *sʃ*, *ʃs*, *ao* and *oa*. When it explores the bigram *sʃ*, one of the paths to consider is $\langle s, \{a\}, \text{ʃ} \rangle$. However, $\langle s, \{\}, \text{ʃ} \rangle$ is also a valid path, so a is not a tier element for the bigram *sʃ*, and neither is o . When the unattested bigram *ao* is explored, the learner does not detect any paths that would involve the symbols $\{s, \text{ʃ}, f\}$. The condition of the if-statement is then trivially satisfied, and therefore s , ʃ and f are removed from the tier of that bigram. A concise representation of the grammar that the learner induced is the following:

- $G_1 = \langle T_1 = \{a, o\}, R_1 = \{ao, oa\} \rangle$;
- $G_2 = \langle T_2 = \{s, \text{ʃ}, f\}, R_2 = \{\text{ʃ}s, s\text{ʃ}\} \rangle$.

However, the *tier-per-bigram* assumption comes with a caveat. It results in the algorithm failing to capture patterns where the same bigram is present on several different tiers. For example, consider an MTSL grammar where the bigram *xx* is prohibited on two tiers: $T_1 = \{x, a\}$ and $T_2 = \{x, b\}$. Instead, the MTSL2IA learner would converge on the incorrect tier $T = \{x, a, b\}$. Tier configurations that cannot be learned by this learner is a sub-case of a general case when two tier alphabets have a non-empty intersection that does not overlap with either of the alphabets. Interestingly, we show in Aks nova and Deshmukh (2018) that in natural languages, if two agreements require two different tiers, those tiers never overlap unless one of them is properly contained within the other one. Therefore if

applied to phonological data, this learner could be more efficient in comparison to the learner that would also explore the typologically unattested class of tier configurations.

As noted previously, this algorithm learns 2-local MTSL grammars, but we are currently working on extending it to arbitrary k . Intuitively, this can be done by extending the notion of a path. Its shape could be generalized as $\langle \rho_1, X_1, \rho_2, X_2, \dots, \rho_{n-1}, X_{n-1}, \rho_n \rangle$, where $\rho_1 \rho_2 \dots \rho_n$ is a k -long sequence, and X_i is the set of symbols that occurred in-between ρ_i and ρ_{i+1} in the training sample. The condition of the if-statement needs to also be adjusted to accommodate for longer paths; but otherwise, the logic of the algorithm stays the same.

3.5.2 Successful experiments

In this subsection, I show that MTSL grammars can be used to successfully model all of the discussed types of local and long-distant dependencies. Even when challenged with the raw data of German, Finnish, and Turkish, the MTSL learner extracts the corresponding MTSL grammars with the impressive accuracies of 100%, 100%, and 95%, correspondingly. The patterns of unbounded tone plateauing and the first-last harmony are not MTSL in their nature, and therefore cannot be learned using the MTSL inference algorithm.

Experiment 1: word-final devoicing Since MTSL grammars are a proper superclass of TSL grammars, and, consequently, of the SL ones, the MTSL learning algorithm acquires the pattern of word-final devoicing. The performance of the MTSL model on the raw German dataset is 100%, as well as on the other representations of that pattern.

Experiment 2: a single vowel harmony without blocking Similarly, the MTSL learner extracted the grammar representing a single vowel harmony pattern

Pattern	<i>word-final devoicing</i>
Type of data	raw German data
Example of data	hochjagende, zugebliebener, verbricht, besuchszimmer, ...
Learned 2-MTSL grammar	<i>too large: 294 tiers!</i>
Generated sample	mugoftkuhämpo, kisizkkokgüp, rkümsübtal...
Evaluation	<code>evaluate_wfd_words(sample)</code>
Score	100%

Table 3.47: MTSL learning of the word-final devoicing; raw representation.

without a blocking effect. The learner induced a single tier containing symbols *a* and *o*. The grammar for this tier was the same one as in the TSL version of this experiment: *ao, oa*. 100% of the words generated by the obtained grammar were well-formed. The success of the MTSL learner on this and further experiments where the TSL learner performed well follows from the fact that the class of MTSL languages subsumes TSL languages.

Pattern	<i>one vowel harmony, no blockers</i>
Type of data	artificial data
Example of data	oxxxooxxxx, oxxxooxxo, aaxxxaaxxx, oxxxoxxxo, ...
Learned 2-MTSL grammar	$(a, o)_T$: <i>ao, oa</i>
Generated sample	xxoox, xxaxaxa, axaaax, xooox, ...
Evaluation	<code>harmonic_evaluator(sample, single_harmony_no_blockers)</code>
Score	100%

Table 3.48: MTSL learning of a single harmony without blockers; abstract representation.

The MTSL inference algorithm also successfully learned the generalization from raw and masked Finnish datasets. Indeed, 100% of the words generated by the grammar, such as *rjegovnj* or *läyömppl*, are harmonic. Although the grammar is

transparent and fully interpretable, it postulates 266 tiers. An open question is to explain *how exactly* increasing the number of tiers helped the learner to tackle this challenge.

Pattern	<i>one vowel harmony, no blockers</i>
Type of data	raw Finnish data
Example of data	mathilden, lisänimen, macmillanin, urquhartin, ...
Learned 2-MTSL grammar	<i>too large: 266 tiers!</i>
Generated sample	rjegovnj, läyömppl, axiflt, silöäämydv, ...
Evaluation	harmonic_evaluator(sample, front_harmony)
Score	100%

Table 3.49: MTSL learning of a single harmony without blockers; raw representation.

Experiment 3: a single vowel harmony with blocking Again, the success of the MTSL learner in this experiment follows from the fact that TSL grammars are a proper subset of the MTSL ones. However, what is surprising is that the MTSL inference algorithm did not converge on a single tier: instead, it postulated 3 different tiers.

The learner discovered 3 unattested bigrams: *ao*, *fo*, and *oa*. However, in none of the data points *a* was ever followed by *o*, so there were no paths of the type $\langle a, X, o \rangle$: trivially, elements *f* and *x* were considered irrelevant for this restriction. Similarly, *a* was excluded from a tier induced for the restriction *fo* because *f* is never followed by *o*. But when considering the unattested bigram *oa*, paths such as $\langle o, \{f\}, a \rangle$ and $\langle o, \{f, x\}, a \rangle$ were found in the data, while the ones such as $\langle o, \{\}, a \rangle$ were not. A symbol *x* was hence removed from the tier of the bigram *oa*, but the blocker *f* was not. In such a way, MTSL learner constructs 3 different tiers, but the language of the obtained grammar is equivalent to the one of the TSL grammar

$\{oa, ao, fo\}$ with the tier $T = \{a, o, f\}$.

Pattern	<i>one vowel harmony with blockers</i>
Type of data	artificial data
Example of data	oxxxooxxxx, xxooxfaaax, aaxxxaaxxx, ofxxafxxaa, ...
Learned 2-MTSL grammar	$(a, o)_T$: ao; $(f, o)_T$: fo; $(a, f, o)_T$: oa.
Generated sample	oxffxax, faaxffa, ofxaaf, fa, oooooof, ...
Evaluation	<code>harmonic_evaluator(sample, single_harmony_with_blockers)</code>
Score	100%

Table 3.50: MTSL learning of a single harmony with blockers; abstract representation.

Experiment 4: several vowel harmonies without blocking This experiment was successful since the MTSL learner extracted the grammar for the pattern of several vowel harmonies without a blocking effect. However, similarly to the previous example, the resulting grammar was not the same as the one extracted by the TSL learner. The MTSL algorithm constructed a separate tier for every pair of the potentially disagreeing elements, while correctly noticing that the transparent element x is irrelevant for the generalization.

Experiment 5: several vowel harmonies with blocking The MTSL induction algorithm found a way to model several vowel harmonies with a blocking effect. Also, similarly to the examples discussed above, more than a single tier was inferred. All of the words generated by the extracted MTSL grammar were well-formed regarding the rules of Turkish harmony.

Some of the configurations that the MTSL learner was looking for were missing in the masked and raw representations of the Turkish data, and therefore the accuracies of those models were slightly worse than ideal: both of them scored

Pattern	<i>several vowel harmonies, no blockers</i>
Type of data	artificial data
Example of data	xuuuxxxuuu, xxxeeexeee, xxxaaxxxaa, xoooxooxox, ...
Learned 2-MTSL grammar	$(u, o)_T$: uo, ou; $(a, u)_T$: au, ua; $(o, e)_T$: eo, oe; etc.
Generated sample	xuxuuuxu, xoox, aaa, exexxe ...
Evaluation	harmonic_evaluator(sample, double_harmony)
Score	100%

Table 3.51: MTSL learning of several vowel harmonies without blockers; abstract representation.

Pattern	<i>several vowel harmonies with blockers</i>
Type of data	artificial data
Example of data	xxöexxix, xxüüxüüx, exxiixee, iiexxxex, xuuxxuux, ...
Learned 2-MTSL grammar	$(\ddot{u}, e, i)_T$: üi; $(\ddot{u}, e)_T$: eü; $(\ddot{u}, \ddot{o})_T$: iö, öi; etc.
Generated sample	ixxaaaa, üexi, üxeexe, öüüüe, öüexe, ...
Evaluation	harmonic_evaluator(sample, backness_and_rounding)
Score	100% overall (100% backness only, 100% rounding only)

Table 3.52: MTSL learning of several harmonies with blockers; abstract representation.

95%. As of the MTSL grammar inferred from the raw data, it relies on 266 tiers, and the way it is able to perform so well is worth further investigation.

Experiment 6: vowel harmony and consonant harmony without blocking The pattern of independent vowel and consonant harmonies can be captured using two tiers: one for vowels, and another one for consonants. The tier of vowels prohibits *oa* and *ao*, and the tier of consonants rules out *pb* and *bp*. To evaluate the well-formedness of a word, both of its tiers need to be inspected individually. For

Pattern	<i>several vowel harmonies with blockers</i>
Type of data	raw Turkish data
Example of data	som, lafazan, konuk, kekti, lafzan, ...
Learned 2-MTSL grammar	<i>too large: 266 tiers!</i>
Generated sample	apnıcırısaa, telçitçeeriden, mbezkdenic, ...
Evaluation	harmonic_evaluator(sample, backness_and_rounding)
Score	95% overall (100% backness only, 95% rounding only)

Table 3.53: MTSL learning of several harmonies with blockers; raw representation.

example, consider a word *ababbabb*. Its consonant tier contains *bbbbbb*, and the vowel tier is *aaa*: both of them are well-formed. However, words such as *ababbbob* are not grammatical: even though the consonant tier does not contain violations, the vowel tier is *aaö*, and it violates the rules of the vowel harmony. The language of this MTSL grammar is the intersection of two TSL grammars, one per every harmony. The accuracy of this model is 100%.

Pattern	<i>vowel and consonant harmonies, no blockers</i>
Type of data	artificial data
Example of data	bbbaaabbaa, bbooboboob, pppoopppop, appaaappaa, ...
Learned 2-MTSL grammar	$(a, o)_T$: ao, oa; $(b, p)_T$: pb, bp.
Generated sample	oapapaaa, obbb, babbba, poop, ...
Evaluation	harmonic_evaluator(sample, double_harmony_no_blockers)
Score	100%

Table 3.54: MTSL learning of vowel and consonant harmonies w/o blockers; abstract representation.

Experiment 7: vowel harmony and consonant harmony with blocking MTSL learner performs 100% accurate on the pattern with vowel and consonant

harmonies even if they include blockers, and it is the only subregular model among the discussed ones that is able to do so. In this case, the learner extracts 4 tiers, and a total of 5 prohibited bigrams. The choice of the tiers can be explained in the same way it was done for the third experiment. On the tier of vowels, the grammar prohibits their disagreeing combinations *ao* and *oa*. The consonant-related restrictions are located across 3 different tiers due to the inference steps of the algorithm, but these restrictions, in fact, can be expressed on a single tier containing *p*, *b*, and *t*. Figure 3.2 shows the MTSL evaluation of strings *aabbotoob* and *aabbbaaap* using a simplified yet equivalent MTSL grammar containing only 2 tiers: one for vowels, and another for consonants.

Pattern	<i>vowel and consonant harmonies with blockers</i>
Type of data	artificial data
Example of data	pppoootopt, obbbtpooot, aabbbaatat, pppaapapp, ...
Learned 2-MTSL grammar	(b, p, t) _T : bp; (a, o) _T : ao, oa; (b, p) _T : pb; (b, t) _T : tb.
Generated sample	obtpoppo, totoo, ap, ooptpp, abtatat, ...
Evaluation	harmonic_evaluator(sample, double_harmony_with_blockers)
Score	100%

Table 3.55: MTSL learning of vowel and consonant harmonies with blockers; abstract representation.

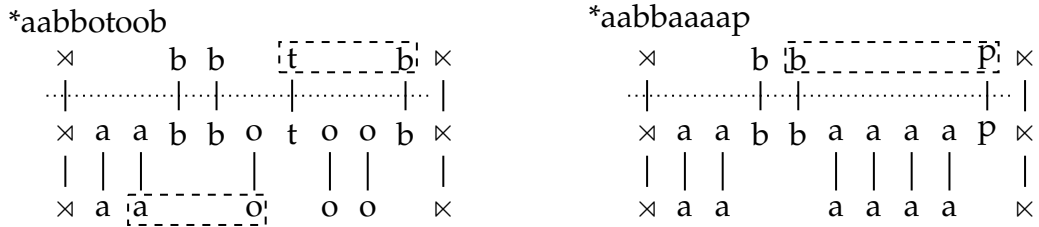


Figure 3.2: Experiment 7: the extracted MTSL grammar evaluating the ungrammatical strings *aabbotoob* and *aabbbaaap*.

3.5.3 Unsuccessful experiments

I was not able to test the performance of the MTSL learner on the UTP pattern since this learner currently exists only for 2-local dependencies, and UTP requires postulating a 3-local restriction. However, this pattern is not MTSL expressible since there is no tier or a combination of tiers that would be able to express that generalization. Hence the only unsuccessful experiment that I present in this subsection is the expected inability of MTSL grammars to express the first-last harmony.

Experiment 9: first-last harmony MTSL grammars cannot encode the pattern of the first-last harmony. The MTSL learner extracts exactly the same grammar as TSL and SL learners: it only notices that the “non-agreeing” item x cannot occur string-initially and string-finally. It fails to generalize that the string-initial and string-final symbols need to match, and therefore the accuracy of this model is 50%.

Pattern	<i>first-last harmony</i>
Type of data	artificial data
Example of data	axoaaxaxaa, aaxaaxxxoa, ooaxaoaooo, axxoaxaaaa, ...
Learned 2-MTSL grammar	$(a, o, x)_T: \bowtie x, x \bowtie$
Generated sample	ooooa, aaoa, ooooaxxa, oaaaxao, ...
Evaluation	<code>evaluate_first_last_words(sample)</code>
Score	50%

Table 3.56: MTSL learning of first-last harmony; abstract representation.

3.5.4 MTSL experiments: interim summary

The MTSL learner successfully extracted MTSL grammars corresponding to all types of harmonic systems present in the list of the experiments, performing

equally well on cases with or without the blocking effect. While being able to capture long-distance dependencies, it also performed extremely well on the local pattern of word-final devoicing. Importantly, apart from learning the patterns from the artificially generated datasets, it also was able to generalize the rules from the raw data, scoring 100% on German and Finnish, and 95% on Turkish datasets. The experiment using the non-MTSL pattern of unbounded tone plateauing is not discussed due to the unavailability of the 3-local MTSL learner at the current moment. Finally, as expected, the first-last harmony is not learnable by either of the discussed subregular learners.

However, as explained before in Section 3.5.1, there is a type of MTSL grammars that the current learner cannot induce due to its tier-per-bigram assumption. Namely, it cannot learn an MTSL grammar where one bigram belongs to two different tiers. Interestingly, according to Aks nova and Deshmukh (2018), languages with multiple harmonies typologically lack this type of tier configuration. Therefore this learner could be more efficient for language-related tasks than the one that would investigate typologically unattested possibilities.

3.6 Learning languages: summary

In this chapter, I discussed possibilities of modeling natural language patterns using subregular methods. Namely, I explored the performance of strictly piecewise (SP), strictly local (SL), tier-based strictly local (TLS), and multi-tier strictly local (MTSL) learning algorithms using different datasets exhibiting natural language dependencies. The experiments ranged from ones that were using artificially generated samples imitating linguistic patterns, to extracting grammars from raw language data. Artificial language learning shows if the modeling of those generalizations is possible *conceptually*, whereas using raw data

shows what is possible *in practice*.

The conducted learning experiments confirmed the learning expectations for the artificial datasets, showing how different linguistic patterns are captured by subregular models. However, the performance of the learners on raw natural language data was worse, and in some cases, a more powerful model was required to capture a pattern of lower complexity.

The experiments targeted following patterns: word-final devoicing, a single vowel harmony pattern with/without a blocking effect, several vowel harmonies with/without a blocking effect, independent vowel and consonant harmonies with/without blocking effect, and the unbounded tone plateauing. Additionally, I also challenged the learners with a typologically unattested pattern of first-last harmony. Every one among these 9 patterns can be theoretically modeled using different set of subregular classes. Namely, word-final devoicing can be captured by SL, TSL, and MTSL grammars; several vowel harmonies with blocking are expressible by TSL and MTSL grammars, and the unbounded tone plateauing can only be encoded using a SP grammar. Finally, none of the subregular languages should be able to capture the first-last harmony since it is not SL, SP, TSL, or MTSL. In 3.57, I repeat the table with the expected results of the language learning experiments that was previously shown in Table 3.10.

Every experiment included 4 steps: data collection or generation, subregular learning, sample generation using the constructed grammar, and model evaluation. At first, I prepared the *training samples*. They range from the automatically generated artificial languages, to simplified (masked) representations of the natural language data, to wordlists of German, Finnish and Turkish. During the *learning* step, a grammar was obtained by the inference algorithm based on the provided training data. Then I *generated* a large set of strings that are grammatical according to the extracted grammar. Finally, I computed the number of strings of the generated sample that are well-formed

according to the target generalization thus numerically *evaluating* the performance of the model. Table 3.58 summarizes how the automatically extracted subregular grammars performed on those experiments.

There are several implications of this work. I show that every artificial language learning experiment that was predicted to be successful given some particular subregular model was, in fact, successful. It confirms that the implemented algorithms are indeed implemented correctly, and therefore can be reliably used in future. Also, the MTSL learner performed extremely well on raw language data: it learned German word-final devoicing and Finnish harmonic system from a raw data with an accuracy of 100%, and scored 95% on a challenge of learning Turkish harmony. However, a TSL learner was not able to learn a TSL pattern from a realistic data due to the expectations of the algorithm.

However, any non-perfect score implies that the pattern was not acquired. Indeed, due to the non-probabilistic nature of the learners, results below 100%

Target patterns	SP	SL	TSL	MTSL
<i>word-final devoicing</i>	✗	👍	👍	👍
<i>a single vowel harmony without blocking</i>	👍	✗	👍	👍
<i>a single vowel harmony with blocking</i>	✗	✗	👍	👍
<i>several vowel harmonies without blocking</i>	👍	✗	👍	👍
<i>several vowel harmonies with blocking</i>	✗	✗	👍	👍
<i>vowel harmony and consonant harmony without blocking</i>	👍	✗	✗	👍
<i>vowel harmony and consonant harmony with blocking</i>	✗	✗	✗	👍
<i>unbounded tone plateauing</i>	👍	✗	✗	✗
<i>first-last harmony</i>	✗	✗	✗	✗

Table 3.57: The expected results of the language learning experiments; repeated as in Section 3.1.4.

indicate the presence of ill-formed words generated by the learned grammar, showing that the learner did not converge. The learned grammars can do mistakes due to overgeneration or overfitting, and further research is needed to develop metrics similar to the precision and recall that would highlight these problems. The current metric only shows the overall performance of the model, without focusing on the issues of overgeneration and overfitting.

For example, the SP learner scores 89% on the German dataset. Given that the exemplified phenomenon of the word-final devoicing is not SP, this result is quite surprising. Transparency of the subregular learners allowed to look inside the algorithm and see the reason behind this surprisingly good performance. It showed that the learner is *overgenerating*: indeed, it observed voiced obstruents indirectly followed by the word-final marker, and thus assumed that such configuration is grammatical. If we limited our attention to only generated strings that end in an obstruent, it would become clear that the learned grammar generates voiced final obstruents as frequently as the voiceless ones. The accuracy scores can be misleading without the analysis of the errors, and the transparency of the subregular grammars allows us to see the performance of the grammars behind-the-scenes.

The experiments also confirmed that SP grammars do not differentiate between long-distance and local dependencies, and therefore after observing a word such as $\times aba \times$ it assumed that all its subsequences are also grammatical. Indeed, it results in allowing words such as $\times ab \times$ that violate the rule. The score is relatively high only due to a low probability for a word to end with a voiced obstruent: among 30 German segments, only 5 of them are voiced obstruents. This type of problem is caused by the overgeneration that arises in some of the learning experiments.

Another issue – *overfitting* – emerges when the model represents the training data but fails to generalize beyond it. Although further research is needed, the results suggest that it is indeed the case with the MTSL grammars capturing

phenomena such as Turkish vowel harmony. Theoretically, we know that this pattern, as well as the pattern of Finnish harmony, is TSL, i.e. requires just a single tier. However, the learned MTSL grammar extracts 266 tiers instead. This shows that the marvelous performance of the MTSL grammars is not due to a deep understanding of the pattern, but rather because of the memorized configurations of tiers observed during the training.

Although both Finnish and Turkish harmony is TSL, the TSL learner failed to extract the corresponding grammar. This is due to a problem of *combinatorial explosion*: the TSL algorithm assumes that missing combinations always convey meaningful information about which sounds do or do not matter for the dependency. As a result, these algorithms are misled by accidental gaps in the data. Improving the subregular learning algorithms can help to overcome this issue.

Both the experimental pipeline and the learning algorithms can be greatly improved by introduction of linguistic notions such as natural classes and features, see Section 2.4. It can help to learn harmonies more efficiently: instead of considering segments individually, the feature-based representation helps to detect the common behavior of segments bearing a particular feature. Alternatively, a greater accuracy can be achieved by combining the learners together, as suggested in Heinz (2010a); Heinz and Idsardi (2013).

This line of research needs to be further investigated, as many questions are yet to be answered. These models need to be challenged with more data exhibiting different linguistic dependencies. In case of a successful learning outcome, we need to understand *how exactly* the learner came to the convergence. Otherwise, we need to know *what exactly* prevented the learner from discovering the pattern. Also, there are other subregular classes, such as IO-TSL and IBSP, that are important for natural language modeling: learning algorithms for those classes need to be implemented and explored as well.

This chapter, however, is only concerned with modeling the *well-formedness conditions*. In the next chapter, I discuss ways to model *processes* that apply to strings, and transform them according to some set of rules. Namely, similarly to this chapter, I will focus on the ways to infer those rules automatically. Since subregular grammars are interpretable, and subregular learning algorithms are fully transparent, this type of research can in a long run give us larger insights in understanding how human language works.

Data	SP	SL	TSL	MTSL
<i>Experiment 1: word-final devoicing</i>				
Theoretical expectations	✗	👍	👍	👍
Artificial (1,000)	68%	100%	100%	100%
German simplified (658,147)	58%	100%	100%	100%
German (658,147)	89%	100%	100%	100%
<i>Experiment 2: a single vowel harmony without blocking</i>				
Theoretical expectations	👍	✗	👍	👍
Artificial (1,000)	100%	83%	100%	100%
Finnish simplified (250,805)	100%	72%	100%	100%
Finnish (250,805)	100%	41%	42%	100%
<i>Experiment 3: a single vowel harmony with blocking</i>				
Theoretical expectations	✗	✗	👍	👍
Artificial (1,000)	84%	89%	100%	100%
<i>Experiment 4: several vowel harmonies without blocking</i>				
Theoretical expectations	👍	✗	👍	👍
Artificial (1,000)	100%	69%	100%	100%
<i>Experiment 5: several vowel harmonies with blocking</i>				
Theoretical expectations	✗	✗	👍	👍
Artificial (15,000)	76%	59%	100%	100%
Turkish simplified (14,434)	76%	70%	67%	95%
Turkish (14,434)	89%	30%	30%	95%
<i>Experiment 6: vowel harmony and consonant harmony without blocking</i>				
Theoretical expectations	👍	✗	✗	👍
Artificial (1,000)	100%	64%	74%	100%
<i>Experiment 7: vowel harmony and consonant harmony with blocking</i>				
Theoretical expectations	✗	✗	✗	👍
Artificial (1,000)	83%	64%	69%	100%
<i>Experiment 8: unbounded tone plateauing</i>				
Theoretical expectations	👍	✗	✗	✗
Artificial (1,000)	100%	85%	90%	
<i>Experiment 9: first-last harmony</i>				
Theoretical expectations	✗	✗	✗	✗
Artificial (5,000)	32%	51%	50%	50%

Table 3.58: The expected vs. the actual results of the subregular language learning experiments; the experiment 8 cannot be conducted using MTSL learner because it is currently not available for $k > 2$; all other learners are used with $k = 2$.

Chapter 4

Learning mappings

Finite-state transducers are a convenient way to represent natural language processes: they rewrite strings according to the rules they encode. Koskenniemi (1983) and Kiraz (1996), among the first ones, show that concatenative and non-concatenative morphological processes can be modeled using FSTs. Chandlee (2014) in her dissertation shows that subregular functions are a good fit for phonology, and later extends the results to also include morphology (Chandlee, 2017). Heinz and Lai (2013) argue that subsequentiality is crucially important for long-distant phonological processes such as different types of harmonies. Subsequential transducers encode subsequential transformations: they read the input string symbol-by-symbol and output the translation, or a modified representation of that string. Thus, automatically extracting subsequential transducers from data allows to computationally model natural language processes. The learning algorithms analyze the provided pairs of underlying representations (UR) and surface forms (SF), therefore inducing the changes applied to the URs.

In his chapter, I explore the automatic extraction of linguistic patterns using a well-known transduction learning algorithm OSTIA (Oncina et al., 1993). Previously, Gildea and Jurafsky (1996) showed that a corpus of English



pronunciations was not enough for OSTIA to generalize the rule of English flapping. However, they further proceeded to test modified versions of the algorithm on the same corpus yielding improved accuracy. My aim here is to explore what generalizations are possible to model, and which ones cannot be extracted given the current version of the learner. The focus of the chapter is thus understanding what *types* of patterns OSTIA can learn from samples of automatically generated data.

4.1 The OSTIA algorithm

The name *OSTIA* stands for **O**nward **S**ubsequential **T**ransducer **I**nterference **A**lgorithm. Discussed in Oncina et al. (1993) and de la Higuera (2010), this algorithm infers subsequential functions mapping input strings to output strings from a finite sample of such input-output pairs. It identifies any subsequential function in the limit. In other words, given a finite sample of pairs of strings before and after the application of some rule, it extracts a subsequential transducer representing that rule. The property of *the identification in the limit* means that the learner would need a *finite* number of such pairs to induce the target machine. Below I discuss the main steps of this algorithm in Section 4.1.1, and then present a walk-through of examples in Sections 4.1.2 and 4.1.3, one successful and one unsuccessful.

4.1.1 The pipeline

This algorithm requires a sample of input-output pairs of strings for training, and returns a finite-state subsequential transducer as the output. The algorithm consists of two main parts: creating a representation of data as an onward prefix tree transducer (PTT), thus *structuring* the input data, and *merging* the states of the PTT, therefore, formulating the hypothesis about the underlying rule. The

structuring step includes building a PTT for the input sample and making that PTT onward. Folding sub-trees into one another results in pairs of states being *merged* into a single state. For the pseudocode of the algorithm, refer to Oncina et al. (1993) and de la Higuera (2010). The implementation of OSTIA which I used to obtain the results is a part of the *SigmaPie* package  (Aks nova, 2020c), and the discussion of that implementation is available on GitHub  (Aks nova, 2019). The main steps are presented in Figure 4.1.

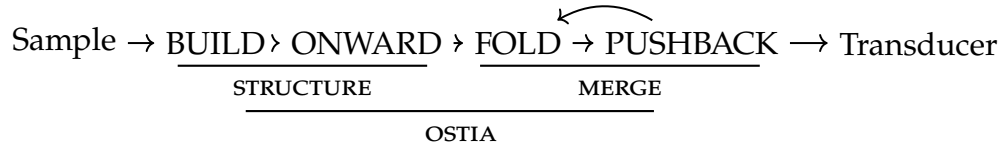


Figure 4.1: The main steps of OSTIA: BUILD, ONWARD, FOLD and PUSHBACK.

BUILD The first step is to represent the input data using a transducer-like data structure. For this purpose, we can build a *prefix-tree transducer* that reads input strings of the training sample symbol-by-symbol, with the common prefixes of those strings stored in the states. The initial state q_ε of such a PTT refers to the only common prefix of all the input strings: ε . The names of the later states refer to the common prefix those strings are sharing: the states accessible from the state q_ε correspond to different first symbols of the input strings. So, for example, a state q_{aba} reads a prefix *aba* by passing through the following states: q_ε , q_a , q_{ab} , and q_{aba} . State outputs are set to the translations of the input strings that end up in that state. For example, given the input pair $(ab, 01)$, we save 01 in the state output of the state q_{ab} .

If the state output is not known, it is marked as \perp , or *unknown*. The unknown state output has two properties: *absorbency* and *neutrality*. It is absorbent since its concatenation with any other string returns the same “unknown” output \perp . It is neutral because the longest common prefix of any set of strings W and \perp is the same

as the one of W by itself, i.e. \perp is transparent for this operation. In such a way, the training sample provided to OSTIA is represented as a PTT.

ONWARD The outputs of the PTT are then modified to be *onward*: such a PTT outputs translations as early as possible. During this step, common prefixes of state outputs are pushed closer to the initial state. For example, assume that the intermediate state of the PTT is the one as pictured in Figure 4.2 on the left side, with the onward version of that PTT on the right side. In the input PPT, the state output of the state q_a is 1, and the translations on all edges coming out of q_a ($q_a \xrightarrow{a:10} q_{aa}$ and $q_a \xrightarrow{b:11} q_{ab}$) also contain 1 as their prefix. Therefore, this prefix can be removed from the state output and transitions, and be introduced in the transducer earlier, namely, on the transition incoming into the state q_a . Onwarding starts from the *leaves* of the PTT (the nodes that do not have any outgoing arcs), and percolates to the initial state q_ϵ .

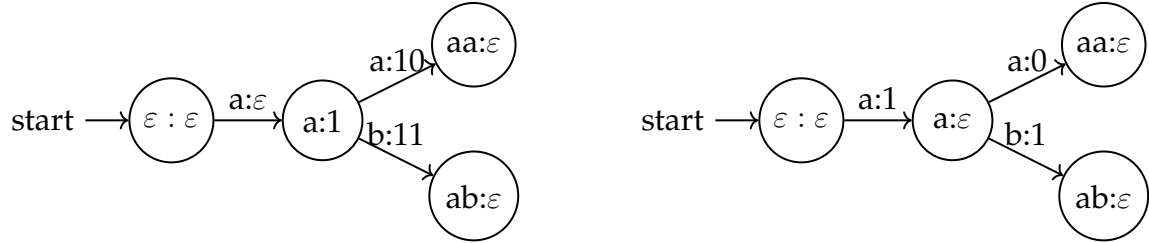


Figure 4.2: Non-onward and onward PTTs that are otherwise equivalent.

FOLD Then, we try to merge every pair of states of the PTT. If (a) the state outputs of q and q' are the same or are \perp , (b) all the incoming branches of q' can be redirected to q , and (c) all outgoing branches from q' are consistent with the outgoing branches of q , states q and q' are merged. Consistency implies either having matching outgoing branches, a possibility to add a missing branch, or, if required, being able to successfully delay a part of the output during the *pushback*

step. Folding one state into another decreases the size of the transducer, and shows that the learner generalized the pattern.

PUSHBACK The pushback operation checks if a part of the output can be delayed and therefore removed from some transitions. If pushing back a portion of the output is possible, states q and q' considered during the previous *merge* step are combined, otherwise, their merge is rejected. For example, consider the FST on the left side in figure 4.3. Reading a from the state q_ε yields the translation uv . However, as the machine on the right shows, the translation's suffix v can be delayed to the state output of q_a and all the transitions outgoing from q_a . It could let the state q_e be merged with some other state in the FST. After the pushback, OSTIA returns to the merging step and checks if there are other pairs of states that could be merged. When no such pairs remain, OSTIA outputs the FST. In some sense, *pushback* is the operation opposite to *onward* since it delays the outputs, but the resulting FST is always onward.

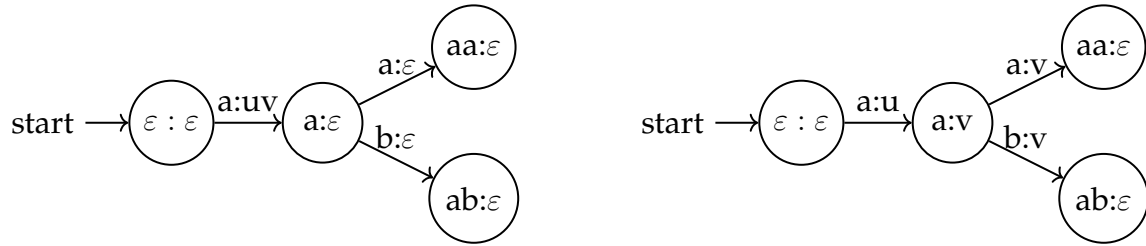


Figure 4.3: OSTIA pushes back the suffix v .

In such a way, OSTIA constructs a subsequential FST that generalizes the mapping from the input strings into their output representations. Note, that as well as the subregular learning algorithms discussed earlier in Chapter 3, OSTIA requires a sample of only positive data.¹ The next subsection presents the inference steps of this algorithm given a concrete example. Although there are

¹The algorithmic complexity of OSTIA is $\mathcal{O}(n^3(m + |\Sigma|) + nm|\Sigma|)$, where n is the sum of the

several versions of OSTIA in the literature, the version I use here mostly follows de la Higuera (2010); this exact version is implemented in *SigmaPie*

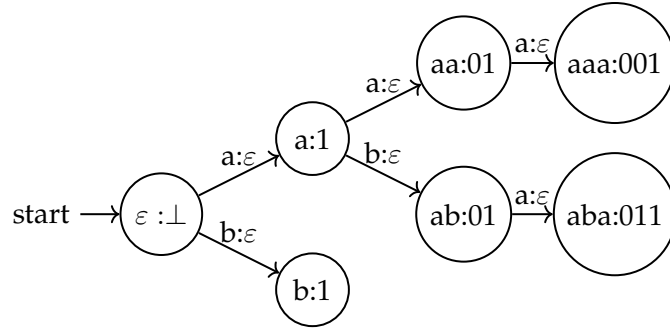
4.1.2 The successful example

Here, I discuss a slightly modified example of the OSTIA inference steps originally presented in de la Higuera (2010). The task is to learn the following mapping: word-final a is rewritten as 1, non-word-final a corresponds to 0, and b is always translated as 1. Notice, that this pattern can be viewed as a generalization of a linguistically-motivated process of word-final devoicing since it involves a segment changing its value to the opposite at the end of the word. The training sample that I use in this example is enlarged in comparison to the one presented by de la Higuera (2010): it provides *all* the necessary pairs that guarantee the extraction of the pattern.

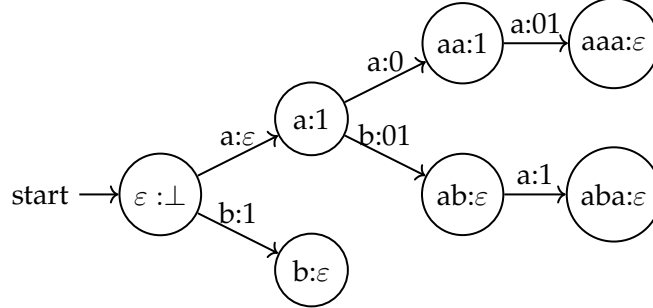
Sample = [(b, 1), (a, 1), (aa, 01), (ab, 01), (aba, 011), (aaa, 001)]

Step I. At first, OSTIA constructs a PTT representing the input sample. This PTT reads the left sides of the training sample one symbol at a time. For every string w of the input pair (w, o) , there exists a state q_w with the state output o . All transitions of this PTT output an empty string. If there is a state $q_{w'}$ that does not correspond to any input string of the training sample, its state output is \perp . For example, there is no empty string in the given sample, so the state output of q_ϵ is \perp .

input string lengths, m is the length of the longest output string, and Σ is the input alphabet (de la Higuera, 2010).

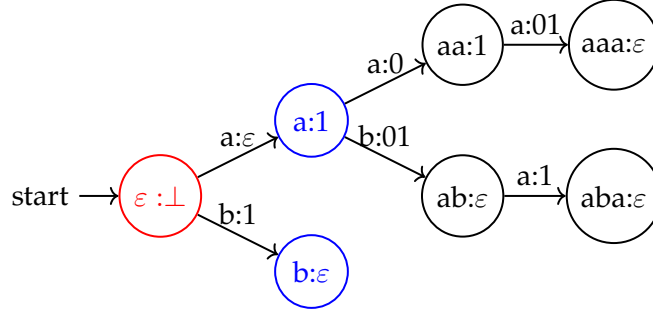


Step II. Then, this PTT is onwarded. For example, consider the state q_{aaa} with the state output 001. We can replace it by ε , and instead move 001 to the incoming arc therefore obtaining a transition $q_{aa} \xrightarrow{a:001} q_{aaa}$. The longest common prefix of the modified transition and the state output of q_{aa} is the longest common prefix of 01 and 001, and that 0 can be moved to the output of the arc $q_a \xrightarrow{a:0} q_{aa}$. Other leaves of the FST are processed similarly. After this step, the input sample is represented as an onward PTT.

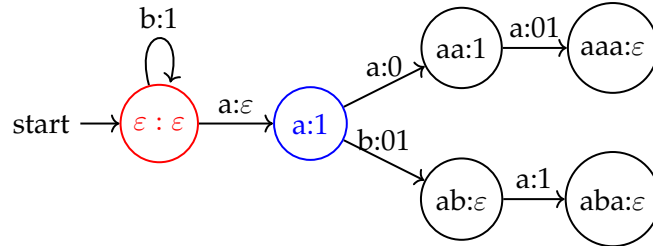


Step III. Next, we start the process of generalizing the obtained PTT by trying to merge pairs of its states. States are colored in two colors: red and blue. *Red states* cannot be eliminated from the FST: they are crucial and therefore cannot be folded into any other state. At first, only the initial state q_ε is colored red. All states that can be reached in one step from the red states are colored blue. The status of *blue states* is unclear: either they will be folded into some red states, or they will eventually be re-colored red. After a state was colored red, its immediate children

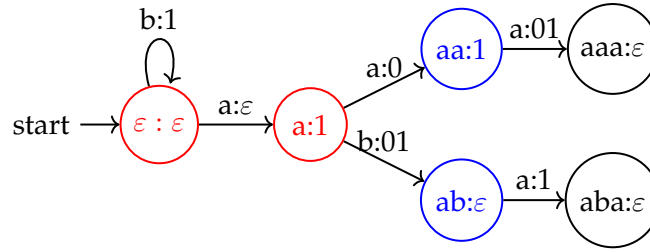
are automatically added to the list of blue states. In our example, two states are colored blue – q_a and q_b – since they can be reached from q_ε in one step.



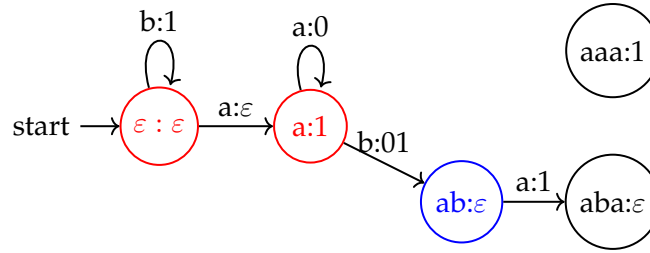
Step IV. Then, the algorithm considers pairs where one state is red and another one is blue and tries to fold the blue state into the red one. Let us then fold the state q_b into q_ε . At first, we check if the state outputs of q_b and q_ε are compatible. They are \perp and ε , and therefore could be merged: they are *not different* due to the transparency of \perp , so we assign ε to the state output of q_ε . The transition coming to the state q_b is re-directed into the state q_ε thus yielding a loop on that state. There is no other sub-tree rooted in q_b , so folding q_b into q_ε can be finalized, and q_b is removed from the FST.



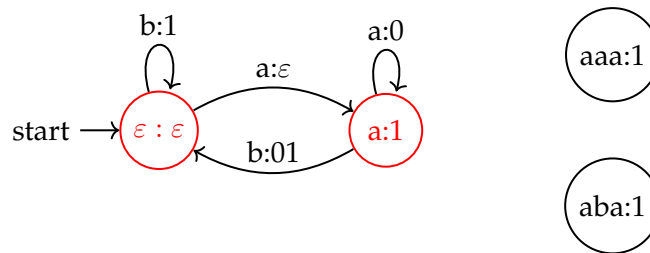
Step V. After the state q_b is eliminated, q_a is the only blue state left. We therefore consider merging q_a into q_ε . However, these two states have different state outputs, and therefore it is impossible. As the result, q_a is re-colored red, and q_{aa} and q_{ab} accessible in one step from q_a are colored blue.



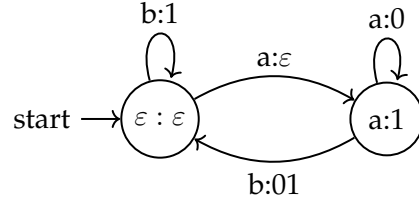
Step VI. We then try to merge q_ε and q_{aa} , but it is not possible since they have different state outputs. States q_a and q_{aa} could be merged because they have the same state output: 1. The outgoing arcs reading a from these two states are different: one outputs 0, and another outputs 01. However, the difference is the suffix 1 that can be pushed further to the state output of q_{aaa} , therefore making those two transitions identical. The arrow incoming to q_{aa} is then re-directed to q_a , and q_{aa} is eliminated from the list of states.



Step VII. The state q_{ab} is then folded into q_ε . The incoming arrow is re-directed to q_ε , and 1 is pushed back to state state output of q_{aba} . Since q_{ab} was merged with another state, it is eliminated from the machine. This leaves no other blue states in the machine, and it signifies that OSTIA completed the inference.



Step VIII. All blue states are now eliminated from the machine. However, the states that were never colored are still present. In SigmaPie, the last step included in the *OSTIA* algorithm is the elimination of the unaccessible states from the machine. After those steps are completed, we obtain the FST visualized below.



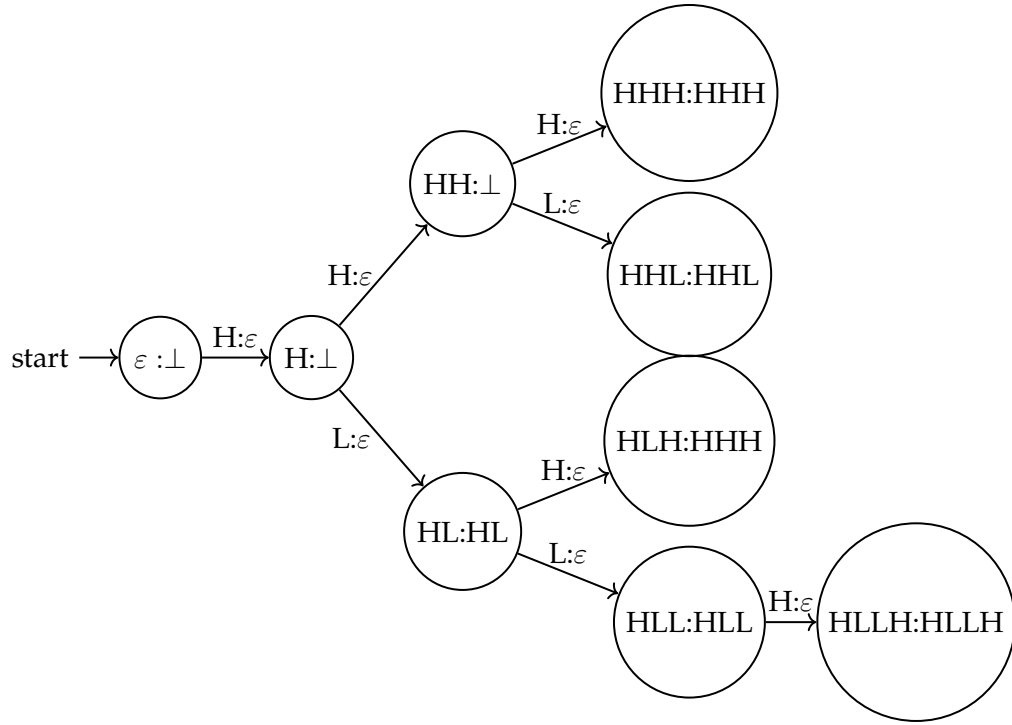
4.1.3 The unsuccessful example

Now, consider a pattern of *unbounded tone plateauing* (UTP). In a pattern like that, a sequence of low tones is converted to high if surrounded by high tones. For example, inputs *HLH* and *HLLH* are mapped to the outputs *HHH* and *HHHHH*, correspondingly. When a low tone *L* follows a high tone, it might be written as either *L* or *H* depending on the presence of another *H* anywhere further in the input. In other words, it requires an *unbounded lookahead*.

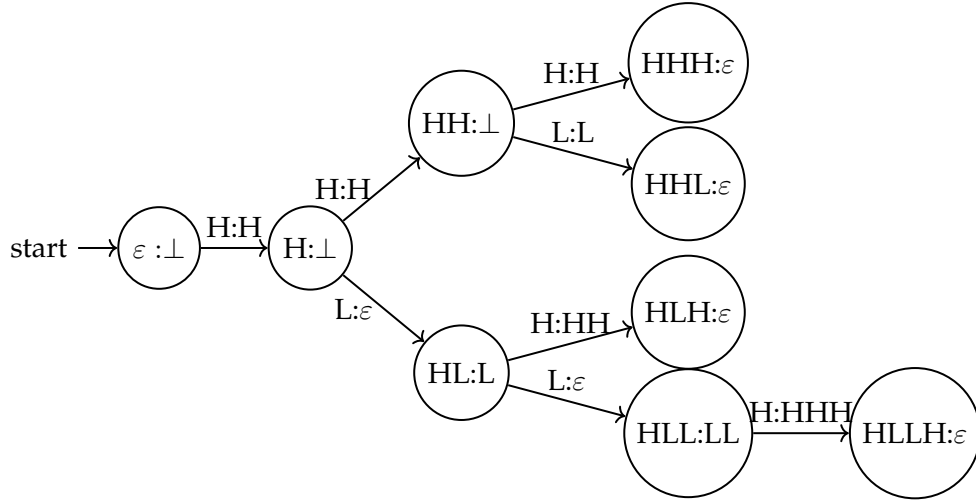
Patterns requiring lookahead, such as UTP, are called *unbounded circumambient processes* since the triggers are located on both sides of the undergoer, and they can be arbitrary far from it. Unbounded circumambient processes are not subsequential (Jardine, 2016a), and therefore it is expected that *OSTIA* is unable to capture UTP. I show that *OSTIA* fails to learn UTP with the following sample.

Sample = [(HHH, HHH), (HHL, HHL), (HL, HL), (HLH, HHH), (HLL, HLL), (HLLH, HHHH)]

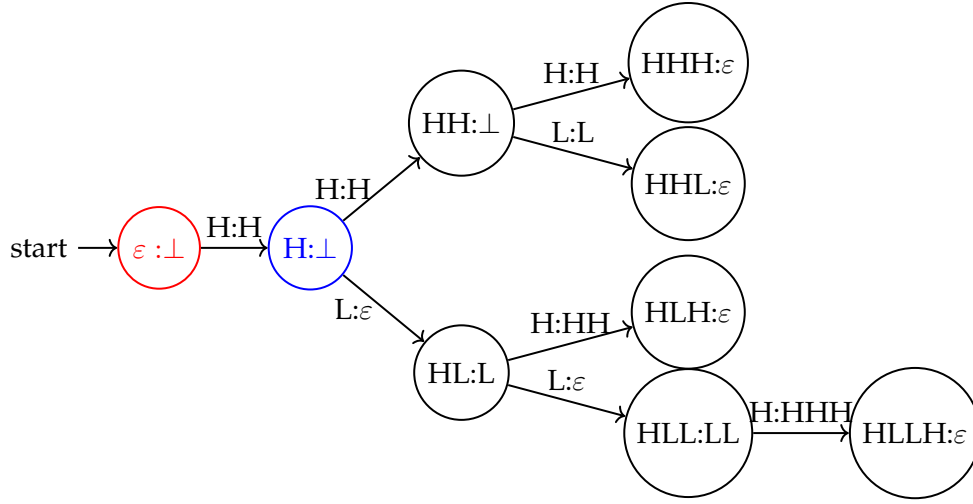
Step I. At first, consider a PTT corresponding to the given training sample *S*.



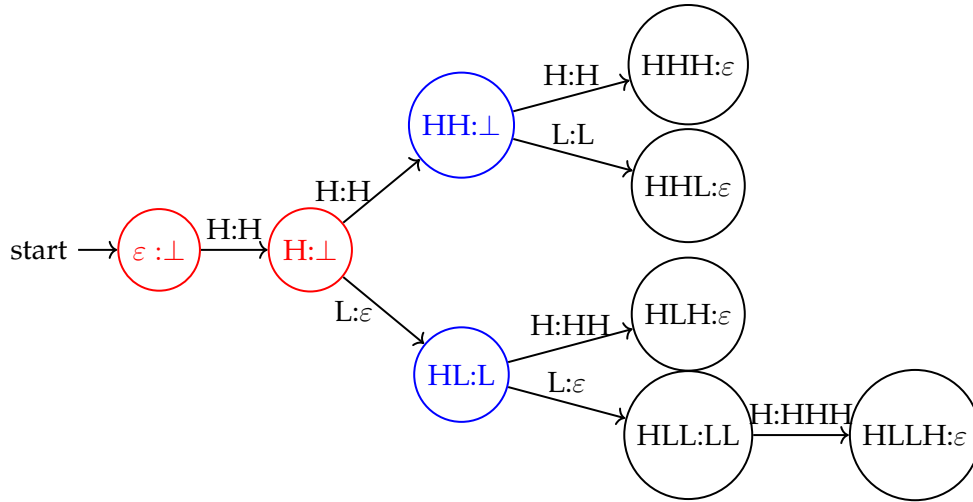
Step II. Then, as previously, let us push the state outputs from the leaf nodes closer to the initial state q_ε . The resulting PTT is onward.



Step III. Next, we prepare to start folding states and sub-trees of the PTT into each other by coloring the states in red and blue. As previously, the initial state q_ε is colored red, and the state q_H available from q_ε in one step is colored blue.

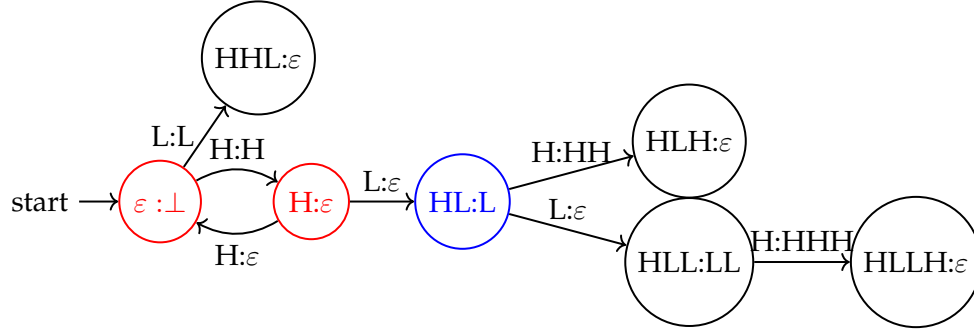


Step IV. The algorithm attempts to merge the blue state into the red state. However, it is not possible to fold the sub-tree of q_H into q_ε . It would cause the arrow $q_{HH} \xrightarrow{L:L} q_{HHL}$ to be changed to $q_\varepsilon \xrightarrow{L:L} q_{HHL}$. It means that states q_{HHL} and q_{HL} need to be merged since both of them would be available from q_ε by reading L , but it is not possible because the state outputs of q_{HHL} and q_{HL} are different: ε and L , correspondingly. Therefore the merge is rejected, and q_H is colored red. Its daughter nodes q_{HH} and q_{HL} are now blue.

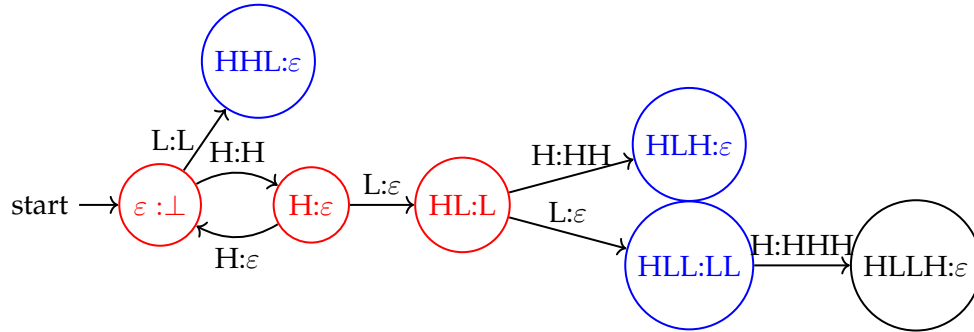


Step V. The state q_{HH} can be merged with q_ε . Indeed, the outgoing arcs reading and writing H are present in both of these states, and the outgoing arc from q_{HH} to

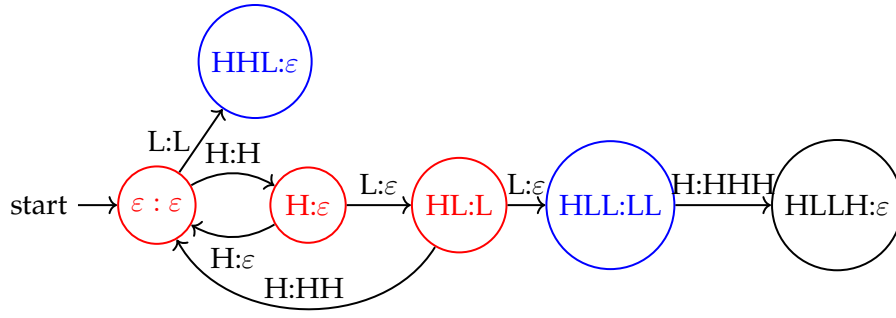
q_{HHL} is now re-directed and originates from q_ε . All the incoming arcs into the state q_{HH} are re-directed to target q_ε . It created two outgoing from the state q_ε arrows reading H : $q_\varepsilon \xrightarrow{H:H} q_H$ and $q_\varepsilon \xrightarrow{H:H} q_{HHH}$, so q_{HHH} needed to be folded into q_H . Their state outputs are compatible since they are \perp and ε , therefore, the output of the state q_H was rewritten to ε .



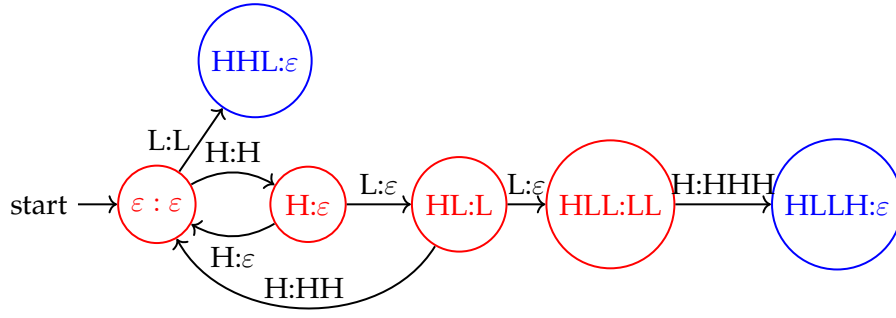
Step VI. The state q_{HL} can be merged with neither q_ε nor q_H because the arrows reading L bring the machine to states with different state outputs. While the state output of q_{HLL} is LL , q_{HL} and q_{HHL} output L and ε , correspondingly. Therefore q_{HL} is colored red, and its children q_{HLH} and q_{HLL} are now blue. Additionally, q_{HHL} is also blue because it originates from the red state q_ε .



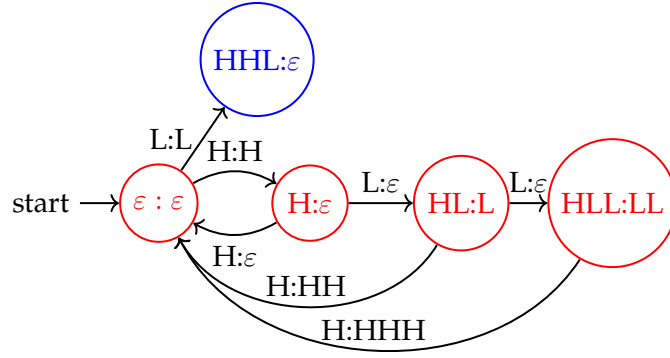
Step VII. The state q_{HLH} is merged with q_ε , and the only arrow incoming in q_{HLH} from q_{HL} is now targeting q_ε . Since the state output of q_{HLH} was ε and the one of q_ε was unknown, it is now re-defined as ε .



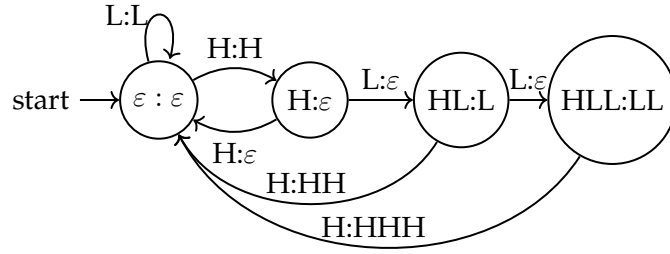
Step VIII. The state q_{HLL} cannot be merged with any red state. Its state output differs from those of all the red states. The state q_{HLL} is thus colored red, and its daughter state q_{HLLH} is blue.



Step IX. The state q_{HLLH} is then merged with q_{ε} , and the arrow incoming in it from the state q_{HLL} is re-directed. At this moment it is already clear that the algorithm failed to learn the UTP pattern. The learner memorized that one or two L need to be substituted by H if they are followed by H , but did not generalize it to an unbounded number of L s.



Step X. Finally, the only remaining state q_{HHL} is merged with q_ϵ , therefore, creating a loop that reads and writes L on that state. There are no other remaining blue states, and therefore the learner outputs the FST.




As one can see, this transducer does not represent the UTP pattern. For example, it would re-write an input string $HLHLH$ as $HHHLH$ by passing through the following states: $q_\epsilon \xrightarrow{H:H} q_H \xrightarrow{L:\epsilon} q_{HL} \xrightarrow{H:HH} q_\epsilon \xrightarrow{L:L} q_\epsilon \xrightarrow{H:H} q_H$. Indeed, UTP cannot be expressed using a subsequential function: it requires an unbounded lookahead (Jardine, 2016a).

4.2 Learning experiments

Here, I discuss the learning experiments that I used to explore the capacities of the OSTIA algorithm. Interestingly, OSTIA performed extremely well (100%) on one or more harmonies without blockers. However, the blocking effect showed itself as

a challenge for the learner: the accuracy was falling drastically with the increasing length of the evaluated strings.

In this chapter, in contrast to the previous one, the learner extracts the “rewrite rules” instead of acquiring well-formedness conditions. Namely, the learner is given a pair of strings imitating the underlying representation (UR) and the surface form (SF), and its goal is to learn how to map one into another. This allows us to explore the capacities of OSTIA when challenged with natural language-like patterns discussed in the previous chapter: single and double harmonic systems with or without blockers, and others. The code behind the experiments is available on GitHub  (Aksénova, 2020d).

Note, however, the critical importance of the concrete implementation for the results of OSTIA. For example, the condition activating pushback is slightly different in various OSTIA’s pseudocodes. Oncina et al. (1993) in the original formulation of OSTIA execute the pushback step depending on the output of q_a transitions being a prefix of the corresponding q_b transitions. The core architecture of their learner, however, is a bit different from the one described in this section since their learner necessarily annotates the data with the end-markers and uses this information for the inference steps. de la Higuera (2010) executes the pushback and folds the states q_a and q_b if all outgoing transitions from those states carry the same output. As one can see, in this case, the pushback step would not be useful: if the outputs of the transitions are identical, there is no disagreeing affix to be pushed further in the FST. In the errata for his book, de la Higuera (2011) changes that condition to depend on the color of the states accessible from q_b . The OSTIA version implemented and used in this chapter has its core architecture following de la Higuera (2010), but the condition is in line with Oncina et al. (1993). There is a multitude of different versions of pseudocodes, and, therefore, even more versions of the possible implementations. Thus the results obtained in this chapter are specific to the

concrete interpretation of the fold and pushback conditions and need to be tested with different perspectives as well.

4.2.1 Experimental setup

As before, the experiments include 3 main steps: *data generation*, *learning*, and *model evaluation*.

At first, the training pairs were generated. For example, assume that we are trying to learn a single vowel harmony without blockers, where vowels are $A = \{a, o\}$, and the only consonant is x that is making this harmony long-distant. The training sample will then contain pairs such as $(xoxxAxAxxxA, xoxxoxxxxo)$ and $(axxAxAxxA, axaxxxa)$, where A refers to an underspecified harmonizing vowel. The left side of every pair contains the “underlying representation”, where only the value of the first vowel is established, and all the consecutive vowels are hidden and represented as the name of their harmonic set, in this case, A . The right side contains the “surface forms”, where all the vowels harmonize with each other. Such training pairs were then fed to OSTIA that outputted an FST representing the pattern.

To evaluate the performance of the obtained FST, following Gildea and Jurafsky (1996), I generated another set of pairs that are used as a testing sample. I provided the left-hand sides of those pairs to the FST as input and observed if the output strings were the same as the right-hand sides of the testing sample.

I used two types of testing samples: one includes strings of the same length as the ones that were used for training, and the second one contains strings that are twice longer than the latter. The test sets containing a longer strings helped me to explore how well OSTIA generalized the target pattern beyond memorization of the concrete shapes found in the training sample.

4.2.2 Target patterns

Among the patterns that I targeted while exploring the capacities of the learner, there were some local patterns such as word-final devoicing, different types of long-distance harmonies, and some circumambient and unattested patterns. Below I explain the parameters that I considered when choosing the learning experiments, see the summary in figure 4.1.

Long-distance The difference between local and long-distance processes is one of the very important distinctions for phonology. In the first case, the process is locally bounded, whereas, in the second one, it involves a potentially unbounded amount of the intervening material. As I show in chapter 3, this difference is crucial for strictly local models. They can evaluate local dependencies, but cannot capture long-distant ones. As an example of a purely local process, I use the phenomenon of word-final devoicing.

Includes blockers The blocking effect is widely discussed in the phonological literature. Harmony systems with and without blockers cannot always be modeled in the same way. For example, in chapter 3, I show that strictly piecewise models can express multiple well-formedness conditions, but they cannot capture even simple cases of blocking effects. In the sample of explored datasets, 3 out of the 7 employed harmonies involve blockers.

Multiple processes A model cannot always handle multiple processes at the same time. For example, a single tier-based strictly local grammar can express a vowel or a consonant harmony, but it cannot capture both of them at the same time. There are a total of 4 harmonies that involve several harmonic spreadings, and 2 of them exhibit a blocking effect.

Different undergoers Some models can express several spreadings at once if all the harmonizing features are spread among the same sets of elements. For example, the only case when a tier-based strictly local grammar can capture the agreement in two features is when both features are affecting vowels. Therefore, 2 of the explored datasets present this type of a harmonic system, with and without a blocking effect.

Unbounded lookahead In Subsection 4.1.3, I showed that processes that require an unbounded lookahead are not subsequential, and therefore cannot be learned by OSTIA. Therefore, I use 2 automatically generated datasets that exhibit circumambient patterns, and show that they cannot be learned by a subsequential learner.

Typologically attested Finally, I explore both typologically attested and unattested patterns. All types of harmonic processes are indeed attested in natural languages, as well as the unbounded tone plateauing. As an example of a typologically unattested pattern, I use the first-last harmony enforcing the agreement among the initial and the final vowels. Two datasets are exhibiting the first-last harmony: one of them includes an unbounded lookahead, and the other one does not.

4.2.3 Experiment 1: word-final devoicing

The rule of word-final devoicing prohibits underlyingly voiced obstruents from being voiced at the end of the word. So, for example, in German, word-final /b/, /d/, and /g/ are realized as [p], [t], and [k] (Brockhaus, 1995). While the word for ‘children’ is *Kinder*, its singular form is *Kin[t]*, i.e. the underlyingly voiced segment is voiceless at the end of the word.

Encoding As previously in Chapter 3, I used 3 elements to encode this pattern: *b* corresponding to voiced obstruents, *p* to their voiceless counterparts, and *a*

long-distant	includes blockers	multiple processes	different undergoers	unbounded lookahead	typologically attested
<i>word-final devoicing</i>					
×	×	×	×	×	✓
<i>a single vowel harmony without blocking</i>					
✓	×	×	×	×	✓
<i>a single vowel harmony with blocking</i>					
✓	✓	×	×	×	✓
<i>several vowel harmonies without blocking</i>					
✓	×	✓	×	×	✓
<i>several vowel harmonies with blocking</i>					
✓	✓	✓	×	×	✓
<i>vowel harmony and consonant harmony without blocking</i>					
✓	×	✓	✓	×	✓
<i>vowel harmony and consonant harmony with blocking</i>					
✓	✓	✓	✓	×	✓
<i>unbounded tone plateauing</i>					
✓	×	×	×	✓	✓
<i>simple first-last harmony</i>					
✓	×	×	×	×	×
<i>complex first-last harmony</i>					
✓	×	×	×	✓	×

Table 4.1: Parameters of the explored natural language patterns.

standing for any other sound. Like this, I generated pairs such as (*apab*, *apap*), (*aba*, *aba*) and (*app*, *app*), where every *b* of the first word of the pair is rewritten as *p* in the second one.

Results I produced 1,500 pairs exhibiting word-final devoicing and used them to build an FST using OSTIA. The obtained FST performed excellently on both testing samples. The first testing sample contained strings 1 to 5 characters long, similar to the training sample. The second testing sample contained longer strings, namely 5 to 10 characters. The perfect score of the FST on both tests signifies that it correctly

acquired the pattern.

Pattern:	word-final devoicing
Training sample (info):	1500 pairs, 1 to 5 characters long
Testing sample 1 (info):	1000 pairs, 1 to 5 characters long
Testing 1, accuracy:	100%
Testing 1, predictions:	('apaap', 'apaap'), ('bpaab', 'bpaap'), ('abppp', 'abppp'), ...
Testing sample 2 (info):	1000 pairs, 5 to 10 characters long
Testing 2, accuracy:	100%
Testing 2, predictions:	('pappbab', 'pappbap'), ('aapppbapbb', 'aapppbapbp'), ...
Number of states:	2
Number of transitions:	5

Table 4.2: Results of OSTIA learning word-final devoicing.

The FST outputted by OSTIA is fully interpretable. It has 2 states and 5 transitions in-between them. In such a machine, the first state corresponds to the state of not observing b , and the second state to keeping b in memory. If a or p follow the memorized b , that b is outputted together with a or p . If another b follows a b , only one b is written. If b is a final character of the input sequence, p is written instead by the state output of q_b . The obtained machine exactly corresponds to the target generalization, see Figure 4.4.

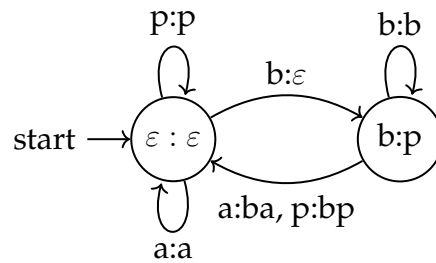


Figure 4.4: FST for word-final devoicing obtained by OSTIA.

4.2.4 Experiment 2: a single vowel harmony without blocking

The next challenge for OSTIA is to learn a pattern of a single vowel harmony without blocking. For example, in Finnish, vowels harmonize in fronting. Let us generalize a harmonic system where a single feature is spread without the possibility of being blocked.

Encoding Such a pattern can be generalized to a system where among vowels $A = \{a, o\}$, either o or a can occur in a surface representation, but not both. We can then refer to the underspecified vowel of the underlying representation as A . In order to make the spreading long-distant, x encodes the transparent element. This encoding defines pairs such as $(axAxxAAxx, axaxxaaxx)$ and $(xxoxxAxAxx, xxoxxoxoxx)$.

Results OSTIA induces the FST that correctly generalizes the pattern, therefore, scoring 100% on both testing samples. The inferred FST has 4 states and 14 transitions in-between them. It is depicted in Figure 4.5: note, that this machine is not minimal, i.e. there are states that do not express any information significant for the rule of harmony. For example, q_x and q_{xx} only keep track of one or two x . After a was observed and written in the translation, the machine moves to the state q_a and any A from the input side is written as a on the output side. Instead, observing o keeps the FST in the initial state q_e , and any following A is then re-written as o . Such an FST, although not minimal, correctly captures the intended harmonic system.

4.2.5 Experiment 3: a single vowel harmony with blocking

While the previous experiment explores the performance of OSTIA on a dataset exhibiting no blocking effect, this one adds it to the picture. In this case, while vowels within a word need to agree with respect to a certain feature, a blocker stops the spreading and only allows for its particular value after itself.

Pattern:	a single vowel harmony without blocking
Training sample (info):	5000 pairs, 1 to 10 characters long
Testing sample 1 (info):	1000 pairs, 1 to 10 characters long
Testing 1, accuracy:	100%
Testing 1, predictions:	('oAxxxAxxx', 'ooxxxoxxx'), ('xxaAxxAAxA', 'xxaaxxaaxa'), ...
Testing sample 2 (info):	1000 pairs, 15 to 20 characters long
Testing 2, accuracy:	100%
Testing 2, predictions:	('oAxAxaxxAxxxAxAAxA', 'ooxooxxooxxxoxooxo'), ...
Number of states:	4
Number of transitions:	14

Table 4.3: Results of OSTIA learning a single vowel harmony without blocking.

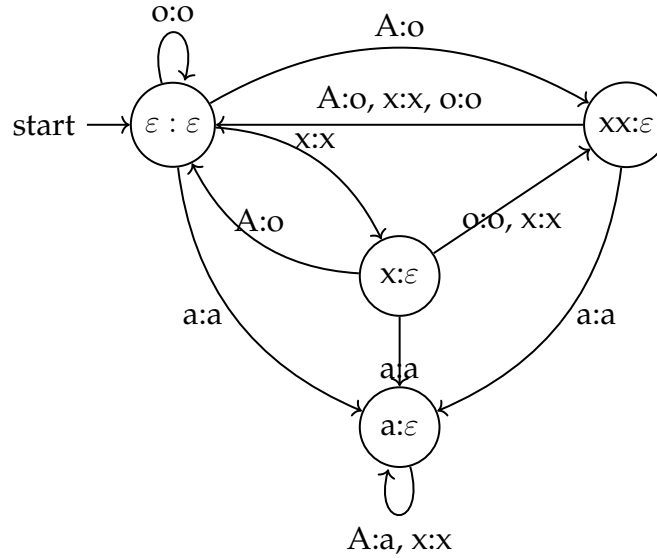


Figure 4.5: FST for a single vowel harmony without blocking obtained by OSTIA.

Encoding This pattern can be encoded as earlier, by using a class of vowels $A = \{a, o\}$, but now only a can be observed after the blocker f . As before, x stands for a transparent element. This defines pairs such as $(oxAA, oxoo)$, $(xaxxAxxA, xaxxaxxa)$ and $(xoxxAxfxxAx, xoxxoxfxxax)$.

Results In this case, the performance of the learner was not perfect. Namely, if faced with a testing sample where the length of the words is 1 to 10 characters, it performs with the accuracy of 99.2%. While mostly predicting the correct forms, for example, it rewrites the underlying form *oxAxAA* as *oxoxoof*, incorrectly adding two extra characters to the end of the word. The accuracy falls when the length of the testing sample is increased to 15-20 characters: it only predicts 91.2% of the correct transformations.

Pattern:	a single vowel harmony with blocking
Training sample (info):	5000 pairs, 1 to 10 characters long
Testing sample 1 (info):	1000 pairs, 1 to 10 characters long
Testing 1, accuracy:	99.2%
Testing 1, predictions:	('oxAxAA', 'oxoxoof'), ('xfxxaxAAx', 'xfxxaxaax'), ...
Testing sample 2 (info):	1000 pairs, 15 to 20 characters long
Testing 2, accuracy:	91.2%
Testing 2, predictions:	('xxxoxfAxxxffxAxxx', 'xxxoxfxxaaxxxffxaxxx'), ...
Number of states:	74
Number of transitions:	247

Table 4.4: Results of OSTIA learning a single vowel harmony with blocking.

The obtained machine is not correct since some of the surface forms that it predicts are wrong. However, the machine encoding the target generalization can be represented as a simple FST with 3 states, see Figure 4.6 for the expected result. It raises a question of what obstructed the inference of that machine, and why it happened in any consecutive experiment targeting a harmonic system involving a blocking effect. I leave this issue aside for now, and come back to it further in the very end of Section 4.2.13.

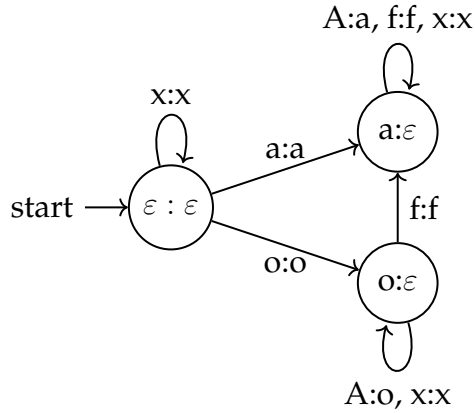


Figure 4.6: The expected FST for a single vowel harmony with blocking.

4.2.6 Experiment 4: several vowel harmonies without blocking

While the previous two experiments modeled spreadings of a single feature, this experiment targets the agreement in several features. For example, in Kyrgyz, vowels agree in backness and rounding. Abstractly, these features can be referred to as $[\alpha]$ and $[\beta]$. Thus all possible stems can be of 4 different types $[-\alpha, -\beta]$, $[-\alpha, +\beta]$, $[+\alpha, -\beta]$, and $[+\alpha, +\beta]$.

Encoding Now, let us assume that the class of vowels includes 4 elements $A = \{a, e, o, u\}$. Every one of these options encodes a possible type of vowel in a well-formed surface form. As previously, x is a transparent element. Such encoding defines pairs $(xxoxxAx, xxoxxoox)$ and $(xxxaxAxxx, xxxaxaxxx)$, among others.

Results Although the inferred machine is large (37 states and 90 transitions), it performs perfectly on both testing samples. In both cases, none of the forms predicted by the FST were disharmonic.

Interestingly, the learned machine has 37 states, whereas smaller versions can easily be constructed, see Figure 4.7. It requires additional investigation to understand the conditions that were not satisfied during OSTIA execution,

Pattern:	several vowel harmonies without blocking
Training sample (info):	5000 pairs, 1 to 10 characters long
Testing sample 1 (info):	1000 pairs, 1 to 10 characters long
Testing 1, accuracy:	100%
Testing 1, predictions:	('xxoxxAAxAx', 'xxoxxooxox'), ('xxxexAxxA', 'xxxexexxe'), ...
Testing sample 2 (info):	1000 pairs, 15 to 20 characters long
Testing 2, accuracy:	100%
Testing 2, predictions:	('xXoAxxxAAxxAxxxAAx', 'xXoOxxxOoxxOxxxOoX'), ...
Number of states:	37
Number of transitions:	90

Table 4.5: Results of OSTIA learning several vowel harmonies without blocking.

therefore, yielding the machine with a greater number of states than possible.

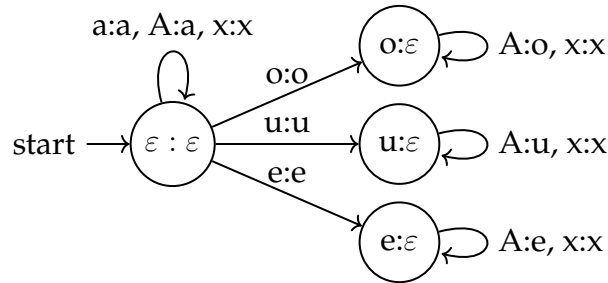


Figure 4.7: The expected FST for several vowel harmonies without blocking.

4.2.7 Experiment 5: several vowel harmonies with blocking

The next task included learning Turkish vowel harmony. It enforces vowels to agree in backness and rounding. While all vowels within a word agree in backness, only high vowels acquire the rounding value of a previous vowel. For example, the word *son-lar-ın* ‘end-PL-GEN’ exemplifies that a non-high vowel from the plural suffix cannot acquire a rounding feature from the previous vowel, and therefore

cannot transmit it to the following high vowel. However, in *son-un* ‘end-GEN’, the high vowel is realized rounded because it is preceded by a rounded vowel. In both words, all vowels agree in backness. In such a system, non-high vowels have a double nature: they are undergoers for the backness harmony, however, behave as blockers for the rounding one.

Encoding In the abstract representation of this pattern, it is impossible to use fewer vowels than already employed by Turkish. This harmony depends on 3 features (backness, rounding, and height), and therefore the minimum amount of vowels to encode it is $2^3 = 8$. Now, there are two classes of underspecified vowels in the URs of the strings: high (*H*) and low (*L*). The training pairs look like (*uxHxLxxLLxxHxxL*, *uxuxaxxaaxxuuxxa*): the initial underspecified vowel is high, and therefore it agrees in rounding with a previous back rounded vowel, becoming *u*. The next underspecified vowel is low and therefore is realized as unrounded *a*. After several other low vowels, another high one follows, but it is not rounded (*u*) since it follows a non-round vowel. Similarly to the earlier experiments, *x* is transparent and makes this harmony long-distant. The rules below summarize how exactly the underspecified segments *H* and *L* are realized in the SFs.

$$L = \left\{ \begin{array}{l} \text{'a' if the previous vowel is 'o', 'u', 'a' or 'u'} \\ \text{'e' if the previous vowel is 'ö', 'ü', 'e' or 'i'} \end{array} \right\}$$

$$H = \left\{ \begin{array}{l} \text{'ö' if the previous vowel is 'a' or 'u'} \\ \text{'a' if the previous vowel is 'e' or 'i'} \\ \text{'o' if the previous vowel is 'o' or 'u'} \\ \text{'e' if the previous vowel is 'ö' or 'ü'} \end{array} \right\}$$

Results Given the data sample of 5,000 words 1 to 10 characters long, OSTIA did not learn this harmonic pattern completely. When evaluated using the test

Pattern:	several vowel harmonies with blocking
Training sample (info):	5000 pairs, 1 to 10 characters long
Testing sample 1 (info):	1000 pairs, 1 to 10 characters long
Testing 1, accuracy:	97.9%
Testing 1, predictions:	(<i>'exLxHxL', 'exexixe'</i>), (<i>'xüxxLxHxxL', 'xüxxexüxxe'</i>), ...
Testing sample 2 (info):	1000 pairs, 15 to 20 characters long
Testing 2, accuracy:	87%
Testing 2, predictions:	(<i>'uxHxLxxLLxxHxxL', 'uxuxaxxaaxxuxxa'</i>), ...
Number of states:	107
Number of transitions:	318

Table 4.6: Results of OSTIA learning several vowel harmonies with blocking.

data of the same length as the one in the training sample, 97.9% of the predicted surface forms were as expected. On a test sample with longer words, the accuracy decreased to 87%. Such a model consistently makes incorrect predictions such as (*uxHxLxxLLxxHxxL*, *uxuxaxxaaxxuxxa*), where a rounded high vowel *u* occurs after a non-rounded low vowel *a*, instead of the expected high vowel *ü*. Interestingly, the performance of the algorithm did not increase significantly with the increased size of the training sample.

4.2.8 Experiment 6: vowel and consonant harmonies without blocking

Now, let us consider two simultaneous yet independent harmonies. A frequent case is when there are two classes of harmonizing elements: consonants and vowels. Such a pattern is attested in several Bantu languages (Kikongo, Kiyaka, Bukusu a.o.).

Encoding Let us assume that vowels agree in $[\alpha]$, and consonants agree in $[\beta]$. Such system would need at least 2 vowels and 2 consonants: $A = \{a, o\}$ and $B = \{b, p\}$. Note that a special transparent element is not necessary since the presence of vowels makes the consonant harmony long-distant, and vice versa. This encoding defines pairs such as $(aApBAA, aappaa)$ and $(boABBABA, boobbobo)$, where in URs, every non-initial value of consonants and vowels is hidden under the name of the corresponding harmonic set.

Results The learner easily inferred the simultaneous vowel and consonant harmonies and scored 100% on both tests. The FST has 4 states and 16 transitions in-between them. Notice, that so far, the performance of OSTIA is 100% in every case when harmony does not include the blocking effect since it also performed extremely well on a single or double vowel harmonic systems earlier.

Pattern:	vowel and consonant harmonies without blocking
Training sample (info):	5000 pairs, 1 to 10 characters long
Testing sample 1 (info):	1000 pairs, 1 to 10 characters long
Testing 1, accuracy:	100%
Testing 1, predictions:	('oApBAA', 'ooppoo'), ('boABBABA', 'boobbobo'), ...
Testing sample 2 (info):	1000 pairs, 15 to 20 characters long
Testing 2, accuracy:	100%
Testing 2, predictions:	('opBAABAABBAABBAA', 'oppoopoppoppoopoo'), ...
Number of states:	4
Number of transitions:	16

Table 4.7: Results of OSTIA learning vowel and consonant harmonies without blocking.

The inferred FST is visualized in Figure 4.8. It has 4 states, and every state corresponds to a type of vowel and consonant in a stem. In particular, q_ε

corresponds to stems where the vowel and consonant values are a and p ; q_o corresponds to o and p ; q_b to a and b ; and, finally, q_{ob} encodes stems with o and b .

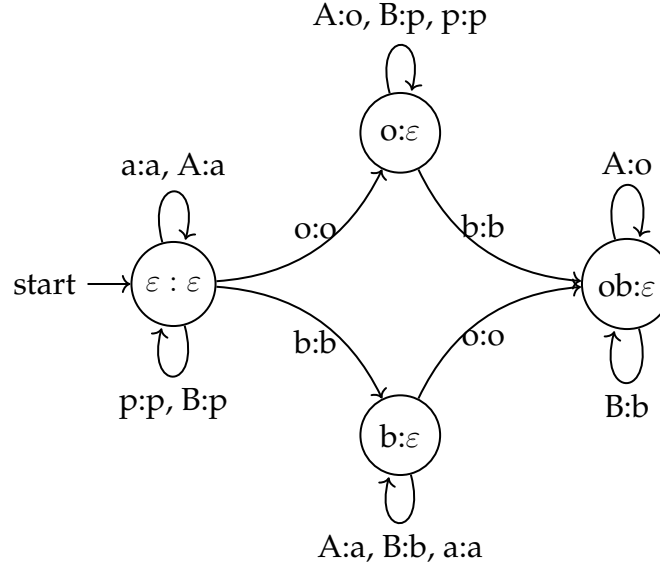


Figure 4.8: FST for vowel and consonant harmonies without blocking obtained by OSTIA.

4.2.9 Experiment 7: vowel and consonant harmonies with blocking

Let us add a blocking effect to the pattern from the previous experiment. Earlier we saw that OSTIA performs extremely well on data exhibiting a harmonic system that does not involve blockers. However, adding a blocking effect in all cases resulted in the obtained FST not scoring 100% on either of the training datasets.

Encoding Let us use the encoding as in the previous experiment, where a stem is able to “pick” one vowel from the set $A = \{a, o\}$ and one consonant from $B = \{b, p\}$. Additionally, I will introduce a blocker t , after which b cannot occur, and needs to be realized as p instead. Along with all pairs that are well-formed for the same pattern

without the blocker, it also introduces pairs such as (*abABAtAABAB*, *ababataapap*), where *B* is rewritten as *b* before the blocker since it inherited its value from the initial consonant *b*, however, *B* is realized as *p* after the blocker *t*.

Results The performance of OSTIA on this dataset is far from perfect. While it scores 96.4% on the testing sample that includes strings of the same length as the training ones, the accuracy falls to 77.4% when the length of the test words is doubled. It goes along with the previous results showing that OSTIA fails to generalize a blocking effect.

Pattern:	vowel and consonant harmonies with blocking
Training sample (info):	5000 pairs, 1 to 10 characters long
Testing sample 1 (info):	1000 pairs, 1 to 10 characters long
Testing 1, accuracy:	96.4%
Testing 1, predictions:	('aApABB', 'aapapp'), ('pBtaA', 'pptaa'), ('tpaBBAtAt', 'tpappatattppa'), ...
Testing sample 2 (info):	1000 pairs, 15 to 20 characters long
Testing 2, accuracy:	77.4%
Testing 2, predictions:	('pBaBABBABttttABABBAB', 'ppapappapttttopoppop'), ...
Number of states:	101
Number of transitions:	406

Table 4.8: Results of OSTIA learning vowel and consonant harmonies with blocking.

4.2.10 Experiment 8: unbounded tone plateauing

Now, consider a circumambient pattern of *unbounded tone plateauing* (UTP). This pattern is observed in some Niger-Congo languages such as Luganda, where all low tones (L) are realized as high (H) if they are surrounded by high tones. As Section 4.1.3 shows, that pattern is not learnable by OSTIA since circumambient dependencies require an unbounded lookahead, and therefore cannot be expressed

as subsequential transducers (Jardine, 2016a).

Encoding This process involves low tones (*L*) changing their value to high (*H*) if they are surrounded by high tones. To encode this pattern, we can simply create pairs where the underlying stretches of *L*s are realized as *H* in the surface forms if surrounded by high tones, such as (*LHHLHH*, *LHHHHH*). In all other cases, the underlying and the surface representations match.

Pattern:	unbounded tone plateauing
Training sample (info):	5000 pairs, 1 to 10 characters long
Testing sample 1 (info):	1000 pairs, 1 to 10 characters long
Testing 1, accuracy:	100%
Testing 1, predictions:	(‘HHHHL’, ‘HHHHL’), (‘LLLHL’, ‘LLLHL’), (‘LHHLHH’, ‘LHHHHH’), ...
Testing sample 2 (info):	1000 pairs, 15 to 20 characters long
Testing 2, accuracy:	94.9%
Testing 2, predictions:	(‘HLLLLLLLLHHLHHH’, ‘HLLLLLLLLHHHHHH’), ...
Number of states:	32
Number of transitions:	64

Table 4.9: Results of OSTIA learning UTP.

Results The obtained FST performs extremely well on the test set where the length of the words is the same as in the training sample. However, the accuracy falls to 94.9% when the length of the test words is doubled. This suggests that instead of capturing the pattern, the resulting machine simply memorized long substrings of tones that can be observed in the input. Indeed, UTP cannot be captured as a subsequential machine.

4.2.11 Experiment 9: a “simple” first-last harmony

Now, let us consider learning a typologically unattested pattern such as *first-last harmony* (Lai, 2015). This pattern enforces agreement among the first and the last

vowels, while nothing else needs to agree. First, let us consider a case when vowels are always the first and last elements of the word.

Encoding The encoding involves vowels a and o , and a transparent element x . In this representation of the pattern, words always start and end with a vowel, therefore the sample pairs look as follows: $(oaoxaa, oaoxao)$, $(axooxa, axooxa)$, etc. If a final vowel of the underlying representation disagrees with the initial vowel, it is rewritten to match the initial vowel.

Results Such a pattern is easily induced by OSTIA. The obtained model scores 100% on both test datasets. The FST is pretty small and therefore interpretable: it has only 5 states and 14 transitions.

Pattern:	a “simple” first-last harmony
Training sample (info):	5000 pairs, 1 to 6 characters long
Testing sample 1 (info):	1000 pairs, 1 to 6 characters long
Testing 1, accuracy:	100%
Testing 1, predictions:	$(\text{'oaoxaa'}, \text{'oaoxao'})$, $(\text{'axooxa'}, \text{'axooxa'})$, $(\text{'oo'}, \text{'oo'})$, ...
Testing sample 2 (info):	1000 pairs, 10 to 15 characters long
Testing 2, accuracy:	100%
Testing 2, predictions:	$(\text{'aoaxoaaaoaaaoxaa'}, \text{'aoaxoaaaoaaaoxaa'})$, ...
Number of states:	5
Number of transitions:	14

Table 4.10: Results of OSTIA learning a “simple” first-last harmony.

This FST is visualized below. After starting to process the input string in q_ε , it moves to either q_a or q_o depending on the first vowel that it reads. States q_o and q_{ao} handle strings that start and end with o ; similarly, the agreement within words that start with a is enforced by states q_a and q_{oa} . Note the similarity of these two

branches with the way the word-final devoicing was encoded earlier in FST 4.4. While the disagreeing vowel is deleted from the transitions incoming to the states q_{oa} and q_{ao} , that vowel is returned if it is not final. If that vowel was, in fact, the last element of the input word, the other, “agreeing” vowel is written instead by the corresponding state output.

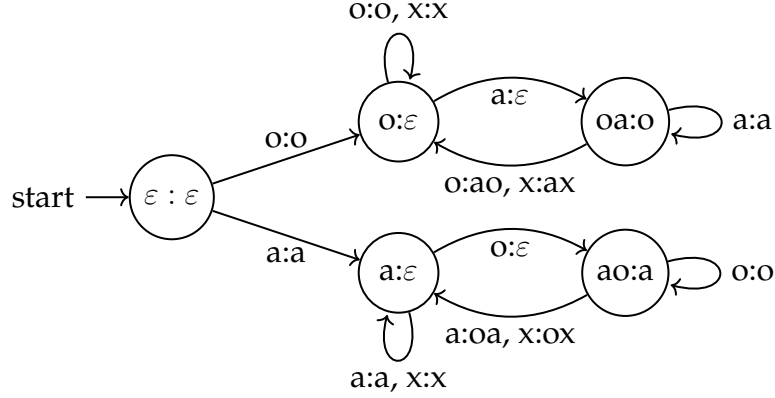


Figure 4.9: FST for a “simple” first-last harmony obtained by OSTIA.

4.2.12 Experiment 10: a “complex” first-last harmony

The previous experiment targeted a pattern of the first-last harmony, where all words started and ended with a vowel. Indeed, OSTIA learned that pattern with the accuracy of 100%. Now, let us challenge the learner with a more complicated version of this rule: in this case, words are also able to start and end with a transparent element, however, the first vowel of the word still agrees with the final vowel.

Encoding The training sample, apart from including everything possible for the previous experiment, also includes pairs where the forms have a sequence of initial or final x . So, for example, pairs such as $(xxoxoaooaxx, xxoxoaooxx)$ and $(axxoxoxxx, axxoxaxxx)$ are added to the training sample. Now, not all input-output pairs begin

and end with a vowel.


Results The performance of OSTIA is not perfect on either of the tests. The score is 98.6% on the test set that includes strings of the same length as the training sample, while it falls to 28.1% on a test set that includes longer words. While OSTIA learned the previous version of this pattern, it failed to generalize a more complicated one. Indeed, this result is expected since this case of first-last harmony requires an unbounded lookahead: there can be an unbounded amount of intervening material between the final vowel and the end of the word. Patterns like this are not subsequential.

Pattern:	“complex” first-last harmony
Training sample (info):	5000 pairs, 1 to 12 characters long
Testing sample 1 (info):	1000 pairs, 10 to 29 characters long
Testing 1, accuracy:	98.6%
Testing 1, predictions:	(‘oxaxooxx’, ‘oxaxoo xxaxx ’), (‘xxaoxxaaxx’, ‘xxaoxxa xx ’). ...
Testing sample 2 (info):	1000 pairs, 15 to 20 characters long
Testing 2, accuracy:	28.1%
Testing 2, predictions:	(‘ooxaxoxoo xxxxxx ’, ‘ooxaxoxoo x ’), ...
Number of states:	79
Number of transitions:	235

Table 4.11: Results of OSTIA learning a “complex” first-last harmony.

4.2.13 Summary of the results

Here, I explored automatic extraction of different types of harmonic or other assimilation processes, both attested and non-attested in natural languages. These patterns were word-final devoicing, single and several vowel harmonies with and without blocking, independent vowel and consonant harmonies, unbounded tone

plateauing, and different kinds of first-last harmony. I discuss how to learn the mappings representing the listed above phenomena automatically, namely, using the OSTIA algorithm. The training sample then consists of pairs of examples, where the first element of the pair stands for the underlying representation, and the second element is the corresponding surface form. Given such automatically generated sets of examples, I explored if OSTIA is capable of extracting the generalized rule from it. The code of the experiments is available on GitHub  (Aksënova, 2020d).

As the first step, I generated the training data using the extension of the codebase explained in Section 3.1.3. Then, I provided those pairs as a training sample to OSTIA. To test the performance of the learned FST, I generated another set of pairs and provided the left sides of those pairs as input to that FST. The accuracy of the learned model is the percentage of times the FST outputted the same surface form as the right-hand side of the generated test pair. I tested the obtained model on two types of test samples: in the first test sample, the strings are of the same length as in the training sample, and in the second one, they are approximately twice as long. The first test sample evaluates the “baseline” performance of the learned models, while the second one uses longer strings to see how well the pattern was generalized.

Table 4.12 provides a summary of the results discussed in this section. The first column describes the results of testing on the same-length testsets, while the second one summarizes the performance of the models on the strings that are approximately twice longer. Out of 10 experiments, OSTIA generalized 5 patterns extremely well, so its performance is 100% on both test sets. These experiments were word-final devoicing, single and several vowel harmonies, independent vowel and consonant harmony, and a “simple” version of the first-last harmony. Interestingly, none of the successful experiments included a pattern with a blocking effect. In fact, on the datasets with blocking, OSTIA performed

Experiments	$ \mathbf{W}_{\text{train}} = \mathbf{W}_{\text{test}} $	$ \mathbf{W}_{\text{train}} = 2 \times \mathbf{W}_{\text{test}} $
E1: word-final devoicing	100%	100%
E2: a single vowel harmony without blocking	100%	100%
E3: a single vowel harmony with blocking	99.2%	91.2%
E4: several vowel harmonies without blocking	100%	100%
E5: several vowel harmonies with blocking	97.9%	87%
E6: vowel and consonant harmonies without blocking	100%	100%
E7: vowel and consonant harmonies with blocking	96.4%	77.4%
E8: unbounded tone plateauing	100%	94.9%
E9: “simple” first-last harmony	100%	100%
E10: “complex” first-last harmony	98.6%	28.1%

Table 4.12: Results of the learning experiments using OSTIA.

significantly worse, scoring 91.2%, 87%, and 77.4% during the evaluations that used longer words. Unbounded circumambient processes are not subsequential (Jardine, 2016a), so OSTIA expectedly did not learn UTP. Finally, the “complex” version of first-last harmony is also beyond the capacities of this learner because it requires an unbounded lookahead: only 28.1% of the predicted transformations are indeed correct.

The current implementation of OSTIA cannot capture the blocking effect, as the experiments 3, 5 and 7 show. Theoretically, this can be caused by 3 different reasons: the inability of the algorithm to learn the blocking effect, the absence of the crucially important data points, and the inability of the current implementation of the algorithm to learn the blocking effect. The algorithm behind OSTIA is proven to be correct by Oncina et al. (1993). The average error was not decreasing with the increased number of the training examples, and that shows that the problem is not rooted in the absence of some pairs of examples. It only leaves one source of the issue, namely, the concrete implementation of the algorithm. Indeed, as I discuss in the beginning of Section 4.2, different

pseudocodes of OSTIA have different conditions behind the activation of the pushback module. In future work, re-implementing OSTIA with different versions of that condition is necessary to find the concrete implementation that can learn the full class of subsequential functions in practice².

4.3 Beyond OSTIA

So far, I presented OSTIA as the only way to learn mappings. Alternatively, one might want to either specify OSTIA given some concrete assumptions or to use other transduction learners. OSTIA learns *total* functions, i.e. functions that are defined for all possible values of their input. However, natural language input to output mappings are not total: not all inputs can be mapped to their output counterparts because some forms simply do not exist. This results in the learner never having a chance to satisfy a certain condition, and therefore it might not converge on the target FST. Learners can be redefined with respect to the natural language restrictions in ways that use negative data, require a deterministic finite-state acceptor (DFA) corresponding to the input or output, or define different types of locality. In this section, I discuss available extensions of OSTIA (OSTIA-D/R, OSTIA-N), other learning algorithms (SOSFIA, ISLFLA, OSLFIA), and propose some ideas for further learners. To the best of my knowledge, the performance of other transduction learners on different datasets was not explored as of now, and it would be an interesting project to be carried out in future.

²For example, one can attempt the pushback and fold of the states q_a and a_b if the outputs of the transitions with the same input symbol originating in those states have a non-empty common prefix. Preliminary results show that OSTIA implementing this condition is capable of learning the blocking effect; however, it does not perform well on local processes.

4.3.1 Specifying OSTIA

Earlier in this chapter, I discussed the main version of the OSTIA algorithm: it builds a prefix tree using the input sides of the training sample, and then folds some states one into another, therefore generalizing the pattern. However, the FST extraction can be greatly simplified by providing some extra information about the shape of the input or output strings, as it is done in OSTIA-D, OSTIA-R, and OSTIA-DR, or by giving a sample of negative strings, as in OSTIA-N.

A transducer encodes a mapping. But in some cases, this mapping is not defined for *any* input string, but rather for a subset of the possible strings. If the constraints on the input are available a priori, one might use a form of OSTIA that encodes **Domain** knowledge, or OSTIA-D (Oncina and Varó, 1996). It takes as input not only the training sample but also the DFA describing the language of the input strings. If that information is available for the output strings of the intended mapping, then the **Range** is defined a priori. OSTIA-R requires a DFA describing the output language (Castellanos et al., 1998). Consequently, OSTIA-DR takes advantage of both domain and range DFAs (Oncina and Varó, 1996).

As another type of prior knowledge, OSTIA-N uses the **Negative** data (Oncina and Varó, 1996). Such a learner is given a set of well-formed pairs, as well as a set of input strings that should *not* be translated by the learned machine. While merging the states, OSTIA-N checks that none of the prohibited inputs obtained a translation.

4.3.2 Fixing outputs of some input symbols

We might have information about some of the outputs. Namely, the outputs of some input symbols can be fixed thus accelerating the convergence if the learner explores all possible options. For example, assume observing a pair (*sim*, *seen*) in the training sample. Based on exclusively this pair, we can construct a total of 35

prefix tree-shaped FSTs with different output values of input symbols s , i and m , see some of the machines in 4.10. Some of these FSTs output the translation *seen* as soon as they read s , some of them distribute the string among different transitions, some of them only have this string as the state output of q_{sim} , and so on.

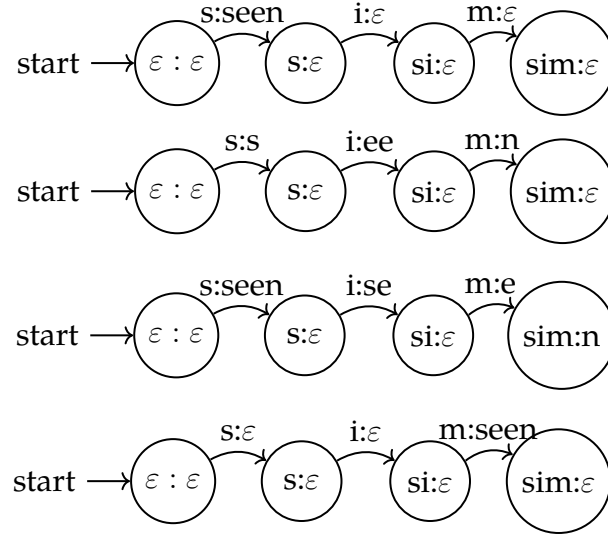



Figure 4.10: Some of the FSTs that can be built from the pair $(sim, seen)$ in the “unbiased” way; to be contrasted with the following figure.

However, if it is known in advance that some of the outputs can be fixed, the number of such 4-state FSTs processing $(sim, seen)$ decreases significantly. For example, if the output of the input symbol s is fixed to s , only 10 machines are possible. In all of them, a transition $q_\epsilon \xrightarrow{s:s} q_s$ is fixed to only read and output s . The number of possible machines then decreases to 10, see Figure 4.11.

Instead, if we fix the output of the symbol i to ee , there will be only 2 possible machines that employ 4 states. The output of s would be s in both cases, but the way of obtaining n in the translation will differ: in one case, its source is the transition $q_{si} \xrightarrow{m:n} q_{sim}$, and in another case, it is the state output of q_{sim} that yields n .

See the implementation of OSTIA with the possibility of fixing outputs of some input symbols on GitHub  (Aksénova, 2020e). However, this solution is

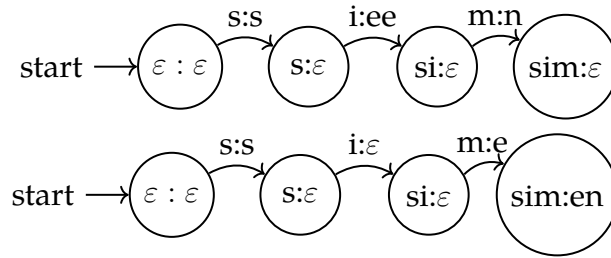


Figure 4.11: Some of the FSTs that can be built from the pair (*sim*, *seen*) if the output of the input symbol *s* is fixed to the output symbol *s*.

not applicable if there are processes happening across the “fixed” symbol. If a metathesis occurs across some segment the output of which is fixed, extraction of this pattern becomes tricky. For example, in an Austronesian language Hawu, some vowels undergo metathesis across a consonant (Blust, 2012). In this case, fixing the output of that consonant will make it more complicated for the learner to discover the pattern.

4.3.3 Other transduction learners

In this chapter, I only discussed the learning results obtained by conducting toy learning experiments using OSTIA. However, there are several other subsequential learners available in the literature. One of them presents a different from OSTIA approach to the induction of subsequential transducers from the set of training pairs, and the other two rely on the particular assumptions about the shape of the dependencies encoded in the mapping.

Structured Onward Subsequential Function Inference Algorithm (SOSFIA) proposed by Jardine et al. (2014) assumes the existence of the k -local DFA that helps to navigate through the input sides of the training pairs. The learner then induces a subsequential function that reads the input strings one-by-one and outputs their translations. The obtained FST is onward, i.e. at any step, the biggest known part

of the output string is produced.

ISLFLA and OSLFIA encode assumptions about the sources of dependencies. **Input Strictly Local Function Learning Algorithm** (ISLFLA) assumes that the translations only depend on the input string, i.e. there is enough information in the input itself to construct the translation (Chandlee et al., 2014). **Output Strictly Local Function Inference Algorithm** (OSLFIA), on the contrary, considers both the input string and the currently known output prefix as sources of the information for the prediction of the next output symbol (Chandlee et al., 2015). See chapter 2 for the examples of input/output local functions. Both learners require some integer k to be known a priori, and their first step is a constriction of k -local DFA accepting input or output strings.

An enlarged set of experiments needs to be used when exploring SOSFIA, ISLFLA and OSLFIA. The expected result is that SOSFIA will learn all subsequential mappings (word final devoicing, all types of harmonies, and the “simple” case of vowel harmony). However, OSLFIA and ISLFLA cannot learn processes where a potentially unbounded number of segments can intervene in-between two agreeing elements, because such processes are neither ISL nor OSL (Chandlee et al., 2015). It would imply that those two learners only capture the word-final devoicing, and fail on all other experiments, see Figure 4.13. Extending the list of the experiment by different local dependencies, such as metathesis, epenthesis, and deletion, would allow one to explore the practical capabilities of those learning algorithms better.

4.3.4 Learning groups of transducers

Currently, the transduction learners proposed in the literature have a goal of constructing a working generalized transducer based on the finite data sample. Different algorithms perform different strategies of pattern recognition. However, all of them have an assumption that the input sample is sufficiently representative.

Experiments	SOSFIA	OSLFIA	ISLFLA
<i>E1: word-final devoicing</i>	👍*	👍*	👍*
<i>E2: a single vowel harmony without blocking</i>	👍*	✖*	✖*
<i>E3: a single vowel harmony with blocking</i>	👍*	✖*	✖*
<i>E4: several vowel harmonies without blocking</i>	👍*	✖*	✖*
<i>E5: several vowel harmonies with blocking</i>	👍*	✖*	✖*
<i>E6: vowel and consonant harmonies without blocking</i>	👍*	✖*	✖*
<i>E7: vowel and consonant harmonies with blocking</i>	👍*	✖*	✖*
<i>E8: unbounded tone plateauing</i>	✖*	✖*	✖*
<i>E9: “simple” first-last harmony</i>	👍*	✖*	✖*
<i>E10: “complex” first-last harmony</i>	✖*	✖*	✖*

Table 4.13: Predicted results (marked as *) of the learning experiments using SOSFIA, OSLFIA and ISLFLA learning algorithms.

This is a very strong requirement: a fully representative data sample is not always available. For this reason, it is possible to think of an algorithm that instead of extracting a single machine, builds a class of machines that behave equally with respect to the training sample but are non-equivalent otherwise.

For example, consider a learning algorithm for a group of equivalent yet not identical input local FSTs. Such FSTs only rely on the information available in the input to predict the output. A learner could start by taking an input k -local subsequential transducer template with unfilled outputs of the transitions. Then the transducer reads the input strings and saves all substrings of the corresponding translation string in the outputs of the transitions taken to read the input string. If the transition was taken before, the algorithm intersects the set of substrings of the current translation with the set of saved candidates, therefore, leaving only the candidates that are consistent throughout the whole training sample. After the training data is processed, the algorithm builds a set of

transducers based on the obtained guesses for every transition.

For example, when the pair (ab, aab) is provided as the input to the learner, two out of many guesses about the target FST would be either (1) outputting ab if we read b after an a , or (2) a is translated to aa , and b stays intact, see Figure 4.12. However, as soon as the training pair (a, aa) is encountered, the first machine from Figure 4.12 is rejected, leaving the second machine as the applicable candidate.

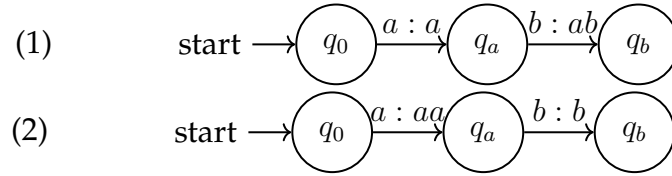



Figure 4.12: Possible guesses of the transition that can be built after observing the pair (ab, aab) .

Similarly to OSTIA-D and SOSFIA, such a learner needs to know a priori the DFA corresponding to the input side of the language. Therefore, assume that we have the input k -local DFA pre-initialized. Every transition q of that DFA corresponds to the set Ω_q , and that set is empty upon the initialization. Then, we read one pair from the training sample. If Ω_q of that transition is empty, we fill every state activated while reading the input string with all the substrings of the right side of the training pair. If Ω_q is not empty, we intersect all substrings of the newly encountered output string with the guesses that those transitions contain. After the whole training sample is processed, we can build all possible transducers based on the remaining guesses in Ω of the transitions. Finally, we can run the input sides of the training pairs through the transducers again to validate that it predicts only correct outputs.

At the moment, the algorithm is implemented  (Aks nova, 2020a), but it has not been extensively tested or optimized yet. Further work on this algorithm includes elaborate presentation of the pseudocode, evaluating its time complexity, improving the implementation, and testing its performance on language data, as

well as presenting the proof of its correctness.

4.4 Learning processes: summary

In this chapter, I discussed the automatic extraction of subsequential finite-state transducers from a sample of input-output pairs. Namely, I summarized the main steps of the OSTIA algorithm, presented two walk-through examples, demonstrated the results of the learning experiments, and proposed ways to go beyond OSTIA's performance.

The learning experiments targeted extraction of natural language-like patterns. The training samples exhibited in simplified ways such typologically attested processes as word-final devoicing, one or multiple harmonies with and without blocking effect, and unbounded tone plateauing. Additionally, OSTIA was presented with a dataset exemplifying the unattested pattern of first-last harmony.

Although the expected results of the learning experiments were mostly confirmed, there were some surprises. Indeed, OSTIA successfully learned the generalization behind word-final devoicing, all harmonies without a blocking effect, and a “simple” version of first-last harmony. Also, expectedly, the generalizations behind tone plateauing and the “complex” version of first-last harmony remained unlearned since they involve an unbounded lookahead, so these patterns are not subsequential. However, if the target pattern exhibited a blocking effect, it significantly decreased the accuracy of OSTIA. Throughout the chapter, I described and sometimes visualized the obtained FSTs, but more research is needed to explain the learning outcomes of some of the experiments.

Several questions remain unanswered. Firstly, it is unclear what makes it impossible for OSTIA to learn even a simple case of harmony with a blocking effect. Interpreting the algorithmic steps and learning outcomes can help to explain such behavior. Second, it is also important to test OSTIA on non-length

preserving processes and other phonological phenomena such as epenthesis, deletion, and metathesis. Finally, there are learners such as ISLFLA and OSLFIA that induce input and output-local functions (Chandlee et al., 2014, 2015), and their performance on natural language patterns needs to be evaluated as well.

In this chapter, I discussed automatic learning subsequential transformations that capture processes that change underlying representations into the corresponding surface forms. This allows encoding various phonological and morphological processes, such as harmony, word-final devoicing, and others. The well-formedness conditions imposed by phonotactics and morphotactics on shapes of the allowed words can be captured by subregular languages, that can also be learned from data, as Chapter 3 shows. The results of these two chapters are preliminary, however, this meant to be a starting point for using tools such as *SigmaPie* to experimentally test theoretical claims. This helps us to explore the ways to create computational models of language, and, in turn, it can give us insights into how languages work.

Chapter 5

Conclusion and future work


The last decade was very fruitful in the field of subregular research. New classes of subregular languages and mappings were uncovered for modeling natural language phenomena, and new learning algorithms were developed for these classes. The subregular approach has been successfully applied to phonotactics (Heinz, 2010a), rewrite processes in phonology and morphology (Chandlee, 2014), and even syntactic constraints over tree structures (Graf, 2018b). However, the rapid pace of the theoretical research has not been matched when it comes to engineering considerations. Many of the proposed learning algorithms have not been implemented, and as a result, their performance on concrete data sets was not known.

My thesis is a first step towards closing this gap. The development of my toolkit *SigmaPie* has made it possible to evaluate subregular proposals over data sets of various degrees of abstractness. The results in Chapters 3 and 4 show that this is a worthwhile enterprise that yields new results that are relevant to computational and theoretical linguists. Issues that may be negligible in theory become much more relevant when dealing with real-world data. For instance, phonological features and natural classes are immaterial for claims about subregular complexity, nor do they affect learning under the idealized assumptions that are commonly made in

the grammatical inference literature. But when learning with realistic data, the inability to generalize across phonologically related sounds can cause the learner to fail unexpectedly, as was the case with the TSL learner 3.4. This is a powerful demonstration of the importance of features and natural classes, two concepts for which linguists were advocating for decades.

That said, the work reported in this thesis is a starting point. *SigmaPie* and the experimental modeling approach I developed in this thesis could be taken in numerous directions to improve the balance between theory and practice in the subregular field. In the last few pages of this thesis, I revisit the findings of the previous chapters, assess their implications for computational and theoretical linguistics, and outline potential future work. The latter might be the most important aspect of this thesis: *SigmaPie* provides a sandbox for tool-assisted subregular research, and there are many different things that can be done in this sandbox. My thesis presented one particular use of *SigmaPie*, but in order to unlock its full potential, the subregular community must keep adding new functionality to it and keep using it to probe the practical ramifications of its theorems and algorithms.

5.1 Summary of the results

My dissertation brings a two-sided approach to the problem of the theory-practice misbalance in subregular research. First, I designed the Python package *SigmaPie* , which includes different subregular learners, scanners, sample generators, and some other functions that support subregular research (Aksënova, 2020b). Building on this package, I then explored the performance of several subregular learning algorithms on datasets that are modeled after widespread linguistic patterns such as word-final devoicing, harmonies of different types, and tone plateauing, among others.

5.1.1 *SigmaPie*

The package *SigmaPie* mostly focuses on subregular languages and grammars, but also includes an implementation of *OSTIA*, a learner for subsequential transducers (Oncina et al., 1993; de la Higuera, 2010). The functionality of the package includes various functions that can be used to simplify the practical work with subregular languages. *Learners* extract subregular grammars from the provided dataset. *Scanners* evaluate the well-formedness of data items with respect to the given grammar. *Sample generators* produces a dataset of the required size that follows the given grammar. *Polarity switchers* convert the grammars from positive to negative, and the other way around. Finally, *FSM constructors* build a finite state machine based on the given grammar. The implemented learning algorithms for strictly piecewise, strictly local, tier-based strictly local, and multi-tier strictly local languages are proposed in (Heinz, 2010b; Jardine and McMullin, 2017; McMullin et al., 2019). All of these aspects of *SigmaPie* played a key role in the design of the experiments for this thesis.

SigmaPie is implemented in Python 3, and uses the copyleft open-source GNU General Public License v3.0. It is available on PyPI and in pip. *SigmaPie* is an ongoing project and, by design, cannot be feature-complete as long as new subregular research keeps being published. Researchers who modify or extend the code for their own projects are highly encouraged to create a pull request in the GitHub repository so that their code can be incorporated into future releases.

5.1.2 Tool-assisted learning experiments: overview

Building on the functionality provided by *SigmaPie*, this dissertation also presented several learning experiments in Chapters 3 and 4. I used several wordlists from natural languages (Finnish, German, Turkish), and I also constructed artificial datasets exhibiting different linguistic patterns, e.g.

word-final devoicing. I then used *SigmaPie* to test whether subregular learning algorithms can extract suitable grammars from these datasets. The experiments conducted were of two types: the first type probed the learning of well-formedness conditions, while the second one explored generalizing the rules of rewrite processes.

The experiments on well-formedness conditions all follow the same procedure. The input consists of lists of words that obey a specific well-formedness condition. For example, if the condition to be tested is vowel harmony, then the training data includes only forms where all vowels agreed in the relevant harmony feature. Alternatively, in the case of the word-final obstruent devoicing, the dataset only includes words that do not end in a voiced obstruent. One of *SigmaPie*'s learning algorithms is then used to infer a grammar from the dataset. This grammar is then fed into *SigmaPie*'s sample generator to produce a set of strings that are well-formed according to the learned grammar. Finally, one of *SigmaPie*'s scanner implementations is used to determine how many of these strings are well-formed with respect to the original grammar. This generate-and-test paradigm is repeated multiple times to calculate an average accuracy score for the learner.

The learning of rewrite rules by the OSTIA algorithm follows a similar paradigm but changes some technical details. Each training sample now consists of pairs of strings, which encode the underlying representation (UR) and the corresponding surface form (SF) that is produced by some rewrite rule. As a toy example, assume that the inventory of vowels only contains *a* and *o*, and that we have a progressive vowel harmony process that requires all vowels to agree in rounding. Valid SFs then include either only *o* vowels or only *a* vowels. The corresponding URs have all the non-initial vowels hidden (for example, represented as *A*), and only the initial vowel is specified as *a* or *o* to trigger the agreement. In such a way, these pairs encode the URs that contain the underspecified elements, and the SFs where those

elements are specified.

Note that the training data can exhibit various degrees of abstractness. Consider the case of word-final obstruent devoicing in German, analyzed as a well-formedness condition rather than a rewrite rule. A realistic dataset would be a finite list of attested German words. A highly abstracted representation, on the other hand, would replace each German word with a string of *as* and *bs* such that *a* represents a voiced obstruent and *b* any sound that is not a voiced obstruent. One important insight of the experiments conducted in Chapter 3 is that the performance of a learning algorithm is not always uniform across these different levels of abstractness. That is because a more abstract representation allows for fewer combinatorial possibilities — with k symbols, there are k^n distinct n -grams, so the larger the value of k , the more n -grams there are. The larger the space of combinatorial options, the more likely it is that the training data will miss a combination. Some subregular learners can easily get led astray by missing combinations, e.g. the TSL learner, and as a result these learners fail to learn some phenomena over realistic data even if they succeed with the highly abstracted data sample. Intuitively, this shows the importance of phonological features and natural classes, which allow the learner to generalize from observed combinations of sounds to other combinations that are missing in the data set.

The results of the learning experiments are summarized in Figure 5.1. According to de la Higuera (2010), the task of grammatical inference algorithms is to *constantly* predict the next correct element. Therefore, an algorithm has not fully learned a pattern as long as it is still making errors, no matter how negligible or rare those errors are. A single mistake means that the algorithm has failed to learn, and successful learning means perfect learning without any mistakes. For this reason, Figure 5.1 provides an abridged overview of the full results that were summarized in Figures 3.58 and 4.12. In this abridged format, a success (👍) indicates that the learner achieved an accuracy of 100%, and anything less than

that is represented as a failure (✖).

Experiments	Well-formedness				Transformations
	SP	SL	TSL	MTSL	OSTIA
<i>E1: word-final devoicing</i>	✖	👍	👍	👍	👍
<i>learning from raw German data</i>	✖	👍	👍	👍	
<i>E2: a single vowel harmony without blocking</i>	👍	✖	👍	👍	👍
<i>learning from raw Finnish data</i>	👍	✖	✖	👍	
<i>E3: a single vowel harmony with blocking</i>	✖	✖	👍	👍	✖
<i>E4: several vowel harmonies without blocking</i>	👍	✖	👍	👍	👍
<i>E5: several vowel harmonies with blocking</i>	✖	✖	👍	👍	✖
<i>learning from raw Turkish data</i>	✖	✖	✖	✖	
<i>E6: vowel and consonant harmonies without blocking</i>	👍	✖	✖	👍	👍
<i>E7: vowel and consonant harmonies with blocking</i>	✖	✖	✖	👍	✖
<i>E8: unbounded tone plateauing</i>	👍	✖	✖		✖
<i>E9: “simple” first-last harmony</i>	✖	✖	✖	✖	👍
<i>E10: “complex” first-last harmony</i>					✖

Table 5.1: Learning results that were experimentally obtained in this dissertation. Black cells indicate that the experiments were not conducted due to the reasons discussed in Section 5.1.5.

While these results largely mirror the theoretical expectations, they do not tell the full story. The experiments for well-formedness conditions as well as the experiments for rewrite rules reveal subtle nuances of the subregular learning approach that deserve closer attention.

5.1.3 Learning well-formedness conditions

The learning of well-formedness conditions focused on four important subregular classes: strictly piecewise (SP), strictly local (SL), tier-based strictly local (TSL), and multi-tier strictly local (MTSL) languages.

SP grammars encode long-distance dependencies that prohibit certain substructures, while the distance between the elements of that substructure, as well as the type of intervening material, plays no role (Heinz and Rogers, 2010; Heinz, 2010b). As a result, SP grammars are ideally suited to long-distance patterns as long as they do not involve blocking. This is reflected in the training data. The SP model achieved an accuracy of 100% on all harmonies that do not exhibit a blocking effect, including the pattern of Finnish harmony learned from raw Finnish data, and even unbounded tone plateauing, which is challenge for other classes such as TSL and MTSL. But the SP learner failed consistently on local processes such as word-final devoicing, and on long-distance processes that involve blocking. Overall, then, the SP learning results are in line with the theoretical expectations.

At the same time, though, the SP learner performed unexpectedly well on some processes it should have failed on. Most notably, it achieved an accuracy of 89% on word-final devoicing. But this should not be construed as a surprising ability of SP grammars to handle local processes over realistic data samples. Thanks to the transparent nature of subregular grammars and learners, we could inspect the learned grammar and see that it does not enforce any kind of word-final devoicing. The high accuracy score is an artefact that arises from the fact that it is very unlikely for a randomly generated string to have any obstruent at the end. If we limited our attention to only strings that end in an obstruent, the performance of the learned SP grammar would be abysmal. We see, then, that accuracy scores can be misleading when considered in a vacuum, and the linguistic transparency of the subregular approach allows us to reliably identify cases where the quantitative results do not match the qualitative facts.

The other classes SL, TSL, and MTSL also provide some interesting insights. SL models only local phenomena and cannot handle long-distance dependencies. This is reflected by learning results, where the SL learner succeeded only on

word-final devoicing, but did so uniformly on all data sets, whether they were realistic or highly abstracted. With SL learning, the previously mentioned issues of combinatorial explosion and data sparsity are much less relevant, at least as long as the n -grams are short.

A TSL grammar captures a single long-distance dependency (Heinz et al., 2011; Jardine and McMullin, 2017). In contrast to SP, it can handle blocking effects, but it fails on some long-distance phenomena such as unbounded tone plateauing. Moreover, if different agreements affect different sets of elements, such as in the case of independent vowel and consonant harmonies, one needs several tiers. This marks the step from TSL to MTSL. Again the learning results largely match theoretical expectations (De Santo and Graf, 2019; McMullin et al., 2019), with two notable exceptions. The first one is the failure of the TSL algorithm to learn some phenomena over realistic data sets even though the algorithm succeeds over the abstracted dataset. As explained earlier, this is a problem of combinatorial explosion: the TSL algorithm assumes that missing combinations always convey meaningful information about which sounds do or do not matter for the dependency, and as a result it is easily led astray by accidental gaps in the data. The second unexpected result pertains to the MTSL learner. This algorithm sometimes produced unnaturally large grammars with hundreds of tiers while a standard linguistic analysis would only posit a handful of tiers. It is only because of the transparency of subregular methods that this shortcoming could even be noticed — if the learners and grammars were opaque to human inspection, MTSL would seem to turn in a stellar performance across the board. By looking under the hood, we see that the quantitative performance conceals some qualitative shortcomings, the cause of which will have to be left to future research.

Finally, none of the learners captured the unattested pattern of first-last harmony. This is again in line with the theoretical predictions as first-last

harmony does not fit into any of the classes SP, SL, TSL, or MTSL. In sum, the finding of the learning experiments for well-formedness conditions can be summarized in the form of three key insights:

1. Theoretical predictions borne out

When trained on abstracted, artificially generated data, the subregular learners performed exactly as predicted by the theoretical work on subregular learning.

2. Learning failure on realistic data

When trained on realistic data, subregular learners can fail in unexpected ways. This is because realistic data uses a richer alphabet that causes data sparsity and a combinatorial explosion. In addition, realistic data will contain accidental gaps that a subregular learner could misinterpret as a part of the phenomenon. Natural classes and representations built on phonological features may mitigate this issue.

3. Understanding requires transparency

There are several cases where the quantitative performance of a learning algorithm paints an incomplete picture at best. The SP learner performs surprisingly well for word-final devoicing in German even though the learned grammar does not enforce any constraints on obstruents. The MTSL learner sometimes achieves a perfect accuracy score of 100% but does so with a very complex grammar that does not reflect the linguistic naturalness of the relevant phenomena. Since subregular grammars and learners can be easily inspected by humans, these issues do not escape notice and can be explored further in future work.

5.1.4 Learning rewrite rules

For the learning of rewrite rules I chose to focus on the OSTIA inference algorithm for subsequential mappings (Oncina et al., 1993; de la Higuera, 2010). This choice was made because many phonological and morphological processes discussed in Section 2.2.2 are subsequential in nature.

As with the learning of well-formedness condition, the results of the learning experiments largely match the theoretical predictions but also hold some surprises. OSTIA succeeded on the local process of word-final devoicing, as well as harmonies that do not exhibit a blocking effect. Additionally, it also learned a simple version of first-last harmony where the two harmonic elements must be adjacent to the left and right word edge, respectively. It failed on the more complex version of first-last harmony where the harmonic elements must be the first and last symbol of a specific type, but can occur anywhere in the word (for instance, this kind of first-last harmony might target the first and last vowel, but the vowel is not necessarily the first or the last sound in the word). It also failed on the process of unbounded tone plateauing. These learning successes as well as the learning failure on the more complex version of first-last harmony and unbounded tone plateauing are expected.

A major surprise, on the other hand, was the failure of OSTIA to learn harmony systems that include a blocking effect. Such processes are subsequential, yet they were not generalized correctly by OSTIA. In Section 4.2.13 I suggest that this might be rooted in the choice of OSTIA's "pushback" condition: several versions of it are proposed in the literature (Oncina et al., 1993; de la Higuera, 2010, 2011), and the one implemented in *SigmaPie* may not handle blocking effects correctly. Further work is needed to accurately pinpoint the reason for the unexpected behavior of *SigmaPie*'s implementation of OSTIA. In particular, other versions of OSTIA should be implemented, and quite generally *SigmaPie* needs a wider variety of transduction learners.

5.1.5 Omitted experiments

Some experiments were omitted for technical reasons or because they would not be insightful. In the learning of well-formedness conditions, there was no reason to test the learner’s performance on the complex first-last harmony since they already performed very poorly on the simple version of the harmony. Unbounded tone plateauing was not tested for MTSL because the existing learner is limited to MTSL with bigrams (2-MTSL) whereas tone plateauing would require at least trigrams. If the experiment were to be carried out with a 3-MTSL learner, the learner should still fail because tone plateauing is not an MTSL phenomenon.

Finally, OSTIA was not tested on realistic data from German, Finnish, or Turkish. The large alphabet of these data sets would induce a very large memory load during the learning process. It would be interesting to test in future work if OSTIA fails on realistic data sets for word-final devoicing or vowel harmony without a blocker, both of which it learned correctly from the abstract data set.

Quite generally, the results in this thesis should be taken as just a first step. My goal was to demonstrate *how* artificial learning experiments can be set up and evaluated with the help of SigmaPie. The obtained results are preliminary and far from exhaustive. Further research could extend this approach to other subregular learners and experimental datasets for a more comprehensive picture.

Although I only explored the very tip of an iceberg, some of the results came out to be significant. For example, I was able to show that some patterns that are theoretically TSL cannot be learned from natural language data using a TSL learner (see Turkish harmony in Section 3.4.3), and that this problem does not arise with SP patterns (see Finnish harmony in Section 3.3.2). This project is just the beginning, and it opens up plenty of directions of future work and highlights the importance of further research regarding the applications of subregular models.

5.2 Future directions

This dissertation is aimed towards supporting the balance between theory and applications within the subregular approach. It cannot be complete as long as there are new advancements in the field or ideas for their applications. The balance, however, can be maintained by following the cycle of invention, development, and implementation. In this case, the implemented subregular tools, such as *SigmaPie*, can be applied to accomplish concrete language learning or generating task, as I exemplify in Chapters 3 and 4. The outcomes of those applications inform the subregular theory and provoke the development of improved algorithms and models.

Subregular languages seem to be a good fit for natural language dependencies, and there are plenty of promising ideas and algorithms currently available in subregular literature. However, a large number of those algorithms are not implemented, and this slows the development of the applications of subregular models. Implementing those algorithms provides tools to linguists working on the subregular nature of human language patterns. Insights from the side of linguistics guide the development of new algorithms and the improvement of the old ones.

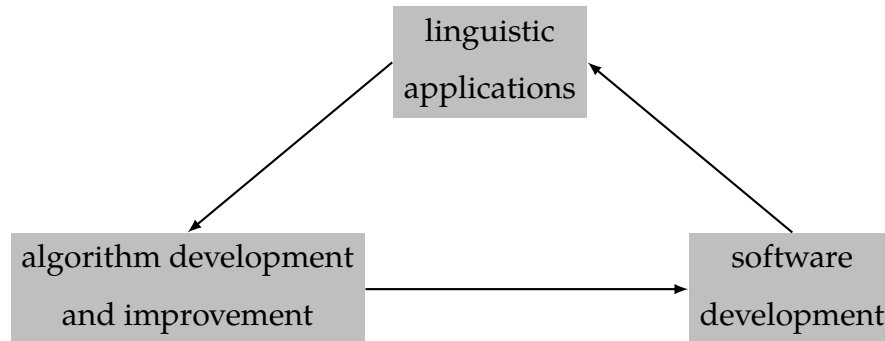


Figure 5.1: Exchange of ideas and innovations among applications of the subregular approach.

5.2.1 Linguistic applications

The availability of subregular tools allows making progress in linguistic applications of subregular proposals. So, for instance, one could evaluate subregular proposals in a tool-assisted way, using the encoded or automatically learned subregular models. Subregular learning experiments, in turn, can yield important theoretical results, and highlight the improvements that can be made to the subregular algorithms or software.

Evaluating the subregular proposals One of the applications of the subregular tools is to test ideas that are available in the literature, therefore evaluating the existent subregular proposals. So, for example, if a TSL model is proposed for a certain phenomenon, tools allow to automatically test if the TSL hypothesis is indeed consistent with the data. Alternatively, if literature claims that some phenomenon is subsequential, it is important to verify that current implementations of the learners are indeed capable of discovering that pattern. In such a way, implemented learners and scanners allow to verify claims made in the literature, and at the same time see the further improvements that can be made.

Not learning the impossible If an upper bound is proposed on the complexity of linguistic patterns, it is important to understand if there are any exceptions to the rule. One of the ways to do so is to attempt learning those unattested patterns using the available subregular models. Additionally, it is also important to research why the unattested patterns are impossible: due to the non-learnable nature of those patterns, as Lai (2015) suggests, or because of the unlikelihood of such a system evolving (Blevins, 2004). Knowing *what* patterns are not possible and *why* helps to get closer to understanding the core nature of linguistic dependencies, and it, in turn, helps us to form requirements for learning algorithms extracting natural language patterns.

Learning experiments from data Finally, it is crucially important to know if the proposed subregular learners are capable of learning the target patterns of the corresponding complexity from data. The data can be of different degrees of abstractness, ranging from the artificially generated sample with the minimal possible alphabet to raw natural language data. Different types of linguistic phenomena need to be targeted so that we can better understand which classes and learners should be used in which case. In my thesis, I only evaluated the behavior of learners using datasets exhibiting local dependencies, harmonies with or without blocking, and some other patterns. Other possible target phenomena include epenthesis, deletion, metathesis, different types of dissimilations, and a variety of suprasegmental patterns. Additionally, learning from data allows to explore the performance of the subregular learners under circumstances such as the increased size of the alphabet, the sparsity of the natural language data, or the small/large size of the training sample. Conducting such learning experiments helps not only to evaluate the practical aspects of theoretical advancements but also to assess the performance of subregular learners on real data.

Critically evaluating linguistic ideas and new findings helps to detect the improvements that need to be implemented in the subregular learning algorithms and models. So, for example, linguists were for decades advocating for the importance of features and natural classes. In turn, subregular algorithms would greatly benefit from a way to represent data in a less sparse way, therefore simplifying the learning. In such a way, insights from linguistics help to highlight which algorithms need to be developed in the future, and how to improve the existent learners.

5.2.2 Algorithm development and improvement

Linguistics and applications to language patterns help to see the potential improvements of the subregular learning paradigm. Typological work uncovers new types of dependencies and that, in turn, inspires the definition of new subregular language classes and the corresponding learners. Old learners can be improved as well, for example, by adding linguistic features, probabilities, or combining powers of several learners.

Designing new algorithms Apart from the discussed SL, SP, TSL, and MTSL subregular languages, there are other subregular classes that capture long-distance linguistic dependencies in other ways. Among them, there is an extension of TSL languages with the tier projection function that is sensitive to the local context (input-TSL, or ITSL), and several other classes such as MITSL, OTSL, IOTSL, and IBSP (Graf, 2017b; De Santo and Graf, 2019). Additionally, one could extend the 2-MTSL learner from 2 to k , or make sure that the learner always induces the minimal number of tiers. Other ideas for the design of the learning algorithms are listed in section 4.3 and could be explored as well. Additionally, the topic of adding more “naturalness” to the learning algorithms needs to be further explored, such as learning the feature systems of the language or finding a way to encode linguistic notions such as natural classes.

Implementing linguistic notions As mentioned in the previous subsection, the subregular learners could greatly benefit from implementing linguistic notions such as features or natural classes. It would allow seeing the behavior of elements of the alphabet as *groups* sharing some feature, instead of the current independent treatment of every segment. Potentially, this could improve the performance of the subregular learners on natural language data. The first steps towards incorporating features and natural classes into subregular models are taken by

Strother-Garcia et al. (2016) and Chandlee et al. (2019), and show promising results. In the future, this line of research needs to be expanded as well.

Implementing probabilities Another way to improve the performance of the subregular algorithms is to add probabilities to the models. Probabilistic modeling would allow to recognize harmony patterns even when the disharmonic words are present. Some theoretical research is already done in this direction by Heinz and Rogers (2010) and Shibata and Heinz (2019). Also, probabilistic modeling can be combined with the feature-based and natural class-based approaches (Heinz and Koirala, 2010; Vu et al., 2018).

Combining the learners Sometimes, a target language is at the intersection of different string-based subregular languages. For example, it can exhibit tone plateauing (SP) together with a long-distance harmony with blocking (TSL). To learn this pattern, the SP and TSL learning algorithms can be run in parallel, and the intersection of the obtained languages yields the target language (Heinz, 2010a; Heinz and Idsardi, 2013). In case of learning complex rewrite rules, further research is required since it is not clear if transformations can be combined in a way that would preserve properties such as subsequentiality.¹

The availability of new ideas and algorithms in the literature gives a way of implementing them in practice. Researchers can access the needed tools without the need to implement them from scratch if toolkits such as *SigmaPie* are available and up-to-date. Since the subregular languages and learners are closely interconnected and rely on the same basis of assumptions, the modularity of such a toolkit allows integrating new classes and learners easily. This is an essential

¹Although this is an open question, research groups at Stony Brook University, University of Ottawa, and UC San Diego are currently working on it.

step for keeping a mutually beneficial exchange between the theory and the practice.

5.2.3 Software development


Some algorithms are proposed in the literature but are not yet available in the form of tools or software. Bridging this gap helps to fast-forward the applications of the subregular models in linguistics, which, in turn, discovers the possible ways to improve those subregular algorithms.

Implementation of algorithms Some of the subregular learning algorithms are not yet implemented and therefore their practical applications are not explored. Among them, there are the learning algorithms ISLFLA and OSLFIA which extract two subclasses of subsequential mappings that are especially useful for local phonological processes (Chandlee et al., 2014, 2015). A learner for the class of Output 2-TSL functions is available in (Burness and McMullin, 2019) and needs to be implemented as well. Chandlee et al. (2019) also proposes a transduction learner for feature-based representations learning long-distance dependencies.

Software correctness To confirm the correctness of software, it is important to not rely on a single implementation. For every subregular algorithm, there need to be several different independent implementations. Also, some algorithms, such as OSTIA, are presented in the literature using several different pseudocodes implementing the same idea, and all those versions need to be implemented as well. Additionally, the speed of the original implementations could be increased as well, by decreasing the big \mathcal{O} complexity of the algorithm or by implementing memory-efficient techniques such as caching.

Implementing the subregular learners and other functionality like scanners or sample generators helps to provide tools to linguistics, which, in its turn, can yield

new results, or confirm old results using the newly available learners or models. Also, the availability of the tools makes subregular projects easier to be approached by a beginner's level linguists, such as undergraduate researchers.

During the last decade, the field of subregular research grew in its popularity, with theoretical advancements showing that it could be used for modeling different phonological, morphological, and even syntactic patterns. *SigmaPie*  is the first toolkit directed towards the development of subregular tools. It allows evaluating subregular proposals over data sets of various degree of abstractness. In my dissertation, I showed that *SigmaPie* can be used to yield new results the are relevant for theoretical and computational linguistics. These results, in turn, can bring insights into understanding the nature of human language.

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Appendix A

Code of *SigmaPie*

This appendix lists the full Python code for the package *SigmaPie* that was used in the experiments reported in Chapters 3 and 4. However, note, that future versions may yield different results. The most recent version of *SigmaPie* can be installed via pip and is also available on GitHub:

<https://pypi.org/project/SigmaPie/>

The Github repository also contains additional documentation on how to use *SigmaPie*. The code of the experiments themselves is available on GitHub as well:

<https://github.com/alenaks/subregular-experiments>

A.1 Grammar class

```
1 """A module with the definition of the grammar class. Copyright (C)
   2019 Alena
2 Aksenova.
3
4 This program is free software; you can redistribute it and/or modify
   it
```

```

5 under the terms of the GNU General Public License as published by
   the
6 Free Software Foundation; either version 3 of the License, or (at
   your
7 option) any later version.
8 """
9
10 from itertools import product
11 from sigmapie.helper import *
12
13
14 class L(object):
15     """A general class for grammars and languages.
16
17     Implements methods that
18     are applicable to all grammars in this package.
19     Attributes:
20         alphabet (list): alphabet used in the language;
21         grammar (list): the list of substructures;
22         k (int): locality window;
23         data (list): input data;
24         edges (list): start- and end-symbols for the grammar;
25         polar ("p" or "n"): polarity of the grammar.
26     """
27
28     def __init__(
29         self, alphabet=None, grammar=None, k=2, data=None, edges=[">
30         ", "<"], polar="p"
31     ):
32         """Initializes the L object."""
33         if polar not in ["p", "n"]:
34             raise ValueError(
35                 "The value of polarity should be either "
36                 "positive ('p') or negative ('n')."
```

```

36         )
37     self.__polarity = polar
38     self.alphabet = alphabet
39     self.grammar = [] if grammar is None else grammar
40     self.k = k
41     self.data = [] if data is None else data
42     self.edges = edges
43
44     def extract_alphabet(self):
45         """Extracts alphabet from the given data or grammar and
46         saves it into
47         the 'alphabet' attribute.
48
49         CAUTION: if not all symbols were used in the data or grammar
50         ,
51         the result is not correct: update manually.
52         """
53         if self.alphabet is None:
54             self.alphabet = []
55             symbols = set(self.alphabet)
56             if self.data:
57                 for item in self.data:
58                     symbols.update({j for j in item})
59             if self.grammar:
60                 for item in self.grammar:
61                     symbols.update({j for j in item})
62             symbols = symbols - set(self.edges)
63             self.alphabet = sorted(list(symbols))
64
65     def well_formed_ngram(self, ngram):
66         """Tells if the given ngram is well-formed. An ngram is ill-
67         formed if:
68
69         * there is something in-between two start- or end-symbols

```



```

67         ('>a>'), or
68     * something is before start symbol or after the end symbol
69         ('a>'), or
70     * the ngram consists only of start- or end-symbols.
71     Otherwise it is well-formed.
72     Arguments:
73         ngram (str): The ngram that needs to be evaluated.
74     Returns:
75         bool: well-formedness of the ngram.
76     """
77     start, end = [], []
78     for i in range(len(ngram)):
79         if ngram[i] == self.edges[0]:
80             start.append(i)
81         elif ngram[i] == self.edges[1]:
82             end.append(i)
83
84     start_len, end_len = len(start), len(end)
85     if any([start_len == len(ngram), end_len == len(ngram)]):
86         return False
87
88     if start_len > 0:
89         if ngram[0] != self.edges[0]:
90             return False
91         if start_len > 1:
92             for i in range(1, start_len):
93                 if start[i] - start[i - 1] != 1:
94                     return False
95
96     if end_len > 0:
97         if ngram[-1] != self.edges[1]:
98             return False
99         if end_len > 1:
100             for i in range(1, end_len):

```

```

101         if end[i] - end[i - 1] != 1:
102             return False
103
104     return True
105
106     def generate_all_ngrams(self, symbols, k):
107         """Generates all possible ngrams of the length k based on
108 the given
109     alphabet.
110
111     Arguments:
112         alphabet (list): alphabet;
113         k (int): locality window (length of ngram).
114     Returns:
115         list: generated ngrams.
116     """
117     symb = symbols[:]
118     if not ((self.edges[0] in symb) or (self.edges[1] in symb)):
119         symb += self.edges
120
121     combinations = product(symb, repeat=k)
122     ngrams = []
123     for ngram in combinations:
124         if self.well_formed_ngram(ngram) and (ngram not in
ngrams):
125
126             ngrams.append(ngram)
127
128     return ngrams
129
130     def opposite_polarity(self, symbols):
131         """Returns the grammar opposite to the one given.
132
133     Arguments:
134         symbols (list): alphabet.

```

```

133     Returns:
134         list: ngrams of the opposite polarity.
135     """
136     all_ngrams = self.generate_all_ngrams(symbols, self.k)
137     opposite = [i for i in all_ngrams if i not in self.grammar]
138
139     return opposite
140
141     def check_polarity(self):
142         """Returns the polarity of the grammar ("p" or "n")."""
143         if self.__polarity == "p":
144             return "p"
145         return "n"
146
147     def change_polarity(self, new_polarity=None):
148         """Changes the polarity of the grammar.
149
150         Warning: it does not rewrite the grammar!
151         """
152         if new_polarity is not None:
153             if new_polarity not in ["p", "n"]:
154                 raise ValueError(
155                     "The value of polarity should be either "
156                     "positive ('p') or negative ('n').")
157             )
158             self.__polarity = new_polarity
159         else:
160             if self.__polarity == "p":
161                 self.__polarity = "n"
162             elif self.__polarity == "n":
163                 self.__polarity = "p"

```

A.2 Strictly local class

```

1  """A class of Strictly Local Grammars. Copyright (C) 2019 Alena
    Aksenova.
2
3  This program is free software; you can redistribute it and/or modify
    it
4  under the terms of the GNU General Public License as published by
    the
5  Free Software Foundation; either version 3 of the License, or (at
    your
6  option) any later version.
7  """
8
9  from random import choice
10 from sigmapie.helper import *
11 from sigmapie.fsm import *
12 from sigmapie.grammar import *
13
14
15 class SL(L):
16     """A class for strictly local grammars and languages.
17
18     Attributes:
19         alphabet (list): alphabet used in the language;
20         grammar (list): collection of ngrams;
21         k (int): locality window;
22         data (list): input data;
23         edges (list): start- and end-symbols for the grammar;
24         polar ("p" or "n"): polarity of the grammar;
25         fsm (FSM): corresponding finite state machine.
26     """
27
28     def __init__(
29         self, alphabet=None, grammar=None, k=2, data=None, edges=[">
    ", "<"], polar="p"

```

```

30     ):
31         """Initializes the SL object."""
32         super().__init__(alphabet, grammar, k, data, edges, polar)
33         self.fsm = FSM(initial=self.edges[0], final=self.edges[1])
34
35     def learn(self):
36         """Extracts SL grammar from the given data."""
37         self.grammar = self.ngramize_data()
38         if self.check_polarity() == "n":
39             self.grammar = self.opposite_polarity(self.alphabet)
40
41     def annotate_string(self, string):
42         """Annotates the string with the start and end symbols.
43
44         Arguments:
45             string (str): a string that needs to be annotated.
46         Returns:
47             str: annotated version of the string.
48         """
49         return ">" * (self.k - 1) + string.strip() + "<" * (self.k -
50 1)
51
52     def ngramize_data(self):
53         """Creates set of n-grams based on the given data.
54
55         Returns:
56             list: collection of ngrams in the data.
57         """
58         if not self.data:
59             raise ValueError("The data is not provided.")
60
61         ngrams = []
62         for s in self.data:
63             item = self.annotate_string(s)

```

```

63         ngrams.extend(self.ngramize_item(item))
64
65     return list(set(ngrams))
66
67     def ngramize_item(self, item):
68         """This function n-gramizes a given string.
69
70         Arguments:
71             item (str): a string that needs to be ngramized.
72         Returns:
73             list: list of ngrams from the item.
74         """
75         ng = []
76         for i in range(len(item) - (self.k - 1)):
77             ng.append(tuple(item[i : (i + self.k)]))
78
79         return list(set(ng))
80
81     def fsmize(self):
82         """Builds FSM corresponding to the given grammar and saves
83         it in the
84         fsm attribute."""
85         if not self.grammar:
86             raise (IndexError("The grammar must not be empty."))
87         if not self.alphabet:
88             raise ValueError(
89                 "The alphabet is not provided. " "Use 'grammar.
90                 extract_alphabet()'."
91             )
92
93         if self.check_polarity() == "p":
94             self.fsm.sl_to_fsm(self.grammar)
95         else:
96             opposite = self.opposite_polarity(self.alphabet)

```

```

95         self.fsm.sl_to_fsm(opposite)
96
97     def scan(self, string):
98         """Checks if the given string is well-formed with respect to
99         the given
100         grammar.
101
102         Arguments:
103             string (str): the string that needs to be evaluated.
104         Returns:
105             bool: well-formedness value of a string.
106         """
107         if not self.fsm.transitions:
108             self.fsmize()
109
110         string = self.annotate_string(string)
111         return self.fsm.scan_sl(string)
112
113     def generate_sample(self, n=10, repeat=True, safe=True):
114         """Generates a data sample of the required size, with or
115         without
116         repetitions depending on 'repeat' value.
117
118         Arguments:
119             n (int): the number of examples to be generated;
120             repeat (bool): allows (rep=True) or prohibits (rep=False)
121             repetitions within the list of generated items;
122             safe (bool): automatically breaks out of infinite loops,
123             for example, when the grammar cannot generate the
124             required number of data items, and the repetitions
125             are set to False.
126
127         Returns:
128             list: generated data sample.

```

```

126     """
127     if not self.alphabet:
128         raise ValueError("Alphabet cannot be empty.")
129     if not self.fsm.transitions:
130         self.fsmize()
131
132     statemap = self.state_map()
133     if not any([len(statemap[x]) for x in statemap]):
134         raise (
135             ValueError(
136                 "There are ngrams in the grammar that are"
137                 " not leading anywhere. Clean the grammar "
138                 " or run 'grammar.clean_grammar()'".
139             )
140         )
141
142     data = [self.generate_item(statemap) for i in range(n)]
143
144     if not repeat:
145         data = set(data)
146         useless_loops = 0
147         prev_len = len(data)
148
149         while len(data) < n:
150             data.add(self.generate_item(statemap))
151
152             if prev_len == len(data):
153                 useless_loops += 1
154             else:
155                 useless_loops = 0
156
157             if safe and useless_loops > 500:
158                 print(
159                     "The grammar cannot produce the requested "

```



```

160         "number of strings. Check the grammar, "
161         "reduce the number, or allow repetitions."
162     )
163     break
164
165     return list(data)
166
167 def generate_item(self, statemap):
168     """Generates a well-formed string with respect to the given
169     grammar.
170
171     Arguments:
172         statemap (dict): a dictionary of possible transitions in
173         the
174         corresponding fsm; constructed inside
175         generate_sample.
176
177     Returns:
178         str: a well-formed string.
179     """
180     word = self.edges[0] * (self.k - 1)
181     while word[-1] != self.edges[1]:
182         word += choice(statemap[word[-(self.k - 1) :]])
183     return word[(self.k - 1) : -1]
184
185 def state_map(self):
186     """
187     Generates a dictionary of possible transitions in the FSM.
188     Returns:
189         dict: the dictionary of the form
190         {"keys": [list of possible next symbols]}, where
191         keys are (k-1)-long strings.
192     """
193     local_alphabet = self.alphabet[:] + self.edges[:]
194     poss = product(local_alphabet, repeat=(self.k - 1))

```

```

191
192     smap = {}
193     for i in poss:
194         for j in self.fsm.transitions:
195             if j[0] == i:
196                 before = "".join(i)
197                 if before in smap:
198                     smap[before] += j[1]
199                 else:
200                     smap[before] = [j[1]]
201     return smap
202
203     def switch_polarity(self):
204         """Changes polarity of the grammar, and changes the grammar
205         to the
206         opposite one."""
207         if not self.alphabet:
208             raise ValueError("Alphabet cannot be empty.")
209
210         self.grammar = self.opposite_polarity(self.alphabet)
211         self.change_polarity()
212
213     def clean_grammar(self):
214         """Removes useless ngrams from the grammar.
215
216         If negative, it just removes duplicates. If positive, it
217         detects
218         bigrams to which one cannot get      from the initial symbol
219         and
220         from which one cannot get      to the final symbol, and
221         removes
222         them.
223         """
224         if not self.fsm.transitions:

```

```

221         self.fsmize()
222
223         if self.check_polarity() == "n":
224             self.grammar = list(set(self.grammar))
225         else:
226             self.fsm.trim_fsm()
227             self.grammar = [j[0] + (j[1],) for j in self.fsm.
transitions]

```

A.3 Strictly piecewise class

```

1  """A class of Strictly Piecewise Grammars. Copyright (C) 2019  Alena
   Aksenova.
2
3  This program is free software; you can redistribute it and/or modify
   it
4  under the terms of the GNU General Public License as published by
   the
5  Free Software Foundation; either version 3 of the License, or (at
   your
6  option) any later version.
7  """
8
9  from random import choice
10 from itertools import product
11
12 from sigmapie.grammar import *
13 from sigmapie.fsm import *
14 from sigmapie.fsm_family import *
15 from sigmapie.helper import *
16
17
18 class SP(L):
19     """A class for strictly piecewise grammars and languages.

```

```

20
21     Attributes:
22         alphabet (list): alphabet used in the language;
23         grammar (list): collection of ngrams;
24         k (int): locality window;
25         data (list): input data;
26         polar ("p" or "n"): polarity of the grammar;
27         fsm (FSM): corresponding finite state machine.
28     """
29
30     def __init__(self, alphabet=None, grammar=None, k=2, data=None,
31 polar="p"):
32         """Initializes the SP object."""
33         super().__init__(alphabet, grammar, k, data, polar=polar)
34         self.fsm = FSMFamily()
35
36     def subsequences(self, string):
37         """Extracts k-long subsequences out of the given word.
38
39         Arguments:
40             string (str): a string that needs to be processed.
41
42         Returns:
43             list: a list of subsequences out of the string.
44         """
45         if len(string) < self.k:
46             return []
47
48         start = list(string[: self.k])
49         result = [start]
50
51         previous_state = [start]
52         current_state = []
53
54         for s in string[self.k :]:

```

```

53         for p in previous_state:
54             for i in range(self.k):
55                 new = p[:i] + p[i + 1 :] + [s]
56                 if new not in current_state:
57                     current_state.append(new)
58             result.extend(current_state)
59             previous_state = current_state[:]
60             current_state = []
61
62     return list(set([tuple(i) for i in result]))
63
64 def learn(self):
65     """Extracts k-long subsequences from the training data.
66
67     Results:
68         self.grammar is updated.
69     """
70     if not self.data:
71         raise ValueError("The data must be provided.")
72     if not self.alphabet:
73         raise ValueError(
74             "The alphabet must be provided. To "
75             "extract the alphabet automatically, "
76             "run 'grammar.extract_alphabet()'."
77         )
78
79     self.grammar = []
80     for i in self.data:
81         for j in self.subsequences(i):
82             if j not in self.grammar:
83                 self.grammar.append(j)
84
85     if self.check_polarity() == "n":
86         self.grammar = self.opposite_polarity()

```

```

87
88     def opposite_polarity(self):
89         """Returns the grammar opposite to the current one."""
90         all_ngrams = product(self.alphabet, repeat=self.k)
91         return [i for i in all_ngrams if i not in self.grammar]
92
93     def fsmize(self):
94         """Creates FSM family for the given SP grammar by passing
95 every
96 encountered subsequence through the corresponding automaton.
97 """
98
99         if not self.grammar:
100             self.learn()
101
102         if self.check_polarity() == "p":
103             data_subseq = self.grammar[:]
104         else:
105             data_subseq = self.opposite_polarity()
106
107         # create a family of templates in fsm attribute
108         seq = product(self.alphabet, repeat=self.k - 1)
109         for path in seq:
110             f = FSM(initial=None, final=None)
111             f.sp_build_template(path, self.alphabet, self.k)
112             self.fsm.family.append(f)
113
114         # run the input/grammar through the fsm family
115         for f in self.fsm.family:
116             for r in data_subseq:
117                 f.sp_fill_template(r)
118
119         # clean the untouched transitions
120         for f in self.fsm.family:
121             f.sp_clean_template()

```

```

119
120 def scan(self, string):
121     """Tells if the input string is well-formed.
122
123     Arguments:
124         string (str): string to be scanned.
125     Returns:
126         bool: True is well-formed, otherwise False.
127     """
128     subseq = self.subsequences(string)
129     found_in_G = [(s in self.grammar) for s in subseq]
130
131     if self.check_polarity == "p":
132         return all(found_in_G)
133     else:
134         return not any(found_in_G)
135
136 def generate_item(self):
137     """Generates a well-formed string.
138
139     Returns:
140         str: the generated string.
141     """
142     if not self.alphabet:
143         raise ValueError("The alphabet must be provided.")
144
145     string = ""
146     while True:
147         options = []
148         for i in self.alphabet:
149             if self.scan(string + i):
150                 options.append(i)
151
152         add = choice(options + ["EOS"])

```

```

153         if add == "EOS":
154             return string
155         else:
156             string += add
157
158     def generate_sample(self, n=10, repeat=False, safe=True):
159         """Generates data sample of desired length.
160
161         Arguments:
162             n (int): the number of examples to be generated,
163                     the default value is 10;
164             repeat (bool): allow (rep=True) or prohibit (rep=False)
165                           repetitions, the default value is False;
166             safe (bool): automatically break out of infinite loops,
167                          for example, when the grammar cannot generate the
168                          required number of data items, and the repetitions
169                          are set to False.
170
171         Returns:
172             list: a list of generated examples.
173         """
174         sample = [self.generate_item() for i in range(n)]
175
176         if not repeat:
177             useless_loops = 0
178             sample = set(sample)
179             prev_len = len(sample)
180
181             while len(list(set(sample))) < n:
182                 sample.add(self.generate_item())
183                 if prev_len == len(sample):
184                     useless_loops += 1
185                 else:
186                     useless_loops = 0

```



```

187         if safe and useless_loops > 100:
188             print(
189                 "The grammar cannot produce the requested
190                 number" " of strings."
191             )
192             break
193
194         return list(sample)
195
196     def switch_polarity(self, new_polarity=None):
197         """Changes the polarity of the grammar.
198
199         Arguments:
200             new_polarity ("p" or "n"): the new value of the polarity
201             .
202
203         """
204         old_value = self.check_polarity()
205         self.change_polarity(new_polarity)
206         new_value = self.check_polarity()
207
208         if old_value != new_value:
209             self.grammar = self.opposite_polarity()
210
211     def clean_grammar(self):
212         """Removes useless ngrams from the grammar.
213
214         If negative, it just removes duplicates. If positive, it
215         detects
216         bigrams to which one cannot get      from the initial symbol
217         and
218         from which one cannot get      to the final symbol, and
219         removes
220         them.
221         """

```

```
216 self.grammar = list(set(self.grammar))
```

A.4 Tier-based strictly local class

```
1  """A class of Tier-based Strictly Local Grammars. Copyright (C) 2019
    Alena
2  Aksenova.
3
4  This program is free software; you can redistribute it and/or modify
    it
5  under the terms of the GNU General Public License as published by
    the
6  Free Software Foundation; either version 3 of the License, or (at
    your
7  option) any later version.
8  """
9
10 from random import choice, randint
11 from sigmapie.sl_class import *
12
13
14 class TSL(SL):
15     """A class for tier-based strictly local grammars and languages.
16
17     Attributes:
18         alphabet (list): alphabet used in the language;
19         grammar (list): the list of substructures;
20         k (int): locality window;
21         data (list): input data;
22         edges (list): start- and end-symbols for the grammar;
23         polar ("p" or "n"): polarity of the grammar;
24         fsm (FSM): finite state machine that corresponds to the
        grammar;
25         tier (list): list of tier symbols.
```

```

26     """
27
28     def __init__(
29         self,
30         alphabet=None,
31         grammar=None,
32         k=2,
33         data=None,
34         edges=[">", "<"],
35         polar="p",
36         tier=None,
37     ):
38         """Initializes the TSL object."""
39         super().__init__(alphabet, grammar, k, data, edges, polar)
40         self.tier = tier
41         self.fsm = FSM(initial=self.edges[0], final=self.edges[1])
42
43     def learn(self):
44         """Learns tier and finds attested (if positive) or
45         unattested (if
46         negative) ngrams of the tier images of the data."""
47         if not self.alphabet:
48             raise ValueError("Alphabet cannot be empty.")
49         if not self.data:
50             raise ValueError("Data needs to be provided.")
51
52         self.learn_tier()
53         tier_sequences = [self.tier_image(i) for i in self.data]
54         self.grammar = TSL(k=self.k, data=tier_sequences).
55         ngramize_data()
56
57         if self.check_polarity() == "n":
58             self.grammar = self.opposite_polarity(self.tier)

```

```

58     def learn_tier(self):
59         """This function determines which of the symbols used in the
        language
60         are tier symbols, algorithm by Jardine & McMullin (2017).
61
62         Updates tier attribute.
63         """
64         self.tier = self.alphabet[:]
65         ngrams = self.ngramize_data()
66
67         ngrams_less = TSL(data=self.data, k=(self.k - 1)).
ngramize_data()
68         ngrams_more = TSL(data=self.data, k=(self.k + 1)).
ngramize_data()
69
70         for symbol in self.alphabet:
71             if self.test_insert(symbol, ngrams, ngrams_less) and
self.test_remove(
72                 symbol, ngrams, ngrams_more
73             ):
74                 self.tier.remove(symbol)
75
76     def test_insert(self, symbol, ngrams, ngrams_less):
77         """Tier presense test #1.
78
79         For every (n-1)-gram ('x','y','z'),
80         there must be n-grams of the type ('x','S','y','z') and
81         ('x','y','S','z').
82         Arguments:
83             symbol (str): the symbol that is currently being tested;
84             ngrams (list): the list of n-gramized input;
85             ngrams_less (list): the list of (n-1)-gramized input.
86         Returns:
87             bool: True if a symbol passed the test, otherwise False.

```

```

88     """
89     extension = []
90     for small in ngrams_less:
91         for i in range(len(small) + 1):
92             new = small[:i] + (symbol,) + small[i:]
93             if self.well_formed_ngram(new):
94                 extension.append(new)
95
96     # needs to be here: otherwise no local WF/WE processes
97     edgecase1 = tuple(self.edges[0] * (self.k - 1) + symbol)
98     edgecase2 = tuple(symbol + self.edges[1] * (self.k - 1))
99     extension.extend([edgecase1, edgecase2])
100
101     return set(extension).issubset(set(ngrams))
102
103 def test_remove(self, symbol, ngrams, ngrams_more):
104     """Tier presense test #2.
105
106     For every (n+1)-gram of the type
107     ('x','S','y'), there must be an n-gram of the type ('x', 'y
108     ').
109
110     Arguments:
111         symbol (str): the symbol that is currently being tested;
112         ngrams (list): the list of n-gramized input;
113         ngrams_more (list): the list of (n+1)-gramized input.
114
115     Returns:
116         bool: True if a symbol passed the test, otherwise False.
117     """
118     extension = []
119     for big in ngrams_more:
120         if symbol in big:
121             for i in range(len(big)):
122                 if big[i] == symbol:
123                     new = big[:i] + big[i + 1 :]

```

```

121         if self.well_formed_ngram(new):
122             extension.append(new)
123
124         return set(extension).issubset(set(ngrams))
125
126     def tier_image(self, string):
127         """Function that returns a tier image of the input string.
128
129         Arguments:
130             string (str): string that needs to be processed.
131         Returns:
132             str: tier image of the input string.
133         """
134         return "".join(i for i in string if i in self.tier)
135
136     def fsmize(self):
137         """Builds FSM corresponding to the given grammar and saves
138         in it the
139         fsm attribute."""
140         if not self.grammar:
141             raise (IndexError("The grammar must not be empty."))
142         if not self.tier:
143             raise ValueError(
144                 "The tier is not extracted or empty. "
145                 "Switch to SL or use 'grammar.learn()'".
146             )
147
148         if self.check_polarity() == "p":
149             self.fsm.sl_to_fsm(self.grammar)
150         else:
151             opposite = self.opposite_polarity(self.tier)
152             self.fsm.sl_to_fsm(opposite)
153
154     def switch_polarity(self):

```

```

154     """Changes polarity of the grammar, and rewrites grammar to
the
155     opposite one."""
156     if not self.tier:
157         raise ValueError(
158             "Either the language is SL, or the tier "
159             "is not extracted, use 'grammar.learn()'. "
160         )
161
162     self.grammar = self.opposite_polarity(self.tier)
163     self.change_polarity()
164
165     def generate_sample(self, n=10, repeat=True, safe=True):
166         """Generates n well-formed strings, with or without
repetitions.
167
168         Arguments:
169             n (int): the number of examples to be generated;
170             repeat (bool): allow (rep=True) or prohibit (rep=False)
171                 repetitions of the same data items;
172             safe (bool): automatically break out of infinite loops,
173                 for example, when the grammar cannot generate the
174                 required number of data items, and the repetitions
175                 are set to False.
176
177         Returns:
178             list: generated data sample.
179         """
180         if not self.alphabet:
181             raise ValueError("Alphabet cannot be empty.")
182         if not self.tier:
183             raise ValueError(
184                 "Either the language is SL, or the tier "
185                 "is not extracted, use 'grammar.learn()'. "
186             )

```

```

186
187     if len(self.alphabet) == len(self.tier):
188         sl = SL(polar=self.check_polarity())
189         sl.alphabet = self.alphabet
190         sl.grammar = self.grammar
191         sl.k = self.k
192         sl.edges = self.edges
193         sl.fsmize()
194         return sl.generate_sample(n, repeat, safe)
195
196     if not self.fsm.transitions:
197         self.fsmize()
198
199     statemap = self.state_map()
200     data = [self.generate_item() for i in range(n)]
201
202     if not repeat:
203         data = set(data)
204         useless_loops = 0
205         prev_len = len(data)
206         while len(data) < n:
207             data.add(self.generate_item())
208             if prev_len == len(data):
209                 useless_loops += 1
210             else:
211                 useless_loops = 0
212
213             if safe and useless_loops > 100:
214                 print(
215                     "The grammar cannot produce the requested
number" " of strings."
216                 )
217                 break
218

```



```

219         return list(data)
220
221     def generate_item(self):
222         """Generates a well-formed sequence of symbols.
223
224         Returns:
225             str: a well-formed string.
226         """
227         if not self.fsm.transitions:
228             self.fsmize()
229
230         statemap = self.state_map()
231         if not any([len(statemap[x]) for x in statemap]):
232             raise (
233                 ValueError(
234                     "There are ngrams in the grammar that are"
235                     " not leading anywhere. Clean the grammar "
236                     " or run 'grammar.clean_grammar()'.")
237             )
238
239         tier_seq = self.annotate_string(super().generate_item(
240 statemap))
241         ind = [x for x in range(len(tier_seq)) if tier_seq[x] not in
242 self.edges]
243         if not ind:
244             tier_items = []
245         else:
246             tier_items = list(tier_seq[ind[0] : (ind[-1] + 1)])
247
248         free_symb = list(set(self.alphabet).difference(set(self.tier
249 )))
250
251         new_string = self.edges[0] * (self.k - 1)

```

```

250         for i in range(self.k + 1):
251             if randint(0, 1) and free_symb:
252                 new_string += choice(free_symb)
253
254         if not tier_items:
255             return "".join([i for i in new_string if i not in self.
edges])
256
257         for item in tier_items:
258             new_string += item
259             for i in range(self.k + 1):
260                 if randint(0, 1) and free_symb:
261                     new_string += choice(free_symb)
262
263             return "".join([i for i in new_string if i not in self.edges
])
264
265     def state_map(self):
266         """
267         Generates a dictionary of possible transitions in the FSM.
268         Returns:
269             dict: the dictionary of the form
270                 {"keys": [list of possible next symbols]}, where
271                 keys are (k-1)-long strings.
272         """
273         if self.fsm is None:
274             self.fsmize()
275
276         local_alphabet = self.tier[:] + self.edges[:]
277         poss = product(local_alphabet, repeat=(self.k - 1))
278
279         smap = {}
280         for i in poss:
281             for j in self.fsm.transitions:

```

```

282         if j[0] == i:
283             before = "".join(i)
284             if before in smap:
285                 smap[before] += j[1]
286             else:
287                 smap[before] = [j[1]]
288         return smap
289
290     def scan(self, string):
291         """Checks if the given string is well-formed with respect to
292         the given
293         grammar.
294
295         Arguments:
296             string (str): the string that needs to be evaluated.
297         Returns:
298             bool: well-formedness value of a string.
299         """
300         tier_img = self.annotate_string(self.tier_image(string))
301         matches = [(n in self.grammar) for n in self.ngramize_item(
302             tier_img)]
303
304         if self.check_polarity() == "p":
305             return all(matches)
306         else:
307             return not any(matches)

```

A.5 Multi-tier strictly local class

```

1  """A class of Multiple Tier-based Strictly Local Grammars. Copyright
   (C) 2019
2  Alena Aksenova.
3
4  This program is free software; you can redistribute it and/or modify

```

```

    it
5 under the terms of the GNU General Public License as published by
    the
6 Free Software Foundation; either version 3 of the License, or (at
    your
7 option) any later version.
8 """
9
10 from copy import deepcopy
11 from random import choice, randint
12 from itertools import product
13 from sigmapie.tsl_class import *
14 from sigmapie.fsm_family import *
15
16
17 class MTSL(TSL):
18     """A class for tier-based strictly local grammars and languages.
19
20     Attributes:
21         alphabet (list): alphabet used in the language;
22         grammar (list): the list of substructures;
23         k (int): locality window;
24         data (list): input data;
25         edges (list): start- and end-symbols for the grammar;
26         polar ("p" or "n"): polarity of the grammar;
27         fsm (FSMFamily): a list of finite state machines that
28             corresponds to the grammar;
29         tier (list): list of tuples, where every tuple lists
30             elements
31             of some tier.
32         Learning for  $k > 2$  is not implemented: requires more theoretical
33         work.
34     """

```

```

34     def __init__(
35         self, alphabet=None, grammar=None, k=2, data=None, edges=[">
", "<"], polar="p"
36     ):
37         """Initializes the TSL object."""
38         super().__init__(alphabet, grammar, k, data, edges, polar)
39         self.fsm = FSMFamily()
40         if self.k != 2:
41             raise NotImplementedError(
42                 "The learner for k-MTSL languages is " "still being
designed."
43             )
44         self.tier = None
45
46     def learn(self):
47         """
48         Learns 2-local MTSL grammar for a given sample. The
algorithm
49         currently works only for k=2 and is based on MTSL2IA
designed
50         by McMullin, Aksenova and De Santo (2019). We are currently
51         working on lifting the locality of the grammar to arbitrary
k.
52         Results:
53             self.grammar is updated with a grammar of the following
shape:
54             {(tier_1):[bigrams_for_tier_1],
55              ...
56              (tier_n):[bigrams_for_tier_n]}
57         """
58         if not self.data:
59             raise ValueError("Data needs to be provided.")
60         if not self.alphabet:
61             raise ValueError(

```

```

62         "The alphabet is empty. Provide data or "
63         "run 'grammar.extract_alphabet'."
64     )
65
66     possible = set(self.generate_all_ngrams(self.alphabet, self.
67 k))
68
69     attested = set()
70     for d in self.data:
71         bigrams = self.ngramize_item(self.annotate_string(d))
72         attested.update(set(bigrams))
73     unattested = list(possible.difference(attested))
74
75     paths = self.all_paths(self.data)
76     grammar = []
77
78     for bgr in unattested:
79         tier = self.alphabet[:]
80
81         for s in self.alphabet:
82             rmv = True
83
84             # condition 1
85             if s in bgr:
86                 rmv = False
87                 continue
88
89             # condition 2
90             relevant_paths = []
91             for p in paths:
92                 if (p[0] == bgr[0]) and (p[-1] == bgr[-1]) and (
93 s in p[1]):
94                     relevant_paths.append(p)
95             for rp in relevant_paths:
96                 new = [rp[0], set(i for i in rp[1] if i != s),

```

```

rp[2]]
94         if new not in paths:
95             rmv = False
96             break
97
98         # remove from the tier if passed both conditions
99         if rmv:
100             tier.remove(s)
101
102         grammar.append((tier, bgr))
103     gathered = self.gather_grammars(grammar)
104
105     self.grammar = gathered
106     self.tier = [i for i in self.grammar]
107
108     if self.check_polarity() == "p":
109         self.grammar = self.opposite_polarity()
110
111     def scan(self, string):
112         """Scan string with respect to a given MTSL grammar.
113
114         Arguments:
115             string (str): a string that needs to be scanned.
116         Returns:
117             bool: well-formedness of the string.
118         """
119         tier_evals = []
120
121         for tier in self.grammar:
122             t = tier
123             g = self.grammar[tier]
124
125             delete_non_tier = "".join([i for i in string if i in t])
126             tier_image = self.annotate_string(delete_non_tier)

```

```

127         ngrams = self.ngramize_item((tier_image))
128
129         this_tier = [(ngr in g) for ngr in ngrams]
130
131         if self.check_polarity() == "p":
132             tier_evals.append(all(this_tier))
133         else:
134             tier_evals.append(not any(this_tier))
135
136         return all(tier_evals)
137
138     def gather_grammars(self, grammar):
139         """Gathers grammars with the same tier together.
140
141         Arguments:
142             grammar (list): a representation of the learned grammar
143                             where there is a one-to-one mapping between tiers
144                             and bigrams.
145
146         Returns:
147             dict: a dictionary where keys are tiers and values are
148                   the restrictions imposed on those tiers.
149
150         """
151         G = {}
152         for i in grammar:
153             if tuple(i[0]) in G:
154                 G[tuple(i[0])] += [i[1]]
155             else:
156                 G[tuple(i[0])] = [i[1]]
157         return G
158
159     def path(self, string):
160         """Collects a list of paths from a string.
161
162         A path is a

```



```

161 triplet <a, X, b>, where 'a' is a symbol, 'b' is a symbol
162 that follows 'a' in 'string', and 'X' is a set of symbols
163 in-between 'a' and 'b'.
164 Arguments:
165     string (str): a string paths of which need to be found.
166 Returns:
167     list: list of paths of 'string'.
168 """
169 string = self.annotate_string(string)
170 paths = []
171
172 for i in range(len(string) - 1):
173     for j in range(i + 1, len(string)):
174         path = [string[i]]
175         path.append(set(k for k in string[(i + 1) : j]))
176         path.append(string[j])
177
178         if path not in paths:
179             paths.append(path)
180
181 return paths
182
183 def all_paths(self, dataset):
184     """Finds all paths that are present in a list of strings.
185
186 Arguments:
187     dataset (list): a list of strings.
188 Returns:
189     list: a list of paths present in 'dataset'.
190 """
191 paths = []
192 for item in dataset:
193     for p in self.path(item):
194         if p not in paths:

```

```

195         paths.append(p)
196
197     return paths
198
199     def opposite_polarity(self):
200         """Generates a grammar of the opposite polarity.
201
202         Returns:
203             dict: a dictionary containing the opposite ngram lists
204                   for every tier of the grammar.
205         """
206         if not self.grammar:
207             raise ValueError(
208                 "Grammar needs to be provided. It can also "
209                 "be learned using 'grammar.learn()'."
210             )
211         opposite = {}
212         for i in self.grammar:
213             possib = self.generate_all_ngrams(list(i), self.k)
214             opposite[i] = [j for j in possib if j not in self.
grammar[i]]
215
216         return opposite
217
218     def switch_polarity(self):
219         """Changes polarity of the grammar, and rewrites grammar to
the
220         opposite one."""
221         self.grammar = self.opposite_polarity()
222         self.change_polarity()
223
224     def map_restrictions_to_fsms(self):
225         """Maps restrictions to FSMs: based on the grammar, it
creates a list

```

```

226         of lists, where every sub-list has the following shape:
227
228         [tier_n, restrictions_n, fsm_n]. Such sub-list is
constructed
229         for every single tier of the current MTSL grammar.
230         Returns:
231             [list, list, FSM]
232                 list: a list of current tier's symbols;
233                 list: a list of current tier's restrictions;
234                 FSM: a FSM corresponding to the current tier.
235         """
236         if not self.grammar:
237             raise (IndexError("The grammar must not be empty."))
238
239         restr_to_fsm = []
240
241         for alpha, ngrams in self.grammar.items():
242             polarity = self.check_polarity()
243             tsl = TSL(
244                 self.alphabet,
245                 self.grammar,
246                 self.k,
247                 self.data,
248                 self.edges,
249                 polar=polarity,
250             )
251             if not tsl.alphabet:
252                 tsl.extract_alphabet()
253             tsl.tier = list(alpha)
254             tsl.grammar = list(ngrams)
255             tsl.fsmize()
256             restr_to_fsm.append([tsl.tier[:], tsl.grammar[:], tsl.
fsm])
257

```

```

258         return restr_to_fsm
259
260     def fsmize(self):
261         """Builds FSM family corresponding to the given grammar and
262         saves in it
263         the fsm attribute."""
264         restr_to_fsm = self.map_restrictions_to_fsms()
265         self.fsm.family = [i[2] for i in restr_to_fsm]
266
267     def generate_sample(self, n=10, repeat=True, safe=True):
268         """Generates a data sample of the required size, with or
269         without
270         repetitions depending on 'repeat' value.
271
272         Arguments:
273             n (int): the number of examples to be generated;
274             repeat (bool): allows (rep=True) or prohibits (rep=False)
275             repetitions within the list of generated items;
276             safe (bool): automatically breaks out of infinite loops,
277             for example, when the grammar cannot generate the
278             required number of data items, and the repetitions
279             are set to False.
280
281         Returns:
282             list: generated data sample.
283         """
284         if not self.alphabet:
285             raise ValueError("Alphabet cannot be empty.")
286         if not self.fsm.family:
287             self.fsmize()
288
289         tier_smap = self.tier_state_maps()
290         if not any([len(tier_smap[x]) for x in tier_smap]):
291             raise (

```

```

289         ValueError(
290             "There are ngrams in the grammar that are"
291             " not leading anywhere. Clean the grammar "
292             " or run 'grammar.clean_grammar()'."
293         )
294     )
295
296     data = [self.generate_item(tier_smap) for i in range(n)]
297
298     if not repeat:
299         data = set(data)
300         useless_loops = 0
301         prev_len = len(data)
302
303         while len(data) < n:
304             data.add(self.generate_item(tier_smap))
305
306             if prev_len == len(data):
307                 useless_loops += 1
308             else:
309                 useless_loops = 0
310
311             if safe and useless_loops > 500:
312                 print(
313                     "The grammar cannot produce the requested "
314                     "number of strings. Check the grammar, "
315                     "reduce the number, or allow repetitions."
316                 )
317                 break
318
319         return list(data)
320
321     def tier_image(self, string):
322         """

```

```

323         Creates tier images of a string with respect to the
different
324         tiers listed in the grammar.
325         Returns:
326             dict: a dictionary of the following shape:
327                 { (tier_1): "string_image_given_tier_1",
328                   ...,
329                   (tier_n): "string_image_given_tier_n"
330                 }
331         """
332         tiers = {}
333         for i in self.grammar:
334             curr_tier = ""
335             for s in string:
336                 if s in self.edges or s in i:
337                     curr_tier += s
338             tiers[i] = curr_tier
339         return tiers
340
341     def generate_item(self, tier_smap):
342         """Generates a well-formed string with respect to the given
grammar.
343
344         Returns:
345             str: a well-formed string.
346         """
347         word = self.edges[0] * (self.k - 1)
348         main_smap = self.general_state_map(tier_smap)
349         tier_images = self.tier_image(word)
350
351         while word[-1] != self.edges[1]:
352             maybe = choice(main_smap[word[-(self.k - 1) :]])
353             good = True
354             for tier in tier_smap:

```

```

355         if maybe in tier:
356             old_image = tier_images[tier]
357             if maybe not in tier_smap[tier][old_image[-(self
.k - 1) :]]:
358                 good = False
359             if good:
360                 word += maybe
361                 tier_images = self.tier_image(word)
362
363     newword = word[(self.k - 1) : -1]
364     if self.scan(newword):
365         return newword
366     else:
367         return self.generate_item(tier_smap)
368
369 def tier_state_maps(self):
370     """
371     Generates a dictionary of transitions within the FSMs
372     that correspond to the tier grammars.
373     Returns:
374         dict: the dictionary of the form
375         {
376             (tier_1):{"keys":[list of next symbols]},
377             (tier_2):{"keys":[list of next symbols]},
378             ...
379             (tier_n):{"keys":[list of next symbols]},
380         }, where keys are (k-1)-long tier representations.
381     Warning: the list of next symbols is tier-specific,
382             so this estimates the rough options: refer to
383             generate_item for the filtering of wrongly
384             generated items.
385     """
386     restr_to_fsm = self.map_restrictions_to_fsms()
387     tier_smaps = {}

```

```

388
389     for curr_tier in restr_to_fsm:
390         sl = SL()
391         sl.change_polarity(self.check_polarity())
392         sl.edges = self.edges
393         sl.k = self.k
394         sl.alphabet = curr_tier[0]
395         sl.grammar = curr_tier[1]
396         sl.fsm = curr_tier[2]
397         tier_smaps[tuple(sl.alphabet)] = sl.state_map()
398
399     return tier_smaps
400
401 def general_state_map(self, smaps):
402     """
403     Generates a dictionary of transitions within all
404     FSMs of the FSM family.
405     Returns:
406         dict: the dictionary of the form
407             {"keys": [list of next symbols]}, where
408             keys are (k-1)-long strings.
409     Warning: the list of next symbols is tier-specific,
410             so this estimates the rough options: refer to
411             generate_item for the filtering of wrongly
412             generated items.
413     """
414     local_smaps = deepcopy(smaps)
415
416     for tier in local_smaps:
417         non_tier = [i for i in self.alphabet if i not in tier]
418         for entry in local_smaps[tier]:
419             local_smaps[tier][entry].extend(non_tier)
420
421     local_smaps = list(local_smaps.values())

```



```

422     main_smap = deepcopy(local_smaps[0])
423
424     for other in local_smaps[1:]:
425         for entry in other:
426
427             if entry not in main_smap:
428                 main_smap[entry] = other[entry]
429             else:
430                 inter = [i for i in main_smap[entry] if i in
other[entry]]
431                 main_smap[entry] = inter
432
433     free_ones = []
434     for i in self.alphabet:
435         for j in self.grammar:
436             if i in j:
437                 break
438             free_ones.append(i)
439
440     ext_alphabet = deepcopy(self.alphabet) + [self.edges[1]]
441     for x in free_ones:
442         main_smap[x] = ext_alphabet
443
444     return main_smap
445
446     def clean_grammar(self):
447         """Removes useless ngrams from the grammar.
448
449         If negative, it just removes duplicates. If positive, it
detects
450         ngrams to which one cannot get      from the initial symbol
and
451         from which one cannot get      to the final symbol, and
removes

```

```

452         them.
453         """
454         for tier in self.grammar:
455             sl = SL()
456             sl.change_polarity(self.check_polarity())
457             sl.edges = self.edges
458             sl.alphabet = list(tier)
459             sl.k = self.k
460             sl.grammar = self.grammar[tier]
461             sl.fsmize()
462             sl.clean_grammar()
463             self.grammar[tier] = deepcopy(sl.grammar)

```

A.6 FSM class

```

1  """A class of Finite State Machines. Copyright (C) 2019  Alena
   Aksenova.
2
3  This program is free software; you can redistribute it and/or modify
   it
4  under the terms of the GNU General Public License as published by
   the
5  Free Software Foundation; either version 3 of the License, or (at
   your
6  option) any later version.
7  """
8
9
10 class FSM(object):
11     """This class implements Finite State Machine.
12
13     Attributes:
14         initial (str): initial symbol;
15         final (str): final symbol;

```

```

16         transitions (list): triples of the form [prev_state,
17             transition, next_state].
18     """
19
20     def __init__(self, initial, final, transitions=None):
21         if transitions == None:
22             self.transitions = []
23         else:
24             self.transitions = transitions
25
26         self.initial = initial
27         self.final = final
28
29     def sl_to_fsm(self, grammar):
30         """Creates FSM transitions based on the SL grammar.
31
32         Arguments:
33             grammar (list): SL ngrams.
34         """
35         if not grammar:
36             raise ValueError("The grammar must not be empty.")
37         self.transitions = [(i[:-1], i[-1], i[1:]) for i in grammar]
38
39     def scan_sl(self, string):
40         """Scans a given string using the learned SL grammar.
41
42         Arguments:
43             string (str): a string that needs to be scanned.
44         Returns:
45             bool: well-formedness value of the string.
46         """
47         if string[0] != self.initial or string[-1] != self.final:
48             raise ValueError("The string is not annotated with " "
the delimiters.")

```

```

49         if not self.transitions:
50             raise ValueError(
51                 "The transitions are empty. Extract the"
52                 " transitions using grammar.fsmize()."
53             )
54
55         k = len(self.transitions[0][0]) + 1
56         for i in range(k - 1, len(string)):
57             move_to_next = []
58             for j in self.transitions:
59                 can_read = string[(i - k + 1) : (i + 1)] == "".join(
60                     j[0]) + j[1]
61                 move_to_next.append(can_read)
62
63             if not any(move_to_next):
64                 return False
65
66         return True
67
68     def trim_fsm(self):
69         """This function trims useless transitions.
70
71         1. Finds the initial state and collects the set of states to
72            which one
73            can come from that node and the nodes connected to it.
74            2. Changes direction of the transitions and runs algorithm
75            again to
76            detect states from which one cannot get to the final
77            state.
78
79            As the result, self.transitions only contains useful
80            transitions.
81
82            """
83
84         if not self.transitions:
85             raise ValueError("Transitions of the automaton must "

```

```

not be empty.")

78     can_start = self.accessible_states(self.initial)
79     self.transitions = [(i[2], i[1], i[0]) for i in can_start]
80     mirrored = self.accessible_states(self.final)
81     self.transitions = [(i[2], i[1], i[0]) for i in mirrored]
82
83     def accessible_states(self, marker):
84         """Finds accessible states.
85
86         Arguments:
87             marker (str): initial or final state.
88         Returns:
89             list: list of transitions that can be made from
90                   the given initial or final state.
91         """
92         updated = self.transitions[:]
93
94         # find initial/final transitions
95         reachable = []
96         for i in self.transitions:
97             if i[0][0] == i[0][-1] == marker:
98                 reachable.append(i)
99                 updated.remove(i)
100
101         # to keep copies that can be modified while looping
102         mod_updated = updated[:]
103         mod_reachable = []
104         first_time = True
105
106         # find transitions that can be reached
107         while mod_reachable != [] or first_time:
108             mod_reachable = []
109             first_time = False
110             for p in updated:

```

```

111         for s in reachable:
112             if p[0] == s[2]:
113                 mod_reachable.append(p)
114                 mod_updated.remove(p)
115             updated = mod_updated[:]
116             reachable.extend(mod_reachable)
117
118         return reachable
119
120     def sp_build_template(self, path, alphabet, k):
121         """Generates a template for the given k-SP path.
122
123         Arguments:
124             path (str): the sequence for which the template is
125             generated;
126             alphabet (list): list of all symbols of the grammar;
127             k (int): window size of the grammar.
128         """
129
130         # creating the "skeleton" of the FSM
131         for i in range(k - 1):
132             # boolean shows whether the transition was accessed
133             self.transitions.append([i, path[i], i + 1, False])
134
135         # adding non-final loops
136         newtrans = []
137         for t in self.transitions:
138             for s in alphabet:
139                 if s != t[1]:
140                     newtrans.append([t[0], s, t[0], False])
141
142         # adding final loops
143         for s in alphabet:
144             newtrans.append(

```

```

144         [self.transitions[-1][2], s, self.transitions
145         [-1][2], False]
146     )
147
148     self.transitions += newtrans
149
150     def sp_fill_template(self, sequence):
151         """Runs the input sequence through the SP automaton and
152         marks
153         transitions if they were taken.
154
155         Cleans
156         transitions that were not taken afterwards.
157         Arguments:
158             sequence (str): sequence of symbols that needs to be
159                             passed through the automaton.
160         """
161         state = 0
162         for s in sequence:
163             for t in self.transitions:
164                 if (t[0] == state) and (t[1] == s):
165                     state = t[2]
166                     t[3] = True
167                     break
168
169     def sp_clean_template(self):
170         """Removes transitions that were not accessed."""
171         self.transitions = [i[:3] for i in self.transitions if i[3]
172                             == True]
173
174     def scan_sp(self, string):
175         """Runs the given sequence through the automaton.
176
177         Arguments:

```

```

175         string (str): string to run through the automaton.
176     Returns:
177         bool: True if input can be accepted by the automaton,
178             otherwise False.
179     """
180     state = 0
181     for s in string:
182         change = False
183         for t in self.transitions:
184             if (t[0] == state) and (t[1] == s):
185                 state = t[2]
186                 change = True
187                 break
188
189         if not change:
190             return False
191
192     return True

```

A.7 FSM family class

```

1  """A class of Families of Finite State Machines. Copyright (C) 2019
   Alena
2  Aksenova.
3
4  This program is free software; you can redistribute it and/or modify
   it
5  under the terms of the GNU General Public License as published by
   the
6  Free Software Foundation; either version 3 of the License, or (at
   your
7  option) any later version.
8  """
9

```



```

10 from sigmapie.fsm import *
11
12
13 class FSMFamily(object):
14     """
15     This class encodes Family of Finite State Machines. Used for
16     a simple encoding of FSMs corresponding to SP languages.
17     Attributes:
18         transitions(list): triples of the form
19         [prev_state, transition, next_state].
20     """
21
22     def __init__(self, family=None):
23         """Initializes the FSMFamily object."""
24         if family is None:
25             self.family = []
26         else:
27             self.family = family
28
29     def run_all_fsm(self, string):
30         """Tells whether the given string is accepted by all the
31         automata of
32         the family.
33
34         Arguments:
35             string (str): the input string.
36
37         Returns:
38             bool: True if the string is accepted by all the
39             fsm's, otherwise False.
40         """
41         return all([f.scan_sp(string) for f in self.family])

```

A.8 FST class

```

1  """A class defining the Finite State Transducer. Copyright (C) 2019
    Alena
2  Aksenova.
3
4  This program is free software; you can redistribute it and/or modify
    it
5  under the terms of the GNU General Public License as published by
    the
6  Free Software Foundation; either version 3 of the License, or (at
    your
7  option) any later version.
8  """
9
10 from copy import deepcopy
11
12
13 class FST:
14     """A class representing finite state transducers.
15
16     Attributes:
17         Q (list): a list of states;
18         Sigma (list): a list of symbols of the input alphabet;
19         Gamma (list): a list of symbols of the output alphabet;
20         qe (str): name of the unique initial state;
21         E (list): a list of transitions;
22         stout (dict): a collection of state outputs.
23     """
24
25     def __init__(self, Sigma=None, Gamma=None):
26         """Initializes the FST object."""
27         self.Q = None
28         self.Sigma = Sigma
29         self.Gamma = Gamma
30         self.qe = ""

```

```

31         self.E = None
32         self.stout = None
33
34     def rewrite(self, w):
35         """Rewrites the given string with respect to the rules
36         represented in
37         the current FST.
38
39         Arguments:
40             w (str): a string that needs to be rewritten.
41         Outputs:
42             str: the translation of the input string.
43         """
44         if self.Q == None:
45             raise ValueError("The transducer needs to be constructed
46             .")
47
48         # move through the transducer and write the output
49         result = ""
50         current_state = ""
51         moved = False
52         for i in range(len(w)):
53             for tr in self.E:
54                 if tr[0] == current_state and tr[1] == w[i]:
55                     result += tr[2]
56                     current_state, moved = tr[3], True
57                     break
58             if moved == False:
59                 raise ValueError(
60                     "This string cannot be read by the current
61                     transducer."
62                 )
63
64         # add the final state output

```

```

62         if self.stout[current_state] != "*":
63             result += self.stout[current_state]
64
65         return result
66
67     def copy_fst(self):
68         """Produces a deep copy of the current FST.
69
70         Returns:
71             T (FST): a copy of the current FST.
72         """
73         T = FST()
74         T.Q = deepcopy(self.Q)
75         T.Sigma = deepcopy(self.Sigma)
76         T.Gamma = deepcopy(self.Gamma)
77         T.E = deepcopy(self.E)
78         T.stout = deepcopy(self.stout)
79
80         return T

```

A.9 OSTIA

```

1  """An implementation of the learning algorithm OSTIA. Copyright (C)
   2019 Alena
2  Aksenova.
3
4  This program is free software; you can redistribute it and/or modify
   it
5  under the terms of the GNU General Public License as published by
   the
6  Free Software Foundation; either version 3 of the License, or (at
   your
7  option) any later version.
8  """

```

```

9
10 from sigmapie.fst_object import *
11 from sigmapie.helper import *
12
13
14 def ostia(S, Sigma, Gamma):
15     """This function implements OSTIA (Onward Subsequential
16     Transduction
17     Inference Algorithm).
18
19     Arguments:
20         S (list): a list of pairs (o, t), where 'o' is the original
21         string, and 't' is its translation;
22         Sigma (list): the input alphabet;
23         Gamma (list): the output alphabet.
24
25     Returns:
26         FST: a transducer defining the mapping.
27     """
28     # create a template of the onward PTT
29     T = build_ptt(S, Sigma, Gamma)
30     T = onward_ptt(T, "", "")[0]
31
32     # color the nodes
33     red = [""]
34     blue = [tr[3] for tr in T.E if tr[0] == "" and len(tr[1]) == 1]
35
36     # choose a blue state
37     while len(blue) != 0:
38         blue_state = blue[0]
39
40         # if exists state that we can merge with, do it
41         exists = False
42         for red_state in red:

```

```

42         # if you already merged that blue state with something,
stop
43         if exists == True:
44             break
45
46         # try to merge these two states
47         if ostia_merge(T, red_state, blue_state):
48             T = ostia_merge(T, red_state, blue_state)
49             exists = True
50
51         # if it is not possible, color that blue state red
52         if not exists:
53             red.append(blue_state)
54
55         # if possible, remove the folded state from the list of
states
56         else:
57             T.Q.remove(blue_state)
58             del T.stout[blue_state]
59
60         # add in blue list other states accessible from the red ones
that are not red
61         blue = []
62         for tr in T.E:
63             if tr[0] in red and tr[3] not in red:
64                 blue.append(tr[3])
65
66         # clean the transducer from non-reachable states
67         T = ostia_clean(T)
68         T.E = [tuple(i) for i in T.E]
69
70     return T
71
72

```

```

73 def build_ptt(S, Sigma, Gamma):
74     """Builds a prefix tree transducer based on the data sample.
75
76     Arguments:
77         S (list): a list of pairs (o, t), where 'o' is the original
78             string, and 't' is its translation;
79         Sigma (list): the input alphabet;
80         Gamma (list): the output alphabet.
81     """
82
83     # build a template for the transducer
84     T = FST(Sigma, Gamma)
85
86     # fill in the states of the transducer
87     T.Q = []
88     for i in S:
89         for j in prefix(i[0]):
90             if j not in T.Q:
91                 T.Q.append(j)
92
93     # fill in the empty transitions
94     T.E = []
95     for i in T.Q:
96         if len(i) >= 1:
97             T.E.append([i[:-1], i[-1], "", i])
98
99     # fill in state outputs
100     T.stout = {}
101     for i in T.Q:
102         for j in S:
103             if i == j[0]:
104                 T.stout[i] = j[1]
105             if i not in T.stout:
106                 T.stout[i] = "*"

```

```

107
108     return T
109
110
111 def onward_ptt(T, q, u):
112     """Function recursively pushing the common parts of strings
113     towards the
114     initial state therefore making the machine onward.
115
116     Arguments:
117         T (FST): a transducer that is being modified;
118         q (str): a state that is being processes;
119         u (str): a current part of the string to be moved.
120
121     Returns:
122         (FST, str, str)
123         FST: the updated transducer;
124         str: a new state;
125         u: a new string to be moved.
126
127     """
128     # proceed as deep as possible
129     for tr in T.E:
130         if tr[0] == q:
131             T, qx, w = onward_ptt(T, tr[3], tr[1])
132             if tr[2] != "*":
133                 tr[2] += w
134
135     # find lcp of all ways of leaving state 1 or stopping in it
136     t = [tr[2] for tr in T.E if tr[0] == q]
137     f = lcp(T.stout[q], *t)
138
139     # remove from the prefix unless it's the initial state
140     if f != "" and q != "":
141         for tr in T.E:
142             if tr[0] == q:

```



```

140         tr[2] = remove_from_prefix(tr[2], f)
141         T.stout[q] = remove_from_prefix(T.stout[q], f)
142
143     return T, q, f
144
145
146 def ostia_outputs(w1, w2):
147     """Function implementing a special comparison operation:
148
149     it returns a string if two strings are the same and if
150     another string is unknown, and False otherwise.
151     Arguments:
152         w1 (str): the first string;
153         w2 (str): the second string.
154     Returns:
155         bool | if strings are not the same;
156         str | otherwise.
157     """
158     if w1 == "*":
159         return w2
160     elif w2 == "*":
161         return w1
162     elif w1 == w2:
163         return w2
164     else:
165         return False
166
167
168 def ostia_pushback(T_orig, q1, q2, a):
169     """Re-distributes lcp of two states further in the FST.
170
171     Arguments:
172         T_orig (FST): a transducer;
173         q1 (str): the first state;

```

```

174         q2 (str): the second state;
175         a (str): the lcp of q1 and q2.
176     Returns:
177         FST: an updated transducer.
178     """
179     # to avoid rewriting the original transducer
180     T = T_orig.copy_fst()
181
182     # states where you get if follow a
183     q1_goes_to = None
184     q2_goes_to = None
185
186     # what is being written from this state
187     from_q1, from_q2 = None, None
188     for tr in T.E:
189         if tr[0] == q1 and tr[1] == a:
190             from_q1 = tr[2]
191             q1_goes_to = tr[3]
192         if tr[0] == q2 and tr[1] == a:
193             from_q2 = tr[2]
194             q2_goes_to = tr[3]
195     if from_q1 == None or from_q2 == None:
196         raise ValueError("One of the states cannot be found.")
197
198     # find the part after longest common prefix
199     u = lcp(from_q1, from_q2)
200     remains_q1 = from_q1[len(u) :]
201     remains_q2 = from_q2[len(u) :]
202
203     # assign lcp as current output
204     for tr in T.E:
205         if tr[0] in [q1, q2] and tr[1] == a:
206             tr[2] = u
207

```

```

208     # find what the next state writes given any other choice
209     # and append the common part in it
210     for tr in T.E:
211         if tr[0] == q1_goes_to:
212             tr[2] = remains_q1 + tr[2]
213         if tr[0] == q2_goes_to:
214             tr[2] = remains_q2 + tr[2]
215
216     # append common part to the next state's state output
217     if T.stout[q1_goes_to] != "*":
218         T.stout[q1_goes_to] = remains_q1 + T.stout[q1_goes_to]
219     if T.stout[q2_goes_to] != "*":
220         T.stout[q2_goes_to] = remains_q2 + T.stout[q2_goes_to]
221
222     return T
223
224
225 def ostia_merge(T_orig, q1, q2):
226     """Re-directs all branches of q2 into q1.
227
228     Arguments:
229         T_orig (FST): a transducer;
230         q1 (str): the first state;
231         q2 (str): the second state.
232
233     Returns:
234         FST: an updated transducer.
235     """
236     # to avoid rewriting the original transducer
237     T = T_orig.copy_fst()
238
239     # save which transition was changed to revert in case cannot
240     # merge the states
241     changed = None
242     for tr in T.E:

```

```

241         if tr[3] == q2:
242             changed = tr[:]
243             tr[3] = q1
244
245         # save the state output of the q1 originally
246         changed_stout = T.stout[q1]
247
248         # check if we can merge the states
249         can_do = ostia_fold(T, q1, q2)
250
251         # if cannot, revert the change
252         if can_do == False:
253             for tr in T.E:
254                 if tr[0] == changed[0] and tr[1] == changed[1] and tr[2]
255                 == changed[2]:
256                     tr[3] = changed[3]
257                     T.stout[q1] = changed_stout
258                 return False
259
260         # if can, do it
261         else:
262             return can_do
263
264 def ostia_fold(T_orig, q1, q2):
265     """Recursively folds subtrees of q2 into q1.
266
267     Arguments:
268         T_orig (FST): a transducer;
269         q1 (str): the first state;
270         q2 (str): the second state.
271
272     Returns:
273         FST: an updated transducer.
274     """

```

```

274     # to avoid rewriting the original transducer
275     T = T_orig.copy_fst()
276
277     # compare the state outputs
278     w = ostia_outputs(T.stout[q1], T.stout[q2])
279     if w == False:
280         return False
281
282     # rewrite * in case it's the output of q1
283     T.stout[q1] = w
284
285     # look at every possible subtree of q_2
286     for a in T.Sigma:
287         add_new = False
288
289         for tr_2 in T.E:
290             if tr_2[0] == q2 and tr_2[1] == a:
291
292                 # if the edge exists from q1
293                 edge_defined = False
294                 for tr_1 in T.E:
295                     if tr_1[0] == q1 and tr_1[1] == a:
296                         edge_defined = True
297
298                 # fail if inconsistent with output of q2
299                 if tr_1[2] not in prefix(tr_2[2]):
300                     return False
301
302                 # move the mismatched suffix of q1 and q2
303                 further
304
305                 T = ostia_pushback(T, q1, q2, a)
306                 T = ostia_fold(T, tr_1[3], tr_2[3])
307                 if T == False:
308                     return False

```

```

307
308         # if the edge doesn't exist from q1 yet, add it
309         if not edge_defined:
310             add_new = [q1, a, tr_2[2], tr_2[3]]
311
312         # if the new transition was constructed, add it to the list
of transitions
313         if add_new:
314             T.E.append(add_new)
315
316     return T
317
318
319 def ostia_clean(T_orig):
320     """Removes the disconnected branches from the transducer that
appear due to
321     the step folding the sub-trees.
322
323     Arguments:
324         T_orig (FST): a transducer.
325     Returns:
326         FST: an updated transducer.
327     """
328     # to avoid rewriting the original transducer
329     T = T_orig.copy_fst()
330
331     # determine which states are reachable, i.e. accessible from the
initial state
332     reachable_states = [""]
333     add = []
334     change_made = True
335     while change_made == True:
336         change_made = False
337         for st in reachable_states:

```

```

338         for tr in T.E:
339             if tr[0] == st and tr[3] not in reachable_states and
tr[3] not in add:
340                 add.append(tr[3])
341                 change_made = True
342
343         # break out of the loop if after checking the list once
again, no states were added
344         if change_made == False:
345             break
346         else:
347             reachable_states.extend(add)
348             add = []
349
350     # clean the list of transitions
351     new_E = []
352     for tr in T.E:
353         if tr[0] in reachable_states and tr[3] in reachable_states:
354             new_E.append(tr)
355     T.E = new_E
356
357     # clean the dictionary of state outputs
358     new_stout = {}
359     for i in T.stout:
360         if i in reachable_states:
361             new_stout[i] = T.stout[i]
362     T.stout = new_stout
363
364     # clean the list of states
365     new_Q = [i for i in T.Q if i in reachable_states]
366     T.Q = new_Q
367
368     return T

```

A.10 Additional functions

```
1 """Module with general helper functions for the subregular package.
   Copyright
2 (C) 2019 Alena Aksenova.
3
4 This program is free software; you can redistribute it and/or modify
   it
5 under the terms of the GNU General Public License as published by
   the
6 Free Software Foundation; either version 3 of the License, or (at
   your
7 option) any later version.
8 """
9
10
11 def alphabetize(data):
12     """Detects symbols used in the input data.
13
14     Arguments:
15         data (list): Input data.
16     Returns:
17         list: Symbols used in these examples.
18     """
19     alphabet = set()
20     for item in data:
21         alphabet.update({i for i in item})
22     return sorted(list(alphabet))
23
24
25 def get_gram_info(ngrams):
26     """Returns the alphabet and window size of the grammar.
27
28     Arguments:
```



```

29         ngrams (list): list of ngrams.
30     Returns:
31         (list, int)
32             list: alphabet;
33             int: locality window.
34     """
35     alphabet = list(set([i for i in "".join(ngrams) if i not in [ ">"
36 , "<"]]))
37     k = max(len(i) for i in ngrams)
38     return alphabet, k
39
40 def prefix(w):
41     """Returns a list of prefixes of a given string.
42
43     Arguments:
44         w (str): a string prefixes of which need to be extracted.
45     Returns:
46         list: a list of prefixes of the given string.
47     """
48     return [w[:i] for i in range(len(w) + 1)]
49
50
51 def lcp(*string):
52     """
53     Finds the longest common prefix of an unbounded number of
54     strings.
55     Arguments:
56         *string (str): one or more strings;
57     Returns:
58         str: a longest common prefix of the input strings.
59     """
60     w = list(set(i for i in string if i != ""))
61     if not w:

```

```

61         raise IndexError("At least one non-unknown string needs to
be provided.")
62
63     result = ""
64     n = min([len(x) for x in w])
65     for i in range(n):
66         if len(set(x[i] for x in w)) == 1:
67             result += w[0][i]
68         else:
69             break
70
71     return result
72
73
74 def remove_from_prefix(w, pref):
75     """Removes a substring from the prefix position of another
string.
76
77     Arguments:
78         w (str): a string that needs to be modified;
79         pref (str): a prefix that needs to be removed from the
string.
80     Returns:
81         str: the modified string.
82     """
83     if w.startswith(pref):
84         return w[len(pref) :]
85     elif w == "*":
86         return w
87
88     raise ValueError(pref + " is not a prefix of " + w)

```

A.11 Package initialization

```

1  """
2      SigmaPie: a toolkit for subregular grammars and languages.
3      Copyright (C) 2019  Alena Aksenova
4
5      This program is free software; you can redistribute it and/or
6      modify
7      it under the terms of the GNU General Public License as published
8      by
9      the Free Software Foundation; either version 3 of the License, or
10     (at your option) any later version.
11 """
12
13 from sigmapie.sl_class import *
14 from sigmapie.tsl_class import *
15 from sigmapie.mtsl_class import *
16 from sigmapie.sp_class import *
17 from sigmapie.ostia import *
18
19 print(
20     "\nYou successfully loaded SigmaPie. \n\n"
21     "Formal language classes and grammars available:\n"
22     "\t* strictly piecewise: SP(alphabet, grammar, k, data, polar);\n"
23     "\n"
24     "\t* strictly local: SL(alphabet, grammar, k, data, edges, polar\n"
25     ");\n"
26     "\t* tier-based strictly local: TSL(alphabet, grammar, k, data,\n"
27     "edges,\n"
28     "    polar, tier);\n"
29     "\t* multiple tier-based strictly local: MTSL(alphabet, grammar,\n"
30     "k, "\n"
31     "data, edges, polar).\n\n"
32     "Alternatively, you can initialize a transducer: "\n"
33     "FST(states, sigma, gamma, initial, transitions, stout).\n"
34     "Learning algorithm:\n"

```

```
29     "\tOSTIA: ostia(sample, sigma, gamma)."  
30 )
```

Appendix B

Unit tests

B.1 Unit test for Grammar

```
1 #!/bin/python3
2
3 """A module with the unittests for the grammar module. Copyright (C)
4     2019 Alena
5     Aksenova.
6
7     This program is free software; you can redistribute it and/or modify
8     it
9     under the terms of the GNU General Public License as published by
10    the
11    Free Software Foundation; either version 3 of the License, or (at
12    your
13    option) any later version.
14 """
15
16 import sys, os
17
18 sys.path.insert(0, os.path.join(os.path.abspath(".."), ""))
```

```

16 import unittest
17 from grammar import L
18
19
20 class TestGeneralLanguages(unittest.TestCase):
21     """Tests for the L class."""
22
23     def test_good_ngram_standard_edges(self):
24         """Checks if ill-formed ngrams are correctly recognized, and
25         that the
26
27         well-formed ones are not blocked.
28
29         Tests standard edge-markers.
30         """
31         l = L()
32         self.assertTrue(l.well_formed_ngram(("a", "b", "a")))
33         self.assertTrue(l.well_formed_ngram((">", "a", "b")))
34         self.assertTrue(l.well_formed_ngram((">", "a", "<")))
35         self.assertTrue(l.well_formed_ngram((">", "<")))
36         self.assertTrue(l.well_formed_ngram(("b", "<")))
37         self.assertTrue(l.well_formed_ngram(("a", "a", "a", "a", "a"
38         )))
39
40         self.assertFalse(l.well_formed_ngram(("a", ">")))
41         self.assertFalse(l.well_formed_ngram(("?", "d", "<", ">")))
42         self.assertFalse(l.well_formed_ngram(("a", ">", "a")))
43         self.assertFalse(l.well_formed_ngram((">", ">")))
44         self.assertFalse(l.well_formed_ngram(("<")))
45
46     def test_good_ngram_non_standard_edges(self):
47         """Checks if ill-formed ngrams are correctly recognized, and
48         that the
49
50         well-formed ones are not blocked.

```

```

47     Tests user-provided edge markers.
48     """
49     l = L()
50     l.edges = ["$", "#"]
51     self.assertTrue(l.well_formed_ngram(("$", "a", "b")))
52     self.assertTrue(l.well_formed_ngram(("$", "a", "#")))
53     self.assertTrue(l.well_formed_ngram(("$", "#")))
54     self.assertTrue(l.well_formed_ngram(("b", "#")))
55
56     self.assertFalse(l.well_formed_ngram(("a", "$")))
57     self.assertFalse(l.well_formed_ngram(("$", "d", "#", "$")))
58     self.assertFalse(l.well_formed_ngram(("a", "$", "a")))
59     self.assertFalse(l.well_formed_ngram(("$", "$")))
60     self.assertFalse(l.well_formed_ngram(("#")))
61
62     def test_ngram_gen(self):
63         """Checks if ngram generation method produces the expected
64         results."""
65         l = L(alphabet=["a", "b"])
66         ngrams = l.generate_all_ngrams(l.alphabet, l.k)
67
68         ng = {
69            (">", "<"),
70            (">", "a"),
71            ("a", "<"),
72            (">", "b"),
73            ("b", "<"),
74            ("a", "a"),
75            ("b", "b"),
76            ("b", "a"),
77            ("a", "b"),
78         }
79         self.assertTrue(set(ngrams) == ng)

```

```

80     def test_switch_same_alpha(self):
81         """Checks if the generated grammar is correct when all
alphabet symbols
82         are used in the grammar, also checks that polarity was
changed."""
83         g = [(">", "a"), ("b", "<"), ("a", "b"), ("b", "a")]
84         l = L(grammar=g)
85         l.extract_alphabet()
86
87         old_polarity = l.check_polarity()
88
89         g_opp = {(">", "<"), ("a", "<"), (">", "b"), ("b", "b"), ("a
", "a")}
90         self.assertTrue(set(l.opposite_polarity(l.alphabet)) ==
g_opp)
91         self.assertFalse(old_polarity == l.check_polarity)
92
93     def test_switch_different_alpha(self):
94         """Checks if the generated grammar is correct when not all
alphabet
95         symbols are used in the grammar; also checks that polarity
was
96         changed."""
97         g = [(">", "b"), ("b", "<"), (">", "<")]
98         l = L(grammar=g)
99         l.alphabet = ["a", "b"]
100
101         old_polarity = l.check_polarity()
102
103         g_opp = {(">", "a"), ("a", "<"), ("a", "a"), ("b", "a"), ("a
", "b"), ("b", "b")}
104         self.assertTrue(set(l.opposite_polarity(l.alphabet)) ==
g_opp)
105         self.assertFalse(old_polarity == l.check_polarity)

```



```

106
107     def test_change_polarity(self):
108         """Tests the correctness of change_polarity."""
109         a = L(polar="n")
110         a.change_polarity(new_polarity="n")
111         self.assertTrue(a.check_polarity() == "n")
112         a.change_polarity()
113         self.assertFalse(a.check_polarity() == "n")
114
115         b = L()
116         old_polarity = b.check_polarity()
117         b.change_polarity()
118         self.assertTrue(b.check_polarity() != old_polarity)
119
120
121 if __name__ == "__main__":
122     unittest.main()

```

B.2 Unit test for SL

```

1 #!/bin/python3
2
3 """A module with the unittests for the SL module. Copyright (C) 2019
4     Alena
5     Aksenova.
6
7 This program is free software; you can redistribute it and/or modify
8     it
9     under the terms of the GNU General Public License as published by
10     the
11     Free Software Foundation; either version 3 of the License, or (at
12     your
13     option) any later version.
14 """

```

```

11
12 import unittest
13 from sl_class import *
14
15
16 class TestSLLanguages(unittest.TestCase):
17     """Tests for the SL class."""
18
19     def test_scan_pos(self):
20         """Checks if well-formed strings are detected correctly
21         given the
22         provided positive grammar."""
23         slp = SL()
24         slp.grammar = [(">", "a"), ("b", "a"), ("a", "b"), ("b", "<")
25         ])
26         slp.alphabet = ["a", "b"]
27         self.assertTrue(slp.scan("abab"))
28         self.assertTrue(slp.scan("ab"))
29         self.assertTrue(slp.scan("ababababab"))
30         self.assertFalse(slp.scan("abb"))
31         self.assertFalse(slp.scan("a"))
32         self.assertFalse(slp.scan(""))
33
34     def test_scan_neg(self):
35         """Checks if well-formed strings are detected correctly
36         given the
37         provided negative grammar."""
38         sln = SL(polar="n")
39         sln.grammar = [("<", "a"), ("a", "b")]
40         sln.alphabet = ["a", "b"]
41         self.assertFalse(sln.scan("abab"))
42         self.assertFalse(sln.scan("ab"))
43         self.assertFalse(sln.scan("ababababab"))
44         self.assertTrue(sln.scan("bbbb"))

```

```

42         self.assertTrue(sln.scan("aaaaa"))
43         self.assertTrue(sln.scan(""))
44
45     def test_ngramize_2(self):
46         """Checks if ngramize() correctly constructs bigrams."""
47         sl = SL()
48         sl.data = ["aaa", "bbb"]
49         ngrams = set(sl.ngramize_data())
50         goal = {(">", "b"), (">", "a"), ("a", "a"), ("b", "b"), ("a"
51 , "<"), ("b", "<")}
52         self.assertTrue(ngrams == goal)
53
54     def test_ngramize_3(self):
55         """Check if ngramize() correctly constructs trigrams."""
56         sl = SL()
57         sl.k = 3
58         sl.data = ["aaa", "bbb"]
59         ngrams = set(sl.ngramize_data())
60         goal = {
61             (">", "a", "a"),
62             (">", "b", "b"),
63             ("b", "b", "<"),
64             ("b", "<", "<"),
65             ("a", "<", "<"),
66             (">", ">", "a"),
67             ("a", "a", "a"),
68             ("a", "a", "<"),
69             (">", ">", "b"),
70             ("b", "b", "b"),
71         }
72         self.assertTrue(ngrams == goal)
73
74     def test_learn(self):
75         """Checks if positive and negative grammars are learned

```

```

correctly."""
75     data = ["abab", "ababab"]
76     gpos = {(">", "a"), ("b", "a"), ("a", "b"), ("b", "<")}
77     gneg = {(">", "<"), ("a", "<"), (">", "b"), ("b", "b"), ("a"
, "a")}

78
79     a = SL(data=data, alphabet=["a", "b"])
80     a.learn()
81     self.assertTrue(set(a.grammar) == gpos)
82
83     a.change_polarity()
84     a.learn()
85     self.assertTrue(set(a.grammar) == gneg)
86
87     def test_fsmize_pos(self):
88         """Checks if the transitions of the fsm corresponding to the
positive
89         grammar are constructed correctly."""
90         sl = SL(polar="p")
91         sl.alphabet = ["a", "b"]
92         sl.grammar = {(">", "a"), ("b", "a"), ("a", "b"), ("b", "<")}
93     ]
94
95     sl.fsmize()
96
97     f = FSM(initial=">", final="<")
98     f.sl_to_fsm([(">", "a"), ("b", "a"), ("a", "b"), ("b", "<")
99 ])
100
101     self.assertTrue(set(sl.fsm.transitions) == set(f.transitions
))

102
103     def test_fsmize_neg(self):
104         """Checks if the transitions of the fsm corresponding to the
negative

```

```

102         grammar are constructed correctly."""
103         sl = SL()
104         sl.change_polarity("n")
105         sl.alphabet = ["a", "b"]
106         sl.grammar = [(">", "<"), ("a", "<"), (">", "b"), ("b", "b")
, ("a", "a")]
107         sl.fsmize()
108
109         f = FSM(initial=">", final="<")
110         f.sl_to_fsm([(">", "a"), ("b", "a"), ("a", "b"), ("b", "<")
])
111
112         self.assertTrue(set(sl.fsm.transitions) == set(f.transitions
))
113
114     def test_generate_sample(self):
115         """Checks if all generated data points are actually well-
formed with
116         respect to the given grammar, and that the number of
generated data
117         points is correct."""
118         sl = SL()
119         sl.alphabet = ["a", "b"]
120         sl.grammar = [(">", "a"), ("b", "a"), ("a", "b"), ("b", "<")
]
121         sl.fsmize()
122
123         sample = sl.generate_sample(n=10)
124         self.assertTrue(all([sl.scan(i) for i in sample]))
125         self.assertTrue(len(sample) == 10)
126
127     def test_switch_polarity(self):
128         """Makes sure that switch_polarity actually switches the
grammar to the

```

```

129         opposite, and that switching it again will result in the
original
130         grammar."""
131         gpos = {(">", "a"), ("b", "a"), ("a", "b"), ("b", "<")}
132         gneg = {(">", "<"), ("a", "<"), (">", "b"), ("b", "b"), ("a"
, "a")}
133         sl = SL(polar="n")
134         sl.alphabet = ["a", "b"]
135         sl.grammar = list(gneg)
136
137         sl.switch_polarity()
138         self.assertTrue(set(sl.grammar) == gpos)
139         self.assertTrue(sl.check_polarity() == "p")
140
141         sl.switch_polarity()
142         self.assertTrue(set(sl.grammar) == gneg)
143         self.assertTrue(sl.check_polarity() == "n")
144
145     def test_clean_grammar_2_pos(self):
146         """Tests if clean_grammar correctly cleans 2-local positive
SL
147         grammar."""
148         goal = {(">", "a"), ("b", "a"), ("a", "b"), ("b", "<")}
149         s = SL()
150         s.grammar = [
151            (">", "a"),
152            ("b", "a"),
153            ("a", "b"),
154            ("b", "<"),
155            (">", "g"),
156            ("f", "<"),
157            ("t", "t"),
158         ]
159         s.extract_alphabet()

```

```

160         s.clean_grammar()
161         self.assertTrue(set(s.grammar) == goal)
162
163     def test_clean_grammar_2_neg(self):
164         """Tests if clean_grammar correctly cleans 2-local negative
165         SL
166         grammar."""
167         goal = {(">", "<"), ("a", "<"), (">", "b"), ("b", "b"), ("a",
168         , "a")}
169         a = SL(polar="n")
170         a.alphabet = ["a", "b"]
171         a.grammar = [
172             (">", "<"),
173             ("a", "<"),
174             (">", "b"),
175             ("b", "b"),
176             ("a", "a"),
177             (">", "<"),
178             ("b", "b"),
179         ]
180         a.clean_grammar()
181         self.assertTrue(set(a.grammar) == goal)
182
183     def test_clean_grammar_3_pos(self):
184         """Tests if clean_grammar correctly cleans 2-local positive
185         SL
186         grammar."""
187         goal = {
188             (">", "a", "a"),
189             (">", "b", "b"),
190             ("b", "b", "<"),
191             ("b", "<", "<"),
192             ("a", "<", "<"),
193             (">", ">", "a"),

```

```

191         ("a", "a", "a"),
192         ("a", "a", "<"),
193         (">", ">", "b"),
194         ("b", "b", "b"),
195     }
196     s = SL()
197     s.grammar = [
198         (">", "a", "a"),
199         (">", "b", "b"),
200         ("b", "b", "<"),
201         ("b", "<", "<"),
202         ("a", "<", "<"),
203         (">", ">", "a"),
204         ("a", "a", "a"),
205         ("a", "a", "<"),
206         (">", ">", "b"),
207         ("b", "b", "b"),
208         (">", ">", "f"),
209         ("b", "d", "c"),
210     ]
211     s.extract_alphabet()
212     s.clean_grammar()
213     self.assertTrue(set(s.grammar) == goal)
214
215
216 if __name__ == "__main__":
217     unittest.main()

```

B.3 Unit test for SP

```

1 #!/bin/python3
2
3 """A module with the unittests for the SP module. Copyright (C) 2019
   Alena

```



```

4 Aksenova.
5
6 This program is free software; you can redistribute it and/or modify
   it
7 under the terms of the GNU General Public License as published by
   the
8 Free Software Foundation; either version 3 of the License, or (at
   your
9 option) any later version.
10 """
11
12 import unittest
13 from sp_class import *
14
15
16 class TestSPLanguages(unittest.TestCase):
17     """Tests for the SP class."""
18
19     def test_subsequences_2(self):
20         """Tests extraction of 2-subsequences."""
21         str1 = "abab"
22         ssq1 = {("a", "a"), ("a", "b"), ("b", "a"), ("b", "b")}
23         str2 = "a"
24         ssq2 = set()
25         str3 = "abcde"
26         ssq3 = {
27             tuple(i)
28             for i in ["ab", "ac", "ad", "ae", "bc", "bd", "be", "cd",
29 , "ce", "de"]
30         }
31         sp = SP()
32         self.assertTrue(set(sp.subsequences(str1)) == ssq1)
33         self.assertTrue(set(sp.subsequences(str2)) == ssq2)
34         self.assertTrue(set(sp.subsequences(str3)) == ssq3)

```

```

34
35     def test_subsequences_3(self):
36         """Tests extraction of 3-subsequences."""
37         str1 = "abab"
38         ssq1 = {tuple(i) for i in ["aba", "abb", "bab", "aab"]}
39         str2 = "abcde"
40         ssq2 = {
41             tuple(i)
42             for i in [
43                 "abc",
44                 "abd",
45                 "abe",
46                 "acd",
47                 "ace",
48                 "ade",
49                 "bcd",
50                 "bce",
51                 "bde",
52                 "cde",
53             ]
54         }
55         sp = SP(k=3)
56         self.assertTrue(set(sp.subsequences(str1)) == ssq1)
57         self.assertTrue(set(sp.subsequences(str2)) == ssq2)
58
59     def test_learn_pos(self):
60         """Tests learning of the positive grammar."""
61         data = ["abab", "abcde"]
62         goal = {
63             tuple(i)
64             for i in [
65                 "aba",
66                 "abb",
67                 "bab",

```

```

68         "aab",
69         "abc",
70         "abd",
71         "abe",
72         "acd",
73         "ace",
74         "ade",
75         "bcd",
76         "bce",
77         "bde",
78         "cde",
79     ]
80 }
81 sp = SP(k=3)
82 sp.data = data
83 sp.alphabet = ["a", "b", "c", "d", "e"]
84 sp.learn()
85 self.assertTrue(set(sp.grammar) == goal)
86
87 def test_learn_neg(self):
88     """Tests learning of the negative grammar."""
89     data = ["aaaaabbbb", "abbbb", "aaab"]
90     goal = {tuple("ba")}
91     sp = SP(polar="n")
92     sp.data = data
93     sp.alphabet = ["b", "a"]
94     sp.learn()
95     self.assertTrue(set(sp.grammar) == goal)
96
97 def test_change_polarity(self):
98     """Tests change_polarity function."""
99     sp1 = SP(polar="p")
100    sp1.change_polarity()
101    self.assertTrue(sp1.check_polarity() == "n")

```

```

102
103     sp2 = SP()
104     sp2.change_polarity("p")
105     sp2.change_polarity()
106     self.assertTrue(sp2.check_polarity() == "n")
107
108     sp3 = SP(polar="n")
109     sp3.change_polarity()
110     self.assertTrue(sp3.check_polarity() == "p")
111
112     sp4 = SP()
113     sp4.change_polarity("n")
114     sp4.change_polarity()
115     self.assertTrue(sp4.check_polarity() == "p")
116
117     sp5 = SP()
118     sp5.change_polarity("p")
119     self.assertTrue(sp5.check_polarity() == "p")
120
121     def test_scan_neg(self):
122         """Tests if automata correctly recognize illicit
123         substructures."""
124         sp = SP(polar="n")
125         sp.grammar = [tuple("aba")]
126         sp.k = 3
127         sp.extract_alphabet()
128         sp.fsmize()
129
130         self.assertTrue(sp.scan("aaaa"))
131         self.assertTrue(sp.scan("aaabbbbb"))
132         self.assertTrue(sp.scan("baaaaaabbbbb"))
133         self.assertTrue(sp.scan("a"))
134         self.assertTrue(sp.scan("b"))

```

```

135     self.assertFalse(sp.scan("aaaabaabbbba"))
136     self.assertFalse(sp.scan("abababba"))
137     self.assertFalse(sp.scan("abbbbabbaababab"))
138
139     def test_generate_item(self):
140         """Tests string generation."""
141         sp = SP(polar="n")
142         sp.grammar = [tuple("aba")]
143         sp.k = 3
144         sp.extract_alphabet()
145         sp.fsmize()
146
147         for i in range(30):
148             self.assertTrue(sp.scan(sp.generate_item()))
149
150     def test_generate_sample_pos(self):
151         """Tests sample generation when the grammar is positive."""
152         sp = SP()
153         sp.grammar = [tuple(i) for i in ["ab", "ba", "bb"]]
154         sp.extract_alphabet()
155         sp.fsmize()
156
157         a = sp.generate_sample(n=10)
158         self.assertTrue(len(a) == 10)
159
160     def test_generate_sample_neg(self):
161         """Tests sample generation when the grammar is negative."""
162         sp = SP(polar="n")
163         sp.grammar = [tuple("aba")]
164         sp.k = 3
165         sp.extract_alphabet()
166         sp.fsmize()
167
168         a = sp.generate_sample(n=15, repeat=False)

```

```

169         self.assertTrue(len(set(a)) == 15)
170
171
172 if __name__ == "__main__":
173     unittest.main()

```

B.4 Unit test for TSL

```

1  #!/bin/python3
2
3  """A module with the unittests for the TSL module. Copyright (C)
4      2019 Alena
5      Aksenova.
6
7  This program is free software; you can redistribute it and/or modify
8      it
9  under the terms of the GNU General Public License as published by
10     the
11     Free Software Foundation; either version 3 of the License, or (at
12     your
13     option) any later version.
14
15 """
16
17 import unittest
18
19 from tsl_class import *
20
21
22 class TestTSLLanguages(unittest.TestCase):
23     """Tests for the TSL class."""
24
25     def test_tier_learning(self):
26         """Tests the tier learning function."""
27         a = TSL()
28         a.data = ["aaaab", "abaaaa", "b"]

```

```

23     a.alphabet = ["a", "b"]
24     a.learn_tier()
25     self.assertTrue(a.tier == ["b"])
26
27     b = TSL()
28     b.data = ["ccaccaccbc", "acbbaababc", "ababbab"]
29     b.alphabet = ["a", "b", "c"]
30     b.learn_tier()
31     self.assertTrue(set(b.tier) == {"a", "b"})
32
33     def test_tier_learning_raised_issue(self):
34         """Checks a specific case related to GitHub issue #6."""
35         tsl = TSL()
36         tsl.data = [
37             "aa", "ab", "ax", "ay",
38             "ba", "bb", "bx", "by",
39             "xa", "xb", "xx",
40             "ya", "yb", "yx", "yy"
41         ]
42         tsl.alphabet = ["a", "b", "x", "y"]
43         tsl.learn_tier()
44         self.assertTrue(set(tsl.tier) == {"x", "y"})
45
46     def test_tier_image(self):
47         """Tests the erasing function."""
48         a = TSL()
49         a.tier = ["a"]
50         self.assertTrue(a.tier_image("cvamda") == "aa")
51
52     def test_learn_pos(self):
53         """Tests learning of the positive TSL grammar."""
54         a = TSL()
55         a.data = [
56             "o",

```

```

57         "oko",
58         "a",
59         "aka",
60         "oo",
61         "aa",
62         "kak",
63         "kok",
64         "kk",
65         "kkakka",
66         "akk",
67         "kkokko",
68         "okk",
69     ]
70     a.extract_alphabet()
71     a.learn()
72     goal = {
73         (">", "<"),
74         (">", "a"),
75         ("a", "a"),
76         (">", "o"),
77         ("o", "o"),
78         ("a", "<"),
79         ("o", "<"),
80     }
81     self.assertTrue(set(a.grammar) == goal)
82     self.assertTrue(set(a.tier) == {"a", "o"})
83
84     def test_learn_neg(self):
85         """Tests learning of the negative TSL grammar."""
86         a = TSL(polar="n")
87         a.data = [
88             "o",
89             "oko",
90             "a",

```



```

91         "aka",
92         "oo",
93         "aa",
94         "kak",
95         "kok",
96         "kk",
97         "kkakka",
98         "akk",
99         "kkokko",
100        "okk",
101    ]
102    a.extract_alphabet()
103    a.learn()
104    goal = {("a", "o"), ("o", "a")}
105    self.assertTrue(set(a.grammar) == goal)
106    self.assertTrue(set(a.tier) == {"a", "o"})
107
108    def test_scan_pos(self):
109        """Tests recognition of strings."""
110        a = TSL(polar="p")
111        a.data = [
112            "o",
113            "oko",
114            "a",
115            "aka",
116            "oo",
117            "aa",
118            "kak",
119            "kok",
120            "kk",
121            "kkakka",
122            "akk",
123            "kkokko",
124            "okk",

```

```

125         ]
126         a.extract_alphabet()
127         a.learn()
128         self.assertTrue(a.scan("akkaka"))
129         self.assertTrue(a.scan("kkk"))
130         self.assertTrue(a.scan("okoko"))
131         self.assertTrue(a.scan("ookokkk"))
132         self.assertFalse(a.scan("okoak"))
133         self.assertFalse(a.scan("okakok"))
134         self.assertFalse(a.scan("kakokak"))
135
136     def test_scan_neg(self):
137         """Tests recognition of strings."""
138         a = TSL(polar="n")
139         a.data = [
140             "o",
141             "oko",
142             "a",
143             "aka",
144             "oo",
145             "aa",
146             "kak",
147             "kok",
148             "kk",
149             "kkakka",
150             "akk",
151             "kkokko",
152             "okk",
153         ]
154         a.extract_alphabet()
155         a.learn()
156         self.assertTrue(a.scan("akkaka"))
157         self.assertTrue(a.scan("kkk"))
158         self.assertTrue(a.scan("okoko"))

```

```

159         self.assertTrue(a.scan("ookokkk"))
160         self.assertFalse(a.scan("okoak"))
161         self.assertFalse(a.scan("okakok"))
162         self.assertFalse(a.scan("kakokak"))
163
164     def test_generate_item_pos(self):
165         """Tests that the generated items are grammatical."""
166         a = TSL(polar="p")
167         a.data = [
168             "o",
169             "oko",
170             "a",
171             "aka",
172             "oo",
173             "aa",
174             "kak",
175             "kok",
176             "kk",
177             "kkakka",
178             "akk",
179             "kkokko",
180             "okk",
181         ]
182         a.extract_alphabet()
183         a.learn()
184         gen_items = [a.generate_item() for i in range(15)]
185         for i in gen_items:
186             self.assertTrue(a.scan(i))
187
188     def test_generate_item_neg(self):
189         """Tests that the generated items are grammatical."""
190         a = TSL(polar="n")
191         a.data = [
192             "o",

```

```

193         "oko",
194         "a",
195         "aka",
196         "oo",
197         "aa",
198         "kak",
199         "kok",
200         "kk",
201         "kkakka",
202         "akk",
203         "kkokko",
204         "okk",
205     ]
206     a.extract_alphabet()
207     a.learn()
208     gen_items = [a.generate_item() for i in range(15)]
209     for i in gen_items:
210         self.assertTrue(a.scan(i))
211
212     def test_change_polarity_pos_to_neg(self):
213         """Checks that the polarity switching works."""
214         a = TSL(polar="p")
215         a.grammar = [
216            (">", "o"),
217            ("a", "<"),
218            ("a", "a"),
219            ("o", "o"),
220            ("o", "<"),
221            (">", "a"),
222            (">", "<"),
223         ]
224         a.tier = ["a", "o"]
225         a.switch_polarity()
226         self.assertTrue(set(a.grammar) == {("a", "o"), ("o", "a")})

```

```

227     self.assertTrue(a.check_polarity() == "n")
228
229     b = TSL(polar="p")
230     b.data = ["aaaab", "abaaaa", "b"]
231     b.extract_alphabet()
232     b.learn()
233     b.switch_polarity()
234     self.assertTrue(set(b.grammar) == {("b", "b"), (">", "<")})
235     self.assertTrue(b.check_polarity() == "n")
236
237     def test_change_polarity_neg_to_pos(self):
238         """Checks that the polarity switching works."""
239         a = TSL(polar="n")
240         expected = {
241             (">", "o"),
242             ("a", "<"),
243             ("a", "a"),
244             ("o", "o"),
245             ("o", "<"),
246             (">", "a"),
247             (">", "<"),
248         }
249         a.grammar = [("a", "o"), ("o", "a")]
250         a.tier = ["a", "o"]
251         a.switch_polarity()
252         self.assertTrue(set(a.grammar) == expected)
253         self.assertTrue(a.check_polarity() == "p")
254
255         b = TSL(polar="n")
256         b.data = ["aaaab", "abaaaa", "b"]
257         b.extract_alphabet()
258         b.learn()
259         b.switch_polarity()
260         self.assertTrue(set(b.grammar) == {(">", "b"), ("b", "<")})

```

```

261         self.assertTrue(b.check_polarity() == "p")
262
263     def test_polarity_raised_issue(self):
264         """Checks a specific case from the GitHub issue."""
265         a = TSL(polar="p")
266         a.grammar = [(">", "a"), ("a", "b"), ("b", "<"), ("b", "a")]
267         a.tier = ["a", "b"]
268         a.switch_polarity()
269         expected = {("a", "a"), ("a", "<"), ("b", "b"), (">", "b"),
270                     (">", "<")}
271         self.assertTrue(set(a.grammar) == expected)
272         self.assertTrue(a.check_polarity() == "n")
273
274     def test_generate_sample(self):
275         a = TSL(polar="p")
276         a.grammar = [(">", "a"), ("a", "b"), ("b", "<"), ("b", "a")]
277         a.tier = ["a", "b"]
278         a.alphabet = ["a", "b", "c"]
279
280         sample = a.generate_sample(n=10, repeat=False)
281         for i in sample:
282             self.assertTrue(a.scan(i))
283
284 if __name__ == "__main__":
285     unittest.main()

```

B.5 Unit test for MTSL

```

1 #!/bin/python3
2
3 """A module with the unit tests for the MTSL module. Copyright (C)
   2019 Alena
4 Aksenova.

```

```

5
6 This program is free software; you can redistribute it and/or modify
   it
7 under the terms of the GNU General Public License as published by
   the
8 Free Software Foundation; either version 3 of the License, or (at
   your
9 option) any later version.
10 """
11
12 import unittest
13 import unittest.mock
14 from mtsl_class import *
15
16
17 class TestMTSLLanguages(unittest.TestCase):
18     """Tests for the MTSL class."""
19
20     def test_grammar_learning_neg(self):
21         """Tests the learner."""
22         a = MTSL(polar="n")
23         VC = [
24             "aabbaabb",
25             "abab",
26             "aabbab",
27             "abaabb",
28             "aabaab",
29             "abbabb",
30             "ooppoopp",
31             "opop",
32             "ooppop",
33             "opoopp",
34             "oopoop",
35             "oppopp",

```

```
36     "aappaapp" ,
37     "apap" ,
38     "aappap" ,
39     "apaapp" ,
40     "aapaap" ,
41     "appapp" ,
42     "oobboobb" ,
43     "obob" ,
44     "oobbob" ,
45     "oboobb" ,
46     "ooboob" ,
47     "obbobb" ,
48     "aabb" ,
49     "ab" ,
50     "aab" ,
51     "abb" ,
52     "oopp" ,
53     "op" ,
54     "oop" ,
55     "opp" ,
56     "oobb" ,
57     "ob" ,
58     "oob" ,
59     "obb" ,
60     "aapp" ,
61     "ap" ,
62     "aap" ,
63     "app" ,
64     "aaa" ,
65     "ooo" ,
66     "bbb" ,
67     "ppp" ,
68     "a" ,
69     "o" ,
```



```

70         "b",
71         "p",
72         "",
73     ]
74     expected = {
75         ("a", "o"): [("a", "o"), ("o", "a")],
76         ("b", "p"): [("b", "p"), ("p", "b")],
77     }
78     a.data = VC[:]
79     a.extract_alphabet()
80     a.learn()
81
82     correct = True
83     for i in a.grammar:
84         if not (i in expected and set(a.grammar[i]) == set(
expected[i])):
85             correct = False
86     if len(a.grammar) != len(expected):
87         correct = False
88
89     self.assertTrue(correct)
90
91     def test_grammar_learning_pos(self):
92         """Tests the learner."""
93         b = MTS�(polar="p")
94         VC = [
95             "aabbaabb",
96             "abab",
97             "aabbab",
98             "abaabb",
99             "aabaab",
100             "abbabb",
101             "ooppoopp",
102             "opop",

```

```
103     "ooppop" ,
104     "opoopp" ,
105     "oopoop" ,
106     "oppopp" ,
107     "aappaapp" ,
108     "apap" ,
109     "aappap" ,
110     "apaapp" ,
111     "aapaap" ,
112     "appapp" ,
113     "oobboobb" ,
114     "obob" ,
115     "oobbob" ,
116     "oboobb" ,
117     "ooboob" ,
118     "obbobb" ,
119     "aabb" ,
120     "ab" ,
121     "aab" ,
122     "abb" ,
123     "oopp" ,
124     "op" ,
125     "oop" ,
126     "opp" ,
127     "oobb" ,
128     "ob" ,
129     "oob" ,
130     "obb" ,
131     "aapp" ,
132     "ap" ,
133     "aap" ,
134     "app" ,
135     "aaa" ,
136     "ooo" ,
```

```

137         "bbb",
138         "ppp",
139         "a",
140         "o",
141         "b",
142         "p",
143         "",
144     ]
145     expected2 = {
146         ("a", "o"): [
147            (">", "a"),
148             ("a", "<"),
149             ("a", "a"),
150            (">", "o"),
151             ("o", "o"),
152             ("o", "<"),
153            (">", "<"),
154         ],
155         ("b", "p"): [
156            (">", "b"),
157             ("b", "b"),
158             ("b", "<"),
159            (">", "p"),
160             ("p", "p"),
161             ("p", "<"),
162            (">", "<"),
163         ],
164     }
165
166     b.data = VC[:]
167     b.extract_alphabet()
168     b.learn()
169
170     correct = True

```

```

171         for i in b.grammar:
172             if not (i in expected2 and set(b.grammar[i]) == set(
expected2[i])):
173                 correct = False
174             if len(b.grammar) != len(expected2):
175                 correct = False
176
177         self.assertTrue(correct)
178
179     @unittest.mock.patch(
180         # Artificially enforce a particular case of list(set())'s
naturally-
181         # occurring non-determinism with respect to ordering:
182         # make it ascending if odd number of elements, descending if
even.
183
184         # While impractical, this re-implementation of list(set())
is perfectly
185         # legal. It could be discarded, but that way, the test
becomes
186         # non-deterministic and reveals the bug only in some 10% of
runs.
187
188         "mtsl_class.list",
189         new=lambda x: sorted(x, reverse=len(x) % 2 == 0) \
            if type(x) == set else list(x)
190     )
191
192     def test_grammar_learning_raised_issue(self):
193         """Checks a specific case related to GitHub issue #6."""
194         mtsl = MTS�(k=2, polar="n")
195         mtsl.data = ["axb", "ayxb", "azxb", "azxyb"]
196         mtsl.extract_alphabet()
197         mtsl.learn()
198         self.assertTrue(all({*tier} == {"a", "b", "x"} for tier,

```

```

restrict \
199                                     in mtsl.grammar.items() if ("a", "b") in
restrict))

200

201 def test_convert_pos_to_neg(self):
202     """Tests conversion of a positive grammar to a negative one.
203     """
204     z = MTSL(polar="p")
205     z.grammar = {
206         ("a", "o"): [
207            (">", "a"),
208             ("a", "<"),
209             ("a", "a"),
210            (">", "o"),
211             ("o", "o"),
212             ("o", "<"),
213            (">", "<"),
214         ],
215         ("b", "p"): [
216            (">", "b"),
217             ("b", "b"),
218             ("b", "<"),
219            (">", "p"),
220             ("p", "p"),
221             ("p", "<"),
222            (">", "<"),
223         ],
224     }
225     z.switch_polarity()
226     expected = {
227         ("a", "o"): [("a", "o"), ("o", "a")],
228         ("b", "p"): [("b", "p"), ("p", "b")],
229     }
230     self.assertTrue(z.grammar == expected)

```

```

230
231 def test_scan_pos(self):
232     """Tests scanning using a positive grammar."""
233     c = MTSL(polar="p")
234     c.grammar = {
235         ("a", "o"): [
236            (">", "a"),
237             ("a", "<"),
238             ("a", "a"),
239            (">", "o"),
240             ("o", "o"),
241             ("o", "<"),
242            (">", "<"),
243         ],
244         ("b", "p"): [
245            (">", "b"),
246             ("b", "b"),
247             ("b", "<"),
248            (">", "p"),
249             ("p", "p"),
250             ("p", "<"),
251            (">", "<"),
252         ],
253     }
254     for s in ["apapappa", "ppp", "appap", "popo", "bbbooo"]:
255         self.assertTrue(c.scan(s))
256     for s in ["aoap", "popa", "pbapop", "pabp", "popoa"]:
257         self.assertFalse(c.scan(s))
258
259 def test_scan_neg(self):
260     """Tests scanning using a positive grammar."""
261     d = MTSL(polar="n")
262     d.grammar = {
263         ("a", "o"): [("a", "o"), ("o", "a")],

```

```

264         ("b", "p"): [("b", "p"), ("p", "b")],
265     }
266     for s in ["apapappa", "ppp", "appap", "popo", "bbbooo"]:
267         self.assertTrue(d.scan(s))
268     for s in ["aoap", "popa", "pbapop", "pabp", "popoa"]:
269         self.assertFalse(d.scan(s))
270
271
272 if __name__ == "__main__":
273     unittest.main()

```

B.6 Unit test for FSA

```

1  #!/bin/python3
2
3  """A module with the unittests for the fsm module. Copyright (C)
4      2019 Alena
5      Aksenova.
6
7  This program is free software; you can redistribute it and/or modify
8  it
9  under the terms of the GNU General Public License as published by
10 the
11 Free Software Foundation; either version 3 of the License, or (at
12 your
13 option) any later version.
14
15 """
16
17 import unittest
18 from fsm import FSM
19
20 class TestFSM(unittest.TestCase):
21     """Tests for the FSM class."""

```

```

18
19     def test_sl_to_fsm_2(self):
20         """Checks if a 2-SL grammar translates to FSM correctly."""
21         f = FSM(initial=">", final="<")
22         grammar = [(">", "a"), ("b", "a"), ("a", "b"), ("b", "<")]
23         f.sl_to_fsm(grammar)
24
25         tr = {
26             (("a",),), "a", ("a",)),
27             (("b",),), "a", ("a",)),
28             (("a",),), "b", ("b",)),
29             (("b",),), "<", ("<",)),
30         }
31         self.assertTrue(set(f.transitions) == tr)
32
33     def test_sl_to_fsm_3(self):
34         """Checks if a 3-SL grammar translates to FSM correctly."""
35         f = FSM(initial=">", final="<")
36         grammar = [
37             (">", "a", "b"),
38             ("a", "b", "a"),
39             ("b", "a", "b"),
40             ("a", "b", "<"),
41             (">", ">", "a"),
42             ("b", "<", "<"),
43         ]
44         f.sl_to_fsm(grammar)
45
46         tr = {
47             (("a", "a"), "b", ("a", "b")),
48             (("a", "b"), "a", ("b", "a")),
49             (("b", "a"), "b", ("a", "b")),
50             (("a", "b"), "<", ("b", "<")),
51             (("a", ">"), "a", ("a", "a")),

```



```

52         (("b", "<"), "<", ("<", "<")),
53     }
54     self.assertTrue(set(f.transitions) == tr)
55
56     def test_scan_sl_2(self):
57         """Checks if a FSM for 2-SL grammar can correctly recognize
58         strings."""
59         f = FSM(initial=">", final="<")
60         f.transitions = [
61             (">",), "a", ("a",)),
62             ("b",), "a", ("a",)),
63             ("a",), "b", ("b",)),
64             ("b",), "<", ("<",)),
65         ]
66
67         self.assertTrue(f.scan_sl(">abab<"))
68         self.assertTrue(f.scan_sl(">ab<"))
69         self.assertTrue(f.scan_sl(">abababab<"))
70
71         self.assertFalse(f.scan_sl("><"))
72         self.assertFalse(f.scan_sl(">a<"))
73         self.assertFalse(f.scan_sl(">ba<"))
74         self.assertFalse(f.scan_sl(">ababbab<"))
75
76     def test_scan_sl_3(self):
77         """Checks if a FSM for 3-SL grammar can correctly recognize
78         strings."""
79         f = FSM(initial=">", final="<")
80         f.transitions = [
81             (">", "a"), "b", ("a", "b")),
82             ("a", "b"), "a", ("b", "a")),
83             ("b", "a"), "b", ("a", "b")),
84             ("a", "b"), "<", ("b", "<")),
85             (">", ">"), "a", (">", "a")),

```

```

84         (("b", "<"), "<", ("<", "<")),
85     ]
86
87     self.assertTrue(f.scan_sl(">>abab<<"))
88     self.assertTrue(f.scan_sl(">ab<"))
89     self.assertTrue(f.scan_sl(">>abababab<<"))
90
91     self.assertFalse(f.scan_sl(">><<"))
92     self.assertFalse(f.scan_sl(">>a<<"))
93     self.assertFalse(f.scan_sl(">>ba<<"))
94     self.assertFalse(f.scan_sl(">>ababbab<<"))
95
96     def test_trim_fsm_2(self):
97         f = FSM(initial=">", final="<")
98         f.transitions = [
99             ((" ">,), "a", ("a",)),
100             (("b",), "a", ("a",)),
101             (("a",), "b", ("b",)),
102             (("b",), "<", ("<",)),
103             ((" ">,), "c", ("c",)),
104             (("d",), "<", ("<",)),
105         ]
106         goal = {
107             ((" ">,), "a", ("a",)),
108             (("b",), "a", ("a",)),
109             (("a",), "b", ("b",)),
110             (("b",), "<", ("<",)),
111         }
112         f.trim_fsm()
113         self.assertTrue(set(f.transitions) == goal)
114
115     def test_trim_fsm_3(self):
116         f = FSM(initial=">", final="<")
117         f.transitions = [

```

```

118         ((">", "a"), "b", ("a", "b")),
119         (("a", "b"), "a", ("b", "a")),
120         (("b", "a"), "b", ("a", "b")),
121         (("a", "b"), "<", ("b", "<")),
122         ((">", ">"), "a", (">", "a")),
123         (("b", "<"), "<", ("<", "<")),
124         ((">", "b"), "j", ("b", "j")),
125         ((">", ">"), "j", (">", "j")),
126         (("j", "k"), "o", ("k", "o")),
127     ]
128     goal = {
129         ((">", "a"), "b", ("a", "b")),
130         (("a", "b"), "a", ("b", "a")),
131         (("b", "a"), "b", ("a", "b")),
132         (("a", "b"), "<", ("b", "<")),
133         ((">", ">"), "a", (">", "a")),
134         (("b", "<"), "<", ("<", "<")),
135     }
136     f.trim_fsm()
137     self.assertTrue(set(f.transitions) == goal)
138
139
140 if __name__ == "__main__":
141     unittest.main()

```

B.7 Unit test for OSTIA

```

1 #!/bin/python3
2
3 """A module with the unittests for the fsm module. Copyright (C)
4     2020 Alena
5     Aksenova.
6
7 This program is free software; you can redistribute it and/or modify

```

```

    it
7 under the terms of the GNU General Public License as published by
    the
8 Free Software Foundation; either version 3 of the License, or (at
    your
9 option) any later version.
10 """
11
12 import unittest
13 from ostia import ostia
14
15
16 class TestOSTIA(unittest.TestCase):
17     """Tests for the OSTIA learner.
18
19     Warning: updated versions of the learner might require updating
20     the unittests.
21     """
22
23     def test_ostia_success(self):
24         """Checks if OSTIA can learn a rule rewriting "a" as "1" if
25         "a" is
26         final and as "0" otherwise, and always mapping "b" to "1".
27         """
28         S = [
29             ("a", "1"),
30             ("b", "1"),
31             ("aa", "01"),
32             ("ab", "01"),
33             ("aba", "011"),
34             ("aaa", "001"),
35         ]
36         t = ostia(S, ["a", "b"], ["0", "1"])

```

```

36     transitions = {
37         ("", "a", "", "a"),
38         ("", "b", "1", ""),
39         ("a", "a", "0", "a"),
40         ("a", "b", "01", ""),
41     }
42     stout = {"": "", "a": "1"}
43
44     self.assertTrue(set(t.E) == transitions)
45     self.assertTrue(stout == t.stout)
46
47     def test_ostia_fail(self):
48         """Checks that OTSIA cannot learn an unbounded tone
49         plateauing."""
50         S = [
51             ("HHH", "HHH"),
52             ("HHL", "HHL"),
53             ("HLH", "HHH"),
54             ("HLL", "HLL"),
55             ("HLLH", "HHHH"),
56             ("HL", "HL"),
57         ]
58         t = ostia(S, ["H", "L"], ["H", "L"])
59
60         transitions = {
61             ("", "H", "H", "H"),
62             ("H", "H", "H", ""),
63             ("H", "L", "", "HL"),
64             ("HL", "H", "HH", ""),
65             ("HL", "L", "", "HLL"),
66             ("HLL", "H", "HHH", ""),
67             ("", "L", "L", ""),
68         }
69         stout = {"": "", "H": "", "HL": "L", "HLL": "LL"}

```

```
69
70     self.assertTrue(set(t.E) == transitions)
71     self.assertTrue(stout == t.stout)
72
73
74 if __name__ == "__main__":
75     unittest.main()
```