TÍTULO TRABAJO FIN DE MÁSTER:

MODELLING FIRST AND SECOND LANGUAGE ACQUISITION AND PROCESSING WITH TEMPORAL SELF-ORGANIZING MAPS

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1. INTRODUCTION

According to the vast literature on word processing and access, in perception and production, an input word may concurrently activate non-target lexical neighbors that become available for further processing stages. The growing body of psycholinguistic evidence shows how competition based on word similarity and lexical redundancy affect speakers’ anticipation of incoming stimuli, improving lexical decision and facilitating word recognition.

In the domain of bilingual performance – in terms of first language (hereafter L1) and second language (hereafter L2) interaction - the interference from one language to the other may occur with respect to both language structure and linguistic processing, and can be noticed at the phonological and the syntactical levels, as well as in lexical borrowings (Van Heuven et al., 1998).

The main goal of this thesis is to model second language acquisition and processing with Temporal Self-Organizing Maps (TSOMs, Ferro et al., 2011; Marzi et al., 2012, 2014a, 2015, 2016; Pirrelli et al., 2014, 2015) by simulating some basic cognitive processes that govern lexical processing in the mental lexicon. In particular, I pretend to bridge the gap by extending the application of computational modelling of language acquisition in monolingual and bilingual contexts to Spanish, which has not yet been treated within the given research framework.

My specific objectives are the following:

- Explore the dynamics of lexical organization by means of computational modelling in Spanish language in monolingual regime, then contrast the results to the already existing Italian and German sets.
- Explore the dynamics of interplay between the above-mentioned three languages in contexts of partial as well as perfect bilingualism.
- Provide further evidence that type/token frequency, formal redundancy and lexical neighborhood affect perception, acquisition, and processing.
Since the software for TSOM training is yet neither available for an open-source download, nor for a web-service training, the experiments have been run by Dr. Marzi at the Institute for Computational Linguistics, ComPhys Lab\(^1\) (Italian National Research Council, Pisa, Italia). Dr. Marzi also took over the extraction of the data. I myself compiled the Spanish dataset and analyzed the results in both L1/L1 and L1/L2 regimes.

Modelling human lexical processing must take into account adaptive mechanism of storage and representation of lexical input, in consideration of the fact that the way a speaker stores lexical information reflects the way it is perceived and dynamically processed.

With no information of morpho-syntactic or semantic features, the acquisition of language-specific orthotactic constraints\(^2\) delineate the propensity to acquire novel words, and show how acquisitional strategies are affected by the past knowledge of language and the entrenched expectations on incoming stimuli. In this perspective, a strong expectation based on L1 influences the way L2 inputs are perceived. The entrenchment can be described as a specialization of most frequent input stimuli in highly routinized clusters aimed at the optimization of our mental resources\(^3\).

This study is based on the work of and has been completed in collaboration with my external supervisor, Claudia Marzi, who provided me with some essential information to the completion of this dissertation, i.e. both the Italian and German datasets, as well as the experimental results that I will analyze in Chapter 5.

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\(^1\) ComPhys Lab investigates the interplay between language-specific processes and language-aspecific cognitive functions. Its cooperation with CNR Institute of Clinical Physiology (IFC) aims at contributing to the research related to the language and communication disorders in the field of biomedical sector. For further information: [www.comphyslab.eu](http://www.comphyslab.eu)

\(^2\) Orthotactic constraints refer to the fact that certain letter sequences are perceived as more typical in a given language. The acoustic counterpart of the Orthotactic constraints are the Phonotactic constraints, which considers the typicality of sound patterns, rather than letters.

\(^3\) See 2.1 for a SLA perspective of the entrenchment mechanism explained by the Neuronal Commitment feature within the MacWhinney’s Competition Model (2001).
To achieve my goal, a series of TSOM-based experiments will be run, where language acquisition is modelled as the storage of “time series of symbolic units (words) as routinized patterns of short-term node activation” (Marzi & Pirrelli, 2015).

Each input form is represented by a unique time-series of symbols (orthographical representations⁴ in the present work), administered one symbol at a time. Since words are permanently coded in our long-term memory as neuron activation patterns that sequentially fire, they can be represented as time series of symbols, whose receptors are time-bound to one another through associative connections. To put it simply, the incoming words are intuitively processed one symbol at a time. This kind of sequential processing is mimicked by means of computational simulations.

In this perspective, each input word form is represented by a unique time-series of symbols that are vector-coded⁵ on the input layer and administered to the TSOM one at a time.

With the goal of simulating paradigmatic acquisition and perception of morphological relations between fully-inflected word forms, an identical set of verb forms have been selected for Spanish, German and Italian, and administered in different training regime conditions, namely monolingual (L1), bilingual (L1/L1) and incremental first and second language (L1+L2) regimes. Within the framework of this study, TSOM training corresponds to the initial learning period when a random frequency-arranged words are showed to the input layer of the map. In this way, groups of nodes “specialize” in regard to a

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⁴ Phonological vs. Orthographic distinction corresponds to acoustic vs. visual word recognition. In terms of input stimuli, words can be perceived in two different ways, that is, phonologically and orthographically. By way of example, computational coding of the incoming word drive can be administered to the input layer of the map in the following two ways: phonetic transcription /draɪv/, transformed in $d,r,a,i,v,#$, as opposed to the orthographic $d,r,i,v,e#$, respectively.

⁵ Geometrically speaking, a vector is essentially an arrow whose dimension is specified by coordinates. In the field of neural networks, a vector corresponds to an incoming input. See Anderson (2014) for more detail.
certain input stimulus as a result of repeated pattern activations. Such mechanism roughly corresponds to the early language acquisition in children, where morphological structure gradually emerges without the need to resort to the explicit rote rehearsal techniques, and explicit rule-based learning, typically adopted by adult second language learners.

The advantage of computational simulations is offered by the possibility of (i) gaining a deep understanding of the mutual relationship between representation (memory) and processing strategies (e.g. input perception, or word production); (ii) verifying, under controlled simulations of word stimuli, that memory structures represent the way input stimuli are perceived and coherently processed; (iii) analytically studying the developmental processes that govern the acquisition of the morphological lexicon in different languages, in different language exposure conditions; (iv) monitoring the interplay between input frequency and perception of formal redundancy.

The thesis is organized as follow: in Chapter 2, I will firstly introduce some fundamental models for language acquisition, based on psycholinguistic approaches. In Chapter 3 I will review and discuss the most influential models for lexical processing, and outline some computational architectures based on artificial neural networks. Chapter 4 will include a detailed description of the experimental method and corpora adopted for computational simulations, which will be described in detail in Chapter 5. Finally, a concluding Chapter (6) will follow, with some general remarks and considerations on prospective research.
2. FIRST AND SECOND LANGUAGE ACQUISITION MODELS

There is abundant literature concerning both first language (L1) and second language (L2) acquisition. Objectives of linguistic and psycholinguistic approaches may be focused either on competence or performance. Competence refers to the abstract knowledge of language, performance relates to the actual process of language use (Bates & MacWhinney, 1989).

Although several factors — age of acquisition, social environment, and language transfer among others — may affect second language acquisition (hereafter SLA) in regards to vocabulary extension, pragmatic competence, and so forth, it is widely assumed that L1 and L2 acquisition are strongly related processes. Learning new word forms in a L2 is an extension of what we use for acquiring words in our L1. By paraphrasing MacWhinney, the strong influence and interference that L1 has onto L2 supports the position that a model of L2 learning must take into account L1 linguistic structures (MacWhinney, 2005: 49).

In what follows here, I will briefly introduce MacWhinney’s Competition Model and Unified Model, as well as Bailey’s work on the effects of wordlikeness on language acquisition.

2.1. The Competition Model (MacWhinney, 2001)

The Competition Model is a psycholinguistic theory of language acquisition and processing, which postulates that language is interpreted on the basis of linguistic cues within the input, and that language is acquired relying on competing mechanisms in an input rich linguistic environment.

Bates & MacWhinney (1989) describe their Competition Model in this way:
The Competition Model is a framework for the crosslinguistic study of language use. It is designed to capture facts about the comprehension, production, and acquisition of language by real human beings, across a variety of qualitatively and quantitatively distinct language types. (Bates & MacWhinney, 1989: 3)

Contrary to what was assumed by Chomsky’s Universal Grammar (Chomsky, 1968), the Competition Model posits that first and second language acquisition relies on cognitive universals, rather than linguistic universals (MacWhinney, 2001: 1). Both theories try to determine the “universal properties of human language” (Bates & MacWhinney, 1989), although the two of them adopt sharply distinct starting points. The claim that grammar can be explained in cognitive terms means that language depends on properties of human mind, which is modelled by experience, individual differences and culture, among others. The Competition Model can be defined as an emergentist theory of language acquisition, assuming simple learning mechanisms, common to other cognitive processes, which support language acquisition, with word learning and grammar acquisition seen as the final result of these processes (MacWhinney, 1999).

The Competition Model is compatible with functionalism, where function is assimilated to the concept of goal. According to this viewpoint, language is viewed as a set of goal-directed activities.

Three are the pillars that determine interaction within language learning: the input, the learner, and the context. First, Input-Driven Learning is one of the three commitments of the Competition Model, which contrasts the nativist approach by assuming that instead of innate properties, language is learned by means of the incoming stimuli acquired through the so-called cues. The strength of the cues corresponds to the weight of the connections between units and is determined by their own reliability and availability. Cue validity can be defined as follows: “cue

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6 The fundamental postulate of Universal Grammar is the genetic component of the language faculty, with a set of structural rules that are innate in humans, independent of experience.
validity, that is, the information value of a given linguistic device as a cue to an underlying meaning or intention" (MacWhinney & Bates, 1989: 29).

Cue validity measures the predictability in adult language processing, as well as children language acquisition (MacWhinney & Bates, 1989: 34). The higher the predictability, the better the cue.

In addition, four other dimensions contribute to cue strength (MacWhinney, 1992):

1. **Task Frequency.** The basic principle is that the frequency of the task will determine the cue’s strength and ultimately enhance the validity of the latter. For example, the determination of the agent of a transitive verb is an easier task compared to anaphoric reference determination (MacWhinney, 1992:122).

2. **Availability.** The availability expresses whether a cue is present or not. For example, in Italian, the cue suggesting a preverbal position to the agent of a transitive verb has a low availability because the omission of the subject is quite frequent. This is not the case in English.

3. **Simple Reliability.** A cue is said reliable when it leads to the correct conclusion. To get back to the previous example, the cue suggesting a preverbal position to the agent of a transitive verb is unreliable in the Italian language, whereas it is highly reliable in English.

4. **Conflict Reliability,** called Conflict validity in the previous version of this model, refers to the situation in which different cues are competing and ultimately one particular cue wins over all the other available cues for the same task. Again, this can be illustrated with the example provided by MacWhinney (1992): in Dutch, case cue of a noun phrase will dominate on its preverbal position of the noun phrase.

The goodness-of-fit criteria to find the winner is determined by all the above-mentioned variables. In principle, every cue is assessed in comparison to other available cues, which means that the final result is obtained through the competition process among the existing alternatives. That is to say, the selection
of the best possible linguistic unit within any linguistic task is accurately calculated on the bases of the above-mentioned set of criteria.

The second component of the Competition Model listed below is the Learner. It addresses the effect of individual differences on language acquisition. The human brain is better described as a neural network in which neurons “fire information” to each other through axons. This vision of brain relies on the assumption that neural activity is performed through associative networks. In brief, mental processing is viewed as a highly interactive and competitive net of units. Within this dimension of the Competition Model, at least five distinct features must be outlined (MacWhinney, 1992, 2001):

1. **Transfer.** As already mentioned, within brain structure neurons are arranged into layers of connections. Therefore, we can say that the architecture of the human brain is intrinsically interactive, allowing the interconnection of its building blocks, that is to say, neural units. Some scholars (Chomsky, 1980; Fodor, 1983) split language into separate cognitive modules. However, connectionist theories in general and the Competition Model, in particular, argue that even if “a certain limited form of emergent linguistic modularity is achieved” (MacWhinney, 1992: 120), the resulting emergent modules are far from being encapsulated. As a result, the transfer of information takes place when, let’s say, a second language is being acquired. The transfer component can be resumed as follows: “[…] whatever can transfer will.” (MacWhinney, 2004: 18). The general assumption in the field of second language acquisition is that L2 is parasitic on L1 in a number of ways. Accordingly, L2 relies on transfer mechanisms to build its own linguistic structure to the detriment of L1. MacWhinney (2004) lists at least four classes of transfer, as follows: Sentence Comprehension, Transfer in Pragmatics, Transfer in Morphology, and Transfer in Sentence Production. For example, in Sentence Production L2 learner will use L1 articulatory patterns to pronounce L2 sentences, which is quite logical if we think that the learner’s phonetic inventory completely depends on his/her native language. Zhao & Li (2007) establish a relation between parasitism and decreasing plasticity under late learning, the latter being
likely to decrease as a separate system of L2 linguistic representations is gradually built up. Besides, the evidence mentioned in the same study shows that early L2 learning leads to a lesser degree of L2 parasitism on L1, as the plasticity of the brain allows L2 to occupy more space.

2. **Neuronal Commitment.** To say that a neural area is committed means that it has attained a defined structure by establishing a set of weights that will govern the processing. Such weights configuration points at the gradual loss of brain plasticity. In a L2 learner, such a pre-existing neural arrangement will cause “catastrophic” interference of L1 onto L2, which can only be avoided with the intercession of functional neural circuits and transfer.

3. **Automaticity.** The basic principle underlying automaticity is that highly recurrent tasks will lead to a certain level of automaticity in lexical and syntactic access. The automaticity of linguistic retrieval is apparently slower in bilinguals compared to monolinguals, when both languages are involved in the lexical decision tasks (Segalowitz & Hulstijn, 2005).

4. **Functional Circuits.** Within the framework of the Competition Model, Functional Neural Circuits account for the hindering of L2 parasitism and negative transfer on L1. Phonological loop⁷ and mental imagery⁸ are two of the mechanisms embedded in the working principles of the Functional Circuits. Such mechanisms boost the reinforcement of language acquisition and processing (MacWhinney, 2001: 16). In other words:

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⁷ Phonological loop is a Working Memory (WM) component that both retains phonological information and provides a rehearsal process (as theorized by Baddeley, 1986). WM is characterized by its temporary retention capacity, and the phonological loop may neutralize the decay of verbal information retained in it (Christoffels & De Groot, 2004; De Groot & Van Hell, 2005).

⁸ The concept of Mental Imagery refers to the “quasi perceptual experience” of mental representations that take place without any external stimuli (Thomas, 2017).
Theories of the neural basis of verbal memory view this storage as involving a functional neural circuit that coordinates inputs from Broca’s area, lexical storage in the temporal lobe, and additional structures that support phonological memory. Unlike local lexical maps, which are neurologically stable, this functional circuit is easily disrupted and relies heavily on access to a variety of cognitive resources. (MacWhinney, 2004: 13)

5. **Perspective-taking**, which is the last point of the Competition Model from the learner’s perspective, assumes that the interpretation of a clause begins from a certain starting point, that is, from a perspective that goes beyond the positional relation of the words and ultimately achieves the conceptual representation (MacWhinney, 2001: 17).

The third point in this tripartite explanation of the Competition Model is the Context. The interactional context is seen as an essential component of the language acquisition process, both in L1 as well as in L2.

### 2.2. The Unified Model (MacWhinney, 2004)

The Unified Model is an extended formulation of the Competition Model, which incorporates an additional subset of components accounting for multilingual acquisition, transfer promotion or inhibition among others. The main difference is that the original Competition Model did not account for learning processes, whereas the Unified Model does. Learning is intended “[…] as a resonant process that relies on storage, chunking, and support to acquire new mappings.” (MacWhinney, 2004: 1).

In a simplistic way, SLA consists in applying to the L2 the acquisition patterns we assimilated while acquiring our L1. In this way, L2 “borrows” the mechanisms developed during L1 acquisition. The main distinctions between the first language and the following languages acquisition lie in the fact that L1 is learned at the same time as the infant discovers the world (MacWhinney, 2004: 2), when the brain has not yet lost its original plasticity as a result of the neuronal commitment,
and when learning is supported by an intense interaction provided by the caregivers (Snow, 1999).

While some researchers maintain two different and separate processes accounting for first and second language acquisition, MacWhinney (2004) claims that some phenomena, such as transfer, suggest otherwise. For this reason, he considers more reasonable to develop a unified model of first and second language acquisition.

In Figure 1 the seven building blocks of the Unified Model are sketched, where chunking, codes, and resonance are the newly added aspects.

![Figure 1. The Unified Competition Model general architecture (from MacWhinney, 2004).](image)

The load-bearing component of both the earlier version of the Competition Model and the Unified Competition Model is, intuitively, competition. In the earlier model, competition was solely accounted for by the cue summation and interactive activation. Whereas, in the Unified Model competition is also based on resonance.
In summary, competitive processes take place within and between the competitive arenas, as well as between the available codes. This will be explained in some more detail in what follows.

The concept of arenas, or competitive arenas, refers to the four linguistic processing domains, namely phonology, lexicon, morphosyntax, and conceptualization. Each of them has a double representation, corresponding to the two levels of production and comprehension (e.g. phonology corresponds to the message formulation in production and to the auditory processing in comprehension). Besides, as it is to be expected, older learners develop one more competitive arena: the orthographic competition.

Cues are the other pillar of the two above-mentioned models. If we consider words as form-function mappings, cues are what allows us to establish the very connection between form and function of the linguistic sign. To put it simply, on the comprehension level, forms are cues that lead to the underlying intentions/functions; on the production level, functions are cues that lead to surface forms (forms compete to express functions).

Concerning storage, two distinct types of processing involve two distinct types of memory: offline processing mainly relies on long-term memory, with online processing mainly involving short-term memory. As emphasized by MacWhinney himself (2004), decision tasks that have no time restriction better show the validity of cue-based mechanism, since sufficient time is provided to ponder and select the best possible cue. The online processing, instead, relies on working memory and cue cost procedure supplants the cue validity mechanism. Cue cost (Bates & MacWhinney, 1987: 178) relates to the perceivability (or detectability) and assignability of the cue, the former relating to the difficulty that a listener may face in detecting cues, the latter referring to the facility to assign a role to a given cue. The assignability is then strictly interconnected with memory. In other words, cue cost increases when more processing is needed to pick up the correct cue.
One of the additional component of the Unified Model is Chunking, which operates on combinations of frequently co-occurring items to build up syllables, words, sentences. They may be found at different levels, starting from the phonology and ending with syntax. Adult learners often fail to assimilate larger inflectional patterns as a result of the tendency to pick shorter units, which are easier to analyze (MacWhinney, 2012: 15). Linguistic units are then learned on their own, instead of being learned within frequently occurring combinatorial patterns. In fact, not only chunking helps to foster fluency in language acquisition, but it can also boost the emergence of grammar by means of analogic relations.

Another additional component to the previous Competition Model is the theory of code interaction, which includes transfer theory as well. Such theory provides an explanation for how codes interact between them, that is, how the code selection happens, and what implies code switching and code mixing processes. Transfer, for its part, can be positive or negative, the former resulting from successful alignment of L2 forms with correspondent L1 forms, the latter reflecting a situation in which the alignment produces unwanted mismatches (MacWhinney, 2012: 18).

The final additional component, resonance, is central to the Unified Model in that it accounts for the code separation and learning process, among others. Structurally, resonance represents the repeated co-activation of neural connections, occurring when overt verbalizations evolve into covert, that is, inner speech that positively affects syntax reinforcement. Simply put, resonance allows the reconfiguration of oldest neural patterns. Technically speaking, resonance has to do with the co-activation of two cortical areas, which is temporarily maintained in the hippocampus (MacWhinney, 2012: 12).

In this perspective, several scenarios are outlined. For instance, in case of bilingualism, simultaneous acquisition can result into equal or unbalanced dominance of the two languages, where weaker language is unable to provide sufficient inner resonance in order to prevent transfer from happening. In contrast, balanced proficiency in the two languages inhibits the code blending. However, in comparison to bilingualism, the L2 acquisition is structurally different, because
the second language tends to be considerably weaker than the native language.
In contrast to child language acquisition, in this case explicit learning strategies
must be implemented.

In addition to the seven components, the Unified Model takes into account Age-
Related Effects on language acquisition. There is convergent evidence that at a
certain point the ability to learn languages decreases. The Unified Model mainly
attributes the Critical Period Hypothesis to the entrenchment of L1, which means
that during the development of L1 specific structures get determined. In such a
way, the human brain commits to specific linguistic paths that increasingly lead
to the limitation of brain flexibility. Self-Organizing Maps may replicate such
phenomena, as will be shown in the following chapter.

Generally speaking, the Unified Model identifies two sets of factors, able of
inhibiting or promoting language acquisition. Doublets of risk vs. support factors
are listed as follows: entrenchment vs. resonance; misconnection vs. connection;
negative vs. positive transfer; parasitism vs. internalization; isolation vs.
participation.

Entrenchment and resonance duo is quite simple to understand, since the
counteraction of resonance to entrenchment consists in providing a mechanism
of re-encoding the already committed neuronal circuitry. Furthermore, other brain
processes may increase the effect of entrenchment. The characteristic structure
of the brain has the tendency to connect words that have similar meaning and
grammatical category into neuron clusters, or cortical maps.

To address the connection vs. misconnection issue, one must consider the
difference in part of speech assignment between L1 and L2: if both languages
rely on the same system of grammatical category attribution, then no obstacle will
interfere in L2 syntactic processing. On the other hand, if the two languages
belong to two very different systems of grammatical category assignment, then
the difficulty to learn L2 syntax will lead to a major parasitism on L1.
As already mentioned, parasitism refers to the mechanisms of emulating pre-existing L1 structures while learning L2. Internalization process has the capacity to neutralize such parasitic mechanisms with the help of the inner speech.

2.3. Generalized Neighborhood Model (GNM, Bailey & Hahn)

At this stage of inquiry, it is important to focus on the following question: how do L1 and L2 interact with each other? How does perception of typicality of lexical input affect L1 and L2 acquisition? Typicality is the extent to which a target word is perceived as similar to other words in the lexicon (Marzi et al., 2014b).

Perception of similarity is recognized to be central to language acquisition and processing as it allows to establish correspondences with other similar words in the lexicon, and, in so doing, accelerate word recognition. Following the definition of Luce (1986: 4): “A similarity neighborhood is defined as a collection of words that are phonetically similar to a given stimulus word.” Similarity goes hand in hand with the concept of wordlikeness that generally refers to a speaker’s knowledge of the phonotactics9 in his/her native language, basically grounded on their lexical competence and consequently put in practice with the help of intuition (Bailey & Hahn, 2001).

Marzi et al. (2016) posit that among phenomena that affect the acquisition of verb paradigms, family effects play an important role, since the neighbor family size effect intervenes during the acquisition of low frequency regular forms. This is not the case when irregular forms are memorized, since no co-activation of neighboring connections can be performed. Both family size and the frequency of the neighboring words can positively or negatively affect the activation of the target word, e.g. if a target word is surrounded by a higher-frequency lexical units,

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9 Phonotactics are to be defined as the frequency of co-occurrence of certain sound patterns. Another concept to take into consideration is that phonology is governed by phonotactic constraints that identify which sound combinations are allowed and which are not in a given language (Välimaa-Blum, 2009).
it will be more difficult to access. Further evidence has shown (Baayen et al., 2006; Milin et al., 2009) that the same facilitatory/inhibitory effects are to observe in the domain of inflectional patterns, as well as inflectional classes\textsuperscript{10}, which are both involved in lexical processing.

In examining the determinants of wordlikeness, Bailey & Hahn (2001) identified two distinct factors, which oppose lexical influence, \textit{lexical neighborhood}, to the statistical knowledge of combinatorial patterns of sequence typicality, or \textit{phonotactic probability}. Table 1 displays Albright’s (2006) review of this dichotomic model:

\begin{table}[h]
\centering
\begin{tabular}{|l|l|}
\hline
\multicolumn{1}{|c|}{\textbf{Lexical knowledge}} & \multicolumn{1}{|c|}{\textbf{Phonotactic knowledge}} \\
\hline
➢ Speakers know the words of their language & ➢ Speakers attend to combinatorial possibilities of different sounds in their language \\
➢ Hearing a novel word activates a set of real words, while attempting lexical access & ➢ Novel words are parsed into constituent sounds, and the likelihood of combinations is assessed \\
➢ The more words it activates, and the more similar it sounds to them, the more plausible it is as a possible word & ➢ The more probable/“less illegal” the combinations are, the better the word sounds \\
\hline
\end{tabular}
\caption{Generalized Neighborhood Model by Bailey & Hahn (2001)}
\end{table}

The main controversy underlying such distinction is whether lexical neighborhoods are fundamentally distinct from phonotactic knowledge or rather they are deeply interconnected in determining the sequence typicality. In their research paper, Bailey & Hahn (2001) set out to explore which one of the two

\textsuperscript{10} Milin & Moscoso Del Prado Martin (2009) define the Inflectional Paradigm as “the set of inflected variants that can be formed for a word by regular or predictable morphological transformations.” In what follows, an Inflectional Class is as well defined as “a set of words that form their IPs in the same way”, which can easily be traced to what is generally called as conjugations for verbs, and declensions for nouns.
above-mentioned phenomena (or alternatively the combination thereof) determines wordlikeness, the key assumption being that there is a constant interplay between the two of them.

In the study mentioned, transition-probabilities measures are employed in order to capture the phonotactic probability at different positions across words. Transition probability is one of the two most common ways phonotactic probability is calculated, the other is bigram co-occurrence within the body of speech. Such metric allows for better exploration of the phonotactic gradience\(^\text{11}\), which can be interpreted as a lack of definite and rigid acceptability rules (Välimaa-Blum, 2009; Bybee, 2001: 64).

On the other hand, lexical neighborhood measure is based on the phonemic overlap among lexical units within the mental lexicon, as well as the quantity of such shared phonemes (Luce, 1986). A neighbor is generally defined as “a word that could be transformed into the target word itself by a one phoneme substitution, insertion, or deletion” (Luce, 1986:17). Consequently, the neighborhood density is defined by the number of neighbor words (NNB) connected to the target word (Bailey & Hahn, 2001:571). The research taken into account here extends the measurement of neighbors to the words that feature two-phoneme edit distance.

The Generalized Neighborhood Model (GNM, from now on) is an adaptation of the Generalized Context Model (GCM; Nosofsky, 1986, 1990), which refused the neighbor vs. non-neighbor dichotomy by assuming that novel words maintain neighboring relationship of different degrees, based on the “aggregate similarity” to the stored words (Albright, 2007: 5). GNM accounts for the effects of lexical neighborhood, namely the extent to which each novel word is to some degree

\(^{11}\) Bybee (2010) defines the concept of gradience as follows: “Gradience refers to the fact that many categories of language or grammar are difficult to distinguish, usually because change occurs over time in a gradual way, moving an element along a continuum from one category to another.”
supported by the similarity to the existing words in the lexicon\textsuperscript{12}. Such supporting effect is provided among others by token frequency, which is believed to benefit word recognition (see Luce, 1986: 5 for further discussion). Furthermore, GNM provides a more realistic measure capable of capturing both monotonic and non-monotonic frequency effects, which better determines the contribution made by words of different frequencies (Bailey & Hahn, 2001; Albright, 2007). In fact, although it seems more intuitive to assume that the frequency increase leads to stronger lexical support, it should be noted, though, that word-frequency paradox comes into play here. Word-frequency paradox (Mandler et al., 1982; Lohnas & Kahana, 2013) lies in the finding that high frequency facilitates word recalling, whereas low frequency benefits word recognition. This phenomenon is explained by Bybee (1995) as the result of the tendency of high frequency words to be processed as autonomous entities, rather than in conjunction with other lexical entries. The fact that high frequency inhibits morphological analysis results into less productivity and hence limits neighborhood interaction. This mechanism gives prominence to medium frequency words as they seem to have a greater role in determining new formations and wordlikeness (Bybee, 1995: 434; Albright, 2007: 6; Bailey & Hahn, 2001: 580).

Another newly added feature is the assessment of phonological differences, specifically aimed at identifying substitution, insertion, and deletion cost between neighbor-words. For example, in \textit{bat-sat} the substitution of the initial consonant is easier when compared to the analogous substitution in \textit{bat-pat} (Bailey & Hahn, 2001: 563). As a result, greater dissimilarity leads to lesser lexical support, therefore to a greater psychological distance and cost (Albright, 2007; Bailey & Hahn, 2001). Structurally speaking, the dis/similarity is calculated by means of

\textsuperscript{12} Albright (2007:5) provides the following definition of the GNM:

\begin{align*}
\text{Support for item } i &= \sum \text{weight}_w \times e^{-d_{i,w}/s}, \\
\text{where} & \quad \text{weight}_w = \text{a function of the token frequency of word } w, \\
& \quad d_{i,w} = \text{psychological distance between nonce item } i \text{ and existing word } w, \\
& \quad s = \text{sensitivity, a parameter that controls the magnitude of the advantage that very similar neighbors have in determining the outcome}, \\
& \quad e \approx 2.71828 \\
\end{align*}

For further discussion, see Albright (2007).
the natural class distance metric, which proceeds to add up all the different phonological features\textsuperscript{13}. Such metric ranges from 0, where no difference is observed between phonemes, to 1, corresponding to completely different phonemes.

GNM’s main point of departure was to determine to what extent sequence typicality is influenced by phonotactic probabilities and by lexical influences. Furthermore, the very nature of sequence typicality was questioned in terms of its submission to neighborhood effects, as opposed to the dependency on statistical knowledge (Bailey & Hahn, 2001: 585).

In conclusion, albeit acknowledging that both lexical neighborhoods and phonotactic (or orthotactic) probability are still far from being completely explored, findings from psycholinguistic and cognitive experiments run within the framework of the GNM indicate that lexical influences better predict wordlikeness than phonotactics do.

\textsuperscript{13} “[…] a natural class is a group of sounds sharing one or more linguistically significant phonetic characteristic” (Bailey & Hahn, 2001: 573).
3. LEXICAL PROCESSING

Over the last forty years, many theoretical and psycholinguistic approaches have focused on the mechanism governing lexical storage and access and on the dynamics of language acquisition and processing (Jackendoff, 1975; Bybee, 1985, 1995; Matthews, 1993; Aitchison, 1994; Aronoff, 1994; Baayen et al., 1997; MacWhinney, 1999; Libben, 2005; among others).

Converging evidence from psycholinguistic studies suggests that lexical knowledge and morphological competence appear to be organized to maximize processing efficiency, rather than to minimize storage. Originally hypothesized by Vennemann (1974), the role of morphological competence is to help organize the lexicon in an appropriate way and to make words easier to be stored and accessed.

In more recent times, this hypothesis has been developed into a view of the mental lexicon as a dynamic memory system (among others, Bybee, 1995; Ellis & Schmidt, 1998; Elman, 1995, 2004; Baayen, 2007; and specifically concerning L1 and L2 interaction, see Ellis, 1998, 2002; Li, 2009).

The way lexical information is stored mirrors the way it is accessed and processed. In this perspective, an analysis of the dynamic interaction between lexical representations and distribution, degrees of regularity in input data, and perceptual competition can explain and illustrate the emergence of structure in the mental lexicon.

3.1. Mental representation and processing

According to psycholinguistic approaches, lexical representations correspond to the projection of a word in one’s mental lexicon, with the latter defined as the mental lexical archive of a speaker. It is generally accepted that in such lexicon, each entry is provided with some additional information, that ranges from
linguistic features to the way that particular unit can relate to other words (Gagné, 2017; Traxler, 2012: 81)

The question to which many linguists attempted to give an answer is how words are stored, processed and retrieved in the mental lexicon. Psycholinguistic evidence has suggested different approaches to lexical representation. Gagné (2017) classifies five different approaches accounting for lexical representation:

i. The first approach posits that no morphological parsing is involved in the first stage of word recognition: whole word forms (be they morphologically simplex or complex) are stored in the mental lexicon. The main line of argument of this model, also defined as a full listing model (Domínguez et al., 2000: 376), is that the lexical representation of new entries is carried out through the mapping of semantic features. However, this approach does not completely exclude morphological analysis of complex morphological units. In fact, according to some theories belonging to this approach, when accessing a new and completely unknown word, an associative mechanism activates connections between the newly input word and already stored words that are perceived as similar (Cutler, 1980), or stored words that share the same root (e.g. Granger et al., 1991).

ii. A second approach, on the contrary, relies on morphological decomposition. In this case, word representation starts with the segmentation of new lexical entries into their morphological constituents (i.e. morphemes). The general assumption of this approach, called full parsing model, is that the meaning of a word can be accessed by means of its isolated morphological constituents (Taft & Forster, 1976; Rastle & Davis, 2008).

iii. The third access corresponds to the dual-route, or mixed models (as defined by Domínguez et al., 2000: 377), which hypothesize either a parallel activation of the first two approaches described above (Schreuder
& Baayen, 1997), or an independent activation of the whole-word access for familiar input and the decomposing access for novel input words (Caramazza et al., 1988). In these models, a line is drawn between mainly orthographic or semantic recognition. Besides, regular and irregular forms are treated differently.

iv. A fourth approach states that the combination of the first two models operate concurrently, at the level of the surface form of the word and at the semantic level (Kuperman et al., 2009). This interactive multiple-routes processing claims that a chronological order must be observed, e.g. in a bottom-up processing, the surface-level must be processed before semantic level. The most important point in this approach is that the two processing routes influence each other. Recent neurophysiological evidence (e.g. Pulvermüller, 2002) suggests that surface and semantic levels get simultaneously activated when processing an input word.

v. The last approach following the overview of Gagné (2017) consists in attributing the morphological representation to the emergence of co-activation of formal features (orthographic and/or phonological patterns) together with semantic features. In other words, the representation of a given word is “dissolved”, or distributed among a set of correlations within a network (Plaut & Gonnerman, 2000; Ferro et al., 2010; Marzi & Pirrelli, 2015).

3.2. Morphological storage and processing models

Originally, the focus of morphological processing was placed on analytical languages, especially English, and limited to the processing model of the past tense of both regular and irregular verbs. In this work, I will revise three processing models, which account for three distinct ways to approach the morphological representation of lexical units. The main two criteria taken into
account are whether verbs are processed through storage or through computation on base-form instead.

3.2.1. Dual processing model

As already mentioned, the point of departure of morphological storage and processing models are mainly for irregular and regular verbal inflections. Pinker & Prince (1991) hold that regular morphology is directly linked to the application of rules, therefore to greater productivity, whereas irregular forms request “memory-driven processing”. From such perspective, it follows that irregular versus regular patterns are subjected to two distinct and dichotomic processing mechanisms.

One assumption of this model predicts that irregular inflection is affected by the frequency rate. In fact, it claims that lower-frequency forms tend to undergo regularization (in a diachronic perspective), because their semantic representation in the mental lexicon is weaker than that of the highly-frequent verbs. Over-regularization is, in fact, a typical phenomenon not only of the U-shaped learning curve in child language acquisition (Marcus et al., 1990; Pinker & Prince, 1991: 242), but also in adult dialects, which allow coexistence of doublets such as dived-dove (Stemberger, 1989; Marcus et al., 1990; Pinker & Prince, 1991: 234).
Although it is accepted that the operativeness of rule-based regular inflection, consisting in online computing of inflected form by adding a suffix to the base form, does not depend on previous storage of regular forms, Pinker and Prince (1991: 237) do not exclude that the system might actually memorize some regular inflections. In fact, this may be the case when past tense doublets coexist in the mental lexicon. Again, in no case, the generalization of the regular rules depends on such storage.

3.2.2. CONNECTIONIST MODEL

Murre (2005) traces back the connectionist models to the Hebbian neural learning rule\textsuperscript{14}, often expressed as follows: “nerve cells that fire together, wire together.” Waskan\textsuperscript{15} explains Hebb’s proposal in the following way: “the connection between two biological neurons is strengthened (that is, the presynaptic neuron will come to have an even stronger excitatory influence) when both neurons are simultaneously active.”

One of the most prominent connectionist model was theorized by Rumelhart & McClelland (1986). They suggest that:

\[
\text{[...]} \text{implicit knowledge of language may be stored in connections among simple processing units organized in networks. While the behavior of such networks may be describable (at least approximately) as conforming to some system of rules, we suggest that an account of the fine structure of the phenomena of language use can best be formulated in models that make reference to the characteristics of the underlying networks. (Rumelhart & McClelland, 1987: 196)}
\]

\textsuperscript{14}Hebb (1949) proposes an explanation for the adaptation of neurons in the brain during the learning process, describing a basic mechanism for synaptic plasticity, where an increase in synaptic efficacy arises from the presynaptic cell's repeated and persistent stimulation of a postsynaptic cell.

According to this model, lexical representation emerges from neural connections, that is, generalization allows language acquisition. In the following citation of their work, Rumelhart & McClelland place great emphasis on one of their key assumptions:

> We have, we believe, provided a distinct alternative to the view that children learn the rules of English past-tense formation in any explicit sense. We have shown that a reasonable account of the acquisition of past tense can be provided without recourse to the notion of a “rule” as anything more than a description of the language. We have shown that, for this case, there is no induction problem. The child need not figure out what the rules are, nor even that there are rules. (Rumelhart & McClelland, 1986: 267)

The main assumption is that no distinction is to be made between regular and irregular verbs processing. The core principle of this model is that base input-forms are linked in the associative memory to the output-past-tense forms. The strengths of such connections constantly rearrange during the learning process. Such neuron-like structures, are characterized by an “all-or-none character” (Waskan, 2010), which means that they are either “firing” or they are inactive. In other words, the signals are associated with an activation value that ranges between 0 (inactive state) and 1 (maximal activation firing), they are transmitted along neural connections. The target behavior is finally achieved thanks to the adaptive learning of neural networks, constantly adjusting to the changing weight of connections. This way, both the structure and the learning process are constantly updated.

### 3.2.3. NETWORK MODEL

The third model of morphological processing in language acquisition that I will sketch here is the Network model, proposed by Bybee (1985; 1988). It shares some essential characteristics with connectionist models, with some fundamental new features that distinguishes it from the previous models.
On the one hand, the common ground between Bybee’s theory and any other connectionist theory is that (i) ir/regular verbs are processed in the same way, contrary to what dual-processing model postulates; and, as a result, (ii) no explicit rules are formulated for language acquisition. Both models state that productivity of a morphological pattern is strictly related to its type frequency, rather than to a different morphological behavior.

On the other hand, criteria such as type and token frequency, lexical strength, and lexical schemas are some of the most relevant properties of this model, which account for distinct lexical representations and different levels of productivity of ir/regular verbs.

Lexical strength is intended as the semantic independence of a word in the mental lexicon: the stronger the representation, the less regularization tendency will emerge, the better accessibility of the entry. Bybee (1995) claims that lexical strength of a lexical item depends on its token frequency. She asserts that “words with higher lexical strength serve as the basis for the formation of new words” (Bybee, 1985).

New lexical entries create associations with other units across the lexicon, enabling the emergence of morphological connections between base forms and complex forms, as well as among complex forms. It is believed that new words do not undergo any segmentation, although a sort of morphological analysis is actually carried out in extracting common phonological and semantic features between new forms and already stored words. The number of detected common features affects lexical representation, which gradually increases as more and more morphological connections are constituted. Thus, this model posits that stronger connections result into major lexical strength. An example of how semantic and phonological connections work is sketched below (Bybee, 1988): the singular form of cat is semantically connected to its plural form cats. Furthermore, the latter form can form further connections with other plural nouns in the mental lexicon. In Figure 2, below, the relevant features are bolded for attention.
The amount of phonological and semantic connections determines the Degree of Relatedness that has a positive effect on word recognition. The author argues that the degree of relatedness depends more on shared semantic features, rather than form features (Bybee, 1988: 129).

Token frequency has a great impact on both lexical strength and lexical connections. This idea can be captured if one accepts Bybee’s (1995: 129) conclusion that words with higher frequency are more autonomous, have stronger lexical representation, hence engage less with other words and are better learnt on their own terms. In contrast, less frequent forms construct a network with other lexical items, and are better learnt through such relations.

Further assumption ascribes to greater frequency the paradigm changes, such as suppletion — a common trait in the most frequent paradigms (Bybee, 1995: 129). With respect to low frequency forms, networks of shared semantic and phonological patterns result in the emergence of generalizations that Bybee
defines as schemas\textsuperscript{16}. The productivity of such schemas depends on the following two criteria: (i) degree of specificity of the schema, and (ii) its lexical strength. The specificity of the schema points to its defining properties: less specific schema will be more open, thus more productive. The productivity of the schema is also positively affected by its strength, which is directly proportional to its type frequency. In this case, the type frequency refers to the occurrence of morphological pattern as a whole. The opposite scenario is as follows: the greater the number of defining features, the closer the schema. Consequently, its low productivity leads to lesser exposure to new items, and ultimately to lower type frequency.

In addition to this line of argument, Bybee (1995) makes a distinction between two sorts of schemas: product-oriented and source-oriented, which correspond to irregular and regular verbs analysis, respectively. As a matter of fact, product-oriented schemas indicate common features between base and derived forms, but do not explain how this derivation is carried out, e.g. string-strung. As a counterpart to this operation, source-oriented schemas do establish inflectional relation by relating the basic form with derived past from in the dental suffix, as in walk-walked. This latter class recalls the generative rules, theorizing online computation of past tense forms, as opposed to representation process.

Since no attempt to avoid redundancy is made according to this model, both schemas can be activated for the same connection.

3.2.4. Discussion

Rule-based and classical connectionist approaches (i.e. one-route vs dual-route processing) have dominated the debate on morphological processing for a couple of decades (around from the mid-80s to the mid-2000s).

\textsuperscript{16} In Bybee’s approach, schemas represent phonological properties of a morphological class that are used to organize and access the lexicon.
According to the dual-route approach (§ 3.2.1), access to a morphologically complex word implicates two steps: (i) a preliminary access to the input full-word, and (ii) an optional morpheme-based access resulting from combinatorial rules. According to the one-route approach (§ 3.2.2), morphological structure is a by-product of a direct correspondence (without combinatorial rules) between a lexical base as an input form and a correspondent output form, namely an inflected or derived form (e.g. *walk*-walked, *ring*-rang).

Both approaches obey to a strictly derivational view of morphological relations, according to which a fully inflected form is always produced/analyzed on the basis of a unique, underlying lexical (base) form. By modelling inflection as a phonological/orthographical mapping function from a lexical base to its range of inflected forms, classical connectionist architectures are closer to a rule-free variant of the classical constructive view (where roots and affixes are the basic building blocks of morphological competence, on the assumption that the lexicon is largely redundancy-free), than to associative models of the mental lexicon.

Nowadays, there is convergent evidence (coming from the large body of psycholinguistic studies) of a distributed account of morphological structure as an emergent property of lexical self-organization, based on relations between surface forms, in line with the network model proposed by Bybee (§ 3.2.3).

It should be assumed that all word forms are memorized in the lexicon, with no distinction between a stored base form and all other related forms, which are processed on-line (see Baayen, 2007, for an overview).

In addition, to capture the fact that words encountered frequently exhibit different lexical properties from words encountered infrequently, any model of the mental lexicon must assume that accessing a word in some way affects the access representation of that word (Marslen-Wilson, 1993; Sandra, 1994; among others).
3.3. **Computational modelling**

The way lexical information is stored may reflect the way it is represented, accessed and retrieved as patterns of concurrent activation of memory areas. Memory, as already pointed out, plays a central role in lexical modelling, and in such account, computer simulations of memory processes can well address issues of lexical acquisition and processing.

From a computational standpoint, lexical processing has to address three fundamental issues: (i) the nature of input representations, (ii) the nature of output representations, (iii) the formal relationship holding between (i) and (ii). Such issues are strongly influenced both by the way specific tasks are modelled, and by the theoretical approach they are related to, as summarized by Ellis:

> […] language researchers take recourse to computer modeling by which the test of the simulation is whether competences emerge that parallel those of human language learners exposed to similar input. In this way, the debate between deductive and inductive approaches to language acquisition is being rephrased in terms of well-articulated models and real-world data. (Ellis, 2005: 7)

Computational simulations may offer the possibility to gain insights into the relationship between representation (memory) and processing strategies (perception and production), and empirically verify, under controlled simulations of word stimuli, that memory structures represent the way external stimuli are perceived and processed in our brain.

In such account, **neural networks**, as adopted in computational modelling, represent simplified models of neural processing in the brain, as they can mimic the behavior of aggregations of neurons in the cortical areas involved in the classification of sensory data.
Kohonen's Self-Organizing Maps (SOMs, Kohonen, 2001) define a class of unsupervised\(^{17}\) artificial neural networks that mimics the behavior of small aggregations of neurons in the cortical areas involved in the classification of input data.

### 3.3.1. Kohonen's Self-Organizing Maps

In such architecture, processing consists in the activation of specific neurons upon presentation of a particular stimulus. A distinguishing feature of this brain maps is their topological organization, where nearby neurons in the map are activated by similar stimuli. There is evidence that at least some aspects of their neural connectivity emerge through self-organization as a function of cumulated sensory experience (Kaas et al., 1983). Functionally, these kind of brain maps are dynamic memory stores, which are directly involved in input processing, exhibiting effects of dedicated long-term topological organization.

Kohonen (2001) points out that artificial neural networks cannot emulate the complex anatomy of human brain, therefore they are meant to describe a limited area of it, which corresponds to a particular function. He suggested that (1982: 64) “This particular network model is first used to demonstrate, in an ultimately simplified configuration, that the activity of neighboring cells, due to the lateral interactions, can become clustered in small groups [...].”

A SOM can be defined as a “topology-preserving" map (Rojas, 1996), in so far as it succeeds in duplicating the topological correspondence, that is to say the spatial relation, between the incoming stimuli and the inputs in the cortex. For

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\(^{17}\) Unsupervised is referred to the fact that there is no human supervision, thus recreating a competitive learning process (Holmén, 1996). Such characteristic of SOMs (and TSOMs as well) reflects the lack of instructions, balanced by the ability of the map to “classify” input stimuli. In other words, perception is what enables the acquisition, where the incoming stimuli are classified, stored, and grouped in order to let shared features to emerge. In this perspective, the classification process optimizes input storage. This characteristic mimics a genuine learning process where a child is exposed to the flow of unknown linguistic information that s/he is supposed to learn without any explicit instruction. The learning process is thus carried out intuitively by detecting similarities across the incoming stimuli.
example, neurobiological evidence has shown that the human brain processes visual information in such a way that a two-dimensional mapping is projected on the cortex (Rojas, 1996: 392). The same experimental evidence points to the fact that external inputs activate the immediate neighbors of the unit.

When presenting the SOMs, Kohonen (1982: 59) explicitly referred to an “idealized neural structure”, although he assumed that this model could have much wider application (Kohonen, 1982, 2001).

This kind of neural modelling realistically explains the organization of certain brain structures, whose characteristics are unfolded through SOM’s adaptive processing (Kohonen, 2001: 85). In simple terms, Self-Organizing Maps originate "elastic net" of points that can be described as “ordered maps of various sensory features onto a layered neural network” (Kohonen, 2001: 69).

The nearest node to a sensory stimulus is the so-called Best Matching Unit (BMU), which is the salient unit. The competition underlying SOMs mechanism yields a winner that represents all the grouping of input vectors (Waskan, 2010). All nodes surrounding the BMU form the neighborhood. To sum up, during the learning process, the neighboring nodes interact in order to learn from the same sensory input. As a consequence, local relaxation on the weight of neuronal vectors within the neighborhood is achieved, which finally results in the global ordering of the map (Kohonen, 2001: 87).

Neural network modelling has been mainly applied to the domain of monolingual lexical acquisition, whereas, up to day, only a few studies implying neural modelling devoted to bilingualism has been carried out (Zhao & Li, 2007). In the attempt to bridge this gap, Zhao & Li (2007) in their study *Bilingual Lexical Representation in a Self-Organizing Neural Network Model*, focused on investigating whether within the framework of bilingualism, the lexicon of the two languages develops into one shared representation in the mental lexical, or rather they are stored separately. Zhao & Li (2007) proposed a SOM-based architecture with three feature maps, corresponding to input level (auditory-phonology),
lexical-semantic representation level, and output level (articulation). Once it receives semantic or phonological input vector, a SOM generates representational mappings on two-dimensional array of nodes that can take a rectangular or hexagonal form.

The Model

![Diagram of the model](image)

Figure 3: DevLex II structure (Li, Zhao & MacWhinney, 2007).

A whole set of variables affects language acquisition, for this reason, the above-mentioned study narrowed down the investigation by focusing on three different L2 acquisition scenarios: simultaneous, early, and late learning. The main hypothesis was that bilingual lexicon evolves progressively as L2 is being learned. For this purpose, the DevLex II, has been used in order to detect the dynamical nature of bilingual lexical organization. The structure of DevLex II is illustrated in Figure 3 above.

The three levels account for phonological, semantic, and production representations. Both the input and semantic information are represented by
SOMs, connected through Hebbian learning.

As already mentioned, DevLex II was trained to simulate three distinct learning contexts. To do so, 500 were presented simultaneously, as well as more or less sequentially, to the network over 10 learning epochs. Each word was input 10 times per epoch. The bilingualism regime was recreated by parallel exposition of the map to both lexica simultaneously, 50 form per epoch. In the second scenario, corresponding to the early learning, L2 lexicon (Chinese) was input after 100 L1 words (English) were presented to the map. Finally, within the late learning context L2 lexicon intervened after the network saw 400 L1 forms.

Figure 4 summarizes the results of such experiments by showing both phonological as well as semantic maps, showcasing the lexical distribution of L1/L2 lexica in three training regimes. Dark areas represent L2 lexicon.

In case of simultaneous learning context, the results reflect a situation in which L1 and L2 achieve two separate lexical representations, where no dominant language is attested. The boundaries of both languages are clear. On the other hand, in early learning situation L2 partially loses its agglomerate characteristic—at least in the phonology map—by giving more space to L1. In this way, L1 starts gaining dominance over L2, which can be observed also in the dedicated semantic map. In the last scenario the distributional pattern drastically changes. In fact, L2 lexicon is assimilated to the dominant L1 lexicon, L2 fragments moving closer to the areas of L1 on the basis of shared features, be they semantic or phonological. Zhao & Li (2007) explain such distribution with plasticity loss18. In other words, in late learning regime lexical organizational structure is already established, thus the difficulty of changing the topology of the network increases with neuronal entrenchment.

18 See § 2.1 for more detail.
One limitation of DevLex II model is pertinent here: the lack of the temporal dimension of input removes the surface word relations that trigger the emergence of lexical structure. In this way, semantic representation gains at the expense of the predictability of the incoming word.

In the following section, I will briefly outline an architecture based on one level of representation, where input words are encoded on the input layer as temporal sequences of symbols.
3.3.2. Temporal Self-Organizing Maps

The main difference between classical SOMs and TSOMs is the temporal dimension: in SOMs input words are shown in a static way, whereas temporality is an essential component of Temporal Self-Organizing Maps (TSOMs hereafter). In fact, sequential representation of words as time-series of symbols is a more realistic way of recreating human language perception, be it based on acoustic, or written input.

To be more specific, TSOMs represent a variant of classical SOMs, by adding a level of temporal connectivity, implemented as a pool of re-entrant connections providing the state of activation of the map at the immediately preceding time tick. Temporal connections encode the map’s expectations of upcoming input on the basis of past experience (Pirrelli et al., 2015). In this way, a map can memorize input words as time-series of symbols (e.g. orthographic letters or phonological representations) as activation chains of nodes.

The TSOM architecture (see Figure 5 below) is characterized by a grid of topologically organized memory node (exactly as Kohonen’s SOMs are), which represents one layer of (artificial) neurons, with two layers of connectivity: (i) all nodes are fully connected with the input vector with no time delay (i.e. the spatial connection layer); (ii) each node is connected with all other nodes (i.e. temporal connection layer), whose connections are updated with one-step time delay, based on activity synchronization between a BMU at a preceding time and the following activating BMU (i.e. the most highly activated node at time \( t-1 \) and the node at time \( t \) that mostly get activated).

Each learning step includes three phases: (i) input encoding, (ii) activation and (iii) weight adjustment. A symbol is represented on the input layer at time \( t \) through an input vector of \( x \) codes (see Figure 5). At each exposure, map nodes are activated in parallel depending on how close their weights on the spatial connection are to the \( x \) input vector, and how strongly nodes are connected with the BMU at time \( t-1 \) over the temporal layer (Ferro et al., 2011).
During training, due to such learning dynamic, each node develops a sensitivity to both a position-specific symbol and a context-specific symbol by incrementally adjusting its weights to recurrent patterns of morphological structure. As a consequence, a pool of nodes tends to specialize to respond to any specific input symbol, by showing higher activity levels than all others when the symbols appear in a particular context (Marzi et al., 2017). In this way, the overall organization of a TSOM will be determined by the morphological structure of training data, depending on three factors: similarity, frequency, and symbol timing. In fact, similar symbol sequences generate overlapping activation patterns; highly frequent symbols and chunks tend to select dedicated nodes; nodes react differently depending on the context where a symbol is repeatedly found.

Perception of similarity between input words can thus be measured in terms of recurrent patterns shared by inflected forms, and TSOMs may provide an explanatory framework by bringing together insights from neighbor family effects.
on word recognition, evidence from family size effects in serial lexical access\textsuperscript{19} and paradigm-based dynamics in lexical acquisition.

### 3.3.3. Modelling First and Second Language Acquisition and Processing with TSOMs

Wordlikeness effects appear to interact with memory issues, and in particular with how lexical representations are encoded in the long-term storage. TSOMs, namely computational models of serial memories may take into account dynamics of lexical acquisition and processing, by relying on some basic mechanisms of co-activation and competition between concurrently stored words.

To make things very simple, lexical processing is based on (i) the co-activation and competition of memory resources, (ii) the activation primacy based on the “winner takes all” principle\textsuperscript{20}, and (iii) selective specialization, over training.

During acquisition, words get permanently coded in our long-term memory as neuron activation patterns that sequentially fire. In such an account, they can be conceptualized as time series of symbols.

In the architecture of TSOMs, words are represented by time-series of symbols, which are vector-coded on the input layer and administered to the TSOM one at a time. During training, words are shown randomly, without any semantic or morpho-syntactic features or any possible inter-word relations. In this way, each node gets attuned to context-specific symbol by incrementally adjusting its synaptic weights to recurrent patterns of morphological structure.

\textsuperscript{19} Serial lexical access refers to the temporal dimension of lexical access, where each word is accessed through sequence of symbols. At this stage of analysis, words shall be thought of as temporal series of inputs, rather than being represented by one node only. In this way, it is possible to appreciate that also at a superficial access of row forms, namely in absence of the semantic dimension, it is possible to find out what words have in common. For example, book and handbook share part of their form, as well as machen and gemacht (German “do” and “done”), which share the stem “mach” even if it appears temporally dis-aligned in these forms, or abriendo, conociendo, etc. sharing the same inflectional suffix “iendo”.

\textsuperscript{20} The principle which is behind the idea of Best Matching Unit, as well.
To sum up, both short-term and long-term memory dynamics cooperate in word processing by TSOMs by triggering the short-term activation and the long-term adjustment. This two-fold dynamic\textsuperscript{21} shows how processing and storage are mutually interdependent: node patterns get activated as input stimuli are sequentially fired, then the connections undergo readjustment that finally leads to the identification of the Best Matching Unit. At the end, the nodes that are directly connected to the BMU gain strength, those that did not get weaker. Finally, the repeated firing of the same input stimulus leads to a stronger activation of the BMU and, as a final result, to the specialization of the pattern. Within the framework of the TSOMs, the specialization of the BMU to a specific activation pattern is given by frequency distribution and formal redundancy in the training data (Marzi & Pirrelli, 2015).

The above described selective specialization simulates the human propensity to show more sensitivity towards most typical chunks in their native language. It is important to observe that during learning, connection adjustment decreases by the decreasing of plasticity. As a consequence, L2 acquisition and processing tend to be affected by a reduced specialization for context-specific symbol identity, and a weaker entrenchment of highly frequent sub-strings.

\textsuperscript{21} Marzi & Pirrelli (2015) for further detail.
4. METHOD AND CORPORA

4.1. Selection criterion from corpora

4.1.1. THE SPANISH DATASET

To investigate the dynamics of word and paradigm acquisition in a bilingual training condition, a set of fifty Spanish verbs is compared with fifty German and fifty Italian verb sub-paradigms, which were selected with the same criterion (respectively from the CELEX Lexical database, Baayen et al. 1995, and Paisà Corpus, Lyding et al. 2014).

Thus, fifty Spanish verb sub-paradigms were selected among the most highly ranked paradigms by cumulative frequency in a European Spanish subcorpus of the larger Spanish TenTen corpus available in the online corpus analysis tool, Sketch Engine (sketchengine.co.uk). The choice of Peninsular Spanish is motivated by the different use of the past tense between European and Latin American Spanish, which would affect the frequency of selected paradigms.

For each paradigm, an identical set of 15 cells was used for training (namely, the infinitive, present and past participle, singular and plural simple present, singular and plural simple past), for an overall number of 750 inflected forms. For each form, a function of real word frequency distributions in the reference corpus is considered (with token frequencies in the range of 1 to 1001). The correlation between corpus frequencies and dataset frequencies is significantly high (r=0.99). See detailed figures in Table 2.

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22 The German and Italian sets of data had been selected and annotated by the ComphysLab at the Institute for Computational Linguistics, National Research Council of Italy.

23 Celex is a web interface to lexical database (http://celex.mpi.nl/). For different languages (English, Dutch, German) it may contain token frequencies, part of speech tagging (POS, namely morpho-syntactic information), lemma, among others.

24 Statistical analyses are run with R (http://cran.r-project.org). This kind of statistical analyses were provided by the Institute for Computational Linguistics (Pisa). Since it was necessary to reduce the whole amount of token frequencies for reducing the computational effort and duration in the arbitrary range of 1-1001, I found it necessary to demonstrate that the adopted function to
In case of any unattested verb form in the reference corpus, the set of the selected 15 cells was completed by adding the missing form as *hapax*.

<table>
<thead>
<tr>
<th>Spanish Set</th>
<th>Corpus frequencies</th>
<th>Dataset frequencies</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean (standard deviation)</td>
<td>117681.6 (357262.1)</td>
<td>23.47 (66.43)</td>
</tr>
<tr>
<td>Minimum</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Maximum</td>
<td>5376382</td>
<td>1001</td>
</tr>
<tr>
<td>1st quantile</td>
<td>1517</td>
<td>2</td>
</tr>
<tr>
<td>3rd quantile</td>
<td>95174</td>
<td>19</td>
</tr>
<tr>
<td>Median</td>
<td>24030</td>
<td>6</td>
</tr>
</tbody>
</table>

Table 2: Detailed figures for the selected dataset with reference corpus frequencies (left column) and the functionally adjusted frequencies (right column)

As expected, in both sets, word token frequencies are not normally distributed. See boxplot distribution and linear regression\(^{25}\) in Figure 6.

\(^{25}\) Linear regression is an approach for modelling the relationship between a variable (y axes, token frequency in this case) and the data (x axes). Boxplots represent a simple and intuitive way to describe data. White circles indicate outliers.
Figure 6: Boxplot distribution of Corpus (top left panel) and dataset frequencies (top right panel). Linear regressions for frequencies in the two sets, which are corpus-based (bottom left panel) and functionally reduced (bottom right panel) show non-normal distributions of token frequencies (y axes).

Detailed figures and the distribution of data confirm that the functionally reduced frequencies of each word form in my dataset did not modify the distribution of variables within the selected sample of paradigms as attested in the reference corpus. The advantage of reducing token frequencies into a range of 1-1001 is represented by a heavily scaling down of computational resources. In addition, reducing frequencies of the selected subset of verb forms for the three languages – Spanish, German and Italian – into the same range, makes them fully comparable, regardless of the different size of the reference corpora.

Out of the 50 selected Spanish sub-paradigms, 27 are irregular and 23 are regular\textsuperscript{26}.

Figure 7 shows token frequencies for the two formally defined categories, namely irregulars and regulars.

\textsuperscript{26} For details, see § 4.2.
A one-way ANOVA test\textsuperscript{27} shows a significant effect of (ir)regularity in frequencies distribution (p-value <0.001).

Concerning words, the average length is 7.235 (with a standard deviation of 2.33). The minimum length is two, and the maximum length is 15.

4.1.2. **THE GERMAN DATASET**

Out of the 50 most frequent German verb paradigms 34 are formally classified as irregulars and 16 as regulars. The average length of fully inflected verb forms is 6.356 (with a standard deviation of 1.57). The minimum length is three and the maximum length is 11.

Once again, corpus-based and functionally-reduced frequency distributions are highly correlated (r=0.99), and frequencies are not normally distributed (p-value < 0.001). Detailed figures are given in Table 3.

\textsuperscript{27} Analysis of variance, or ANOVA, indicates that there are differences between two groups of data – words of irregular paradigms and words in regular ones. The strength of the assertion is quantified by giving the significance strength, i.e. p-value. For each p-value that is lower than 0.05 the hypothesis is accepted.
<table>
<thead>
<tr>
<th><strong>GERMAN SET</strong></th>
<th><strong>Corpus frequencies</strong></th>
<th><strong>Dataset frequencies</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean (standard deviation)</td>
<td>564.3 (2159.77)</td>
<td>13.71 (48.69)</td>
</tr>
<tr>
<td>Minimum</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Maximum</td>
<td>44361</td>
<td>1001</td>
</tr>
<tr>
<td>1&lt;sup&gt;st&lt;/sup&gt; quantile</td>
<td>15</td>
<td>1</td>
</tr>
<tr>
<td>3&lt;sup&gt;rd&lt;/sup&gt; quantile</td>
<td>430</td>
<td>11</td>
</tr>
<tr>
<td>Median</td>
<td>160</td>
<td>5</td>
</tr>
</tbody>
</table>

Table 3: Detailed figures for the selected dataset with reference corpus frequencies (left column) and the functionally adjusted frequencies (right column)

A one-way ANOVA test shows a significant effect of (ir)regularity in frequencies distribution (p-value <0.001). See Figure 8 for frequency distributions in the two formal categories.

![Figure 8: Token frequency distribution for irregular (I) and regular (R) paradigms in the German dataset.](image)

4.1.3. THE ITALIAN DATASET

With the same criterion the Italian set of the 50 most frequent verb paradigms has been selected. As for Spanish and German, corpus-based and functionally-reduced frequency distributions are highly correlated (r=0.99), with the frequencies not normally distributed (p-value < 0.001). See Table 4 for detailed figures.
Table 4: Detailed figures for the selected dataset with reference corpus frequencies (left column) and the functionally adjusted frequencies (right column).

The average length of Italian verb forms is 7.082 (with a standard deviation of 1.88). The minimum length is two and the maximum length is 11. 27 paradigms are formally classified as irregulars and 23 as regulars. Once again, the token frequency is differently distributed depending on (ir)regularity. In fact, a one-way ANOVA test shows a significant effect of (ir)regularity in frequencies distribution (p-value <0.01). Figure 9 shows frequency distributions in the two formal categories.

![Token frequency distribution for irregular (I) and regular (R) paradigms in the Italian dataset.](image)

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28 The third person singular for the simple present of *essere* (be), è (is), is encoded as e’. Thus the input to the TSOM is #,E,’,$. 

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4.2. Spanish dataset annotation

For each fully inflected verb form in the Spanish dataset, stem, suffix, and prefix if any, are annotated by defining their length in terms of the number of symbols. The segmentation has been carried out by separating the endings – representative of the three Spanish conjugations, -ar, -er, -ir – from the stems. Spanish verbal inflection does not present any prefix in the past tense forms. Some difficulties have been experienced due to irregularities of certain inflection pattern, as well as to occasional phonological alternation within the stem.

Spanish verbs are classified as either regulars or irregulars by Nueva gramática de la lengua española (RAE, 2011: 57-69). Whereby verb paradigms did not fit the canonical inflectional patterns of amar, temer, partir (RAE 2011: 57), a more detailed analysis was necessary.

Spanish verbal inflection is subjected to different degrees of irregularities, which can be roughly divided into vowel, consonant, or mixed change. Vowel change leads to the so called diphthongisation, when the stem vowel is replaced by a diphthong, as follows: o - ue, like in contar - cuento; e - ie, like in pensar - pienso. Consonant change produces similar output, resulting into an alternation of a consonant, e.g. in hacer - hago. Both strategies are comprised in the mixed irregular pattern. However, the highest level of irregularity is represented by suppletive roots, which corresponds to a root alternation. This is the case of ir – voy – fui (“to go” – “I go” – “I went”), ser – soy – fui (“to be” – “I am” – “I was”), among others.

Another type of irregularity of Spanish verbs is dictated by the vowel alternation, known as “raising”, because the stem vowel “raises” from “e” to “i”. This phenomenon belongs to the third conjugation, e.g. pedir – pido, and sometimes it also integrates the diphthongisation, like in mentir – miento (Embick, 2012).

As already mentioned, each verb form was annotated with its stem and suffix (i.e. an inflectional ending), corresponding to the Data-Set columns “root length” and “suffix length”. Some verb forms show peculiarities in the inflection pattern, both
within the stem and the ending. For this reason, it seems necessary to explain the reasons of the morphological segmentation adopted in this study. First of all, some orthographic variations are due to different phonological contexts (Zamorano Mansilla, 2008), which are completely predictable, like in *utilizo* - *utilicé*, where *z* and *c* correspond to the same phoneme /θ/.

Where endings are not directly linked to the stem, e.g. *seguir* – *sigue*, I adopted the same criterion as for regular forms, that is to say, solely the suffixes were isolated from the rest of the verb-form, so that the exceeding vowel was considered as part of the stem.

One more category of irregular verbs in Spanish exhibit just one irregular inflected form, usually the first singular of the Present Indicative, e.g. *poner* - *pongo*, *salir* - *salgo*, and *hacer* - *hago*, although in these verbs almost all the other selected forms are completely irregular.

### 4.3. Experimental design

A battery of experiments is designed to investigate the functional behavior of TSOMs, and their morphological organization, when trained on different lexica in different training conditions.

To simulate different conditions of input exposure to more than one language, and to address issues of L2 acquisition and processing and L1/L2 competition, an incremental training regime was adopted. That is, with no resetting of the TSOM parameters and no loss of already stored information, TSOM maps are exposed to the selected datasets in various combinations:

1. one condition of Spanish L1 and German L2, that is the set of 750 inflected forms for Spanish language is shown to the map for 100 epochs (in the range of learning epochs 1-100), and the set of 750 German forms are
shown for 50 epochs (in the range of learning epochs 51-100\(^{29}\));

(ii) the reverse condition, i.e. German L1 and Spanish L2;

(iii) one condition of Spanish L1 and Italian L2, that is the set of 750 inflected forms for Spanish language is shown to the map for 100 epochs (in the range of learning epochs 1-100), and the set of 750 Italian forms are shown for 50 epochs (in the range of learning epochs 51-100);

(iv) the reverse condition, i.e. Italian L1 and Spanish L2;

(v) a perfect bilingual experimental condition, with Spanish and German as both L1 (i.e. both datasets are input in the range of learning epochs 1-100);

(vi) the perfect bilingual experimental condition, with Spanish and Italian as both L1 (i.e. both datasets are input in the range of learning epochs 1-100);

(vii) 3 strictly monolingual contexts – Spanish, German and Italian – for the 3 experimental conditions where only one dataset is shown, to compare results with bilingual regimes.

For each training condition, word forms of the 3 datasets are input according to their token frequencies, and with an identical parametrical set 5 TSOM instances are repeatedly run so to average results\(^{30}\). Each is represented by a time-series of symbols, namely a sequence of orthographic letters, administered one symbol at a time.

The choice of the orthographic code is determined by a better availability of corpora. In addition, Spanish, German and Italian can all be defined as substantially transparent languages, that is with a transparent orthography\(^{31}\).

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\(^{29}\) An exposure to L2 starting from epoch 51 (in a learning range 1-100) cannot be defined as an early bilingualism. However, the richness of L2 input – both in type and token frequency (i.e. richness of the vocabulary and amount of exposure) – brings to high accuracy results at the end of learning. These may be thought as corresponding to a good proficiency in mastering L2 lexicon, although some differences in the overall organization must be noticed.

\(^{30}\) The bigger the number of instances, the more reliable the results, since averaged results minimize randomness factors. When defining the amount of repetitions of the same configuration, the overall computational time must be taken into account. The experiment at issue is quite time-consuming, in fact for each combination, for each dataset, around three hours were devoted to complete the training. The estimation, in this case, for all language combinations, results in about 225 training hours.

\(^{31}\) Spanish and Italian are fully transparent; German is transparent to a lesser extent than Spanish and Italian.
A whole word is presented to a TSOM starting with a start-of-word symbol (#) and ending with the symbol ($) representing the end of a word. Each symbol is coded as orthogonal to any other symbol (see symbol encoding vectors, Annex 1).

For the sake of precision, it must be pointed out that the Spanish and German monolingual maps are 40 x 40 memory node maps, whereas for any other training regime lexica are shown to 42 x 42 node maps. The estimation is based on the overall complexity of lexical input, that is in consideration of the average length of input words, formal redundancy (i.e. recurrent morphological structure shared by word forms, and number of word types). It must be noticed that, for example, in the three sets of 750 words, there are 715 word-types for Spanish, 504 types for German, and 748 for Italian. For the selected 15 cells, there are, in fact, many homographs in German, some homographs in Spanish, and only four in Italian\textsuperscript{32}.

After having outlined the method and the datasets used for the study, I will report in detail on some experimental results in the following Chapter.

\textsuperscript{32} In the Italian dataset we have 	extit{sono} for 	extit{io sono} ‘I am’ and 	extit{essi sono} ‘they are’; 	extit{stato} as the past participle for 	extit{essere} ‘to be’ and 	extit{stare} ‘to stay’. German verbal inflection is strongly characterized by redundancy: infinitive, 1\textsuperscript{st} and 3\textsuperscript{rd} plural persons for the indicative present share the same form, both in regular than in irregular predictable paradigms, as well as 1\textsuperscript{st} and 3\textsuperscript{rd} singular persons for the simple past (präteritum), and 1\textsuperscript{st} and 3\textsuperscript{rd} plural person for the simple past. Idiosyncratic paradigms do not follow this redundancy.
5. EXPERIMENTAL RESULTS

After training, the memory content of each of the trained TSOM maps were tested to verify the internal organization on two tasks: word RECODING and word RECALL. The task of RECODING consists in quantify the accuracy of the map's activation on input forms. An input word is recognized correctly if each best matching unit (BMU) in the activation chain is correctly associated with the current input symbol. Errors are counted when an input symbol activates a BMU associated with a different symbol. In this case, the whole word is considered wrongly recoded. It can be said that word recognition depends on the current input stimulus, that is, as a measure of short-term memory.

Conversely, word RECALL depends on the long-term memory of a map, and simulates the process of retrieving a sequence of symbols from its BMUs. Errors occur when the map misrecalls one or more symbols in the input string, by replacing it with a different symbol or by outputting correct symbols in the wrong order. Also for this task, errors on one symbol only are counted as an error (Marzi et al., 2014a).

Results on recoding and recall tasks for each language in the different learning conditions are averaged over the five repetitions and are given in Table 5.
<table>
<thead>
<tr>
<th>Language – learning epoch</th>
<th>Recoding accuracy</th>
<th>Recall accuracy</th>
<th>standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spanish monolingual - 100</td>
<td>100%</td>
<td>99.30%</td>
<td>0.61</td>
</tr>
<tr>
<td>German monolingual - 100</td>
<td>100%</td>
<td>99.52%</td>
<td>0.27</td>
</tr>
<tr>
<td>Italian monolingual - 100</td>
<td>100%</td>
<td>98.69%</td>
<td>0.55</td>
</tr>
<tr>
<td>Spanish L1 - 50</td>
<td>100%</td>
<td>98.88%</td>
<td>0.56</td>
</tr>
<tr>
<td>Spanish L1 - 100</td>
<td>100%</td>
<td>98.38%</td>
<td>1.23</td>
</tr>
<tr>
<td>German L2 - 100</td>
<td>100%</td>
<td>91.98%</td>
<td>1.92</td>
</tr>
<tr>
<td>German L1 – 50</td>
<td>100%</td>
<td>99.33%</td>
<td>0.36</td>
</tr>
<tr>
<td>German L1 – 100</td>
<td>100%</td>
<td>98.65%</td>
<td>0.51</td>
</tr>
<tr>
<td>Spanish L2 – 100</td>
<td>98.43% (0.88 sd)</td>
<td>92.67%</td>
<td>0.87</td>
</tr>
<tr>
<td>Spanish L1 – 50</td>
<td>100%</td>
<td>99.33%</td>
<td>0.44</td>
</tr>
<tr>
<td>Spanish L1 – 100</td>
<td>100%</td>
<td>99.22%</td>
<td>0.47</td>
</tr>
<tr>
<td>Italian L2 – 100</td>
<td>100%</td>
<td>95.24%</td>
<td>1.26</td>
</tr>
<tr>
<td>Italian L1 – 50</td>
<td>100%</td>
<td>99.06%</td>
<td>0.34</td>
</tr>
<tr>
<td>Italian L1 – 100</td>
<td>100%</td>
<td>96.39%</td>
<td>0.61</td>
</tr>
<tr>
<td>Spanish L2 - 100</td>
<td>100%</td>
<td>97.03%</td>
<td>1.07</td>
</tr>
<tr>
<td>Spanish L1 – 50</td>
<td>100%</td>
<td>97.31%</td>
<td>0.55</td>
</tr>
<tr>
<td>Spanish L1- 100</td>
<td>100%</td>
<td>97.43%</td>
<td>0.47</td>
</tr>
<tr>
<td>German L1 – 50</td>
<td>100%</td>
<td>97.98%</td>
<td>0.66</td>
</tr>
<tr>
<td>German L1 - 100</td>
<td>100%</td>
<td>98.17%</td>
<td>0.55</td>
</tr>
<tr>
<td>Spanish L1 – 50</td>
<td>100%</td>
<td>98.07%</td>
<td>0.46</td>
</tr>
<tr>
<td>Spanish L1 – 100</td>
<td>100%</td>
<td>96.07%</td>
<td>1.69</td>
</tr>
<tr>
<td>Italian L1 – 50</td>
<td>100%</td>
<td>98.07%</td>
<td>0.46</td>
</tr>
<tr>
<td>Italian L1 - 100</td>
<td>100%</td>
<td>96.15%</td>
<td>1.65</td>
</tr>
</tbody>
</table>

Table 5: Recoding and recall accuracy are given in percentage for each language in all training conditions. Scores are averaged on 5 repetitions.

5.1. Monolingual regime

A detailed analysis started from the acquisition time of word forms for the three lexica in the three monolingual training conditions.

In Figure 10, the time course of word acquisition is given for Spanish, German and Italian monolingual training. In detail, recoding and recall are monitored over time.\(^{33}\)

\(^{33}\) In detail, acquisition time is monitored, and plotted accordingly, over the following learning epochs: 1:30, 50, 51:61, and the final epoch, 100.
Figure 10: Recoding and recall accuracy over learning epochs for Spanish (top plot), German (bottom left plot) and Italian (bottom right plot) words. Scores are averaged on 5 repetitions.

Figure 11 shows the acquisition epoch for the 50 most frequent paradigms in three strictly monolingual contexts, going from the fastest – namely the easier to learn - paradigm on the top (ver - restore - werden) to the most difficult paradigm on the bottom. The paradigm acquisition epoch provides an estimate of the average time necessary for all forms of the paradigm to be recoded and recalled correctly.

It shall be observed that regular and irregular verbs are mixed, which reflects the balance between the facility to learn regular patterns and the importance of frequency in the acquisition of irregular patterns. In addition, it should be noticed that in case of one or more forms representing a challenge for storage and
retrieval from memory storage, the whole paradigm acquisition time will result delayed. It is the case, for example, of *arbeiten* in German, and *stare* in Italian, where regular past forms represent a challenge for correctly retrieving their memory traces due to the repetition of chunks (*arbeit-et-et, ste-ste*).

Figure 11: Spanish, Italian, and German data set course of acquisition, where paradigms are ranked by increasing learning epoch (from top to bottom).
The simulation carried out by TSOMs can be thought of as if a child was gradually acquiring a lexicon, starting from the most frequent and short units, then learning increasingly longer and less frequent ones (Marzi & Pirrelli, 2015). For instance, surface word relations lead to the morphological organization in the lexicon. A gradient of perceived regularity-irregularity, rather than regularity vs. dichotomy, plays an important role in the formulation of the morphological organization to the extent to which regularity/predictability facilitates the emergence of common patterns, whereas highly irregularity/unpredictability makes it more difficult.

In fact, regular–irregular distinction is not as categorical as it is commonly held. Degrees of irregularity affect language acquisition differently. This observation should become evident by looking at the Spanish paradigm time of acquisition (Figure 11, left panel), where the first nine verbs are all irregulars. It should be appreciated that these nine verbs exhibit different degrees of irregularity. In fact, the less irregular ones have lower cumulative frequency (reported in brackets)\(^{34}\), meanwhile the highly irregular ones are attested with very high frequency. This observation confirms the assumption that the frequency factor can neutralize the complexity of some irregular patterns, by supporting the acquisition of word forms in isolation. In this case, the situation is diametrically opposed for regulars: among the last forms appear some regular verbs, such as permitir, pasar, and, most importantly, abrir and existir, the latter two being in the very last two positions. Despite their regularity, these forms are on the bottom of the list because of their scant frequency. The case of abrir is especially interesting, because although the paradigm is classified as regular, this verb has an irregular Past Participle abierto that certainly does not support a faster learning. In this, and similar cases, in fact, the whole paradigm can benefit from the cumulated stem frequency of all forms to a lesser extent. This is the overall dynamic that supports some less attested paradigms (see for example gustar, presentar, quedar, llevar).

\(^{34}\) The cumulative frequency refers to the sum of the frequencies for all the selected 15 forms of the verb.
For German and Italian, the paradigm acquisition times confirm that there is not a unique factor determining the acquisitional dynamics. Neither word frequency nor regularity vs irregularity by itself can explain the evidence. All these factors must be considered in their complexity. Moreover, word frequency is not the alone quantitative amount to be taken into account, since the distribution of token frequencies among forms in the same paradigm plays a significant role.

In this perspective, previous studies (e.g. Marzi & Pirrelli, 2015: 519) posit that skewed frequency distributions tend to slow down the acquisition of the paradigm as a whole. Since the paradigm acquisition epoch is calculated as the average acquisition time of all forms, less-frequency items will affect it negatively. This important issue can be illustrated with the form arbeiten, showing a significant acquisitional delay with respect to the other 49 German verbs, which can be attributed to both its skewed frequency distribution and the length of some of its forms.35

Particular cases apart, the paradigm frequency has less effect on regular verbs, whose acquisition is facilitated by the neighboring family of words, rather than by frequency as in the case of irregulars. The regular forms, in fact, can not only be inferred from other forms of the same paradigm, but they can benefit from a sort of boosting effect given by the cumulative frequency of inflected forms that share the same stem (Marzi et al., 2014a).

As already mentioned in §3.3.3, words get coded in our long-term memory as activation patterns of time-series of symbols. When receiving an input stimulus at time $t$, TSOM triggers the competitive activation of all nodes. This dynamic of lexical acquisition and processing is displayed in Figure 12, where concurrently stored words result in a partially overlapping activation pattern between abrir - abierto. The memory grid36 shows here TSOM's both internal synaptic

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35 Within the paradigm of arbeiten, arbeittest and arbeitetest are hapax forms and, interestingly enough, they also belong to the group of the longest units. Other forms, such as arbeittest and arbeiteten, share the same characteristic of sequence repetition, in addition to their low frequency.  
36 The size of memory grid is here 40 X 40 nodes.
connectivity between sequentially activated nodes (see arrows in Figure 12) and levels of co-activation (see color for each node).

Figure 12: Co-activation levels for chain of memory nodes that activate abrir - abierto.

The mapping of colors allows for the reduction of the representation of multidimensional data on two-dimensional grid of nodes (where red stands for maximum activation, and blue for minimum activation). If we follow the activation pattern from the symbol # (start of word) to the symbol $ (end of word)\textsuperscript{37}, we'll notice that the pattern branches off in correspondence of the node b, which is the last shared node between the two forms.

\textsuperscript{37} Abrir and abierto are shown to the map as the input strings #a,b,r,i,r$ and #a,b,i,e,r,t,o$, respectively.
In this way, the correlation between the incoming stimuli and the already stored forms provides evidence to our assumption that storage and processing are two sides of the same coin. As further proof, Figure 13 shows the co-activation of considerar - considerado patterns. Once again, the overlapping nodes c,o,n,s,i,d,e,r,a exhibit high level of co-activation (intense red clusters of nodes) up to the thematic vowel, where the memory chain splits in two different memory traces.

It should be appreciated that although abrir and considerar are both regular paradigms, the irregular past participle form of abrir makes this form less co-activated to the infinitive form, for example, than considerar and considerado.
Although it has been affirmed that regularity/irregularity is a gradient of predictability, it is in any case interesting to monitor the different acquisition pace for regulars and irregulars (as formally classified).

Figure 14: Learning differences between irregulars and regulars for Spanish (top panel), German (bottom left panel) and Italian (bottom right panel). Accuracy is given for word types.

Figure 14 shows for the three monolingual contexts the difference in acquisition pace between regulars (dashed line) and irregulars (solid line). Recall accuracy refers to the capacity of the network to correctly retrieve the stored form. Apparently, the difference between regulars and irregulars in the three languages is very small. Furthermore, as observed in the present experiments, the first 30 learning epochs play a crucial role, because they represent the time span when
the learning process achieves and stabilizes the highest recoding and recall accuracy.
This dynamic can be explained by verifying how the plasticity of the TSOM map lets adapt the spatial clustering firstly to the most frequent input symbols, specializing different nodes in the same cluster for symbol occurrences in different temporal contexts, and then progressively to the less frequently ones. This adaptive self-organization reaches a stable point at around learning epoch 20. In fact, there are no differences in clustering between learning epoch 20 and 30 (see Figure 15 below).
Turning back to the acquisition pace for the three languages (Figure 14), Italian and German show more similarity between them, compared to Spanish results: in both contexts irregulars are more rapidly learnt until the epoch 12 approximately, where the situation overturns. In Spanish the irregular forms lead the learning process (note the gap around epoch 10). This is due to the distribution of frequencies. In fact, it must not be forgotten that irregular forms are more frequent than regular ones (as highlighted in § 4). This is confirmed when instead of monitoring recall accuracy over word types, we observe recall accuracy over tokens (see Figure 16). In such case, differences get more evident, and confirm that irregulars are acquired earlier since they may rely on higher token frequencies of word forms.
Evidence as shown in Figure 16 supports the position that token frequency should be taken into account, since the map (in the present approach) is exposed to as many inputs as the overall amount of tokens. Therefore, it is not surprising that, on average, forms of irregular paradigms strongly benefit from their higher frequency support, compared to regulars.

The importance of type/token frequency has been emphasized by Bybee within the framework of the Network Model (see §3.2.3). In fact, the lack of processability of some idiosyncratic verbs is balanced by their very high token frequency. Figure 16 reveals this difference in frequency effect, by highlighting the huge gap between regular vs. irregular paradigms recall. The bigger difference of this kind is observed in Italian, where irregulars show a remarkable peak in correspondence to the fifth epoch. Conversely, due to their lower token
frequency, regular forms need more training to achieve a better recall with respect to the other two languages.

Preliminarily, I conclude that morphology acquisition is determined by word token frequency as well as by formal redundancy, that is to say, by morphological regularity intended as shared patterns. The more verb inflected forms share part of their superficial forms (i.e. the stem), the better and easier the acquisition of them. It is important at this stage of analysis to move to bilingual learning regimes, where it will be interesting to monitor a somewhat different behavior for L2 forms.

5.2. Bilingual regimes

At the beginning of this chapter, in table 5, I summarized accuracy percentage for each combination of lexical exposure. However, it is more informative to monitor the pace of acquisition during learning epochs, as already pointed out for the monolingual condition.

In detail, I consider the Spanish-L1 German-L2 regime, where the set of 750 inflected Spanish forms is shown to the map for the total amount of 100 epochs, and the set of 750 German forms are shown for a total of 50 epochs, starting from learning epoch 51 up to 100. In comparing Spanish monolingual and bilingual context, the trend is fully comparable until the epoch 51, when the map is for the first time exposed to the second language input. Figure 17 shows recoding and recall accuracy for the two lexica.
Figure 17: Acquisition pace shown as accuracy for the recoding and recall task over learning epochs for Spanish (left panel) and German (left panel) in the training condition Spanish L1 and German L2.

This behavior is due to a competition-based processing. When to the stable organization of a TSOM new lexical items are shown, in particular items of language with own specific orthotactic constraints (L2), it can be observed an initial stage where the overlapping of representations for L1 and L2 may cause an influence on L1 itself (see learning epochs 51-61). However, they are L2 lexical representations that are mostly influenced by competition, since they are also characterized by lack of context-specific specialization of its orthographic representations. A lack of fine specialization may cause processing problems in recognition and access (as observed by Bradlow & Pisoni, 1999, for lack of phonetic specialization). In fact, if an already stored word has an underspecified mental representation, the interference of strongly specified representations (typical of L1) may lead to misidentification (Cook, 2013). I contend here that this is induced by a much reduced amount of memory resources devoted to L2 specific representations.

To verify this position, Figure 18 offers a sequential representation of some stages for the bilingual regime, namely learning epochs 5, 10, 20, 50, which define the monolingual stage of acquisition for Spanish only; and learning epochs 61 and 100 defining the L1-L2 stage. Similar to what happens in the monolingual context (Figure 15), the spatial clustering prioritizes the most frequent inputs first,
finally adapting to the less frequently ones as well. Again, no difference in clustering after the learning epoch 20 is observed. In fact, there are no differences in clustering between learning epoch 20 and 50. When word forms of L2 are input to the map, some marginal nodes get recycled from L1 representations to adapt themselves to the new input. This is necessary, for example, for symbols that do not occur in L1 (in the present case umlauted vowels and sharp-s, ä, ü, ö, ß). See sparse nodes in Figure 18 (bottom left panel) highlighted with black circles.
The recycling process of memory resources during different stages of learning can be quantitatively detected by evaluating the exact percentage of memory nodes activated by lexical representations for each language (see Table 6).

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Table 6: For each training regime, percentage of specialized memory resources are given for each language.
The general trend monitored for the Spanish(L1)-German(L2) exposure condition, is also confirmed for reverse condition, as well as for the Spanish-Italian regime.

Figure 19 shows the incremental learning of the Spanish-L1 Italian-L2 regime, where the set of 750 Italian forms are added to the 750 Spanish forms starting from learning epoch 51 (up to 100). Once again, the Spanish trend for recoding and recall accuracy is comparable to the monolingual regime, with the only exception of learning epochs 51-61, that is when the map is for the first time exposed to the second language input. What is important to notice is that when the Spanish map is tested with the Italian input before learning it, that is before the L2 learning begins (epochs 1-50), a somewhat different behavior can be observed in comparison to the SpanishL1-GermanL2 regime (see Figure 17). The unseen Italian input is recoded with a higher accuracy than German input in the corresponding condition.

This is due the orthotactic likelihood that makes Spanish and Italian forms being perceived as more similar than Spanish and German ones.
In fact, one of the main determinants for lexical acquisition and processing is perception of similarity (see Chapter 2). Words that are perceived as similar to many other words in the lexicon may accelerate word recognition, and acquisition therefore, since wordlikeness effects interact with memory (§3.3.3).

To monitor this effect in different lexical exposures, at the end of training, it is useful to verify the TSOM’s ability to anticipate a target word, that is to predict its continuation as soon as the onset is shown (Figure 20). The more symbols are anticipated, the easier the prediction of the target word.

For the sake of clarity, within the frame of child language acquisition, the best possible learning strategy should lead to generalizations extracted from the (limited) linguistic input at the disposal of the child. Consequently, from the viewpoint of the surface word, formal predictability can be considered a touchstone for lexical acquisition, inasmuch it provides a starting point by relying on the already stored information.

The point has already been made that orthotactics and redundancy play a big role in language acquisition, but what happens when two languages from different families coexist in the same bilingual context?

Figure 20: TSOM’s ability to anticipate input words at the end of learning, by showing progressively the symbol sequences. Lines plot the anticipation over the activation levels for Spanish in the different exposure conditions: in combination with German (left plot) monolingual (grey dashed line), bilingual (dark dashed line), L1 (grey solid line), L2 (dotted line); with Italian (right plot) bilingual (dark dashed line), L1 (grey solid line), L2 (dotted line).
Figure 20 (left plot) shows this ability on the Spanish lexicon in the four training conditions, L1 (when German is L2), L2 (when German is L1), bilingual and monolingual ones. Figure 20 (right plot) shows the ability for Spanish in the Spanish-Italian combination. A gradient trend should be appreciated, ranging from monolingual condition to L2 training condition.

Intuitively, monolingual Spanish condition features the best anticipation ability, as no L2 is there to obstruct it. Conversely, the worst results are to observe in the situation in which Spanish is in the L2 condition. By comparing the three bilingual conditions between the Spanish vs. German and Spanish vs. Italian, the plots reveal that the latter pair offer better results in terms of word anticipation (note the slope difference between the two sets of regressions). Such difference can be attributed to the linguistic distance, that is to more similar orthographic patterns, which ultimately facilitates word processing and acquisition.

I conclude the experimental section by turning back to the paradigm acquisition epoch (as shown in Figure 11, §5.1, for the monolingual contexts) in the bilingual training conditions. It is important to observe the differences for the same dataset in the different training conditions, that is the monolingual regime (Figure 11), and the bilingual ones (Figures 21-28). As already express, the paradigm acquisition epoch provides an estimate of the average time necessary for all forms of a paradigm to be recoded and recalled correctly. In addition, the time span of acquisition displays for each paradigm clear figures of the difficulty of acquisition, as a function of morphological ir/regularity and token frequency. The shorter the span, the easier the acquisition.

It should be observed that when a lexicon is in the L1 training condition, with the only exclusion of a few paradigms for which a couple of forms get never be acquired, the time span of acquisition is short, and benefit by either high token frequency of word forms, or by morphological regularity. On the contrary, when

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38 Paradigm acquisition span has been defined as the number of epochs it takes to complete the acquisition of a paradigm after the first member of the paradigm is acquired (Marzi et al., 2014a).
the same lexicon is in the L2 condition, the acquisition dynamic benefit from these both determinants to a lesser extent. In fact, in a lesser number of cases token frequency and formal regularity (lexical redundancy) succeed in contrasting the competition effect of the L1 lexicon.

Figure 21: Spanish course (left plot) and span (right plot) of acquisition and in the Spanish_L1 and German_L2 condition, with paradigms ranked by increasing learning epoch (from top to bottom).
Figure 22: Spanish course (left plot) and span (right plot) of acquisition and in the Spanish_L2 and German_L1 condition, with paradigms ranked by increasing learning epoch (from top to bottom).
Figure 23: German course (left plot) and span (right plot) of acquisition and in the Spanish_L1 and German_L2 condition, with paradigms ranked by increasing learning epoch (from top to bottom).
Figure 24: Spanish course (left plot) and span (right plot) of acquisition and in the Spanish_L1 and Italian_L2 condition, with paradigms ranked by increasing learning epoch (from top to bottom).
Figure 25: Spanish course (left plot) and span (right plot) of acquisition and in the Spanish_L2 and Italian_L1 condition, with paradigms ranked by increasing learning epoch (from top to bottom).
Figure 26: Italian course (left plot) and span (right plot) of acquisition and in the Spanish_L1 and Italian_L2 condition, with paradigms ranked by increasing learning epoch (from top to bottom).
Figure 27: Spanish course (left plot) and span (right plot) of acquisition and in the Spanish_L1 and German_L1 condition, with paradigms ranked by increasing learning epoch (from top to bottom).
Figure 28: Spanish course (left plot) and span (right plot) of acquisition and in the Spanish L1 and Italian L1 condition, with paradigms ranked by increasing learning epoch (from top to bottom).
6. CONCLUDING REMARKS

Starting from the evidence provided by researchers at ComPhys Lab of the Institute for Computational Linguistics, Italian National Research Council (Pisa, ILC-CNR), the main goal of my thesis was to extend the application of computational modelling of language acquisition in monolingual and bilingual contexts to Spanish, which has not yet been treated within the given research framework.

For the first step, I briefly outlined some of the most prominent psycholinguistic approaches to the study of language acquisition. Secondly, three major models of morphological processing have been presented. For instance, three models of lexical representation and processing have been explained, following the classification proposed by Bybee (1995), i.e. dual-processing model, connectionist model, and network model. The difference between these three models lies in whether they make a distinction between regular and irregular verbs and their processing models, and whether or not the type/token frequency of verbal morphological patterns plays any role at all.

The experimental part of this study was focused on the first and second language acquisition of Spanish verbs, contrasted with parallel datasets in the Italian and German languages. In order to compile the dataset, I extracted the 50 most frequent verb paradigms from European Spanish Web Corpus (2011), available in Sketch Engine, for a total of 750 inflected forms (corresponding to the forms of the infinitive, present, and past participle, singular and plural simple present, singular and plural simple past). The frequency distribution is provided for each inflected form. For an analysis and evaluation of the emergent organization of paradigmatic relations, I annotated each form with morpho-syntactic information (i.e. stem and affix length, paradigmatic cell, formal (ir)regularity, paradigm). Specific difficulties arose during the segmentation of Spanish verbs, due to the peculiarities of some irregular patterns.
The computational modelling and processing of Spanish verbs forms has been simulated with Temporal Self-Organizing Maps (TSOMs), based on Kohonen’s Self-Organizing Maps (2001), augmented with a temporal layer. Basically, this computational model reproduces dynamics of lexical learning and processing by imitating the emergence of neural self-organization, through the incremental adaptation of topologically and temporally aligned synaptic connections.

Starting from the literature review, also in connection with psycholinguistic evidence made available by studies of the last thirty years, I tried to put in evidence here that an adaptive self-organization during learning is conducive to the emergence of relations between word forms, which are stored in the mental lexicon in a concurrent and competitive dynamic. In particular, in the adopted bilingual perspective, monitoring the acquisitional trajectories of more than one lexica (in both L1+L2 and L1/L1 contexts) showed how recycled memory resources and weaker connections affect L2 acquisition and processing, with a smaller specialization for context-specific input chunks, depending on the exposure conditions.

With this goal in mind, experiments in different training conditions were designed. It is obvious that many other experimental conditions could be tested, as for example, more degrees of bilingualism, in a gradient of successive bilingualism ranging from very early, early, up to late, and very late bilingualism. This kind of approach would focus the attention on the plasticity loss and the increasing entrenchment of L1, with a subsequent and gradual difficulty for the L2 lexicon to create its own context-specific specialization.

Although time and space constraints did not allow these additional learning conditions, it is not hard to imagine and predict TSOMs behavior in these regimes. Map plasticity, as often underlined in my thesis, is in fact a determinant for a sufficiently specialized representation of lexical input. Very late exposure to L2 word forms, or early exposure to very reduced evidence of L2 lexicon, will determine a local, parasitic representation for the L2. As observed by Hernandez
et al. (2005), late bilinguals typically learn L2 with a reduced plasticity relying on strategies of “parasitic dependence” of L2 on their L1.

I may conclude that neurally-inspired computational models can provide a computational framework to analytically verify and study the developmental processes governing the acquisition and processing of the morphological lexicon in different languages, and reproduce a wide range of naturalistic conditions of both mono- and multi-lingual input exposure.

In such perspective, a more complex computational architecture, where a temporal self-organizing map is connected to other levels of representation, according to the Hebbian learning principle, may better simulate and predict speakers’ and learners’ lexical behavior. As evidenced in this study, the biologically-inspired TSOM architecture on the one hand provide a temporal layer that succeed in properly reproducing the sequential nature of linguistic inputs; on the other hand, however, it addresses this investigation from an exclusively phonotactic/orthotactic viewpoint, which neglects the semantic level in favor of the surface word relation analysis. Therefore, my suggestion goes in the direction of a combination of the TSOM’s level of representation of lexical input as temporal sequence of symbols with the DevLex II word’s meaning representation.

Prospective research in this direction would give the possibility to simulate, and thus explain, more and more complex interaction and competition effects also at the level of semantic access in the frame of first and second language studies.

On a different dimension, a further development of such an approach could develop a more complex input representation, simulating not only single words but complex words (complex words, sentences).
REFERENCES


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## ANNEX 1

**SYMBOL CODING**

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Esperando pE 14 esperar 0 5 4 R

Esperado pA 14 esperar 0 5 3 R

Espero 1SIE 14 esperar 0 5 1 R

Esperas 2SIE 14 esperar 0 5 2 R

Espera 3SIE 14 esperar 0 5 1 R

Esperamos 1PIE 14 esperar 0 5 4 R

Esperais 2PIE 14 esperar 0 5 3 R

Esperan 3PIE 14 esperar 0 5 2 R

Esperé 1SIA 14 esperar 0 5 2 R

Esperaste 2SIA 14 esperar 0 5 4 R

Esperó 3SIA 14 esperar 0 5 1 R

Esperamos 1PIA 14 esperar 0 5 4 R

Esperasteis 2PIA 14 esperar 0 5 6 R

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Estableciendo pE 15 establecer 0 8 5 I

Establecido pA 15 establecer 0 8 3 I

Establece 1SIE 15 establecer 0 9 1 I

Establecemos 2SIE 15 establecer 0 8 2 I

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Estás i 16 estar 0 3 2 I

Estando pE 16 estar 0 3 4 I

Estado pA 16 estar 0 3 3 I

Estoy 1SIE 16 estar 0 3 2 I

Estás 2SIE 16 estar 0 3 2 I

Está 3SIE 16 estar 0 3 1 I

Estamos 1PIE 16 estar 0 3 4 I

Estás 2PIE 16 estar 0 3 3 I
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#H,E,C,H,O,$ 115 hecho pA 21 hacer 0 2 3 I
#H,A,G,O,$ 20 hago 1SIE 21 hacer 0 3 1 I
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#H,A,C,E,$ 328 hace 3SIE 21 hacer 0 3 1 I
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#I,N,C,L,U,Y,E,N,D,O,$ 21 incluyendo pE 22 incluir 0 5 5 I
#I,N,C,L,U,Y,D,O,$ 20 incluido pA 22 incluir 0 5 3 I
#I,N,C,L,U,Y,O,$ 3 incluyo 1SIE 22 incluir 0 6 1 I
#I,N,C,L,U,Y,E,$ 2 incluyes 2SIE 22 incluir 0 6 2 I
#I,N,C,L,U,Y,E,$ 44 incluye 3SIE 22 incluir 0 6 1 I
#I,N,C,L,U,Y,M,O,S,$ 1 incluimos 1PIE 22 incluir 0 5 4 I
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