

On the Diachronic Stability of Irregularity in Inflectional Morphology

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Abstract

Many languages’ inflectional morphological systems are replete with irregulars, i.e., words that do not seem to follow standard inflectional rules. In this work, we quantitatively investigate the conditions under which irregulars can survive in a language over the course of time. Using recurrent neural networks to simulate language learners, we test the diachronic relation between frequency of words and their irregularity.

1 Introduction

When and why does irregularity persist? It would certainly be easier to learn an exceptionless language. Nevertheless, irregularity abounds at almost every level of language: some words fail to obey otherwise universal phonological patterns, some verbs have irregular conjugations, and some phrases have meanings that cannot be derived compositionally. It is also clear, however, that systematicity is a hallmark of human language—children learn regular rules that allow them to analyze and produce novel utterances (Pinker, 1994). Indeed, it is unlikely that a completely unpredictable language could survive. In this paper, we explore the limits of irregularity in the context of inflectional morphology. We ask how many irregular inflections a language can possess and what their distribution must be before a language becomes unlearnable and regularized by the next generation. We employ neural sequence-to-sequence models in a series of simulations to this end.

The existence and degree of irregularity in inflectional morphology remains a linguistic puzzle. English, for example, possesses a large number of irregular verbs, ranging from full suppletion, e.g., *go* \mapsto *went*, to no-longer-productive ablaut and umlaut patterns, e.g., *sing* \mapsto *sang* and *fall* \mapsto *fell*. Recent work (Ackerman and Malouf, 2013) has

attempted to explain irregularity, and, more generally, morphological complexity, from a *synchronic* perspective; they make a typological claim about what sorts of languages exist in terms of degree of irregularity. The work presented here goes one step further beyond a snapshot of extant languages—we try to explain how language acquisition could allow irregulars over the course of multiple generations. That is, we try to explain morphological complexity from a *diachronic* perspective. Concretely, we conjecture the following: a morphological system will tend to retain irregular forms only if they are “sufficiently frequent.” Inspired by the seminal work of Hare and Elman (1995), we investigate the claim with a series of neural simulations on morphological data.

What makes our work different? Like Hare and Elman (1995), we focus on the diachronic evolution of English verbal paradigms. However, rather than attempting to replicate the development from Old English to modern English, our experiments instead show that the distribution of irregularity in modern English is stable under generational transmission, compared to possible alternative distributions. Furthermore, NLP’s ability to generate inflected morphological forms has greatly improved in recent years (Cotterell et al., 2017), both through the introduction of recurrent neural models to the task and curation of new data. We take advantage of these advances and offer a dramatically updated simulation. In contrast to Hare and Elman (1995), our models generate actual strings at each iteration, rather than pseudo-phonological feature vectors termed Wickelphones (Rumelhart and McClelland, 1986).

A Roadmap through the Paper. In the next two sections (§2 and §3), we briefly overview the language change and acquisition literature and discuss our formalization of inflectional morphology. We

then progress into a discussion of the current state of the art in neural-network modeling for inflection generation in §4. Then, we introduce our simulation scheme in §5, which allows us to show that most, though not all, infrequent irregulars are unsustainable as a language evolves.

2 Language Change and Acquisition

The principles that undergird diachronic language change have fascinated linguists for more than a century. When comparing intentional neologism, e.g. the formation of new technological jargon, Paul (1890) writes: “the significance of such capricious decisions is as nothing compared, with the slow, involuntary and unconscious changes to which the [...] usage of language is perpetually exposed.” The problem is still unsolved, but different theories flourish. There are two primary camps. The first, **acquisition-based change**, argues that language is acquired imperfectly by children and changes slowly over time. The second, **usage-based change**, contrarily, argues that language changes continuously and involves gradual adjustments over each speaker’s life. We discuss each camp in turn and relate them to the view here.

Acquisition-Based Change. In the generative tradition, linguistics has attributed much of language evolution to its acquisition by children (Kroch, 2001). The manner in which children acquire irregular morphology is one of the most-studied problems in psycholinguistics. During acquisition, children in an English-speaking environment display the following pattern. Initially, they apparently memorize irregulars, correctly producing the past tense of *go* as *went*. Afterwards, they overregularize, having picked up on the fact that most English verbs add the ending */-d/*.¹ During this phase, children will produce *goed*, rather than *went*. Finally, the child will recover, correctly producing the past tense forms for both the regulars and irregulars in the lexicon. This pattern has been widely observed and is termed **U-shaped learning** (Warren, 2012). What happens to rare forms, though? The argument then continues that these rarer forms remain regularized, even if they were once produced correctly as irregulars, such as the now-obsolete *shave* \mapsto *shove*. Thus, only frequent forms tend to remain irregular—this is

¹More specifically, regular English verbs select among three allophones: [-d], [-t] and [-id], depending on the previous phoneme.

well-attested cross-linguistically (Lieberman et al., 2007).

Usage-Based Change. Others, however, have argued that language change is continuous. On this view, adult speakers are constantly updating their internal linguistic representations as a result of usage (Langacker, 1987; Bybee, 2006), even though they have passed the so-called “critical period” of language development (Lenneberg, 1967). One example of this comes from the domain of phonetics, where Harrington (2006) has argued that adult speakers modify their speech patterns. It is thus conceivable that some diachronic language changes (perhaps even morphological ones) might be initiated or abetted by adaptations in adult speakers, rather than having to wait till the next generation.

The View in this Paper. The model in this paper assumes that all change is acquisition-based. Following Hare and Elman (1995), we describe a series of simulations, where one generation of a probabilistic model teaches the next. In broad strokes, this is in line with the acquisition account of change. The literature on the acquisition of morphology is rich, however, and we caution that our simulations may not fully do justice to the process. For instance, our simulations train only a single population model at each time step, whereas language is learned and spoken by a community of individuals. Moreover, children often start speaking before they have complete mastery of the tongue, as evinced by the U-shaped pattern. Thus, we view our formulation and experiments as a first pass at the problem, very much in line with other work in cognitive science, discussed in §8.1.

3 Inflectional Morphology Formalized

We briefly outline our formalization for inflectional morphology and thereby develop notation that we will use throughout the paper. We adopt the framework of word-based morphology (Aronoff, 1976; Spencer, 1991). Thus, for the rest of the work we define an **inflected lexicon** as a set of word types.

Each word type is a triple of

- a **lexeme** \mathfrak{l} (an arbitrary integer or string that indexes the word’s core meaning and part of speech)
- a **slot** σ (an arbitrary integer or object that indicates how the word is inflected)

- a **surface form** f (a string over a fixed phonological or orthographic alphabet Σ)

We write $\pi(\mathfrak{b})$ for the set of word types (triples) in the lexicon that share the lexeme \mathfrak{b} , known as the **paradigm** of \mathfrak{b} . The slots that appear in this set are said to be **filled** by corresponding surface forms. For example, in the English paradigm $\pi(\text{walk}_{\text{Verb}})$, the past-tense slot is filled by *walked*. Often the lexeme \mathfrak{b} is cited using its **lemma**, which is the surface word ℓ associated with some particular slot in $\pi(\mathfrak{b})$; for example, in most languages, a verb’s lemma is conventionally taken to be its infinitive. We note that nothing in our method requires a Bloomfieldian structuralist analysis that decomposes each word into underlying morphemes: rather, this paper is a-morphous in the sense of Anderson (1992).

More specifically, we will work within the UniMorph annotation scheme (Sylak-Glassman, 2016). In the simplest case, each slot specifies a morpho-syntactic **bundle** of inflectional features such as tense, mood, person, number, and gender. For example, the English surface form *walks* appears with a slot that indicates that this word has the features [TENSE=PRESENT, PERSON=3, NUMBER=SG].

However, in a language where two or more feature bundles systematically yield the same form across all lexemes, UniMorph generally collapses them into a single slot that realizes multiple feature bundles. Thus, a single “verb lemma” slot suffices to describe all English surface forms in $\{\textit{see}, \textit{go}, \textit{jump}, \dots\}$: this slot indicates that the word can be a bare infinitive verb, but also that it can be a present-tense verb that may have any gender and any person/number pair other than 3rd-person/singular.

4 Neural Transducers for Morphological Inflection Generation

In the NLP literature, producing inflected forms given a lemma has become a common task (Durrett and DeNero, 2013; Nicolai et al., 2015; Ahlberg et al., 2015; Faruqui et al., 2016; Cotterell et al., 2016). It generally involves learning a string-to-string mapping with (often) monotonic alignments between the characters. This is the NLP community’s analogue to the past-tense generation task originally considered by Rumelhart and McClelland (1986). The goal is to train a model capable of mapping the lemma (in the case of English, the stem) to each form in the paradigm. In the case of English, the goal would be to map a lemma, e.g.,

walk, to its past tense word *walked* and to its gerund *walking* and 3rd person present singular *walks*.

The state of the art on this task is currently held by an encoder-decoder recurrent network (Cotterell et al., 2016). This architecture consists of two LSTM (Hochreiter and Schmidhuber, 1997) recurrent neural networks (RNNs) coupled together by an attention mechanism. The encoder RNN reads each symbol in the input string one at a time, first assigning it a unique embedding, then processing that embedding to produce a representation of the phoneme given the rest of the phonemes in the string. The decoder RNN produces a sequence of output phonemes one at a time, using the attention mechanism to peek back at the encoder states as needed. Decoding ends when a halt symbol is output. Given $\mathbf{x}, \mathbf{y} \in \Sigma^*$, the encoder-decoder architecture encodes the probability distribution over forms

$$p(\mathbf{y} \mid \mathbf{x}) = \prod_{i=1}^N p(y_i \mid y_1, \dots, y_{i-1}, c_i) \quad (1)$$

$$= \prod_{i=1}^N g(y_{i-1}, s_i, c_i), \quad (2)$$

where g is a non-linear function (in our case it is a multi-layer perceptron), and s_i is the hidden state of the decoder RNN. Note that we write $\mathbf{x} = (x_1, \dots, x_M)$, where $x_i \in \Sigma$, and $\mathbf{y} = (y_1, \dots, y_N)$, where $y_i \in \Sigma$. Finally, c_i is a convex combination of the the encoder RNN hidden states h_i , using the attention weights $\alpha_k(s_{i-1})$ that are computed based on the previous decoder hidden state: $c_i = \sum_{k=1}^{|\mathbf{x}|} \alpha_k(s_{i-1}) h_k$. We refer the reader to Bahdanau et al. (2015) for the complete architectural specification of the model.

The above formulation works best in the case of a string-to-string translation. However, the inflection task is more accurately described as a **labeled transduction** problem. Specifically, we would like to produce a different output depending on an additional label. In our case, this is the slot σ . To give a concrete example, we would like to transduce the English lemma *walk* to *walked* if we condition on the slot $\sigma = [\text{TENSE} = \text{PAST}]$, but map *walk* to *walking* if we condition on the slot $[\text{TENSE} = \text{GERUND}]$. In the labeled inflection scenario, we define $\mathbf{y} = f$ and \mathbf{x} is a concatenation of σ and ℓ . If we consider the morphological features to be taken from an alphabet Δ , we can then feed in a string $\text{CONCAT}(\sigma, \ell) \in \Delta^* \Sigma^*$. In English,

$\Delta = \{\text{TENSE} = \text{PAST}, \text{TENSE} = \text{GERUND}, \dots\}$. As an actual example, consider the source string GERUND walk and target string walk in g. This encoding procedure is described in detail in Kann and Schütze (2016).

5 Generational Modeling

We focus on a paradigm called **generational learning** (Hare and Elman, 1995), wherein we will examine the ability of neural models to convey their learned linguistic knowledge to other models with the intent of simulating how language is passed on from generation to generation. Our simulations focus on the transmission of knowledge of inflectional morphology in idealized conditions. In our simulations, we define a series of **production** models that will produce inflections, given a lemma and a slot as input. Each of these will be formulated as an LSTM sequence-to-sequence model, as discussed in §4. At each generation, we train the production model off of output samples from the previous generation (with the exception of the first generation, where we train using gold output forms instead). Thus, the previously trained model *teaches* the next generation, simulating, albeit somewhat crudely, how language is passed along over time.

The Production Model $p_{\theta}(f \mid \ell, \sigma)$. Our production model takes the form of a conditional distribution $p_{\theta}(f \mid \ell, \sigma)$, which is parametrized as an LSTM-based sequence-to-sequence model with attention as described in §4. We interpret $p_{\theta}(f \mid \ell, \sigma)$ as a distribution over possible productions the *population* may emit when attempting to inflect the lemma ℓ for the slot σ . We emphasize the population, because an individual is relatively deterministic in how they produce a form—few adult speakers alternate between *goed* and *went* as the past tense of *go* in normal speech, with the exception of occasional speech errors. Instead, at the population level, we interpret the probability as the percentage of the population that utters each string in Σ^* as the target inflection.²

Generational Simulation. Now, given our production model, we describe a procedure for performing a generational simulation, wherein at each generation, a new network learns from the previous

²We emphasize again that this only one way of effecting a generational learning scheme. For instance, a multi-agent model may be more appropriate in that different learners may incorporate input from different sources.

generation. This process is shown in Fig. 1. We simulate T generations, repeatedly sampling from a distribution q over inputs (ℓ, σ) . We will discuss various choices of q in §7.

At generation $t = 0$, our inflected lexicon consists of the *true* set of English triples $(\ell, \sigma, f^{(0)})$.

At each generation $1 \leq t \leq T$, we train morphological parameters $\theta^{(t)}$ to maximize $\mathbb{E}_q[\log p_{\theta^{(t)}}(f^{(t-1)} \mid \ell, \sigma)]$. For this, we run stochastic gradient descent for 100,000 iterations. Thus, at each iteration we draw some $(\ell, \sigma) \sim q$ and adjust the parameters to increase the conditional probability of the corresponding form $f^{(t-1)}$ given (ℓ, σ) .

Then, for each triple $(\ell, \sigma, f^{(t-1)})$ in the lexicon—whether or not it was ever used for training—we replace the form $f^{(t-1)}$ with a random sample $f^{(t)}$ drawn from the newly trained distribution $p_{\theta^{(t)}}(\cdot \mid \ell, \sigma)$. This gives us our new inflected lexicon at generation t .

We can view this process as simulating a Markov chain with a very elaborate transition procedure—one in which we have to train a neural network for a given number of epochs to find the next state. This is in line with previous work that simulates language change through Markov chain modeling (Niyogi and Berwick, 2009).

The Role of Regularization. Our production models are explicitly regularized using both early stopping and dropout. The finite size of the neural networks used is also a form of regularization. In machine learning parlance, this is done to generalize to held-out data. While we typically evaluate our models on held-out data, in our multi-generational setting we are mainly interested in how each subsequent model changes its predictions on the *training* data over time. Why? While most NLP papers are focused on generalization to new data, we are concerned with how the most frequent words in the lexicon evolve. Thus, we consider how a regularized learner performs on the *training* data. As a real-world example of such change, consider the past tense of the relatively frequent regular English verb *bake*: *baked*. The verb is of Germanic stock, derived from the Old English verb *bacan* with irregular past tense *boc* (Lass, 1994). In modern orthography, *boc* would correspond to *boke*. When modeling the evolutionary change of language, we need an external pressure to force the model to create general rules for its morphology rather than simply memorizing every mapping

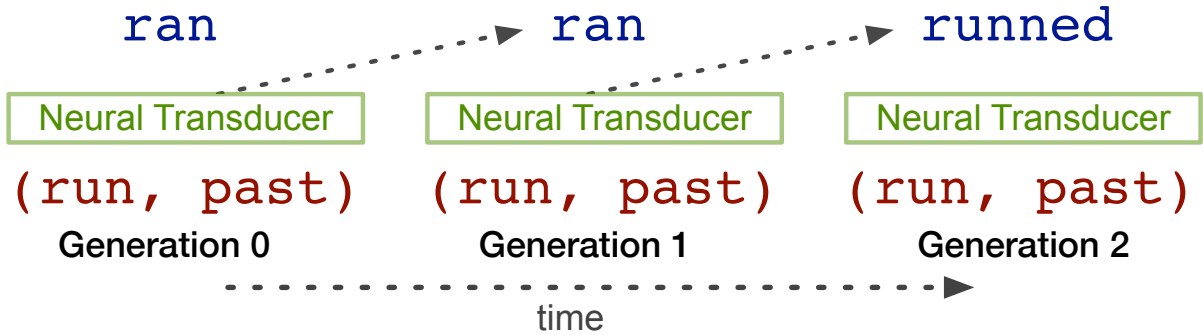


Figure 1: Graphical depiction of our generation learning scheme. At each generation, a form is sampled from the previous generation to retrain the neural transducers. In this toy example, we have that the irregular $run \rightarrow ran$ is conserved in the first time step, but regularizes to $run \mapsto runned$ after two steps.

and passing it on untouched to the next generation. Neither synchronic generalization nor diachronic change would be possible without the kind of pressure that regularization applies.

6 Irregularity and Frequency

In the previous sections we have discussed a formalization of inflectional morphology (discussed in §3) and the development of a simulation scheme for the evolution of inflectional morphology over time (discussed in §5). How does it all piece together? Our interest in simulation rests on our desire to attempt to provide evidence for the following conjecture about language change. Each of the previous sections describes a step towards that goal.

Conjecture. *Over generations, irregular inflectional forms are only able to remain in a language if they appear with sufficient frequency, or are phonologically or morphologically similar to frequent irregular forms (in other words, if they follow a very common irregular pattern). For example, the past tense of undergo is unlikely to regularize to undergoed because speakers will associate it with the extremely common pattern of $go \mapsto went$.*³

The conjecture above has been repeated in a number of places in the scientific literature. For example, Hare and Elman (1995) write “[o]ur claim is that this regularization process resulted from the difficulty in learning of items that had neither high

³ One interesting possible exception to this claim is the case of the *passé simple* in French, where forms—often irregular—that are very uncommon in the spoken vernacular, nevertheless persist in the written form, exhibiting a clear case of diglossia. We believe, however, that without the intervention of the Francophone school system, these forms would naturally die out as they have in other Romance languages such as Romansh (Benincà et al., 2005).

type frequency nor phonological class cohesion to support them.” In other words, they argue that infrequent, irregular verbs should be hard to learn. Likewise, Dowman et al. (2006) write “put simply, frequent verbs can afford to be irregular, since they will have ample opportunity to be transmitted faithfully through the bottleneck (Kirby, 2001).”

What distinguishes our approach? In our view, previous work had the shortcoming of not being able to provide an explicit distribution over sequences in Σ^* . In the last two years, NLP has made large advances in morphological inflection generation and, more generally, sequence-to-sequence transduction tasks such as machine translation. The work of Hare and Elman (1995), which used the model of Rumelhart and McClelland (1986), relies on predicting binary feature vectors associated with strings, rather than the strings themselves. By contrast, we directly parameterize a distribution over all of Σ^* . Thus, our model is capable of sampling full strings at each generation. In short, we believe our work gets the NLP aspect of this cognitive problem right.

7 Experimental Design

The goal of our simulation experiments is to show that infrequent irregular forms in a language will eventually regularize. The experimental variable in this simulation is, thus, the unigram distribution over types.

7.1 Stability under Unigram Distributions

How stable is the irregular system in English? We investigate several different distributions q over inputs (lemma-slot pairs). We contend that if the distribution q does not put sufficient probability on the inputs that map to irregular forms, those

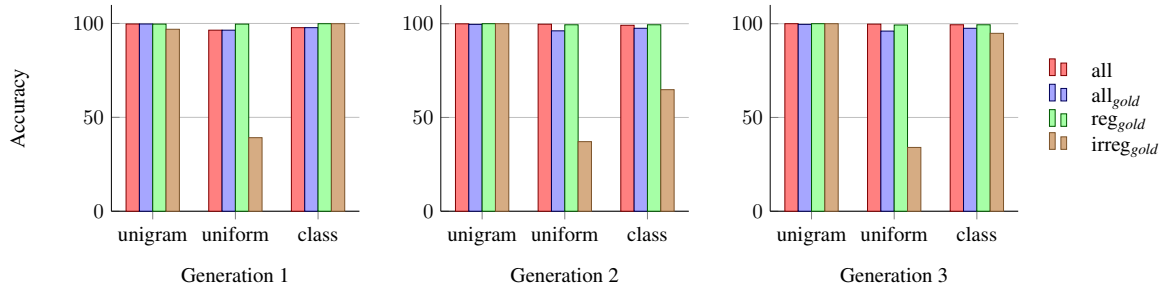


Figure 2: Here, we present accuracy of our model in the first three generations. The red *all* bars indicate how well each generation learns to predict the *previous* generation’s output (even if that output is no longer gold). By contrast, the blue *all_{gold}* bars indicate accuracy as measured against the original morphological lexicon. Thus, if a form regularizes in generation 2, *all* credit would be given in generation 3 only for predicting the regular form, while *all_{gold}* credit would be given only for returning to the original irregular. The bars *reg_{gold}* and *irreg_{gold}* break down the *all_{gold}* bars into a hand-annotated regular and irregular dichotomy, provided by Albright and Hayes (2003). We see that verb production stabilizes over time. After an initial drop in the ability to correctly predict the irregulars at generation 1, the remaining irregulars continue to be passed on unregularized to the following generations. Note that the regular-irregular classification is taken from Albright and Hayes (2003) and does not cover the full training set. Thus, it is not a complete break-down. Some results look fishy, e.g., *reg_{gold}* and *irreg_{gold}* are both better than *all_{gold}* in generation 1 class

forms will regularize over time. We consider three frequency distributions.

True Unigram Distribution. First, we consider the unigram distribution extracted from the Google *n*-gram database (Brants and Franz, 2006). As it is typical for irregulars to be much more frequent than regulars in modern languages, this samples from this distribution will often be irregular. We will refer to this distribution as **unigram** henceforth.

Uniform Distribution over Types. Next, we consider the uniform distribution over types. This distribution treats all forms equally. Thus, irregulars will not be very common. We expect the model to struggle to learn irregulars in this situation, picking up the regular patterns much faster. We will refer to this distribution as **uniform** henceforth.

Teasing Apart Word Classes. Finally, we consider a special type of probability permutation ρ that will tease apart the fact that some frequent phonologically and morphologically irregular forms may prop up less frequent irregulars (“gang effects”). It works as follows.

Suppose our training data consists of a set of complete paradigms for the same part of speech (in our case, verbs), so that the lexemes \mathfrak{h} are taken from a set L , the slots σ are taken from a set S , and all forms that realize pairs in $L \times S$ are included in the dataset.

We now select L_{test} , a random 20% of L , and S_{test} , a random 40% of S . We choose a random permutation $\rho_{\mathfrak{h}}$ of L that preserves the set L_{test} . and a random permutation ρ_{σ} of S that preserves the

set S_{test} . Now, we can define the function

$$\begin{aligned} \rho(\mathfrak{h}, \sigma) &= (\mathfrak{h}, \sigma) \quad \text{if } \mathfrak{h} \in L_{test} \text{ and } \sigma \in S_{test} \\ \rho(\mathfrak{h}, \sigma) &= (\rho_{\mathfrak{h}}(\mathfrak{h}), \rho_{\sigma}(\sigma)) \quad \text{otherwise} \end{aligned} \quad (3)$$

ρ is now itself a permutation that preserves all pairs in $L_{test} \times S_{test}$, but scrambles the others.

Each word type $w \in W$ has some (\mathfrak{h}, σ) pair, and we replace its frequency with the frequency of the word whose pair is instead $\rho(\mathfrak{h}, \sigma)$. If our dataset contains collections of paradigms for several parts of speech, we can run this frequency permutation on each part of speech separately.

We can now run our experiment with the unigram distribution from this modified lexicon, which changes frequencies but not forms. In particular, each lexeme \mathfrak{h} still has the same lemma and the same paradigm. Only the sampling distribution q has changed.

Note that ρ preserves the frequencies of some word types. Under this experimental design, we only evaluate on those word types. This is because we want to check how inputs with their *original, unaltered* frequencies are affected by permuting the frequencies of the *rest* of the verbs in the system, affecting phonological cohesion in the process.

7.2 Evaluation

We consider two evaluation metrics when comparing learning under the different distributions q . These metrics take the form of test statistics over the training data. Using a paired permutation test, we attempt to reject the null hypothesis that the following test statistics are the same under different distributions q : (i) the number of forms that

		Generation 1				Generation 2				Generation 3			
		all	all _{gold}	reg _{gold}	irreg _{gold}	all	all _{gold}	reg _{gold}	irreg _{gold}	all	all _{gold}	reg _{gold}	irreg _{gold}
0/1	unigram	99.72%	99.65%	99.72%	96.91%	99.92%	99.63%	100.0%	100.0%	100.0%	99.63%	100.0%	100.0%
	uniform	96.43%	96.43%	99.65%	39.18%	99.72%	96.19%	99.42%	37.11%	99.76%	96.06%	99.31%	34.02%
	class	97.77%	97.77%	99.88%	95.32%	99.15%	97.56%	99.42%	94.32%	99.43%	97.56%	99.42%	93.95%
D_{KL}	unigram	-1.13	-1.49	-1.13	-11.34	-0.32	-8.72	-8.16	-107.29	-0.34	-11.92	-11.34	-129.72
	uniform	-30.63	-30.63	-0.41	-424.21	-0.23	-239.17	-8.79	-4288.35	-0.24	-254.27	-14.74	-4503.88
	class	-40.83	-40.83	-0.54	-616.61	-0.53	-78.54	-4.84	-1357.41	-0.32	-85.43	-6.78	-1478.45

Table 1: Here we report the performance of the neural transducer under the two metrics across generations. All models were trained for 100 epochs. We see that under all three distributions, predictions stabilize in the sense that later generations learn to replicate the outputs of previous generations without applying any additional changes to verbs such as regularization of irregulars. Note that the regular-irregular classification is taken from [Albright and Hayes \(2003\)](#) and does not cover the full training set. Thus, it is not a complete break-down.

have changed after t generations and (ii) the log-probability of the original forms under the degraded model, i.e., $\text{KL}(p^{(0)} \parallel p^{(t)})$. The first metric tells us how accurate the model remains at predicting the original inflections in the training corpus. This is the standard evaluation metric for morphological generation. The second metric is softer—it can give partial credit if the original form is not *that* unexpected even after t generations.

7.3 Early Stopping as Regularization

The neural transducer we employ in this study is sufficiently high-capacity so as to ensure it can memorize the training data. Thus, in order for our simulation to be a success, we must prevent the network from simply memorizing all the data—this would not give the forms an opportunity to evolve. However, empirical work has suggested that neural networks prioritize learning simpler patterns in the data first ([Arpit et al., 2017](#)). Thus, we opt to stop the learner before it has converged ([Goodfellow et al., 2016](#)). Each generation’s model is trained for $E = 100$ epochs. We also employed drop-out on the recurrent layers with a dropout probability of 0.3. All experiments are performed with the open-source toolkit OpenNMT ([Klein et al., 2017](#)).

7.4 Experimental Data

Following [Hare and Elman \(1995\)](#), we focus on verbal inflection in English. The data are taken from the UNIMORPH collection. English is of Indo-European stock, from the Germanic branch. Its verbal inflection is modest, distinguishing 5 forms, typically. However, it has a large collection of irregular verbs. To create the experimental data, we first took 4039 past tense forms, selected by [Albright and Hayes \(2003\)](#). For each of those forms that has an entry in UNIMORPH, we expand it into its full paradigm.

7.5 Model Parameters

As described in §4, we used encoder-decoder architectures with global attention. Specifically, both the encoder and decoder consisted of 2-layer LSTMs. The encoder was bidirectional and output from the forward and backward LSTMs was concatenated. Both encoder and decoder had 100 hidden units and all character embeddings were 300 hidden units. Networks were trained using Adadelta with a base learning rate of 1.0. Minibatches of size 20 were used. Dropout between layers was set at 0.3.

8 Discussion and Analysis

We find with $p < 0.002$ that *all* pairwise differences between the uniform, unigram and class distributions are significant under a paired permutation test.^{4,5} Moreover, the size of the difference is quite large: while 96.91% of the irregulars are memorized under the true unigram distribution after 100 epochs, only 39.18% are memorized under our artificial uniform distribution. We see clearly in Fig. 2 that the transition stabilizes. In short, the regularized changes that happen during the transmission from generation 1 to 2 are then maintained and ossified during the transmission from generation 2 to 3. Thus, under the neural transducer model, if a language finds itself in an unstable condition with respect to the frequency distribution over its irregulars, it will attempt to regularize it—infrequent forms will become more regular. To show that these forms are actually regularized, we present a smattering of randomly sampled mistakes the neural transducer made after the first genera-

⁴To compare two models, we swap their predictions using a randomly generated permutation. The computation of the p -value is described at http://axon.cs.byu.edu/Dan/478/assignments/permutation_test.php.

⁵In the case of the class distribution, we only compare on the F_{test} set to keep the test paired.

tion, shown in Tab. 2. As expected, we find that the uniform distribution performs significantly worse than the other two in terms of performance with respect to the gold.

The Role of Phonological Cohesion. Our original conjecture stated that less frequent irregulars can be retained in a language if they are part of a pattern—e.g., *underwent* gets support from *went* and also from *undergone*. Under the class distribution, we show evidence for this. We evaluate on irregulars with unpermuted frequency, i.e., F_{test} , while destroying the frequencies of related words through a random permutation. If frequency were all that mattered in preserving the continuation of irregularity, we would expect these irregulars to decay *at the same rate* as the those under the unigram distribution. As evinced in Tab. 1, this is not the case. Irregulars decay at a somewhat faster rate when the frequencies of *other* forms are randomly permuted. This suggests that irregular forms in modern English may have survived in part thanks to the *actual* frequencies of other forms.

What does the simulation tell us? We find that the actual ability to transfer irregularity between generations depends on the frequency distribution. Neural transducers seem to pick up the general pattern of regular verbs long before they master individual irregulars. Of course, this is to be expected as *most* verbs are, in fact, regular. So, in answer to the original question we posed, neural learners can still manage to assimilate irregular patterns if they are frequent enough. Naturally, the modeling assumptions of the neural networks do not perfectly accord with what we know about human learners.

The class permutation experiment also gives us insight into how related irregulars interact. It seems that the network’s ability to learn relatively infrequent irregular forms, such as *underwent*, hinges in part on the frequency of related irregular forms such as *went*. To our knowledge, this work is the first computational experiment that focuses on the actual generation of complete word forms, in contrast to Hare and Elman (1995), that shows such behavior in a simulation.⁶

⁶Our significance test only shows that *this specific* permutation underperforms compared to the true unigram distribution. A better experimental design would be to run thousands of permutations to allow us to test whether the unigram distribution is actually better than an arbitrary permutation of this class. We would also like to run experiments that take $S_{test} = S$ or $L_{test} = L$, to tease apart the effect of high-frequency related lemmata for the same slot (e.g., (*undergo*, PAST) \mapsto *went* is

ℓ	unigram	uniform
buy	bought	buyed
bring	brought	bringed
feel	felt	feeled
fight	fought	fighted
grind	ground	grinded
teach	taught	teached
hang	hanged?	hanged?
think	thought	thinked
sit	sat	sitted
break	broke	breaked
see	saw	seed

Table 2: Sample output from the models trained under the uniform and unigram q distribution at generation $t = 3$. Mistakes are bolded.

8.1 Cognitive Science

Closest to our presented work is the seminal paper of Hare and Elman (1995), that first explored the paradigm of generation learning in the context of the evolution of inflectional morphology. They created a corpus of Old English verbs and modeled the evolution of the verbal system by successively training the neural network (Rumelhart and McClelland, 1986).⁷ Our work is also closely related to **iterative language modeling**, proposed by Kirby (2001). That work, like ours, has a generational scheme where models teach the next generation. Also, as in this work, they discuss the diachronic regularity and irregularity of linguistic structure. The main difference to our work lies in the that our model actually outputs phonological strings. Also, see Xanthos et al. (2011) for a discussion of children’s acquisition of morphology in a variety of languages.

8.2 Related Work in NLP

Recently, NLP has also experienced a renaissance of interest in simulation-based approaches to language emergence. We highlight some recent work

supported by (*go*, PAST) \mapsto *went*) versus high-frequency related slots for the same lemma (e.g., (*think*, PAST_PARTICIPLE) \mapsto *thought* is supported by (*think*, PAST) \mapsto *thought*).

⁷We use the term neural network, but in terms of modern machine learning, Rumelhart and McClelland (1986) is best understood as a linear model for multi-label classification. However, contemporarily, the network still fit well under the moniker of connectionism. Also, despite attempting to solve a string-to-string task, the network used a static computation graph, which required an abstruse encoding scheme: every input was mapping to a set of Wickelphones (Wickelgren, 1969), phoneme n -grams.

in this area and contrast it with our proposal in this paper. The realm of pragmatics offers a natural setting for the exploration of the interaction of agents in an environment. The rational speech act (RSA) framework views pragmatics as a recursive communication between a speaker agent and a hearer agent (Frank and Goodman, 2012). RSA has been the basis for numerous recent simulations in NLP (Andreas and Klein, 2016). Other simulation work has investigated the emergence of language in multi-agent systems. For example, Lazaridou et al. (2016) focus on referential games, where agents discuss an image. They show that neural models develop their own language, as it were, for discussing the images. The work in this paper is similar in spirit in that it involves neural networks communicating with each other, while the underlying motivation is substantially different. We are interested in the linguistic question of how language does or does not stabilize over time, rather than whether neural models will develop language.

9 Conclusion

In this paper, we have revisited generational simulation of the evolution of morphology, originally presented in the seminal work of Hare and Elman (1995). Specifically, we test the hypothesis that the distribution over types determines to what degree regularization of irregulars is possible. Different distributions lead to different stable states for the language, with varying amounts of irregularity retained. Our simulation is significantly updated methodologically—rather than attempting a string-to-string transduction problem with a feed-forward network, we use LSTM recurrent neural models. Moreover, we provide a more concrete experimental design than present in the original study that allows for clean hypothesis testing. We find that (with $p < 0.002$) irregulars are more likely to die out when we use a training distribution that underrepresents these irregular forms or their related forms.

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