

# The Effect of Linguistic Typology on Transfer Learning of Morphological Paradigms

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Conor Stuart Roe

A thesis submitted in partial fulfillment of the requirements for the  
degree of Bachelor of Arts in Linguistics and Computer Science

*November 22, 2019*

Version: Draft 2

Advisor: Jane Chandlee

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# Introduction

In linguistics, morphology refers to alterations to words to reflect changes in meaning or grammatical category. For example, English verbs have differing morphological forms to indicate the simple present and simple past tenses, e.g., *show* → *showed*, *see* → *saw*, etc. (Dreyer et al., 2008). Grammatical inflection in particular has a tendency to be structured into **paradigms** - sets of all possible morphological forms that words of a certain type can take on, often shown arrayed in tables. The table below gives part of the paradigm for the verb *to see*:

	simple		progressive	
	3rd singular	3rd plural	3rd singular	3rd plural
present	(she) <b>sees</b>	(they) <b>see</b>	(she) <b>is seeing</b>	(they) <b>are seeing</b>
past	(she) <b>saw</b>	(they) <b>saw</b>	(she) <b>was seeing</b>	(they) <b>were seeing</b>

Historically, in language technologies and modeling, morphology has been somewhat under-emphasized. This is probably due at least in part to the dominance of English in language technology research, and its below-average morphological complexity (Cotterell, Kirov, Sylak-Glassman, et al., 2017). English lexemes tend to have few grammatically inflected forms compared to in most other languages. This means that in machine learning models which are given an English training corpus and then tested on new material, the occurrence of *out-of-vocabulary* (OOV) inflected forms - that is, forms in the test data that never occur in the training data - are less frequent.

Moreover, as can be seen above, many English grammatical forms are periphrastic, using several words to construct a single inflected form. This means that even with grammatical information removed via lemmatization, the process of reducing words to their citation form, an English sentence may still be fairly understandable. (The *citation form* of a lexeme is the form under which it would appear in a dictionary:

*see, sees, seeing*, and *saw* all belong to the same lexeme, with the citation form *see*.) For instance, given a sentence *she have see it* whose words have been lemmatized, a proficient reader of English can guess that the original sentence was *she has seen it* or *she had seen it*; not much information is lost.

However, in many languages grammatical inflection carries much more semantic burden, and the number of possible inflected forms can be much greater. For instance, a single verb in the Archi language can be inflected in 1,725 ways (Kibrik, 1994). For such highly inflected languages, data sparsity is a significant problem for language models naive to morphology. In languages with a high number of possible forms per lexeme, a much larger number of OOV forms are inevitably encountered in test data, requiring reliance on a model’s representation of OOV words. Even inflected forms that do occur in training data may not appear often enough for a naive model to understand their semantic content. A model that considers grammatical categories separately is better able to understand the semantic content of inflected words (Cotterell, Kirov, Sylak-Glassman, Yarowsky, et al., 2016). It has been empirically shown that comprehending grammatical categories and inflection improves accuracy rates in language modeling and machine translation (Faruqui et al., 2015).

The state of the art for modeling morphology since 2016 has been variants of long short-term memory (LSTM) neural networks and the similar gated recurrent unit (GRU) architecture, operating over individual characters and grammatical category tags. These definitively overtook the field after their strong performance relative to traditional string transduction models in the SIGMORPHON 2016 shared task, a competition among several research teams on a morphology prediction problem. However, learning curve analysis in the SIGMORPHON 2017 task showed that such models, in particular encoder-decoder variants, perform well in high-data settings but, provided with lower volumes of training data, actually fare worse than string transduction models trained on similar amounts of data. To some degree, this poor performance could be ameliorated by pre-training on synthetic data, although this technique worked significantly better for languages with small inflectional paradigms (Cotterell, Kirov, Sylak-Glassman, et al., 2017). In the 2018 shared task, an identical morphology prediction task with data for more languages, the learning curve issue was addressed to some degree by ensembling with string transduction methods

(Cotterell, Kirov, Sylak-Glassman, Walther, et al., 2018), but for languages with low quantities of digital resources, there is still much room for improvement of computational morphology models.

One of the 2019 shared tasks focused on utilizing transfer learning to strengthen neural morphology models, using pretraining or combined models to leverage a high volume of data for one language to better model the morphology of another language for which a low volume of data was provided. The research teams tested their models on 100 transfer learning pairs, of which 80 were closely related languages. Transfer learning produced "modest" performance gains over models without access to transfer learning, with related pairs showing significantly more model improvement than unrelated pairs (McCarthy et al., 2019).

For some low-resource languages closely related to some high-resource language, the outcome of SIGMORPHON 2019 promises improved morphology modeling. But for the many low-resource languages may not closely related to other high-resource languages, it may be worthwhile to assess whether transfer learning can still be useful. It may be that pretraining on a typologically similar language, or simply on some other language(s) to understand the universal patterns of natural language morphology, can help neural models make more of sparse morphological data for low-resource languages. To this end, I'm planning on investigating what typological commonalities are predictive of more effective transfer learning of morphology between languages.

In order to accomplish this, I will need to compile a dataset of morphological typological characteristics of the languages I wish to work with, alongside their morphology data. SIGMORPHON 2018 published an annotated morphological data set for 103 languages, including various training data volumes as well as test data, which I will use for morphology learning; I'll compile typological information from an existing database, the World Atlas of Language Structures (WALS), and via string transduction analyses of the SIGMORPHON data. From there, I'll assess the efficacy of transfer learning between a large number of language pairs, and what relationship that has with various types of typological similarity between the languages. I'll also seek to answer some related questions, such as whether transfer learning efficacy

is typically reciprocal between two languages, how the efficacy of transfer learning interacts with learning curves, and potentially whether transferred knowledge of multiple languages can boost the performance of a morphology model even more.

## Literature Review

### 2.1 Machine learning of morphology: sub-problems and related problems

Within the realm of machine understanding of morphology, there are many sub-problems and related problems. The most basic areas of research involve predicting the morphology of words in isolation - transforming a word into a specific morphological form, or the inverse, tagging a form with its morphological categories. Typically, this has been done with words in regular grammatical paradigms, such as number and case marking on nouns, or tense, aspect, mood, and/or argument agreement patterns on verbs.

#### 2.1.1 Core supervised learning problems

Some of the earliest work in computational morphology involves making specific morphological transformations. That is, given a particular form of a lexeme (often, but not necessarily, a citation form), predicting another form. An example would be learning to transform English verbs from present to past tense, e.g., *show* → *showed*, *see* → *saw*, etc. (Dreyer et al., 2008).

The natural extension of this is aiming to be able to predict any inflected form given one specific form of a lexeme and an arbitrary set of morphological categories. For instance, given a lexeme *see* and the categories 3rd person singular, simple present, generating the correct form *sees*. Generally speaking, a citation form has been used as input (Durrett and DeNero, 2013, Faruqui et al., 2015, Cotterell, Kirov, Sylak-Glassman, et al., 2017). The related "reinflection" problem involves being

given any inflected form as input, and transforming it into any other (Cotterell, Kirov, Sylak-Glassman, Yarowsky, et al., 2016).

A further extension of the morphology generation problem is the generation of complete inflection tables. The exact nature of this problem depends on the type of training and test data used. If a model is only trained on a sparse, random sampling of forms for each lexeme, then a task may consist of filling out the rest of an inflection table for those lexemes. For instance, a model may be given the forms *sees* and *seeing* among its training data, and be required to fill out the remaining forms of that paradigm, including *see* and *saw*.

If a model is instead trained using entire inflection tables, e.g., all forms of the verb *see*, then test data must consist of new lexemes. Another dimension along which paradigm completion tasks differ is whether only a single citation form is provided as a prompt, or whether any form or even multiple forms may be provided as a prompt for producing a single table (Hulden et al., 2014, Ahlberg et al., 2015, Cotterell, Kirov, Sylak-Glassman, et al., 2017).

### 2.1.2 Inflection types

Overall, a diverse set of inflection shapes have been worked with in the most recent efforts of this subfield. Since 2016, the Special Interest Group on Computational Morphology and Phonology (SIGMORPHON), a research collective focused on computational morphology and related problems, has fielded "shared tasks" in which several research teams globally are given training data and a task definition, and attempt to create models which are subsequently compared. The SIGMORPHON shared task 2018 included training data from 103 typologically diverse languages, and paradigms using suffixing, prefixing, infixing, reduplication, and non-concatenative morphology.

However, all SIGMORPHON work has been with well-defined, tabular paradigms of grammatical inflection of fairly moderate size ( $\leq 200$  forms) (Cotterell, Kirov, Sylak-Glassman, Walther, et al., 2018). Other types of morphology such as derivational morphology and cliticization, which have the potential to greatly expand the number



of possible forms and in a less organized fashion, have been less well explored. What Mattissen, 2004 calls "compositionally polysynthetic" languages, those which make extensive use of more expansive types of word building including incorporation and productive derivational morphology, are ripe for future work (Cotterell, Kirov, Sylak-Glassman, Yarowsky, et al., 2016). Such languages include Chukchi, Cherokee, Ainu, Nahuatl, and others (Mattissen, 2004).

The chief challenges with approaching these less paradigmatic types of inflection are data procurement and structuring. For grammatical inflection paradigms, the set of potential forms is simply combinatorial from the set of grammatical categories, and can be specifically enumerated. Concretely, the vast majority of grammatical paradigm data used in SIGMORPHON comes from Wiktionary, a free and collaborative online multilingual dictionary which provides full or partial tables of grammatical inflection along with lexeme definitions; these tables define the space of inflected forms for the task. In contrast, with derivational morphology, noun incorporation, and other less paradigmatic types of inflection, the possibility space is considerably less well-defined. How can a model know a priori that *likeable* is a valid word of English but *hateable* is not, or that the opposite of *accessible* is *inaccessible* and not *unaccessable*? There are no tables for the set of, e.g., derivational forms that a lexeme may take on, since it is constrained by semantics and idiosyncratic usage, and there is considerably more variability among lexemes of the same category (say, verbs) in which derivational categories they may take on than which grammatical categories. Consequently, labeled data is much harder to come by, and it is harder to demonstrate that a dataset of derivational forms is truly exhaustive.

### 2.1.3 Related problems

Within only the last two or so years, there has been work on predicting morphology in context. In the 2018 and 2019 SIGMORPHON shared tasks, to which several teams of researchers submitted solutions, a sub-task was dedicated to cloze challenges, a type of test in which one word in a sentence, given in citation form, was to be inflected based on context (Cotterell, Kirov, Sylak-Glassman, Walther, et al., 2018,

McCarthy et al., 2019). This work is essentially a synthesis of morphology generation and morphosyntactic modeling.

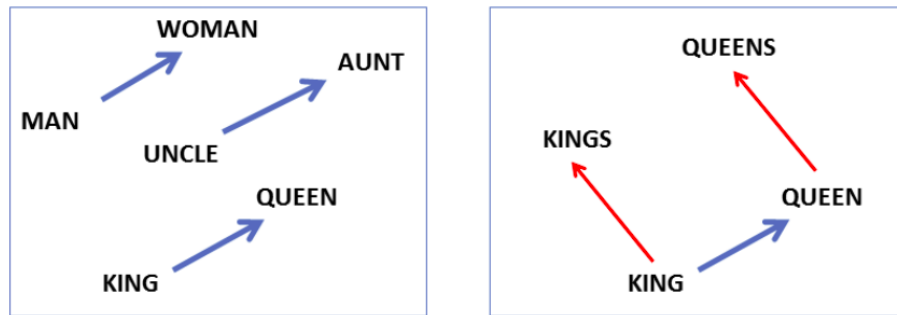
Since 2017, there has been some work done on learning curves for computational morphology. The datasets published for SIGMORPHON 2017 and 2018 include partitions into low ( $\sim 100$  forms), medium ( $\sim 1000$  forms), and high ( $\sim 10,000$  forms) data training sets for the express purpose of assessing the learning curve of different models. Evidence suggests that learning curve varies by model type; LSTM neural models, a type of model generally considered to be state of the art, despite being the most successful models with high-data training sets, often fare worse than more baseline string transduction models with low data training sets (Cotterell, Kirov, Sylak-Glassman, et al., 2017, Cotterell, Kirov, Sylak-Glassman, Walther, et al., 2018). Improving performance with small training sets is of interest, as much of the applicability of computational morphology models is to languages which don't already have high-quality technical tools or datasets.

The most recent new challenge that SIGMORPHON has tried to address is that of transfer learning of morphology, in the shared task earlier this year. Given a state of the art model trained on a language with a high volume of training data, teams were asked to alter it into a model that would perform well on a new language, given a smaller amount of training data for that language. 80% of the pairs of languages were closely related, while 20% were distantly or not at all related. Gains of transfer learning models between closely related languages generally performed better than transfer learning models between more distant languages (McCarthy et al., 2019).

## 2.2 Non-neural approaches

### 2.2.1 Vector embedding

A technique that has found success in a variety of computational linguistics tasks is that of representing words in relatively low-dimensional vector spaces. That is, words are represented as a vector, a series of numbers of fixed length; the length of the vector is typically much smaller than the number of total known words. This



**Fig. 2.1:** Regular spatial transformations encode semantic or grammatical content (Mikolov et al., 2013)

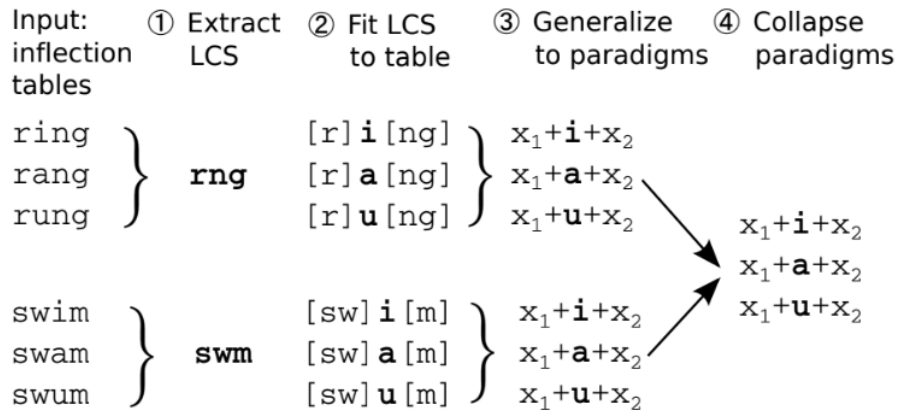
has the intention of capturing semantic and syntactic content in a principled way - similarities between the numbers representing two words are expected to signify actual similarity in their meaning, and regular linear transformations between vectors should roughly correspond to specific semantic or grammatical changes. These vector representations can be generated via various unsupervised learning methods (Bilmes and Kirchhoff, 2003, Alexandrescu and Kirchhoff, 2006).

Regularities in the relative location of semantically related words have been exploited for semantic analysis tasks (Alexandrescu and Kirchhoff, 2006). Similarly, morphological changes may appear as spatial transformations in vector space, and work has been done on discovering morphological relationships between in-vocabulary words based on their relative spatial locations (Mikolov et al., 2013, Soricut and Och, 2015, Dos Santos and Zadrozny, 2014). Figure 2.1 illustrates this idea in a slightly simplified way: once a vector embedding model has been trained on English, it can be discovered that semantic transformations (male to female) and grammatical transformations (singular to plural) roughly correspond to regular spatial translations in vector space.

Vector embedding has the limitation that it cannot extend to words for which a vector representation has not been trained, and so it cannot directly provide understanding of the many OOV forms encountered in test data of highly inflected languages (Soricut and Och, 2015, Cotterell and Schütze, 2019). However, it can be a means to discover relationships between words in an unsupervised manner, which may support labeling tasks in support of computational morphology and other tasks.

a)	s	c	h	l	e	i	c	h	e	n	
	s	c	h	l	e	i	c	h	e		
	s	c	h	l		i	c	h			
g	e	s	c	h	l		i	c	h	e	n

**Fig. 2.2:** Character alignment for various forms of the German verb *schleichen* (Nicolai et al., 2015).



**Fig. 2.3:** Conceptual depiction of a typical example of a string transduction method of morphology learning (Hulden et al., 2014).

## 2.2.2 String transduction

Earlier work specifically focused on the problem of morphology prediction made use of iteratively improving methods of string transduction - in essence, pattern matching on the written representations of words (Durrett and DeNero, 2013, Hulden et al., 2014, Nicolai et al., 2015, Ahlberg et al., 2015). Typical steps of string transduction methods include character alignment (depicted in Figure 2.2), identification of characters that are inserted or deleted based on grammatical form, and generalization of lexemes which are inflected by the same sets of insertions or deletions (depicted in Figure 2.3).

A crucial limitation of string transduction methods are their general assumption that most lexemes have exactly the same set of characterwise transformations as a large group of other lexemes, and that a manageably small number of such inflection classes exist. There are paradigms with such a limited set of inflection classes,

such as Spanish *-ar*, *-er*, and *-ir* verbs. However, when multiple morphological processes are at play, individual lexemes may be nearly unique in their exact set of transformations.

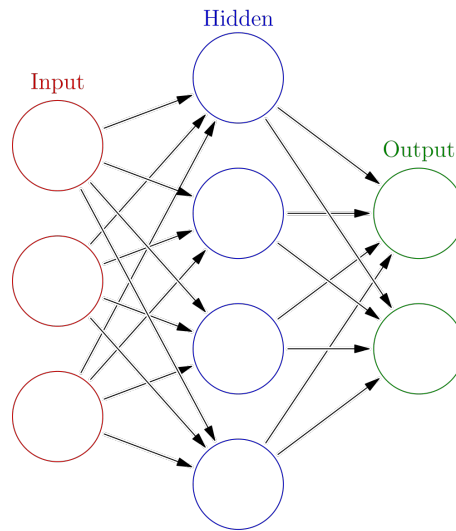
For example, Finnish noun declension has processes of vowel harmony, consonant gradation, and vowel alternation and lengthening operating to produce final inflected forms (Ranta, 2008). As an illustration, consider the Finnish nouns *puku* "suit" and *kenkä* "shoe", which have the inessive singular forms *puvussa* "in the suit" and *kengässä* "in the shoe", respectively. In both forms, the letter *k* is transformed via consonant gradation, but the letter it becomes depends on the surrounding letters. The final vowel of the forms may be *a* or *ä*, depending on vowel harmony. In other inflected forms, the final vowel of the words may be doubled (*English Wiktionary* n.d.). A model that naively seeks to match these words with other words using the same set of character transformations across the paradigm may need to assign nearly every word to its own category, failing to generalize the patterns at work.

The poorer performance of string transduction relative to neural models has led to a move of the field away from string transduction since about 2016 (Cotterell, Kirov, Sylak-Glassman, Walther, et al., 2018).

## 2.3 LSTM and other neural approaches

Since 2016, almost all work on paradigm completion has made use of long short-term memory (LSTM) or related gated recurrent network (GRU) models (Faruqui et al., 2015, Cotterell, Kirov, Sylak-Glassman, Yarowsky, et al., 2016, Cotterell, Kirov, Sylak-Glassman, et al., 2017, Cotterell, Kirov, Sylak-Glassman, Walther, et al., 2018, McCarthy et al., 2019). An LSTM network is a variation on a recurrent neural network (RNN), a variant of neural network (Hochreiter and Schmidhuber, 1997).

Neural networks are a type of function approximation model inspired by the connection of neurons in animal brains. They have come to be implemented in a variety of forms, and underlie state of the art machine learning models in a variety of applications. The common feature of neural models is repeated matrix multiplication

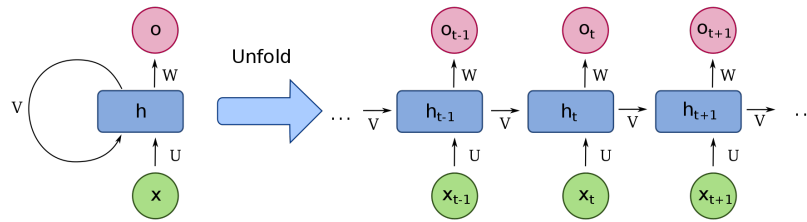


**Fig. 2.4:** The structure of a feed-forward neural network with three inputs, four hidden cells, and two outputs. (commons.wikimedia.org/wiki/File:Colored\_neural\_network.svg)

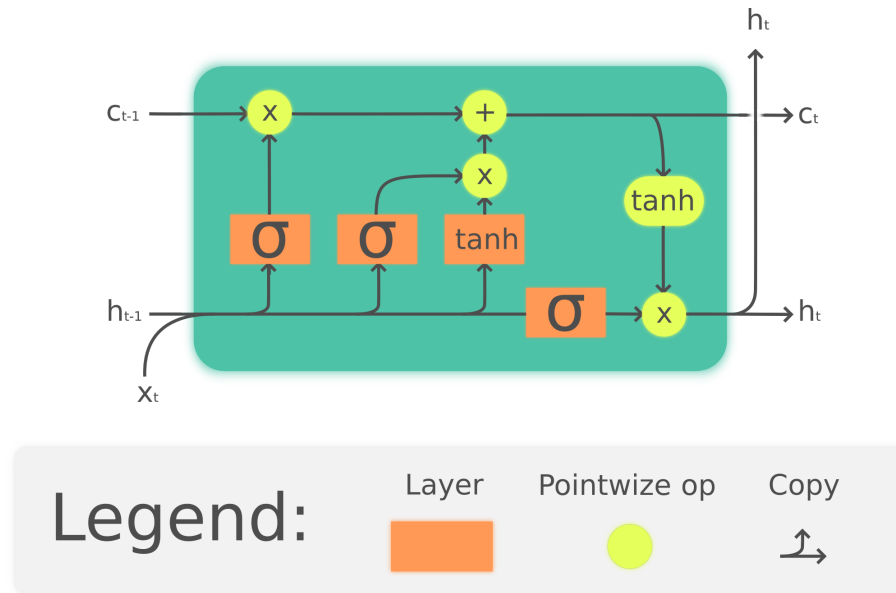
followed by the application of a non-linear "activation" function. Figure 2.4 illustrates a simple feed-forward network, in which a vector of three inputs is multiplied by some  $3 \times 4$  matrix and activated to produce a vector of four intermediate values, which are again multiplied by some  $4 \times 2$  matrix and activated to produce a vector of two outputs.

An RNN is a type of neural network that operates over sequences of inputs, typically with unknown length. Figure 2.5 illustrates the general structure: each input is represented by a vector, which is multiplied by a vector  $U$  to modify state, and the modified state is then multiplied by a vector  $W$  to produce an output vector and a matrix  $V$  to produce the next state. An LSTM network utilizes a specific means of using the inputs to modify state, represented by Figure 2.6, which includes the ability to modify the rate at which information is forgotten. LSTMs are intended to solve the forgetfulness of earlier RNN types, which tend to be unable to recall information from more than a few iterations prior (Hochreiter and Schmidhuber, 1997).

LSTMs have become the dominant model type in a variety of language tasks, including syntactic and morphological tasks. They significantly outperformed other types of models in SIGMORPHON 2016, since which time they have come to underlie nearly



**Fig. 2.5:** The generalized structure of a recurrent neural network. (commons.wikimedia.org/wiki/File:Recurrent\_neural\_network\_unfold.svg)

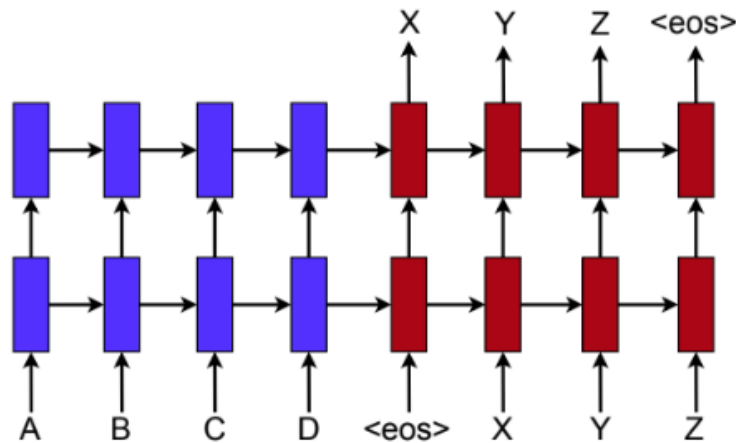


**Fig. 2.6:** The state cell of an LSTM model. (commons.wikimedia.org/wiki/File:The\_LSTM\_cell.png)

all morphology prediction models (Cotterell, Kirov, Sylak-Glassman, Yarowsky, et al., 2016, Cotterell, Kirov, Sylak-Glassman, et al., 2017).

The main differences between the LSTM architectures used in state of the art applications now, as evidenced by the four architectures used as baselines in the SIGMORPHON 2019 transfer learning task, are in their **attention mechanism**, the means by which hidden states are combined to generate sequential output (Cotterell and Schütze, 2019).

The main contrasting terminologies for attention are **hard** vs. **soft**, and **global** vs. **local**. In soft attention models, hidden states are all considered, weighted using an additional layer. In hard attention models, only a limited subset of hidden

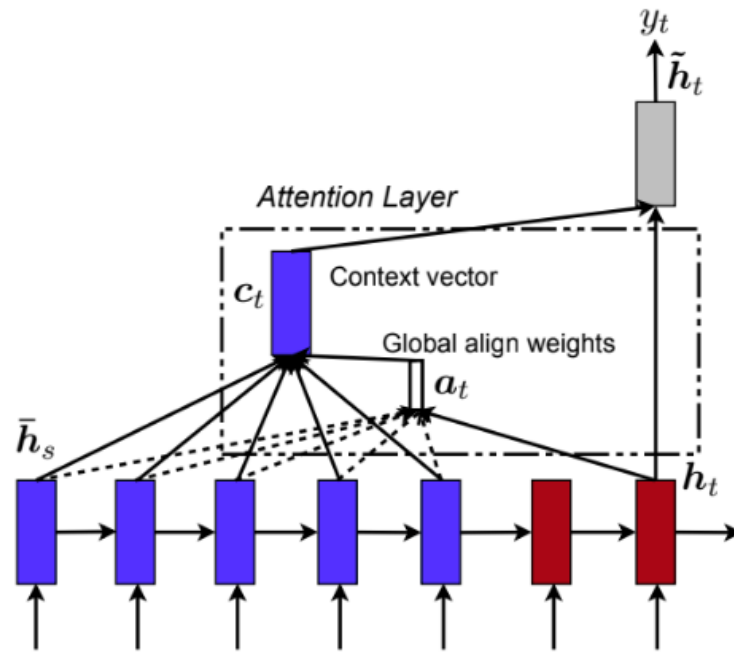


**Fig. 2.7:** A stacked RNN architecture, in which there are two layers of hidden state. In this architecture, hidden states in the second layer are exclusively derived from the aligned cell of the first layer. (Luong et al., 2015)

states are considered, the selection of hidden states may be chosen by the model at each stage or consist of a single sliding window of attention. Soft attention models are straightforward to apply backpropagation to, since each hidden state has a differentiable relationship to the output, while hard attention models that select which hidden states are used at a particular time step are not. A **monotonic** hard attention model is one in which the window of attention moves through the input at the same rate that the output is generated, which is applicable in scenarios when corresponding positions in input and output are expected to be strictly related. **Global** vs. **local** attention refers to whether all or only a narrow range of hidden states contribute to a hard attentional layer, as depicted in Figs. 2.8 and 2.9 (Luong et al., 2015).

The SIGMORPHON 2019 transfer learning task used a diverse set of architectures as baselines, including a soft attention, a non-monotonic hard attention, and two monotonic hard attention models, reflecting a diversity of strategies employed by the best current models. Soft attention has dominated prior morphology learning work, but Wu and Cotterell (2019) demonstrate that hard monotonic models may be more appropriate for morphology tasks, where string transductions are mostly monotonic - that is, (except for in instances of reduplication or metathesis) characters in an input word correspond to characters in the same order in the output (McCarthy et al., 2019, Wu and Cotterell, 2019).



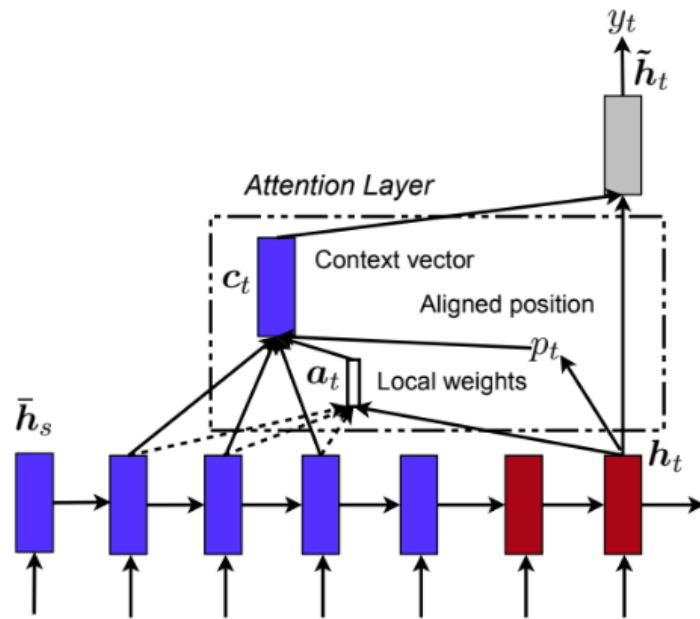


**Fig. 2.8:** An RNN architecture with global attention: all first-layer hidden states are used to construct an output. (Luong et al., 2015)

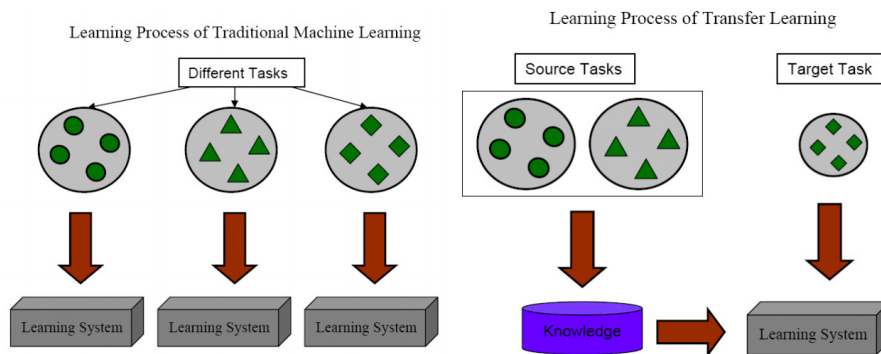
## 2.4 Transfer learning

Transfer learning is a high-level term for any machine learning process for which either the domain or the distribution of some or all training data inputs is different from that of the inputs to which a model will ultimately be applied. Such techniques arise in response to the conundrum that many real-world machine learning problems face: a lack of data that looks like the system that one wishes to predict or understand, either due to insufficient available quantity, or altogether lack in the case of seeking to predict the outcome of future events of which no past equivalents exist. The machine learning problem for which a model is initially trained is called the **source task**; the problem which the model is being constructed to solve is called the **target task**. Typically, the source model is not the only component of the eventual target model - manual output transformations or additional machine learning is usually applied (Pan and Yang, 2010).

Some examples are provided by Pan and Yang 2010. One is the problem of seeking to classify web documents by topic. If a significant portion of the documents that will need to be classified bear on topics rarely covered in an existing corpus of web



**Fig. 2.9:** An RNN architecture with local attention: only a subset of hidden states, not necessarily contiguous, are used to construct an output. (Luong et al., 2015)



**Fig. 2.10:** An abstract characterization of traditional ML vs. transfer learning

documents, this is an example where the training and test domains are roughly similar but their distribution is different; it is perhaps a less obvious transfer learning problem. Another example is that of attempting to gauge sentiment of reviews of cameras, when the only available data is a corpus of reviews of other types of products. In this case, knowledge of many domains, none of which is equal to the target domain, must be transferred to attempt to make predictions about the target domain.

There are three broad categories of transfer learning that Pan and Yang identify, which differ in their intrinsic difficulty. **Inductive transfer learning** describes a modeling scenario in which the domains of source and target are identical, but

the target task is different, that is, the codomain of the model differs. In inductive transfer learning, output from the source model is used to inform a model of the target task. **Transductive transfer learning** describes the scenario that the task is the same but the source and target domains are in some way different, either differing in feature space, or having the same feature space but differing in distribution over that space. The two examples above are both instances of transductive transfer learning; the web document categorization problem is an example of differing distribution while the review sentiment analysis problem is an example of differing feature space. **Unsupervised transfer learning** describes the scenario that source and target differ in both domain and codomain.

An example of unsupervised transfer learning is the morphology transfer learning problem that this thesis undertakes: labeled training inputs and outputs from the source (one language) are used to inform a model of the target task (a different language), and the feature spaces of both domain (lexemes and morphological categories) and codomain (inflected forms) differ between the two. After all, no two languages share the same set of words, and only in the case of very closely related languages or extreme coincidence will all grammatical paradigms inflect for the same set of morphological categories (one language is likely to have a grammatical gender, a verb tense, or some other category that the other language lacks).

There is precedent for transfer learning on LSTMs for language technology tasks, typically with the explicit goal of dealing with low data volume in the target task due to sparse language resources. The baseline for SIGMORPHON 2019 was based on the LSTM transfer learning architecture introduced in Zoph et al. 2016 (McCarthy et al., 2019), which was applied there to a transductive machine translation task. Their approach is relatively straightforward - they use an LSTM encoder-decoder model to train a machine translation system from French to English on a high data volume, then use that model as the initialization of an architecturally identical Uzbek-English model, holding the decoder fixed and simply allowing the encoder to learn encodings for Uzbek with quite a small dataset. Their results showed considerable improvements over similarly low-data machine translation techniques (Zoph et al., 2016).

## Research proposal

The primary research question of this thesis is which typological, lexical, and genealogical similarities, if any, are predictive of more effective transfer learning of morphology between languages. For instance, if language A is exclusively prefixing while languages B and C are exclusively suffixing, and if there is considerably less training data available for language C than the others, is it likely that a neural model pre-trained on language B is likely to make a better transfer learning candidate for modeling language C than one pre-trained on language A, due to the relative typological similarity between B and C?

Fortunately, I already have access to a morphological dataset for 103 languages, which can be used to train neural morphology models. In order to measure typological similarities, I'll need to compile a set of typological category information for these 103 languages, using existing research and computational analysis of the morphological dataset. Typological characteristics I'm planning on assessing include affixation strategy, set of grammatical categories inflected for, overall morphological paradigm size, occurrence of fusion between grammatical categories, and presence of long-distance morphophonological processes and/or reduplication. I will also assess genealogical closeness and potentially lexical similarity. The details of my data sourcing and generation can be found in section 4.

To assess transfer learning efficacy, I will first training and scoring models for all 103 languages with low ( 100 forms) and/or medium ( 1,000 forms) resource settings as a baseline. I can then pre-train models on some or all of the 103 languages with a high-resource ( 10,000 forms) setting, and use these as the basis of transfer learned models of other languages with low and medium-resource training sets and assess their performance relative to models without access to transfer learning. With a diverse enough data set of language pairs it should be possible to assess the effect of typological, lexical, and genealogical similarities on transfer learning via simple

regression. Tentatively, I will choose a few hundred pairs randomly with weighting towards pairs of similar languages, since the majority of randomly chosen pairs will be typologically and genealogically distant.

For the architecture of the neural models, I will use some variant of LSTM; I will base it on one or more of the best-performing models submitted to SIGMORPHON 2019.

# Data

## 4.1 Grammatical inflection data

I will be using the data set published for the SIGMORPHON first shared task 2018, which is publicly available on GitHub. It consists of triples - lemma, grammatical categories, and appropriately inflected form - for 103 languages, partitioned into training, development, and test sets. An example of some Finnish triples is shown in Figure 3.2. The training sets are further partitioned into low, medium, and high-resource sets; the low-resource training sets contain about 100 forms, medium about 1,000 forms, and high about 10,000 forms, with the sets being nested so that the smaller training sets are subsets of the larger ones. These data levels are used to simulate different resource settings, e.g., low-resource training sets represent data available for a poorly-resources language; the data levels can also be used to assess model learning curve (Cotterell, Kirov, Sylak-Glassman, Walther, et al., 2018).

### 4.1.1 Language diversity

The languages represented in the data cover a wide range of families and typological categories. Although over half of the languages are from the Indo-European family, a grouping that includes most languages of Europe, Greater Iran, and the northern part of the Indian subcontinent, one or more languages each of the Athabaskan, Kartvelian, Quechua, Semitic, Sino-Tibetan, Turkic, and Uralic families, as well as two isolates (Haida and Basque), are represented. Diverse inflection strategies are also represented, including suffixing, prefixing, infixing, ablaut, and introflexion, and long-distance processes like vowel harmony and consonant harmony (Cotterell, Kirov, Sylak-Glassman, Walther, et al., 2018).

Inflection of <i>tukehtua</i> (Kotus type 52/sanoa, <i>t-d</i> gradation)		
indicative mood		
present tense		
person	positive	negative
1st sing.	tukehdun	en <i>tukehdu</i>
2nd sing.	tukehdut	et <i>tukehdu</i>
3rd sing.	tukehtuu	ei <i>tukehdu</i>
1st plur.	tukehdumme	emme <i>tukehdu</i>
2nd plur.	tukehdutte	ette <i>tukehdu</i>
3rd plur.	tukehtuvat	eivät <i>tukehdu</i>
passive	tukehdutaan	ei <i>tukehduta</i>

Fig. 4.1: The English Wiktionary partial inflection table for the Finnish word *tukehtua*.

keisarillinen	keisarillisitta	ADJ;PRIV;PL
tukehtua	tukehdutaan	V;PASS;PRS;POS;IND
juhtaeläin	juhtaeläimille	N;AT+ALL;PL
vastaava	vastaavatta	ADJ;PRIV;SG

Fig. 4.2: A sample of the SIGMORPHON 2018 data for Finnish, scraped from Wiktionary and provided on GitHub (<https://github.com/sigmorphon/conll2018/blob/master/task1/all/finnish-train-high>).

#### 4.1.2 Sourcing and sampling

The English Wiktionary, a collaborative online dictionary, has become something of a standard source of supervised morphological data. It provides full or partial inflection tables alongside lexeme definitions; the structure of tables is consistent for a given language and part of speech. An example table is given in figure 3.1. For some highly inflected languages (e.g., Navajo), Wiktionary only provides a fixed subset of forms. For some relationships between words that could be considered grammatical, it may simply offer them as separate lexical entries; for example, Russian perfect and imperfect forms are given as separate entries, as are Navajo verb forms that vary by aspect or thematic classifier (*English Wiktionary* n.d.).

For most of the languages in the SIGMORPHON 2018 data, forms were gathered via scraping from Wiktionary. Multiple parts of speech are represented for most languages, but only parts of speech with a significant number of entries relative to

all entries in a given language. Inflected forms were sampled for inclusion according to their estimated distribution in the text of Wikipedia for each respective language. For languages with sufficient data, 12,000 forms were sampled, and from these 1,000 were randomly selected for the development set and 1,000 for the testing set; the remaining 10,000 became the high-resource training set, of which 1,000 were randomly chosen as the medium-resource set and 100 of those as the low-resource set. For languages with less available data, sets might be smaller and the high-resource training set might be omitted; 17 languages lack high-resource sets (Cotterell, Kirov, Sylak-Glassman, Walther, et al., 2018).

### 4.1.3 Representation of morphology

The SIGMORPHON data set uses the UniMorph format to indicate grammatical categories (Cotterell, Kirov, Sylak-Glassman, Walther, et al., 2018). The UniMorph project, initially published in 2015, is a format for encoding morphological categories uniformly cross-linguistically (Sylak-Glassman, Kirov, Post, et al., 2015, Sylak-Glassman, Kirov, Yarowsky, et al., 2015, Sylak-Glassman, 2016).

## 4.2 Language typology data

I will need numerical or categorical information about the morphological typology of the languages I consider in order to assess how typological similarities impact transfer learning.

I may be able to gather some useful typological information the World Atlas of Language Structures (WALS), a linguistic typology database, and I also plan on generating my own typological data by computationally analyzing the SIGMORPHON 2018 data. WALS provides much of the same information that



### 4.2.1 Features

The typological features I'm interested in considering include inflection shape (prefixing, suffixing, infixing, introflexion), set of inflected categories and overall paradigm size by part of speech, degree of fusion, and presence of long-distance phonological processes.

Inflection shape may be important in determining, for instance, how soft attention models choose to focus on various parts of a word, so that a model trained on a language with a particular profile of inflection shapes may be more likely to attend to the correct parts of words when readapted to model a language with similar inflection shapes.

Languages with similar sets of inflectional categories, e.g., languages which both mark adjectives for the gender and number of their head noun, or verbs with similar sets of tenses, may similarly benefit from transfer learning between them due to some form of model similarity.

Fusion refers to the marking of multiple categories at once with a single indivisible morpheme, e.g., the Spanish verb *hablé* "I spoke" marks tense and subject person and number with the suffix *-é*, lacking separable morphemes to indicate the preterite tense and first person singular subject (cf. *hablo* "I speak", *habló* "he/she spoke"). Transfer learning may be beneficial between languages that both exhibit or lack fusion, or more specifically between languages that exhibit fusion between the same categories; since fusion operates over combinations of two or more categories, though, the space of possible fusion behaviors is quite large and it may be difficult to find unrelated languages with similar fusion behavior.

Long-distance phonological processes are those by which the surface form of an affix depends on the phonological properties of a segment at some distance from the affixation site; consider my earlier example of vowel harmony in Finnish: the nouns *puku* "suit" and *kenkä* "shoe" have the inessive singular forms *puvussa* "in the suit" and *kengässä* "in the shoe", respectively, with final vowel of the suffix dependent on the set of vowels in the rest of the word. Given that long-distance processes present

considerable difficulty for non-neural morphology models, neural models may have to be intensively trained to attend to such processes, presenting an opportunity for transfer learning to leverage existing knowledge.

I'd also like to take into account a more fine-grained measure of language relatedness, so that incidental typological similarities can be successfully statistically blocked against similarities arising from common origin. Two possible strategies are using detailed language genealogical trees and counting degrees of separation between languages, or finding some way to assess lexical similarity, the proportion of words between two languages which have both similar forms and meanings due to shared origin. Lexical similarity may be a more relevant measure - if word stems are similar between two languages, it is likely that grammatical affixes are as well. However, lexical similarity may also be due to shared areal loanwords, such as the profusion of Arabic loanwords into Turkish, Persian, and Urdu. Areal effects can also cause grammatical similarity to spontaneously arise between geographically collocated languages (Ponti et al., 2018), though grammatical similarities due to shared ancestry are probably stronger. Ultimately, lexical similarity and genealogical closeness measure different types of linguistic relationships, and both should be taken into account if good data is obtainable.

Consistent and quite fine-grained information about language genealogy can be found on Ethnologue, a database of basic typological and sociolinguistic information about all recognized languages (*Ethnologue* n.d.). Finding good data about lexical similarity looks to be significantly more challenging - certainly, no database exists of pairwise lexical similarity between all languages, and automatically calculating lexical similarity from the SIGMORPHON 2018 data would require semantic or translation information about the words, to identify cognate words with corresponding meanings between languages. Such information may be obtainable via the Google Cloud Translation API. An easier mode of estimation may be via the "Translations" tab of entries on English Wiktionary, which provides translations of a word into a potentially large number of other languages. Average Levenshtein distance between translations for entries into a pair of languages might be a good indicator of overall lexical distance - such a method could be attempted on pairs of languages with known lexical distance to assess its utility.

Abkhaz	<input checked="" type="radio"/> Productive full and partial reduplication	Hewitt 1979: 265
Aghul	<input type="radio"/> No productive reduplication	
Agta (Central)	<input checked="" type="radio"/> Productive full and partial reduplication	Healey 1960
Ainu	<input checked="" type="radio"/> Full reduplication only	Refsing 1986

**Fig. 4.3:** A sample of WALS data on reduplication, available at <https://wals.info/feature/27A>, accessed 19 Nov 2019.

## 4.2.2 WALS

The World Atlas of Language Structures is "a large database of structural (phonological, grammatical, lexical) properties of languages gathered from descriptive materials (such as reference grammars) by a team of 55 authors." It contains information about twelve morphology features, such as "Reduplication," "Prefixing vs. Suffixing in Inflectional Morphology," and "Inflectional Synthesis of the Verb" (*The World Atlas of Language Structures Online* n.d.). Some of these may be measurable via analysis of the SIGMORPHON data as well, e.g., "Exponence of Tense-Aspect-Mood Inflection," "Prefixing vs. Suffixing in Inflectional Morphology," and "Case Syncretism," while others, such as "Reduplication" and "Locus of Marking in the Clause" would probably be harder to measure in such a way. For the features which can also be generated by looking at the SIGMORPHON data, the WALS data can at least be used as a gold standard to calibrate and assess the quality of generated metrics. WALS will not be useful in assessing overlap between sets of inflectional categories which are present or exhibit fusion in languages - its categorical tagging is simply not granular enough - but fortunately these will be relatively straightforward measures to generate from the SIGMORPHON 2018 data.

## 4.2.3 Generated metrics

Assessing set of inflectional categories and paradigm size based on the SIGMORPHON 2018 data will be very straightforward - I will simply need to list which UniMorph tags appear, and count the total number of UniMorph tag combinations seen, in each part of speech in each language.

To generate the other metrics, string alignment and transduction methods adopted from pre-neural morphology models will be necessary. Most clear is that to assess inflection shape, I will need to perform character alignment as in Figure 2.2 and count how many string changes take place before, after, or within the stem.

To measure fusion between a pair of grammatical categories, average Levenshtein or LCS distance can be taken between forms that differ along both categories and compared to distance between forms that only differ along one category. For example, recall the Spanish verbs *hablé* "I spoke", *hablo* "I speak", *habló* "he/she spoke". *Hablé* differs from each of the other forms along one category - it has a different tense from *hablo* and a different subject person than *habló* - and its LCS distance from each is 2. *Hablo* and *habló* differ in both tense and subject person but also have a LCS distance of 2; the fact that forms that differ along both categories are no more dissimilar than forms that differ along one is an indicator of the fact that tense and subject agreement are fused in Spanish verbs. In contrast, consider the Finnish verbs *puhuin* "I spoke", *puhun* "I speak", and *puhui* "he/she spoke" - *puhuin* has an LCS distance of 1 from both other forms while they have an LCS distance of 2 from one another, indicating that in this case Finnish does not fuse tense and subject marking - past tense is constructed with a suffix *-i* and first person subject with a subsequent suffix *-n*.

Presence of long-distance phonological processes will be the most difficult to measure by analyzing the SIGMORPHON data. Fortunately, the presence of vowel and consonant harmony is typically quite binary and pervasive throughout a language's morphology, so rather than attempting to generate a measurement of it I may simply hand-annotate languages with a binary indication of whether or not they possess some long-distance process, and perhaps secondarily with a more specific indication of the type (e.g., frontness vowel harmony, sibilant harmony, etc.).

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