# Morphological Paradigm Completion
# with LSTM Neural Models

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# Literature Review

## 1.1  History and Motivation

Historically, in language technologies and modeling, morphology has been somewhat under-emphasized. This is probably due at least in part to the below-average morphological complexity of English. (Cotterell and Heigold, 2017) English lexemes have relatively few inflected forms, so occurrences of out-of-vocabulary inflected forms are less frequent. And even with grammatical information thrown out via lemmatization, English may still be fairly sensible.

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. (Cotterell et al., 2016) 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 out-of-vocabulary (OOV) 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 et al., 2016) It has been empirically shown that comprehending grammatical categories and inflection improves outcomes in language modeling. (Faruqui et al., 2015)

## 1.2  Sub-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.

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 pluralize English nouns, 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 a one form and an arbitrary set of morphological categories. Generally speaking, a citation form has been used as input. (Durrett and DeNero, 2013) (Faruqui et al., 2015) (Cotterell and Heigold, 2017) The related "reinflection" problem involves being given any inflected form as input, and transforming it into any other. (Cotterell 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. If a model is trained using entire inflection tables, 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 and Heigold, 2017)

Overall, a diverse set of inflection shapes have been worked with. SIGMORPHON 2018 included data from 103 typologically diverse languages, and paradigms using suffixing, prefixing, infixing, reduplication, and non-concatenative morphology. However, all work has been with well-defined, tabular paradigms of fairly moderate size ($\leq 200$ forms). (Cotterell 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. Highly synthetic languages with more expansive types of word building, including incorporation and productive derivational morphology, are ripe for future work. (Cotterell et al., 2016)

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 in which one word in a sentence, given in citation form, was to be inflected based on context. (Cotterell et al., 2018) (McCarthy et al., 2019) This work is essentially a synthesis of morphology generation and morphosyntactic modeling.

Lastly, there is 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. The most successful models with high-data training sets are LSTM neural models, generally considered the state of the art model type, yet these often fare worse than baseline string transduction models with low data training sets. (Cotterell and Heigold, 2017) (Cotterell 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.
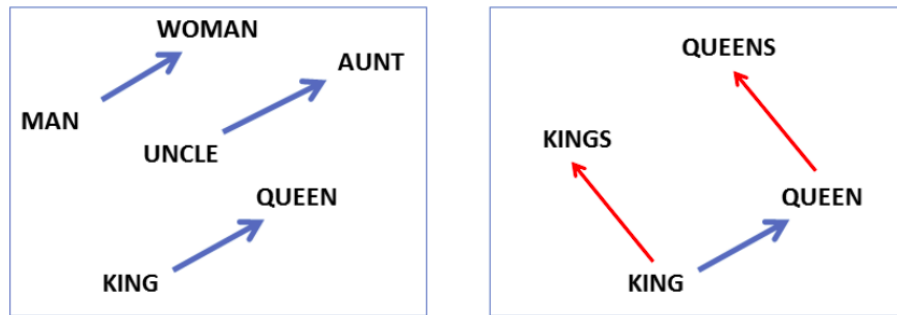
**Fig. 1.1:** Regular spatial transformations encode semantic or grammatical content (Mikolov et al., 2013)

## 1.3 Non-neural approaches

### 1.3.1 Vector embedding

Representing words in relatively low-dimensional vector spaces, with the intention of capturing semantic and syntactic content in a principled way, has found success in a variety of computational linguistics tasks. Regularities in the relative location of semantically related words have been exploited for semantic analysis tasks. (Bilmes and Kirchhoff, 2003) (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. This method has the limitation that it cannot extend to words for which a vector representation has not been trained, and so it cannot provide understanding of the many OOV forms encountered in test data of highly inflected languages. (Mikolov et al., 2013) (Soricut and Och, 2015) (Dos Santos and Zadrozny, 2014) (Cotterell and Schütze, 2019)

### 1.3.2 String transduction

## 1.4 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 et al., 2016) (Cotterell and Heigold, 2017) (Cotterell et al., 2018) (McCarthy et al., 2019) In high-data training settings, encoder-decoder LSTMs have proven over the course of annual SIGMORPHON shared tasks to be the state of the art method of computational morphology. However, they have worse performance with sparse training data, an issue which has seen attempts to address.

# Data

## 2.1 Structured paradigm data

The English Wiktionary, a collaborative online dictionary, has become something of a standard source of supervised morphological data. Durrett and DeNero, 2013 published a Wiktionary dataset of five paradigms from three languages (Finnish, Spanish, and German) which have been used as a benchmark in much future work. (Hulden et al., 2014) (Nicolai et al., 2015) (Ahlberg et al., 2015) (Faruqui et al., 2015) SIGMORPHON 2017 published a dataset partitioned into three training levels (100, 1000, and 10,000 tables), containing both sparse and full inflection tables for one or more parts of speech for each of 52 languages. Most of that data was derived from a January 2017 Wiktionary dump; data for four languages came from the Alexina project and data for Haida was prepared by Jordan Lachler. (Cotterell and Heigold, 2017)

The most complete structured dataset to date was published for the SIGMORPHON shared task 2018, a superset of the SIGMORPHON 2017 data, which is partitioned in the same manner and includes data from 103 languages. For most of the languages, data was scraped from Wiktionary.

## 2.2 Text corpora

## 2.3 Representation of morphology

In earlier work, morphology is encoded in a language-specific and model-specific way.

(Luong et al., 2013) The UniMorph project, initially published in 2015, makes an effort to encode morphological categories uniformly cross-linguistically. (Sylak-Glassman et al., 2015b) (Sylak-Glassman et al., 2015a) (Sylak-Glassman, 2016) The SIGMORPHON data since 2018 has been published in UniMorph format.

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