On the Complexity and Typology of Inflectional Morphological Systems

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What’s your native language?
Do you think your native language more complex than English?
Audience Poll

**Question:** Who thinks their native language is more complex than English?
What makes your native language more complex than English?
More Morphological Variants = A More Complex Language

• I agree: a lot of morphological variants can make a language “difficult”:
  – Mark Twain said it best: “I’d rather decline two drinks than one German adjective.”

• Then, look at how simple English is!
  – Your average verb has four inflections: run, runs, ran, running

• Nouns and adjectives don’t inflect in English according to case
  – The adjective good has one inflection
In Comparison: The Turkish Verb

• **koşmak** = Turkish verb “to run”
  – (partial) paradigm →

• Tense, mood, evidentiality ... marked through morphology
  – 100+ forms in Turkish!

• Archi (Kibrik 1998) has 1.5 million verb forms
  – It’s very, very agglutinative

• This makes a language more complex!
Number of Forms is Only One Dimension of Morphological Complexity

• There are (at least) **two types** of morphological complexity
  – **Type 1:** how big are the paradigms? (seen before)
  – **Type 2:** how irregular are the paradigms?

• Ackerman and Malouf (2013) introduce the technical jargon
  – Enumerative Complexity (E-Complexity)
  – Integrative Complexity (I-Complexity)
English versus Turkish: # Forms

• English
  – 4 verbal slots
  – 2 nominal slots
  – 1 adjectival slot

• Turkish
  – 350 verbal slots
  – 8 nominal slots
  – 1 adjectival slots

7 Total

358 Total

Turkish is more morphologically complex under # forms per verb.
English Versus Turkish: Irregularity

- **English**
  - 224 irregular verbs
  - 10 irregular nouns
  - 0 irregular adjectives

- **Turkish**
  - 1 irregular verb
  - 0 irregular nouns
  - 0 irregular adjectives

234 Total \hspace{1cm} 1 Total

*English is more morphologically complex under amount of irregularity*
What’s This Paper About?

Good Linguistic Question:
How do the # morphological variants and morphological irregularity interact?
Plotting English and Turkish Verbs

Irregularity vs. # Forms

English

Turkish
What about the Rest of the World’s Languages? (For which we have data)
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Pareto Frontier

Irregularity

No Languages Here

# Forms
What about the Rest of the World’s Languages? (For which we have data)

Pareto Frontier

Irregularity

# Forms

No Languages Here
Scientific Hypothesis about Language

• Use machine learning techniques to test hypothesis about Language

• Morphological systems can have *either* a lot of forms or lot of irregularity
  – But not both!

• Why? Speculative reason: memorizing a lot of irregulars would tax human memory
Chinese is Low on *Both* Dimensions of Morphological Complexity

- **Morphology in a language is not necessary!**
- Let’s look at the Chinese verb “to drink”
  - drink = 喝
  - drinking = 喝
  - drank = 喝

- Look mommy, no inflection!
Our Hypothesis Again

- Inflectional, morphological systems have a lot of forms, or a lot irregularity, but not both
A Paired Permutation Test

- There *appears* to be a trend, but is it significant?
  - Is the upper right-hand corner more empty than it would be by chance?

- New Significance Test
  - Keep x-axis in tact, shuffle y-axis
  - Compare area under the Pareto curve
  - Non-parametric test
Random Morphological Trade-Off

Graph showing the relationship between Irregularity and # Forms.
Random Morphological Trade-Off

![Graph showing the relationship between Irregularity and the number of forms.](Image)
Random Morphological Trade-Off
Scientific Finding

Gap in the upper right-hand size with $p < 0.05$
Caution: Limited # Of Languages

• We need to be very cautious about reporting the results!

• The languages are not i.i.d.
  – Some of them are genetically related
  – Focus on Western European Languages

• We have a small sample of size of languages
  – There might be unobserved counterexamples
  – For *this sample*, the Pareto frontier leaves an unusually large gap in the upper right
Technical Contribution:
Operationalizing Morphological Irregularity
Where did the y-axis come from?

What do those numbers mean?
What’s an Irregular Verb?

• **TL;DR:** some grammarian said so

• **Example:** Spanish has three types of regular verbs
  – *ar, er, ir*

• The rest are “irregular”
  – Why???

• Are they equally irregular?
  – Or are some verbs more irregular than others?

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New Insight: We will tackle morphological irregularity \textit{probabilistically}
Regularity = Predictability

• For each language
  – **Step 1**: Build a really good generative probability model \( p \) of the morphological paradigm
  – **Step 2**: Train its parameters on some data
  – **Step 3**: Irregularity = \(-\log p(\text{held-out data})\)
Morphological Reinflection

• Start with pair-wise probability distributions

\[ p (\text{pongamos} \mid \text{pongo}) \]

\[ 1ps;prs;sbjv;pl \quad 1ps;prs;ind;sg \]

• In NLP, this task is known as morphological reinflection
  – Cotterell et al. (2016, 2017) for overview of the results
  – State of the art: LSTM seq2seq model – same as MT
Sequence-to-Sequence Model

\[ x = \text{pongas} \]
\[ y = \text{pongo} \]

\[ p(y \mid x) \text{ reads } x, \text{ then stochastically emits chars of } y, 1 \text{ by } 1, \text{ like a language model} \]
Arrange into a Bayesian Network

poner

puso

pusimos

pusieron

pongo

pondría

pongamos
Each conditional is a LSTM-based seq2seq model!

\[
p(\text{pusieron} \mid \text{puso}) \cdot p(\text{pusimos} \mid \text{puso}) \cdot p(\text{pusieron} \mid \text{puso}) \cdot p(\text{puso} \mid \text{poner}) \cdot p(\text{pongo} \mid \text{poner}) \cdot p(\text{pongamos} \mid \text{poner})
\]
Many Possible Networks

- pusieron
- pusimos
- pusó
- pongamos
- pondría
- pongo
- pongamos

Diagram with connecting arrows.
How to Choose Best Tree?

• Standard structure learning problem in graphical models

• Strategy: Tie parameters among all conditionals
  – Conditionals for every possible tree trained together

• Inspired by Chow-Liu Algorithm
  – Use Chu-Liu-Edmonds
  – Finds optimal directed spanning tree in $O(n^3)$ time
Experimental Languages

- Data from the UniMorph (Kirov et al. 2018)
- Selected languages with "enough" training examples

- Verbal Paradigms:
  - 23 languages / 3 families
- Nominal Paradigms
  - 31 languages / 3 families

Cross-linguistically Compatible Labels

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German Nominal Paradigms
Plug For UniMorph

• Now data for over 100 languages!

• Freely downloadable from unimorph.github.io

UniMorph

The Universal Morphology (UniMorph) project is a collaborative effort to improve how NLP handles complex morphology in the world’s languages. The goal of UniMorph is to annotate morphological data in a universal schema that allows an inflected word from any language to be defined by its lexical meaning, typically carried by the lemma, and by a rendering of its inflectional form in terms of a bundle of morphological features from our schema. The specification of the schema is described here and in Sylak-Glassman (2016).
Estimating the Parameters

• Estimating morphological irregularity is now a standard machine learning problem

• Model is trained using gradient descent on UniMorph data
  – Best model selected on development data

• Irregularity = loss on held-out data
But why is there a trade-off?

• This paper shows the existence of a trade-off between two types of morphological complexity

• The real scientific question is why?

• On-going work guesses that it has to learnability and the learning infrequent, irregular forms
  – I.e., rare forms tend to regularize

• Artificial learnability study already available
  – Preliminary version on arXiv
Linguistic Complexity More Broadly
A Twitter Poll About Complexity

Ryan D. Cotterell
@_shrdlu_

Do you think your native language is more complex than English? (If you speak a language other than English natively.)
#acl2018

Also, come to my talk at 17:00 tomorrow @acl2018 on that very topic!

79% Yes

21% No

109 votes • 1 day left
Equal Complexity Hypothesis

• Hockett (1958) argued that all languages are equally complex

• Idea goes back much further in the linguistics literature

• All languages appear to optimize for efficient communication subject to learnability
Complexity Trade-Offs

• **Corollary**: if one facet of a language is more complex, another is simpler to compensate

• **Trade-Off Example:**
  – German has more inflected forms than English (morphology)
  – English has a more complicated tense system (syntax)
Example: Rate Of Speech (Pellegrino 2011)

- Are all languages spoken equally fast?
  
  No!

- Spoken Rapidly
  - Spanish, Japanese

- Spoken Slowly
  - English, Chinese
John McWhorter on Creoles

• McWhorter wrote the seminal paper in 2001

• Argues creoles are in fact less complex

• Complexity accretes over time
  – Creoles are new languages
Published Work

• Check out our NAACL 2018 paper: *All Are Languages Equally Hard to Language-Model?*
Future Work

• We only looked a specific trade-off in morphological complexity
  – Data-driven methods for trade-offs in other areas of linguistics

• Extensions look at language more holistically
  – Trade-offs between morphology and phonology
  – Trade-offs between morphology and syntax

• Why didn’t linguistics already solve this problem?
  – No big data, no methods
Fin