The UniMelb Submission to the SIGMORPHON 2020 Shared Task 0: Typologically Diverse Morphological Inflection

Andrei Shcherbakov

 ${\tt and reas@software engineer.pro}$

The University of Melbourne

Flexica01: non-neural, alignment based

Lemma-to-inflected form transformation are generated directly by the following simple process:

Step 1. Find maximal continuous matches between lemma and inflected form.

 $Example: \, \texttt{understand} \, \rightarrow \, \texttt{understood}$

Extracted rule: $0an1 \rightarrow 0001$, where 0=underst and 1=d are groups.

Step 2. Starting with previously generated transformation pattern(s), generate a set of patterns more specific to a given training word by treating a limited number of characters as concrete (i.e. standing outside any group).

For the example from previous step and a limit of one character: $\0n\1 \rightarrow \000\1; u\0n\1 \rightarrow u\000\1; \0n\1an\2 \rightarrow \0n\100\2, \dots (3 more), \0s\1an\2 \rightarrow \0s\100\2, \0tan\1 \rightarrow \0too\1, \0and \rightarrow \0ood.$

When predicting a form, score matching candidate patterns using the following three components:

- \Rightarrow A (squashed) **frequency** f of transformation occurrence in a training set;
- \Rightarrow The **diversity** d of marginal (the first one and the last one) letters in groups as they occurred in different fits of a given transformation found in the training set.
- \Rightarrow **Specificity** *s* which here means the number of concrete characters in the pattern (without counting characters falling into groups).

We were using the following empirical formula:

 $G = \frac{1}{2}\log_2 f + 6\log_2 d + 12s$

Near-misses (the second scored transform was correct)





We additionally show the accuracy that would be achieved in a case of ideal selection criteria (labelled as + Ideal Transform Choice category). We also roughly measured potential improvement that may arise from considering correlations between inflection patterns for different grammatical forms of a single lemma.

Only flexica01 got it right

Improvement with Hallucinated Data

INCOMPACT IN INSER (the second scored transform was correct)								
	deu	Kation	Kations	N;GEN;SG				
	eng	upswell	upswollen	V.PTCP;PST				
	est	põlema	olime põlenud	V;PRF;COND;PL;1;POS;PRS;ACT				
	isl	stelkur	stelkinn	N;NOM;DEF;SG				
	nob	pioner	pionerer	N;NDEF;PL				
	udm	patent	patenntem	N;LGSPEC ATTR;LGSPEC1				

Flexica02: Hard attention, multilingual (family-based)

This neural system is based on hard monotonic attention model proposed in [Aharoni and Goldberg(2017)], with the same loss function, but with the following differences:

- ⇒ We combined all the languages belonging to a given family into a single dataset, having added two extra features such as language and genus.
- \Rightarrow We used maximal continuous sub-string search to organize alignment between lemma and its inflected form in order to advance hard attention state (abolishing one-byone alignment of mismatching characters).

Flexica03: Adding hallucinated data

Inspired by [Anastasopoulos and Neubig(2019)]. We added 200 samples per language per part-of-speech (POS) in order to produce hallucinated inflection samples that look like real. We reused the predictor from flexica01. We also enriched the model with word-generator [Shcherbakov et al.(2016)Shcherbakov, Vylomova, and Thieberger], http://regexus.com/wg.php to produce more phonotactically plausible forms: 1) Word generator trained on inflected forms for a given POS produces samples of hallucinated inflected forms (without distinction of grammatical features); 2) The reverse flexica01 predictor produces tag+lemma for each hallucinated inflected form. Accuracy was significantly improved in low-resource languages (such as Maori, Zarma, Tajik, Anglo-Norman, Middle High/Low German).

Conclusion

We proposed and tested (1) multilingual training, and (2) pattern-based hallucinated inflections as possible enhancements of sequence-to-sequence morphology modeling for diverse low-resource languages. We also developed a simple non-neural approach based on multi-variant search of common inflection patterns.

eng	shine	shone	V.PTCP;PST	1.00 -			• mtgpaa • snattsma light • und voo • fitter bigment
eng	overwork	overwrought	V.PTCP;PST		e die	• lin	sot kjh orm ben crift kaak
eng	help	holpen	V.PTCP;PST		aje		zul kon hiel syc kir sea hiel hieldou
eng	belive	belove	V;PST				
eng	arise	arose	V;PST				s ceb bod oligit
eng	belight	belit	V.PTCP;PST	0.75 -	• tak		ood xty kan
eng	dwell	dwelt	V.PTCP;PST		.9.		emwf cre enob ven
eng	bespit	bespat	V;PST				• gsw • cpa
eng	snatch	snaught	V.PTCP;PST				_ € _{iħęb} [•] dan
eng	stink	stank	V;PST				tgl azg ang
eng	uplight	uplit	V.PTCP;PST	50		• xno	● czn ● evn ● antig
dak	Dakota	uDakotapi	V;PL;1;PRS	Acci		•	• cly
krl	pezieie	ei pezieeta	V;IND;PL;3;NEG;PRS				•
isl	aðalkirkja	aðalkirknanna	N;GEN;DEF;PL				vro • gml
isl	hagskælingur	hagskælinginn	N;NOM;DEF;SG				
mhr	popo	popolam	N;HUM;SIM;SG;PSS1S	0.25 -			lud frr
nob	kronprinsesse	kronprinsessa	N;DEF;SG	0.20	-		•
nno	byste	bystar	N;NDEF;P				• vot
udm	million	million' em	N;LGSPEC1				
olo	buabo	buaban	N;GEN;SG				
swe	hålla inne	innehållande	V.PTCP;PRS	0.00-			
vep	pugetas	pugeiihe	V;COND;PL;3;POS;PRS	0.00	•		
ansli	terated words an	e given in <i>italic</i>			1e+(12	1e+03 1e+04 1e+05
							raining set size

Flexica03: Generating Hallucinated Data

