

# Transformers: shining in OOV inflection, but beaten on true neologisms by a non-neural model

## OOVs in the Spotlight: How to Inflect them?

Tomáš Sourada, Jana Straková, Rudolf Rosa

{sourada, strakova, rosa}@ufal.mff.cuni.cz

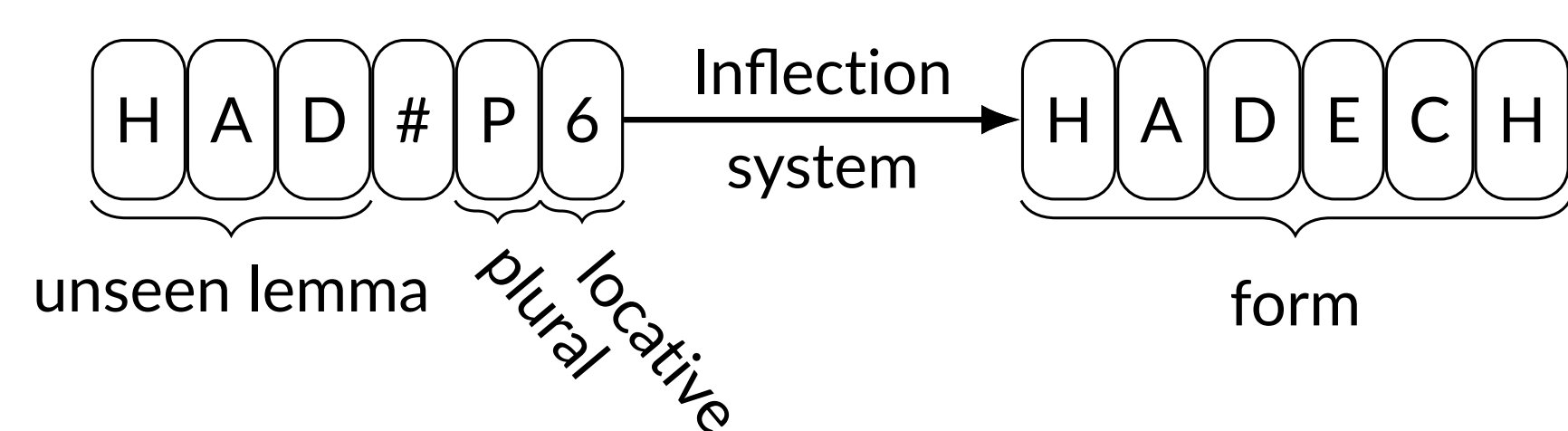
Charles University, Faculty of Mathematics and Physics  
Institute of Formal and Applied Linguistics  
Prague, Czech Republic



### Introduction

#### • task:

lemma + number + case → inflected form



- morphological inflection in out-of-vocabulary (OOV) conditions
- SOTA systems may struggle when asked to inflect unseen lemma
- focus on Czech nouns, extend to 16 languages and all POS

### Data

- train-dev-test split of morphological dictionary (lemma-disjoint)
- additional test set of neologisms (real-world OOVs)
- released as Czech OOV Inflection Dataset

### Methods

- non-neural retrograde model (based on suffix similarity of lemmas)
- LSTM- and Transformer-based encoder-decoder, trained from scratch, extensively tuned

### Results

- SIGMORPHON'22 OOV conditions:
  - our seq2seq SOTA in 9 of 16 langs
- Czech simulated OOV conditions:
  - Transformer performs the best
- Czech true OOVs (neologisms):
  - overall performance drop
  - Transformer defeated by non-neural models

### Discussion

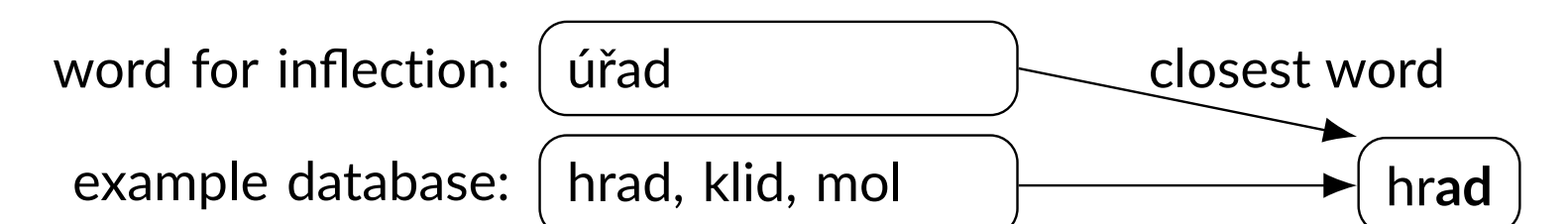
- small test set of neologisms: would the results scale on a large one?
- is morphological dictionary a good train set for inflecting true OOVs?
- if not, how to select the train data?

### Datasets

lemma	tag	form
elektrořidič	S1	elektrořidič
elektrořidič	S2	elektrořidiče
elektrořidič	S3	elektrořidičovi
...		
elektrořidič	P6	elektrořidičích
elektrořidič	P7	elektrořidiči

Set	lemmas	forms	Source
train	360k	5.04M	MorFFlex
dev	44k	616k	MorFFlex
test-MorFFlex	44k	616k	MorFFlex
test-neologisms	101	1.4k	Čeština 2.0

### Non-neural retrograde model



HRAD		ÚŘAD	
hr-ad	hr-ady	úř-ad	úř-ady
hr-adu		úř-adu	
hr-adu	...	úř-adu	...
...		...	
hr-adem	hr-ady	úř-adem	úř-ady

### Results

test set	MorFFlex		neologisms	
	FA	FPA	FA	FPA
copy	22.6	1.5	13.1	0
sklonuj.cz	88.9	74.4	86.2	55
SIG nonneur	94.8	88.2	<b>89.5</b>	<b>71</b>
SIG trm	95.5	87.3	87.5	63
SIG trm-tune	96.2	90.2	86.5	55
Retrograde	94.9	88.6	89.3	<b>71</b>
LSTM	96.2	89.8	87.0	58
Transformer	<b>96.2</b>	<b>90.4</b>	87.2	61
majority-vote	96.4	90.7	90.4	64

### SIGMORPHON 2022 comparison

Lang	CLUZH	Submitted systems					Baselines		Ours	
		Flexica	OSU	TUM	UBC		Neural	NonNeur	LSTM	TRM
ang	76.6	64.4	73.7	71.9	74.1		73.4	68.7	76.3	75.5
ara	81.7	65.5	78.7	78.5	65.5		81.9	50.8	79.2	<b>82.6</b>
asm	83.3	75.0	75.0	<b>91.7</b>	83.3		83.3	83.3	83.3	83.3
got	92.9	41.4	<b>94.1</b>	91.7	91.7		93.5	87.6	92.3	92.3
hun	93.5	62.9	93.1	92.8	91.5		<b>94.4</b>	73.1	92.8	<b>94.4</b>
kat	96.7	95.7	96.7	96.7	96.7		97.3	96.7	97.3	<b>97.8</b>
khk	94.1	47.1	94.1	94.1	88.2		94.1	88.2	<b>100.0</b>	94.1
kor	<b>71.1</b>	55.4	50.6	56.6	60.2		62.7	59.0	49.4	62.7
krl	87.5	69.8	85.9	57.8	85.4		57.8	20.8	<b>89.1</b>	85.9
lud	87.3	92.0	92.9	93.4	88.2		<b>94.3</b>	93.4	89.2	92.0
non	85.2	77.0	85.2	80.3	<b>90.2</b>		88.5	80.3	83.6	88.5
pol	<b>96.1</b>	85.9	94.9	74.0	95.7		74.4	86.3	<b>96.1</b>	95.6
poma	76.1	54.5	70.1	69.4	73.3		74.1	47.8	75.2	<b>76.3</b>
slk	93.5	90.0	92.2	70.4	<b>95.7</b>		71.1	92.4	95.2	<b>95.7</b>
tur	93.7	57.9	<b>95.2</b>	80.2	92.9		79.4	66.7	<b>95.2</b>	92.9
vep	71.5	58.8	70.0	57.5	68.8		59.2	60.4	70.7	68.8
average	<b>86.3</b>	68.3	83.9	78.6	83.8		80.0	72.2	85.3	86.1

