CMU-01 at SIGMORPHON: Morphological Analysis and Lemmatization in Context

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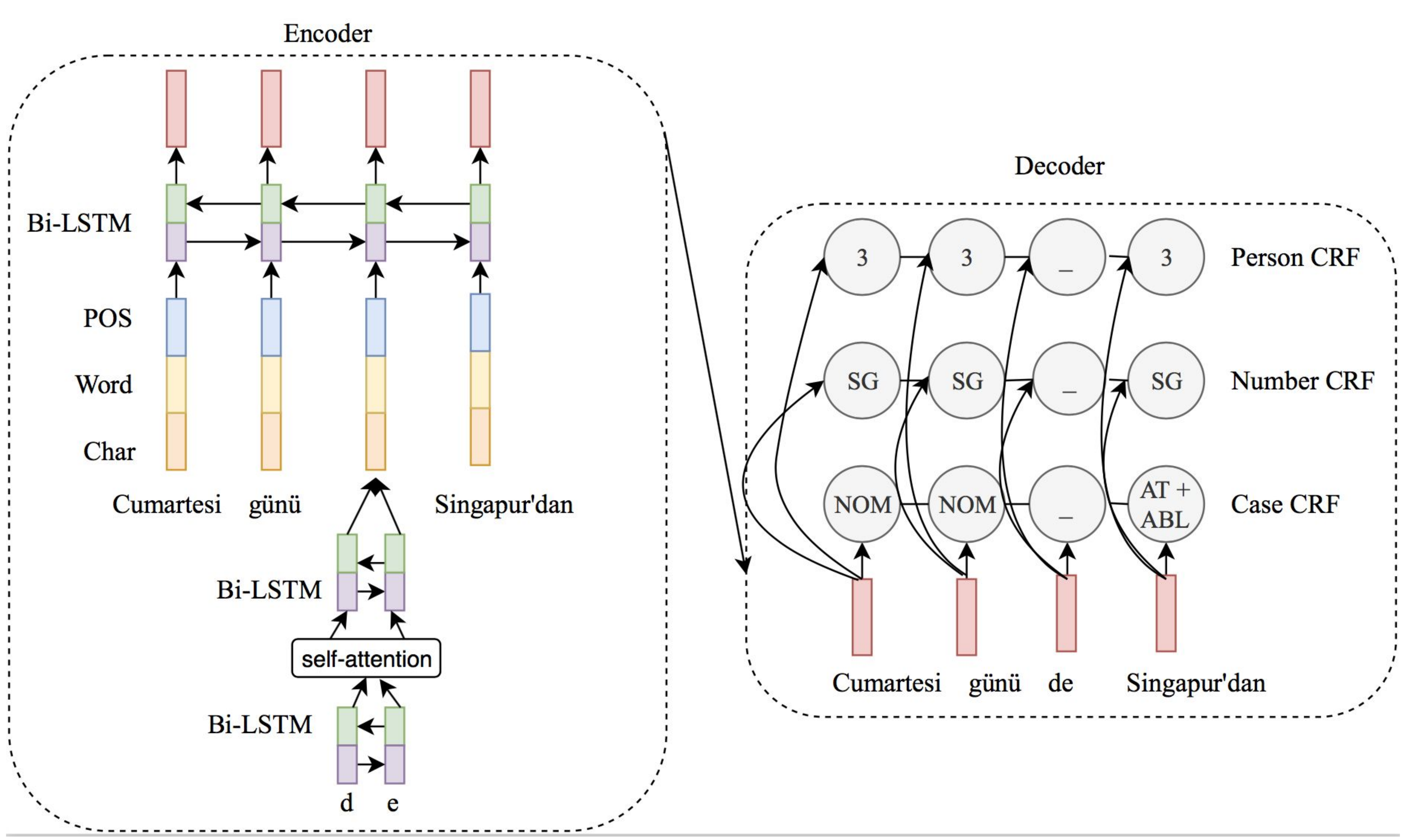
Research Problem

- The SIGMORPHON 2019 Task 2 requires us to produce the lemma and morpho-syntactic description of each token in a sequence, for 107 treebanks.
- However, most treebanks are under-resourced, making it challenging to train deep neural models for them
- We approach this task with a hierarchical neural conditional random field (CRF) model which predicts each coarse-grained feature (eg. POS, Case, etc.) independently.
- To tackle the challenge of data-scarcity we propose a multi-lingual transfer training regime where we transfer from multiple related languages that share similar typology and/or orthography.

Model



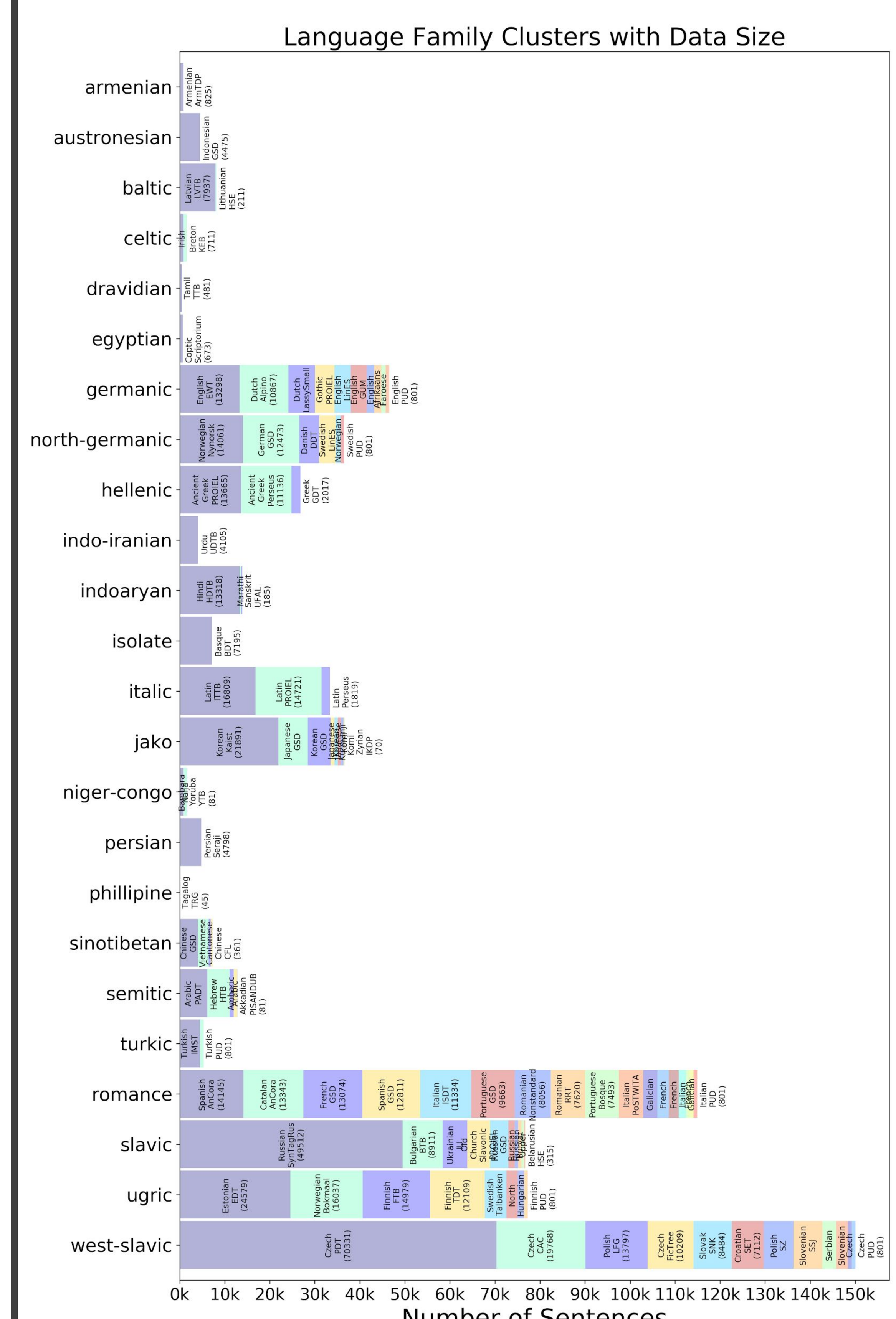
Hierarchical neural model for contextual morphological analysis with independent CRF decoders for each coarse-grained feature *F* such as Number, Person etc. POS embeddings are concatenated to the word and char-level representationse. This model has $|F|$*-1* decoders since POS tagger is run separately as a prior step.
MDCRF refers to the above model without POS embeddings having all $|F|$ decoders.

Training Data

- We model feature-wise prediction for each coarse-grained feature *F*={POS, Gender, …} and transform the dataset from UniMorph schema to key-value format. Therefore, we get:

N;PL;FEM ⇒ POS=N;Number=PL;Gender=FEM

- We augment training data using language clusters based on typographical and orthographic similarity, as shown below:



Results

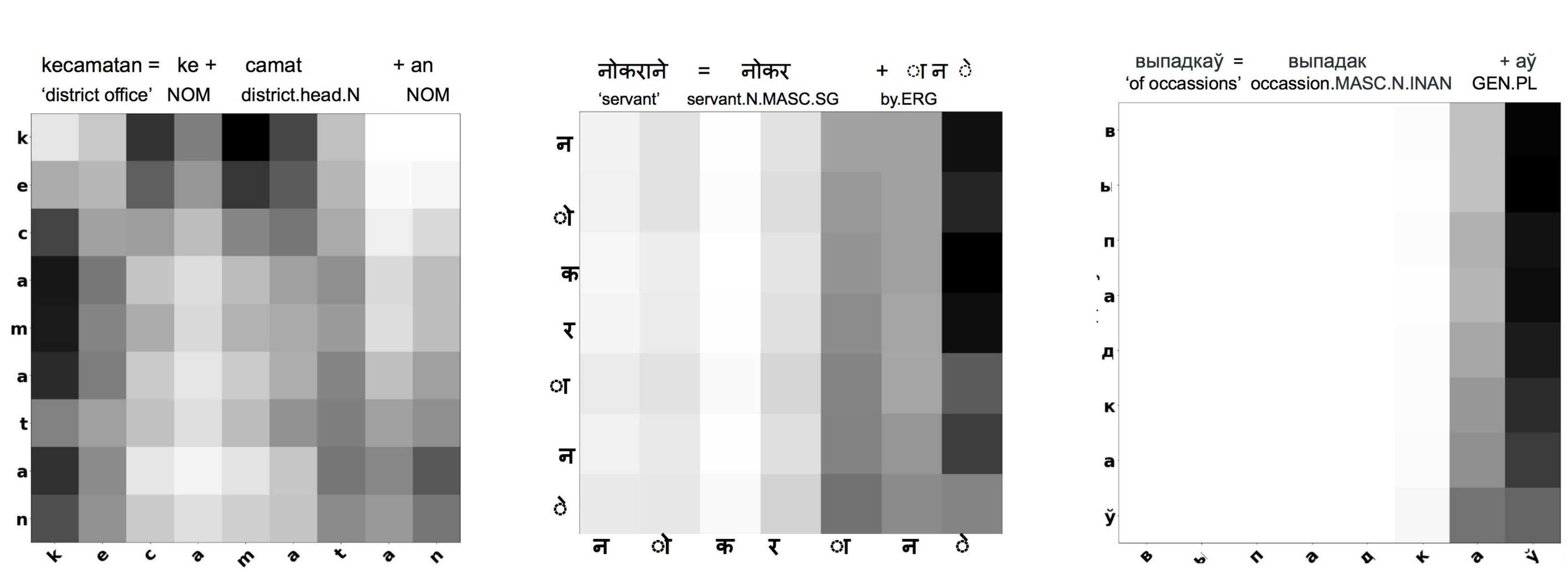
- Our system achieves an average improvement of **+15.30 (accuracy)** and **+4.93 (F1)** over the provided baseline. (McCarthy et al., 2019).
- We compare our model for bi-lingual transfer with previous bsselines:

Language	Model	tgt-size=100 Accuracy	tgt-size=100 F1-Macro	tgt-size=100 F1-Micro	tgt-size=1,000 Accuracy	tgt-size=1,000 F1-Macro	tgt-size=1,000 F1-Micro
RU/BG	MDCRF + POS + MULTI-SOURCE	**69.13**	**85.78**	**85.86**	**82.72**	**92.15**	**92.17**
	(Malaviya et al., 2018)	46.89	64.75	64.46	67.56	82.06	82.11
	(Cotterell and Heigold, 2017)	52.76	58.23	58.41	71.90	77.89	77.97
FI/HU	MDCRF + POS + MULTI-SOURCE	**57.32**	**80.11**	**78.86**	**70.24**	**85.44**	**84.86**
	(Malaviya et al., 2018)	45.41	68.63	68.07	63.93	85.06	84.12
	(Cotterell and Heigold, 2017)	51.74	68.15	66.82	61.8	75.96	76.16

Q. What is the model learning?

- Character-level attention maps for three typologically different languages:

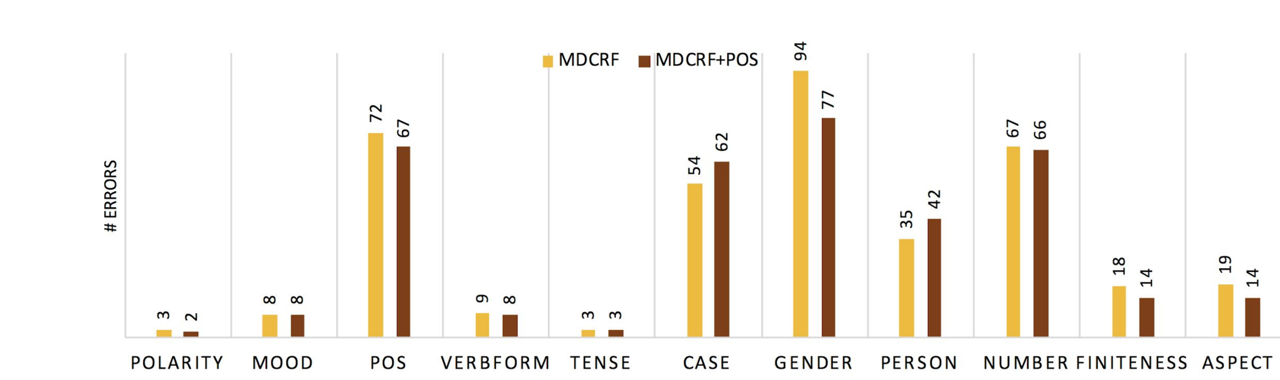
INDONESIAN MARATHI BELARUSIAN



- Marathi and Belarusian display morphological inflections as suffix.
- Indonesian displays inflections in the form of prefix, suffix and circumfix.

Q. Why does adding POS help?

- Removing POS gives a drop in accuracy which is significant for low-medium resource languages: **Maratih (-6.12 acc), Ukrainian (-3.57 acc).**
- Number of errors per feature *F*: POS helped reduced Gender errors in Marathi

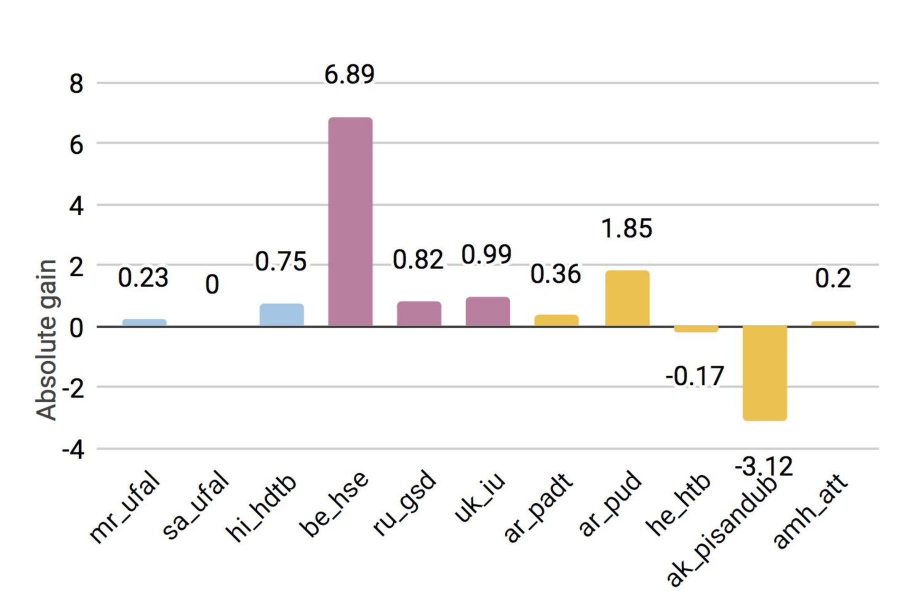


	POLARITY	MOOD	POS	VERBFORM	TENSE	CASE	GENDER	PERSON	NUMBER	FINITENESS	ASPECT
MDCRF	4	4	348	16	14	121	198	91	243	65	49
MDCRF+POS	3	6	348	17	16	121	197	106	248	78	63

- Eg. For some words gender may be inferred from inflectional form, but for others such as **(किंमत N.FEM.SG.ACC)** the traditional female suffix ई is not present, in which casen having the POS information helps.

Q. Does time-depth matter for transfer learning?

- *Time-depth* is period of time that has elapsed since all languages in the group were a single language.
- We study the following clusters: Indo-Aryan, Slavic and Semitic.



- Transfer helps most for Slavic (+2.9 accuracy), and next for Indo-Aryan cluster (+0.32 accuracy). There is a negative effect for the Semitic cluster (-0.0176 accuracy).
- Indo-Aryan and Slavic have shallower time-depths: < 1000 years ⇒ better transfer!

Code: https://github.com/Aditi138/MorphologicalAnalysis
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