Predicting and interpreting embeddings for out of vocabulary words in downstream tasks

Nicolas Garneau†, Jean-Samuel Leboeuf†, Luc Lamontagne

Department of Computer Science and Software Engineering, Université Laval

†Authors contributed equally to this work.

Introduction

We propose a novel way to handle out of vocabulary (OOV) words in downstream natural language processing (NLP) tasks. We implement a network that predicts useful embeddings for OOV words based on their morphology and the context in which they appear.

Motivations :

- OOV words handling in NLP task is an **underestimated problem**.
- Few learned, end-to-end, solutions proposed.

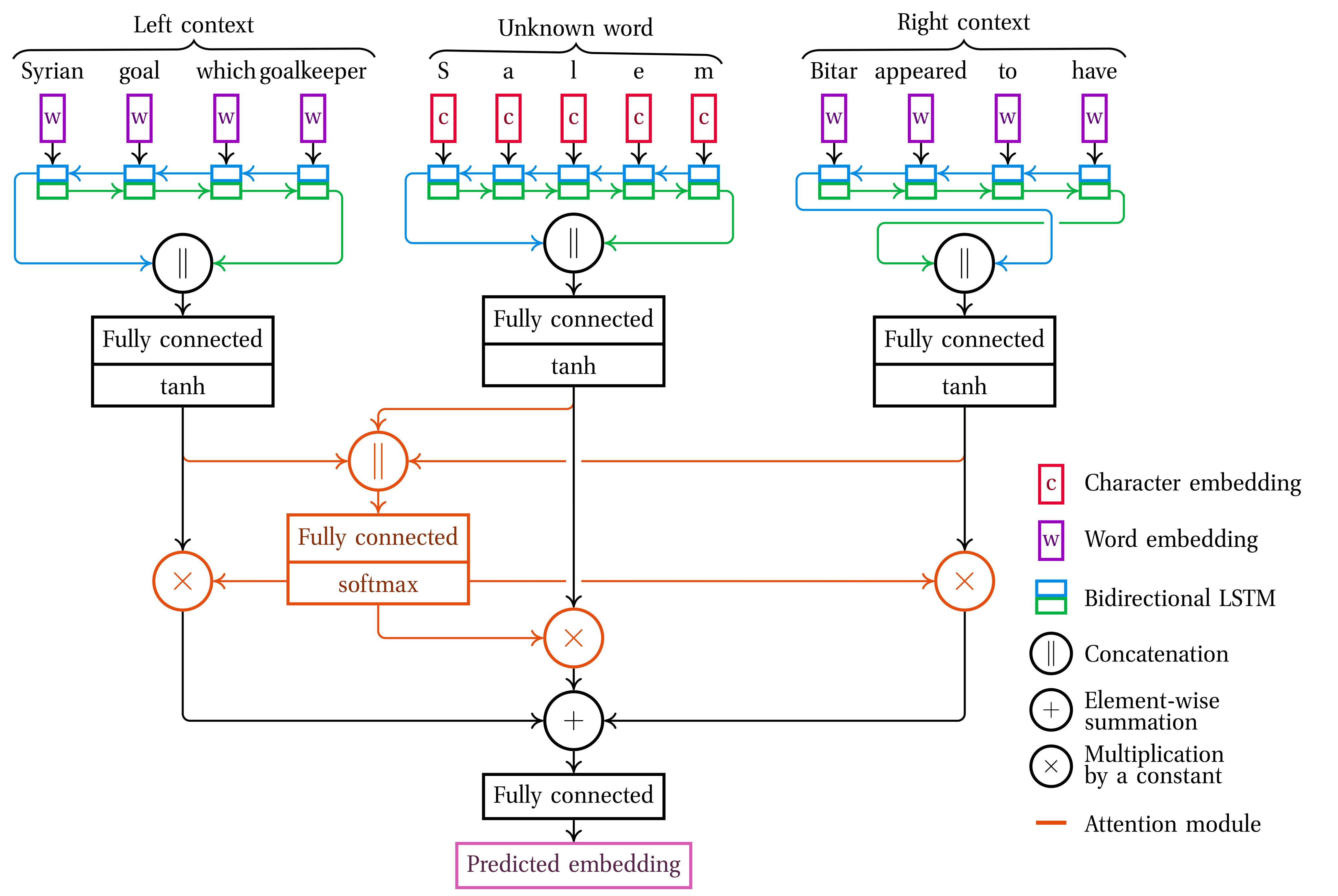
Related work :

- Pinter et al. (2017) : Predict OOV embedding using the characters.
- Bahdanau et al. (2017) : Learn OOV representation from their definition in a dictionary.

Goals :

- Evaluate the impact of OOV words in labeling tasks.
- Provide a more meaningful way to handle OOV words using **context** and **morphology**.
- Understand when it is important and what is relevant to model OOV embeddings.
- **Interpret the predicted embeddings** according to the surrounding linguistic elements.
- Provide a "drop-in", "end-to-end" module.

OOV handling net



The net consists in 3 bi-LSTM taking as input the left context, the right context and the word characters. An attention module ponderates their outputs which are then combined in a last fully connected layer.

Experiments

Set up :

- Labeling tasks :
  - **Named Entity Recognition** (NER).
  - **POS tagging** (POS).
- Dataset : **CoNLL 2003**

Training details :

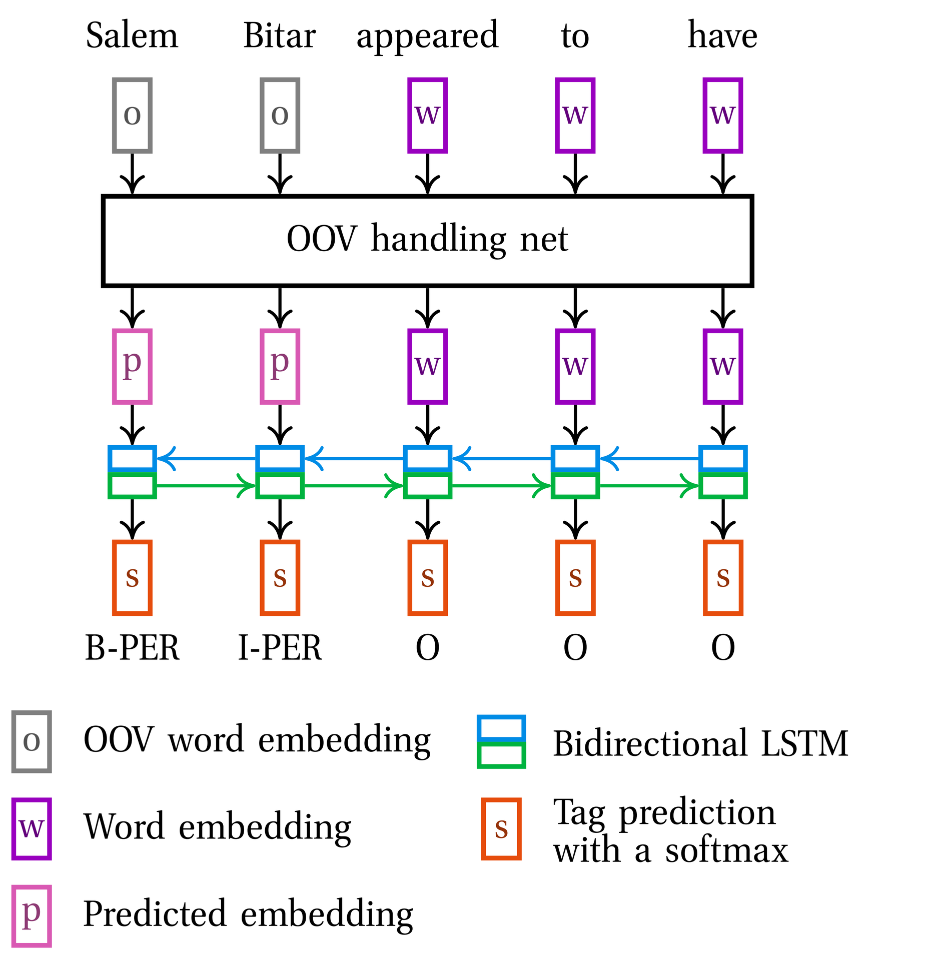
- Tensors sizes :
  - Char. emb. : 20.
  - Word emb. : 100 (**GloVe**).
  - LSTMs hidden state : 128.
- Context size from 2 words to the whole sentence.
- Standard learning rate on the labeling task parameters, reduced learning rate on Comick using SGD (0.01, 0.001).

Examples

Entity	Ponderation			Examples
	Word	Left	Right	
PER	0.19	**0.49**	0.32	**in sentencing darrel** *voeks* , 38 , to a 10-year prison term on thursday
PER	0.15	**0.59**	0.26	<BOS> **australian parliamentarian john** *langmore* has formally resigned from his lower house
PER	0.15	**0.61**	0.24	had received today **from mr john vance** *langmore* , a letter resigning his place as
PER	0.15	**0.69**	0.16	<BOS> **rtrs - australian mp john** *langmore* formally resigns . <EOS>
ORG	0.22	**0.46**	0.32	the number of plastic surgeries in [...] the **brazilian plastic surgery society** (*sbcp*) , said ,
ORG	0.28	0.23	**0.49**	to increase them in the united states , " *sbcp* **vice-president oswaldo saldanha said**
LOC	0.16	0.22	**0.62**	some residents of the *kazanluk* **area are moslems who** converted to islam during
LOC	0.20	**0.47**	0.33	at a mosque in the **central bulgarian town of** *kazanluk* , causing damage but no injuries
MISC	**0.68**	0.11	0.21	freestyle ***skiing-world*** cup aerials results .
MISC	**0.42**	0.18	**0.40**	the ***franco-african*** **summit decided to send** a mission bangui [...] civil war .

Qualitative example on several OOV words (underlined). We can see that depending on the context and the target, the weights may shift drastically.

Labeling task net



Two nets working together : the first predicts OOV embeddings (see OOV handling net section) and the second one predicts tags.
The simple architecture of the labeling net is used to emphasize the usefulness of our module, and to minimize the influence of other factors.

Interpretability

Task	Tag	Ex.	Ponderation		
			Word	Left	Right
NER	O	1039	**0.81**	0.08	0.11
	B-PERS	63	0.21	0.31	**0.49**
	I-PER	119	0.16	**0.52**	0.32
	B-ORG	40	0.26	0.30	**0.44**
	I-ORG	3	0.27	0.31	**0.42**
	B-LOC	13	0.23	0.30	**0.47**
	I-LOC	2	0.16	**0.48**	0.36
	B-MISC	47	**0.40**	0.21	0.39
	I-MISC	5	**0.41**	0.26	0.33
POS	NNP	308	0.29	0.31	**0.40**
	NN	46	**0.45**	0.20	0.35
	CD	827	**0.86**	0.05	0.09
	NNS	23	**0.37**	0.24	**0.39**
	JJ	100	**0.49**	0.15	0.36

Average weights assigned to word's characters, left context and right context by the attention mechanism. We can clearly see the shift of attention according to the target entity. We also observe that the attention depends on the task at hand.

Performance gain

Task	Metric	Random Emb.	Our module	Gain
NER	F1	77.56	**80.62**	3.9%
POS	acc.	91.41	**92.58**	1.2%

The impact of our model on two NLP downstream tasks. We compare our OOV embeddings prediction scheme against random embeddings.

Conclusion

Discussion :

- **Morphology** and **context** help predict useful embeddings.
- **The attention mechanism works** : depending on the task, the network will use either more the context or the morphology to generate an embedding.

Future works :

- Apply the **attention mechanism on each character of the OOV word and each word of the context** instead of using the hidden state of the respective elements only.
- Test our attention model in **different languages** and on other NLP tasks, such as **machine translation**.