

Semantic segmentation for mapping hockey broadcast images in 2D plan

Philippe Blouin-Leclerc[†], Stéphane Caron[†]



Multiplication by a constant

Attention module

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 Right context Left context Unknown word which goalkeeper Syrian goal Bitar appeared have Fully connected Fully connected Fully connected tanh tanh tanh Character embedding Fully connected Word embedding softmax **Bidirectional LSTM)** Concatenation Element-wise summation

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.

Fully connected

Predicted embedding

Experiments

Set up:

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

Training details:

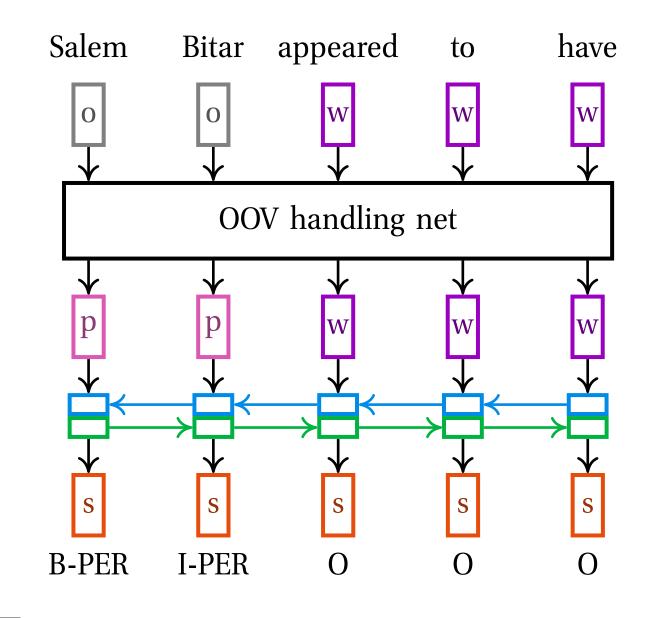
- ► Tensors sizes :
- ► Char. emb. : 20. ► Word emb. : 100 (**GloVe**).
- LSTMs hidden state: 128.
- ► Context size from 2 words to the whole sentence.
- ► Standard learning rate on the labeling task parameters, reduced learning rate on Comick using SGD (0.01, 0.001).

Examples

Entity	Ponderation			Examples	
	Word Left Righ		Right	Examples	
PER	0.19	0.49	0.32	in sentencing darrel <u>voeks</u> , 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</bos>	
PER	0.15	0.61	0.24	had received today ${f from\ mr\ john\ vance\ } {\it langmore}$, a letter resigning his place as	
PER	0.15	0.69	0.16	<bos> ${\sf rtrs}$ - ${\sf australian}$ ${\sf mp}$ ${\sf john}$ ${\it langmore}$ ${\sf formally}$ ${\sf resigns}$. <eos></eos></bos>	
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 <i>kazanluk</i> area are moslems who converted to islam during	
LOC	0.20	0.47	0.33	at a mosque in the $central\ bulgarian\ town\ of\ \underline{kazanluk}$, causing damage but no injuries	
MISC	0.68	0.11	0.21	freestyle <i>skiing-world</i> cup aerials results .	
MISC	0.42	0.18	0.40	the <i>franco-african</i> 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



- OOV word embedding Word embedding
- Tag prediction with a softmax

Bidirectional LSTM

- Predicted embedding

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		
lask	Tag		Word	Left	Right
	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
NER	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
	NNP	308	0.29	0.31	0.40
	NN	46	0.45	0.20	0.35
POS	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.