

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

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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 Multiplication by a constant Fully connected Attention module Predicted embedding

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**).

the whole sentence.

- LSTMs hidden state : 128.
- Context size from 2 words to
- Standard learning rate on the labeling task parameters, reduced learning rate on Co-

mick using SGD (0.01, 0.001).

Examples

Entity	Ponderation			Examples
	Word	Left	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.

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