OOV Handling by Learning Subword using CNN based N-grams

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Overview

Introduction

Why OOV handling is needed?

- Word embedding prefers large corpus [1]
- Language itself is creative and changing overtime [2, 3];
- Some word embedding has no OOV handling method [4, 5, 6]; and
- Improvements should be able to be achieved over using random or unknown embedding for OOV.

Introduction

Previous state-of-the-art Mimick

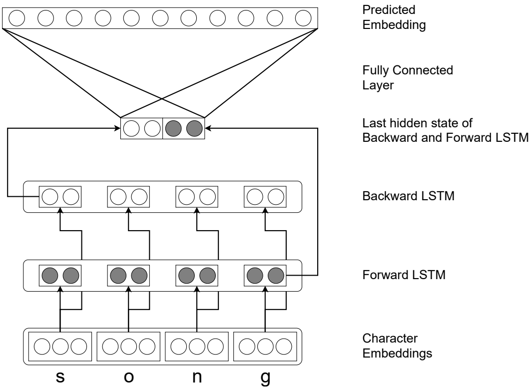


Figure: MIMICK Architecture

Introduction

What could be the problem with Mimick?

- MIMICK used the last hidden state of bi-LSTM to infer OOV embedding [7];
- By default, LSTM has a cell gate that could split the graph of the hidden unit when the input or previous state triggers it
- The last hidden state only encoded the recent sequence
- There is evidence that CNN can performs better than RNN and LSTM in sequence modeling [8]

Objective

- Similar with MIMICK, this problem is tackled from quasi-generative perspective
- Instead of using bi-LSTM, CNN that based on n-grams can be used to learn character sequence [9].
- CNN N-grams can process different length sequence using max-over-time pooling.
- For each kernel K, an input that has similar features to the kernel can still gives a high response.

CNN N-grams for OOV handling

- Given a word and its embedding (w_i, e_i)
- The word is transformed into sequence of character embedding $g_i \in \mathcal{G}$

$$h : w_i \rightarrow [c_1, c_2, \ldots, c_n] \rightarrow [g_1, g_2, \ldots, g_n]$$

- The sequence of character embedding then processed by the OOV handling model to predict the embedding $\tilde{e}_i$

$$OOV_{model}(w_i) = \tilde{e}_i$$

CNN N-grams for OOV handling

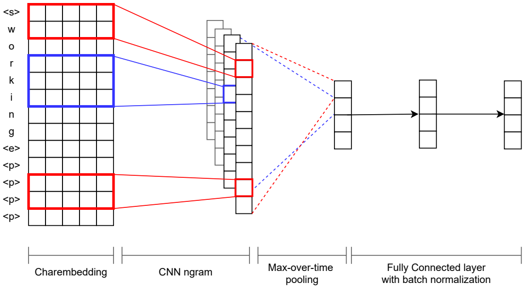


Figure: CNN N-grams for OOV Handling Architecture

- $[2, 3, 4, 5, 6, 7]$-grams were used as the feature extractor
- ReLU activation function was used before the max-over-time pooling

CNN N-grams for OOV handling

- *Hardtanh* is used for predicting embedding
- The predicted embedding was used for calculating the deviation from the original embedding e_i by using MSE

$$\mathcal{L} = \frac{1}{2}\|e_i - \tilde{e}_i\|_2^2$$

Both model trained with three word embedding:

- Polyglot ($\sim$100k words)
- Word2vec first 40k with reduction ($\sim$35k words). If the word contain underscore "_" or "http" then it will be removed
- Dict2vec 100 dimension ($\sim$50k words)

CNN N-grams for OOV handling

Table: OOV Handling Model Parameters

Hyperparameter	**Mimick**	**CNN**
Train-Val split	80%; 20%	
Batch size	64	
Epoch	100	
Momentum	0.5	
Learning Rate (η)	[0.01; 0.1]	0.1
Dropout	0	0.5
Num features	[50; 100; 200; 300]	[20; 50; 100; 150]

Evaluation on Downstream Tasks

Part-of-Speech Tagging

- Using brown POStagging datasets from NLTK[1]
- Following POS-tagger model from Ling et al. (2015) [10]
- Sentence length limited to 5 words
- There are 3 different setup for POS-tagger: Freeze, Continuous, Continuous with Trainable Embedding
- LogSoftmax is used for classifying the tags

[1] Available at `https://www.nltk.org/`

Evaluation on Downstream Tasks

Part-of-Speech Tagging

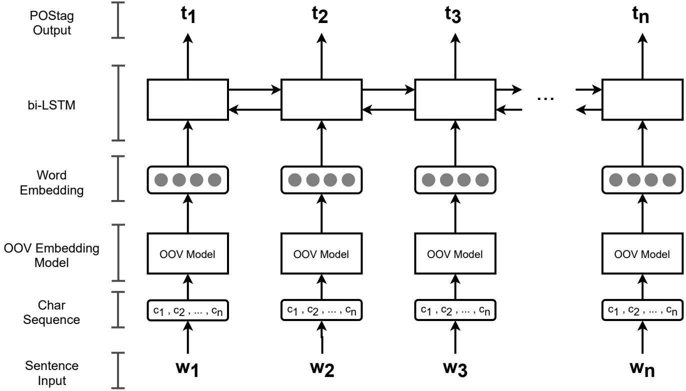


Figure: POS-tagger Model

Evaluation on Downstream Tasks

Part-of-Speech Tagging Result Random

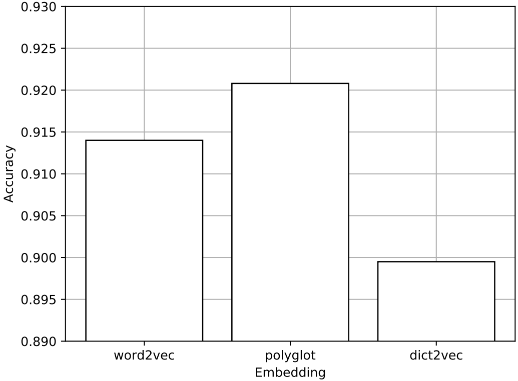
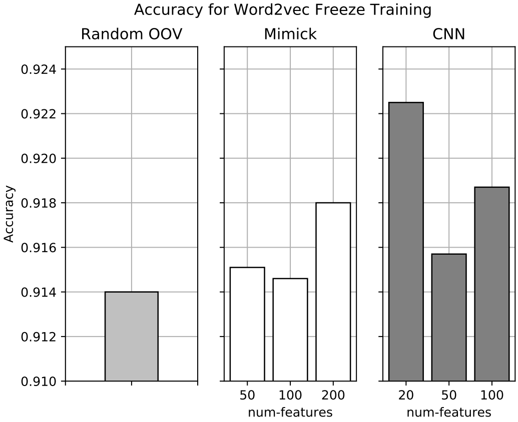


Figure: Random OOV Embedding

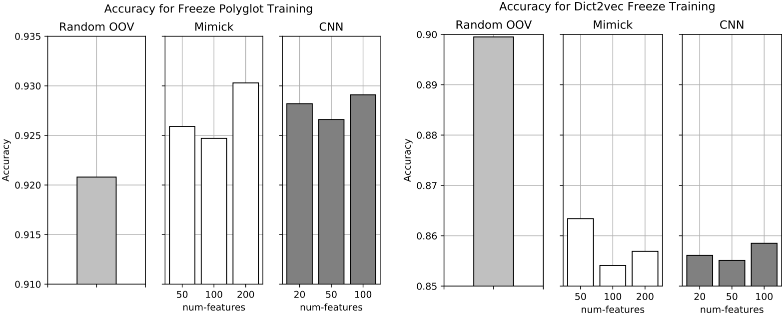
Evaluation on Downstream Tasks

Part-of-Speech Tagging Result Freeze



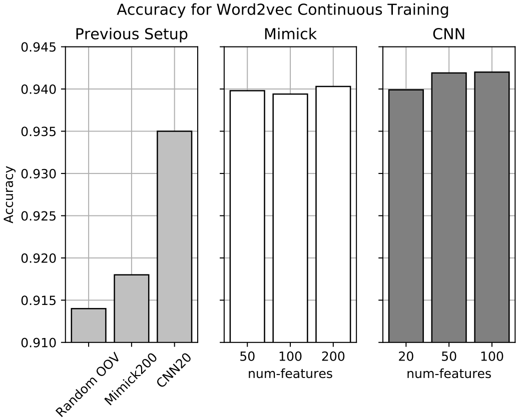
Evaluation on Downstream Tasks

Part-of-Speech Tagging Result Freeze



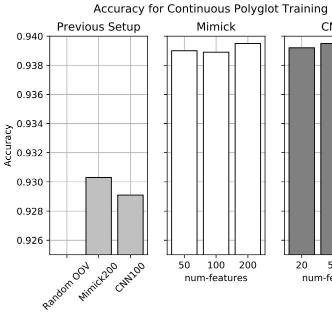
Evaluation on Downstream Tasks

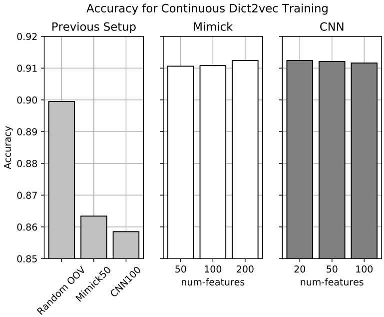
Part-of-Speech Tagging Result Continuous



Evaluation on Downstream Tasks

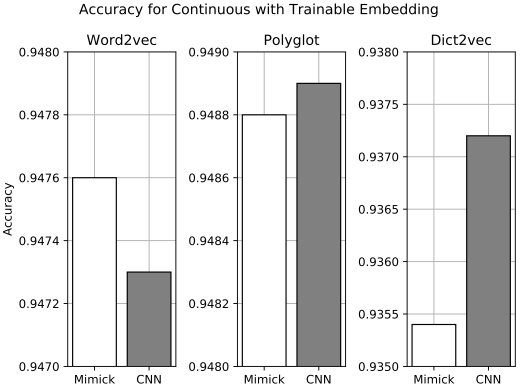
Part-of-Speech Tagging Result Continuous





Evaluation on Downstream Tasks

Part-of-Speech Tagging Result Continuous with Trainable Embedding



Evaluation on Downstream Tasks

Word Similarity

- Using 12 different datasets to increase the data test size
- Only OOV embedding was inferred from the OOV handling model
- The cosine distance of a given pairs was calculated and compared with the dataset with Spearman's rank correlation coefficient.

Evaluation on Downstream Tasks

Word Similarity Results

Table: Word Similarity Task Results (word2vec)

Dataset	OOV	Invocab	OOV Ratio	Mimick*	CNN*
card	989	317	75.73%	**52.27**	27.25
mc30	4	35	10.26%	748.11	**758.79**
men	83	668	11.05%	**672.54**	664.64
mturk287	97	402	19.44%	518.15	**519.76**
mturk771	18	1095	1.62%	**657.93**	657.04
rg65	2	46	4.17%	709.77	**732.61**
rwstanford	1494	1457	50.63%	**233.83**	217.47
simlex	20	1008	1.95%	422.77	**425.90**
simverb	90	737	10.88%	**302.37**	292.91
verb143	4	113	3.42%	467.60	**478.25**
wordsim	15	422	3.43%	**658.92**	648.25
yp130	6	141	4.08%	**460.32**	443.22
			average	**492.05**	488.84

* multiplied by 1000

Evaluation on Downstream Tasks

Word Similarity Results

Table: Word Similarity Task Results (polyglot)

Dataset	OOV	Invocab	OOV Ratio	Mimick*	CNN*
card	864	442	66.16%	**128.93**	114.11
mc30	1	38	2.56%	605.25	605.25
men	14	737	1.86%	490.57	**492.17**
mturk287	76	423	15.23%	443.31	**458.81**
mturk771	3	1110	0.27%	**432.48**	432.20
rg65	1	47	2.08%	531.59	**524.77**
rwstanford	999	1952	33.85%	272.33	**290.78**
simlex	4	1024	0.39%	232.20	**234.16**
simverb	53	774	6.41%	**137.01**	134.42
verb143	0	117	0.00%	335.81	335.81
wordsim	0	437	0.00%	412.83	412.83
yp130	5	142	3.40%	**44.76**	44.62
			average	338.92	**339.99**

* multiplied by 1000

Evaluation on Downstream Tasks

Word Similarity Results

Table: Word Similarity Task Results (Dict2vec)

Dataset	**OOV**	**Invocab**	**OOV Ratio**	**Random***	**Mimick***	**CNN***
card	828	478	63.40%	48.07	80.89	**95.32**
mc30	0	39	0.00%	847.57	847.57	847.57
men	1	750	0.13%	713.16	723.63	**723.89**
mturk287	2	497	0.40%	652.27	**655.32**	653.13
mturk771	0	1113	0.00%	683.91	683.91	683.91
rg65	0	48	0.00%	832.86	832.86	832.86
rwstanford	619	2332	20.98%	214.60	**403.79**	400.27
simlex	3	1025	0.29%	454.80	**460.66**	459.87
simverb	24	803	2.90%	375.15	390.09	**393.39**
verb143	0	117	0.00%	187.82	187.82	187.82
wordsim	18	419	4.12%	642.71	718.72	**723.72**
yp130	2	145	1.36%	577.76	621.38	**621.75**
			average	519.22	550.55	**551.96**

* multiplied by 1000

Conclusion

- Machine learning can be used to generate OOV embedding
- Compared to random OOV embedding, machine learning method has higher performance in downstream tasks
- CNN generally performs better than bi-LSTM for POS-tagging and word similarity tasks
  - MIMICK has higher accuracy in POS-tagging: when the pre-trained embedding & the OOV handling model are non-trainable (*out-of-the-box*)
  - CNN N-grams has higher accuracy in POS-tagging: when both pre-trained embedding and the OOV handling model are trainable
  - Despite that MIMICK preforms better *out-of-the-box* for POS-tagging, this was not the case for word similarity task

Future Works

- A function that can generate an entire embedding
- Save space (e.g. word2vec 3 million words and phrases is around 2GB)
- Save computational needs for new entries cases

Thank you for your attention!

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