



# Towards Better Character-based Word Vectors

Luoshu Wang  
luoshu@stanford.edu

## Overview

### Motivation

- In recent years, a lot of work has been done to update word vectors by combining context information, e.g., BERT, ELMo. More exploration is needed to improve word representation using its internal structure.
- Current character-based word vectors, such as FastText method, implicitly assume that the every morpheme is equally important, but, in reality, that is not the case.

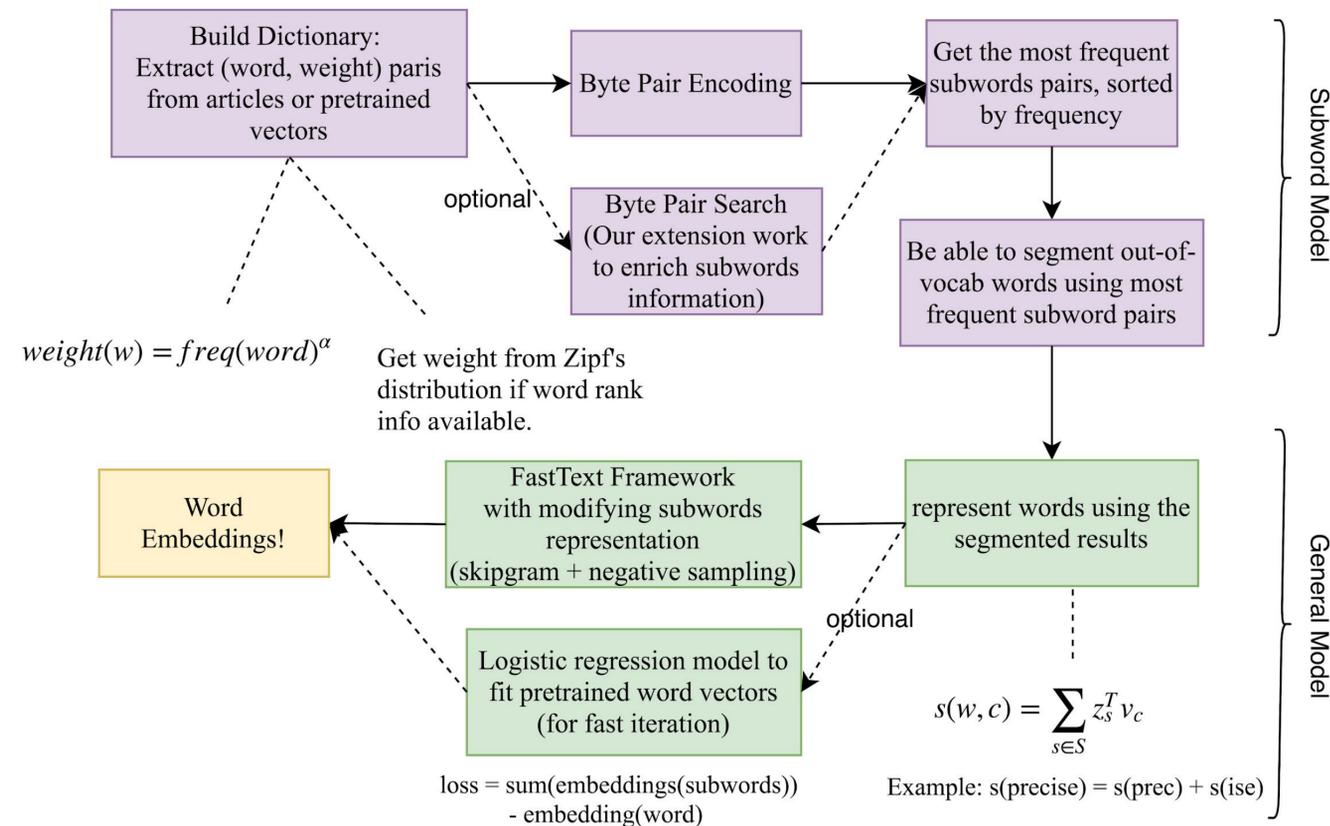
### Key Contributions

- Design an unsupervised word segmentation model to split words into morphemes.
- Propose to represent words using these segmented subwords
- Propose to adopt FastText Framework or simple logistic regression model as general model to train word embeddings.
- Conduct an extensive experimental study.

## Data

- For build vocabulary:
  - Wiki latest pages articles (22G)
  - Enwik9 dataset (~700M)
  - Pre-trained FastText vectors (~1M words)
- Train Embedding:
  - enwiki9 dataset
- Evaluation:
  - WordSim353 dataset
  - Rare Word dataset

## Model and Embedding Creation Example



## Results

### Human Similarity Judgment Task

Model	Dictionary	WS353	Rare Word
FastText	enwik9	74	45
Our model	enwik9	76	41
Our model	large wiki data	76	41

### Segmentation Examples

Word	Results
deliveryman	delivery man
dissociatives	dis soci atives
childishness	child ish ness

## Analysis

- Our model can capture the morphemes within one word as expected.
- Our model outperforms FastText in WS353 dataset: there is more common words in WordSim353 dataset, where our model might be benefited from the morphological decomposition of words.
- The loss in the Rare Word dataset might come from BPE can only split word to non-duplicated subwords, so if the segmentation is imperfect, it might lose important information. (BPS might help with this issue.)

## Important Features

- Word Weight
- Subword Frequency
- Begin-Of-Word / End-Of-Word

## Conclusion

- Our model can capture the morphemes really well, and works better for words that can be decomposed to subwords.
- Our model training is around 2x faster than baseline in enwik9 dataset, which is quite efficiently.

## Future Work

- Learn word vectors in larger wikipedia dataset (22 G).
- Run more evals for Byte Pair Search method. BPS Example:  
Input: low 5, lower 2, newest 6, widest 3  
Both (s, t) and (e, s) pair has subword pair frequency 9, but in the every iteration of BPE, BPE will only merge one pair. Merge order might influence subwords vocabulary and final word segmentation results. To address this issue, BPS will go through all the possibilities and returning more relevant subwords.

## Additional Information

Mentor: Peng Qi (pengqi@cs.stanford.edu)

## References

- [1] Piotr Bojanowski, Edouard Grave, Armand Joulin, and Tomas Mikolov. Enriching word vectors with subword information. CoRR, abs/1607.04606, 2016.
- [2] Rico Sennrich, Barry Haddow, and Alexandra Birch. Neural machine translation of rare words with subword units. CoRR, abs/1508.07909, 2015.
- [3] Yonghui Wu, Mike Schuster, Zhifeng Chen, Quoc V Le, Mohammad Norouzi, Wolfgang Macherey, Maxim Krikun, Yuan Cao, Qin Gao, Klaus Macherey, et al. Google's neural machine translation system: Bridging the gap between human and machine translation. arXiv preprint arXiv:1609.08144, 2016.