91258 Natural Language Processing

Lesson 12. Hands on Word Embeddings

Alberto Barrón-Cedeño

Alma Mater Studiorum-Università di Bologna a.barron@unibo.it @_albarron_

10/11/2022



Previously ► Skip-gram ► CBOW **Pre-Trained Models**

Table of Contents

Pre-Trained Models

Gensim

Model Construction

GloVe

fastText

Chapter 6 of Lane et al. (2019)

Some Pre-Trained Models

| Model | Provider | Description | |
|----------------|-----------|---------------------------------------|--------|
| word2vec | Google | 300D from English Google News article | s^1 |
| fastText | Facebook | 157 languages from Wikipedia and Cra | wl^2 |
| word2vec/GloVe | CNR | Italian embeddings from the Wikipedia | |
| word2vec | UCampania | Italian embeddings ³ | |

There are many pre-trained models and diverse libraries to handle them.

Just go to your favorite search engine

Gensim

Gensim

- ► Scalable, open source, and efficient Python library
- ► It includes many resources, including word2vec, doc2vec, FastText, LDA, and more
- ► All information, including very nice manuals at https://radimrehurek.com/gensim/
- Let us see

Gensim

Gensim

Most similar items

word_vectors.most_similar()

Among the most interesting parameters:

positive list of vectors to be added together before looking for the neighbours

negative subtraction (or exclusion) of the elements

topn number of elements to retrieve



 $^{^{1}} https://drive.google.com/file/d/OB7XkCwpI5KDYNlNUTTlSS21pQmM$

²https://fasttext.cc

https://mlunicampania.gitlab.io/italian-word2vec/

Gensim Gensim Least similar items (closed set) More operations word_vectors.doesnt_match() It returns the element from the input list with the lowest similarity wrt the rest Adding and Subtracting We can use most_similar() again, this time with the negative parameter Let us see Computing similarities word_vectors.similarity() Let us see ■ Let us see Gensim Getting the Vectors

Gensim (and other libraries) have coded these interfaces to perform operations, but one might want to go beyond word_vectors[word]

Let us see

Model Construction

Model Construction

Considerations

- ► If you are working in other language than English, Google's provided word2vec is not an option (FastText might be)
- ► Google's word2vec is built on news; fastText is built on the Wikipedia...analysing scientific papers or literature?

 Probably not
- ► You want to work on COVID-19 or any other recent topic? Many relevant terms wont appear

Alternatives

- ▶ Opting for some of the previous representations
- ► Build your own model

Model Construction

Training

Training the word2vec model with gensim

Documentation:

https://radimrehurek.com/gensim/models/word2vec



Considerations

- ► Training on relatively large corpora might take some time (Brown is small and took me a bit less than 1 minute on a 2.5GHz Quad-Core i7, 16GB RAM)
- ► Large corpora (e.g., the Wikipedia) can require a significant amount of time/memory

Model Construction

Pre-Processing

Typical pre-processing pipeline

- ► Tokenisation
- ► Lowercasing (optional)
- ► Sentence splitting

Input Embedded list of tokenised sentences

$$[[w_{0.0} \ w_{0.1} \ w_{0.2} \dots w_{0.k}], [w_{1.0} \ w_{1.1} \ w_{1.2} \dots w_{1.l}], \dots [w_{x.0} \ w_{x.1} \dots w_{x.m}]]$$

Model Construction

Trimming and Saving

model.init_sims(replace=True)

- ► Freezes the model
- ► Stores the hidden-layer weights
- ► Discards the output-layer weights

apparently not necessary since gensim 4.0

Now we simply have to save the model with model.save()

■ Let us see

GloVe

GloVe

GloVe vs word2vec

RaRe Technologies comparison⁵

Settings: 600 dims \bullet context window of 10 \bullet 1.9B words of *en* Wikipedia.

| Algorithm | acc (word analogy) | wallclock time | peak RAM (MB) |
|-----------------------------|--------------------|-------------------|------------------|
| I/O only | _ | 3m | 25 |
| GloVe, 10 epochs, lr 0.05 | 67.1 | 4h12m | 9,414 |
| GloVe, 100 epochs, Ir 0.05 | 67.3 | 18h39m | 9,452 |
| word2vec, hierarchical | 57.4 | 3h10m | 266 |
| skipgram, 1 epoch | | | |
| word2vec, negative sam- | 68.3 | 8h38m | 628 |
| pling (10 samples), 1 epoch | | | |
| word2vec, Google 300d | 55.3 | _ | _ |

 $^{^5{\}tt rare-technologies.com/making-sense-of-Word2vec/\#glove_vs_word2vec}$

GloVe

Global Vectors Pennington et al. (2014)⁴

- ► It uses a global word-word co-occurrence matrix
- ► Learning objective: word vectors such that their dot product equals the logarithm of the words' probability of co-occurrence
- ► It produces similar matrices to word2vec
- ► It converges, even with smaller corpora
- ▶ It is more accurate with the same amount of data

fastText.

⁴https://nlp.stanford.edu/projects/glove/

fastText

Predicts the surrounding **character** [2,3]-**grams** rather than the surrounding words Bojanowski et al. $(2017)^6$

- ► Pre-trained models available in 250+ languages
- ► Built on Wikipedia editions (variable quality)

Models available at https://github.com/facebookresearch/fastText/blob/master/docs/crawl-vectors.md

■ Let us see

References

Bojanowski, P., E. Grave, A. Joulin, and T. Mikolov 2017. Enriching Word Vectors with Subword Information. *Transactions of the Association for Computational Linguistics*, 5:135–146.

Lane, H., C. Howard, and H. Hapkem 2019. *Natural Language Processing in Action*. Shelter Island, NY: Manning Publication Co.

Pennington, J., R. Socherm, and C. Manning 2014. GloVe: Global Vectors for Word Representation. In *Empirical Methods in Natural Language Processing (EMNLP)*, Pp. 1532–1543.

Some Remarks

LSA is a better (faster) option for long documents e.g., for clustering

Online learning An existing model can be *adapted* (but new words cannot be added)

doc2vec possible representation based on linear combinations of word2vec

⁶https://github.com/facebookresearch/fastText