

91258 / B0385 Natural Language Processing

Lesson 13. Hands on Word Embeddings

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Chapter 6 of Lane et al. (2019)

Previously

• Skip-gram

• CBOW



Some Pre-Trained Models

Model	Provider	Description	
word2vec	Google	300D from English Google News articles ¹	
fastText	Facebook	157 languages from Wikipedia and Common Crawl 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.

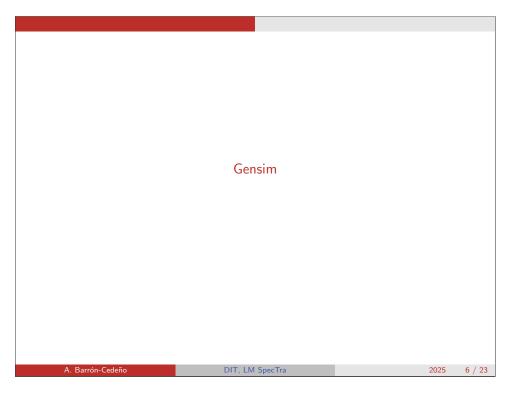
Just query your favorite search engine

¹https://drive.google.com/file/d/0B7XkCwpI5KDYNlNUTTlSS21pQmM

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Gensim

- Scalable, open source, and efficient Python library
- It includes many resources, including word2vec, doc2vec, FastText, LDA, and more
- All information, including (very nice) documentation at https://radimrehurek.com/gensim/



Gensim

Most similar items

word_vectors.most_similar()

Among the most interesting arguments:

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

²https://fasttext.cc

³https://mlunicampania.gitlab.io/italian-word2vec/

Gensim

Least similar items (closed set)

word_vectors.doesnt_match()

It returns the element from the input list with the lowest similarity with respect to the rest

Let us see

Gensim

Getting the Vectors

Gensim (and other libraries) have implemented these interfaces to perform some *standard* operations

To go beyond, one needs to get access to the actual vectors

word_vectors[word]

■ Let us see

Gensim

More operations

Adding and Subtracting

We can use most_similar() again, this time with the negative parameter

Let us see

Computing similarities

word_vectors.similarity()

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Model Construction

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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 has versions built on the Wikipedia and on common crawl... 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
- Getting a more up-to-date existing embedding space
- Build your own model

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Model Construction

Training

Training a word2vec model with gensim

Tutorial: https://rare-technologies.com/word2vec-tutorial/



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

 $[[w_{0,0} \ w_{0,1} \ w_{0,2} \dots w_{0,k}], [w_{1,0} \ w_{1,1} \ w_{1,2} \dots w_{1,l}], \dots [w_{x,0} \ w_{x,1} \dots w_{x,m}]]$

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Model Construction

Trimming and Saving

Reminder We do not care about the output

model.init_sims(replace=True)

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

not necessary since gensim 4.0

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

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GloVe

GloVe

GloVe vs word2vec

RaRe Technologies comparison⁵

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

	acc (word	wallclock	peak RAM
Algorithm	analogy)*	time	(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 skip-	57.4	3h10m	266
gram, 1 epoch			
word2vec, negative sampling	68.3	8h38m	628
(10 samples), 1 epoch			
word2vec, Google 300d	55.3	_	_

^{*} a_is to b as c is to ?

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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

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

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fastText

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Frare-technologies.com/making-sense-of-Word2vec/#glove_vs_word2vec A. Barrón-Cedeño

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)
- Built on common crawl

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

Let us see

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

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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.

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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

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