Word2Vec

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What is Word2Vec?

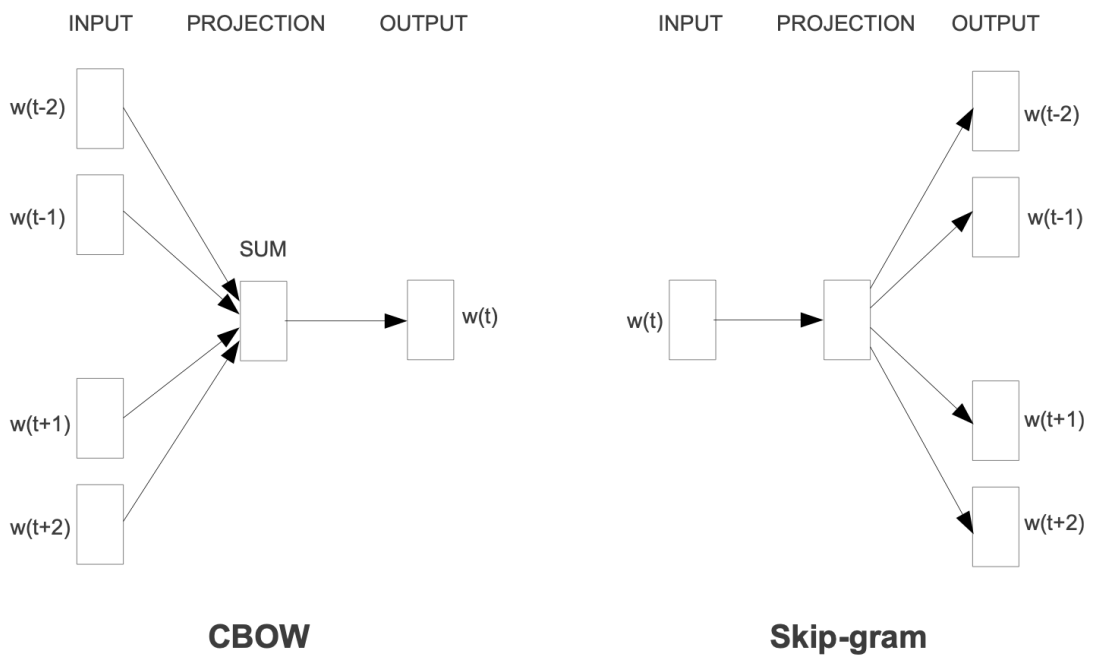
Word2Vec is one of the word embedding techniques in the Natural Language Processing. It was developed by Tomas Mikolov and his team [Mikolov et al., 2013] at Google. Word2Vec is a shallow, two-layer neural network applied to text by vectorizing its words. The input of Word2Vec is a text corpus [**must be in the English language**] and the output is a set of vectors, typically of several hundred dimensions.

Word2Vec turns text into a numerical form, the vectors of similar words clustered together in vector space. The vectors used to represent words are called **neural word embeddings**. So, a neural word embedding represents a word with numbers. By vectorizing words, Word2Vec makes natural language computer-readable; on vectors we can perform powerful mathematical operations in order to detect similarities among words mathematically, **without human intervention**. Word vectors will place similar words close to each other in space. Thus, the words cat, dog, and chicken would most likely cluster in one corner, while car, road, and toll cluster in another.

Similar things and ideas are shown to be “close.” Their relative meanings have been translated to measurable distances. Qualities become quantities, and algorithms can do their work. But similarity is just the basis of many association that Word2Vec can learn. For example, it can gauge relations between words of one language, and map them to another.

Given enough data, usage, and contexts, Word2Vec can make highly accurate guesses about a word’s meaning based on past occurrences. Those guesses can be used to establish a word’s association with other words (e.g. “man” is to “boy” and “woman” is to “girl”), or cluster documents and classify them by topic. Those clusters can form the basis of search, sentiment analysis, and recommendations in such diverse fields as scientific research, legal discovery, e-commerce, and customer relationship management.

Two model architectures



There are two architectures of training Word2Vec: CBOW (Continuous Bag-of-Words) and Skip-gram. Both are to learn the underlying word representation of each word by using neural networks. In the CBOW model, the continuous distributed representations of context (or surrounding words) are combined to predict the target word. While in the Skip-gram model, instead of predicting the target word based on the context, the word is used to predict the context (certain rage begore and after). Generally, the CBOW is much more faster and slightly better accuracy for the frequent words. However, the Skip-gram produces more accurate results on large datasets, and it also works well with a small amount of the training data, represents well even rare words or phrases.

Parameters

There are dozens of parameters that can be used to train Word2Vec; the NLP Suite allows the user to set up the following four parameters.

Learning model architecture

The two architectures for training model – CBOW and Skip-gram.

Vector size

The dimensionality of the resulting word vectors; if you have a large corpus (> few billion tokens) you can go up to 300 dimensions. Generally, word vectors with more dimensions give better result. Word2Vec guidance is vague of this. The standard Word2Vec model pre-trained with Google News has 300 dimensions, and therefore,

usually use 200 or fewer under the rationale that our corpus and vocabulary are much smaller than Google News (default: 100).

Window size

Maximum distance between the current and predicted word within a sentence; in other words, how many words come before and after your given word. This distance varies depending on what you are interested in (between 2-10 in general). Lager windows tend to capture more topic/domain information – what other words are used in related discussions. However, smaller windows tend capture more about word itself – what other words are functionally similar. Therefore, if you are more interested in semantic meaning, smaller window sizes work better (default: 5).

Minimum count

Ignores all words with total frequency lower than this; if all the frequencies of each word are lower than this, an error is raised; cannot train the model. Therefore, when dealing with single text file with low frequency of words, you should set this very low (default: 5).

Result

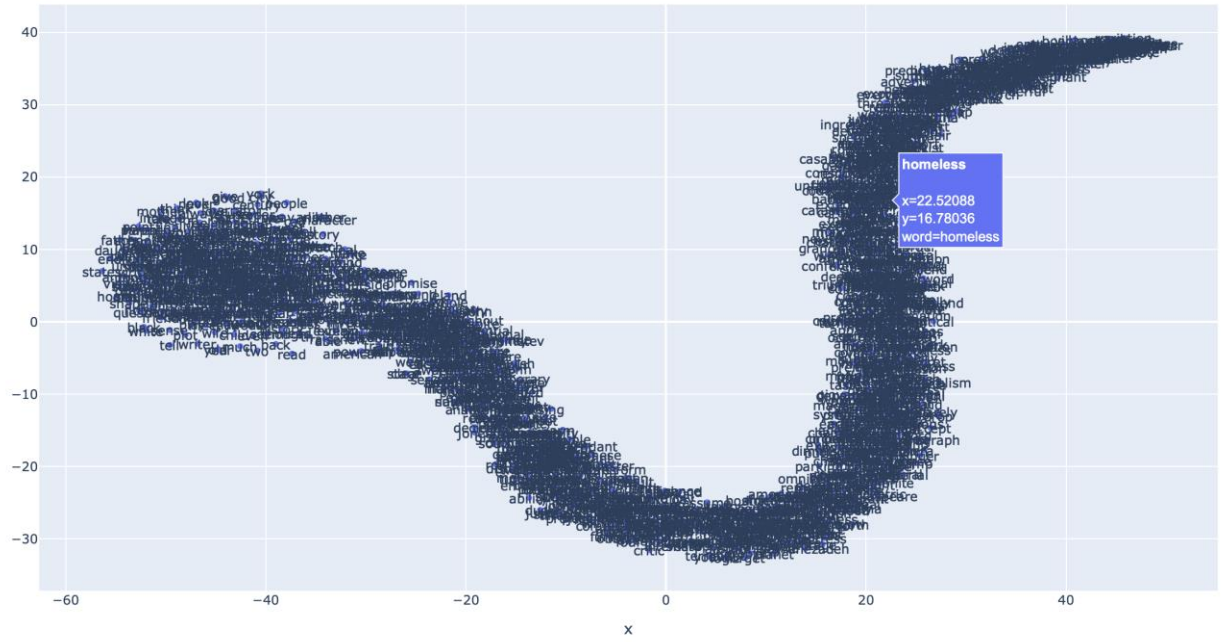
Word2Vec in the NLP Suite will create one csv file and one html file. The csv file is containing 7 columns: a word found in the corpus (column 1), the lemmatized word (column 2), the resulting vector for the word (column 3), the sentence ID of the word (column 4), the sentence where the word appears (column 5), the document ID of the word (column 6), and the document where the word appears (column 6). The resulting vector of each word is multi-dimensional, so the NLP Suite will reduce them in order to represent them in a dimensional space. You can use your own dimension reduction method, and then represent them in 2D or 3D graph.

Visualization

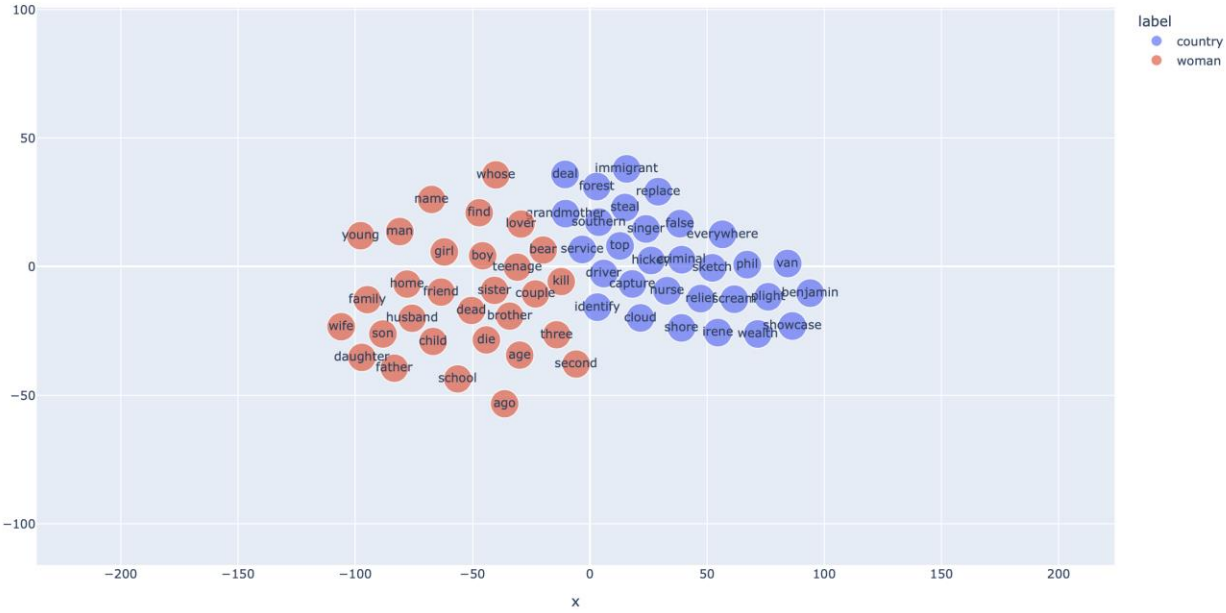
The resulting vectors for each word will be displayed in the two-dimensional Cartesian space in an html file. When you hover over with the mouse on specific points, you can display the words closer together. Look carefully to see whether the spatial distribution of words suggests connections you had not thought about.

Visualization method

There are two options for visualizing high-dimensional word vectors using t-SNE: “Plot all word vectors” and “Clustering of word vectors.” T-SNE is a machine learning algorithm for visualization based on nonlinear dimensionality reduction technique. The basic idea of t-SNE is to reduce dimensional space keeping relative pairwise distance between points, so points which were initially far from each other are also located far away, and close points are also converted to close ones. However, the t-SNE has a non-convex objective function, which is minimized using a gradient descent optimization with random initiation, so different runs produce slightly different results.



The first option, “Plot all word vectors”, literally plots all the words in your corpus in order to see the whole picture. It is very helpful to get some sense of what keywords can be set for clustering of word vectors.



The second option, “Clustering of word vectors”, visualizes groups of the most similar words. It shows the top 30 similar word for each keyword (cluster) you set in the NLP Suite. The format of your keywords should be keyword1, keyword2, keyword3, …, and so on **(you should be include _, (space+comma) between the keywords)**. Also, your keywords must be in your corpus because the word2vec model is trained based on your corpus. It works better when your corpus size is larger.

References

Mikolov, Tomas, Kai Chen, Greg Corrado, Jeffrey Dean. 2013. *Efficient Estimation of Word Representations in Vector Space*. CoRR. abs/1301.378

Gensim API Reference: Word2vec embeddings, https://radimrehurek.com/gensim/models/word2vec.html