# Wikipedia2Vec: An Optimized Tool for Learning Embeddings of Words and Entities from Wikipedia

Ikuya Yamada\* IKUYA@OUSIA.JP
Akari Asai Akari.asai@ousia.JP

Studio Ousia

4F Otemachi Building, 1-6-1 Otemachi, Chiyoda, Tokyo, Japan

Hiroyuki Shindo\* SHINDO@IS.NAIST.JP

Nara Institute of Science and Technology 8916-5 Takayama, Ikoma, Nara, Japan

Hideaki Takeda Takeda Takeda@nii.ac.jp

National Institute of Informatics 2-1-2 Hitotsubashi, Chiyoda, Tokyo, Japan

Yoshiyasu Takefuji

TAKEFUJI@SFC.KEIO.AC.JP

Keio University 5322 Endo, Fujisawa, Kanagawa, Japan

## Abstract

We present Wikipedia2Vec, an open source tool for learning embeddings of words and entities from Wikipedia. This tool enables users to easily obtain quality embeddings of words and entities from a Wikipedia dump with a single command. The learned embeddings can be used as features in downstream natural language processing (NLP) models. The tool can be installed via PyPI. The source code, documentation, and pretrained embeddings for 12 major languages can be obtained at http://wikipedia2vec.github.io.

**Keywords:** Embeddings, distributed representations, neural networks, Wikipedia, knowledge base

#### 1. Introduction

Embeddings (or distributed representations) of lexical items (e.g., words and entities) have been ubiquitously applied to recent NLP models. They map lexical items into a continuous vector space, which enables them to be easily used as features in machine learning models. Wikipedia is a multi-lingual knowledge base (KB) containing a large amount of textual and structured data, and it is frequently used to train embeddings (Pennington et al., 2014; Yamada et al., 2016; Bojanowski et al., 2017; Grave et al., 2018).

In this work, we present Wikipedia2Vec, a tool for learning embeddings of words and entities<sup>1</sup> from Wikipedia. This tool enables users to efficiently learn quality embeddings by running a single command, using a publicly available Wikipedia dump as input. The uniqueness of this tool is that it learns embeddings of words and entities *simultaneously*,

<sup>\*.</sup> These authors are also affiliated with RIKEN AIP.

<sup>1.</sup> In this paper, entities refer to concepts that have corresponding pages in Wikipedia.

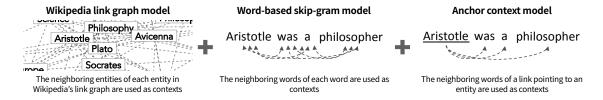


Figure 1: Wikipedia2Vec learns embeddings by jointly optimizing three submodels.

and places similar words and entities close to one another in a continuous vector space. This tool implements the conventional skip-gram model (Mikolov et al., 2013a,b) to learn the embeddings of words, and its extension proposed in Yamada et al. (2016) to learn the embeddings of entities. This tool has been used in several recent state-of-the-art NLP models such as entity linking (Yamada et al., 2016; Eshel et al., 2017), named entity recognition (Sato et al., 2017), and question answering (Yamada et al., 2018).

The source code has been tested on Linux, Windows, and macOS, and released under the Apache License 2.0. The code, documentation, and pretrained embeddings for 12 languages (English, Arabic, Chinese, Dutch, French, German, Italian, Japanese, Polish, Portuguese, Russian, and Spanish) have been publicized at http://wikipedia2vec.github.io.

# 2. Overview

Wikipedia2Vec is an easy-to-use, optimized tool for learning embeddings of words and entities from Wikipedia. It learns embeddings of words and entities by iterating over entire Wikipedia pages and jointly optimizing the following three submodels (see also Figure 1):

- Wikipedia link graph model, which learns entity embeddings by predicting neighboring entities in Wikipedia's link graph, an undirected graph whose nodes are entities and edges represent links between entities, based on each entity in Wikipedia. Here, an edge is created between a pair of entities if the page of one entity has a link to that of the other entity or if both pages link to each other.
- Word-based skip-gram model, which learns word embeddings by predicting neighboring words given each word in a text contained on a Wikipedia page.
- Anchor context model, which aims to place similar words and entities near one another
  in the vector space, and to create interactions between embeddings of words and
  those of entities. Here, we obtain referent entities and their neighboring words from
  links contained in a Wikipedia page, and the model learns embeddings by predicting
  neighboring words given each entity.

These three submodels are based on the skip-gram model (Mikolov et al., 2013a,b), which is a neural network model with a training objective to find embeddings that are useful for predicting context items (i.e., neighboring words or entities) given a target item. For further details of these submodels, see Mikolov et al. (2013a,b) and Yamada et al. (2016).

# 2.1 Learning Embeddings Using Wikipedia2Vec

Wikipedia2Vec can be installed via PyPI (pip install wikipedia2vec). With this tool, embeddings can be learned by running a *train* command with a Wikipedia dump as input.

For example, the following commands download the latest English Wikipedia dump and learn embeddings from this dump:

```
% wget https://dumps.wikimedia.org/enwiki/latest/enwiki-latest-pages-articles.xml.bz2% wikipedia2vec train enwiki-latest-pages-articles.xml.bz2 MODEL_FILE
```

Then, the learned embeddings are written to MODEL\_FILE. Note that this command can take many optional parameters; details are provided in our documentation.

## 2.2 Optimized Implementation for Learning Embeddings

Wikipedia2Vec is implemented in Python, and most of its code is converted into C++ using Cython to boost its performance. Linear algebraic operations required to learn embeddings are performed by Basic Linear Algebra Subprograms (BLAS). We store the embeddings as a float matrix in a shared memory space and update it in parallel using multiple processes.

#### 2.3 Automatic Generation of Links

One challenge is that many entity names do not appear as links in Wikipedia. This is because Wikipedia instructs its contributors to create a link only when the name first occurs on the page. This is problematic because Wikipedia2Vec uses links as a source to learn embeddings. To address this, our tool automatically generates links as follows: It first creates a dictionary that maps each entity name to its possible referent entities. This is done by extracting all names and their referring entities from all links contained in Wikipedia. Then, during training, our tool takes all words and phrases from the target page and converts each into a link to an entity, if the entity is referred by a link on the same page, or if there is only one referent entity associated to the name in the dictionary.

# 3. Empirical Comparison with Existing Tools

In this section, we compare our tool with two types of existing tools: (1) tools to learn entity embeddings, and (2) tools to learn word embeddings.

To evaluate the quality of the entity embeddings, we used the entity relatedness task with the KORE entity relatedness data set (Hoffart et al., 2012). We report Spearman's rank correlation coefficient between human judgment scores and the cosine similarity between the entity embeddings. For baselines, we use two state-of-the-art entity embedding models implemented in the RDF2Vec (Ristoski et al., 2018) and Wiki2vec<sup>2</sup> tools.

Furthermore, we employ two standard tasks to evaluate the quality of the embeddings of words: (1) a word analogy task using the semantic subset (G-SEM) and the syntactic subset (G-SYN) of the Google Word Analogy data set (Mikolov et al., 2013a), and (2) a word similarity task using two standard data sets, namely SimLex-999 (SL999) (Hill et al., 2015) and WordSim-353 (WS353) (Finkelstein et al., 2002). The word analogy task consists of questions of the form "a is to b as c is to d," where a, b, and c are the question words, and d is the answer word that must be predicted by the models. Following previous work (Mikolov et al., 2013a), we addressed this by finding d whose embedding  $w_d$  is closest to  $w_b - w_a + w_c$  according to the cosine similarity, and reported the accuracy. Regarding

<sup>2.</sup> https://github.com/idio/wiki2vec

	KORE	G-SEM	G-SYN	SL999	WS353	Time
Wikipedia2Vec	0.71	0.79	0.68	0.40	0.71	276min
Wikipedia2Vec (w/o autolink)	0.69	0.79	0.67	0.39	0.72	$211 \mathrm{min}$
Wikipedia2Vec (w/o linkgraph)	0.61	0.77	0.67	0.39	0.70	$170 \min$
RDF2Vec (Ristoski et al., 2018)	0.69	-	-	-	-	-
Wiki2vec	0.52	-	-	-	-	-
Gensim (ehek and Sojka, 2010)	-	0.75	0.67	0.37	0.70	$197 \mathrm{min}$
FastText (Bojanowski et al., 2017)	-	0.63	0.70	0.37	0.69	243 min

Table 1: Empirical results of Wikipedia2Vec and the baselines.

the word similarity task, we report Spearman's rank correlation coefficient between human judgment scores and the cosine similarity between word embeddings. As baselines for these tasks, we use the skip-gram model (Mikolov et al., 2013a) implemented in the Gensim library 3.6.0 (ehek and Sojka, 2010) and the extended skip-gram model implemented in the FastText tool 0.1.0 (Bojanowski et al., 2017). To create the training corpus for the baseline models, we extracted texts from the Wikipedia dump using WikiExtractor<sup>3</sup>. We also report the time required for training based on the dump. Additionally, to the extent possible, we use the same hyper-parameters to train our models and the baseline models.<sup>4</sup>

We conducted all experiments using Ubuntu Server 16.04 LTS with Python 3.5 and OpenBLAS 0.3.3 installed on the c5d.9xlarge instance with 36 CPU cores deployed on Amazon Web Services. To train our models and the baseline models of word embeddings, we used the April 2018 version of the English Wikipedia dump.

#### 3.1 Results

Table 1 shows the comparison of our models with the baseline models in terms of the performance of the tasks described above, as well as the time needed for training. We obtained the results of the RDF2Vec and Wiki2vec models from Ristoski et al. (2018). Here, w/o autolink and w/o linkgraph stand for the model without using automatic generation of links (see Section 2.3) and the Wikipedia link graph model (see Section 1), respectively.

Overall, our model provided enhanced performance. It outperformed the RDF2Vec and Wiki2vec models and achieved a new state-of-the-art result on the KORE data set. Furthermore, the feature of automatic link generation and the Wikipedia link graph model improved performance with the KORE data set. Moreover, our model performed better than the baseline word embedding models on one out of two word analogy data sets, as well as on both word similarity data sets. This demonstrates that the semantic signals of entities provided by the Wikipedia link graph and anchor context models are beneficial for improving the quality of word embeddings.

The training time of our model was comparable to that of the baseline word embedding models. Furthermore, our w/o linkgraph model was the fastest among the models and also achieved competitive performance on the word similarity and word analogy tasks.

<sup>3.</sup> https://github.com/attardi/wikiextractor

<sup>4.</sup> We used the following settings:  $dim\_size = 500$ , window = 5, negative = 5, iteration = 5

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