Semantic Entity Retrieval Toolkit

Van Gysel, C.; de Rijke, M.; Kanoulas, E.

Published in:
Neu-IR: Workshop on Neural Information Retrieval

Citation for published version (APA):

General rights
It is not permitted to download or to forward/distribute the text or part of it without the consent of the author(s) and/or copyright holder(s), other than for strictly personal, individual use, unless the work is under an open content license (like Creative Commons).

Disclaimer/Complaints regulations
If you believe that digital publication of certain material infringes any of your rights or (privacy) interests, please let the Library know, stating your reasons. In case of a legitimate complaint, the Library will make the material inaccessible and/or remove it from the website. Please Ask the Library: https://uba.uva.nl/en/contact, or a letter to: Library of the University of Amsterdam, Secretariat, Singel 425, 1012 WP Amsterdam, The Netherlands. You will be contacted as soon as possible.

UvA-DARE is a service provided by the library of the University of Amsterdam (http://dare.uva.nl)
Abstract

Unsupervised learning of low-dimensional, semantic representations of words and entities has recently gained attention. In this paper we describe the Semantic Entity Retrieval Toolkit (SERT) that provides implementations of our previously published entity representation models. The toolkit provides a unified interface to different representation learning algorithms, fine-grained parsing configuration and can be used transparently with GPUs. In addition, users can easily modify existing models or implement their own models in the framework. After model training, SERT can be used to rank entities according to a textual query and extract the learned entity/word representation for use in downstream algorithms, such as clustering or recommendation.

Keywords

Neural information retrieval; Entity retrieval; Toolkit

1 Introduction

The unsupervised learning of low-dimensional, semantic representations of words and entities has recently gained attention for the entity-oriented tasks of expert finding [9] and product search [8]. Representations are learned from a document collection and domain-specific associations between documents and entities. Expert finding is the task of finding the right person with the appropriate skills or knowledge [1] and an association indicates document authorship (e.g., academic papers) or involvement in a project (e.g., annual progress reports). In the case of product search, an associated document is a product description or review [8].

In this paper we describe the Semantic Entity Retrieval Toolkit (SERT) that provides implementations of our previously published entity representation models [8, 9]. Beyond a unified interface that combines different models, the toolkit allows for fine-grained parsing configuration and GPU-based training through integration with Theano [3, 6]. Users can easily extend existing models or implement their own models within the unified framework. After model training, SERT can compute matching scores between an entity and a piece of text (e.g., a query). This matching score can then be used for ranking entities, or as a feature in a downstream machine learning system, such as the learning to rank component.

2 The Toolkit

SERT is organized as a pipeline of utilities as depicted in Fig. 1. First, a collection of documents and entity associations is processed and packaged using a numerical format (§2.1). Low-dimensional representations of words and entities are then learned (§2.2) and afterwards the representations can be used to make inferences (§2.3).

2.1 Collection parsing and preparation

To begin, SERT constructs a vocabulary that will be used to tokenize the document collection. Non-significant words that are too frequent (e.g., stopwords), noisy (e.g., single characters) and rare words are filtered out. Words that do not occur in the dictionary are ignored. Afterwards, word sequences are extracted from the documents and stored together with the associated entities in the numerical format provided by NumPy [7]. Word sequences can be extracted consecutively or a stride can be specified to extract non-consecutive windows. In addition, a hierarchy of word sequence extractors can be applied to extract skip-grams, i.e., word sequences where a number of tokens are skipped after selecting a token [4]. To support short documents, a special-purpose padding token can be used to fill up word sequences that are longer than a particular document.

After word sequence extraction, a weight can be assigned to each word sequence/entity pair that can be used to re-weight the training objective. For example, in the case of expert finding [9], this weight is the reciprocal of the document length of the document where the sequence was extracted from. This avoids a bias in the objective towards long documents. An alternative option that exists within the toolkit is to resample word sequence/entity pairs such that every entity is associated with the same number of word sequences, as used for product search [8].
Apart from entity ranking, the learned representations and model-specific parameters can be extracted conveniently from the models through the interface² and used for downstream tasks such as clustering, recommendation and determining entity importance as shown in [10].

3 CONCLUSIONS

In this paper we described the Semantic Entity Retrieval Toolkit, a toolkit that learns latent representations of words and entities. The toolkit contains implementations of state-of-the-art entity representations algorithms [8, 9] and consists of three components: text processing, representation learning and inference. Users of the toolkit can easily make changes to existing model implementations or contribute their own models by extending an interface provided by the SERT framework.

Future work includes integration with Pyndri [11] such that document collections indexed with Indri can transparently be used to train entity representations. In addition, integration with machine learning frameworks besides Theano, such as TensorFlow and PyTorch, will make it easier to integrate existing models into SERT.

Acknowledgments. The authors would like to thank the anonymous reviewers for their valuable comments and suggestions. This research was supported by Ahold Delhaize, Amsterdam Data Science, the Bloomberg Research Grant program, the Criteo Faculty Research Award program, the Dutch national program COMMIT, Elsevier, the European Community’s Seventh Framework Programme (FP7/2007-2013) under grant agreement nr 312827 (VOX-Pol), the Google Faculty Research Award scheme, the Microsoft Research Ph.D. program, the Netherlands Institute for Sound and Vision, the Netherlands Organisation for Scientific Research (NWO) under project nr 612.001.116, HOR-11-10, CI-14-25, 652.002.001, 612.001.551, 652-001.003, and Yandex. All content represents the opinion of the authors, which is not necessarily shared or endorsed by their respective employers and/or sponsors.

REFERENCES


2See get representations in Snippet 1.

# Code snippet 1: Illustrative example of the SERT model interface. The full interface supports more functionality omitted here for brevity. Users can define a symbolic graph of computation using the Theano library [6] in combination with Lasagne [3].

```python
class ExampleModel(VectorSpaceLanguageModelAttribute):
    def __init__(self, *args, **kwargs):
        super(ExampleModel, self).__init__(
            *args, **kwargs)

        # Define model architecture.
        input_layer = InputLayer(
            shape=(self.batch_size, self.window_size))

        ...

        def loss_fn(pred, actual, _):
            # Compute symbolic loss between predicted/actual entities.
            # The framework deals with underlying boilerplate.
            return symbolic_expression(loss_fn, ****)

        def get_representations(self):
            # Returns the representations and parameters to be extracted.
```