

Semantic Matching of Documents from Heterogeneous Collections: A Simple and Transparent Method for Practical Applications

Mark-Christoph Müller
 Heidelberg Institute for Theoretical Studies gGmbH
 Heidelberg, Germany
 mark-christoph.mueller@h-its.org

Abstract

We present a very simple, unsupervised method for the pairwise matching of documents from heterogeneous collections. We demonstrate our method with the Concept-Project matching task, which is a binary classification task involving pairs of documents from heterogeneous collections. Although our method only employs standard resources without any domain- or task-specific modifications, it clearly outperforms the more complex system of the original authors. In addition, our method is *transparent*, because it provides explicit information about how a similarity score was computed, and *efficient*, because it is based on the aggregation of (pre-computable) word-level similarities.

1 Introduction

We present a simple and efficient unsupervised method for pairwise matching of documents from *heterogeneous* collections. Following Gong et al. (2018), we consider two document collections heterogeneous if their documents differ systematically with respect to vocabulary and / or level of abstraction. With these *defining* differences, there often also comes a difference in length, which, however, by itself does not make document collections heterogeneous. Examples include collections in which *expert* answers are mapped to *non-expert* questions (e.g. *InsuranceQA* by Feng et al. (2015)), but also so-called *community* QA collections (Blooma and Kurian (2011)), where the lexical mismatch between Q and A documents is often less pronounced than the length difference.

Like many other approaches, the proposed method is based on word embeddings as universal meaning representations, and on vector cosine as the similarity metric. However, instead of computing pairs of document representations and measuring their similarity, our method assesses the document-pair similarity on the basis of selected pairwise word similarities. This has the following advantages, which make our method a viable candidate for practical, real-world applications: **efficiency**, because pairwise word similarities can be efficiently (pre-)computed and cached, and **transparency**, because the selected words from each document are available as evidence for what the similarity computation was based on.

We demonstrate our method with the *Concept-Project matching* task (Gong et al. (2018)), which is described in the next section.

2 Task, Data Set, and Original Approach

The *Concept-Project matching* task is a binary classification task where each instance is a pair of heterogeneous documents: one **concept**, which is a short science curriculum item from NGSS¹, and one **project**, which is a much longer science project description for school children from ScienceBuddies².

¹<https://www.nextgenscience.org>

²<https://www.sciencebuddies.org>

CONCEPT LABEL: ecosystems: - ls2.a: interdependent relationships in ecosystems

CONCEPT DESCRIPTION: Ecosystems have carrying capacities , which are limits to the numbers of organisms and populations they can support . These limits result from such factors as the availability of living and nonliving resources and from such challenges such as predation , competition , and disease . Organisms would have the capacity to produce populations of great size were it not for the fact that environments and resources are finite . This fundamental tension affects the abundance (number of) individuals) of species in any given ecosystem .

PROJECT LABEL: Primary Productivity and Plankton

PROJECT DESCRIPTION: Have you seen plankton? I am not talking about the evil villain trying to steal the Krabby Patty recipe from Mr. Krab. I am talking about plankton that live in the ocean. In this experiment you can learn how to collect your own plankton samples and see the wonderful diversity in shape and form of planktonic organisms. The oceans contain both the earth's largest and smallest organisms. Interestingly they share a delicate relationship linked together by what they eat. The largest of the ocean's inhabitants, the Blue Whale, eats very small plankton, which themselves eat even smaller phytoplankton. All of the linkages between predators, grazers, and primary producers in the ocean make up an enormously complicated food web. The base of this food web depends upon phytoplankton, very small photosynthetic organisms which can make their own energy by using energy from the sun. These phytoplankton provide the primary source of the essential nutrients that cycle through our ocean's many food webs. This is called primary productivity, and it is a very good way of measuring the health and abundance of our fisheries. There are many different kinds of phytoplankton in our oceans. [...] One way to study plankton is to collect the plankton using a plankton net to collect samples of macroscopic and microscopic plankton organisms. The net is cast out into the water or trolled behind a boat for a given distance then retrieved. Upon retrieving the net, the contents of the collecting bottle can be removed and the captured plankton can be observed with a microscope. The plankton net will collect both phytoplankton (photosynthetic plankton) and zooplankton (non-photosynthetic plankton and larvae) for observation. In this experiment you will make your own plankton net and use it to collect samples of plankton from different marine or aquatic locations in your local area. You can observe both the abundance (total number of organisms) and diversity (number of different kinds of organisms) of planktonic forms to make conclusions about the productivity and health of each location. In this experiment you will make a plankton net to collect samples of plankton from different locations as an indicator of primary productivity. You can also count the number of phytoplankton (which appear green or brown) compared to zooplankton (which are mostly marine larval forms) and compare. Do the numbers balance, or is there more of one type than the other? What effect do you think this has on productivity cycles? Food chains are very complex. Find out what types of predators and grazers you have in your area. You can find this information from a field guide or from your local Department of Fish and Game. Can you use this information to construct a food web for your local area? Some blooms of phytoplankton can be harmful and create an anoxic environment that can suffocate the ecosystem and leave a "Dead Zone" behind. Did you find an excess of brown algae or diatoms? These can be indicators of a harmful algal bloom. Re-visit this location over several weeks to report on an increase or decrease of these types of phytoplankton. Do you think that a harmful algal bloom could be forming in your area? For an experiment that studies the relationship between water quality and algal bloom events, see the Science Buddies project Harmful Algal Blooms in the Chesapeake Bay.

Figure 1: C-P Pair (Instance 261 of the original data set.)

The publicly available data set³ contains 510 labelled pairs⁴ involving $C = 75$ unique concepts and $P = 230$ unique projects. A pair is annotated as 1 if the project matches the concept (57%), and as 0 otherwise (43%). The annotation was done by undergrad engineering students. Gong et al. (2018) do not provide any specification, or annotation guidelines, of the semantics of the 'matches' relation to be annotated. Instead, they create gold standard annotations based on a majority vote of three manual annotations. Figure 1 provides an example of a matching C-P pair. The concept labels can be very specific, potentially introducing vocabulary that is not present in the actual concept descriptions. The extent to which this information is used by Gong et al. (2018) is not entirely clear, so we experiment with several setups (cf. Section 4).

2.1 Gong et al. (2018)'s Approach

The approach by Gong et al. (2018) is based on the idea that the longer document in the pair is reduced to a set of *topics* which capture the essence of the document in a way that eliminates the effect of a potential length difference. In order to overcome the vocabulary mismatch, these topics are not based on *words* and their distributions (as in LSI (Deerwester et al. (1990)) or LDA (Blei et al. (2003))), but on word embedding vectors. Then, basically, matching is done by measuring the cosine similarity between the topic vectors and the short document words. Gong et al. (2018) motivate their approach mainly with the length mismatch argument, which they claim makes approaches relying on document representations (incl. vector averaging) unsuitable. Accordingly, they use Doc2Vec (Le and Mikolov (2014)) as one of their baselines, and show that its performance is inferior to their method. They do not, however, provide a much simpler averaging-based baseline. As a second baseline, they use Word Mover's Distance (Kusner et al. (2015)), which is based on word-level distances, rather than distance of global document representations, but which also fails to be competitive with their topic-based method. Gong et al. (2018) use two different sets of word embeddings: One (topic_wiki) was trained on a full English Wikipedia dump, the other (wiki_science) on a smaller subset of the former dump which only contained science articles.

3 Our Method

We develop our method as a simple alternative to that of Gong et al. (2018). We aim at comparable or better classification performance, but with a simpler model. Also, we design the method in such a way that it provides human-interpretable results in an efficient way. One common way to compute

³<https://github.com/HongyuGong/Document-Similarity-via-Hidden-Topics>

⁴Of the original 537 labelled pairs, 27 were duplicates, which we removed.

the similarity of two documents (i.e. word sequences) c and p is to average over the word embeddings for each sequence first, and to compute the cosine similarity between the two averages afterwards. In the first step, weighting can be applied by multiplying a vector with the TF, IDF, or TF*IDF score of its pertaining word. We implement this standard measure (**AVG_COS_SIM**) as a baseline for both our method and for the method by Gong et al. (2018). It yields a single scalar similarity score. The core idea of our alternative method is to turn the above process upside down, by computing the cosine similarity of *selected* pairs of words from c and p first, and to average over the similarity scores afterwards (cf. also Section 6). More precisely, we implement a measure **TOP_n_COS_SIM_AVG** as the average of the n highest pairwise cosine similarities of the n top-ranking words in c and p . Ranking, again, is done by TF, IDF, and TF*IDF. For each ranking, we take the top-ranking n words from c and p , compute $n \times n$ similarities, rank by decreasing similarity, and average over the top n similarities. This measure yields both a scalar similarity score and a list of $\langle c_x, p_y, sim \rangle$ tuples, which represent the qualitative aspects of c and p on which the similarity score is based.

4 Experiments

Setup All experiments are based on off-the-shelf word-level resources: We employ WOMBAT (Müller and Strube (2018)) for easy access to the 840B GloVe (Pennington et al. (2014)) and the GoogleNews⁵ Word2Vec (Mikolov et al. (2013)) embeddings. These embedding resources, while slightly outdated, are still widely used. However, they cannot handle out-of-vocabulary tokens due to their fixed, word-level lexicon. Therefore, we also use a pretrained English fastText model⁶ (Bojanowski et al. (2017); Grave et al. (2018)), which also includes subword information. IDF weights for approx. 12 mio. different words were obtained from the English Wikipedia dump provided by the Polyglot project (Al-Rfou et al. (2013)). All resources are case-sensitive, i.e. they might contain different entries for words that only differ in case (cf. Section 5).

We run experiments in different setups, varying both the input representation (GloVe vs. Google vs. fastText embeddings, \pm TF-weighting, and \pm IDF-weighting) for concepts and projects, and the extent to which concept descriptions are used: For the latter, **Label** means only the concept *label* (first and second row in the example), **Description** means only the textual *description* of the concept, and **Both** means the concatenation of **Label** and **Description**. For the projects, we always use both label and description. For the project descriptions, we extract only the last column of the original file (CONTENT), and remove user comments and some boiler-plate. Each instance in the resulting data set is a tuple of $\langle c, p, label \rangle$, where c and p are bags of words, with case preserved and function words⁷ removed, and *label* is either 0 or 1.

Parameter Tuning Our method is unsupervised, but we need to define a threshold parameter which controls the *minimum* similarity that a concept and a project description should have in order to be considered a match. Also, the **TOP_n_COS_SIM_AVG** measure has a parameter n which controls how many ranked words are used from c and p , and how many similarity scores are averaged to create the final score. Parameter tuning experiments were performed on a random subset of 20% of our data set (54% positive). Note that Gong et al. (2018) used only 10% of their 537 instances data set as tuning data. The tuning data results of the best-performing parameter values for each setup can be found in Tables 1 and 2. The top F scores per type of concept input (Label, Description, Both) are given in **bold**. For **AVG_COS_SIM** and **TOP_n_COS_SIM_AVG**, we determined the threshold values (T) on the tuning data by doing a simple .005 step search over the range from 0.3 to 1.0. For **TOP_n_COS_SIM_AVG**, we additionally varied the value of n in steps of 2 from 2 to 30.

⁵<https://code.google.com/archive/p/word2vec/>

⁶<https://dl.fbaipublicfiles.com/fasttext/vectors-crawl/cc.en.300.bin.gz>

⁷We use the list provided by Gong et al. (2018), with an additional entry for *cannot*.

Results The top **tuning data** scores for AVG_COS_SIM (Table 1) show that the Google embeddings with TF*IDF weighting yield the top F score for all three concept input types (.881 - .945). Somewhat expectedly, the best overall F score (.945) is produced in the setting **Both**, which provides the most information. Actually, this is true for all four weighting schemes for both GloVe and Google, while fastText consistently yields its top F scores (.840 - .911) in the **Label** setting, which provides the least information. Generally, the level of performance of the simple baseline measure AVG_COS_SIM on this data set is rather striking.

Concept Input → Embeddings	TF	IDF	Label				Description				Both			
			T	P	R	F	T	P	R	F	T	P	R	F
GloVe	-	-	.635	.750	.818	.783	.720	.754	.891	.817	.735	.765	.945	.846
	+	-	.640	.891	.745	.812	.700	.831	.891	.860	.690	.813	.945	.874
	-	+	.600	.738	.873	.800	.670	.746	.909	.820	.755	.865	.818	.841
	+	+	.605	.904	.855	.879	.665	.857	.873	.865	.715	.923	.873	.897
Google	-	-	.440	.813	.945	.874	.515	.701	.982	.818	.635	.920	.836	.876
	+	-	.445	.943	.909	.926	.540	.873	.873	.873	.565	.927	.927	.927
	-	+	.435	.839	.945	.889	.520	.732	.945	.825	.590	.877	.909	.893
	+	+	.430	.943	.909	.926	.530	.889	.873	.881	.545	.945	.945	.945
fastText	-	-	.440	.781	.909	.840	.555	.708	.927	.803	.615	.778	.891	.831
	+	-	.435	.850	.927	.887	.520	.781	.909	.840	.530	.803	.964	.876
	-	+	.435	.850	.927	.887	.525	.722	.945	.819	.600	.820	.909	.862
	+	+	.420	.895	.927	.911	.505	.803	.891	.845	.520	.833	.909	.870

Table 1: Tuning Data Results **AVG_COS_SIM**. Top F per Concept Input Type in **Bold**.

For TOP_n_COS_SIM_AVG, the **tuning data** results (Table 2) are somewhat more varied: First, there is no single best performing set of embeddings: Google yields the best F score for the **Label** setting (.953), while GloVe (though only barely) leads in the **Description** setting (.912). This time, it is fastText which produces the best F score in the **Both** setting, which is also the best overall **tuning data** F score for TOP_n_COS_SIM_AVG (.954). While the difference to the Google result for **Label** is only minimal, it is striking that the best overall score is again produced using the 'richest' setting, i.e. the one involving both TF and IDF weighting and the most informative input.

Concept Input → Embeddings	TF	IDF	Label				Description				Both			
			T/n	P	R	F	T/n	P	R	F	T/n	P	R	F
GloVe	+	-	.365/6	.797	.927	.857	.690/14	.915	.782	.843	.675/16	.836	.927	.879
	-	+	.300/30	.929	.236	.377	.300/30	.806	.455	.581	.300/30	.778	.636	.700
	+	+	.330/6	.879	.927	.903	.345/6	.881	.945	.912	.345/6	.895	.927	.911
Google	+	-	.345/22	.981	.927	.953	.480/16	.895	.927	.911	.520/16	.912	.945	.929
	-	+	.300/30	1.00	.345	.514	.300/8	1.00	.345	.514	.300/30	1.00	.600	.750
	+	+	.300/10	1.00	.509	.675	.300/14	.972	.636	.769	.350/22	1.00	.836	.911
fastText	+	-	.415/22	.980	.873	.923	.525/14	.887	.855	.870	.535/20	.869	.964	.914
	-	+	.350/24	1.00	.309	.472	.300/30	1.00	.382	.553	.300/28	1.00	.673	.804
	+	+	.300/20	1.00	.800	.889	.300/10	.953	.745	.837	.310/14	.963	.945	.954

Table 2: Tuning Data Results **TOP_n_COS_SIM_AVG**. Top F per Concept Input Type in **Bold**.

We then selected the best performing parameter settings for every concept input and ran experiments on the held-out **test data**. Since the original data split used by Gong et al. (2018) is unknown, we cannot exactly replicate their settings, but we also perform ten runs using randomly selected 10% of our 408 instances test data set, and report average P, R, F, and standard deviation. The results can be found in Table 3. For comparison, the two top rows provide the best results of Gong et al. (2018).

The first interesting finding is that the AVG_COS_SIM measure again performs very well: In all three settings, it beats both the system based on general-purpose embeddings (topic_wiki) and the one that is adapted to the science domain (topic_science), with again the **Both** setting yielding the best overall result (.926). Note that our **Both** setting is probably the one most similar to the concept input used by Gong et al. (2018). This result corroborates our findings on the tuning data, and clearly contradicts the (implicit) claim made by Gong et al. (2018) regarding the infeasibility of document-level matching for documents of different lengths. The second, more important finding is that our proposed TOP_n_COS_SIM_AVG measure is also very competitive, as it also outperforms both systems by Gong et al. (2018) in two out of three settings. It only fails in the setting using only the **Description**

					P	R	F
Gong et al. (2018)	topic_science				.758 ± .012	.885 ± .071	.818 ± .028
	topic_wiki				.750 ± .009	.842 ± .010	.791 ± .007
Method	Embeddings	Settings	T/n	Conc. Input			
	Google	+TF +IDF	.515	Label	.939 ± .043	.839 ± .067	.884 ± .038
	AVG_COS_SIM	+TF +IDF	.520	Description	.870 ± .068	.834 ± .048	.849 ± .038
TOP_n_COS_SIM_AVG	Google	+TF +IDF	.545	Both	.915 ± .040	.938 ± .047	.926 ± .038
	Google	+TF -IDF	.345/22	Label	.854 ± .077	.861 ± .044	.856 ± .054
	GloVe	+TF +IDF	.345/6	Description	.799 ± .063	.766 ± .094	.780 ± .068
	fastText	+TF +IDF	.310/14	Both	.850 ± .059	.918 ± .049	.881 ± .037

Table 3: Test Data Results

input.⁸ This is the more important as we exclusively employ off-the-shelf, general-purpose embeddings, while Gong et al. (2018) reach their best results with a much more sophisticated system and with embeddings that were custom-trained for the science domain. Thus, while the performance of our proposed TOP_n_COS_SIM_AVG method is superior to the approach by Gong et al. (2018), it is itself outperformed by the ‘baseline’ AVG_COS_SIM method with appropriate weighting. However, apart from raw classification performance, our method also aims at providing human-interpretable information on how a classification was done. In the next section, we perform a detail analysis on a selected setup.

5 Detail Analysis

The similarity-labelled word pairs from concept and project description which are selected during classification with the TOP_n_COS_SIM_AVG measure provide a way to qualitatively evaluate the basis on which each similarity score was computed. We see this as an advantage over average-based comparison (like AVG_COS_SIM), since it provides a means to check the plausibility of the decision. Here, we are mainly interested in the overall best result, so we perform a detail analysis on the best-performing **Both** setting only (fastText, TF*IDF weighting, $T = .310$, $n = 14$). Since the *Concept-Project matching* task is a binary classification task, its performance can be qualitatively analysed by providing examples for instances that were classified correctly (True Positive (TP) and True Negative (TN)) or incorrectly (False Positive (FP) and False Negative (FN)).

Table 5 shows the concept and project words from selected instances (one TP, FP, TN, and FN case each) of the tuning data set. Concept and project words are ordered alphabetically, with concept words appearing more than once being grouped together. According to the selected setting, the number of word pairs is $n = 14$. The bottom line in each column provides the average similarity score as computed by the TOP_n_COS_SIM_AVG measure. This value is compared against the threshold $T = .310$. The similarity is higher than T in the TP and FP cases, and lower otherwise. Without going into too much detail, it can be seen that the selected words provide a reasonable idea of the gist of the two documents. Another observation relates to the effect of using unstemmed, case-sensitive documents as input: the top-ranking words often contain inflectional variants (e.g. *enzyme* and *enzymes*, *level* and *levels* in the example), and words differing in case only can also be found. Currently, these are treated as distinct (though semantically similar) words, mainly out of compatibility with the pretrained GloVe and Google embeddings. However, since our method puts a lot of emphasis on individual words, in particular those coming from the shorter of the two documents (the *concept*), results might be improved by somehow merging these words (and their respective embedding vectors) (see Section 7).

6 Related Work

While in this paper we apply our method to the *Concept-Project matching* task only, the underlying task of matching text sequences to each other is much more general. Many existing approaches follow

⁸Remember that this setup was only minimally superior (.001 F score) to the next best one on the tuning data.

TP (.447 > .310)			FP (.367 > .310)			TN (.195 < .310)			FN (.278 < .310)		
Concept Word	Project Word	Sim	Concept Word	Project Word	Sim	Concept Word	Project Word	Sim	Concept Word	Project Word	Sim
cells	enzymes	.438	co-evolution	dynamic	.299	energy	allergy	.147	area	water	.277
cells	genes	.427	continual	dynamic	.296	energy	juice	.296	climate	water	.269
molecules	DNA	.394	delicate	detail	.306	energy	leavening	.186	earth	copper	.254
molecules	enzyme	.445	delicate	dynamic	.326	energy	substitutes	.177	earth	metal	.277
molecules	enzymes	.533	delicate	texture	.379	surface	average	.212	earth	metals	.349
molecules	gene	.369	dynamic	dynamic	1.00	surface	baking	.216	earth	water	.326
molecules	genes	.471	dynamic	image	.259	surface	egg	.178	extent	concentration	.266
multiple	different	.550	dynamic	range	.377	surface	leavening	.158	range	concentration	.255
organisms	enzyme	.385	dynamic	texture	.310	surface	thickening	.246	range	ppm	.237
organisms	enzymes	.512	surface	level	.323	transfer	baking	.174	systems	metals	.243
organisms	genes	.495	surface	texture	.383	transfer	substitute	.192	systems	solution	.275
organs	enzymes	.372	surface	tiles	.321	transfer	substitutes	.157	typical	heavy	.299
tissues	enzymes	.448	systems	dynamic	.272	warms	baking	.176	weather	heavy	.248
tissues	genes	.414	systems	levels	.286	warms	thickening	.214	weather	water	.308
Avg. Sim .447			Avg. Sim .367			Avg. Sim .195			Avg. Sim .278		

Table 4: **TOP_n_COS_SIM_AVG** Detail Results of Best-performing fastText Model on **Both**.

the so-called *compare-aggregate* framework (Wang and Jiang (2017)). As the name suggests, these approaches collect the results of element-wise matchings (*comparisons*) first, and create the final result by aggregating these results later. Our method can be seen as a variant of *compare-aggregate* which is characterized by extremely simple methods for comparison (cosine vector similarity) and aggregation (averaging). Other approaches, like He and Lin (2016) and Wang and Jiang (2017), employ much more elaborated supervised neural networks methods. Also, on a simpler level, the idea of averaging similarity scores (rather than scoring averaged representations) is not new: Camacho-Collados and Navigli (2016) use the average of pairwise word similarities to compute their *compactness score*.

7 Conclusion and Future Work

We presented a simple method for semantic matching of documents from heterogeneous collections as a solution to the *Concept-Project matching* task by Gong et al. (2018). Although much simpler, our method clearly outperformed the original system in most input settings. Another result is that, contrary to the claim made by Gong et al. (2018), the standard averaging approach does indeed work very well even for heterogeneous document collections, if appropriate weighting is applied. Due to its simplicity, we believe that our method can also be applied to other text matching tasks, including more ‘standard’ ones which do not necessarily involve **heterogeneous** document collections. This seems desirable because our method offers additional transparency by providing not only a similarity score, but also the subset of words on which the similarity score is based. Future work includes detailed error analysis, and exploration of methods to combine complementary information about (grammatically or orthographically) related words from word embedding resources. Also, we are currently experimenting with a pretrained ELMo (Peters et al. (2018)) model as another word embedding resource. ELMo takes word embeddings a step further by dynamically creating *contextualized* vectors from input word sequences (normally sentences). Our initial experiments have been promising, but since ELMo tends to yield *different*, context-dependent vectors for the *same* word in the *same* document, ways have still to be found to combine them into single, document-wide vectors, without (fully) sacrificing their context-awareness.

The code used in this paper is available at <https://github.com/nlpATHits/TopNCosSimAvg>.

Acknowledgements The research described in this paper was funded by the Klaus Tschira Foundation. We thank the anonymous reviewers for their useful comments and suggestions.

References

- Al-Rfou, R., B. Perozzi, and S. Skiena (2013, August). Polyglot: Distributed word representations for multilingual nlp. In *Proceedings of the Seventeenth Conference on Computational Natural Language Learning*, Sofia, Bulgaria, pp. 183–192. Association for Computational Linguistics.
- Blei, D. M., A. Y. Ng, and M. I. Jordan (2003). Latent dirichlet allocation. *Journal of Machine Learning Research* 3, 993–1022.
- Blooma, M. J. and J. C. Kurian (2011). Research issues in community based question answering. In P. B. Seddon and S. Gregor (Eds.), *Pacific Asia Conference on Information Systems, PACIS 2011: Quality Research in Pacific Asia, Brisbane, Queensland, Australia, 7-11 July 2011*, pp. 29. Queensland University of Technology.
- Bojanowski, P., E. Grave, A. Joulin, and T. Mikolov (2017). Enriching word vectors with subword information. *TACL* 5, 135–146.
- Camacho-Collados, J. and R. Navigli (2016). Find the word that does not belong: A framework for an intrinsic evaluation of word vector representations. In *Proceedings of the 1st Workshop on Evaluating Vector-Space Representations for NLP, RepEval@ACL 2016, Berlin, Germany, August 2016*, pp. 43–50. Association for Computational Linguistics.
- Deerwester, S. C., S. T. Dumais, T. K. Landauer, G. W. Furnas, and R. A. Harshman (1990). Indexing by latent semantic analysis. *JASIS* 41(6), 391–407.
- Feng, M., B. Xiang, M. R. Glass, L. Wang, and B. Zhou (2015). Applying deep learning to answer selection: A study and an open task. In *2015 IEEE Workshop on Automatic Speech Recognition and Understanding, ASRU 2015, Scottsdale, AZ, USA, December 13-17, 2015*, pp. 813–820. IEEE.
- Gong, H., T. Sakakini, S. Bhat, and J. Xiong (2018). Document similarity for texts of varying lengths via hidden topics. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 2341–2351. Association for Computational Linguistics.
- Grave, E., P. Bojanowski, P. Gupta, A. Joulin, and T. Mikolov (2018). Learning word vectors for 157 languages. In N. Calzolari, K. Choukri, C. Cieri, T. Declerck, S. Goggi, K. Hasida, H. Isahara, B. Maegaard, J. Mariani, H. Mazo, A. Moreno, J. Odijk, S. Piperidis, and T. Tokunaga (Eds.), *Proceedings of the Eleventh International Conference on Language Resources and Evaluation, LREC 2018, Miyazaki, Japan, May 7-12, 2018*. European Language Resources Association (ELRA).
- He, H. and J. J. Lin (2016). Pairwise word interaction modeling with deep neural networks for semantic similarity measurement. In K. Knight, A. Nenkova, and O. Rambow (Eds.), *NAACL HLT 2016, The 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, San Diego California, USA, June 12-17, 2016*, pp. 937–948. The Association for Computational Linguistics.
- Kusner, M. J., Y. Sun, N. I. Kolkin, and K. Q. Weinberger (2015). From word embeddings to document distances. In F. R. Bach and D. M. Blei (Eds.), *Proceedings of the 32nd International Conference on Machine Learning, ICML 2015, Lille, France, 6-11 July 2015*, Volume 37 of *JMLR Workshop and Conference Proceedings*, pp. 957–966. JMLR.org.
- Le, Q. V. and T. Mikolov (2014). Distributed representations of sentences and documents. In *Proceedings of the 31th International Conference on Machine Learning, ICML 2014, Beijing, China, 21-26 June 2014*, Volume 32 of *JMLR Workshop and Conference Proceedings*, pp. 1188–1196. JMLR.org.
- Mikolov, T., I. Sutskever, K. Chen, G. S. Corrado, and J. Dean (2013). Distributed representations of words and phrases and their compositionality. In *Proceedings of Advances in Neural Information Processing Systems 26*. Lake Tahoe, Nev., 5–8 December 2013, pp. 3111–3119.

Müller, M. and M. Strube (2018). Transparent, efficient, and robust word embedding access with WOMBAT. In D. Zhao (Ed.), *COLING 2018, The 27th International Conference on Computational Linguistics: System Demonstrations, Santa Fe, New Mexico, August 20-26, 2018*, pp. 53–57. Association for Computational Linguistics.

Pennington, J., R. Socher, and C. D. Manning (2014). Glove: Global vectors for word representation. In A. Moschitti, B. Pang, and W. Daelemans (Eds.), *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing, EMNLP 2014, October 25-29, 2014, Doha, Qatar, A meeting of SIGDAT, a Special Interest Group of the ACL*, pp. 1532–1543. ACL.

Peters, M. E., M. Neumann, M. Iyyer, M. Gardner, C. Clark, K. Lee, and L. Zettlemoyer (2018). Deep contextualized word representations. In M. A. Walker, H. Ji, and A. Stent (Eds.), *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT 2018, New Orleans, Louisiana, USA, June 1-6, 2018, Volume 1 (Long Papers)*, pp. 2227–2237. Association for Computational Linguistics.

Wang, S. and J. Jiang (2017). A compare-aggregate model for matching text sequences. In *5th International Conference on Learning Representations, ICLR 2017, Toulon, France, April 24-26, 2017, Conference Track Proceedings*. OpenReview.net.