A Comprehensive Analysis of PMI-based Models for Measuring Semantic Differences

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Abstract

The task of detecting words with semantic differences across corpora is mainly addressed by word representations such as word2vec or BERT. However, in the real world where linguists and sociologists apply these techniques, computational resources are typically limited. In this paper, we extend an existing simultaneously optimized model that can be trained on CPU to perform this task. Experimental results show that the extended models achieved comparable or superior results to strong baselines in English corpora and SemEval-2020 Task 1, and also in Japanese. Furthermore, we compared the training time of each model and conducted a comprehensive analysis of Japanese corpora.[1]

1 Introduction

Words can have different meanings at different times and domains. For example, the word *meat* means *food* in Old English but *animal meat* in Modern English; the word *interface* means a *boundary surface*, but in the domain of computer science, it means *software that allows users to communicate with computers*. The task of detecting words with semantic differences provides significant insights into human language (Kutuzov et al., 2018); for instance, linguists often discuss the semantic differences between words in different corpora, such as written and spoken Japanese (Fujimura et al., 2012), British and American English (Lei and Liu, 2014), native speakers and learners of English (McEnery et al., 2019), or web-crawled and traditional corpora in Czech (Cvrček et al., 2020). Automatic methods can facilitate such analyses comprehensively, and can also help lexicographers describe when and how the meanings of words change substantially.

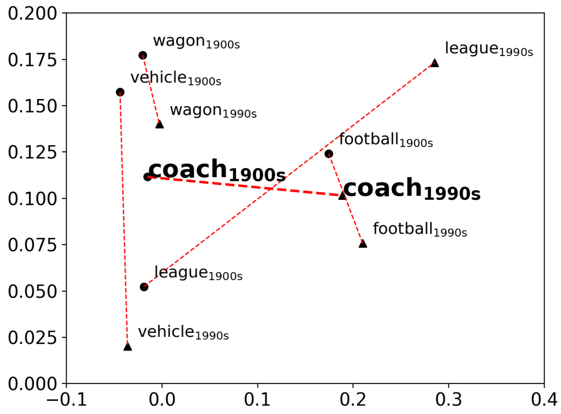


Figure 1: Diachronic differences in the meaning of *coach* and its neighbors, identified by our extended model.

Recent progress in representation learning has provided a useful tool for finding semantic differences in words, known as word embeddings. Figure 1 shows an example of the two-dimensional word embedding space. In this figure, $\overrightarrow{coach}_{1900s}$ and $\overrightarrow{coach}_{1990s}$ are shown in the learned vector space. The shift in the meaning of the word *coach* can be analyzed from the distance between $\overrightarrow{coach}_{1900s}$ and $\overrightarrow{coach}_{1990s}$. Such embeddings are often obtained by training word vectors independently from the corpora of the 1900s and the 1990s, and then aligning them (Kim et al., 2014; Kulkarni et al., 2015; Hamil-

[1] The source code is available at `https://github.com/a1da4/pmi-semantic-difference`

ton et al., 2016). These alignment-based methods learn distributional semantic models efficiently because they use non-contextual word representations, such as word2vec (Mikolov et al., 2013). Thus, researchers can easily introduce them without abundant computational resources (Sommerauer and Fokkens, 2019; Zimmermann, 2019). However, alignment-based methods are based on the strong assumption that they align word representations from different time periods or domains linearly to one another. Recent studies have proposed alignment-independent methods (Yao et al., 2018; Dubossarsky et al., 2019), but existing approaches to this task involve the following problems.

First, one of the alignment-independent methods requires an extensive hyperparameter search. Yao et al. (2018) proposed a model that did not assume linear alignments based on simultaneous learning of word representations. However, as shown later, it includes three sensitive hyperparameters that need to be tuned, which incurs a complex combinatorial optimization problem.

Second, a properly chosen list of target words is not available in a realistic scenario. Dubossarsky et al. (2019) proposed a simultaneously optimized word representation that overcame the abovementioned problems with another simple but not necessarily correct assumption that words other than the target word do not change over time. This model, called Temporal Referencing, is easy to train on CPU without any assumptions on linear transformations, and without an extensive hyperparameter search. However, in the real world, linguists and sociologists may not have a well-selected list of target words.

Third, only a few studies have quantitatively compared each method (Schlechtweg et al., 2019; Shoemark et al., 2019; Tsakalidis and Liakata, 2020; Schlechtweg et al., 2020). The comparisons have been mainly conducted in European languages such as English or German; only a few studies have evaluated these methods in multiple languages (Schlechtweg et al., 2020) due to the lack of evaluation data. In these analyses, many studies cite target words whose meanings have clearly changed, such as the well-known semantic shift of the word *gay* (Kim et al., 2014; Kulkarni et al., 2015; Hamilton et al., 2016; Hu et al., 2019). However, few studies have focused on semantic changes of more ordinary words (Gonen et al., 2020).

In this paper, we address these issues. For the first two problems, we modified Temporal Referencing. We first considered all the words in the vocabulary as the target words, to reflect more realistic scenarios. We then proposed an extended model that allows context vectors to change across corpora. For the third problem, we conducted a quantitative comparison between the extended method and strong baselines not only in English and SemEval-2020 Task 1 (Schlechtweg et al., 2020), but also in Japanese. In the experiments, we compared the task performance and training time of each model. To address the lack of evaluation data, we used pseudo words whose meanings were artificially changed (Rosenfeld and Erk, 2018; Shoemark et al., 2019). In the analyses, we focused on ordinary words as well as words with well-known semantic shifts in Japanese.

The contributions of this paper are as follows.

- We extend the existing simultaneously optimized model that can be trained on CPU regarding the real situation.
- Experiments on multiple languages using actual or pseudo-words show that the extended methods learn faster and perform similar to or better than strong baselines.
- We conduct comprehensive analyses, and the experimental results demonstrate that the extended method achieves better results for words with well-known semantic shifts, and detects semantic differences between corpora for words that are not widely known.

2 Related Work

Semantic differences are often detected by comparing word frequencies between corpora (Fujimura et al., 2012; Lei and Liu, 2014; McEnery et al., 2019; Cvrček et al., 2020); however, manually checking all text to be processed is not a straightforward or facile task. Therefore, several automatic methods have been proposed to detect semantic differences across times or domains.

Several studies have been conducted to detect synchronic differences using data from social media. Zhao et al. (2011) compared Twitter and traditional media based on topic modeling. Aoki et al. (2017) used word2vec as a language model to detect non-standard usages from context words in web corpora. Gonen et al. (2020) proposed a metric that compared the nearest neighbors of each target word vector and analyzed the differences in word usage of different age groups on social media. Here, we focus on methods that capture diachronic meaning differences.

2.1 Non-contextual word embeddings

The task of detecting diachronic semantic difference refers to the task of finding words that have different meanings in corpora with different time periods (e.g., SemEval-2020 Task 1). A standard approach involves the comparison of the vectors of the same word over different time periods (e.g., $\overrightarrow{coach}_{1900s}$ and $\overrightarrow{coach}_{1990s}$ in Figure 1).

Early studies on this task often used count-based methods to obtain word vectors for each time period (Sagi et al., 2009; Cook and Stevenson, 2010; Gulordava and Baroni, 2011). However, count-based methods cannot directly model word meanings. Mikolov et al. (2013) proposed word2vec, which solved the abovementioned problem by embedding word meanings into a vector space. To detect semantic difference between corpora, the vector spaces for each corpus must be aligned with one another. For this purpose, Kim et al. (2014) proposed to set the initial word vectors at time t to the corresponding word vectors learned from the corpus for time $t-1$ to train a word2vec model at time t. Then, Kulkarni et al. (2015) and Hamilton et al. (2016) proposed alignment methods with a linear transformation and a rotation, respectively. For each target word w, Kulkarni et al. (2015) used a linear transformation $\mathbf{R}(w)_{t\mapsto t+1}$ to align a target word vector $\mathbf{W}_t(w)$ to an adjacent vector space $\mathbf{W}_{t+1}(w)$. $\mathbf{R}(w)_{t\mapsto t+1}$ was obtained by solving a piecewise linear regression among $\mathbf{W}_t(w)$'s k-nearest neighbors k-NN$(\mathbf{W}_t(w))$:

$$\mathbf{R}(w)_{t\mapsto t+1} = \operatorname*{argmin}_{\mathbf{R}} \sum_{s \,\in\, k\text{-NN}(\mathbf{W}_t(w))} ||\mathbf{W}_t(s)\mathbf{R} - \mathbf{W}_{t+1}(s)||_F^2, \tag{1}$$

where $||\cdot||_F$ is the Frobenius norm. Conversely, Hamilton et al. (2016) introduced a rotation matrix $\mathbf{R}_{t\mapsto t+1}$ to map word representations $\mathbf{W}_t$ to $\mathbf{W}_{t+1}$, which was obtained by solving the orthogonal procrustes problem:

$$\mathbf{R}_{t\mapsto t+1} = \operatorname*{argmin}_{\mathbf{R}:\ \mathbf{R}\mathbf{R}^{\mathsf{T}}=1} ||\mathbf{W}_t\mathbf{R} - \mathbf{W}_{t+1}||_F^2. \tag{2}$$

Alignment-based methods have achieved improved performance compared to count-based methods (Schlechtweg et al., 2019). However, they are based on a strong assumption that word representations are linearly aligned with one another, which might not hold in the actual situations.

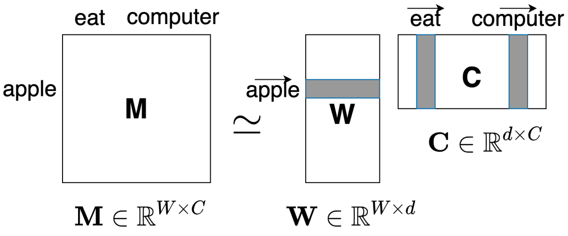
By contrast, Yao et al. (2018) proposed a model called Dynamic Word Embeddings (DWE) that relaxed the constraint of linear alignment. They did not use any transformations for learning word representations across time periods. Instead, they were learned simultaneously. The word representations $\mathbf{W}_t$ were obtained by minimizing the following objective function using context representations $\mathbf{C}_t$ and word-context positive pointwise mutual information (PMI) matrices $\mathbf{M}_t$:

$$\begin{aligned} &\frac{1}{2}\sum_{t=1}^{T} ||\mathbf{M}_t - \mathbf{W}_t\mathbf{C}_t||_F^2 + \frac{\gamma}{2}\sum_{t=1}^{T} ||\mathbf{W}_t - \mathbf{C}_t^{\mathsf{T}}||_F^2 \\ &+ \frac{\lambda}{2}\sum_{t=1}^{T} ||\mathbf{W}_t||_F^2 + \frac{\tau}{2}\sum_{t=1}^{T-1} ||\mathbf{W}_{t+1} - \mathbf{W}_t||_F^2 \\ &+ \frac{\lambda}{2}\sum_{t=1}^{T} ||\mathbf{C}_t||_F^2 + \frac{\tau}{2}\sum_{t=1}^{T-1} ||\mathbf{C}_{t+1} - \mathbf{C}_t||_F^2, \end{aligned} \tag{3}$$

where γ, λ, and τ are hyperparameters. The parameters γ and τ control the strengths of alignments, and λ controls the strength of regularization. This model assumes that the vectors of the same word in the same time period $(\mathbf{W}_t, \mathbf{C}_t^{\mathsf{T}})$ were close; the vectors of the same word at adjacent time points $(\mathbf{W}_t, \mathbf{W}_{t+1})$, $(\mathbf{C}_t, \mathbf{C}_{t+1})$ were also close. Therefore, the model was sensitive to hyperparameters, and an extensive hyperparameter search was required.

2.2 Contextual word embeddings

Contextual word embeddings, such as BERT (Devlin et al., 2019), can also be used for the task of semantic difference detection. However, methods based on contextual word embeddings have been reported to exhibit lower performance than those based on non-contextual word embeddings in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$\mathbf{W} \in \mathbb{R}^{W \times d}$

Figure 2: Overview of PMI-SVD (Levy and Goldberg, 2014) that acquires a word representation $\mathbf{W}$ from the matrix factorization of a PMI matrix by SVD.

the SemEval-2020 Task 1 (Kutuzov and Giulianelli, 2020; Martinc et al., 2020b). Contextual word embeddings are mainly used for polysemous word analysis over time, which cannot be performed using non-contextual word embeddings. Hu et al. (2019) trained each usage-level vector of each word from example sentences in a dictionary using BERT. They tracked each sense of polysemous words, such as *gay*, which can mean either *carefree* or *homosexual* depending on context. Instead of using dictionaries, Giulianelli et al. (2020) performed *k*-means clustering on all token-level vectors obtained by BERT. Their method also provided semantic transitions of polysemous words without any lexicographic supervision.

3 Method: Jointly Optimized Word Representations

Base idea: Temporal Referencing As described in Section 2.1, existing methods involve two problems. First, alignment-based methods (Equations (1) and (2)) are based on the strong assumption that word representations from different periods or domains can be linearly aligned to one another. Second, DWE (Equation (3)) incurs optimizing combinatorial number of its hyperparameters. To address these problems, Dubossarsky et al. (2019) proposed a jointly optimized word representation called Temporal Referencing. This method is based on an assumption that words other than the target word do not change over time. Given a target word list $L = \{w^1, w^2, ..., w^{|L|}\}$, the authors trained a model by distinguishing the target words over time $\{w^i_1, ..., w^i_t, ..., w^i_T | w^i \in L\}$. However, in the real world, there is often no list of well-chosen target words. In this paper, we propose two extensions to Temporal Referencing: (1) considering all words in the vocabulary as target words, and (2) allowing context vectors to change across corpora.

Base model: PMI-SVD We first explain the underlying model introduced by Levy and Goldberg (2014). They show that the model of skip-grams with negative sampling (SGNS) (Mikolov et al., 2013) is equivalent to the factorization of a matrix consisting of PMI between each word and its surrounding context words, as shown in Figure 2. Let $p(w)$, $p(c)$, and $p(w, c)$ denote empirical probabilities of word w, context word c, and their cooccurrence, respectively. Word representations can be learned as follows. First, a PMI matrix[2] $\mathbf{M} \in \mathbb{R}^{W \times C}$ (W and C indicate the total numbers of target words and context words, respectively) is computed.

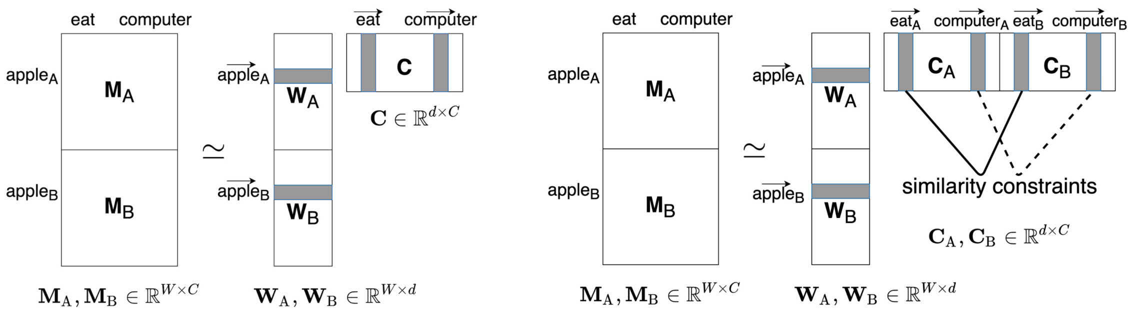
$$\mathrm{M}[w, c] = \max\left(\log \frac{p(w, c)}{p(w)p(c)}, 0\right) \tag{4}$$

Then, $\mathbf{M}$ is decomposed as $\mathbf{M} = \mathbf{U\Sigma V}^\mathsf{T}$ through singular value decomposition (SVD), where $\mathbf{U}$ and $\mathbf{V}$ are orthogonal matrices, and $\mathbf{\Sigma}$ is a diagonal matrix consisting of singular values of $\mathbf{M}$. Based on this factorization, a d-dimensional matrix $\mathbf{W} \in \mathbb{R}^{W \times d}$ of word vectors and a matrix $\mathbf{C} \in \mathbb{R}^{d \times C}$ of context vectors are obtained by $\mathbf{M} = \mathbf{WC}$ as shown in Figure 2, where $\mathbf{W}$ and $\mathbf{C}$ are computed by $\mathbf{W} = \mathbf{U\Sigma}^{1/2}$ and $\mathbf{C} = \mathbf{\Sigma}^{1/2}\mathbf{V}^\mathsf{T}$.

PMI-SVD$_{\text{joint}}$: To modify Temporal Referencing, we consider all words in the vocabulary as target words. We assume that the context vectors represented by each column in $\mathbf{C}$ are fixed across corpora A and B, in line with the existing approach. Based on this assumption, we can perform matrix factorization on $\mathbf{M} = [\mathbf{M}_\mathrm{A}; \mathbf{M}_\mathrm{B}]$, which are vertically stacked PMI matrices $\mathbf{M}_\mathrm{A}$ and $\mathbf{M}_\mathrm{B}$ for corpora A and B (Figure 3(a)).

$$\begin{bmatrix}\mathbf{M}_\mathrm{A}\\ \mathbf{M}_\mathrm{B}\end{bmatrix} = \begin{bmatrix}\mathbf{W}_\mathrm{A}\\ \mathbf{W}_\mathrm{B}\end{bmatrix}\begin{bmatrix}\mathbf{C}\end{bmatrix}. \tag{5}$$

[2] SGNS has been shown to be equivalent to a shifted version of PMI. However, because Levy et al. (2015) showed that it had no performance benefit in the case of PMI matrix factorization, we simply discarded the shift and used the original PMI.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$\mathbf{C}$
$\mathbf{C} \in \mathbb{R}^{d\times C}$
$\mathbf{M}_\mathrm{A}, \mathbf{M}_\mathrm{B} \in \mathbb{R}^{W\times C}$
$\mathbf{W}_\mathrm{A}, \mathbf{W}_\mathrm{B} \in \mathbb{R}^{W\times d}$
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$\overrightarrow{\text{computer}}_B$
$\mathbf{C}_A$
$\mathbf{C}_B$
similarity constraints
$\mathbf{C}_\mathrm{A}, \mathbf{C}_\mathrm{B} \in \mathbb{R}^{d\times C}$

(a) PMI-SVD$_{\text{joint}}$

(b) PMI-SVD$_c$

Figure 3: Overview of the slightly modified Temporal Referencing (Dubossarsky et al., 2019) (left) and the extended model (right). They acquired word representations $\mathbf{W}_\mathrm{A}$ and $\mathbf{W}_\mathrm{B}$ for each corpus using the matrix factorization of PMI matrices by SVD.

PMI-SVD$_c$: The method introduced above is based on the assumption that context word vectors remain unchanged across corpora. We relax this assumption to propose a model that allows the vectors of context words to change, as in Figure 3(b). In contrast to PMI-SVD$_{\text{joint}}$, context representations $\mathbf{C}_\mathrm{A}$ and $\mathbf{C}_\mathrm{B}$ are also computed in the decomposition of the stacked PMI matrix $\mathbf{M}$. One straightforward method to obtain word and context embeddings is to factorize $\mathbf{M}_y$ in each corpus y. However, the word vectors obtained for different corpora would not correspond to each other. Hence, we added an additional constraint that the context representations of adjacent corpora are close to each other. Therefore, the objective function used to obtain word representations $\mathbf{W}_y$ is as follows:

$$\sum_{y\in\{A,B\}} \|\mathbf{M}_y - \mathbf{W}_y\mathbf{C}_y\|_F + \tau\|\mathbf{C}_\mathrm{B} - \mathbf{C}_\mathrm{A}\|_F, \quad (6)$$

where τ is the only hyperparameter that controls the strength of the constraint. This model seems close to DWE, but our model has only one hyperparameter, whereas DWE has three hyperparameters with an exponential number of combinations. Moreover, we show later that PMI-SVD$_c$ achieved the same or better performance experimentally than DWE, yet it runs several orders of magnitude faster than DWE.

4 Preliminary Experiment: Detecting Semantic Change from a List of Words

We performed the SemEval-2020 Task 1 using PMI-SVD$_c$. The SemEval-2020 Task 1 has two subtasks: one is a binary classification task that detects whether or not the meanings of target words have changed, and the other is a ranking task that sorts the target words by the degree of change in meaning. Classification was evaluated by accuracy, and ranking was evaluated using the Spearman's rank correlation coefficient. For overall performance, the average over the four languages (English, German, Latin, and Swedish) were evaluated.

Task		Oracle	PMI-SVD$_c$	
Classification (Accuracy)	Avg	0.713	0.645	(5)
	En	0.676	0.649	(4)
	De	0.750	0.667	(10)
	La	0.650	0.650	(4)
	Sv	0.774	0.613	(16)
Ranking (Spearman)	Avg	N/A	0.433	(6)
	En	N/A	0.424	(2)
	De	N/A	0.597	(9)
	La	N/A	0.328	(10)
	Sv	N/A	0.328	(11)

Table 1: Results for the extended model PMI-SVD$_c$ in the SemEval-2020 Task 1. Oracle used an optimal threshold for classification in each language.

In our models for SemEval-2020 Task 1, we mainly used the cosine similarity between two time periods of each target word. For classification, we used the average cosine similarity of the target words as the threshold for each language. We used the optimal threshold for classification in each language as an oracle, similarly to previous reports that used a test set to adjust hyperparameters. For ranking, the target words were ranked in ascending order of the cosine similarity.

From Table 1, we confirmed that our model worked consistently across the four languages. At the oracle, the model was able to achieve high performance, with an average score of 0.713.

5 Experiments: Detecting Semantic Change from All Words

In this section, we describe the experimental setup and results of quantitative and qualitative evaluations performed on English and Japanese.

5.1 Data and preprocessing

English: We used the Corpus of Historical American English (COHA)[3]. We selected documents from the 1900s and 1990s. After removing stopwords and proper nouns, we chose nouns, verbs, adjectives, and adverbs that appeared more than 100 times in both documents, following (Hamilton et al., 2016). We regarded the chosen words as target words.

Japanese: We used the Corpus of Historical Japanese (CHJ) and the Showa-Heisei Corpus of Written Japanese[4]. We merged these two corpora and split them into two periods based on World War II because the Japanese language has changed significantly since that war. Target words were selected similar to the experiments in English.

5.2 Models

We compared the model with minor modifications (PMI-SVD$_{\mathrm{joint}}$) and our extended model (PMI-SVD$_c$) with the following previous methods. For all non-contextual word representations, we used a window size of 4, 100 dimensions, and contextual distributional smoothing of 0.75. Then, we performed a post-processing called all-but-the-top (Mu and Viswanath, 2018) simultaneously for the representation of each period (Kaiser et al., 2021).

Word2Vec$_{\mathbf{align}}$ (Hamilton et al., 2016): We trained word2vec SGNS models on different time periods separately. Then, we aligned these models with a rotation matrix using Equation (2).

PMI-SVD$_{\mathbf{align}}$ (Hamilton et al., 2016): We trained PMI-SVD models instead. Subsequently, these models were aligned similarly with Word2Vec$_{\mathrm{align}}$.

DWE (Yao et al., 2018): In line with a previous study, we minimized Equation (3) with block coordinate descent to obtain word representations. To find the best setting for this model and PMI-SVD$_c$, a grid search was performed out of seven values 10^x, $-3 \leq x \leq 3$ for each hyperparameter by taking the hyperparameters with the highest AUC.

BERT (Martinc et al., 2020a): Target word vectors in each period were obtained by averaging usage-level vectors computed by a BERT model. For both languages, we used pre-trained *bert-base-uncased* models published in the Huggingface[5].

5.3 Evaluation

To evaluate the proposed approach, we computed the mean reciprocal rank (MRR) (Kulkarni et al., 2015; Yao et al., 2018). Each model first ranked all words in the vocabulary in ascending order of the cosine similarity between the two periods. Subsequently, MRR is computed as the average of the inverse of the rank of each word in a reference list that contains words with known semantic change. The Spearman's rank correlation coefficient used in SemEval-2020 Task 1 could not be used because the evaluation lists of the words were not annotated with the degree of semantic change.

To visualize the detection of words with changed meanings in the reference list, we calculated the recall with top-k words and a reference list called Recall@k (Kulkarni et al., 2015).

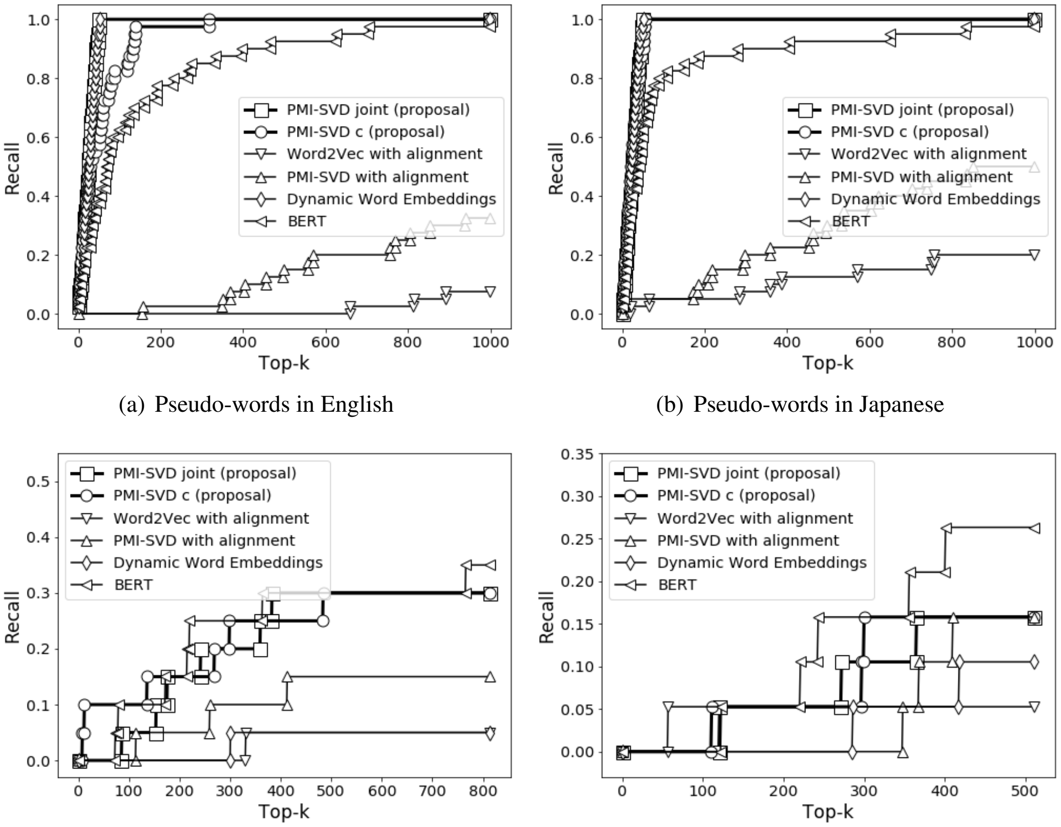
5.4 Quantitative results on pseudo-words

Settings For a theoretical investigation, we generated words with semantic changes artificially, similar to Shoemark et al. (2019). The pseudo-word α, whose meaning changes from α to β, was generated following by replacing of all occurrences of the word β in the last time period with α and deleting the original occurrence. In this paper, we randomly sampled 50 pairs of words whose absolute cosine similarity of word vectors was 0.01 or less in both periods. We used 10 words for the hyperparameter search and the rest for evaluations.

[3] https://www.english-corpora.org/coha/

[4] https://ccd.ninjal.ac.jp/chj/overview-en.html

[5] https://github.com/huggingface/transformers



(a) Pseudo-words in English

(b) Pseudo-words in Japanese

(c) Actual words in English

(d) Actual words in Japanese

Figure 4: Plot of Recall@k for words that have changed semantically. For English and Japanese, reference lists of words with semantic changes (see text) were employed.

Models	English	Japanese
PMI-SVD$_{\text{joint}}$	**0.0933**	0.0737
PMI-SVD$_c$	0.0870	0.0781
Word2Vec$_{\text{align}}$	0.0004	0.0022
PMI-SVD$_{\text{align}}$	0.0010	0.0171
DWE	0.0835	**0.0913**
*BERT**	*0.0590*	*0.0776*

Table 2: Mean Reciprocal Rank (MRR) in pseudo-words. *Using external datasets in pre-training.

Models	English	Japanese	Time
PMI-SVD$_{\text{joint}}$	0.00186	0.00131	**2m58s**
PMI-SVD$_c$	**0.01045**	0.00120	26m01s
Word2Vec$_{\text{align}}$	0.00040	**0.00137**	6m22s
PMI-SVD$_{\text{align}}$	0.00100	0.00091	3m26s
DWE	0.00047	0.00058	30h20m
*BERT**	*0.00250*	*0.00163*	2h23m
BERT-tiny	0.00100	0.00078	12days
BERT-mini	0.00135	0.00119	2weeks

Table 3: Mean Reciprocal Rank (MRR) in actual words. The time indicates the training time for each model in the English experiment. BERT models (BERT-tiny, BERT-mini) were trained from scratch using diachronic corpora. *Using external datasets in pre-training.

The extended methods vs. baselines Figures 4(a) and 4(b) show the Recall@k of each language. Our models perfectly detected pseudo-words with semantic change in the reference list, as in DWE and BERT. These figures and MRR (Table 2) show that our models performed better than or comparable to the existing models.

Linear alignment The linear alignment (Hamilton et al., 2016) performed poorly in this experiment where the words were completely changed in meaning. Therefore, we conclude that the assumption that separately trained models can be aligned by a linear transformation is too strong.

	BERT		PMI-SVD$_c$	
rank	word	description	word	description
1	若く	comparable, young → young	行い	behavior → behavior, execute
2	触れ	fall, mention, violate → mention, touch	かねて	before → before, simultaneous
3	行い	behavior → behavior, execute	おまけ	in addition → in addition, discount
4	公明	fairness → [organization], fairness	無論	[adverb] → [adverb]
5	思い	thinking, emotion → thinking	年中	year around, officer → year around
6	削除	delete → delete	キー	music, [person] → music, key
7	在り	physical existence → conceptual existence	欠け	missing → lack
8	参議	participate → [organization]	皆無	nothing → nothing
9	欠け	missing → lack	馬場	[person], turf → [person], turf
10	幼稚	childish → kindergarten, childish	反面	opposite, while → while

Table 4: Top 10 actual words with the smallest cosine similarity that have changed semantically in Japanese. We excluded single-character words that are less meaningful.

5.5 Quantitative results on actual words

Settings Next, we evaluated each model using actual words. For English, we used the word sense change testset[6] for the hyperparameter search and the list of Kulkarni et al. (2015) for the evaluation. For Japanese, we used the list of words with semantic differences by Mabuchi and Ogiso (2021) for both the hyperparameter search and the evaluation.

Proposed methods vs. baselines The performance is shown in Figures 4(c) and 4(d), and Table 3. Overall, the results were worse than those obtained with the use of pseudo-words. According to these figures and MRR (Table 3), PMI-SVD$_c$ outperformed previous works with the exception of Word2Vec$_{\text{align}}$ and BERT in Japanese. In addition, Table 3 shows that PMI-SVD$_c$ is computationally more efficient than DWE and BERT[7].

Pre-training BERT from diachronic corpus We mainly used BERT-base models (12 layers, 768 hidden sizes) pre-trained with huge amounts of data. In this part, we trained BERT models from scratch with the diachronic corpora used in Section 5.1. Due to the small amount of diachronic corpora, the availability of which is limited, we trained BERT-tiny (2 layers, 128 hidden sizes) and BERT-mini (4 layers, 256 hidden sizes) models. Table 3 shows that our models perform better than BERT-tiny and BERT-mini when they were trained with the same amount of data. Moreover, our models required only minutes to hours to train on CPU, as opposed to BERT models, which require tremendous computational resources and more than two weeks to train from scratch.

5.6 Qualitative results

Top-10 words found by BERT and PMI-SVD$_c$ We compared the top-10 words with the highest degree of semantic differences sorted by the cosine similarity in each of BERT and the proposed method (PMI-SVD$_c$), which performed the best in a quantitative evaluation (Section 5.5). In Japanese, Table 4 shows that both methods included ordinary words with semantic differences like "行い (behavior)" and "欠け (missing)." In particular, BERT generally captured semantic-level differences, such as "若く (young)," "触れ (touch)," "在り (existence)," and "幼稚 (childish)," and PMI-SVD$_c$ captures syntactic-level differences such as "おまけ (in addition)" and "反面 (while)." This may be attributed to the difference in the window size; BERT creates a word vector from an entire sentence, whereas the proposed method creates a word vector from the information obtained from surrounding words.

Analyzing (non-)famous words Next, we compared neighbors of each word (Kim et al., 2014; Hamilton et al., 2016). Again, we compared BERT and PMI-SVD$_c$. We investigated a famous word "了解 (understand)" in the list of Mabuchi and Ogiso (2021) and the ordinary word "欠け (missing)" in Table 4. Tables 5(a) and 5(b) show the top-5 similar words, "了解" and "欠け," in the prewar and

[6] https://zenodo.org/record/495572

[7] The time was measured on a machine with 2 CPUs (Intel Xeon 2.60 GHz, with a total of 56 cores) and 512 GB of RAM.

(a) 了解 (*understand*→*consent*)

BERT		PMI-SVD$_c$	
prewar	postwar	prewar	postwar
承諾	承諾	理解	承諾
(consent)	(consent)	(understand)	(consent)
承知	承知	納得	承知
(consent)	(consent)	(understand)	(consent)
納得	承認	推測	納得
(understand)	(consent)	(estimation)	(understand)
理解	同意	判断	同意
(understand)	(agreement)	(decision)	(agreement)
断定	納得	断定	理解
(conclusion)	(understand)	(decision)	(understand)

(b) 欠け (*missing*→*lack*)

BERT		PMI-SVD$_c$	
prewar	postwar	prewar	postwar
マイナス	欠如	切り	有し
(minus)	(lack)	(cut)	(have)
決まり	乏しい	切ら	欠如
(rule)	(poor)	(cut)	(lack)
構え	不足	諦め	富ん
(posture)	(lack)	(give up)	(rich)
重み	崩れ	箸	づけ
(weight)	(collapse)	(fleeting)	(attach)
当て	破れ	つける	把握
(aim)	(tear)	(attach)	(grasp)

Table 5: Top-5 similar words for each period. We excluded single-character words that are less meaningful.

the postwar sets using BERT and PMI-SVD$_c$. First, considering the word "了解," both methods found words with the meanings *understand* ("納得 (understand)," and "理解 (understand)") in the prewar, and *consent* ("承諾 (consent)," "承知 (consent)," "承認 (consent)," and "同意 (agreement)") in the postwar (Table 5(a)). However, BERT found some words that have a meaning *consent* in the prewar ("承諾 (consent)" and "承知 (consent)"). Second, in the case of the word "欠け," both methods yielded words such as *missing* ("マイナス (minus)," "切り (cut)," or "切ら (cut)") in the prewar, and words meaning *lack* ("欠如 (lack)" and "不足 (lack)") in the postwar (Table 5(b)). From these results, PMI-SVD$_c$ detected differences in the meanings of words between corpora, even for word that are not widely known.

6 Conclusion

We have extended an existing simultaneously optimized method to address real-world situations in which there is no target word list or abundant computational resources are available for semantic change detection. For a theoretical investigation, we conducted quantitative evaluations to measure diachronic meaning differences with pseudo- and actual word lists in two languages. Experimental results show that our extended methods can be learned faster, required less hyperparameter search, and achieved better or comparable performances than strong baselines. In the future work, we plan to apply these models to different domains, such as books and social media datasets.

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