Autoencoding Word Representations through Time for Semantic Change Detection

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Abstract
Semantic change detection concerns the task of identifying words whose meaning has changed over time. The current state-of-the-art detects the level of semantic change in a word by comparing its vector representation in two distinct time periods, without considering its evolution through time. In this work, we propose three variants of sequential models for detecting semantically shifted words, effectively accounting for the changes in the word representations over time, in a temporally sensitive manner. Through extensive experimentation under various settings with both synthetic and real data we showcase the importance of sequential modelling of word vectors through time for detecting the words whose semantics have changed the most. Finally, we take a step towards comparing different approaches in a quantitative manner, demonstrating that the temporal modelling of word representations yields a clear-cut advantage in performance.

1 Introduction
Identifying words whose lexical meaning has changed over time is a primary area of research at the intersection of natural language processing and historical linguistics. Through the evolution of language, the task of “semantic change detection” (Tang, 2018) can provide valuable insights on cultural evolution over time (Michel et al., 2011). Measuring linguistic change more broadly is also relevant to understanding the dynamics in online communities (Danescu-Niculescu-Mizil et al., 2013) and the evolution of individuals, e.g. in terms of their expertise (McAuley and Leskovec, 2013). Recent years have seen a surge in interest in this area since researchers are now able to leverage the increasing availability of historical corpora in digital form and develop algorithms that can detect the shift in a word’s meaning through time.

However, two key challenges in the field still remain. (a) Firstly, there is little work in existing literature on model comparison (Schlechtweg et al., 2019; Dubossarsky et al., 2019; Shoemark et al., 2019). Partially due to the lack of labelled datasets, existing work assesses model performance primarily in a qualitative manner, without comparing results against prior work in a quantitative fashion. Therefore, it becomes impossible to assess what constitutes an appropriate approach for semantic change detection. (b) Secondly, on a methodological front, a large body of related work detects semantically shifted words by pairwise comparisons of their representations in distinct periods in time, ignoring the sequential modelling aspect of the task (Hamilton et al., 2016; Tsakalidis et al., 2019). Since semantic change is a time-sensitive process (Tsakalidis et al., 2019), considering intermediate vector representations in consecutive time periods can be crucial to improving model performance (Shoemark et al., 2019). This type of modelling approach is very different from considering changes between two distinct bins of word representations (Schlechtweg et al., 2018, 2020).

Here we tackle both of the above challenges by approaching semantic change detection as an anomaly identification task. We propose an encoder-decoder architecture for learning word representations across time. We hypothesize that once such a model has been successfully trained on temporally sensitive word sequences it will be able to accurately predict the evolution of the semantic representation of any word through time. Words that have undergone semantic change will be exactly those that yield the highest errors by the prediction model. Specifically we make the following contributions:

- we develop three variants of an LSTM-based neural architecture which enable us to mea-
sure the level of semantic change of a word by tracking its evolution through time in a sequential manner. These are: (a) a current word representation autoencoder, (b) a future word representation decoder and (c) a hybrid approach combining (a) and (b);

- we showcase the effectiveness of the proposed models under thorough experimentation with synthetic data;
- we compare our models against current practices and competitive baselines using real-world data, demonstrating important gains in performance and highlighting the importance of sequential modelling of word vectors across time.

2 Related Work

One can distinguish two directions within the literature on semantic change (Tang, 2018; Kutuzov et al., 2018): (a) learning word representations over discrete time intervals and comparing the resulting vectors and (b) jointly learning the (diachronic) word representations across time (Bamler and Mandt, 2017; Rosenfeld and Erk, 2018; Yao et al., 2018; Rudolph and Blei, 2018). In this work, we focus on (a) due to scalability issues in (b) associated with learning diachronic representations from very large corpora. Our methods, presented in Section 3, are applicable to any type of pre-trained word vectors across time.

Related work in (a) derives word representations $W_t$, $i \in [0\ldots|T-1|]$ across $|T|$ different time intervals and performs pairwise comparisons for different values of $i$. Early work used frequency- and co-occurrence-based representations for $W_i$ (Sagi et al., 2009; Cook and Stevenson, 2010; Galairda and Baroni, 2011; Mihalcea and Nastase, 2012); however, word2vec-based representations (Mikolov et al., 2013) has been the standard practice in recent years. Due to the stochastic nature of word2vec, Orthogonal Procrustes (OP) is often firstly applied to the resulting vectors, aiming at aligning the pairwise representations (Kulkarni et al., 2015; Hamilton et al., 2016; Del Tredici et al., 2019; Shoemark et al., 2019; Tsakalidis et al., 2019; Schlechtweg et al., 2019). Given two word matrices $W_k$, $W_j$ at times $k$ and $j$ respectively, OP finds the optimal transformation matrix $R = \arg \min_{\Omega} \|\Omega W_k - W_j\|_F$ and the semantic shift level of a word $w$ during the time interval $[k,j]$ is defined as the cosine distance $\cos(Rw_j, w_k)$ (Hamilton et al., 2016). To tackle the drawback of basing the alignment of the matrices on the whole vocabulary, which assumes that the vast majority of the words remain stable across time, Tsakalidis et al. (2019) learn the alignment based only on a few semantically stable words across time. However, both approaches operate in a linear pairwise fashion, thus ignoring the time-sensitive, sequential and possibly non-linear nature of semantic change.

By contrast, Kim et al. (2014), Kulkarni et al. (2015) and Shoemark et al. (2019) derive time series of a word’s level of semantic change and use those to detect semantically shifted words. Even though these methods incorporate temporal modelling, they still rely heavily either on the linear transformation $R$ (Kulkarni et al., 2015; Shoemark et al., 2019) or on the similarity of a word with itself across time via continuous representation learning (Kim et al., 2014). The latter has recently been demonstrated to lead to worse performance (Shoemark et al., 2019).

Finally, the comparative evaluation of semantic change detection models is still in its infancy. Most related work assesses model performance based either on an artificial task (Rosenfeld and Erk, 2018; Shoemark et al., 2019) or on a few hand-picked examples (Del Tredici et al., 2019), without cross-model comparison. Setting a benchmark for model comparison with real-world and sequential word representations would be of great importance to the field.

3 Methods

We formulate semantic change detection as an anomaly detection task. We hypothesize that the pre-trained word vectors $W_t \in [W_0, ..., W_{|T|-1}]$, where $W_t \in \mathbb{R}^{|V| \times d}$ ($|V|$: vocabulary size; $d$: word representation size) in a historical corpus over $|T|$ time periods, evolve according to a non-linear function $f(W_t)$. By providing an approximation for $f$, we obtain the level of semantic shift of a word $w$ at time $t$ by measuring the distance between its word representation $w_t$ against $f(w_t)$. A key novelty of our work is that we approximate $f$ via a temporally sensitive model using a deep neural network architecture. Shoemark et al. (2019) showed that accounting for the full sequence of word vec-
Word Representations

§3.1: Reconstructing Word Representations

$\{W_0, ..., W_{T-1}\}$ is more appropriate for detecting semantically shifted words, compared to accounting only for the first and the last representations $\{W_0, W_{T-1}\}$, as is the practice in most earlier work. Following Shoemark et al. (2019) we model word evolution by accounting for all intermediate representations across time.

Our modelling of the semantic change function $f$ is based on two components: (a) an autoencoder, which aims to reconstruct a word’s trajectory up to a given point in time $i$ $[w_0, ..., w_i]$ (section 3.1); and (b) a future predictor, which aims to predict future representations of the word $[w_{i+1}, ..., w_{T-1}]$ (section 3.2). The two models can be trained either individually or (c) in combination, in a multi-task setting (section 3.3).

Figure 1: Overview of our proposed model: the sequence of the representation of a set of word vectors (Vocabulary) over different time steps $W_{0:i-1}$ is encoded through two LSTM layers and then passed over to a reconstruction (3.1) and a future prediction decoder (3.2). The model is trained by utilising either decoder in isolation, or both of them in parallel (3.3).

3.1 Reconstructing Word Representations

Given an input sequence of vectors representing the Vocabulary across $i$ points in time $W_{0:i-1} = [W_0, W_1, ..., W_{i-1}]$, the goal of the autoencoder is to reconstruct the input sequence $W_{0:i-1}$, by minimising some loss function. Since the task of semantic change includes a natural temporal dimension, we model our autoencoder via a RNN architecture (see Figure 1). The encoder is composed of two LSTM layers (Hochreiter and Schmidhuber, 1997) with Dropout layers operating on their outputs, for regularisation (Srivastava et al., 2014). The first layer encodes the input sequence of $W_{0:i-1}$ and returns the hidden states to be fed as input to the second layer. The output of the second layer is the final encoded state, which is then copied $|i|$ times and fed as input to the decoder. The decoder has the exact same architecture as the encoder, albeit with additional dense layers on top of the second LSTM layer, fed with the hidden states of the latter, to make the final reconstruction $W_{0:i-1}$ on the $|i|$ time steps. The model is trained by minimising the mean squared error (MSE) loss function:

$$L_r = \frac{1}{T} \sum_{j=0}^{i-1} (W_j - W_j')^2.$$  \hspace{1cm} (1)

After training, the words that yield the highest error rates in a given test set of word representations through time are considered to be the ones whose semantics have changed the most during the given time period. This assumption is in line with prior work based on word alignment (Hamilton et al., 2016; Tsakalidis et al., 2019), where the alignment error of a word indicates its level of semantic change.

3.2 Predicting Future Word Representations

Reconstructing the input sequence of word vectors can reveal which words have changed their semantics in the past (i.e., up to time $i - 1$, see section 3.1). If we are interested in predicting changes in the semantics of future word representations (i.e., word vectors after time $i - 1$), then we can set up a future word representation prediction task, based on a sequence-to-sequence architecture. Formally, given the sequence of past word representations $W_{0:i-1} = [W_0, W_1, ..., W_{i-1}]$ over the first $i$ time points, we want to predict the future representations of the words in the vocabulary $W_{i:T-1} = [W_i, W_{i+1}, ..., W_{T-1}]$, for a sequence of overall length $|T|$ (see Figure 1). We follow the same model architecture as described in section 3.1, with the only difference being the number of time steps $(T - i)$ that are used in the decoder in order to make $|T - i|$ predictions. The model is trained using the MSE loss function $L_f$:

$$L_f = \frac{1}{T-i} \sum_{j=i}^{T-1} (W_j - W_j')^2.$$  \hspace{1cm} (2)

3.3 Joint Model

The two models can be combined into a joint one, where, given an input sequence of representations
of the vocabulary $W_{0:i−1}$ over $i$ points in time, the goal is both to (a) reconstruct the input sequence and (b) predict the future word $[T−i]$ representations $W_{i:T−1}$. The complete model architecture is provided in Figure 1: the encoder is identical to the one used in 3.1 and 3.2. However, the bottleneck is now copied $[T]$ times and passed to the decoders of the reconstruction ($[i]$ times) and future prediction ($[T−i]$ times) components. The loss function $L_{rf}$ used to tune the model parameters is the summation of Eq. 1 and 2:

$$L_{rf} = \frac{1}{i} \sum_{j=0}^{i-1} (W_j - W^f_j)^2 + \frac{1}{T−i} \sum_{j=i}^{T−1} (W_j - W^f_j)^2.$$  

(3)

There are two main reasons for modelling semantic change in this multi-task setting. Firstly, we benefit from the finer granularity of the two decoders due to their handling of only part of the sequence in a more fine-grained manner, compared to the individual task models. Secondly, the joint model is insensitive to the value of $i$ in Eq. 3 compared to Eq. 1 and 2. We provide more details on this aspect in 3.4.

3.4 Model Equivalence

The three models perform different operations; however, setting the operational time periods appropriately in Eq. 1-3 can result in model equivalence. Specifically, to detect the words whose semantics have changed during $[0, T−1]$, the autoencoder in Eq. 1 needs to be fed and reconstruct the full sequence across $[0, T−1]$ (i.e., $i=T−1$). Reducing this interval (reducing $i$) would limit the autoencoder’s operational time period. On the other hand, an increase in the value of $i$ in Eq. 2 of the future prediction component shortens the time period during which it can detect the words whose semantics have changed the most – to account for the whole sequence (i.e., $[1, T−1]$), the future prediction model requires only the $W_0$ word representations in the first time interval to then detect the words whose semantics have changed within $[1, T−1]$. Therefore, setting the parameter $i$ can be crucial for the performance of the two individual models. By contrast, the joint model in section 3.3 is able to detect the words that have undergone semantic change, regardless of the value of $i$ (see Eq. 3), since it is still able to operate on the full sequence – we showcase these effects in section 5.2.

4 Experiments with Synthetic Data

In this section we explore the three proposed models and their ability to detect words that have undergone semantic change on an artificial dataset. Tasks ran on artificial data have been used in recent work for evaluation purposes (Shoemark et al., 2019). We work with artificial data in the current section as a proof-of-concept of our proposed models – we compare against state-of-the-art models and other baseline methods with real-world data in the following sections. In particular, here we employ a longitudinal dataset of word representations (4.1) and artificially alter the representations of a small set of words across time (4.2). We then train (4.3) our models and evaluate them on the basis of their ability to identify those words that have undergone (artificial) semantic change (4.4).

4.1 Dataset

We make use of the UK Web Archive dataset introduced by Tsakalidis et al. (2019), which contains 100-dimensional representations of 47.8K words for each year in the period 2000-2013. These were generated by employing word2vec (i.e., skip-gram with negative sampling)(Mikolov et al., 2013) on the documents published in each year independently. Each year corresponds to a time step in our modelling. The dataset contains 65 words whose meaning is known to have changed during the same time period as indicated by the Oxford English Dictionary. These are removed for the purposes of this section, to avoid interference with the artificial data modeling. We use one subset (80%) of the remaining word representations across time for training our models and the rest (20%) for evaluation purposes.

4.2 Artificial Examples of Semantic Change

We generate artificial examples of words with changing semantics, by following a paradigm inspired by Rosenfeld and Erk (2018). We uniformly at random select 5% of the words in the test set to alter their semantics. For every selected “source” word $\alpha$, we select a “target” word $\beta$. Details about the selection process of the target words are provided in the next paragraph. We then alter the representation $w_t^{(\alpha)}$ of the source word at each point in time $t$ so that it shifts towards the representation $w_t^{(\beta)}$ of the target word at this point in time as:

$$w_t^{(\alpha)} = \lambda_t w_t^{(\alpha)} + (1 − \lambda_t) w_t^{(\beta)}.$$  

(4)
In our modelling, \( \lambda_t \) receives values between 0 and 1 and acts as a decay function that controls the speed of the change in the source word’s semantics towards the target. As in Rosenfeld and Erk (2018), we model \( \lambda_t \) via a sigmoid function. Thus, the semantic representation of the word \( \alpha \) is not altered during the first time points and then it gradually shifts towards the representation of word \( \beta \) (for middle values of \( t \)), where it stabilizes towards the last time points. Since the duration of the semantic shift of a word may vary, we experiment under three different scenarios, as presented below.

Different modelling approaches of (artificial) semantic change have been presented in Shoemark et al. (2019) – e.g., forcing a word to acquire a new sense while also retaining its original meaning. Here we opted for the “stronger” case of semantic shift in Eq. 4 as a proof of concept for our models. In the next section we experiment with uncontrolled (real-world) examples of semantic change, without the need for any hypothesis on the underlying function.

**Conditioning on Target Words** The selection of the target words should be such that they allow the representation of the source word to change through time. This will not be the case if we select a pair of \( \{ \alpha, \beta \} \) {source, target} words whose representations are very similar (e.g., synonyms). Thus, for each source word \( \alpha \) we select uniformly at random a target word \( \beta \) s.t. the cosine similarity of their representations at the initial time point \( t = 0 \) (i.e., in year 2000) falls within a certain range \( (c - 0.1, c) \). Higher values of \( c \) enforce a lower semantic change level for \( \alpha \) through time, since its representation will be shifted towards a similar word \( \beta \), and vice versa. To assess the performance of our models across different semantic change levels, we experiment with varying values for \( c \): \( \{0.0, 0.1, ..., 0.5\} \).

**Conditioning on Duration of Change** The duration of the semantic change affects the value of \( \lambda_t \) in Eq. 4. We conventionally set \( \lambda_{2007} = 0.5 \), s.t. the artificial word representation \( w^{a}_{2007}(\alpha) \) of a source word \( \alpha \) in the year 2007 (i.e., the middle between 2001-2013) to be equal to \( 0.5(w^{(\alpha)}_{2007} + w^{(\beta)}_{2007}) \). We then experiment with four different duration [start, end] ranges for the semantic change: (a) “Full” [2001-13], (b) “Half” [2005-10], (c) “OT” (One-Third) [2006-09] and (d) “Quarter” [2007-08]. A longer lasting semantic change duration implies a smoother transition of word \( \alpha \) towards the meaning of word \( \beta \), and vice versa (see Figure 2). By generating synthetic examples of varying lengths of semantic change duration we are able to measure the performance of the models under different conditions.

![Figure 2: The different functions used to model \( \lambda_t \) in Eq. 4, indicating the speed and duration of the semantic change of our synthetic examples (see section 4.2).](image)

### 4.3 Artificial Data Experiment

Our task is to rank the words in the test set by means of their level of semantic change. We first train our three models on the training set and then we apply them on the test set. Finally, we measure the semantic change level of a word by means of the average cosine similarity between the predicted and actual word representations at each time step of the decoder. Model performance is assessed via rank-based metrics (Basile and McGillivray, 2018; Tsakalidis et al., 2019; Shoemark et al., 2019).

**Model Training** The following is applicable to training of models for both the artificial and real-world data experiments. We define and train our models as follows:

- \( \text{seq2seq}_r \): the autoencoder (section 3.1) receives and reconstructs the full sequence of the word representations in the training set: \([W_{00}, ..., W_{13}] \rightarrow [W'_{00}, ..., W'_{13}]\).

- \( \text{seq2seq}_f \): the future prediction model (section 3.2) receives the representation of the words in the training set in the year 2000 and learns to predict the rest of the sequence: \([W_{00}] \rightarrow [W'_{01}, ..., W'_{13}]\).

- \( \text{seq2seq}_{r,f} \): the multi-task model (section 3.3) is fed with the first half of the sequence of the word representations in the training set and jointly learns to (a) reconstruct the
input sequence and (b) predict the word representations in the future: $[W_{00}, ..., W_{06}] \rightarrow \{[W_{00}^f, ..., W_{06}^f], [W_{07}^f, ..., W_{13}^f]\}$.

We vary the input in terms of number of time steps for seq2seq and seq2seq$_f$ so that the decoder in each model operates on the maximum possible output sequence, thus exploiting the semantic change of the words over the whole time period (see section 3.4). seq2seq$_{rf}$ is expected to be insensitive to the number of input time steps, therefore we conventionally set it to half of the overall sequence. We keep 25% of our training set for validation purposes and train our models using the Adam optimiser (Kingma and Ba, 2015). Parameter selection is performed based on 25 trials using the Tree of Parzen Estimators algorithm of the hyperopt module (Bergstra et al., 2013), by means of the maximum average (i.e., per time step) cosine similarity in the validation set.\(^2\)

Testing and Evaluation The following applies to experiments with both artificial and real-world data. After training, each model is applied to the test set, yielding its predictions for every word across time.\(^3\)

The level of semantic change of a word in the test set is then calculated as the average cosine similarity between the actual and the predicted word representations through time (Hamilton et al., 2016; Tsakalidis et al., 2019), with higher values indicating a better model prediction – thus, a lower level of semantic change. The words are ranked in descending order of their level of semantic change, so the lowest rank indicates a word whose vector representation has changed the most (i.e., indicating the most semantically shifted word). For evaluation purposes, similarly to Tsakalidis et al. (2019), we employ the average rank across all of the semantically changed words (in %, denoted as $\mu_r$), with lower scores indicating a better model. We prefer $\mu_r$ to the mean reciprocal rank, because the latter puts more weight on the first rankings. Since semantic change detection is an under-explored task in quantitative terms, we aim at getting better insights on model performance by working with an averaging metric such as $\mu_r$. For the same reason, in the current section we avoid using classification-based metrics that are based on a cut-off point (e.g., recall at $k$ (Basile and McGillivray, 2018)).

\(^2\)For the complete list of parameters tested, refer to Appendix A.

\(^3\)Note that the future prediction model does not make a prediction for the first time step (year 2000).

do make use of such metrics in the cross-model comparison in section 5.2.

4.4 Results

Model Comparison Figure 3 presents the results of the three models on our synthetic data across all $(c, \lambda)$ combinations. seq2seq$_{rf}$ performs consistently better than the individual reconstruction (seq2seq$_r$) and future prediction (seq2seq$_f$) models across all experimental settings, showcasing that combining the two models under a multitask setting benefits from the joint and finer-grained parameter tuning of the two components. The autoencoder performs slightly better than seq2seq$_f$ – a difference partially attributed to the fact that the autoencoder has a longer sequence to output ($W_{00}^f$), which helps explore the temporal variation of the words more effectively.

Figure 4 shows the cosine similarity between the predicted and actual representation of each synthetic word per time step for the “Full” case when $c=0.0$ (highest level of change, see section 4.2). A darker colour indicates a better model prediction – thus a lower level of semantic change. seq2seq$_r$ reconstructs the input sequence of the synthetic examples more accurately than the future prediction component (average cosine similarity per year $\text{avg}_\text{cos}$: .65 vs .50). It particularly manages to reconstruct the synthetic word representations during the years 2006-2008 ($\text{avg}_\text{cos}_{06:08}=.75$), which are the points when $\lambda_t$ varies more rapidly (see Figure 2); however, it fails to reconstruct equally well their representations before ($\text{avg}_\text{cos}_{00:00:.05}=.65$) and after ($\text{avg}_\text{cos}_{00:13}=.59$) this sharp change. On the contrary, seq2seq$_f$ predicts more accurately the synthetic word representations during the first years ($\text{avg}_\text{cos}_{01:.05}=.74$), when the change in their semantics is minor, but completely fails after the semantic change is almost complete (i.e., when $\lambda_t \leq .25$, $\text{avg}_\text{cos}_{09:13}=.24$). seq2seq$_{rf}$ benefits from the individual components’ advantage: it appropriately reconstructs the artificial examples in the first years ($\text{avg}_\text{cos}_{00:00:.05}=.85$) so that their semantic shift is highlighted more clearly during ($\text{avg}_\text{cos}_{06:08}=.62$) and after the process is almost complete ($\text{avg}_\text{cos}_{09:13}=.26$). Finally, $\text{avg}_\text{cos}$ in seq2seq$_{rf}$ highly correlates with $\lambda_t$ ($r=987$), potentially providing insights on how to measure the speed of semantic change of a word.

Effect of Conditioning Parameters Regardless of the duration of the semantic change process and
Figure 3: $\mu_r$ of our models on the synthetic dataset for different values of the threshold $c$ and the four different periods of duration of semantic change (see 4.2). Lower values of $\mu_r$ indicate a better performance.

![Graphs showing $\mu_r$ for different values of $c$ and periods of duration of semantic change.](image)

Figure 4: Cosine similarity between the actual and the predicted word vectors of the synthetic words that have undergone artificial semantic change (rows), per year (columns). Lighter colours indicate poorer model performance – thus indicating that the corresponding words have undergone semantic change. Note that seq2seq$_f$ does not make a prediction for the first time step (i.e., year 2000).

![Cosine similarity heatmaps for different models and periods of change.](image)

5 Model Comparison with Real-World Data

5.1 Experimental Setting

We approach the task in a rank-based manner, as in section 4. However, here we are interested in (a) detecting uncontrolled real-world examples of semantic change in words and (b) comparing our models against strong baselines and current practices.

**Data and Task** We make use of the UK Web Archive dataset (see section 4.1). We keep the same 80/20 train/test split as in section 4 and incorporate in the test set the 65 words with known changes in meaning according to the Oxford English Dictionary. We train our models as in section 4.3, aiming at detecting (i.e., ranking lower) the 65 words in the test set. We use $\mu_r$ (as in section 4) and additionally recall at $k$ ($\text{Rec}@k$, $k=5\%, 10\%, 50\%$) as our evaluation metrics. Lower $\mu_r$ and higher $\text{Rec}@k$ scores indicate better models.

**Models** We compare the three variants from section 3 against four types of baselines:

- A random word rank generator (RAND). We report average metrics after 1K runs on the test set.

- Variants of Procrustes Alignment (Schönemann, 1966), as the standard practice in past work (Hamilton et al., 2016; Shoemark et al., 2019; Tsakalidis et al., 2019): Given the word representations in two different years $[W_0, W_i]$, PROCR transforms $W_i$ into $W_i^*$ s.t. the squared differences between $W_0$ and $W_i^*$ are minimised. We also use the PROCR$_k$ and PROCR$_kt$ variants (Tsakalidis et al., 2019), which first detect the $k$ most stable words across either $[W_0, W_i]$ (PROCR$_k$) or $[W_0, ..., W_{T-1}]$ (PROCR$_kt$) to learn the alignment on and then transform $W_i$ into $W_i^*$. Words are ranked based on the cosine distance between $[W_0, W_i^*]$. 

The decrease of the duration of semantic change has a positive effect on our models (see Figure 3). This is more evident in the cases of high value of $c$, where seq2seq$_r$ ($\mu_r$: 26.09-18.21 in the Full-to-Quarter cases), seq2seq$_f$ ($\mu_r$: 28.17-22.48) and seq2seq$_rf$ ($\mu_r$:20.38-13.09) all show important gains in performance. This indicates that the models can capture the semantic change in small sub-sequences of the time-series. Studying this effect in datasets with a longer time span is an important future direction.
Table 1: Performance of our models and the baselines when operating on the entire time sequence (2000-2013) and averaged across time (2000-01, ..., 2000-13). PROCR and PROCR_k(t) are based on the methods employed in Hamilton et al. (2016) and Tsakalidis et al. (2019), respectively; GT_c,β models are based on the work by Shoemark et al. (2019). The complete results in µ_k across all runs are provided in Appendix B.

|          | µ_k | Rec@5 | Rec@10 | Rec@50 |
|----------|-----|-------|--------|--------|
| Rand     | 49.97 ± 0.04 | 5.00 ± 0.03 | 10.01 ± 0.04 | 50.02 ± 0.08 |
| PROCR    | 30.63 ± 0.68 | 18.46 ± 5.00 | 27.69 ± 6.44 | 78.46 ± 3.79 |
| PROCR_d | 31.47 ± 2.65 | 20.00 ± 3.85 | 29.23 ± 4.32 | 75.31 ± 4.49 |
| PROCR_k | 31.91 ± 2.85 | 20.00 ± 4.23 | 27.69 ± 4.45 | 70.77 ± 4.53 |
| RF       | 27.87 ± 2.65 | 12.31 ± 5.94 | 29.23 ± 6.39 | 80.00 ± 4.72 |
| LSTM     | 28.62 ± 3.47 | 16.92 ± 5.60 | 32.31 ± 6.07 | 76.92 ± 8.83 |

– Models leveraging the first and last word representations only. We use a Random Forest (Breiman, 2001) regression model (RF) that predicts W_i, given W_0. We also use the same architectures presented in sections 3.1-3.2, trained on [W_0, W_i] (ignoring the full sequence): LSTM_r reconstructs the sequence [W_0, W_i]; LSTM_f predicts W_i, given W_0, similarly to RF. Words are ranked in inverse order of the (average, for LSTM_r) cosine similarity between their predicted and actual representations.

– Models operating on the time series of distances. Given a sequence of vectors [W_0, ..., W_i], we construct the time series of cosine distances that result by PROCR (Kulkarni et al., 2015; Shoemark et al., 2019). Then, we use two global trend models as in Shoemark et al. (2019): GT_r ranks the words by means of the absolute value of the Pearson correlation of their time series; GT_c fits instead a linear regression model for every word and ranks the words by the absolute value of the slope. Finally, we employ PROCR_c, ranking words based on the average cosine distance within [0, i].

We report the performance of our models and baselines (a) when they operate on the full interval [2000-2013] and (b) averaged across all intermediate intervals [2000-2001, ..., 2000-2013]. In the latter case, our models use additional (future) information compared to our baselines (e.g., when seq2seq is fed with the word sequences of [2000, 2001], it makes a prediction for the years [2002, ..., 2013] – such information cannot be lever-

4We refrain from evaluating the GT models when i ≤ 2, due to the very short time interval that does not allow for correlations to appear in the data, leading to very poor performance.

5All parameters tested during the training process of our baselines are provided in Appendix A.

5.2 Results

Our models vs baselines The results are shown in Table 1. The three models proposed in this work consistently achieve the lowest µ_k and highest Rec@k when working on the whole time sequence (‘00-’13 columns in Table 1). The comparison between {seq2seq, LSTM} and {seq2seq, LSTM} in the years 2000-13 showcases the benefit of modelling the full sequence of the word representations across time, compared to using the first and last representations only. Overall, our models provide a relative boost of 4.6% in µ_k and [35.7%, 42.8%, 5.8%] in Rec@k (for k=[5, 10, 50]) compared to the best performing baseline. seq2seq and seq2seq models outperform the autoencoder (seq2seq) in most metrics, while seq2seq yields the most stable results across all experiments. We explore these differences in detail in the last paragraph of this section.

Intra-baseline comparison Models operating only on the first and last word representations fail to outperform the simplistic Procrustes-based baselines in Rec@k, demonstrating again the weakness of operating in a non-sequential manner. The LSTM models achieve low µ_k on the 2000-13 experiments; however, the difference with the rest of the baselines in µ_k across all years is negligible. The intra-Procrustes model comparison shows that the benefit of selecting a few anchor words to learn a better alignment (PROCR_k, PROCR_k(t)) shown in Tsakalidis et al. (2019) in examining semantic change over two consecutive years does not apply when ex-
amining a longer time period. Finally, contrary to Shoemark et al. (2019), we find that time sensitive models operating on the word distances across time (GT, GTβ) perform worse than the baselines that leverage only the first and last word representations. This difference is attributed to the low number of time steps in our dataset that does not allow the GT models to exploit long-term correlations (i.e., considering the average distance across time (PROCR) performs better), but also highlights the importance of leveraging the full word sequence across time.

Figure 5: $\mu_r$ of our models for varying value of $i$ (Eq. 1–3).

6 Effect of input/output lengths Figure 5 shows the $\mu_r$ of our three variants when we alter the length of the input and, therefore, also the length of the output (see section 3.4). The performance of seq2seqr increases with the input size since by definition the decoder is able to detect words whose semantics have changed over a longer period of time (i.e., within $[2000, i]$, with $i$ increasing), while also modelling a longer sequence of a word’s representation through time. On the contrary, the performance of seq2seqf increases alongside the decrease of the number of input time steps. This is expected since, as $i$ decreases, seq2seqf encodes a shorter input sequence and the decoding (and hence the semantic change detection) is applied on the remaining (and increased number of) time steps within $[i + 1, 2013]$. These findings provide empirical evidence that both models can achieve better performance if trained over longer sequences of time steps. Finally, the stability of seq2seqrf showcases its input length-invariant nature, which is also clearly evident in all of the averaged results (standard deviation in avg±std columns) in Table 1: in its worst performing setting, seq2seqrf still manages to achieve results that are close to the best performing model ($\mu_r=25.17$, Rec@$k=[21.54, 36.92, 83.08]$ for the three thresholds) and always better (or equal to) the best performing baseline shown in Table 1 in Rec@$k$. This is a very attractive aspect of the model as it removes the need to manually define the number of time steps to be fed to the encoder.

6 Conclusion and Future Work

We have proposed three variants of sequential models for semantic change detection that effectively exploit the full sequence of a word’s representation through time to determine its level of semantic change. Through extensive experimentation based on synthetic and real-world data, we have demonstrated that the proposed models can surpass state-of-the-art results on the UK Web Archive Dataset. Importantly, their performance increases alongside the duration of the time period under study, confidently outperforming competitive baselines and common practices in the literature on semantic change.

In future work we plan to incorporate anomaly detection approaches operating on the model’s predicted word vectors instead of considering the average similarity between the predicted and the actual representations as the level of semantic change of a word. Employing contextual word representations (Devlin et al., 2019; Hu et al., 2019) can also be of high importance in detecting new senses of the words across time. Finally, we plan to investigate different architectures, such as Variational Autoencoders (Kingma and Welling, 2014), and test our models in datasets of different duration and in different languages to provide clearer evidence on their effectiveness.

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### A List of Hyperparameters

**Our models** We test the following hyperparameters for our seq2seq_{rf/r} models:

- **encoder_LSTM_{i}**, number of units: [32, 64, 128, 256, 512]
- **encoder_LSTM_{1}**, number of units: [32, 64]
- **decoder_LSTM_{0}**, number of units: [32, 64, 128, 256, 512] (x2, for the case of seq2seq_{rf} – for (a) the autoencoding and (b) future prediction component)
- **decoder_LSTM_{1}**, number of units: [32, 64, 128, 256, 512] (x2, for the case of seq2seq_{rf})
- dropout rate in dropout layers: [.1, .25, .5]
- batch size: [32, 64, 128, 256, 512, 1024]
- number of epochs: [10, 20, 30, 40, 50]

We optimise our parameters using the Adam optimiser in *keras*, using the default learning rate (.001).

**Baselines** We experiment with the following hyper-parameters per model:

- **LSTM_{rf}**: we follow the exact same settings as in our models.
- **RF**: we experiment with the number of trees ([50, 100, 150, 200]) and select the best model based on the maximum average cosine similarity across all predictions, as in our models.
- **PROCR_{k/kt}**: we experiment with different rate [.001, .01, .05, .1, .2, ... .9] of anchor (or diachronic anchor) words on the basis of the size of the test set. We select to display in our results the best model based on the average performance in the test set ($k=.9$ for PROCR_{k}, $k=.5$ for PROCR_{kt}).
- **GT_{c}**: we explore different correlation metrics (Spearman Rank, Pearson Correlation, Kendall Tau) and select to display the best one (Pearson Correlation) on the basis of its average performance on the test set across all experiments. Due to the very poor performance
of all metrics when operating on a small number of time-steps ($\leq 2$), we only provide the results in Table 1 (avg±std columns) when these models operate on longer sequences.

- PROCR, PROCR, GT, GT, RAND: there are no hyper-parameter to tune in these models.

## B Complete Results on Real Data

The complete list of results ($\mu_r$) that were presented in Table 1 are provided in Table 2. The interpretation of the “year” for each model is provided in Table 3.

| Model      | Example (year=2006)                                                                 |
|------------|-------------------------------------------------------------------------------------|
| PROCR      | Date to use for aligning the word vectors with their corresponding ones in the year 2000. |
| PROCR      | The model aligns the word vectors in the year 2006 with the word vectors in the year 2000. |
| PROCR      | The date indicating the word vectors to reconstruct, along with those in the first time-step. |
| LSTM       | LSTM receives as input the word vectors in the years 2000 and 2006 and reconstructs them. |
| LSTM       | LSTM receives the word vectors in the years 2000 & predicts the word vectors in the year 2006. |
| LSTM       | LSTM receives the word vectors in the years 2000 & predicts their representations in [2007-2013]. |
| seq2seq    | seq2seq is fed with the word representations in the years [2000-2006] and reconstructs them. |
| seq2seq    | seq2seq predicts the word vectors in the years [2007-2013], given the vectors during the years [2000-2006] as input. |
| seq2seq    | seq2seq receives the word vectors during the years [2000-2006] and (a) reconstructs them & (b) predicts their representations in [2007-2013]. |

Table 3: Explanation of the variable “year” in Table 2.