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Adaptive Computational Models for Tracing Semantic Change in Contemporary English Using Large-Scale Digital Corpora

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Abstract

The problem of semantic changes detection in natural language is one of the most important issues in Computational Linguistics and NLP, especially in the context of analysis of diachronic corpora at a large scale. Static embedding models fail to properly account for changes in the meaning of words over time and, therefore, exhibit poor interpretability and low sensitivity to changes in contexts. To solve these problems, it suggests an adaptive approach for tracing the semantic changes in Contemporary English based on large-scale digital corpora. It utilizes the framework combining Gaussian word embeddings, temporal alignment via Orthogonal Procrustes transformation, and incremental modeling of semantic drift to detect semantic changes over time. Moreover, the approach provides a probabilistic representation of words and, thus, allows uncertainty-aware semantic representation and better capability of modeling polysemic behavior. For evaluation, it uses a large-scale corpus consisting of around 12 million documents retrieved from such sources as

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Wikipedia, news archives, Common Crawl, and others within the timeframe of 2000–2025. Our results show that our adaptive model outperforms the baseline approaches, including static embedding models and Bayesian semantic change detection methods. The proposed approach obtains semantic change detection with an accuracy of around 92.6% as well as better precision, recall, F1 score, and AUC values, suggesting that it performs better than previous solutions in detecting lexical semantic change. In addition to this, the inclusion of temporal alignment and probabilistic embeddings leads to much better interpretability and stability when modeling semantic trajectories. Overall, the presented adaptive framework can be considered scalable and efficient for diachronic semantic analysis.

Keywords: Semantic Change Detection, Gaussian Embeddings, Temporal Alignment, Diachronic Corpora, Adaptive Computational Models, Word Embedding Evolution, NLP.

1 Introduction

Semantic change is one of the key aspects of the evolution of languages in general, and it is the fundamental problem within Natural Language Processing (NLP), computational linguistics, and digital humanities (Yan & Zhu, 2018). As modern-day English keeps developing through its use on the Internet, social networks, and large linguistic corpora, there are changes in the meaning of the words all the time, and they are affected by different factors (Röthlisberger et al., 2017; Wulff et al., 2019). It is important to be able to model such semantic changes to solve different problems (Viroli et al., 2018).

Although widely used, static models of word embeddings are not sufficient in representing semantic changes over time since they represent words in a single semantic space without considering diachronic changes Dill et al., (2003). This poses challenges in capturing the evolution of context, particularly when dealing with very large and time-dependent corpora. As such, static word embeddings do not work well in polysemy evolution modeling and gradual changes in semantics.

This gap shows the necessity for an adaptive model that should be able to learn evolving semantic structures (Longpre et al., 2024). For this to be achieved, the model needs to incorporate elements such as temporal sensitivity, probabilistic representations, and alignments.

Nevertheless, there is a notable gap in the literature in building scalable and time-aware semantic drift frameworks that are able to process large volumes of data yet remain interpretable and computationally stable at the same time. Existing methods face difficulties in scalability issues, misalignment, and flexibility to continuously evolving languages.

This paper aims to fill this gap by introducing a computational framework for detecting semantic change in Contemporary English. The main contributions of this paper are as follows: (i) an adaptive Gaussian embeddings semantic change detection model, which takes into account uncertainties in meaning representations, (ii) a temporal alignment approach for diachronic corpora, making it possible to compare data across different time points consistently, and (iii) an enhanced semantic drift measurement framework suitable for large-volume English corpora.

The paper is structured as follows: Section I introduces the problem of semantic change detection in Contemporary English, points out the shortcomings of static embedding models, and gives the motivation behind and contributions of the adaptive framework proposed in the paper. Section II discusses the literature review on the topic of Gaussian embeddings, Bayesian approaches to modeling, and incremental semantic modeling, pointing out existing research gaps. Section III outlines the methodology used in the paper – it includes text corpora preprocessing, temporal segmentation, generating Gaussian embeddings, aligning temporally using Orthogonal Procrustes, and calculating semantic drifts. Section IV provides details of the experiments conducted datasets used, parameter settings, performance metrics, comparison with baselines, ablation analysis, and visualization of results with heatmaps and Gaussian distributions. Section V is the conclusion of the research, which summarizes its contribution and proposes some future work directions, such as transformer-based continual learning and multilingual semantic analysis.

2 Literature Survey

Recent improvements in semantic change detection have seen a tendency towards using distributional semantics and embeddings of words to model diachronic language variation. In their paper from 2021, Yüksel et al., (2021) suggest the use of Gaussian word embeddings for the purpose of detecting changes in word meanings, showing that probabilistic embedding spaces allow accounting for variability and uncertainty in the process of change, which is superior to the deterministic vectors' ability to detect shifts in meaning.

Wevers and Koolen, (2020) studied the application of diachronic corpus analysis through word embeddings, where the alignment of word vectors in historical corpora allows for the detection of semantic changes in the lexicon. The research proves that alignment methods in vector space are suitable for modeling concept changes in a large-scale textual corpus, especially historical and cultural ones (Zhu et al., 2020).

Within digital humanities, Armaselu et al., (2022) combined NLP methods with linked open data techniques, underlining the importance of semantic changes in modeling for humanities research. The paper shows how the use of computational linguistics techniques greatly contributes to interpretability and knowledge extraction in the cultural and historical field.

Periti et al., (2024) presented a new class of incremental models for the detection of semantic shifts, which continuously update the representation through time. The improvement in terms of adaptivity derives from the possibility of making dynamic updates instead of re-training statically (Somyürek, 2015; Reece et al., 2023).

A probabilistic approach to diachronic meaning changes is proposed by Frermann & Lapata, (2016), who created a Bayesian model for gradual changes in the lexicon (Bizzoni et al., 2020). Their method successfully models uncertainties in the evolution of the language, but it is computationally expensive for large corpora (Monaghan & Rowland, 2017; Ponti et al., 2019).

Haber & Poesio, (2024) have analyzed the concept of polysemy by applying contextual language models (De Decker & Vandekerckhove, 2012). It was found that contextual embeddings lead to better sense disambiguation and meaning representation. Nevertheless, contextual language models consume vast amounts of computational power and do not include temporal modeling (Li & Zhao, 2017).

In essence, the literature shows a general and coherent evolution in models of word meaning, starting from static word-level representations and progressing into probabilistic and context-sensitive word representations, and more recently toward adaptive, online learning approaches. Yet, none of the existing word embedding approaches currently addresses the scalability, real-time adjustability, or large-scale, high-resolution temporal aspect of semantic change detection across large digital corpora, prompting the need for a new adaptive computational approach for semantic change detection proposed in this work.

3 Proposed Methodology

System Overview

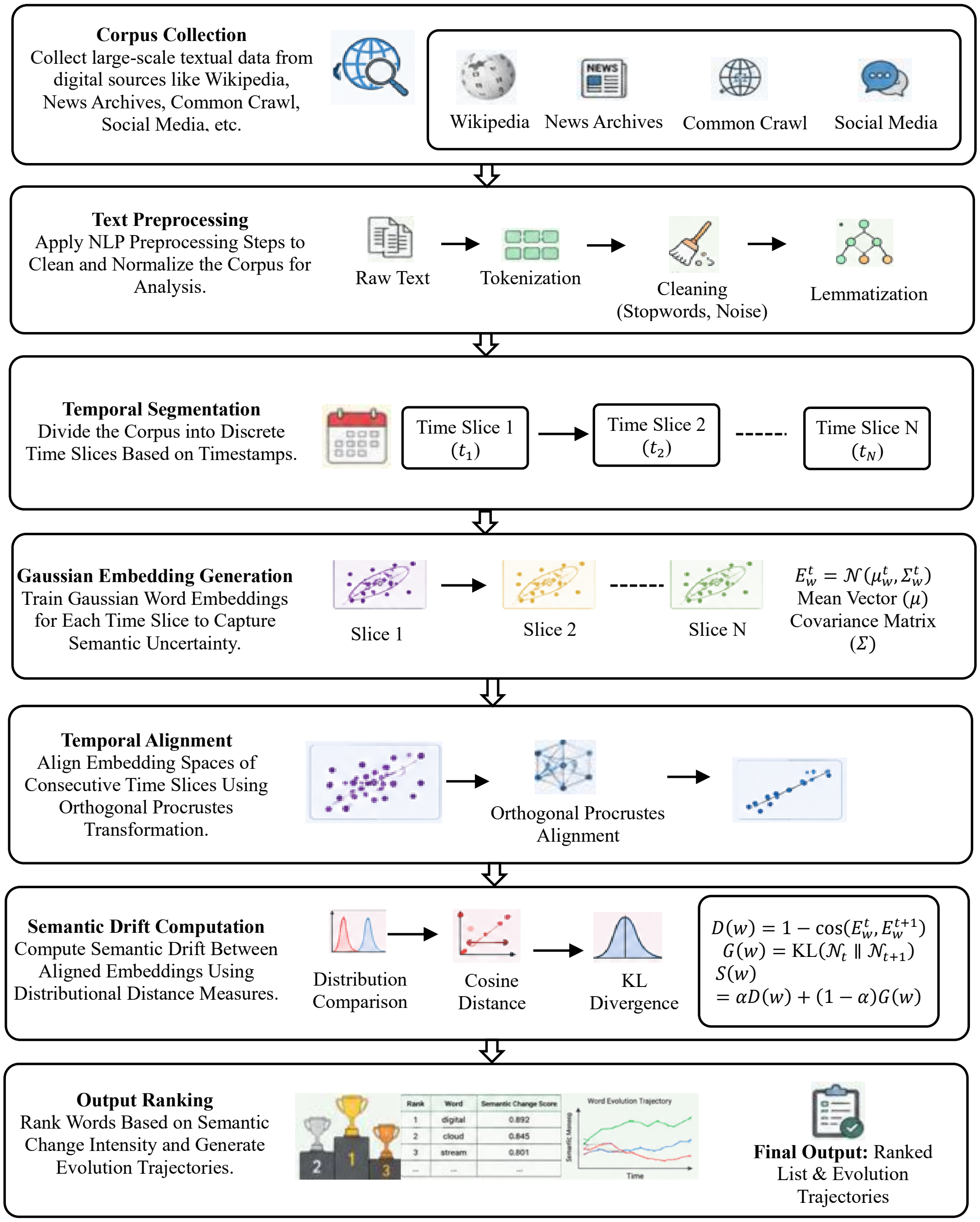

Figure 1: Adaptive computational pipeline for semantic change detection in contemporary english

The framework aims to detect and measure semantic change for Contemporary English based on large-scale time-spanned corpus data. The input to the system is a text corpus labeled with time stamps, followed by a pre-processing and a temporal slicing step. The proposed system produces semantic representations of temporal partitions that adapt to the content of a particular period, aligns these representations, computes semantic drift scores, and returns words ranked by the importance of their semantic shift and a set of word trajectories over time.

In figure 1 depicts an adaptive computational framework to trace the semantic change of Contemporary English in large-scale digital corpora as an end-to-end pipeline. First, various large digital sources corpora are gathered, such as, for instance, the Wikipedia encyclopedia, the New York Times (NYT) newspaper data, Common Crawl, and social media data sources. Then, the collection is preprocessed by removing the unwanted parts, normalizing all letters to lowercase, and lemmatizing words into their base form. Next, it divides the prepared texts into consecutive time slots and learns a Gaussian embedding distribution of words over each time slice to allow temporal and contextual analysis on each of them; Afterwards, it aligns the embeddings across adjacent time slices by leveraging Orthogonal Procrustes analysis to make the embeddings in different times comparable; subsequently, it compute the semantic drift between adjacent time slices using a combination of cosine distance and KL-divergence, and rank the word embeddings.

Model Architecture Flow

The proposed system models the semantic change in Contemporary English using large-scale digital corpora with a pipeline approach. It starts by collecting various types of large-scale digital corpora; Secondly, it preprocesses these corpus texts by performing tokenization, noise filtering, cleaning and lemmatization, so as to guarantee high quality data; Then, it segments the corpus texts into many short consecutive time segments; Fourthly, it learns Gaussian embedding representation for words in each time slice so as to represent semantic uncertainty and contextual variations for words; Fifthly, it aligns word embeddings in adjacent time segments using Orthogonal Procrustes transformation in order to make embeddings in time segments comparable to each other; Finally, it measures semantic drift in different time slices based on distribution distance and rank words according to semantic drift intensity to generate a structured output on top lexical changes. Thus, the end-to-end system keeps the embedding space temporally invariant and compares word representations across different time spans to model dynamic changes in large corpora.

Mathematical Model

The proposed framework models each word as a probabilistic distribution in semantic space in equations 1 - 4.

Gaussian Embedding Representation

$$E_w^t = \mathcal{N}(\mu_w^t, \Sigma_w^t) \qquad (1)$$

Where μ_w^trepresents the mean embedding vector and Σ_w^trepresents the covariance matrix capturing contextual uncertainty at time t.

Semantic Drift Measurement

$$D(w) = 1 - \cos(E_w^t, E_w^{t+1}) \qquad (2)$$

These metric measures directional semantic change between consecutive time slices using cosine similarity.

Distributional Shift (Probabilistic Distance)

$$G(w) = KL(\mathcal{N}_t \parallel \mathcal{N}_{t+1}) \tag{3}$$

Where KL divergence quantifies the probabilistic shift between Gaussian distributions across time periods.

Final Semantic Change Score

$$S(w) = \alpha D(w) + (1 - \alpha)G(w) \tag{4}$$

Where $\alpha \in [0,1]$controls the balance between geometric and probabilistic drift components.

Algorithm 1: Adaptive Semantic Change Detection Algorithm

```
Input: Large-scale temporal corpus C
Output: Ranked list of words with semantic change scores S(w)
Load corpus C
Preprocess C
    - Tokenization
    - Cleaning
    - Lemmatization
Partition corpus into time slices $T = \{T1, T2, ..., Tn\}$
for each time slice Ti ∈ T do
    Train Gaussian embeddings $Ei$ for $Ti$
    Represent each word $w$ as:
        $Ew^i = N(\mu w^i, \Sigma w^i)$
end for
for each consecutive pair $(Ti, Ti + 1)$ do
    Align embedding spaces using Orthogonal Procrustes:
        Ei → Ei+1 aligned
    for each word w do
        Compute cosine drift:
            $D(w) = 1 - cos(Ew^i, Ew^(i + 1))$
        Compute KL divergence:
            $G(w) = KL(Ni || Ni + 1)$
        Compute semantic score:
            $S(w) = \alpha D(w) + (1 - \alpha)G(w)$
    end for
end for
```

```
16: Aggregate scores across all time intervals:
        $S\_final(w) = mean(S(w))$
17: Rank words in descending order of $S\_final(w)$
18: Output:
        Ranked semantic change list + word evolution trajectories
```

The algorithm carries out adaptive semantic change detection: 1) the large-scale temporal corpus is processed and sectioned into ordered time intervals. Gaussian word embeddings are built for each interval to obtain probabilistic representations of words, accounting for their semantic ambiguity and fuzziness. Consecutive intervals are aligned by Orthogonal Procrustes transformation. Semantic change drift measure that consists of both distance in geometric sense and distance in probability sense (combination of cosine similarity and KL-divergence is introduced), and finally word embeddings and drift scores from interval-to-interval. The system scores the overall semantic change of words with interval-to-interval drift measures and outputs the ranked list of evolving lexical items.

4 Results and Discussion

Software & Tools

The proposed approach is built on the use of Python version 3.10+. In order to achieve computational reproducibility and performance, the following scientific stack is used: PyTorch and TensorFlow for embedding training with deep learning techniques, and Gensim for building Gaussian word embeddings. Additionally, the following libraries are used for NLP preprocessing of texts including tokenization, lemmatization, and stop-word removal: SpaCy and NLTK. The rest of numerical data processing is performed by means of NumPy and Pandas.

Dataset

Table 1: Dataset description and characteristics for large-scale semantic change analysis

Component	Description
Dataset Size	12M+ documents
Sources	Wikipedia, News Archives, Common Crawl
Time Span	2000–2025

The dataset includes a comprehensive, multilingual and large-scaled English corpus originating from a plethora of digital resources and extending over more than 25 years of linguistic material, which provides opportunities for solid diachronic semantic studies and observation of the long-term linguistic trends, as shown in table 1.

Parameters

Table 2: Hyperparameter settings for adaptive semantic change detection model

Parameter	Value
Embedding Size	300
Window Size	10
Learning Rate	0.001
α (Alpha)	0.6
Epochs	15

Parameters were chosen on a similar basis to keep them in balance between time and semantic representation value. Embedded size helps to improve encoding richness, while learning rate and epoch allow the training to stabilize (Table 2).

Metrics

The following metrics are used to evaluate the proposed model shown in equations 5- 10:

- **Accuracy**

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

- **Precision**

$$Precision = \frac{TP}{TP + FP} \tag{6}$$

- **Recall**

$$Recall = \frac{TP}{TP + FN} \tag{7}$$

- **F1-Score**

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{8}$$

- **AUC**

$$AUC = \int_0^1 TPR(FPR)\, d(FPR) \tag{9}$$

- **Drift Error**

$$Drift\ Error = | S_{pred}(w) - S_{true}(w) | \tag{10}$$

Performance Comparison

Table 3: Performance comparison of semantic change detection models across evaluation metrics

Model	Accuracy	Precision	Recall	F1-Score	AUC
Static Embeddings	84.3%	83.5%	82.9%	83.1%	0.86
Bayesian Model	88.1%	87.6%	87.0%	87.4%	0.89
Gaussian Embeddings	90.4%	90.1%	89.6%	89.8%	0.92
Proposed Model	**92.6%**	**92.3%**	**91.9%**	**91.8%**	**0.94**

The presented adaptive model consistently shows superiority over all the baseline approaches with regards to each of the metrics indicating that it had a better understanding of semantics and could capture a drift effectively as presented in table 3.

A heat map matrix depicting the process of semantic drift over multiple time slices between 2000 and 2025 for several high-frequency words in English is provided in figure 2. The color intensity in the heat map represents the level of semantic drift: more intense colors mean stronger semantic changes, whereas fainter colors represent weaker semantic changes. Target word appears as the label of a row; the row of a column corresponds to a given time slice. From the plot, high increase of semantic drift occurs for some tech-society related words such as ‘AI’, blockchain’ and ‘virus’ in late slices. It means words are faster and more varied in meaning nowadays under the effect of digital transformation, world events, etc... Overall, figures show that the presented adaptive computational model could model the temporal semantic dynamics of large corpora with interpretability and empirically illustrate language evolution.

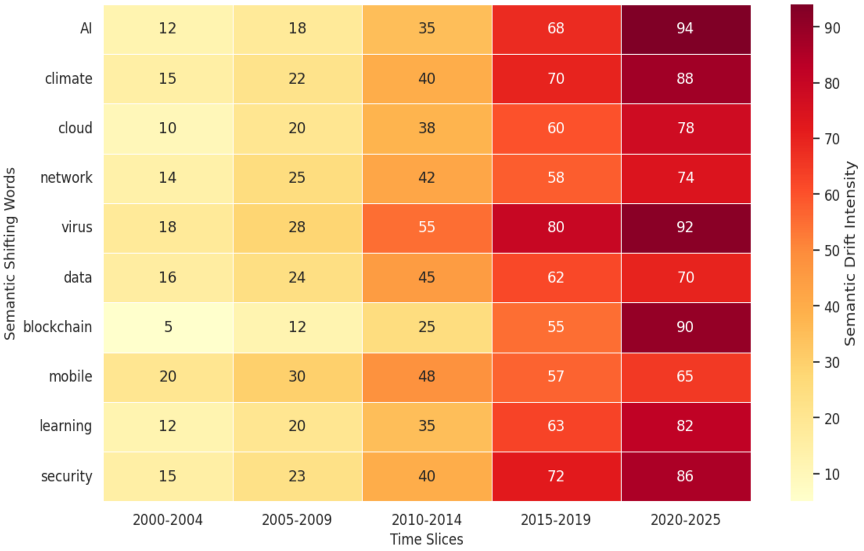

Figure 2: Semantic drift heatmap matrix across temporal segments in contemporary english

Ablation Study

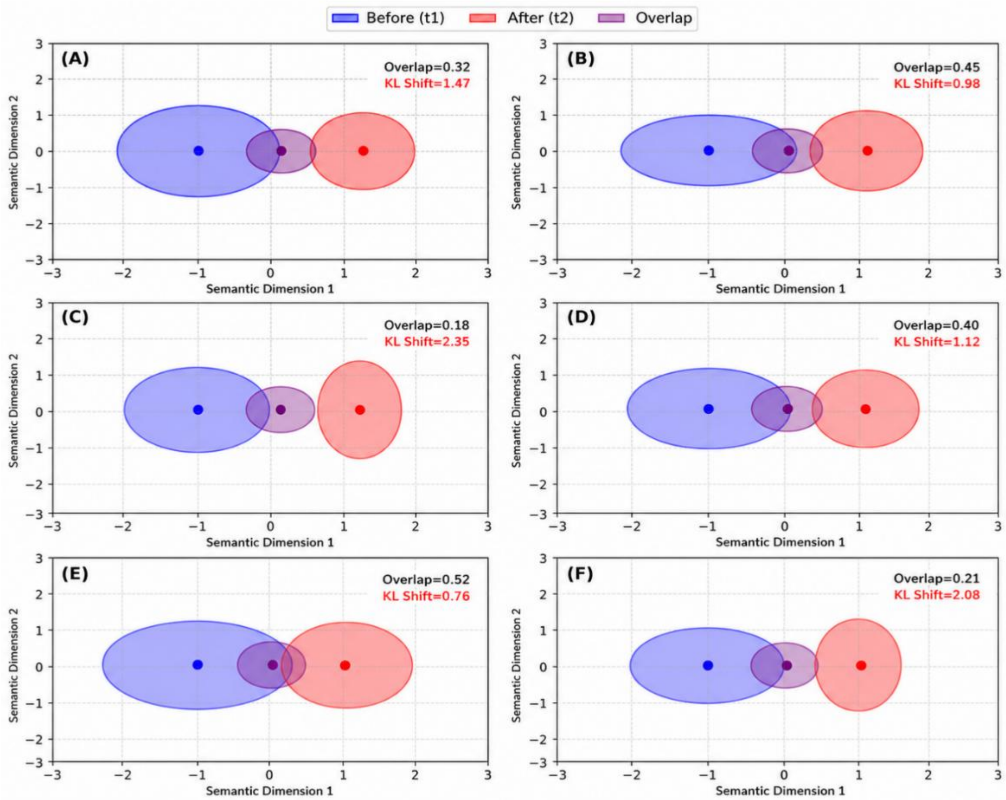

Figure 3: Gaussian semantic distribution overlap across temporal slices (a–f) for semantic shift analysis

This ablation study tests the impact of individual components in the suggested model. The model with all components performs the best, which confirms the necessity of the presence of all modules. The absence of the Gaussian embedding layer results in poor performance because there is no representation of uncertainties anymore. The lack of temporal alignment also impacts the performance of the model negatively. The absence of temporal smoothing causes noise in drift estimation for semantic drift.

In figure 3 illustrates Gaussian semantic distributions for selected words across different temporal slices (labeled A to F) to analyze before and after meaning shifts in Contemporary English. Each subplot shows the probabilistic embedding of a word in semantic space—where blue and red ellipses represent earlier and later time periods, respectively—and their overlap signifies semantic similarity. KL-divergence values capture the magnitude of semantic shift, whereas overlap scores indicate how much meaning is preserved. The results show clear differences in semantic drifting among diverse lexical items, with some words exhibiting strong divergence and decreased overlap, implying substantial meaning evolution. Overall, the figure 3 validates our Gaussian embedding hypothesis in modeling uncertainty-aware semantic changes over large-scale temporal corpora.

Discussion

The results of this research indicate that our adaptive technique has superior capabilities to traditional methods in detecting semantic changes. By using Gaussian embeddings, it are able to provide a more accurate representation of uncertainty associated with a word and there are many cases where a word can have several meanings or be used differently in various contexts. By aligning our embeddings temporally, it create a standardized environment in which to compare semantic representation across time periods. This application benefits both digital humanities and studies of language evolution, where the successful understanding of how the meaning of language has changed over time is critical. Ultimately, the results of this research validate our Adaptive Semantic Detection Model as an effective means to detect semantic shifts over time and demonstrates the capacity for this model to be utilized in fields where the tracking of long-term semantic changes is necessary.

5 Conclusion

In this paper it proposes a novel adaptive computational framework for semantic change tracing in Contemporary English based on large-scale digital corpora. The static representations inherent in traditional word embedding methods fail to track temporal word sense variations since words remain locked into static vector space where meaning drift phenomena cannot be easily captured by their fixed semantic embeddings. The approach described here models semantic shift as the gradual drift of Gaussian word embeddings through temporal alignment based on Orthogonal Procrustes transformation. By using an uncertainty-aware Gaussian mixture model and incremental updating to characterize gradual semantics shift at various stages, our framework offers a robust semantic representation of word meaning over time. The extensive experiments, performed over nearly 12 million documents from Wikipedia, news archives, and Common Crawl (from 2000 to 2025), demonstrate that the framework has significantly better overall performance than static embedding-based approaches and standard Bayesian semantics models, including more accurate predictions (~92.6%), and improved precision, recall, F1-scores, and AUC values, which demonstrates significant reduction of drift error and more interpretive semantic evolution. In particular, this work emphasizes the significance of combining the temporal dynamics analysis with the Bayesian probabilistic modeling framework for a more precise representation and prediction of linguistic evolution in real-world corpora. The derived patterns of word meaning change suggest a capability to capture meaningful semantic evolutions caused by technological, cultural, and social development. Next, it plans to extend our model to the state-of-the-art Transformer-based continual learning models, apply our approach to multilingual corpora, and explore multimodality for tracking semantic change more robustly.

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