

# Statistical Semantic Change Detection via Usage Similarities

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## Abstract

*Semantic change detection* comprises two sub-tasks: **classification**, which predicts whether a target word has undergone a semantic shift, and **ranking**, which orders words according to the degree of their semantic change. While most prior studies concentrated on **ranking** subtask, the **classification** subtask plays an equally important role, since many practical scenarios require a yes/no decision on semantic change rather than a global ranking. In this work, we propose a novel statistical method that predicts the presence or absence of semantic change. While most existing approaches infer semantic change by comparing word embeddings across time periods or domains, our method directly models the diachronic/synchronic consistency of usage-level similarity scores. Our experiments on SemEval-2020 Task 1 and WUGS datasets demonstrate that the proposed formulation outperforms existing state-of-the-art embedding-based methods, and robustly detects semantic change across languages in both diachronic and synchronic settings.<sup>1</sup>

## 1 Introduction

The meanings of words naturally evolve over time and across domains. Detecting such semantic change is essential for linguistic and lexicographic research, as well as for studying cultural and societal dynamics (Traugott and Dasher, 2001; Cook and Stevenson, 2010). Beyond these humanities-oriented applications, recent work has highlighted the importance of semantic change detection for various additional purposes, including information retrieval (Kutuzov et al., 2018) and efficient updating of masked language models (Su et al., 2022).

The Semantic Change Detection (SCD) task aims to automatically identify words that have undergone semantic shift. Recent shared tasks

<sup>1</sup>Source code is available at <https://github.com/a1da4/usage-similarity-polya>.

Method	EN	DE	LA	SV
SGNS (Rother et al., 2020)	73.0	54.2	45.0	61.3
SGNS (Pražák et al., 2020)	62.2	75.0	<b>70.0</b>	67.7
BERT (Asgari et al., 2020)	70.3	75.0	55.0	74.2
Pólya (ours)	<b>76.1</b>	<b>80.0</b>	N/A	<b>88.6</b>

Table 1: Accuracy (in %) in SemEval-2020 Task 1 (Schlechtweg et al., 2020); our method does not rely on word embeddings contrary to prior state-of-the-arts.

such as SemEval-2020 Task 1 (Schlechtweg et al., 2020) and the WUGS (Schlechtweg et al., 2021) framework have established benchmark datasets and evaluation protocols for this task. There are two subtasks in SCD: **classification**, which predicts whether a target word is semantically changed, and **ranking**, which orders target words according to the degree of semantic change (Schlechtweg et al., 2020). Due to the unsupervised nature of the problem, most prior studies have focused on the ranking subtask, evaluating models based on similarity scores derived from word embeddings across two periods/domains (Rosin et al., 2022; Rosin and Radinsky, 2022; Cassotti et al., 2023; Periti and Tahmasebi, 2024; Aida and Bollegala, 2024). However, ranking-based evaluation has inherent limitations, including limited interpretability of raw similarity scores and uncertainty about which parts of the ranked list are reliable. These issues motivate a stronger emphasis on the classification subtask.

In this work, we propose a new method that statistically determines whether a word has undergone semantic change by assessing the diachronic/synchronic consistency of a set of usage-level similarity scores. We consider SCD under the assumption that usage-level similarity scores are available, as is the case in current benchmark datasets such as SemEval-2020 Task 1 and WUGS, where these scores are provided via human annotations. Rather than addressing how such similarity scores should be predicted, our focus is on how semantic change can be statistically determined once



where  $n_k = \sum_{ij} \mathbb{I}(x_{ij} = k)$  is the frequency of score  $k$  in  $\mathbf{X}$  and  $L$  is the number of annotated entries.

This formula (4) is known as a Pólya distribution (Minka, 2000; Murphy, 2022). For the case semantic change, the likelihood is a product of block-wise Pólya distributions according to the Equation (2):

$$p(\mathbf{X}|\theta=1) = \prod_{n=1}^4 p(\mathbf{X}_n) \quad (5)$$

Here, each  $\mathbf{X}_n$  ( $n=1, \dots, 4$ ) is a submatrix of  $\mathbf{X}$  defined by Equation (2), and  $n_k$  and  $L$  are similarly computed within each  $\mathbf{X}_n$ . Therefore, when  $p(\theta=0) = p(\theta=1) = 1/2$ , we can compute a posterior probability of  $\theta$  as follows:

$$p(\theta|\mathbf{X}) \propto p(\mathbf{X}|\theta)p(\theta) \propto \begin{cases} p(\mathbf{X}|\theta=0) \\ p(\mathbf{X}|\theta=1) \end{cases} \quad (6)$$

where  $p(\mathbf{X}|\theta=0)$  and  $p(\mathbf{X}|\theta=1)$  are given by Equations (4) and (5), respectively. Intuitively speaking, this probability measures whether the observed score matrix is homogeneous or not.

## 4 Experiments

**Datasets** We evaluate our method on two benchmark resources: SemEval-2020 Task 1 and a subset of the WUGS datasets.<sup>2</sup>

**Evaluation** We evaluate all methods using Accuracy, following the standard classification protocol adopted in the WUGS framework. Each target word is labeled as stable or changed, and predictions are compared to gold-standard WUGS-derived binary labels.

**Baselines** For SemEval-2020 Task 1, we compare our proposal against the three best-performing systems for each language reported in the shared task (Rother et al., 2020; Pražák et al., 2020; Asgari et al., 2020). All of these baselines rely on static or contextualized word embeddings. For WUGS datasets, where system outputs are not directly comparable across languages or domains, we adopt a simple baseline: MostFreq, which predicts the majority class (stable or changed) for each dataset.

**Proposed Method** To provide intuition for our method in practice, we illustrate how the proposed

<sup>2</sup>Datasets are available at <https://www.ims.uni-stuttgart.de/en/research/resources/experiment-data/wugs/>. We select only datasets with usage-usage similarity annotations, since our method requires similarity-score distributions.

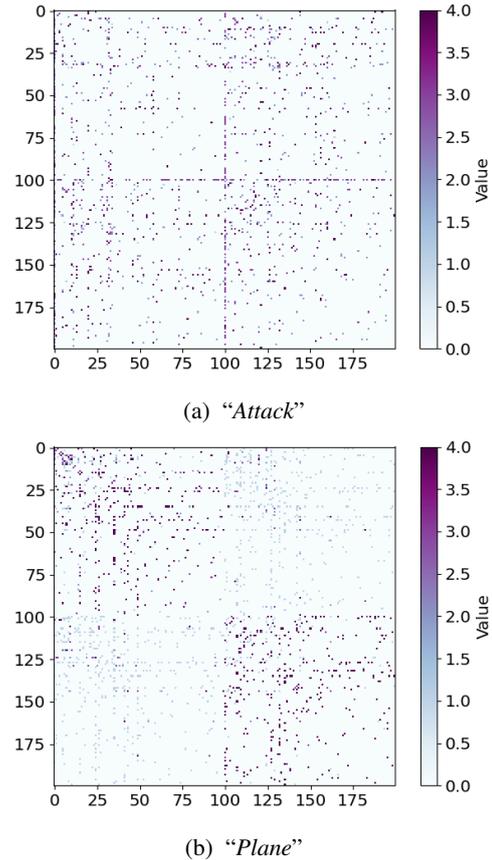


Figure 2: Visualization of score matrices for *attack* and *plane*. *Attack* represents a word whose meaning has not changed, whereas *plane* represents a word that has undergone semantic change. In each graph, instances indexed from 0–99 correspond to the earlier period, and those from 100–199 correspond to the later period. Annotations are assigned on a scale from 1 (Unrelated) to 4 (Identical), while 0 indicates no annotation or an unknown label (Schlechtweg et al., 2021).

decision rule behaves on individual targets. Figure 2 shows the score matrices for *attack* (a semantically stable word) and *plane* (a semantically changed word).<sup>3</sup> This figure highlights a key intuition behind our method: for semantically stable/changed words, the score matrix tends to be homogeneous/heterogeneous. The prediction is made by comparing the log-likelihoods under the **Stable** and **Changed** hypotheses (we predict **Changed** when  $p(\mathbf{X}|\theta=1) > p(\mathbf{X}|\theta=0)$ ). For *attack*, we obtain  $\log p(\mathbf{X}|\theta=0) = -6213.9$  and  $\log p(\mathbf{X}|\theta=1) = -6282.8$ , so the model favors the **Stable** hypothesis; the gold label is **Stable**. For

<sup>3</sup>The cross-shaped pattern in Figure 2a reflects the WUGS annotation procedure, which prioritizes informative usage pairs rather than annotating all pairs exhaustively (Schlechtweg et al., 2021). As a result, some usages are compared with many others, while many entries remain unannotated (0), producing the observed cross-shaped structure.

Data	Language	Grouping 1	Grouping 2	Accuracy (%)	
				MostFreq	Pólya
DWUG EN (Schlechtweg et al., 2021)	EN	1810–1860	1960–2010	54.3	<b>76.1</b>
DWUG EN Resampled (Schlechtweg et al., 2024a)	EN	1810–1860	1960–2010	60.0	<b>80.0</b>
DWUG DE (Schlechtweg et al., 2021)	DE	1800–1899	1946–1990	60.0	<b>80.0</b>
DWUG DE Resampled (Schlechtweg et al., 2024a)	DE	1800–1899	1946–1990	60.0	<b>73.3</b>
DiscoWUG (Kurtyigit et al., 2021)	DE	1800–1899	1946–1990	51.0	<b>72.0</b>
RefWUG (Schlechtweg, 2023)	DE	1750–1800	1850–1900	<b>54.5</b>	45.5
DURel (Schlechtweg et al., 2018)	DE	1750–1800	1850–1900	<b>63.6</b>	<b>63.6</b>
SURel (Hätty et al., 2019)	DE	general	domain specific	63.6	<b>68.2</b>
RuSemShift 1 (Rodina and Kutuzov, 2020)	RU	1682–1916	1918–1990	<b>77.5</b>	<b>77.5</b>
RuSemShift 2 (Rodina and Kutuzov, 2020)	RU	1918–1990	1991–2016	<b>62.3</b>	<b>62.3</b>
RuShiftEval 1 (Kutuzov and Pivovarova, 2021)	RU	1700–1916	1918–1990	<b>74.8</b>	<b>74.8</b>
RuShiftEval 2 (Kutuzov and Pivovarova, 2021)	RU	1918–1990	1992–2016	<b>70.3</b>	<b>70.3</b>
RuShiftEval 3 (Kutuzov and Pivovarova, 2021)	RU	1700–1916	1992–2016	<b>68.5</b>	<b>68.5</b>
DWUG ES (Zamora-Reina et al., 2022)	ES	1810–1906	1994–2020	55.5	<b>78.0</b>
DiaWUG (Baldissin et al., 2022)	ES	Spanish variant 1	Spanish variant 2	65.6	<b>81.3</b>
DWUG SV (Schlechtweg et al., 2021)	SV	1790–1830	1895–1903	68.1	<b>88.6</b>
DWUG SV Resampled (Schlechtweg et al., 2024a)	SV	1790–1830	1895–1903	60.0	<b>73.3</b>
ChiWUG (Chen et al., 2023)	ZH	1954–1978	1979–2003	<b>57.5</b>	52.5
DWUG IT (Cassotti et al., 2024)	IT	1948–1970	1990–2014	<b>69.2</b>	N/A
DWUG LA (Schlechtweg et al., 2021)	LA	–200–0	0–2000	<b>55.5</b>	N/A
NorDiaChange 1 (Kutuzov et al., 2022)	NO	1929–1965	1970–2013	67.5	<b>75.0</b>
NorDiaChange 2 (Kutuzov et al., 2022)	NO	1980–1990	2012–2019	<b>77.5</b>	70.0

Table 2: Results on WUGS datasets. For each dataset, we report accuracy for the MostFreq baseline and our Pólya-based method. The proposed approach yields strong performance across languages and dataset types, demonstrating robustness in both diachronic and synchronic SCD.

plane, we obtain  $\log p(\mathbf{X}|\theta = 0) = -7427.2$  and  $\log p(\mathbf{X}|\theta = 1) = -7095.6$ , leading the model to favor the **Changed** hypothesis; the gold label is **Changed**. These examples illustrate the qualitative behavior of our decision rule and provide intuition for the quantitative results presented next.

**Results** Table 1 summarizes the results on SemEval-2020 Task 1. Despite not relying on any word embeddings, our method achieves higher accuracy than all embedding-based state-of-the-art systems in three out of four languages, demonstrating the effectiveness of modeling temporal consistency in usage similarity distributions. To assess the robustness of our framework beyond the SemEval setting, Table 2 presents results on the WUGS datasets. Our method consistently attains strong accuracy across all languages and performs robustly in both diachronic and synchronic settings. These findings indicate that the proposed framework generalizes well beyond the SemEval datasets and is applicable to diverse languages and domains.

**Discussion and Future Work** Although our experiments rely on human usage-similarity annotations, recent studies suggest that high-quality labels can be obtained easily through automatic methods. The DURel Annotation Tool (Schlechtweg et al., 2024b) already integrates XL-LEXEME (Cassotti et al., 2023) to automatically propose usage-

similarity annotations. Moreover, Periti and Tahmasebi (2024) show that contextualized embedding models and large language models can generate annotation labels that approach the quality of human annotations. These developments indicate that our statistical framework may be deployed in a fully automatic setting in the future, where usage-similarity labels are predicted rather than manually collected.

## 5 Conclusion

We proposed a statistical framework for lexical semantic change detection that models temporal consistency in usage-similarity score distributions. By evaluating whether the observed similarity structure is better explained by a single sense distribution or by distinct distributions across periods, our method provides a simple yet effective decision rule. Experiments on SemEval-2020 Task 1 and the WUGS datasets show that our approach achieves competitive or superior accuracy across languages and settings. These findings demonstrate that modeling usage-level similarity scores enables effective detection of semantic change. Together with recent advances in automatically predicting high-quality similarity labels, our framework offers a promising path toward fully automatic and interpretable semantic change detection.

## Limitations

The proposed framework has several limitations that should be considered when interpreting the results and assessing its applicability.

First, our method assumes the availability of usage-level similarity scores and focuses on statistically modeling their distributions, rather than addressing how such scores are obtained. In this study, we rely on human-annotated usage-similarity labels provided by existing benchmarks. Although recent work suggests that automatic methods can generate high-quality similarity annotations (Periti and Tahmasebi, 2024), the performance of our framework under fully automatic annotation pipelines has not been empirically evaluated. In particular, automatically predicted similarity scores may exhibit different noise characteristics or systematic biases compared to human judgments, which could affect the reliability of the statistical test.

Second, related to this issue, our model treats observed similarity scores as independent samples from underlying distributions. This simplifying assumption enables an interpretable and tractable formulation, but its validity depends on the amount and structure of available data. When the number of annotations is small or unevenly distributed across usage pairs, deviations from this assumption may have a stronger impact on the estimated likelihoods. Understanding the interaction between annotation density and model reliability remains an open direction for future investigation.

Finally, our empirical evaluation is restricted to lexical semantic change detection benchmarks based on usage-similarity annotations. The applicability of the framework to other tasks or domains that can be modeled in terms of pairwise similarity judgments has not been empirically investigated. Exploring these alternative application settings would be necessary to assess the broader usefulness and generality of the proposed statistical formulation.

## Acknowledgments

This work was partly supported by JST, PRESTO Grant Number JPMJPR2366, Japan, and by the NINJAL collaborative research project ‘Extending the Diachronic Corpus through an Open Co-construction Environment’.

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