Definition generation for lexical semantic change detection

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Definitions as senses

- We use LLM-generated contextualized word definitions for lexical semantic change detection (LSCD)
  - ...by comparing vectorized definitions
  - ...by comparing the distributions of definitions ('definitions-as-senses')
- Dictionary-like definitions give us interpretability:
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- fine-tuned definition generation models from [Kutuzov et al., 2024]

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Good performance, but interpretability is lost after vectorizing definitions.

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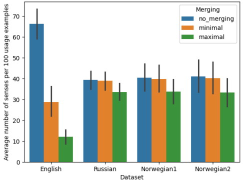
Merging reduces the number of unique definitions: more realistic as senses.



Average number of senses per 100 usages before and after merging, calculated across all datasets for each language.
(should be done cautiously: merging too much can degrade the performance)

One English example

3 most frequent definitions/senses per time period for *ball* (high predicted change rate):

	Period 1 (1810-1860)	**Period 2** (1960-2010)
ball Jensen-Shannon divergence (change score): 0.83	*A spherical object especially one that is round in shape* (82%)	*The object hit in a game* (80%)
	A party (6%)	*The object used in various sports especially in soccer tennis basketball etc* (<1%)
	A wedding (<1%)	*The object used in various sports especially in soccer basketball and other games which is thrown or kicked* (<1%)

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More examples, data and code at
`https://github.com/ltgoslo/Definition-generation-for-LSCD`

Performance across different generation and merging strategies

	English		**Norwegian-1**		**Norwegian-2**		**Russian-1**		**Russian-2**		**Russian-3**	
	Cosine	JS	Cosine	JS	Cosine	JS	Cosine	JS	Cosine	JS	Cosine	JS
No merging:												
Greedy	0.461	0.405	*0.303*	0.332	*0.211*	*0.232*	0.299	0.390	0.337	0.427	0.383	0.469
Beam	0.457	0.476	*0.268*	*0.238*	*0.216*	*0.201*	0.304	0.368	0.297	0.403	0.317	0.417
Diverse	0.449	0.382	*0.241*	*0.280*	*0.069*	*0.164*	0.301	0.345	0.310	0.389	0.348	0.421
Minimalist merging:												
Greedy	0.564	**0.565**	*0.251*	*0.280*	*0.192*	*0.197*	0.271	**0.391**	0.233	**0.431**	0.325	**0.491**
Beam	0.510	0.500	*0.297*	*0.240*	*0.112*	*0.189*	0.298	0.366	0.252	0.383	0.301	0.409
Diverse	0.478	0.434	0.325	*0.296*	*0.162*	*0.215*	0.265	0.354	0.268	0.406	0.287	0.443
Full-fledged merging:												
Greedy	0.417	0.418	*0.261*	**0.362**	*0.193*	***0.260***	0.286	**0.391**	0.250	0.416	0.360	0.476
Beam	0.492	0.493	*0.265*	*0.215*	*0.186*	*0.226*	0.304	0.360	0.250	0.347	0.327	0.420
Diverse	*0.312*	*0.301*	*0.209*	*0.315*	*0.202*	*0.221*	0.236	0.301	0.217	0.379	0.262	0.411
Threshold	50		10		10		10		10		10	

LSCD performance (Spearman's ρ) with different generation, merging and distance calculation strategies.

Threshold: Levenshtein edit distance threshold for merging definitions.

Results (Spearman's ρ for graded LSCD) compared to the baselines

Method	**English**	**Norwegian-1**	**Norwegian-2**	**Russian-1**	**Russian-2**	**Russian-3**
			Non-interpretable methods:			
XLM-R token embeddings	0.514$^{\diamondsuit}$	0.394$^{\diamondsuit}$	0.387$^{\diamondsuit}$	0.376$^{\diamondsuit}$	**0.480**$^{\diamondsuit}$	0.457$^{\diamondsuit}$
XL-LEXEME+APD (WiC-based)	0.886	0.659	0.640	0.796	0.820	0.863
Definition embeddings (ours)	**0.637**	**0.496**	**0.565**	**0.488**	0.462	**0.504**
			Interpretable methods:			
Lesk without PoS	0.423$^{\clubsuit}$	*0.178*	0.500	0.294	0.279	0.286
Lesk with PoS	0.587	*0.150*	0.474			
ARES sense embeddings	0.529$^{\clubsuit}$	—	—	—	—	—
LMMS sense embeddings	0.589$^{\clubsuit}$	—	—	—	—	—
Definitions as senses (ours)	0.565	0.362	*0.260*	0.391	0.431	0.491

($\diamondsuit$: best results from [Giulianelli et al., 2022], $\clubsuit$: [Tang et al., 2023], XL-LEXEME results from [Periti and Tahmasebi, 2024])

Definition embeddings yield better performance, but definitions as senses are interpretable and explainable.

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