Computational approaches to semantic change detection Day 5, Part 2 Explainable semantic change modeling via definition generation

Andrey Kutuzov, Lidia Pivovarova

University of Oslo, University of Helsinki ESSLLI'2023





A retelling of [Giulianelli et al., 2023] (https://aclanthology.org/2023.acl-long.176/)

Austin C. Kozlowski,^a Matt Taddy,^b and James A. Evans^{a,c}

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A computational analysis of crosslinguistic regularity in semantic change

Olivia Fugikawa^{1*†}, Oliver Hayman^{2*†}, Raymond Liu^{3*†}, Lei Yu⁴, Thomas Brochhagen⁵ and Yang Xu^{6*}

Annual Review of Linguistics Semantic Structure in Deep Learning

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Word embeddings quantify 100 years of gender and ethnic stereotypes

Nikhil Garg^{a,1}, Londa Schiebinger^b, Dan Jurafsky^{c,d}, and James Zou^{e,f,1}

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Semantic Structure in

Deep Learning

Ellie Pavlick

Disentangling the cultural evolution of ancient China: a digital humanities perspective

Siyu Duan^{1,2}, Jun Wang^{1,2,3}, Hao Yang^{2,3} & Qi Su^{2,3,4⊠}

A computational analysis of crosslinguistic regularity in semantic change

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Characterizing English Variation across Social Media Communities with BERT

Li Lucy and David Bamman

What about Grammar? Using BERT Embeddings to Explore Functional-Semantic Shifts of Semi-Lexical and Grammatical Constructions

Lauren Fonteyn

Slangvolution: A Causal Analysis of Semantic Change and Frequency Dynamics in Slang

Daphna Keidar*,* Andreas Opedal*,* Zhijing Jin,* Mrinmaya Sachan*

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The Geometry of Culture:

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Follow the leade semantic change Historical linguistics

Psycholinguistics

Cognitive science

Sociology

Gender and cultural studies

Political science

Natural language processing

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Annual Review of Linguistics

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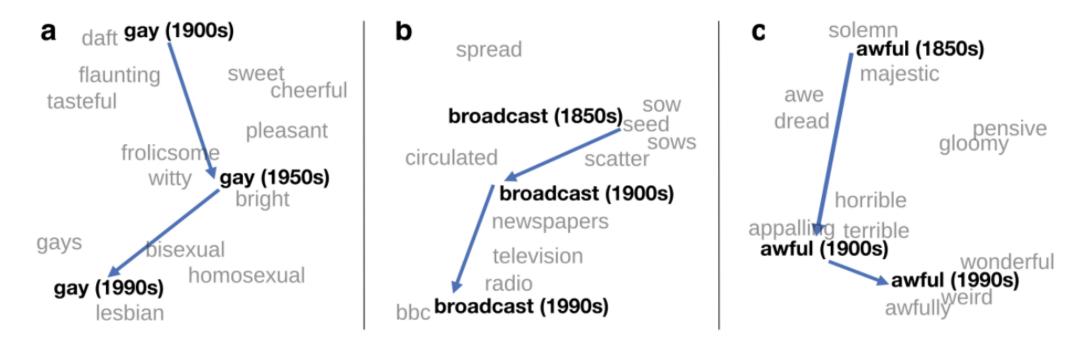
David Bamman

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Mrinmaya Sachan[®]

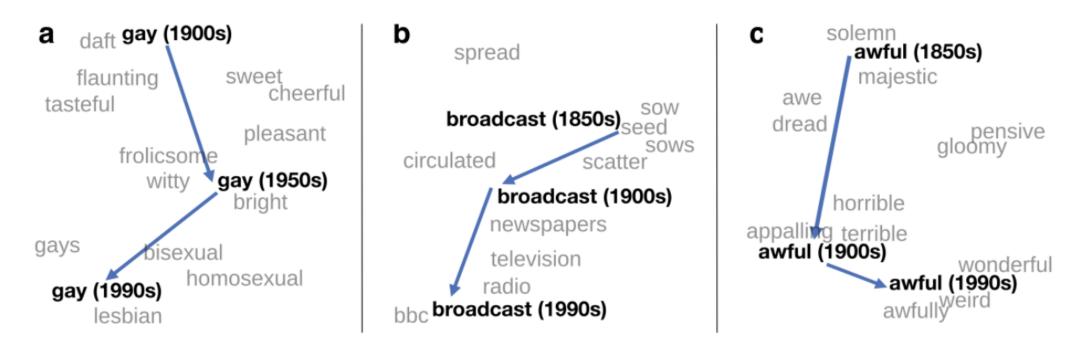
Adel Explanations

Static



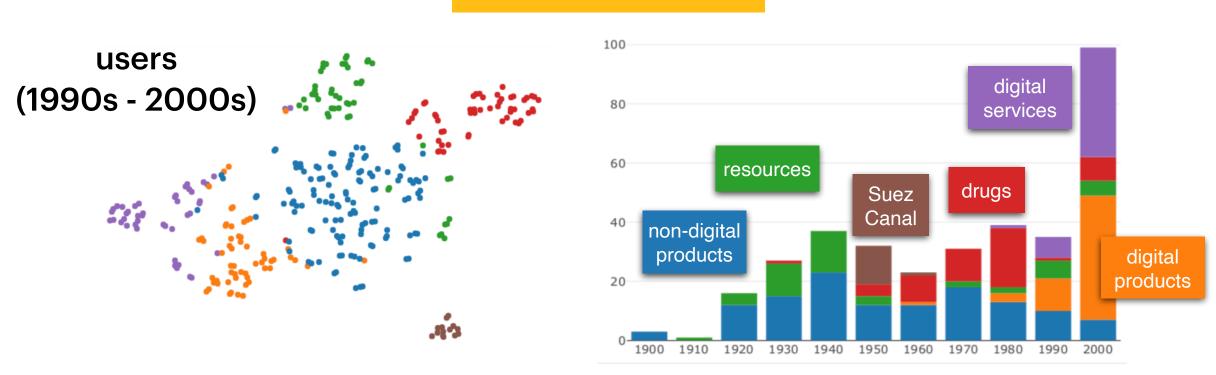
Hamilton, Leskovec, Jurafsky. ACL 2016.

Static



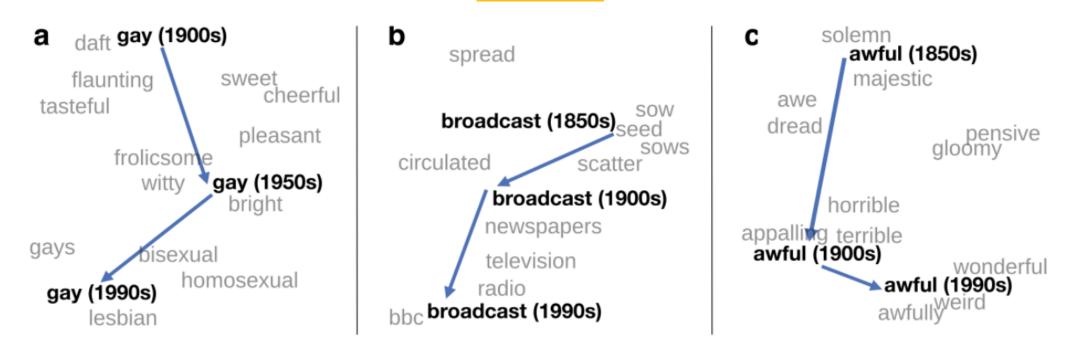
Hamilton, Leskovec, Jurafsky. ACL 2016.

Contextualised



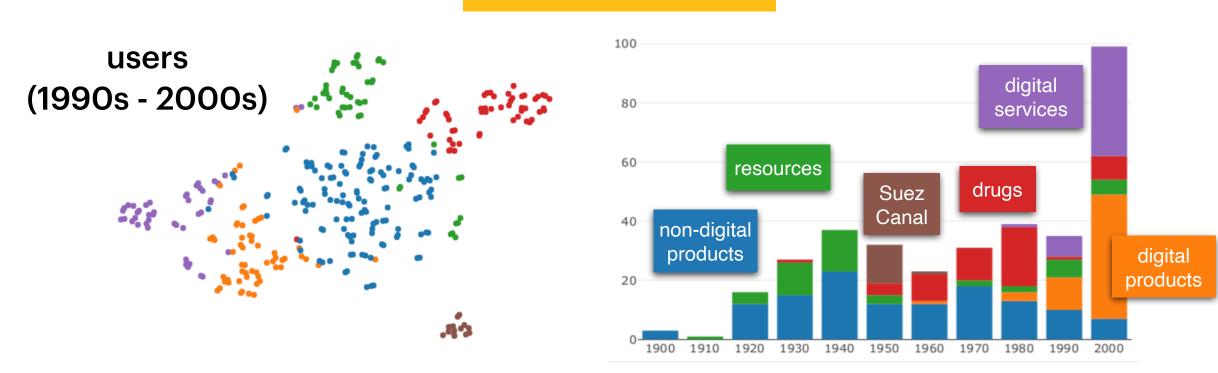
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Static



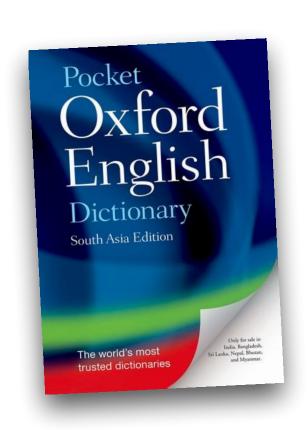
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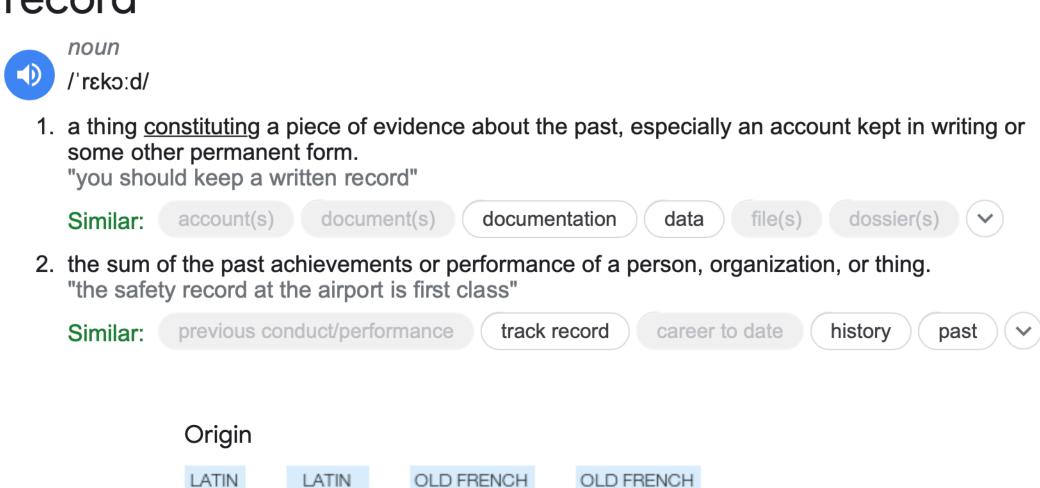


Giulianelli, Del Tredici, Fernández. ACL 2020.

Definitions



record



recorder

bring to

remembrance

record

remembrance

record

Middle English

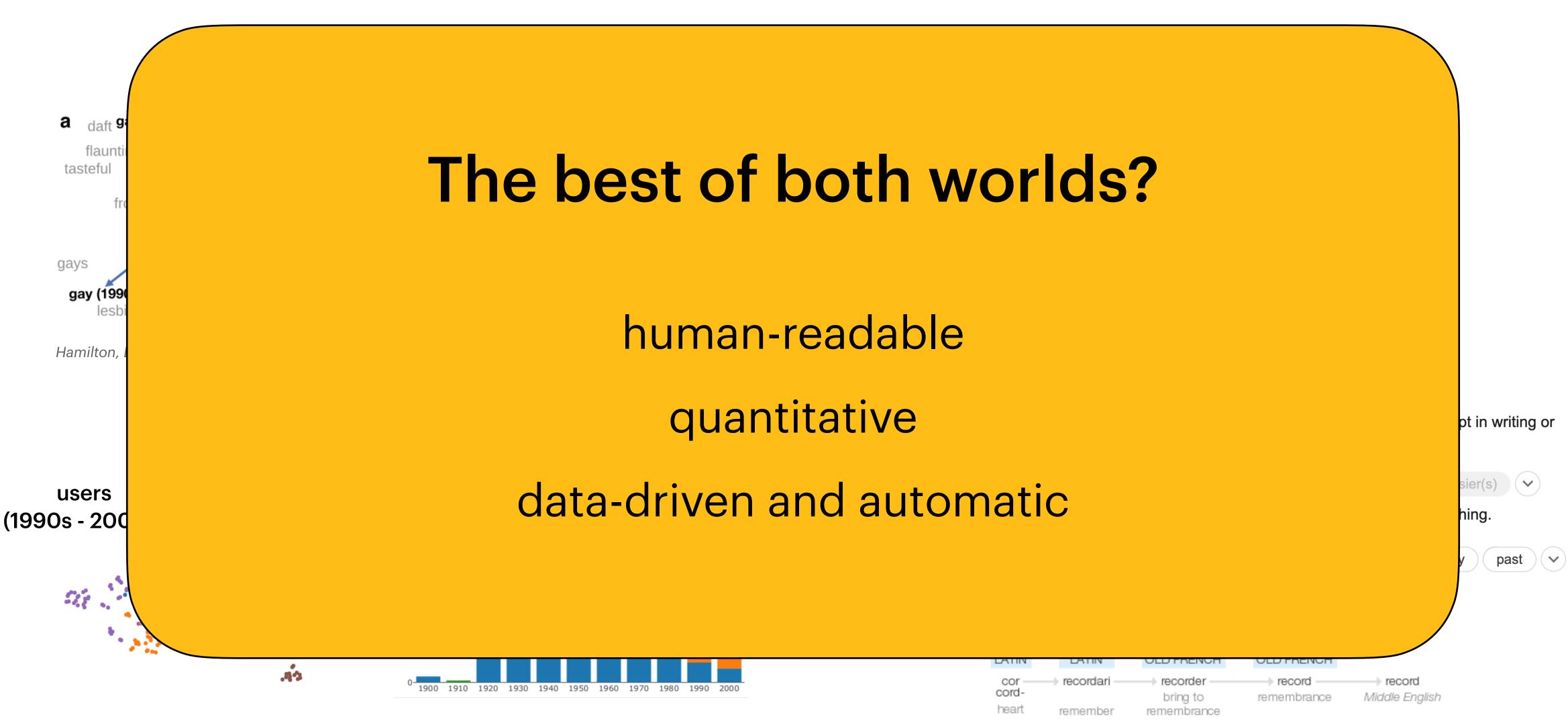
→ recordari

remember

cord-

heart

Definitions



"you should keep a written record"

"you should keep a written record"



A document or other means of providing information about past events.

"you should keep a written record"



A document or other means of providing information about past events.

"she held the world **record** for ten years"

"you should keep a written record"



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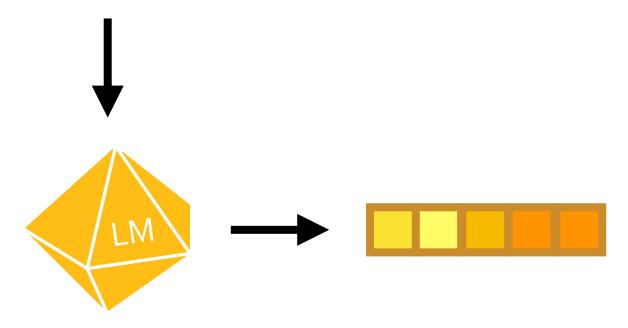


The highest score or other achievement in a game.

"you should keep a written **record**"



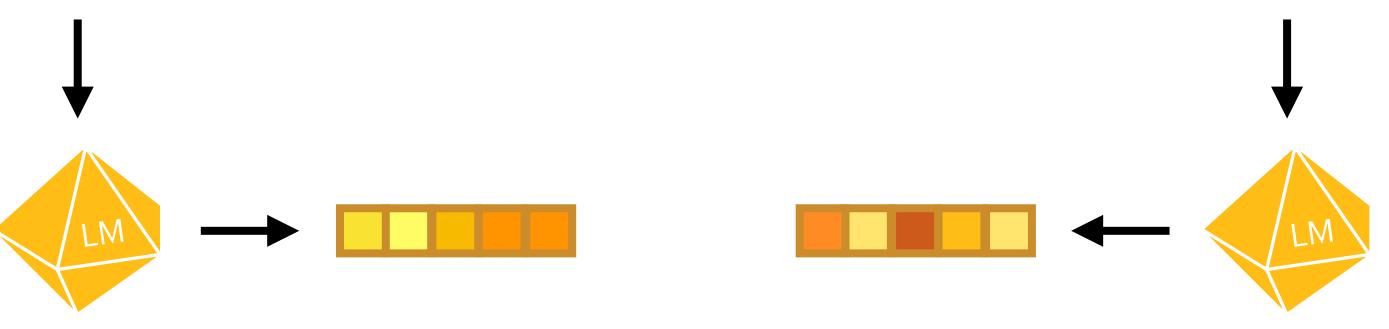
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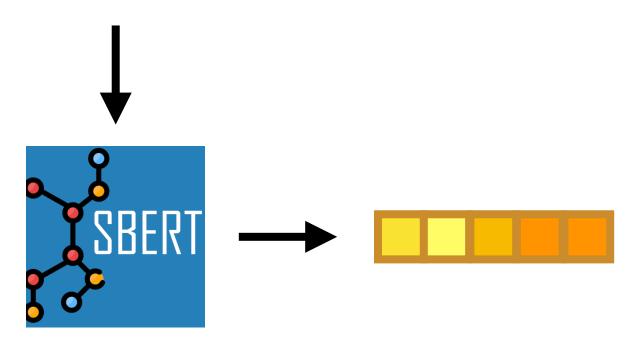
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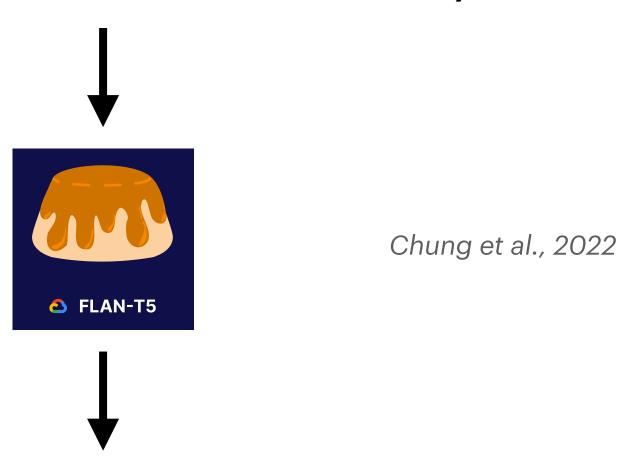
"you should keep a written record"



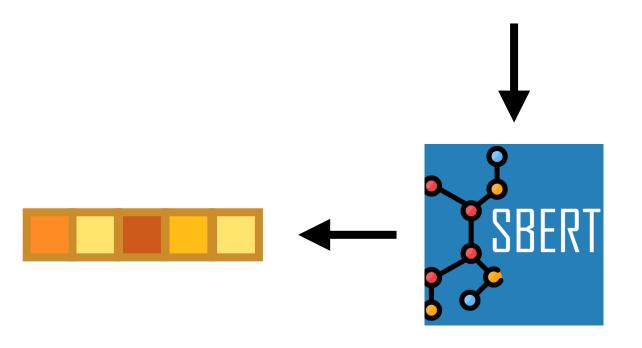
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"she held the world **record** for ten years"



The highest score or other achievement in a game.



Reimers and Gurevych, 2019



usage examples

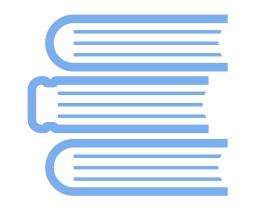
"she held the world record for ten years"

+ "what is the definition of record?"

usage-specific definitions

The best performance or most remarkable event of its kind.

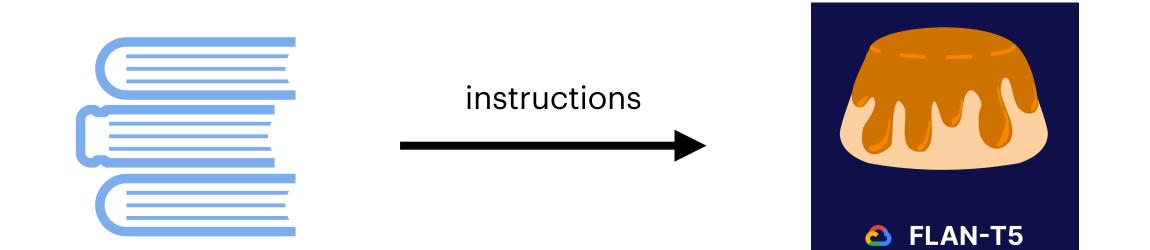
3 datasets of definitions

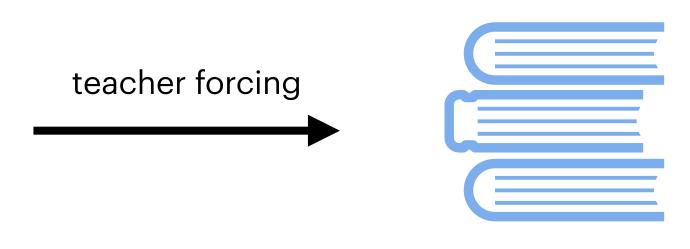


WordNet (Ishiwatari et al., 2019)

Oxford (Gadetsky et al., 2018)

CoDWoE (Mickus et al., 2022)





usage examples

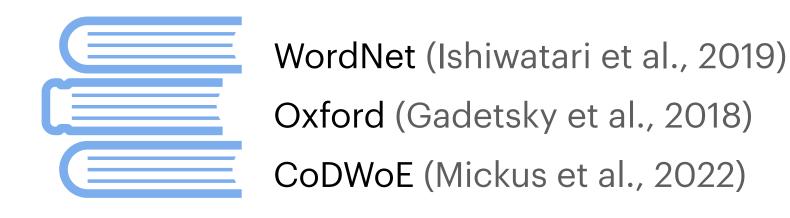
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8 task verbalisations

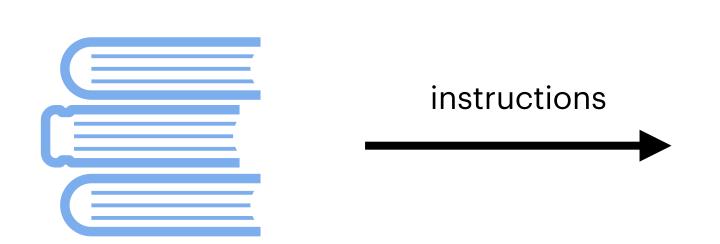
"define w"

"define the word w"

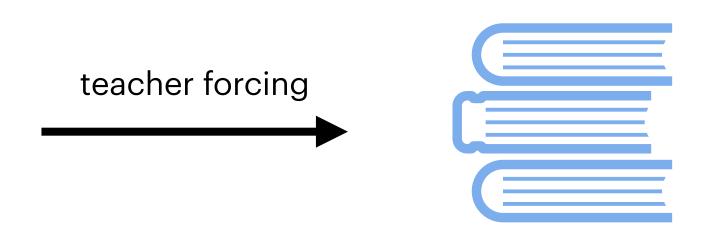
"give the definition of w"

"what is the definition of w?"

• • •







usage examples

usage-specific definitions

"she held the world record for ten years"

+ "what is the definition of record?"

The best performance or most remarkable event of its kind.

3 datasets of definitions



WordNet (Ishiwatari et al., 2019)

Oxford (Gadetsky et al., 2018)

CoDWoE (Mickus et al., 2022)

8 task verbalisations

"define w"

"define the word w"

"give the definition of w"

"what is the definition of w?"

• • •

3 variants of Flan-T5

Base
Large
XL
+ vanilla T5 (Raffel et al., 2020)



usage examples

usage-specific definitions

"she held the world record for ten years"

+ "what is the definition of record?"

The best performance or most remarkable event of its kind.

			WordNet			Oxford	
Model	Test	BLEU	ROUGE-L	BERT-F1	BLEU	ROUGE-L	BERT-F1
[Huang et al., 2021]	Unknown	32.72	-	-	26.52	-	-
Flan-T5 XL	Zero-shot (task shift)	2.70	12.72	86.72	2.88	16.20	86.52
Flan-T5 XL	In-distribution	11.49	28.96	88.90	16.61	36.27	89.40
Flan-T5 XL	Hard domain shift	29.55	48.17	91.39	8.37	25.06	87.56
Flan-T5 XL	Soft domain shift	32.81	52.21	92.16	18.69	38.72	89.75



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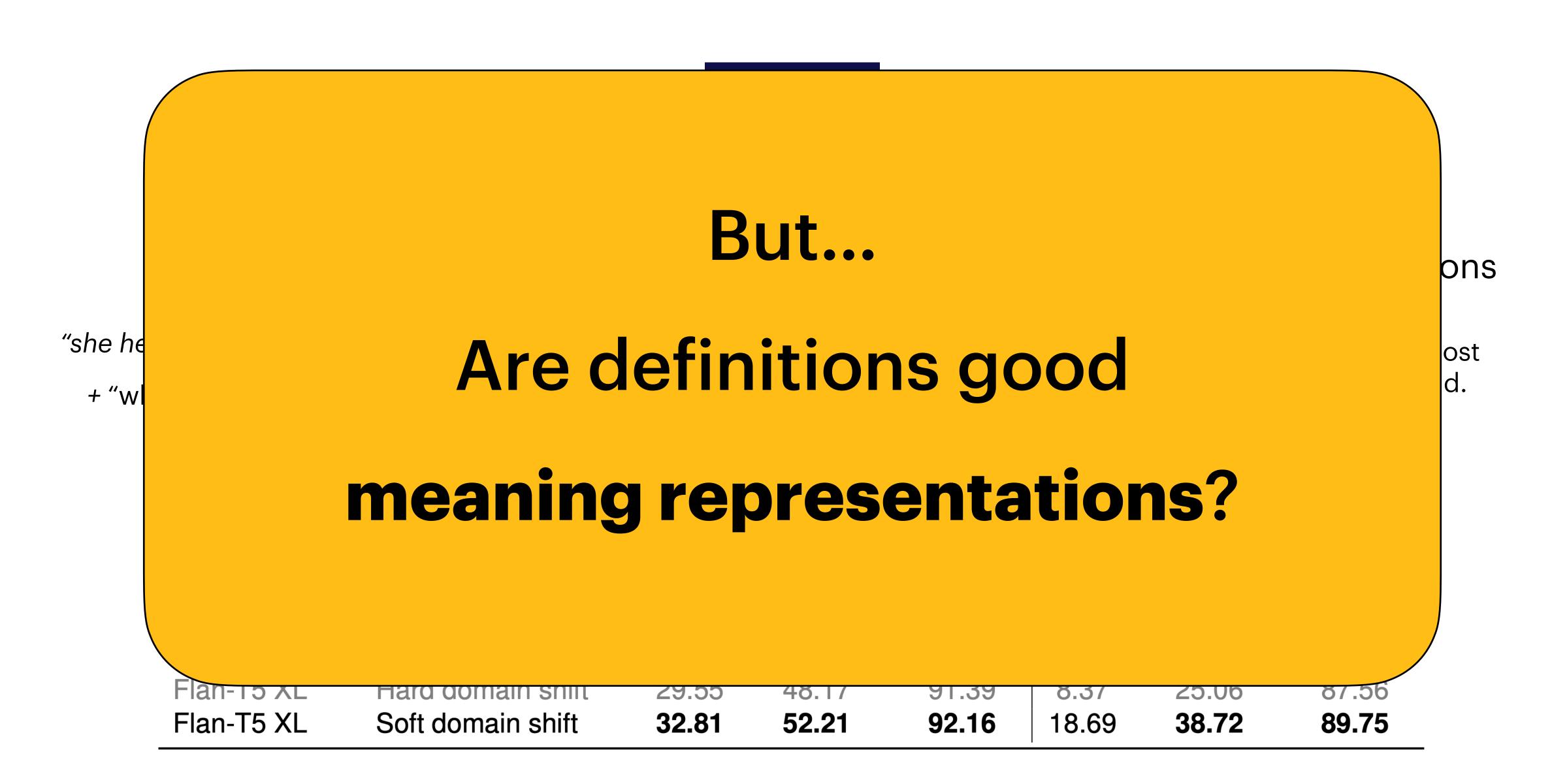
usage-specific definitions

"she held the world record for ten years"

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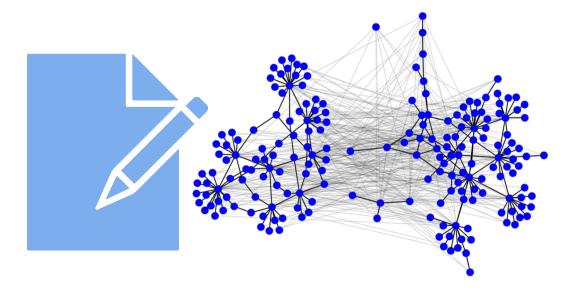
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Correlation with human pairwise similarity judgements

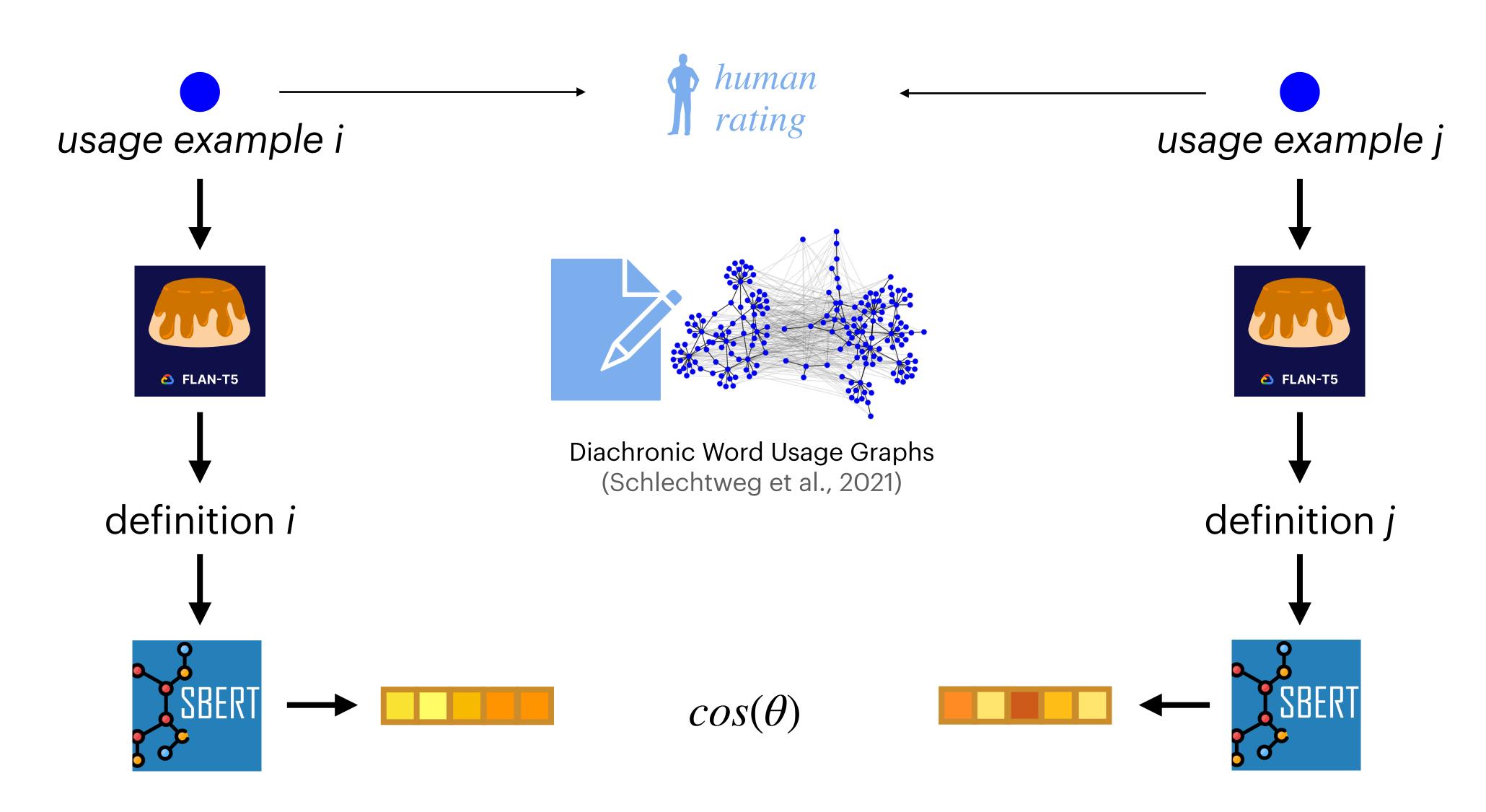




Diachronic Word Usage Graphs

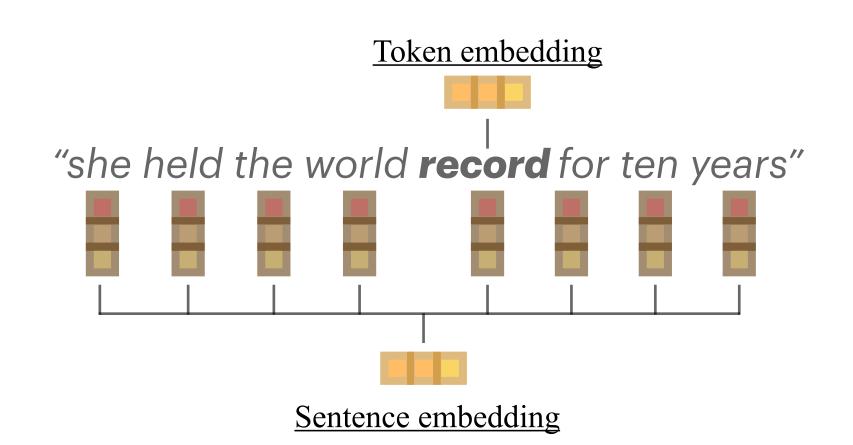
(Schlechtweg et al., 2021)

Correlation with human pairwise similarity judgements





Correlation with human pairwise similarity judgements



Spearman's correlation.

Method	Cosine SacreBLEU		METEOR	
	0.1.11			
Token embeddings	0.141			
Sentence embeddings	0.114			

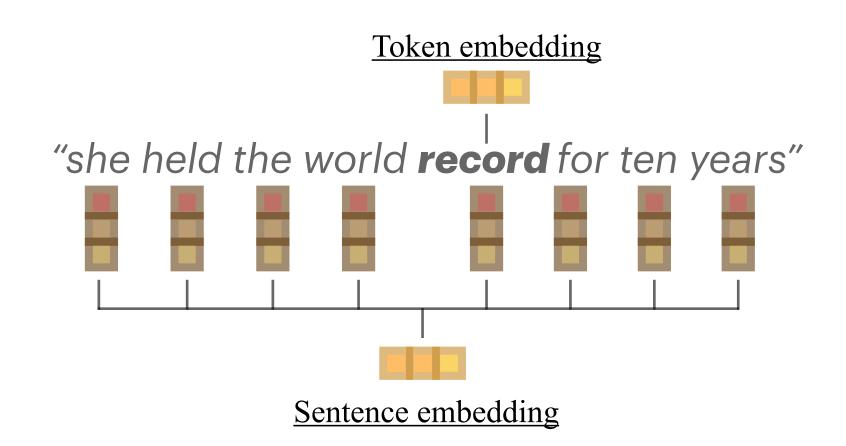
Definition

"**record**": the best performance or most remarkable event of its kind

FLAN-T5 XL Zero-shot	0.188
FLAN-T5 XXL Zero-shot	0.206
FLAN-T5 base FT	0.221
FLAN-T5 XL FT	0.264



Correlation with human pairwise similarity judgements



Spearman's correlation.

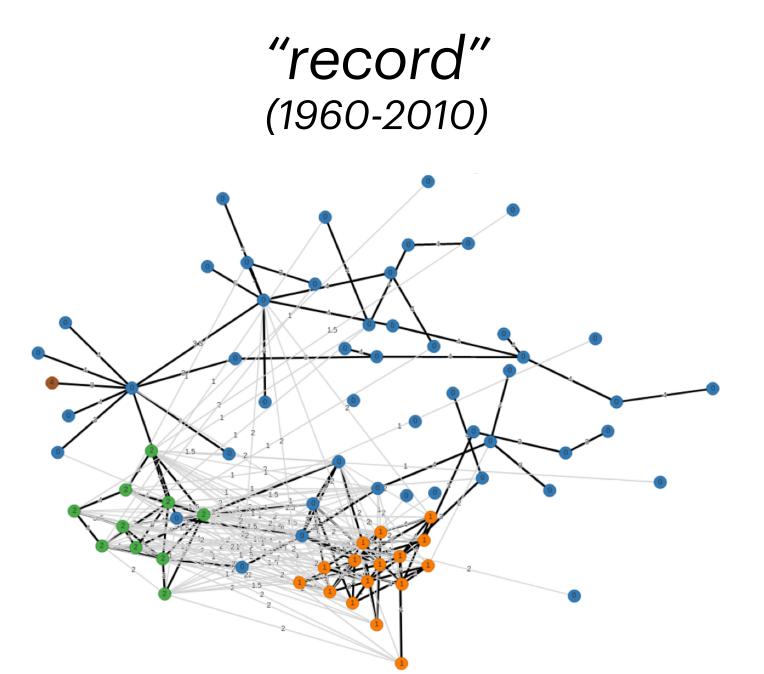
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Token embeddings	0.141	-	-	
Sentence embeddings	0.114	-	-	

Definition

"**record**": the best performance or most remarkable event of its kind

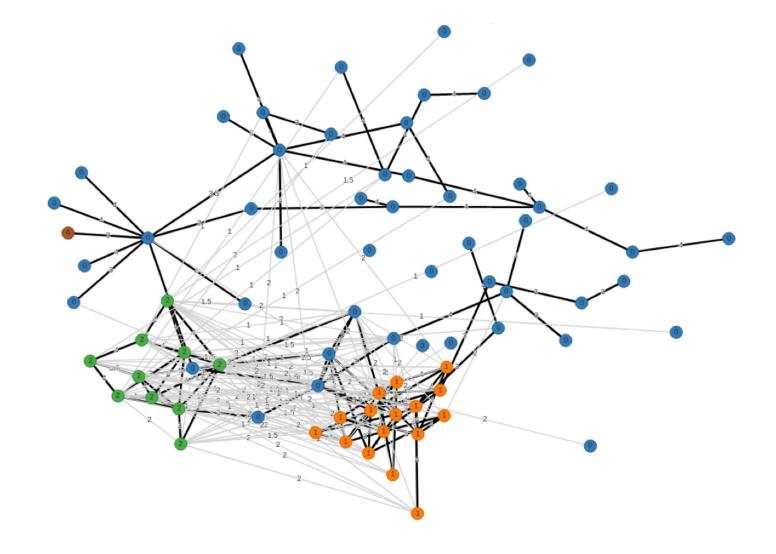
FLAN-T5 XL Zero-shot	0.188	0.041	0.083
FLAN-T5 XXL Zero-shot	0.206	0.045	0.092
FLAN-T5 base FT	0.221	0.078	0.077
FLAN-T5 XL FT	0.264	0.108	0.117

Case study: Semantic change analysis

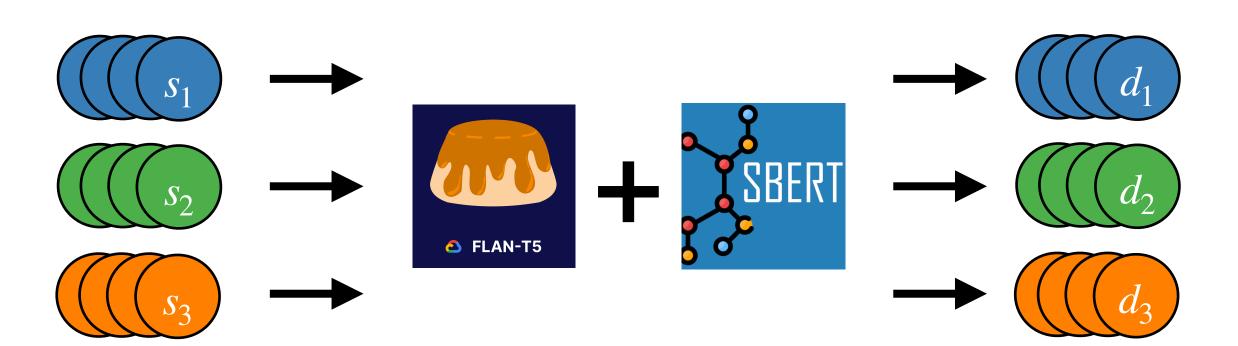


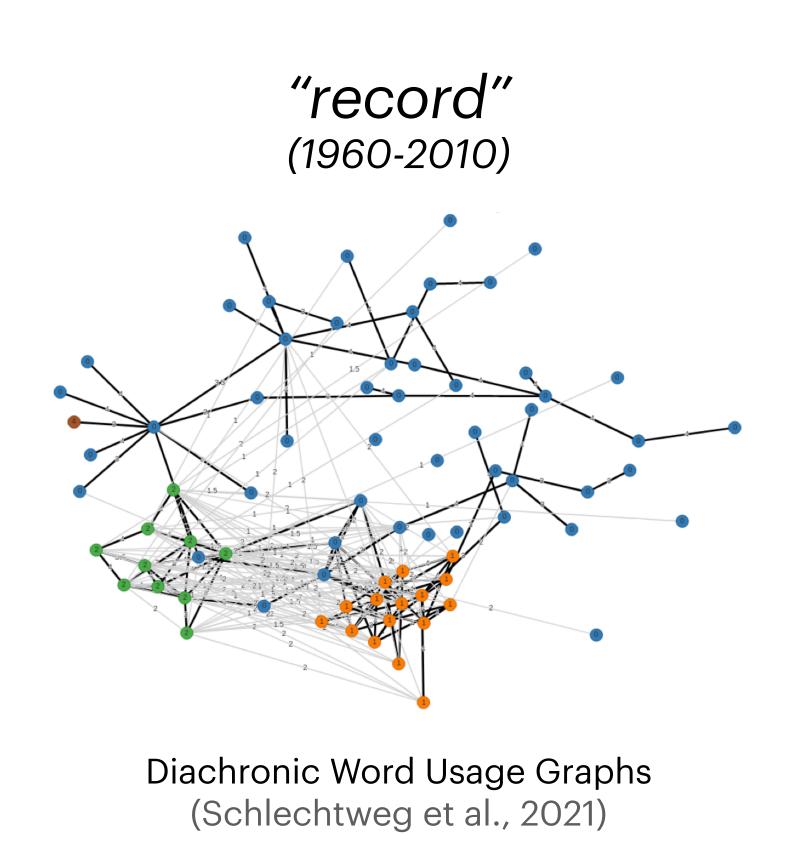
Diachronic Word Usage Graphs (Schlechtweg et al., 2021)

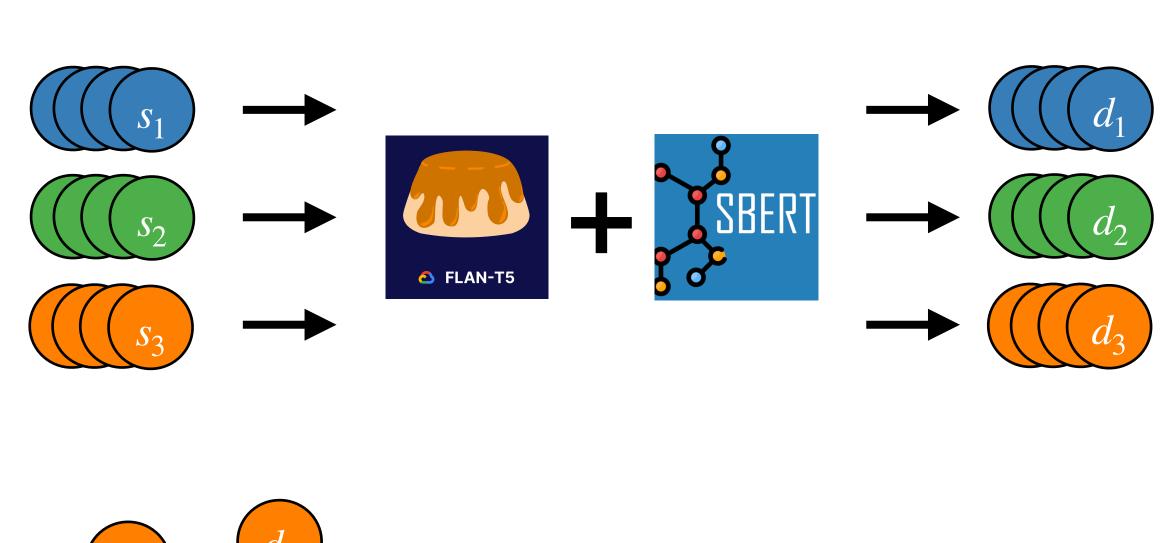
"record" (1960-2010)

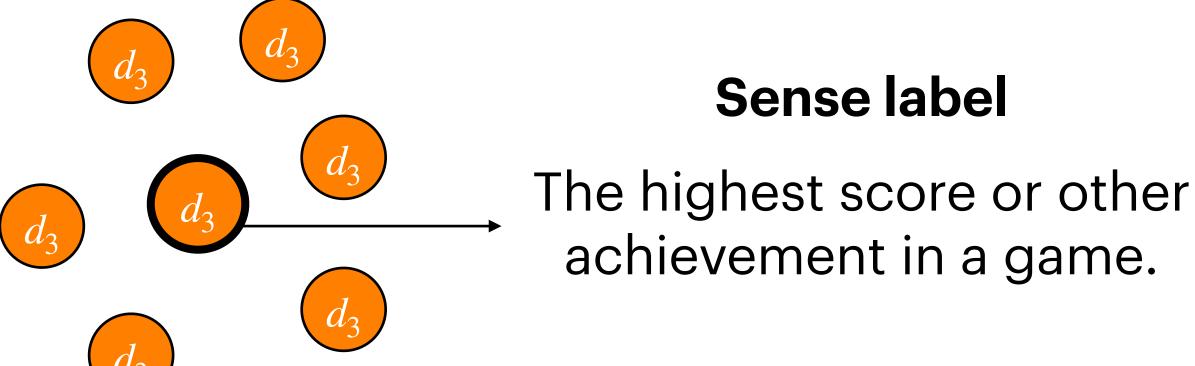


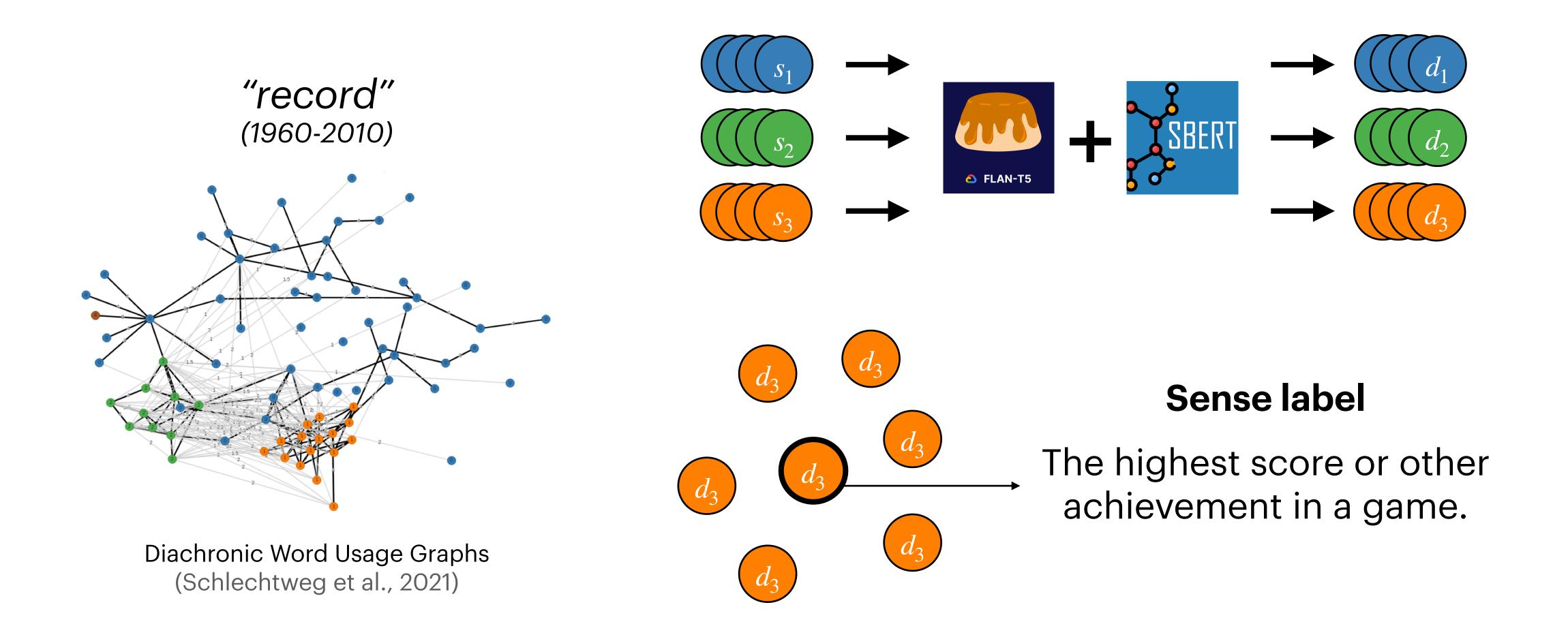
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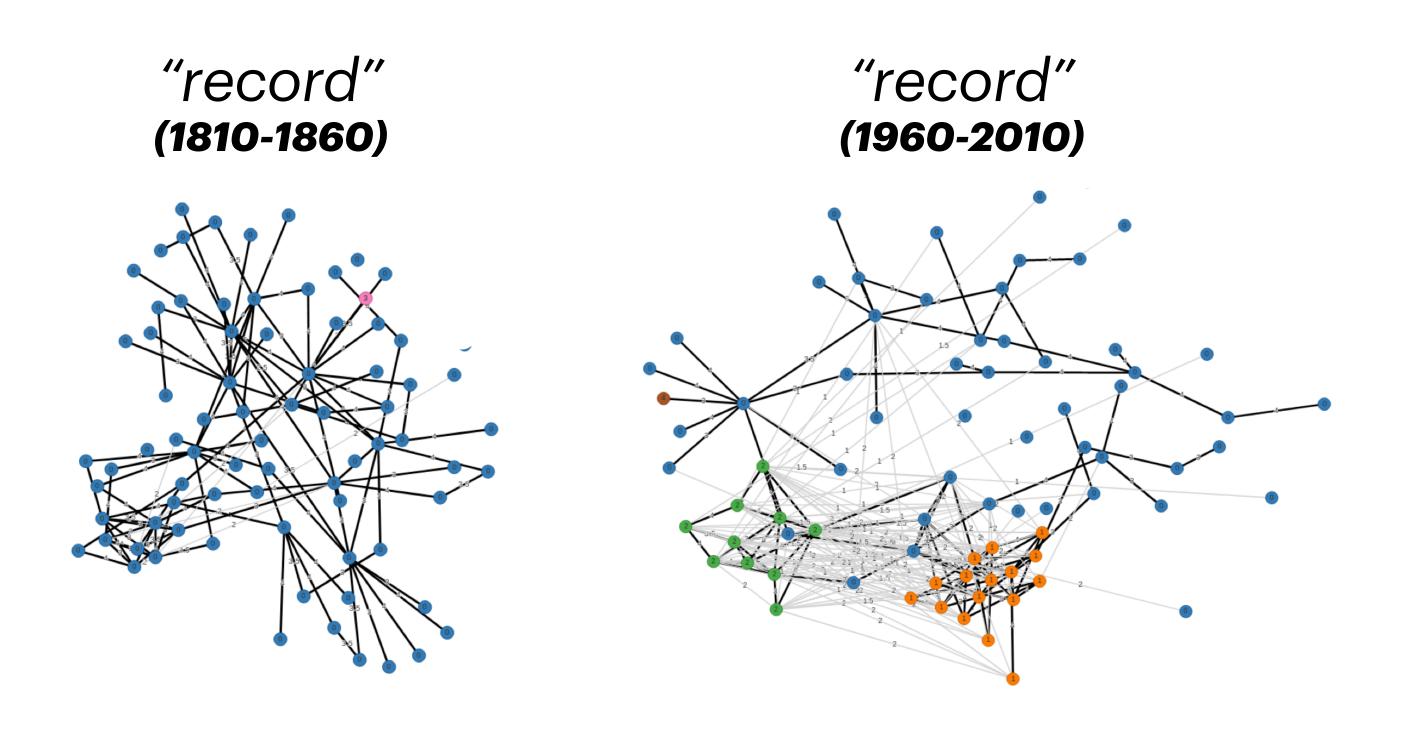




Human evaluation: 80% sufficient quality, 31% better than usage-based labels.

Explainable semantic change detection

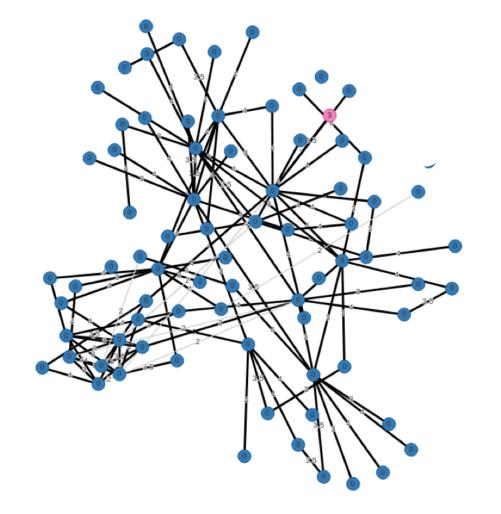
Sense dynamic maps by measuring similarity between sense labels



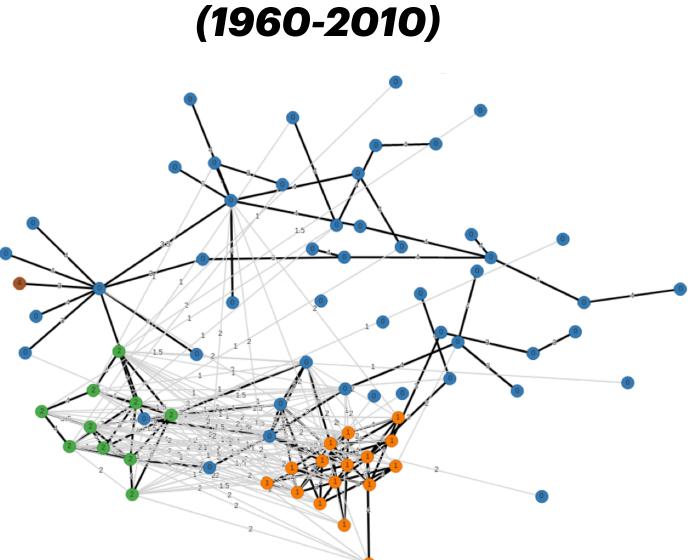
Explainable semantic change detection

Sense dynamic maps by measuring similarity between sense labels

"record" (1810-1860)



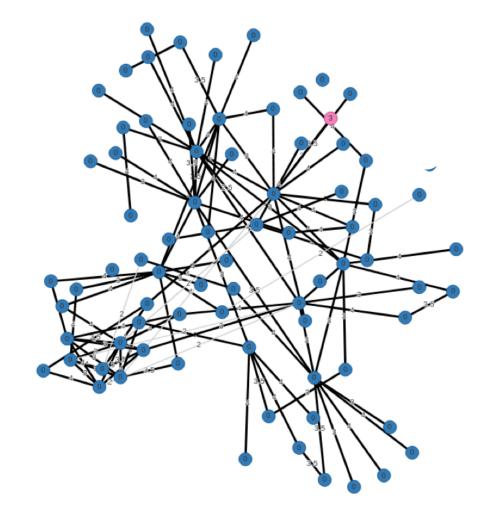
"record" (1960-2010)



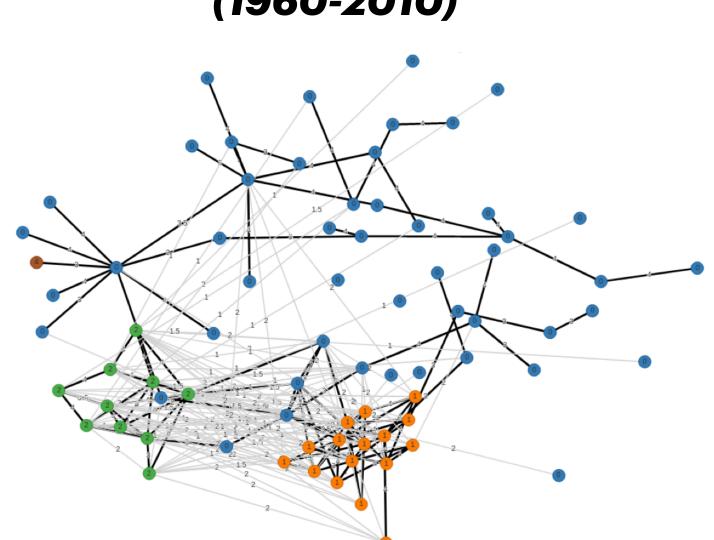
- A document or other means of providing information about past events.
- A phonograph or gramophone cylinder containing an audio recording.
- The highest score or other achievement in a game.

Sense dynamic maps by measuring similarity between sense labels

"record" (1810-1860)



"record" (1960-2010)



- A document or other means of providing information about past events.
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Fixing DWUGs

- ▶ trace incorrect or inconsistent DWUG clustering
- ► Two sense clusters have the same label? Likely, they are one cluster/sense.

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'Ball' example

- ► Sense similarities are non-transitive:
 - ▶ Ball 0: 'A SPHERE OR OTHER OBJECT USED AS THE OBJECT OF A HIT'
 - ▶ Ball 2: 'A ROUND SOLID PROJECTILE, SUCH AS IS USED IN SHOOTING'
 - ► Ball 3: 'A BULLET'
- $ightharpoonup c_0$ to c_2 : 0.70
- $ightharpoonup c_2$ to c_3 : 0.53
- $ightharpoonup c_0$ to c_3 : 0.50 (below the outlier threshold)

Inconsistent clustering, but also interesting insights about meaning trajectory of 'ball'.

► Semantic change modelling with definitions as lexical representations

- Semantic change modelling with definitions as lexical representations
- ► Benefits:
 - human-readable representations
 - more abstract and robust to noise
 - outperforms 'standard' embeddings in word-in-context similarity judgements
 - ► for humanities, it's easier to operate in the space of the definitions.

More in the paper: [Giulianelli et al., 2023]

Full results

		WordNet test set			Oxford test set		
Model	Generalization test	BLEU	ROUGE-L	BERT-F1	BLEU	ROUGE-L	BERT-F1
[Huang et al., 2021]	Unknown	32.72	-	-	26.52	-	-
T5 base	Zero-shot (task shift)	2.01	8.24	82.98	1.72	7.48	78.79
T5 base	Soft domain shift	9.21	25.71	86.44	7.28	24.13	86.03
Flan-T5 base	Zero-shot (task shift)	4.08	15.32	87.00	3.71	17.25	86.44
Flan-T5 base	In-distribution	8.80	23.19	87.49	6.15	20.84	86.48
Flan-T5 base	Hard domain shift	6.89	20.53	87.16	4.32	17.00	85.88
Flan-T5 base	Soft domain shift	10.38	27.17	88.22	7.18	23.04	86.90
Flan-T5 large	Soft domain shift	14.37	33.74	88.21	10.90	30.05	87.44
T5 XL	Zero-shot (task shift)	2.05	8.28	81.90	2.28	9.73	80.37
T5 XL	Soft domain shift	34.14	53.55	91.40	18.82	38.26	88.81
Flan-T5 XL	Zero-shot (task shift)	2.70	12.72	86.72	2.88	16.20	86.52
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Contents

- Why definitions?
- 2 Automatic definition generation
- (Diachronic) sense labeling
- Explainable semantic change detection
- 5 Future directions and open problems

Still much to be done in the field of semantic change modeling

Better methods (of course).

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- ► Wider scope of languages required.

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- Wider scope of languages required.
- ► More gold standard test sets for different languages and domains are needed (especially beyond Indo-European).
- ► Explainable semantic change modeling:
 - 1. Sub-classification of types of semantic shifts.
 - 2. Identifying the source of a shift (linguistic or extra-linguistic causes).
 - 3. Quantifying the weight of senses acquired over time.
 - 4. Identifying groups of words that change their meaning together in correlated ways (co-evolution).
- ► Is it possible to to multi-modal semantic change detection?

► How to infer the temporal dynamics of semantic relations between persons and organizations, ideas and technologies, etc.

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- ► How to tell words used in different lexicographic senses from words used in contextually varied surroundings, but in the same sense? Does this difference even exist?

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- ► How to model onomasiological change?
 - 'How do you call a hand-held peripheral device designed to provide input to a computer or a gaming console? And how was this object called in the 60's?'

- ► How to infer the temporal dynamics of semantic relations between persons and organizations, ideas and technologies, etc.
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- ► How to model onomasiological change?
 - ► 'How do you call a hand-held peripheral device designed to provide input to a computer or a gaming console? And how was this object called in the 60's?'

Despite the challenges, significant results in semantic change modeling are already achieved. You are welcome to try these methods in your own work!

This is it!

Thanks for coming to our course! Any questions?

References I



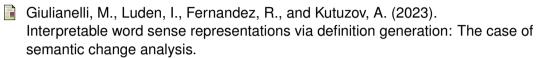
Chung, H. W., Hou, L., Longpre, S., Zoph, B., Tay, Y., Fedus, W., Li, E., Wang, X., Dehghani, M., Brahma, S., et al. (2022). Scaling instruction-finetuned language models. arXiv preprint arXiv:2210.11416.



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