



Advanced Contextualized Models

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TempoBERT

- Use time as additional context
- Exploit time masking



YEAR: 1800 —> "<1800> The mountains have an awful majesty."

YEAR: 2020 —> "<2020> You look awful today."

(a) TempoBERT is trained on temporal corpora, where each sequence is prepended with temporal context information.

Time prediction:

"[MASK] Today's weather is awful." —> <2020>

Time-dependent MLM:

"<1800> He has an awful [MASK]." —> presence
"<2020> He has an awful [MASK]." —> temper

(b) TempoBERT can be used for inference in two modes: (1) time prediction; (2) time-dependent mask filling.

Figure 1: Example of TempoBERT’s time masking for training and inference. The word ‘awful’ changed its meaning in the last two centuries from marvelous to disgusting.

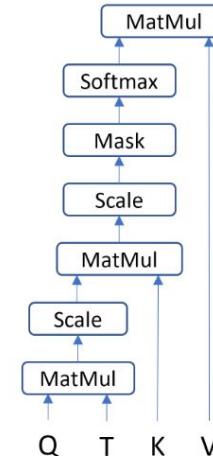
Temporal Attention

- Extends self-attention to include time dimension

$\text{TemporalAttention}(Q, K, V, T) =$

$$\text{softmax} \left(-\frac{Q \frac{T^\top T}{\|T\|} K^\top}{\sqrt{d_k}} \right) V$$

Time-specific weight matrix



XLM-RoBERTa

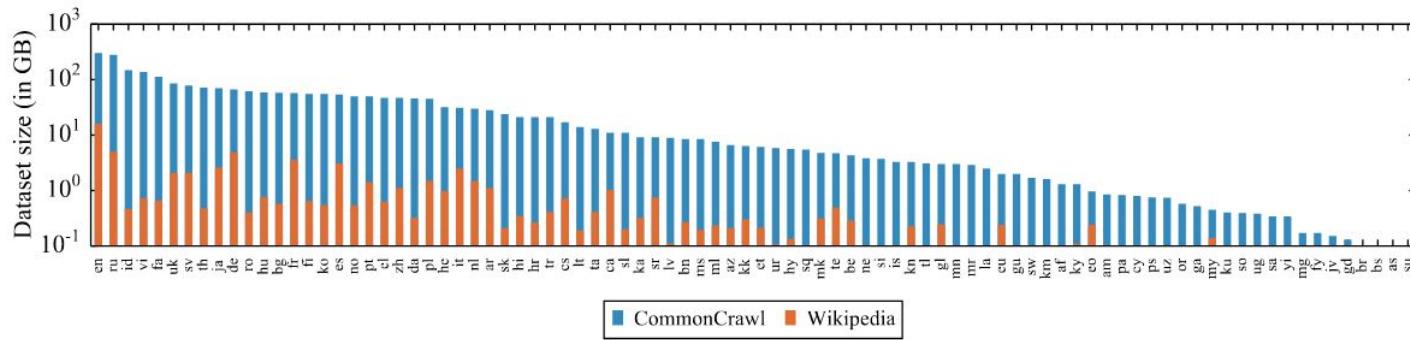


Figure 1: Amount of data in GiB (log-scale) for the 88 languages that appear in both the Wiki-100 corpus used for mBERT and XLM-100, and the CC-100 used for XLM-R. CC-100 increases the amount of data by several orders of magnitude, in particular for low-resource languages.

Gloss Reader

- Rely on XLM-RoBERTa and trained on a English Word Sense Disambiguation (WSD) dataset (SemCor)
- Zero-shot ability on other languages such as Russian

The bank can guarantee deposits will eventually cover future tuition costs because it invests in adjustable-rate mortgage securities.

**Context
Encoder**

bank¹ Gloss: a financial institution that accepts deposits and channels the money into lending activities

**Gloss
Encoder**

bank² Gloss: sloping land (especially the slope beside a body of water)

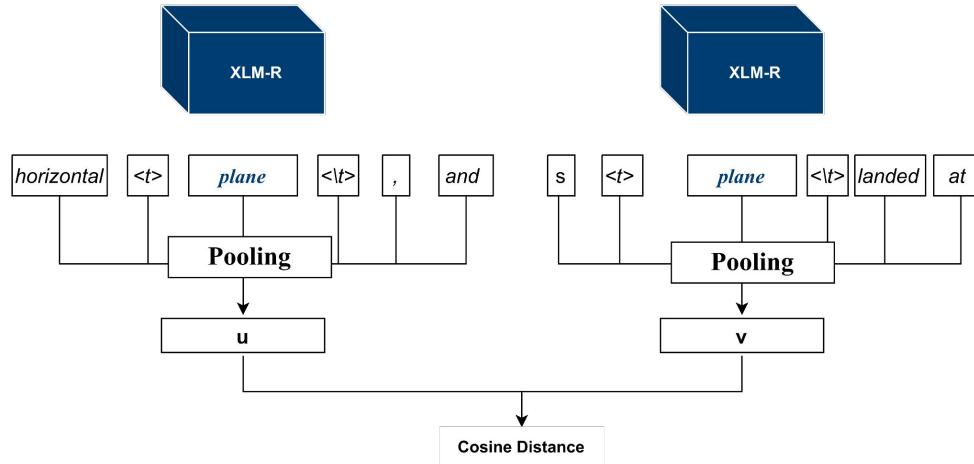
Deep Mistake

- Pretrained XLM-R fintuned on MCL-WiC task
- Not depends on fixed sense inventories

Lang	Target	Context-1	Context-2	Label
EN	Beat	We <u>beat</u> the competition	Agassi <u>beat</u> Becker in the tennis championship.	True
DA	Tro	Jeg <u>tror</u> på det, min mor fortalte.	Maria <u>troede</u> ikke sine egne øjne.	True
ET	Ruum	Uhel hetkel olin v aljaspool aega ja <u>ruumi</u> .	Umberringi oli'l oputu t uhi <u>ruum</u> .	True
FR	Causticité	Sa <u>causticité</u> lui a fait bien des ennemis.	La <u>causticité</u> des acides.	False
KO	틀림	틀림이 있는지 없는지 세어 보시오.	그 아이 하는 짓에 틀림이 있다면 모두 이 어미 죄이지요.	False
ZH	發	建築師希望發大火燒掉城市的三分之一。	如果南美洲氣壓偏低，則印度可能發乾旱	True
FA	صرف	صرف غذا نیم ساعت طول کشید	علم صرف افعال ماضی عربی را آموزش داد	False

XL-LEXEME

Provide a large table; this is a horizontal plane, and will represent the ground plane, viz.



The President's
plane landed at
Goose Bay at 9:03 p.
m.

XL-LEXEME

<u>Dataset</u>	<u>Languages</u>
WiC Pilehvar et al., (2019)	Monolingual EN
XL-WiC (Raganato et al., 2020)	Multilingual EN, BG, ZH, HR, DA, NL, ET, FA, FR, DE, IT, JA, KO
MCL-WiC (Martelli et al., 2021)	Multilingual EN, AR, FR, RU, ZH
	Crosslingual AR, FR, RU, ZH
AM ² ICO (Liu et al., 2021)	Crosslingual EN, DE, RU, JA, KO, ZH, AR, IN, FI, TR, EU, KA, UR, BN, KK

Pierluigi Cassotti, Lucia Siciliani, Marco DeGemmis, Giovanni Semeraro, and Pierpaolo Basile. 2023. [XL-LEXEME: WiC Pretrained Model for Cross-Lingual LEXical sEMantic changE](#). In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 1577–1585, Toronto, Canada. Association for Computational Linguistics.

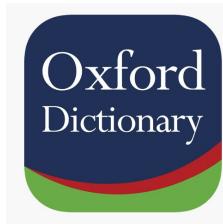
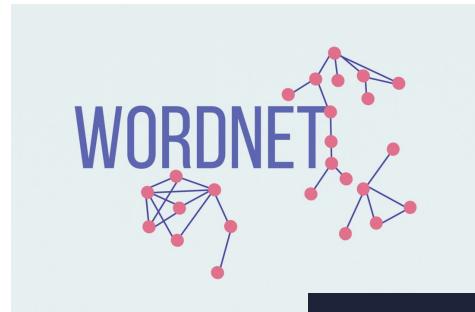
XL-LEXEME

		EN	LA	DE	SV	ES	RU		NO	ZH	Avg. _w
		$C_1 - C_2$	$C_2 - C_3$	$C_1 - C_3$	$C_1 - C_2$	$C_2 - C_3$	$C_1 - C_2$				
APD	BERT	.563	-	.271	.270	.335	.518	.482	.416	.441	.466
	mBERT	.363	.102	.398	.389	.341	.368	.345	.386	.279	.488
	XLM-R	.444	.151	.264	.257	.386	.290	.287	.318	.195	.379
	XL-LEXEME	.886*	.231	.839*	.812*	.665*	.796*	.820*	.863*	.659	.640*
	SOTA: sup.	.757	-.056	.877	.754	n.a.	.799	.833	.842	.757	.757
	SOTA: uns.	.706	.443	.731	.602	n.a.	.372	.480	.457	.389	.387
PRT	BERT	.457	-	.422	.158	.413	.400	.374	.347	.507	.444
	mBERT	.270	.380	.436	.193	.543	.391	.356	.423	.219	.438
	XLM-R	.411	.424	.369	.020	.505	.321	.443	.405	.387	.149
	XL-LEXEME	.676	.506*	.824	.696	.632	.704	.750	.727	.764*	.519
	SOTA: sup.	.531	n.a.								
	SOTA: uns.	.467	.561	.755	.392	n.a.	.294	.313	.313	.378	.270
AP+JSD	BERT	.289	-	.469	-.090	.225	.069	.279	.094	.314	.011
	mBERT	.181	.277	.280	.023	.067	.017	.086	-.116	.035	-.090
	XLM-R	.278	.398	.224	-.076	.224	-.068	.209	.130	-.100	.030
	XL-LEXEME	.493	.033	.499	.118	.392	.106	.053	.117	.297	.381
	SOTA: sup.	n.a.									
	SOTA: uns.	.436	.481	.583	.343	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
WiDiD	BERT	.385	-	.355	.106	.383	.135	.102	.243	.233	.087
	mBERT	.323	-.039	.312	.195	.343	-.068	.160	.142	.241	.290
	XLM-R	.564	-.064	.499	.129	.459	.268	.216	.342	.226	.349
	XL-LEXEME	.652	.236	.677	.475	.522	.178	.354	.364	.561	.457
	SOTA: sup.	n.a.									
	SOTA: uns.	.651	-.096	.527	.499	.544	.273	.393	.407	n.a.	n.a.

XL-LEXEME

	EN	DE	SV	ES	RU		NO	ZH	Avg _w		
	$C_1 - C_2$	$C_1 - C_2$	$C_1 - C_2$	$C_1 - C_2$	$C_1 - C_2$	$C_2 - C_3$	$C_1 - C_3$	$C_1 - C_2$	$C_2 - C_3$	$C_1 - C_2$	$C_i - C_j$
WIC	BERT	.503	.350	.221	.319	.314	.344	.350	.429	.406	.516
	mBERT	.332	.344	.284	.289	.280	.273	.293	.283	.333	.413
	XLM-R	.352	.289	.255	.288	.212	.250	.251	.317	.261	.392
	XL-LEXEME	.626	.628	.631	.547	.549	.558	.564	.484	.521	.630
	GPT-4.0	.606	-	-	-	-	-	-	-	-	-
	Agreement	.633	.666	.672	.531	.531	.567	.564	.761	.667	.602
WSI	BERT	.136 / .700	.047 / .662	.023 / .596	.189 / .695	- / -	- / -	- / -	.251 / .771	.247 / .758	.279 / .759
	mBERT	.067 / .644	.054 / .679	.024 / .648	.228 / .700	- / -	- / -	- / -	.241 / .759	.159 / .753	.172 / .713
	XLM-R	.068 / .737	.024 / .725	.031 / .680	.164 / .755	- / -	- / -	- / -	.179 / .775	.183 / .715	.279 / .806
	XL-LEXEME	.273 / .834	.300 / .788	.249 / .766	.400 / .820	- / -	- / -	- / -	.337 / .806	.304 / .808	.448 / .836
	GPT-4.0	.340 / .877	- / -	- / -	- / -	- / -	- / -	- / -	- / -	- / -	- / -
GCD	BERT	.425	.116	.148	.284	.487	.452	.469	.571	.521	.808
	mBERT	.120	.205	.234	.394	.372	.325	.408	.290	.454	.737
	XLM-R	.219	.069	.143	.464	.284	.301	.375	.395	.345	.557
	XL-LEXEME	.801	.799	.721	.655	.780	.824	.851	.620	.567	.716
	GPT-4.0	.818	-	-	-	-	-	-	-	-	-

Definition Generation



Mario Julianelli, Iris Luden, Raquel Fernandez, and Andrey Kutuzov. 2023. [Interpretable Word Sense Representations via Definition Generation: The Case of Semantic Change Analysis](#). In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 3130–3148, Toronto, Canada. Association for Computational Linguistics.

Definition Generation

Model	Test	WordNet			Oxford		
		BLEU	ROUGE-L	BERT-F1	BLEU	ROUGE-L	BERT-F1
Huang et al. (2021)	<i>Unknown</i>	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

Table 3: Results of the definition generation experiments.

Definition Generation

Usage example	Target word	Generated definition
'about half of the soldiers in our rifle platoons were draftees whom we had trained for about six weeks'	draftee	'A PERSON WHO IS BEING ENLISTED IN THE ARMED FORCES'

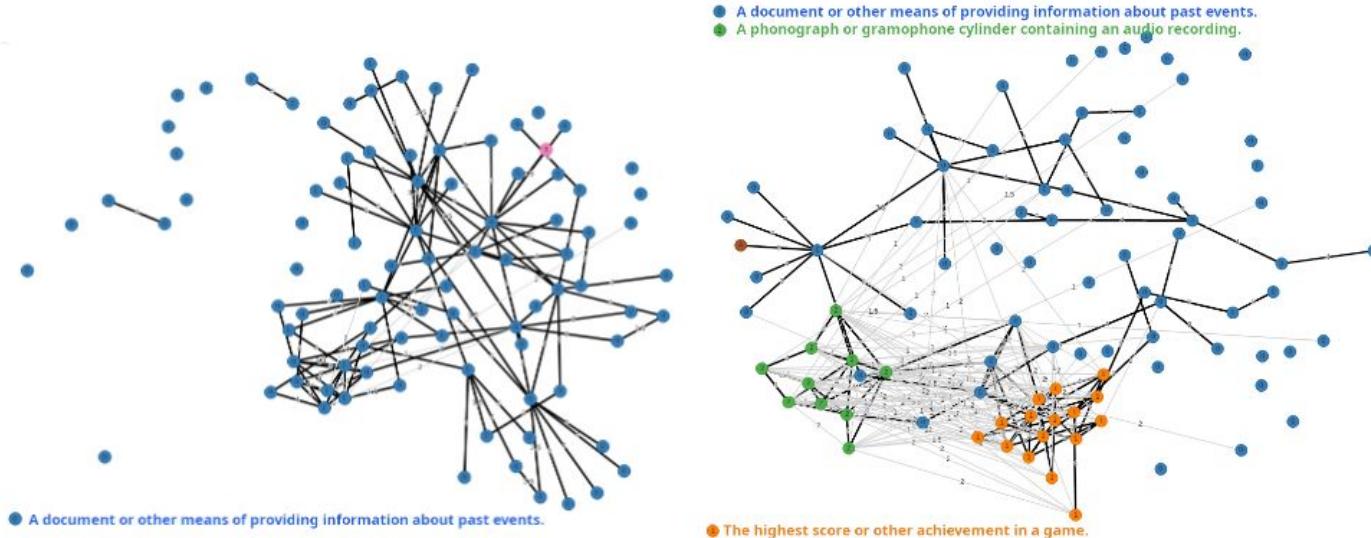
Table 1: An example of a definition generated by our fine-tuned Flan-T5 XL. The model is prompted with the usage example, post-fixed with the phrase '*What is the definition of draftee?*'

Method	Cosine	SacreBLEU	METEOR
Token embeddings	0.141	-	-
Sentence embeddings	0.114	-	-
Generated definitions			
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

Table 4: Correlations with pairwise similarity judgments by humans. 'FT' stands for 'fine-tuned model'.

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Definition Generation



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Substitution-based

	GEMS	SE Eng	SE Ger	SE Lat	SE Swe	Average	Average (weighted)
Number of words	96*	37	40	48	31		
<i>Static Embedding Methods</i>							
Pömsl and Lyapin (2020)	-	0.422	0.725	0.412	0.547	-	-
Montariol et al. (2021) [static]	0.347	0.321	0.712	0.372	0.631	0.477	0.452
<i>Contextual Embedding Methods</i>							
Martinc et al. (2020b)	0.510	0.313	0.436	0.467	-0.026	0.340	0.394
Montariol et al. (2021) [contextual]	0.352	0.437	0.561	0.488	0.321	0.432	0.422
Scaled JSD	0.535	0.547	0.563	0.533	0.310	0.498	0.514

Dallas Card. 2023. [Substitution-based Semantic Change Detection using Contextual Embeddings](#). In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 590–602, Toronto, Canada. Association for Computational Linguistics.

Substitution-based

Word	SE rating	SE rank	Scaled JSD	Scaled JSD rank	Corpus A substitutes (1810–1860)	Corpus B substitutes (1960–2010)
plane	0.88	1	0.97	1	plane line planes point surface lines	plane aircraft planes jet airplane car
graft	0.55	4	0.97	2	tree plant stock vine fruit wood	corruption bribery fraud crime violence
tip	0.68	2	0.85	7	tipped tip covered end filled tips give	tip tips end tipped edge point top ends
gas	0.16	23	0.72	14	gas gases vapor air fire water	gas gasoline oil gases fuel water air
head	0.30	10	0.68	16	head face hand heads hands eyes	head face heads hand body hands eyes
bit	0.31	9	0.51	23	bit piece sort little pieces bits kind	bit little lot touch tad piece bits pieces
fiction	0.02	35	0.41	27	fiction history literature art poetry	fiction fact fantasy story stories novels
tree	0.07	33	0.22	33	trees tree plants branches plant wood	trees tree plants woods branches bushes
ounce	0.28	11	0.08	37	ounce inch pounds hour acre dollars	ounce pounds inch inches cups pieces

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