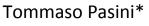


XL-WiC: A Multilingual Benchmark for Evaluating Semantic Contextualization

https://pilehvar.github.io/xlwic/

Alessandro Raganato*





Jose Camacho-Collados

Mohammad Taher Pilehvar







Tehran Institute for Advanced Studies



WiC: The Word-in-Context Task



• **Binary classification task:** recognising whether a target word is used with the same meaning or not in two different contexts.

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• **Binary classification task:** recognising whether a target word is used with the same meaning or not in two different contexts.

Target word: **bed.**

Context-1: There's a lot of trash on the **bed** of the river.

Context-2: I keep a glass of water next to my **bed** when i sleep.







XL-WiC: The Multilingual Benchmark



So far WiC benchmark (featured as a part of the SuperGLUE benchmark, and for a shared task at SemDeep-5 IJCAI workshop) - English only.

XL-WiC extends the WiC dataset to **12 new languages** from different families and with different degrees of resource availability:

- Bulgarian (BG)
- Danish (DA)
- German (DE)
- Estonian (ET)

- Farsi (FA)
- French (FR)
- Croatian (HR)
- Italian (IT)

- Japanese (JA)
- Korean (KO)
- Dutch (NL)
- Chinese (ZH)

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Lang	Target	Context-1	Context-2	Label
EN	Beat	We <u>beat</u> the competition	Agassi beat Becker in the tennis championship.	True
DA	Tro	Jeg <u>tror</u> p°a det, min mor fortalte.	Maria <u>troede</u> ikke sine egne øjne.	True
ET	Ruum	Uhel hetkel olin ÿ aljaspool aega ja <u>ruumi</u> .	Umberringi oli Ĩ oputu ť uhi <u>ruum</u> .	True
FR	Causticité	Sa <u>causticité</u> lui a fait bien des ennemis.	La <u>causticité</u> des acides.	False
КО	틀림	<u>틀림이</u> 있는지 없는지 세어 보시오.	그 아이 하는 짓에 <u>틀림이</u> 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	<u>صرف</u> غذا نيم ساعت طول كشيد	معلم <u>صرف</u> افعال ماضی عربی را آموزش داد	False

XL-WiC: The Multilingual Benchmark

XL-WiC was built using example sentences from two type of resources: WordNet and Wiktionary







- Example usages from 9 languages:
 - Bulgarian, Chinese, Croatian, Danish, Dutch, Estonian, Japanese, Korean and Farsi
- We provide **dev** and **test** data for each language



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- ★ WordNet is known to be a fine-grained resource:
 - often different senses of the same word are hardly distinguishable from one another even for humans.
- → Filtering step:
 - automatic pruning of subtle sense distinctions leveraging WordNet structure itself. We removed all pairs whose senses were:
 S
 first degree connections in the WordNet semantic graph;
 Sister senses;
 - S belonged to the same supersense.



- Case study: Farsi
 - make a challenging dataset with sense distinctions that are easily interpretable by humans.

- → Semi-automatic extraction:
 - we extracted all example usages and asked an annotator to group them into positive and negative pairs.

シ み 御 え ゆ が ず 维 W Wiktionary The free dictionary

XL-WiC: The Multilingual Benchmark - Wiktionary

XL-WiC: The Multilingual Benchmark - Wiktionary

• We extracted examples for three European languages for which we did not have WordNet-based data:

シやジ

λ W m

★维V

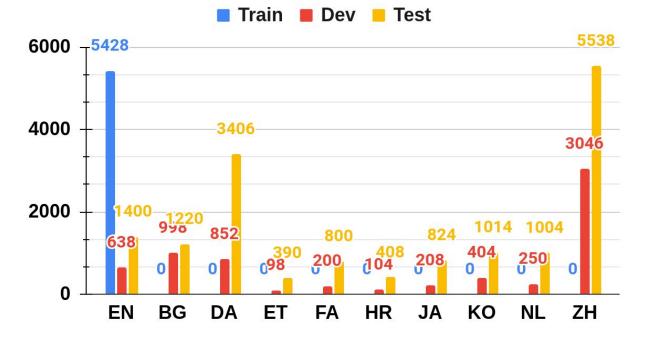
Wiktionary The free dictionary

- French, German, and Italian.
- We provide **train**, **dev** and **test** data for each language.



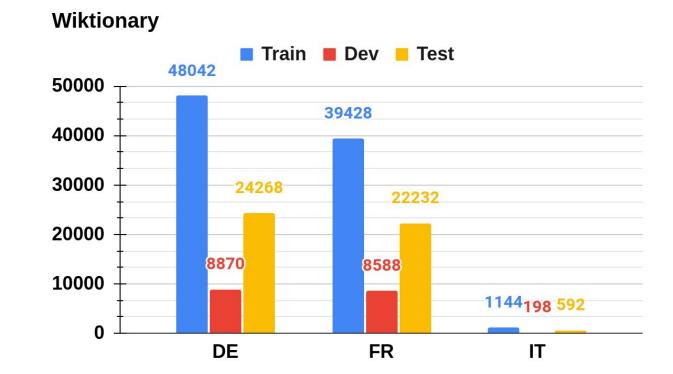
XL-WiC: The Multilingual Benchmark - Statistics

Multilingual WordNet





XL-WiC: The Multilingual Benchmark - Statistics





XL-WiC: human performance

WiC	WordNet							ionary
EN	DA	FA	IT	JA	KO	ZH	DE	IT
80.0*	87.0	97.0	82.0	75.0	76.0	85.0	74.0	78.0

Human performance (in terms of accuracy) on 100 random instances for different languages in XL-WiC .

XL-WiC: Experimental setup



- Models:
 - mBERT
 - XLM-R-base
 - XLM-R-large
 - L-BERT (language specific BERT models used in monolingual setting)
- Evaluation settings:
 - Cross-Lingual Zero-shot
 - Multilingual Fine-Tuning
 - Monolingual
 - Translation

- Evaluation metric:
 - accuracy

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XL-WiC: Experiments and results

• Cross-Lingual Zero-shot: WordNet

Model	BG	DA	ET	FA	HR	JA	KO	NL	ZH
				Zero-s	hot cross-li	ingual setti	ng Train	: <u>EN</u> –	Dev: EN
mBERT	58.28	64.86	62.56	71.50	63.97	62.26	59.76	63.84	69.36
XLMR-base	60.73	64.79	62.82	69.88	62.01	60.44	66.96	65.73	65.78
XLMR-large	66.48	71.11	68.71	75.25	72.30	63.83	69.63	72.81	73.15



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• Cross-Lingual Zero-shot: Wiktionary

	Model	DE	FR	IT
ot	mBERT	58.27	56.00	58.61
Z-Shot	XLMR-base	58.30	56.13	55.91
Z	XLMR-large	65.83	62.50	64.86



XL-WiC: Experiments and results

• Monolingual: Wiktionary

	Model	DE	FR	IT
	mBERT	81.58	73.67	71.96
DO	XLMR-base	80.84	73.06	68.58
Mono	XLMR-large	84.03	76.16	72.30
	L-BERT	82.90	78.14	72.64



XL-WiC: Analysis

- Seen (IV) and Unseen (OOV) Words:
 - IV: is a test set containing instances where the target words were seen at training time.
 - OOV: is a test set containing instances where the target words were NOT seen at training time.

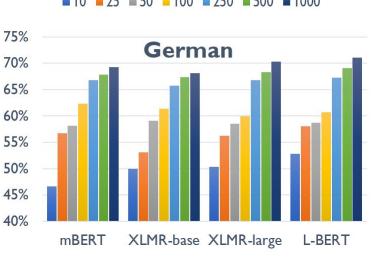
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N	XLMR-large	84.24	75.61	75.12
	L-BERT	83.23	77.62	73.89
000	mBERT	70.08	71.24	68.54
	XLMR-base	71.31	71.14	62.36
	XLMR-large	72.54	73.93	65.17
	L-BERT	76.64	78.00	69.10



XL-WiC: Analysis

- Few-shot Monolingual: •
 - Evaluation performed when training each model on 10, 25, 50, Ο 100, 250, 500, 1000 annotated examples.





XL-WiC: Conclusions



- **XL-WiC**: a large benchmark with **over 80K instances** for evaluating context-sensitive models in **13 languages**!
- Testbed for **cross-lingual experimentation** in settings such as zero-shot or few-shot transfer across languages.
- We provide **performance baselines with current multilingual neural language models**, showing that **there is still room for improvement**, especially for languages such as Japanese, Korean or Farsi in the cross-lingual zero-shot setting.

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Thank you!