The 12th International Global Wordnet Conference(GWC2023) Donostia / San Sebastian (Spain) 23-27/01/2023



A Benchmark and Scoring Algorithm for Enriching

Arabic Synonyms

Sana Ghanem Birzeit University, Palestine

Radi Jarrar Birzeit University, Palestine **Mustafa Jarrar** Birzeit University, Palestine

Ibrahim Bounhas Carthage University, Tunisia

Why do we need Synonyms?

The importance of synonyms is growing:

- Application areas: computational linguistics, information retrieval, question answering, and machine translation.
- Essential parts in thesauri, wordnets (Miller et al., 1990), and linguistic ontologies (Jarrar, 2021).

Notions of Synonymy

Thesauri: closely related words.

- Wordnets: based on substitutionablity: "two expressions are synonymous in a linguistic context c if the substitution of one for the other in c does not alter the truth value" (Miller et al., 1990).
- * Linguistic Ontology: equivalence relation (i.e., reflexive, symmetric, and transitive). Two terms are synonyms *iff* they have the exact same concept (i.e., refer, intentionally, to the same set of instances). Thus, $T_1 =_{Ci} T_2$. (Jarrar, 2021)



We treat synonymy as a fuzzy value

1. Experiment: how much linguist agree on synonymy

2. Algorithm to Extract/Extend/Evaluate synsets

How much linguists agree on synonyms?

Experiment to measure this agreement:

- Selected 500 synsets from Arabic WordNet, each extended with a number of candidate synonyms (3K synonyms in total).
- Each candidate synonyms was annotated with a fuzzy value by four different linguists.
- The dataset is also used to train our proposed algorithm (i.e., tune its fuzzy model) for extracting synonyms from dictionaries.

The Dataset Construction Synset Selection

500 synsets selected from Arabic WordNet.

Selection:

- Part of speech (POS)
- 1. 350 noun synsets.
- 2. 140 verb synsets.
- 3. 10 adjective synsets.



- 1. Length(2), 142 synsets.
- 2. Length (4), 207 synsets.
- 3. Length (6), 151 synsets.

- → Each of the selected synsets was extuded with a number of candidate synsets (using our algorithm) 3k candidates.
- → Uploaded to Google Sheets (for annotation)

The Dataset Construction Annotation Setup

- Four Linguists (3 training workshops + quiz).
- Each candidate synonyms was annotated with a score based on the linguist's understanding:

confederacy confederation federation اِتِّحَاد فِدْرَالِي حِلْف تَحَالُف							
a union of po	litica	al organizations					
مُحَالَفَة	•	60 نفس الدلالة، الأسلوب ضعيف ، غير شائعة					
اِئْتِلاف	•	80 نفس الدلالة، الأسلوب صحيح ، شائعة الى حد قليل					
اِتِّحَاد	•	100 نفس الدلالة والاسلوب والشيوع					
جامِعَة	•	60 نفس الدلالة، الأسلوب ضعيف ، غير شائعة					

Score	Meaning
100	Same semantics, style, use
90	Same semantics, style, less used
80	Same semantics, style, rarely used
70	Same semantics, style, not used
60	Close semantics, weak style, uncommon
50	Close semantics, not exact purpose
40	Semantically related
30	Semantically related (somehow)
20	Semantically different
10	Semantically very different
0	Semantically unrelated

The Dataset Construction Scoring Guidelines

Scale from 0 to 100 representing the strength of the synonymy relation.

Score	Meaning]
100	Same semantics, style, use	
90	Same semantics, style, less used	Same semantics
80	Same semantics, style, rarely used	Same Semanties
70	Same semantics, style, not used	
60	Close semantics, weak style, uncommon	Close semantics
50	Close semantics, not exact purpose	Close semantics
40	Semantically related	
30	Semantically related (somehow)	
20	Semantically different	Related/different semantics
10	Semantically very different	
0	Semantically unrelated	

Results Linguists Agreement Evaluation

To measure the (dis/)agreements between linguists, we computed:

1. The Root Mean Squared Error (RMSE).

2.	The	Mean	Average	Error	(MAE).
----	-----	------	---------	-------	--------

	L1		L2		L3		L4		Avg		Algorithm	
	RMSE	MAE	RMSE	MAE								
L1			0.19	0.14	0.19	0.14	0.22	0.16	0.13	0.10	0.35	0.30
L2	0.19	0.14			0.16	0.12	0.20	0.15	0.10	0.11	0.31	0.26
L3	0.19	0.14	0.16	0.12			0.20	0.16	0.11	0.08	0.32	0.26
L4	0.22	0.16	0.20	0.15	0.20	0.15			0.13	0.08	0.39	0.34
Avg	0.13	0.10	0.10	0.08	0.11	0.08	0.13	0.11			0.32	0.27
Algorithm	0.35	0.30	0.31	0.26	0.32	0.26	0.39	0.34	0.32	0.27		

Download Dataset: https://portal.sina.birzeit.edu/synonyms/

The Algorithm Extract Synonyms from mono or multiple dictionary

Input: a mono or multiple dictionary (*D*), and a synset (*S*)

dictionary *D* consists of set of synsets, $S_i \in D$. Each synset is a tuple $\langle t_1, ..., t_n \rangle$ of linguistic terms regardless language it belongs to.



The Algorithm Examples of Usage Scenarios

Extend a synset with more synonyms above a given fuzzy value



15% , Lane 15% , Boulevard 15% , Avenue 15%

Evaluate/rank synonyms in a given synset (wordnets, BERT's output, etc.)

شارع | طريق | street | road

Evaluate

درْبِ 31% . درب 31% . وَحُه 15% . وحه 15% . نَفْج 15% . نَفْج 15% . نَفِج

61 , road 41%, street 41% , مطريق 62% , شارع 61 ,

The Algorithm **Step 1: Candidate Synonym Extraction**

Build directed cyclic graph, from a dictionary: keep expanding until:

- 1) The root node is found, i.e., cycle,
- 2) No more synonyms are found,3) The max k level is reached.



Output: Nodes participating in these cyclic paths are considered candidate synonyms for the given synset. i کت→ride→sit ز ک بجت → إمتقلي →ride → sit وجد

10 cyclic paths at level 4

; کت→ride کہ زكِبَ→إمتَظى→ride-زكِد کِبَ→sit آمنَظی oride درکِبَ sit→ride کن~sit ride→انتظىsit→بانتظىride ride→کی→ride ride→إمتَظى→ride sit→rideبَقظى→رَكِبَ→sit→ride

12

The Algorithm Step 2: Candidate Synonym Selection

$$Fuzzy(f_i) = \emptyset_1 \cdot Pi + \emptyset 2 \cdot Q_i$$

 P_i number of cyclic paths that ci appears in, divided by the total number of cyclic paths. Q_i number of root nodes t that appear in the cyclic paths of ci, divided by the total number of terms in the synset S.

Output: a set of candidate synonyms (C), each synonym (c_i) is assigned a fuzzy value (f_i).

Example:
$$Fuzzy(sit) = \frac{6}{10} \times 0.5 + \frac{2}{2} \times 0.5 = 0.8$$

 $Fuzzy(sit) = \frac{6}{10} \times 0.5 + \frac{2}{2} \times 0.5 = 0.8$
{ sit 80%, يواإمتظى 80%}

13

The Algorithm Parameter Tuning

Our proposed Fuzzy function depends on two constant weights (θ_1 and θ_2).

We used our Annotated dataset with Arabic WordNet to generate a model with the best results.

we varied the values of the parameters θ_1 and θ_2 by selecting their values within the range of [0.1, 0.9] with a step of 0.1 for each parameter.

$ heta_1, heta$	$\mathbf{)}_2$	Level 4	Level 3
[0 1 0 9]	RMSE	0.459	0.377
[0.1, 0.7]	MAE	0.375	0.319
[0 2 0 8]	RMSE	0.408	0.362
[0.2, 0.0]	MAE	0.330	0.304
[0307]	RMSE	0.366	0.352
[0.5, 0.7]	MAE	0.299	0.296
[04 06]	RMSE	0.336	0.349
[0.4, 0.0]	MAE	0.280	0.293
[0.5, 0.5]	RMSE	0.321	0.352
[0.5, 0.5]	MAE	0.271	0.296
[0.6, 0.4]	RMSE	0.323	0.363
[0.0, 0.4]	MAE	0.271	0.304
[0,7, 0,3]	RMSE	0.343	0.382
[0.7, 0.5]	MAE	0.272	0.316
[0.8, 0.2]	RMSE	0.378	0.407
[0.0, 0.2]	MAE	0.302	0.335
[0 9 0 1]	RMSE	0.425	0.437
[0.9, 0.1]	MAE	0.335	0.357

Algorithm Evaluation

→ Evaluation of synonyms is known to be difficult (Wu et al., 2003).

Our **Evaluation Methodologies**:

- Compare the results with linguists' scores.
 - Behavior (statistically significant)
 - close to the linguists' scores
- Accuracy of the algorithm.

Algorithm Evaluation Testing the algorithm's behavior

Goal: whether the scores of the algorithm are statistically significant.

Statistical test: One-way ANOVA test (at p < 0.05) between the algorithm and the other linguists.

Prerequisites: Normality test.

Result: The algorithm's scores are not normally distributed.

Check the univariate and multivariate outlier analysis.

Results: no outliers, (thus the non-normality of the algorithm's scores are due to skewness in the data and not because of outliers.)

* Therefore, the one-way ANOVA test can be applied.

Result of the one-way ANOVA test: The algorithm has shown to be not statistically different with the other linguists and their average. This test confirms that **the algorithm behaves as a linguist**.

Algorithm Evaluation Comparing the Algorithm with the Baseline

Goal: compares the results of our algorithm with the average of the linguists' scores (as a baseline).

Evaluation matrics: Root Mean Squared Error (RMSE) and Mean Average Error (MAE).

Result:

algorithm's scores are **close to the linguists' scores**, which is a good indication that the algorithm scores are realistic.

	L1		L1 L2		L3		L4		Avg		Algorithm	
	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE
L1			0.19	0.14	0.19	0.14	0.22	0.16	0.13	0.10	0.35	0.30
L2	0.19	0.14			0.16	0.12	0.20	0.15	0.10	0.11	0.31	0.26
L3	0.19	0.14	0.16	0.12			0.20	0.16	0.11	0.08	0.32	0.26
L4	0.22	0.16	0.20	0.15	0.20	0.15			0.13	0.08	0.39	0.34
Avg	0.13	0.10	0.10	0.08	0.11	0.08	0.13	0.11			0.32	0.27
Algorithm	0.35	0.30	0.31	0.26	0.32	0.26	0.39	0.34	0.32	0.27		

Algorithm Evaluation Accuracy Evaluation

Input: 10K synsets from the Arabic WordNet (AWN).

Remarks: (*i*) no language-specific treatment, (*ii*) AWN is polysemous

Prerequisites

- 1. Calculate the frequency of each synonym (Arabic and English) of all synsets.
- 2. Select the synonyms with (highest, lowest, average, and random) frequencies in each synset.
- 3. We considered synsets that contain more than two synonyms, regardless of the language.
- 4. The terms with the frequency of 1 are not selected.

Algorithm Evaluation Accuracy Evaluation

Experiment setup

Perform four masking experiments with (highest, lowest, average, and random) frequencies of each synset, at level 3 and level 4.

For each experiment:

- 1. Masking a synonym with the required frequency in a given synset.
- 2. Apply the algorithm individually on the masked synset.
- 3. Measure the accuracy of the algorithm in terms of retrieved words for each synset.

Algorithm Evaluation Accuracy Evaluation

Top rank correctly retrieved synonyms

Accuracy =

Sample size

Results:	Experiment	Sample Size	Accuracy at Level 3	Accuracy at Level 4
	Exp.1 (Highest)	7,219	99.1%	95.2%
	Exp.2 (Average)	5,207	98.7%	92.0%
	Exp.3 (Lowest)	1,085	88.4%	62.0%
	Exp.4 (Random)	4,153	98.1%	89.3%



- Benchmark dataset fuzzy values.
- Measuring how much linguists dis/agree on synonymy,
- Algorithm to extend/ evaluate synsets (for wordnet, BERT output, etc.)
- No language-specific treatments.

DEMO

$\leftrightarrow \rightarrow G$	portal.sina.birzeit.edu/synonyms/	G	Q	Û	☆	<u>m</u> 3	• 0
Home > Resource	Synonyms Generator						
	A dataset and source code for Synonyms Generator Version: 1.0 (updated on 15/12/2022) An algorithm to extend a set of synonyms with more synonyms. Given a set of synonyms, the algorithm builds a graph (using set of candidate synonyms, each with a fuzzy value to indicate how much it is likely to be a synonym. The more synonyms in candidate synonyms. We trained the fuzzy model using a dataset we built manually (500 synsets, with 3K candidate synonym this article for the details. Try the service (type synonym seperated by or , or 4):	g many i the in ns by f	v dictio put, tl our lir	onaries he mor nguists	s) and re acci s). Plea	return: urate t ase rea	s a he ıd
	شارع طريق street road			Extend	Ev	aluate	
	sı شارع, sez شارع, street 41% ، street 41%						
	+ Settings						
	+ Dataset And Downloads						
	+ API						
	- Publications						
	Sana Ghanem, Mustafa Jarrar, Radi Jarrar, Ibrahim Bounhas: A Benchmark and Scoring Algorithm for Enriching Arabic Syr Global WordNet Conference (gwc2023), Donostia, January. 2023	nonym	s. In F	rocee	dings	of the	
	PDF - Slides - Video						

https://portal.sina.birzeit.edu/synonyms/

References

- Moustafa Al-Hajj and Mustafa Jarrar. 2021. Arab- glossbert: Fine-tuning bert on context-gloss pairs for wsd. In *Proceedings of the Interna- tional Conference on Recent Advances in Natu- ral Language Processing (RANLP 2021)*, pages 40–48, Online. INCOMA Ltd.
- Kareem Darwish, Nizar Habash, Mourad Abbas, Hend Al-Khalifa, Huseein T. Al-Natsheh, Houda Bouamor, Karim Bouzoubaa, Violetta Cavalli- Sforza, Samhaa R. El-Beltagy, Wassim El-Hajj, Mustafa Jarrar, and Hamdy Mubarak. 2021. A panoramic survey of natural language processing in the arab worlds. *Commun. ACM*, 64(4):72–81.
- Karim El Haff, Mustafa Jarrar, Tymaa Hammouda, and Fadi Zaraket. 2022. Curras + baladi: To- wards a levantine corpus. In *Proceedings of the International Conference on Language Re- sources and Evaluation (LREC 2022)*, Marseille, France.
- Mamoun Abu Helou, Matteo Palmonari, and Mustafa Jarrar. 2016. Effectiveness of auto- matic translations for cross-lingual ontology mapping. *Journal of Artificial Intelligence Re- search*, 55(1):165–208.
- Mamoun Abu Helou, Matteo Palmonari, Mustafa Jarrar, and Christiane Fellbaum. 2014. Towards building lexical ontology via cross-language matching. In *Proceedings of the 7th Confer- ence on Global WordNet*, pages 346–354. Global WordNet Association.
- Mustafa Jarrar. 2005. Towards Methodological Principles for Ontology Engineering. Ph.D. the-sis, Vrije Universiteit Brussel.
- Mustafa Jarrar. 2011. Building a formal arabic on- tology (invited paper). In *Proceedings of the Experts Meeting on Arabic Ontologies and Se- mantic Networks*. ALECSO, Arab League.
- Mustafa Jarrar. 2020. Digitization of Arabic Lexi- cons, pages 214–217. UAE Ministry of Culture and Youth.
- Mustafa Jarrar. 2021. The arabic ontology an arabic wordnet with ontologically clean content. Applied Ontology Journal, 16(1):1–26.
- Mustafa Jarrar and Hamzeh Amayreh. 2019.
- An arabic-multilingual database with a lexico- graphic search engine. In *The 24th International Conference on Applications of Natural Lan- guage to Information Systems* (*NLDB 2019*), vol- ume 11608 of *LNCS*, pages 234–246. Springer.
- Mustafa Jarrar, Hamzeh Amayreh, and John P. Mc- Crae. 2019. Representing arabic lexicons in lemon a preliminary study. In *The 2nd Confer- ence on Language, Data and Knowledge (LDK 2019)*, volume 2402, pages 29–33. CEUR Work- shop Proceedings.
- Mustafa Jarrar, Nizar Habash, Faeq Alrimawi, Diyam Akra, and Nasser Zalmout. 2017. Curras: An annotated corpus for the palestinian arabic dialect. *Journal Language Resources and Evalu- ation*, 51(3):745–775.
- Mustafa Jarrar, Eman Karajah, Muhammad Khal- ifa, and Khaled Shaalan. 2021. Extracting synonyms from bilingual dictionaries. In *The 11th International Global Wordnet Conference (GWC2021)*, pages 215–222. Global Wordnet Association.
- Mustafa Jarrar, Fadi Zaraket, Rami Asia, and Hamzeh Amayreh. 2018. Diacritic-based match- ing of arabic words. ACM Asian and Low- Resource Language Information Processing, 18(2):10:1–10:21.
- Mustafa Jarrar, Fadi A Zaraket, Tymaa Hammouda, Daanish Masood Alavi, and Martin Waahlisch. 2022. Lisan: Yemeni, irqi, libyan, and sudanese arabic dialect copora with morphological anno- tations.
- Eman Naser-Karajah, Nabil Arman, and Mustafa Jarrar. 2021. Current trends and approaches in synonyms extraction: Potential adaptation to ara- bic. In Proceedings of the 2021 International Conference on Information Technology (ICIT), pages 428–434, Amman, Jordan. IEEE.