"*Definition Modeling* : `To model definitions.`" Generating Definitions With Little to No Semantics

Vincent Segonne*
Université Grenoble Alpes
vincent.segonne
@univ-grenoble-alpes.fr

Timothee Mickus*
Helsinki University
timothee.mickus
@helsinki.fi

Abstract

Definition Modeling, the task of generating definitions, was first proposed as a means to evaluate the semantic quality of word embeddings—a coherent lexical semantic representations of a word in context should contain all the information necessary to generate its definition. The relative novelty of this task entails that we do not know which factors are actually relied upon by a Definition Modeling system. In this paper, we present evidence that the task may not involve as much semantics as one might expect: we show how an earlier model from the literature is both rather insensitive to semantic aspects such as explicit polysemy, as well as reliant on formal similarities between headwords and words occurring in its glosses, casting doubt on the validity of the task as a means to evaluate embeddings.

1 Introduction

Definition Modeling (Noraset et al., 2017, DefMod) is a recently introduced NLP task that focuses on generating a definition gloss given a term to be defined; most implementations rely on an example of usage as auxiliary input (Ni and Wang, 2017; Gadetsky et al., 2018; Mickus et al., 2019, a.o.). In the last few years, it has been the focus of more than a few research works: datasets have been proposed for languages ranging from Japanese (Huang et al., 2022) to Wolastoqey (Bear and Cook, 2021), and DefMod has even been the subject of a recent SemEval shared task (Mickus et al., 2022).

Practical applications for DefMod abound, from the generation of lexicographic data for low-resource languages (Bear and Cook, 2021), to computer-assisted language learning (Kong et al., 2022), creating learners' dictionaries (Jiaxin et al., 2022), and from explaining slang (Ni and Wang, 2017) to clarifying scientific terminology (August et al., 2022). Yet, it was initially conceived by Noraset et al. (2017) as an evaluation task for word embeddings. If a word embedding is a coherent lexical semantic representation, then it ought to contain all the information necessary to produce a coherent gloss. Researchers have kept this semantic aspect firmly in mind: for instance, Bevilacqua et al. (2020) argue that DefMod provides a means to dispense word-sense disambiguation (WSD) applications from fixed, rigid sense inventories. More broadly, dictionaries in NLP are often used to capture some aspect of semantics.

This point bears closer inquiry. One may expect that writing definitions requires some knowledge of the meaning of the headword, but little has been done to confirm this expectation. Here, we focus on empirically verifying what impacts a model's ability to generate valid definitions. As such, our interest lies mostly in examining what factors in the performance of a successful Definition Modeling system, rather than in the engineering aspects of DefMod implementations. We therefore re-purpose the fine-tuning protocol of Bevilacqua et al. (2020) to train a BART model (Lewis et al., 2020) to generate definitions, which we subsequently evaluate on infrequent words: As Bevilacqua et al. have extensively demonstrated the quality of their model on English data, it is suitable for our own endeavor.

Our findings suggest that it is possible to generate definition with little semantic knowledge: Our DefMod system, far from manipulating semantic information, mostly relies on identifying morphological exponents and tying them to lexicographic patterns. Semantic aspects of the headword—e.g., its polysemy or frequency—do not appear to weigh on model performances as captured through automatic metrics.

*Equal contribution.

2 Related Works

There is a broad domain of research that focuses on NLP solutions to lexicography problems and assessing how suitable they are (e.g., Kilgarriff et al., 2008; Frankenberg-Garcia, 2020; Frankenberg-Garcia et al., 2020; Hargraves, 2021). Conversely, many NLP works have used dictionaries to address semantic tasks, such as hypernym or synonym detection (Chodorow et al., 1985; Gaume et al., 2004) word-sense-disambiguation (Lesk, 1986; Muller et al., 2006; Segonne et al., 2019), compositional semantics (Zanzotto et al., 2010; Hill et al., 2016; Mickus et al., 2020), interpretability (Chang and Chen, 2019), representation learning (Bosc and Vincent, 2018; Tissier et al., 2017) or word retrieval (Siddique and Sufyan Beg, 2019, a.k.a. reverse dictionaries). We more narrowly concerned ourselves with definition modeling (Noraset et al., 2017), formulated as a sequence-to-sequence task (Ni and Wang, 2017; Gadetsky et al., 2018; Mickus et al., 2019). Our fine-tuning approach is borrowed from Bevilacqua et al. (2020); note that Huang et al. (2021) also employed a PLM (viz. T5, Raffel et al., 2020). We refer readers to Gardner et al. (2022) for a more thorough introduction.

3 Model & dataset

Datasets We retrieve data from DBnary (Sérasset, 2014),[1] an RDF-formatted dump of Wiktionary projects.[2] This source of data has previously been used to build DefMod datasets (Mickus et al., 2022), and is available in multiple languages—a desirable trait for future replication studies. More details are provided in Appendix B. For each term to be defined, we also tabulate its number of occurrences by tallying the number of string matches in a random subset of 5M documents from the deduplicated English Oscar corpus (Ortiz Suárez et al., 2019).

Headword frequency is worth focusing on, for at least two reasons. First, lexicographers are more likely to cover frequent words: dictionary-makers often espouse a data-driven approach to determine whether words should be included in general or specialized dictionaries (Hartmann, 1992; Frankenberg-Garcia et al., 2020);[3] Second, dictionary users should also be less familiar with rarer words—and likely require definitions. Hence, we set aside definitions where the headword has five or fewer occurrences in our Oscar subset for test purposes only, and further distinguish low-frequency headwords depending on whether they are attested in our Oscar sample. Remaining headwords are then split 80–10–10 between train, validation, and a second held out test set, so as to also measure models on identically distributed items. As such, we have three test sets, distinguished by the frequency of the headword in our Oscar sample: We note as $\# = 0$ the test set comprised of forms unattested in the sample; $\# \leq 5$ corresponds to headwords with five or fewer occurrences; $\# > 5$ matches with train set and validation set conditions.

Model The core of our methodology is borrowed from Bevilacqua et al. (2020): we fine-tune a generative pretrained language model, namely BART (Lewis et al., 2020), to produce an output gloss given an input example of usage, where the term to be defined is highlighted by means of special tokens <define> and </define>. We justify our adoption of their methodology by the fact that they report high results, through extensive NLG and WSD evaluation: as such, the approach they propose is representative of successful modern approaches to DefMod, and is suitable for a study such as ours. We refer the reader to their paper and Appendix A for details.

We expect DefMod systems to be sensitive to the variety of examples of usages and number of target glosses: more examples of usage should lead to higher performances, whereas not exposing the model to polysemy should be detrimental. This can be tested by down-sampling the training set, so as to select one gloss per headword (1G or ∀G) and/or one example of usage per gloss (1E or ∀E). This leads us to defining four related models: ∀G∀E, ∀G1E, 1G∀E, and 1G1E. [4]

4 Impact of frequency, polysemy and contextual diversity

Corresponding results in terms of BLEU, shown in Table 1, are in line with similar results on un-

[1] `http://kaiko.getalp.org/about-dbnary/`

[2] `http://wiktionary.org/`

[3] Lack of corpus evidence may also be reason enough for lexicographers to ignore rarer words (Hanks, 2009, 2012). Dictionaries often rely on usage data to select entries (e.g., `https://www.merriam-webster.com/help/faq-words-into-dictionary`)

[4] Using this notation, 1G∀E means that, for a given headword, we randomly selected one gloss with all its corresponding examples; for ∀G1E, all glosses were considered but with only one randomly selected example for each.

Config	Split			
	Val.	$\# > 5$	$\# \leq 5$	$\# = 0$
∀G∀E	9.07	9.13	11.15	10.85
∀G1E	9.06	9.10	11.11	10.94
1G∀E	8.29	8.32	10.69	10.53
1G1E	8.49	8.53	11.06	10.87

Table 1: Average BLEU performances on held-out sets. Averaged on 5 runs; std. dev. $< \pm 0.001$ always.

seen headwords e.g. in Bevilacqua et al. (2020).[5] They also highlight a strikingly consistent behavior across all four configurations: Mann-Whitney U tests stress that we do not observe lower performances for rarer words, as one would naively expect, except in few cases (∀G∀E, ∀G1E and 1G1E models, when comparing unattested and rare headwords) with relatively high p-values given the sample sizes ($p > 0.01$ always).

Another way to stress the lack of effect related to explicit polysemy or contextual diversity consists in correlating BLEU scores across models: Comparing the BLEU scores obtained by one model (say the ∀G∀E) to those of another model (e.g., the 1G1E model) indicates whether they behave differently or whether BLEU scores are distributed in roughly the same fashion. We systematically observe very high Pearson coefficients ($0.82 < r < 0.90$). In other words, definitions that are poorly handled in any model will in all likelihood be poorly handled in all other models, and definitions that are easy for any single model will be easy for all other models. We provide a breakdown per split and per model in Appendix C, Table 6.

5 Digging further: manual evaluation

To better understand model behavior, we sample 50 outputs of the ∀G∀E model, per BLEU quartile, for the validation split and our three test splits. We then annotate these 800 items as follows.

5.1 Annotation scheme

Sample items for all annotations are provided in Table 2.

[5]We observed similar patterns with most widely-used automatic NLG metrics, and focus on BLEU in the present article for brievity. Nonetheless, see e.g. Roy et al. (2021) for a discussion of the limitations of this metric.

Fluency (FL) measures if the output is free of grammar or commonsense mistakes. For instance, “`(intransitive) To go too far; to go too far.`” is rated with a FL of 1, and “`(architecture) A belfry`” is rated 5.

Factuality (FA) consists in ensuring that generated glosses contain only and all the facts relevant to the target senses. Hence the output “`Not stained.`” generated for the headword *unsatined* is annotated with a FA of 1, whereas the output “`A small flag.`” for the headword *flaglet* is rated with a FA of 5.

PoS-appropriateness (PA) A PoS-appropriate output defines its headwords using a phrase that match its part of speech—e.g., defining adjective with adjectival phrases and nouns with noun phrases. As such, the adjective headword *fried* yields the PoS-inappropriate “`(transitive) To cook (something) in a frying pan.`”, while the production for the verb *unsubstantiate*, viz. “`(intransitive) To make unsubstantiated claims.`” has a PA of 1.

Pattern-based construction (PB) An output is said to display a pattern-based construction whenever it contains only words that are semantically tenuous or morphologically related to the headword. The headword *clacky* thus yield the PB output “`Resembling or characteristic of clacking.`”, and the headword *fare* yields the non-PB production “`(intransitive) To do well or poorly.`”[6]

5.2 Results of the manual evaluation

When looking at all 800 annotations, we find that outputs tend to be fluent (average FL of 4.37) and overwhelmingly PoS-appropriate (95%). They frequently involve patterns (36.5% of PBs) which often involve a straight copy of the headword (10% of all productions). On the other hand, factuality is lacking (average FL of 2.69).

Inter-annotator agreement To quantify how consensual our annotations are, we randomly sample 200 items for dual annotation. Results in Table 3 highlight that, while the two annotators have different sensibilities as to the magnitude of the mistakes in FL and FA (as shown by the low κ), relative judgments on fluency and factuality are

[6]FA and FL are on a 5-point scale, PA and PB are binary.

POS	example	target	hypothesis	annotation	
verb	Thus was th' accomplish'd squire **endued** / With gifts and knowledge per'lous shrewd .	To invest (someone) with a given quality, property etc.; to endow.	(obsolete, transitive) To supply; to supply; to supply.	FL	1
noun	The wealth of those societies in which the capitalist **mode of production** prevails, presents itself as "an immense accumulation of commodities," its unit being a single commodity.	(Marxism) A combination of productive forces such as labour power and means of production, and social and technical relations of production such as property, power, laws and regulations, etc.	(economics) The economic system in which the production of goods and services is based on the production of commodities.	FL	3
noun	Often, though, a **suki** to the chest will cause the sword to become lodged between bone and cartilage making it very difficult to quickly remove.	(martial arts) An opening to the enemy; a weak spot that provides an advantage for one's opponent.	(historical) A blow made by a sword to the chest.	FL	5
verb	[...] the higher of them can never **abut on** a pyknon in the case envisaged here, where the tone is introduced to disjoin the tetrachords.	(transitive) To border on.	(music, transitive) To play (a note) at the same time.	FA	1
noun	"**Kurkuls** are our enemy," he shouted, "and we must exterminate them as a social class. [...]	(historical) A rich or supposedly rich peasant, targeted during Soviet collectivization, especially in the context of Ukraine or Ukrainians; kulak.	(rare) A kurkul.	FA	3
adj.	And its success or failure is likely to tell whether talents [...] make new fortunes from the **nonentertainment** companies that are looking to Hollywood.	Not of or pertaining to entertainment.	Not entertainment.	FA	5
adj.	an **arrant** knave, arrant nonsense	(chiefly, with a negative connotation, dated) Complete; downright; utter.	(obsolete, transitive) To make up; to invent; to invent.	PA	0
noun	[...] Another is to ban planned **obsolescence**, so manufacturers can't create products that are designed to fail .	(uncountable) The state of being obsolete—no longer in use; gone into disuse; disused or neglected.	The state or condition of being obsolescent.	PA	1
noun	A canister of flour from the kitchen had been thrown at the looking-glass and lay like trampled snow over the remains of a decent blue suit with the **lining** ripped out which lay on top of the ruin of a plastic wardrobe.	A covering for the inside surface of something.	The outer layer of a garment.	PB	0
adj.	an **obliquangular** triangle	(archaic, geometry) Formed of oblique angles.	(geometry) Of or pertaining to an oblique angle	PB	1

Table 2: Example of annotated items. Word being defined in **bold** in the example of usage.

Trait	Cohen κ	Spearman ρ	Pearson r
FL	0.405	0.633	0.693
FA	0.374	0.741	0.768
PA	1.000	1.000	1.000
PB	0.780	0.784	0.784

Table 3: Manual annotations, inter-annotator agreement. Pearson r were computed on z-normalized annotations.

consistent (as shown by ρ and r). Hence, we z-normalize FA and FL in the rest of this analysis.

Effects of patterns Mann-Whitney U-tests on FA and FL annotations show that non-pattern-based outputs are statistically rated with lower FL ($p < 3 \cdot 10^{-6}$, common language effect size $f = 42.3\%$) and lower FA ($p < 2 \cdot 10^{-9}$, $f = 37.7\%$) than pattern-based definitions, despite no significant difference in BLEU scores ($p = 0.262$). On the other hand, BLEU scores are correlated with FL and FA ratings (Spearman $\rho = 0.094$ and $\rho = 0.276$ respectively). In sum, the morphologically complex nature of a headword drives much of the behavior of our DefMod system. While BLEU captures some crucial aspects we expect to be assessed in DefMod, it is still impervious to this key factor.

To further confirm that patterns are indeed crucial to a DefMod system's performance, we train a model on data where headwords have been removed from examples of usages, keeping the surrounding control tokens. This in effect creates a 2-token sentinel for which the decoder must gener-

	Split		
Val.	$\# > 5$	$\# \leq 5$	$\# = 0$
5.60	5.72	5.11	4.85

Table 4: Performances with headword ablation

ate a gloss, and deprives the model of information about headword form. BLEU scores drastically drop with this ablated train set, as shown in Table 4. We also find unattested headwords yielding statistically lower BLEUs than rare headwords, which in turn yield lower BLEUs than the other two splits (Mann-Whitney U tests, $p < 10^{-7}$).

Frequency and polysemy We now return to polysemy and word frequency. We consider as an indicator of word polysemy the number of definitions for that headword present in our corpus, whereas we rely on our Oscar sample to derive frequency counts. Frequency and definition counts appear to be highly correlated (Spearman $\rho = 0.406$), and both also anti-correlate with PB ($\rho = -0.1143$ and $\rho = -0.111$ respectively), i.e., rare, monosemous words are defined by the model with patterns (that is, they are likely morphologically complex). We also observe an anticorrelation between FL and definition count (Spearman $\rho = -0.105$), which could be explained by the fact that patterns tend to yield more fluent outputs, as we just saw—however, as we do not observe a correlation between frequency and FL, the interaction between FL and polysemy (as measured by definition count) is likely not so straightforward.[7] Finally, BLEU scores do not correlate with word frequency nor definition counts, which strengthens our claim that this DefMod system makes limited use semantic information to generate glosses—if at all.

	FL	FA
BertScore (Zhang et al., 2020)	0.16	0.37
BLEU (Papineni et al., 2002)	0.09	0.28
chrF (Popović, 2015)	–	0.35
GLEU (Wu et al., 2016)	–	0.29
METEOR (Banerjee and Lavie, 2005)	–	0.31
ROUGE-L (Lin, 2004)	–	0.37
TER (Snover et al., 2006)	−0.10	−0.27

Table 5: Correlation of FA and FL with NLG metrics. Missing values correspond to insignificant coefficients.

[7]Neither do we observe no correlation with FA and PA.

Alternatives to BLEU These annotations leave one question unanswered: is BLEU an adequate means of measuring DefMod productions? In Table 5, we compare the Spearman correlation coefficient of various NLG metrics with our FA and FL annotations. Most NLG metrics do not correlate with fluency ratings: we posit this is due to the overwhelming majority of highly fluent productions in our sample. As for BLEU, it doesn't produce the highest (anti-)correlations—they are instead attested with BertScore for FL and ROUGE-L for FA. Lastly, Mann-Whitney U tests comparing metrics with respect to PB annotations indicate that most of these are not sensitive to the presence or absence of a pattern, with the exception of chrF ($f = 0.43$) and TER ($f = 0.42$). In all, our annotated sample suggests that most NLG metrics appear to display a behavior similar to BLEU: they capture factuality to some extent—but not the importance of patterns.

6 Conclusions

In this work, we have presented how an earlier Definition Modeling system was able to achieve reasonable performances and produce fluent outputs, although the factual validity leave much to be desired. This behavior is almost entirely due to morphologically complex headwords, for which the model is often able to derive reasonable glosses by decomposing the headword into a base and an exponent, and mapping the exponent to one of a limited set of lexicographic patterns. The model we studied seems more sensitive to formal traits than to explicit accounts of polysemy. There are numerous limitations to this work: we focused on one specific fine-tuning approach for one specific English PLM. Nonetheless, we have shown that models can achieve reasonable performances on DefMod without relying on semantics, casting doubt on the task's usefulness for word embedding evaluation, as initially suggested by Noraset et al. (2017)

In other words: using lexicographic data as inputs for an NLP model does not ensure that it will pick up on the semantic aspects contained therein.

Acknowledgments

We thank IWCS and ∗SEM reviewers for their insightful comments on this work.

This work is part of the FoTran project, funded by the European Research Council (ERC) under the EU's Horizon 2020 research and innovation program (agreement № 771113). We also thank the CSC-IT Center for Science Ltd., for computational resources.

References

Tal August, Katharina Reinecke, and Noah A. Smith. 2022. Generating scientific definitions with controllable complexity. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 8298–8317, Dublin, Ireland. Association for Computational Linguistics.

Satanjeev Banerjee and Alon Lavie. 2005. METEOR: An automatic metric for MT evaluation with improved correlation with human judgments. In *Proceedings of the ACL Workshop on Intrinsic and Extrinsic Evaluation Measures for Machine Translation and/or Summarization*, pages 65–72, Ann Arbor, Michigan. Association for Computational Linguistics.

Diego Bear and Paul Cook. 2021. Cross-lingual wolastoqey-English definition modelling. In *Proceedings of the International Conference on Recent Advances in Natural Language Processing (RANLP 2021)*, pages 138–146, Held Online. INCOMA Ltd.

Michele Bevilacqua, Marco Maru, and Roberto Navigli. 2020. Generationary or "how we went beyond word sense inventories and learned to gloss". In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 7207–7221, Online. Association for Computational Linguistics.

Tom Bosc and Pascal Vincent. 2018. Auto-encoding dictionary definitions into consistent word embeddings. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 1522–1532, Brussels, Belgium. Association for Computational Linguistics.

Ting-Yun Chang and Yun-Nung Chen. 2019. What does this word mean? explaining contextualized embeddings with natural language definition. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 6064–6070, Hong Kong, China. Association for Computational Linguistics.

Martin S. Chodorow, Roy J. Byrd, and George E. Heidorn. 1985. Extracting semantic hierarchies from a large on-line dictionary. In *23rd Annual Meeting of the Association for Computational Linguistics*, pages 299–304, Chicago, Illinois, USA. Association for Computational Linguistics.

Ana Frankenberg-Garcia. 2020. Combining user needs, lexicographic data and digital writing environments. *Language Teaching*, 53(1):29–43.

Ana Frankenberg-Garcia, Geraint Paul Rees, and Robert Lew. 2020. Slipping Through the Cracks in e-Lexicography. *International Journal of Lexicography*, 34(2):206–234.

Artyom Gadetsky, Ilya Yakubovskiy, and Dmitry Vetrov. 2018. Conditional generators of words definitions. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 266–271, Melbourne, Australia. Association for Computational Linguistics.

Noah Gardner, Hafiz Khan, and Chih-Cheng Hung. 2022. Definition modeling: literature review and dataset analysis. *Applied Computing and Intelligence*, 2(1):83–98.

Bruno Gaume, Nabil Hathout, and Philippe Muller. 2004. Word sense disambiguation using a dictionary for sense similarity measure. In *COLING 2004: Proceedings of the 20th International Conference on Computational Linguistics*, pages 1194–1200, Geneva, Switzerland. COLING.

Patrick Hanks. 2009. The impact of corpora on dictionaries. In *Contemporary corpus linguistics*, chapter 13, pages 214–236. Continuum London.

Patrick Hanks. 2012. The Corpus Revolution in Lexicography. *International Journal of Lexicography*, 25(4):398–436.

Orin Hargraves. 2021. Lexicography in the post-dictionary world. *Dictionaries*, 42(2):119–129.

R. R. K. Hartmann. 1992. Lexicography, with particular reference to english learners' dictionaries. *Language Teaching*, 25(3):151–159.

Felix Hill, Kyunghyun Cho, Anna Korhonen, and Yoshua Bengio. 2016. Learning to understand phrases by embedding the dictionary. *Transactions of the Association for Computational Linguistics*, 4:17–30.

Han Huang, Tomoyuki Kajiwara, and Yuki Arase. 2021. Definition modelling for appropriate specificity. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 2499–2509, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Han Huang, Tomoyuki Kajiwara, and Yuki Arase. 2022. JADE: Corpus for Japanese definition modelling. In *Proceedings of the Thirteenth Language Resources and Evaluation Conference*, pages 6884–6888, Marseille, France. European Language Resources Association.

Yuan Jiaxin, Kong Cunliang, Xie Chenhui, Yang Liner, and Yang Erhong. 2022. COMPILING: A benchmark dataset for Chinese complexity controllable definition generation. In *Proceedings of the 21st Chinese National Conference on Computational Linguistics*, pages 921–931, Nanchang, China. Chinese Information Processing Society of China.

Adam Kilgarriff, Miloš Husák, Katy McAdam, Michael Rundell, and Pavel Rychlý. 2008. GDEX: Automatically finding good dictionary examples in a corpus. In *Proceedings of the 13th EURALEX International Congress*, pages 425–432, Barcelona, Spain. Institut Universitari de Linguistica Aplicada, Universitat Pompeu Fabra.

Cunliang Kong, Yun Chen, Hengyuan Zhang, Liner Yang, and Erhong Yang. 2022. Multitasking framework for unsupervised simple definition generation. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 5934–5943, Dublin, Ireland. Association for Computational Linguistics.

Michael Lesk. 1986. Automatic sense disambiguation using machine readable dictionaries: How to tell a pine cone from an ice cream cone. In *Proceedings of the 5th Annual International Conference on Systems Documentation*, SIGDOC '86, page 24–26, New York, NY, USA. Association for Computing Machinery.

Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Veselin Stoyanov, and Luke Zettlemoyer. 2020. BART: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 7871–7880, Online. Association for Computational Linguistics.

Chin-Yew Lin. 2004. ROUGE: A package for automatic evaluation of summaries. In *Text Summarization Branches Out*, pages 74–81, Barcelona, Spain. Association for Computational Linguistics.

Timothee Mickus, Timothée Bernard, and Denis Paperno. 2020. What meaning-form correlation has to compose with: A study of MFC on artificial and natural language. In *Proceedings of the 28th International Conference on Computational Linguistics*, pages 3737–3749, Barcelona, Spain (Online). International Committee on Computational Linguistics.

Timothee Mickus, Denis Paperno, and Matthieu Constant. 2019. Mark my word: A sequence-to-sequence approach to definition modeling. In *Proceedings of the First NLPL Workshop on Deep Learning for Natural Language Processing*, pages 1–11, Turku, Finland. Linköping University Electronic Press.

Timothee Mickus, Kees Van Deemter, Mathieu Constant, and Denis Paperno. 2022. Semeval-2022 task 1: CODWOE – comparing dictionaries and word embeddings. In *Proceedings of the 16th International Workshop on Semantic Evaluation (SemEval-2022)*, pages 1–14, Seattle, United States. Association for Computational Linguistics.

Philippe Muller, Nabil Hathout, and Bruno Gaume. 2006. Synonym extraction using a semantic distance on a dictionary. In *Proceedings of TextGraphs: the First Workshop on Graph Based Methods for Natural Language Processing*, pages 65–72, New York City. Association for Computational Linguistics.

Ke Ni and William Yang Wang. 2017. Learning to explain non-standard English words and phrases. In *Proceedings of the Eighth International Joint Conference on Natural Language Processing (Volume 2: Short Papers)*, pages 413–417, Taipei, Taiwan. Asian Federation of Natural Language Processing.

Thanapon Noraset, Chen Liang, Lawrence Birnbaum, and Doug Downey. 2017. Definition modeling: Learning to define word embeddings in natural language. In *AAAI*.

Pedro Javier Ortiz Suárez, Benoit Sagot, and Laurent Romary. 2019. Asynchronous pipelines for processing huge corpora on medium to low resource infrastructures. Proceedings of the Workshop on Challenges in the Management of Large Corpora (CMLC-7) 2019. Cardiff, 22nd July 2019, pages 9 – 16, Mannheim. Leibniz-Institut f"ur Deutsche Sprache.

Myle Ott, Sergey Edunov, Alexei Baevski, Angela Fan, Sam Gross, Nathan Ng, David Grangier, and Michael Auli. 2019. fairseq: A fast, extensible toolkit for sequence modeling. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics (Demonstrations)*, pages 48–53, Minneapolis, Minnesota. Association for Computational Linguistics.

Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002. Bleu: a method for automatic evaluation of machine translation. In *Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics*, pages 311–318, Philadelphia, Pennsylvania, USA. Association for Computational Linguistics.

Maja Popović. 2015. chrF: character n-gram F-score for automatic MT evaluation. In *Proceedings of the Tenth Workshop on Statistical Machine Translation*, pages 392–395, Lisbon, Portugal. Association for Computational Linguistics.

Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. 2020. Exploring the limits of transfer learning with a unified text-to-text transformer. *Journal of Machine Learning Research*, 21(140):1–67.

Devjeet Roy, Sarah Fakhoury, and Venera Arnaoudova. 2021. Reassessing automatic evaluation metrics for code summarization tasks. In *Proceedings of the 29th ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering*, ESEC/FSE 2021, page 1105–1116, New York, NY, USA. Association for Computing Machinery.

Vincent Segonne, Marie Candito, and Benoît Crabbé. 2019. Using Wiktionary as a resource for WSD : the case of French verbs. In *Proceedings of the 13th International Conference on Computational Semantics - Long Papers*, pages 259–270, Gothenburg, Sweden. Association for Computational Linguistics.

Gilles Sérasset. 2014. DBnary: Wiktionary as a Lemon-Based Multilingual Lexical Resource in RDF. *Semantic Web Journal - Special issue on Multilingual Linked Open Data*, pages –. To appear.

Bushra Siddique and Mirza Mohd Sufyan Beg. 2019. A review of reverse dictionary: Finding words from concept description. In *Next Generation Computing Technologies on Computational Intelligence*, pages 128–139, Singapore. Springer Singapore.

Matthew Snover, Bonnie Dorr, Rich Schwartz, Linnea Micciulla, and John Makhoul. 2006. A study of translation edit rate with targeted human annotation. In *Proceedings of the 7th Conference of the Association for Machine Translation in the Americas: Technical Papers*, pages 223–231, Cambridge, Massachusetts, USA. Association for Machine Translation in the Americas.

Julien Tissier, Christophe Gravier, and Amaury Habrard. 2017. Dict2vec : Learning word embeddings using lexical dictionaries. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, pages 254–263, Copenhagen, Denmark. Association for Computational Linguistics.

Yonghui Wu, Mike Schuster, Zhifeng Chen, Quoc V. Le, Mohammad Norouzi, Wolfgang Macherey, Maxim Krikun, Yuan Cao, Qin Gao, Klaus Macherey, Jeff Klingner, Apurva Shah, Melvin Johnson, Xiaobing Liu, Łukasz Kaiser, Stephan Gouws, Yoshikiyo Kato, Taku Kudo, Hideto Kazawa, Keith Stevens, George Kurian, Nishant Patil, Wei Wang, Cliff Young, Jason Smith, Jason Riesa, Alex Rudnick, Oriol Vinyals, Greg Corrado, Macduff Hughes, and Jeffrey Dean. 2016. Google's neural machine translation system: Bridging the gap between human and machine translation.

Fabio Massimo Zanzotto, Ioannis Korkontzelos, Francesca Fallucchi, and Suresh Manandhar. 2010. Estimating linear models for compositional distributional semantics. In *Proceedings of the 23rd International Conference on Computational Linguistics (Coling 2010)*, pages 1263–1271, Beijing, China. Coling 2010 Organizing Committee.

Tianyi Zhang, Varsha Kishore, Felix Wu, Kilian Q. Weinberger, and Yoav Artzi. 2020. Bertscore: Evaluating text generation with bert. In *International Conference on Learning Representations*.

A Hyperparameters

Models are implemented in fairseq (Ott et al., 2019). We used the `bart_large` model and followed the instructions on the github repository for finetuning BART on the summary task.[8] We used the same parameters except for the learning rate, which after some experiments, was set to $5 \cdot 10^{-6}$. For every configuration (∀G∀E, ∀G1E,1G∀E, 1G1E) we kept the model with the best loss on the validation dataset.

B Data preprocessing

In the present work, we retrieve definition glosses (i) associated with an example of usage and (ii) where the term to be defined is tagged as a noun, adjective, verb, adverb or proper noun. Like Bevilacqua et al., we also consider MWEs as potential terms to define.

To highlight a headword within an example of usage, the approach of Bevilacqua et al. (2020) consists in surrounding them with learned task-specific control tokens. We therefore parse example of usages using SpaCy[9] to retrieve the first sequence of tokens whose lemmas match with the lemmas of the term to be defined.

The BART model we fine-tune on DefMod has been pretrained on OpenWebText, which contains some pages retrieved from Wiktionary. We preemptively remove these pages from all dataset splits, so as to ensure there is no overlap between pre-train, train and test data.

Frequencies are tabulated on a case-folded, whitespace-normalized subset of the Oscar corpus. In practice, we extract the number of hard string matches of each headword preprended and appended with word boundaries.

C BLEU scores correlations

In Table 6, we display how similar are the behaviors on different models across splits. Each sub-table corresponds to a different split, and pits all combinations of models. For instance, the last cell in the second row of sub-Table 6c indicates that to the Pearson correlation between the ∀G1E and the 1G1E on the $\# \leq 5$ test split is above 88.4%. The crucial fact that emerges from these tables is the distribution of BLEU is very similar across all models we tested—which entails that explicit polysemy or contextual diversity do not weight on performances, as measured through BLEU scores.

	∀G1E	**1G∀E**	**1G1E**
∀G∀E	0.89	0.87	0.85
∀G1E		0.84	0.87
1G∀E			0.88

(a) Validation split

	∀G1E	**1G∀E**	**1G1E**
∀G∀E	0.89	0.86	0.85
∀G1E		0.83	0.87
1G∀E			0.87

(b) Test $\# > 5$ split

	∀G1E	**1G∀E**	**1G1E**
∀G∀E	0.88	0.89	0.86
∀G1E		0.85	0.88
1G∀E			0.88

(c) Test $\# \leq 5$ split

	∀G1E	**1G∀E**	**1G1E**
∀G∀E	0.88	0.88	0.85
∀G1E		0.86	0.88
1G∀E			0.88

(d) Test $\# = 0$ split

Table 6: BLEU scores correlations (Pearson r)

[8] https://github.com/facebookresearch/fairseq/blob/main/examples/bart/README.summarization.md
[9] https://spacy.io/