Context vs Target Word: Quantifying Biases in Lexical Semantic Datasets

Qianchu Liu, Diana McCarthy, Anna Korhonen
Language Technology Lab, TAL, University of Cambridge, UK
{ql261,alk23}@cam.ac.uk
diana@dianamccarthy.co.uk

Abstract

State-of-the-art contextualized models such as BERT use tasks such as WiC and WSD to evaluate their word-in-context representations. This inherently assumes that performance in these tasks reflect how well a model represents the coupled word and context semantics. This study investigates this assumption by presenting the first quantitative analysis (using probing baselines) on the context-word interaction being tested in major contextual lexical semantic tasks. Specifically, based on the probing baseline performance, we propose measures to calculate the degree of context or word biases in a dataset, and plot existing datasets on a continuum. The analysis shows most existing datasets fall into the extreme ends of the continuum (i.e. they are either heavily context-biased or target-word-biased) while AM2ICo and Sense Retrieval show lower overall biases to challenge a model to represent both the context and target words. Our case study on WiC reveals that human subjects do not share models’ strong context biases in the dataset (humans found semantic judgments much more difficult when the target word is missing) and models are learning spurious correlations from context alone. This study demonstrates that models are usually not being tested for word-in-context representations as such in these tasks and results are therefore open to misinterpretation. We recommend our framework as sanity check for context and target word biases of future task design and application in lexical semantics.

1 Introduction

Meaning contextualization (i.e., identifying the correct meaning of a target word in linguistic context) is essential for understanding natural language, and has been the focus in many lexical semantic tasks. Pretrained contextualized models (PCMs) have brought large improvements in these tasks including WSD (Hadiwinoto et al., 2019; Loureiro and Jorge, 2019; Huang et al., 2019; Blevins and Zettlemoyer, 2020), WiC (Pilehvar and Camacho-Collados, 2019; Garí Soler et al., 2019) and entity linking (EL) (Wu et al., 2020; Broscheit, 2019).

These superior performances have been taken as proof that PCMs can successfully model word-in-context semantics. However, the evaluation benchmarks often vary in their emphasis on context vs target words. For example, WSD relies more on context by design as the target words are given\(^1\). Moreover, models may find shortcuts to avoid learning word-context interaction. What is missing in

\(^1\)The exact amount of context/target word reliance in WSD is to be tested as human naturally use both to make prediction.
the current literature is an accurate quantification of this word-context interplay being tested in each task so that we can fully understand task goals and model performance. In particular, we need to flag heavy word and context reliance where a model can solve a task by relying solely on context or the target words. Notice that such word or context reliance is not necessarily a problem for an application, however it would be undesirable in terms of a scientific understanding of the models’ meaning contextualization abilities as it essentially bypasses the key word-context interaction challenge in meaning contextualization, which requires the modeling of both target words and their contexts\(^2\). Therefore, we refer to models’ heavy reliance on target words or context in a dataset as target word biases or context biases.

To achieve the aforementioned goal, we design an analysis framework to quantify context and target word biases. We first run controlled probing baselines by masking the input to show the context or the target word alone. Based on model’s performance on these probing baselines, we calculate two ratios that reflect how much of the model performance in this dataset comes from context alone or the target word alone, i.e. the degree of context or target word biases (See Figure 1). The design of the probing baselines follows previous studies that applied input permutation techniques for model and task analysis in GLUE (Pham et al., 2020), NLI (Poliak et al., 2018; Wang et al., 2018; Talman et al., 2021) and relation extraction (Peng et al., 2020).

While previous probing studies usually assume no meaningful information from a corrupted input without human verification, we provide fairer comparison with model performance by collecting human judgment on the same partial input in a case study on WiC. Such comparison reveals whether there are biases specific to models or inherent in the task (i.e. for both humans and models).

2 The Analysis Framework

2.1 Pretrained Contextualized Models

The underlying model for our main experiments is BERT (Devlin et al., 2019), one of the most successful PCMs that offer dynamic contextual word representations as bidirectional hidden layers from a transformer architecture. To ensure the general trend of our findings are consistent across different models, we also performed the analysis using ROBERTA (Liu et al., 2019), which improves upon BERT by optimized design decisions during training. In addition, we offer comparison with a more recent PCM, DeBERTa (He et al., 2020), which improves BERT with two novel techniques: disentangled attention that encodes a word’s content and position separately, and an enhanced masked decoder that incorporates absolute position for predicting masked tokens.

2.2 Probing Baselines

Context vs. Word: For the main experiment, we design the WORD baseline where we input only the target word \(^3\) to the model, and the CONTEXT baseline where the target word is replaced with a [MASK] token in the input. A high performance in CONTEXT or WORD will indicate strong context or target word bias. Example input is shown in Table 1.

Lower Bound: Apart from a RANDOM baseline, we also set up a LABEL\(^4\) baseline where all the input is masked and the learning is only from the label distribution in the task. Human Evaluation: For fairer comparison with model performance, we collect human judgment (HUM) on the baseline input in a case study on WiC\(^5\).

We follow Pilehvar and Camacho-Collados (2019) to assign 4 sets of 100 examples sampled from the dev set\(^6\) to native English speakers. Each 100 example receives one annotation but there is a 50 example overlap overlap between two annotators for agreement calculation. The difference in our setup is the annotators performed meaning judgment based on the CONTEXT input and as an additional response they are encouraged to guess the target word.

All the probing baselines are compared with model performance on the full input (FULL). We refer to model M’s performance in WORD, CONTEXT, LABEL and FULL as \(M_W, M_C, M_L\) and \(M_{\text{FULL}}\) respectively.

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\(^2\)Words are frequently ambiguous, but so are contexts. In “I like XX.”, XX could have a number of meanings.

\(^3\)In the surveyed tasks, a target word can show different surface variations of number, case and etc. Eg. breed, breeds.

\(^4\)Training the LABEL baseline is preferable to simply counting label occurrences in the data as the former can work with both continuous and categorical label space.

\(^5\)We choose WiC as a protocol for practical ease. Other tasks involve a too larger time/cost scope (eg. SR requires the annotators to familiarize the whole ontology of WordNet).

\(^6\)We cannot use the WiC test set as the test labels are undisclosed. As the dev set comes from the same distribution
Table 1: An example of BERT’s contextual bias in WiC. The original WiC label for the example is F. Target words are in brackets.

| Input         | Sentence1                                      | Sentence2                                      | BERT  | HUM |
|---------------|-----------------------------------------------|-----------------------------------------------|-------|-----|
| FULL          | Google represents a new [breed] of entrepreneurs. | The [breed] of tulip.                         | F     | F   |
| CONTEXT       | Google represents a new [MASK] of entrepreneurs . | The [MASK] of tulip .                        | F     | T   |
| WORD          | breed                                         | breed                                         | T     |     |

### 2.3 Calculating the Bias Measures

Based on a model $M$’s performance on the full input and on the baseline input, we propose $Bias_{MC}$ and $Bias_{MW}$ (as calculated in Equation (1) and Equation (2)) to measure context and target word biases in a dataset. $Bias_{MC}$ is the ratio of $M_C$ to $M_{Full}$ with the LABEL performance $M_L$ deducted from both $M_C$ and $M_{Full}$. $M_L$ has to be deducted as it is unrelated to the input. Otherwise, the ratio will give an inflated bias measurement. $Bias_{MW}$ is calculated in the same way as $Bias_{MC}$ except that we replace $M_C$ with $M_W$ in the equation. The two measures can also be seen as $M_C$ and $M_W$ under min-max normalization where the min value is $M_L$ and the max value is $M_{Full}$. As such, $Bias_{MC}$ and $Bias_{MW}$ reflect how much of what a model has learned from the input in a dataset is from context alone or target word alone, which will give us indicators of the degree of context and target word biases in the dataset. For example, we can interpret a $Bias_{MC}$ of 0.8 as 80% of what the model has learned from the full input can be achieved by the context alone.

$$Bias_{MC} = \frac{(M_C - M_L)}{(M_{Full} - M_L)} \tag{1}$$

$$Bias_{MW} = \frac{(M_W - M_L)}{(M_{Full} - M_L)} \tag{2}$$

### 3 Experiments

#### 3.1 Task Selection (Examples in Appendix A)

**Word Sense Disambiguation (WSD).** WSD (Navigli, 2009; Raganato et al., 2017) requires a model to assign a sense label to a target word in context from a set of possible candidates for the target word. Following the standard practice, we use SemCor as the train set, Semeval2007 as dev, and report accuracy results on the concatenated ALL testset.

**The WiC-style Tasks (WiC, WiC-TSV, MCL-WiC and XL-WiC).** To alleviate WSD’s requirement for a sense inventory, WiC (Pilehvar and Camacho-Collados, 2019) presents a pairwise classification task where each pair consists of two word-in-context instances. The model needs to judge whether the target words in a pair have the same contextual meanings. WiC-TSV (Breit et al., 2021) extends the WiC framework to multiple domains and settings. This study adopts the combined setting where each input consists of a word in context instance paired with a definition and a hypernym. The WiC-style tasks have also been extended to the multilingual and crosslingual settings in MCL-WiC (Martelli et al., 2021), XL-WiC (Raganato et al., 2020) and more recently in AM²ICO (Liu et al., 2021). MCL-WiC provides test sets for five languages with full gold annotation scores. However, MCL-WiC only covers training data in English. To ensure the analysis will be testing the same data distribution during both training and testing, we will only use the English dataset of MCL-WiC. XL-WiC extends WiC to 12 languages. While most languages in this task do not have training data, we perform analysis on its German dataset which contains both train (50k) and test data (20k). AM²ICO covers 14 datasets, each of which pairs English word-in-context instances with word-in-context instances in a target language. In this study, we perform analysis on the English-Chinese dataset which contains 13k train and 1k test data.

**Sense Retrieval (SR).** Based on WSD with the same train and test data, SR (Loureiro and Jorge, 2019) requires a model to retrieve a correct entry from the full sense inventory of all words from WordNet (Miller, 1998).

**AIDA and Wikification.** An important application scenario for testing meaning contextualization is Entity Linking (EL). EL maps a mention (an entity in its context) to a knowledge base (KB) which is usually Wikipedia in the general domain. The

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7 We performed the analysis on other datasets of AM²ICO and found the trend is similar.
target word and its context help solve name variations and lexical ambiguity, which are the main challenges in EL (Shen et al., 2014). In addition, the context itself can help learn better representations for rare or new entities (Schick and Schütze, 2019; Ji et al., 2017). We test on two popular Wikipedia-based EL benchmarks: AIDA (Hoffart et al., 2011) and Wikification (Wiki) (Ratinov et al., 2011; Bunescu and Pasca, 2006). AIDA provides manual annotations of entities with Wikipedia and YAGO2 labels for 946, 216 and 231 articles as train, dev and test sets respectively. The Wiki Dataset is based on the hyperlinks from Wikipedia. We randomly sampled 50k sentences from Wikipedia as the test and another 50k as the dev set. The rest is used for training. For both AIDA and Wiki, the search space is the full Wikipedia entity list.

WikiMed and COMETA. To test domain effects, we evaluate on two medical EL tasks. We use the WikiMed corpus (Vashishth et al., 2020), an automatically extracted medical subset from Wikipedia, for medical wikification. Each mention is mapped to a Wikipedia page linked to a concept in UMLS (Bodenreider, 2004), a massive medical concept KB. We define the search space as the Wikipedia entities covered in UMLS. With the same Wikipedia ontology but a different domain subset, WikiMed can be directly compared with Wiki for assessing domain influence. We also test on COMETA (Basaldella et al., 2020), a medical EL task in social media. COMETA consists of 20k English biomedical entity mentions from online posts in Reddit. The expert-annotated labels are linked to SNOMED CT (Donnelly et al., 2006), another widely-used medical KB.

We report accuracy for WSD and all the WiC style tasks, and accuracy@1 for retrieval-based tasks including Wiki, Aida, etc.

3.2 Experiment setup

We adopt standard model finetuning setups for each task. We use the base uncased variant of BERT for general domain experiments and PUBLICATION (Gu et al., 2020) for the medical tasks. For WSD, we use GLOSSBERT (Huang et al., 2019) that learns a sentence-gloss pair classification model based on BERT. For WiC and WiC-TSV, we follow the SuperGlue (Wang et al., 2019) practices to concatenate BERT’s last layer of [CLS] and the target words’ token representations for each input pair, followed by a linear classifier. For the retrieval-based tasks including SR and EL, we adopt a bi-encoder architecture to model query and target candidates with BERT (Wu et al., 2020). For the query, we insert \{ and \} to mark the start and end positions of the target word in context. Each target candidate is reformatted as “[CLS]Name || Description[SEP]”, Name is an entity title (EL) or synset lemmas from WordNet (SR). Description is the first sentence in an entity’s Wikipedia page (Wiki & WikiMed), a gloss (SR), or n/a (COMETA). The model learns to draw closer the true query-target pairs’ representations using triplet loss with triplet miners during fine-tuning (Liu et al., 2020). For each experiment, we perform grid search for the learning rate in $[1e-5, 2e-5, 3e-5]$ and select models with early stopping on the dev set.

3.3 Main Results and Discussion

Context vs Target Word Biases. Based on BERT’s baseline performance (Performance for each probing baseline is plotted in Appendix F), we calculate $Bias_{BERT_C}$ and $Bias_{BERT_W}$ for each dataset, and plot the results in Figure 1. One obvious observation from the figure is that most datasets lie close to the dashed red lines which indicate 1.0 (i.e. 100%) context (right) or target word bias (top). Moreover, the datasets tend to lie in two ends: the retrieval-based datasets (eg. Wiki) lie in the top left corner, showing large target word bias and low context bias; the WiC style datasets and WSD lie in the bottom right corner with large context bias and low target word bias. XL-WiC is an exception as it contains both strong context and target word biases. Unlike other WiC-style datasets, XL-WiC shows strong target word bias because the dataset does not contain sufficient ambiguous cases. We confirm this by calculating the per-word average label entropy of the training data as 0.09, and on average a word has the same label for 94% of the contexts. Therefore, a model can perform very well by relying solely on the target words without needing context for disambiguation.

Overall, we found that most of the existing datasets, albeit being context-sensitive lexical semantic tasks, are either “context” tasks or “target word” tasks with strong context or target word
biases. There are currently few datasets that require the modeling of the context-word interaction, which should result in both low context and target word biases. SR and AM\textsuperscript{2}IC\textsubscript{O} are two such datasets which can be found further inside of the red lines in Figure 1. In SR, a system needs to model the target words in order to retrieve all the possible senses associated with the word, and because there is plenty of ambiguity in the dataset, context is also needed to identify the correct sense. AM\textsuperscript{2}IC\textsubscript{O} was specifically designed to include adversarial examples to penalize models that rely only on the context or on the target words.

**Domains and Ontologies.** The retrieval-based tasks in this study offer comparison between two ontologies (WordNet vs Wikipedia) and between two domains (general vs medical). Overall, Wikipedia has a stronger target word bias than WordNet, and this bias is increased in the medical domain where relying on the target words alone gives the best performance (i.e. COMETA and WikiMed both have >1.0 target word bias). Such divergence is arguably caused by the different degrees of lexical ambiguity in these tasks. In particular, domain could reduce ambiguity (Magnini et al., 2002; Koeling et al., 2005), and therefore affect the context and target word bias. As a quantitative measure for lexical ambiguity, we calculate average sense entropy across all words in each task’s training data, see Table 2.

Confirming our hypothesis, sense entropy (lexical ambiguity) in a task correlates well with the FULL-WORD gap. When there is little ambiguity in a task (e.g. medical EL), model learning is dominated by the target words with the context being useless or even harmful (See Appendix B).

**Human vs Models.** As in Table 3, humans exhibit a substantial FULL-CONTEXT gap\textsuperscript{9}(19%): the absence of the target words drastically decreases both performance and agreement, suggesting these target words are indeed crucial for solving the task. In comparison, BERT shows CONTEXT performance (66.35%) close to FULL (69%), even outperforming human CONTEXT baseline (61%). This context bias is more prominent in DEBERTA with a much higher CONTEXT baseline (69.64%) which is on par with its FULL performance (70.35%) and thus largely accounts for its improved performance. As qualitative analysis on the human-model discrepancy on CONTEXT, we examined 20 cases where annotators did not predict WiC F labels (from the corresponding FULL input) while BERT did. In 11 cases, humans guessed other valid target words to justify their predictions resulting in a T (True) instead of the original F (False) label. Table 1 shows such an example. On CONTEXT input, one annotator gave T, guessing the target word is type so that the sentences in the pair become:

1. sentence1: Google represents a new [type] of entrepreneurs.
   sentence2: The [type] of tulip.

The annotator’s T label here is reasonable as type fits the contexts and does hold its meaning across the two sentences. The same annotator was able to give the WiC label F when we reveal the original target word (breed) which has the specific meaning of species in sentence1 and personality in sentence2 (see the FULL input in Table 4). BERT however still predicts F in 1. In fact, we perform preliminary analysis to test BERT on all the 11 cases where the human-elicited target words change the labels to T (We show more examples in the Appendix C.), and found that for 7 out of 11, BERT is insensitive to the changed target words and maintains its F prediction. This suggests BERT does not appreciate the same word-context interaction as humans, and is making prediction mainly based on contexts rather than modeling contextual lexical semantics in WiC.

**4 Conclusion**

We presented an analysis framework to disentangle and quantify context-word interplay in application of popular contextual lexical semantic benchmarks. We plot datasets on the continuum from context-biased (e.g. MCL-WiC, WiC) to target-word-biased (medical EL), and we found that most

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\textsuperscript{9}Note humans predict above 50% in CONTEXT, indicating natural ability to use information from context alone.
existing datasets lie on the two ends with excessive biases that essentially bypass the key challenges in contextual lexical semantics. We identify SR and AM^2IC as two tasks with lower overall biases to necessitate representation of both word and context, and we call for more tasks that challenge models to do so. We further analyzed effect from domains and ontologies on the target word bias: medical>general and Wikipedia>Wordnet. Through controlled comparison and qualitative analysis, we found that models’ heavy context bias in WiC is not attested in humans who need both context and target words to perform well in the task. This suggests that the models are learning spurious correlations rather than genuine contextual lexical semantics. Our paper highlights the importance of understanding these biases in existing datasets and encourages future dataset design to control for these biases and to focus more on testing the challenging word-context interaction in context-sensitive lexical semantics.

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References

Marco Basaldella, Fangyu Liu, Ehsan Shareghi, and Nigel Collier. 2020. COMETA: A corpus for medical entity linking in the social media. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 3122–3137, Online. Association for Computational Linguistics.

Terra Blevins and Luke Zettlemoyer. 2020. Moving down the long tail of word sense disambiguation with gloss informed bi-encoders. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 1006–1017, Online. Association for Computational Linguistics.

Olivier Bodenreider. 2004. The unified medical language system (umls): integrating biomedical terminology. Nucleic acids research, 32(suppl_1):D267–D270.

Anna Breit, Artem Revenko, Kiamehr Rezaee, Mohammad Taher Pilehvar, and Jose Camacho-Collados. 2021. WiC-TSV: An evaluation benchmark for target sense verification of words in context. In Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume, pages 1635–1645, Online. Association for Computational Linguistics.

Samuel Broschiet. 2019. Investigating entity knowledge in BERT with simple neural end-to-end entity linking. In Proceedings of the 23rd Conference on Computational Natural Language Learning (CoNLL), pages 677–685, Hong Kong, China. Association for Computational Linguistics.

Razvan Bunescu and Marius Pa¸asca. 2006. Using encyclopedic knowledge for named entity disambiguation. In 11th Conference of the European Chapter of the Association for Computational Linguistics, Trento, Italy. Association for Computational Linguistics.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.

Kevin Donnelly et al. 2006. Snomed-ct: The advanced terminology and coding system for ehealth. Studies in health technology and informatics, 121:279.

Aina Gari Soler, Marianna Apidianaki, and Alexandre Allauzen. 2019. Word usage similarity estimation with sentence representations and automatic substitutes. In Proceedings of the Eighth Joint Conference on Lexical and Computational Semantics (*SEM 2019), pages 9–21, Minneapolis, Minnesota. Association for Computational Linguistics.

Yu Gu, Robert Tinn, Hao Cheng, Michael Lucas, Naoto Usuyama, Xiaodong Liu, Tristan Naumann, Jianfeng Gao, and Hoifung Poon. 2020. Domain-specific language model pretraining for biomedical natural language processing.

Christian Hadiwinoto, Hwee Tou Ng, and Wee Chung Gan. 2019. Improved word sense disambiguation using pre-trained contextualized word representations. 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 5297–5306, Hong Kong, China. Association for Computational Linguistics.

Pengcheng He, Xiaodong Liu, Jianfeng Gao, and Weizhu Chen. 2020. Deberta: Decoding-enhanced bert with disentangled attention. arXiv preprint arXiv:2006.03654.
Johannes Hoffart, Mohamed Amir Yosef, Ilaria Bordino, Hagen Fürstentau, Manfred Pinkal, Marc Spaniol, Bilyana Taneva, Stefan Thater, and Gerhard Weikum. 2011. Robust disambiguation of named entities in text. In Proceedings of the 2011 Conference on Empirical Methods in Natural Language Processing, pages 782–792, Edinburgh, Scotland, UK. Association for Computational Linguistics.

Luyao Huang, Chi Sun, Xipeng Qiu, and Xuanjing Huang. 2019. GlossBERT: BERT for word sense disambiguation with gloss knowledge. 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 3509–3514, Hong Kong, China. Association for Computational Linguistics.

Yangfeng Ji, Chenzhao Tan, Sebastian Martischat, Yejin Choi, and Noah A. Smith. 2017. Dynamic entity representations in neural language models. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, pages 1830–1839, Copenhagen, Denmark. Association for Computational Linguistics.

Rob Koelbing, Diana McCarthy, and John Carroll. 2005. Domain-specific sense distributions and predominant sense acquisition. In Proceedings of Human Language Technology Conference and Conference on Empirical Methods in Natural Language Processing, pages 419–426, Vancouver, British Columbia, Canada. Association for Computational Linguistics.

Fangyu Liu, Ehsan Shareghi, Zaiqiao Meng, Marco Basaldella, and Nigel Collier. 2020. Self-alignment pre-training for biomedical entity representations. arXiv preprint arXiv:2010.11764.

Qianchu Liu, Edoardo M. Ponti, Diana McCarthy, Ivan Vulić, and Anna Korhonen. 2021. Am2ico: Evaluating word meaning in context across low-resource languages with adversarial examples.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized bert pretraining approach. arXiv preprint arXiv:1907.11692.

Daniel Loureiro and Alípio Jorge. 2019. Language modelling makes sense: Propagating representations through WordNet for full-coverage word sense disambiguation. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 5682–5691, Florence, Italy. Association for Computational Linguistics.

Bernardo Magnini, Carlo Strapparava, Giovanni Pezzulo, and Alfio Gliozzo. 2002. The role of domain information in word sense disambiguation. Natural Language Engineering, 8(4):359–373.

Federico Martelli, Najla Kalach, Gabriele Tola, and Roberto Navigli. 2021. SemEval-2021 Task 2: Multilingual and Cross-lingual Word-in-Context Disambiguation (MCL-WiC). In Proceedings of the Fifteenth Workshop on Semantic Evaluation (SemEval-2021).

George A. Miller. 1998. WordNet: An electronic lexical database. MIT press.

Roberto Navigli. 2009. Word sense disambiguation: A survey. ACM Computing Surveys, 41(2):1–69.

Hao Peng, Tianyu Gao, Xu Han, Yankai Lin, Peng Li, Zhiyuan Liu, Maosong Sun, and Jie Zhou. 2020. Learning from Context or Names? An Empirical Study on Neural Relation Extraction. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 3661–3672, Online. Association for Computational Linguistics.

Thang M Pham, Trung Bui, Long Mai, and Anh Nguyen. 2020. Out of order: How important is the sequential order of words in a sentence in natural language understanding tasks? arXiv preprint arXiv:2012.15180.

Mohammad Taher Pilehvar and Jose Camacho-Collados. 2019. WiC: the word-in-context dataset for evaluating context-sensitive meaning representations. In Proceedings of NAACL-HLT 2019, pages 1267–1273.

Adam Poliak, Jason Naradowsky, Aparajita Haldar, Rachel Rudinger, and Benjamin Van Durme. 2018. Hypothesis only baselines in natural language inference. In Proceedings of the Seventh Joint Conference on Lexical and Computational Semantics, pages 180–191, New Orleans, Louisiana. Association for Computational Linguistics.

Alessandro Raganato, José Camacho-Collados, and Roberto Navigli. 2017. Word sense disambiguation: A unified evaluation framework and empirical comparison. In Proceedings of EACL 2017, pages 99–110.

Alessandro Raganato, Tommaso Pasini, Jose Camacho-Collados, and Mohammad Taher Pilehvar. 2020. XL-WiC: A multilingual benchmark for evaluating semantic contextualization. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 7193–7206, Online. Association for Computational Linguistics.

Lev Ratinov, Dan Roth, Doug Downey, and Mike Anderson. 2011. Local and global algorithms for disambiguation to Wikipedia. In Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies, pages 1375–1384, Portland, Oregon, USA. Association for Computational Linguistics.
Timo Schick and Hinrich Schütze. 2019. Attentive mimicking: Better word embeddings by attending to informative contexts. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 489–494, Minneapolis, Minnesota. Association for Computational Linguistics.

Wei Shen, Jianyong Wang, and Jiawei Han. 2014. Entity linking with a knowledge base: Issues, techniques, and solutions. IEEE Transactions on Knowledge and Data Engineering, 27(2):443–460.

Aarne Talman, Marianna Apidianaki, Stergios Chatzikyriakidis, and Jörg Tiedemann. 2021. Nli data sanity check: Assessing the effect of data corruption on model performance. arXiv preprint arXiv:2104.04751.

Shikhar Vashishth, Denis Newman-Griffis, Rishabh Joshi, Ritam Dutt, and Carolyn Rose. 2020. Improving broad-coverage medical entity linking with semantic type prediction and large-scale datasets. arXiv preprint arXiv:2005.00460.

Alex Wang, Yada Pruksachatkun, Nikita Nangia, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel R Bowman. 2019. Superglue: A stickier benchmark for general-purpose language understanding systems. Advances in Neural Information Processing Systems, 32.

Alex Wang, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel Bowman. 2018. GLUE: A multi-task benchmark and analysis platform for natural language understanding. In Proceedings of the 2018 EMNLP Workshop BlackboxNLP: Analyzing and Interpreting Neural Networks for NLP, pages 353–355, Brussels, Belgium. Association for Computational Linguistics.

Ledell Wu, Fabio Petroni, Martin Josifoski, Sebastian Riedel, and Luke Zettlemoyer. 2020. Scalable zero-shot entity linking with dense entity retrieval. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 6397–6407, Online. Association for Computational Linguistics.

Figure 2: Plotting context and target word biases when applying RoBERTa across popular context-aware lexical semantic datasets. The green shaded area is for target-word-biased datasets (Bias_{RoBERTaW} >0.8) and the yellow shaded area is for context-biased datasets (Bias_{RoBERTaC} >0.8). The dashed red lines indicate 1.0 context (right) and 1.0 target word bias, indicating the model only requires the target words alone or context alone in this dataset.

A Task examples
Table 4 lists example input and labels for tasks surveyed in this study.

B An example of the target word bias in WikiMed
See Table 5 for an example where the context distracts the retrieval model to select the entry that is closer to the context than to the target word, but in fact knowing the target word alone is sufficient to retrieve the correct label.

C Examples of the context bias in WiC
See Table 6 for two examples where the model relies solely on the context to make the prediction.

D Model configurations
ALL PCMs are from https://huggingface.co/. Model configurations are listed in Table 7.
| Task | Input | Label | Label Space | Metrics |
|------|-------|-------|-------------|---------|
| WiC  | Room and [board]. He nailed [boards] across the windows. | F | T or F | Acc |
| WiC-TSV | I spent my [spring] holidays in Morocco. the season of growth; season, time of the year | T | T or F | Acc |
| MCL-WiC | Bolivia holds a key [play] in any process. A musical [play] on the same subject... | F | T or F | Acc |
| XL-WiC | Herr [Starke] wollte uns kein Interview geben. Das kann ich dir aber sagen: Wenn die Frau [Starke] kommt... | T | T or F | Acc |
| AM²ToCo | ...航天员训练[阿波罗]中飞行器... ...the six [Apollo] Moon landings... | T | T or F | Acc |
| WiC-TSV | The [art] of change-ringing is peculiar to the English... | art | art: a superior skill that you can learn by study and practice and observation | F |
| SR | The [art] of change-ringing is peculiar to the English... | art | art: a superior skill that you can learn by study and practice and observation | Acc |
| Wiki | an additional [Hash] literal syntax using colons for symbol keys... | hash table: in computing , a hash table ( hash map ) is a data structure... | hash table: in computing , a hash table ( hash map ) is a data structure... | Acc@1 |
| WikiMed | The flowers produce pollen, but no nectar. Various bees and flies visit the flowers looking in vain for nectar, for instance [sweat bees] in the genera "La-sioglossum" and "Halictus"... | halictidae | halictidae: the Halictidae is the second largest family of Apoidea bees. | Acc@1 |
| COMETA | I am [spacey] because I am thinking and daydreaming about my obsession. | dizziness (finding) | dizziness (finding) | Acc@1 |

Table 4: Examples for a selection of context-sensitive lexical semantic tasks surveyed in this thesis. Acc: accuracy; $\rho$: Spearman’s correlation; $r$: Pearson’s correlation; P&R: precision and recall.

| Baseline | Input | Retrieved concept entry | Result |
|----------|-------|--------------------------|--------|
| FULL | Formerly many more species were attributed to “Miltonia”,... including [Miltoniopsis] and Oncidium ... | miltonia: miltonia is an orchid genus comprising twelve epiphyte species and eight natural hybrids. | Wrong |
| WORD | Miltoniopsis | miltoniopsis: miltoniopsis is a genus of orchids native to costa rica and etc. | Correct |

Table 5: Error analysis on FULL and WORD BERT predictions on WikiMed.

| Input | Sentence1 | Sentence2 | BERT | HUM |
|-------|-----------|-----------|------|------|
| FULL | [Misdirect] the letter . | The pedestrian [misdirected] the out - of - town driver . | F | F |
| CONTEXT | [Mis] the letter . | The pedestrian [mas] the out - of - town driver . | F | T |
| GUESSEDWORD | [Ignore] the letter . | The pedestrian [ig] the out - of - town driver . | F | T |
| FULL | [Kill] the engine . | He [kills] the ball . | F | F |
| CONTEXT | [Mask] the engine . | He [Mask] the ball . | F | T |
| GUESSEDWORD | [Hit] the engine . | He [hits] the ball . | F | T |

Table 6: Examples of BERT’s contextual bias in WiC. The original WiC label for these examples is F. GUESSED-WORD contains human-elicited target words that flip the label.
| Model   | Variant name in Huggingface | Parameters                                     | Pretraining corpus                                      |
|---------|-----------------------------|------------------------------------------------|---------------------------------------------------------|
| BERT    | bert-base-uncased           | 12-layer, 768-hidden, 12-heads, 110M parameters | Lowercased Wikipedia + BookCorpus                       |
| PUBMEDBERT | microsoft/BiomedNLP-PubMedBERT-base-uncased-abstract-fulltext | 12-layer, 768-hidden, 12-heads, 110M parameters | Lowercased abstracts from PubMed and full-text articles from PubMedCentral |
| DeBERTa | microsoft/deberta-large     | 24-layer, 1024-hidden, 16-heads, 400M parameters | Wikipedia + BookCorpus + OPENWEB-TEXT (public Reddit content) + STORIES |

Table 7: Model details in our experiments

Figure 3: BERT performance on probing baselines across popular context-aware lexical semantic tasks. A small gap between FULL and CONTEXT/WORD baselines indicates strong bias on context/target word. For the retrieval-based tasks, we report @1 accuracy, and the LABEL and RANDOM baselines are not visible as they are close to 0.

E  RoBERTa Performance (Figure 2)

F  BERT performance on probing baselines (Figure 3)