Reliable Evaluations for Natural Language Inference  
based on a Unified Cross-dataset Benchmark

Guanhua Zhang\textsuperscript{1,2}, Bing Bai\textsuperscript{1}, Jian Liang\textsuperscript{1}, Kun Bai\textsuperscript{1}, Conghui Zhu\textsuperscript{2}, Tiejun Zhao\textsuperscript{2}  
\textsuperscript{1}Cloud and Smart Industries Group, Tencent, China  
\textsuperscript{2}Harbin Institute of Technology, China  
\{guanhzhang,icebai,joshualiang,kunbai\}@tencent.com, \{chzhu,tjzhao\}@hit-mtlab.net

Abstract

Recent studies show that crowd-sourced Natural Language Inference (NLI) datasets may suffer from significant biases like annotation artifacts. Models utilizing these superficial clues gain mirage advantages on the in-domain testing set, which makes the evaluation results over-estimated. The lack of trustworthy evaluation settings and benchmarks stalls the progress of NLI research. In this paper, we propose to assess a model's trustworthy generalization performance with cross-datasets evaluation. We present a new unified cross-datasets benchmark with 14 NLI datasets, and re-evaluate 9 widely-used neural network-based NLI models as well as 5 recently proposed debiasing methods for annotation artifacts. Our proposed evaluation scheme and experimental baselines could provide a basis to inspire future reliable NLI research.

1 Introduction

Natural Language Inference (NLI) aims to determine whether a hypothesis sentence could be inferred from a premise sentence, and the labels could be entailment, neutral, or contradiction. The development of large-scale datasets, \textit{e.g.}, SNLI (Bowman et al., 2015), and MultiNLI (Williams et al., 2018), have greatly fertilized the research, and state-of-the-art models could achieve benchmark accuracies of over 90\% on the testing set of SNLI\textsuperscript{1}.

However, recent studies have unveiled that these large-scale crowd-sourced datasets suffer from serious biases. The most significant one is the annotation artifacts (Gururangan et al., 2018), \textit{i.e.}, the habits of crowd-sourcing workers when they write hypotheses leave clues for the labels. For example, negation words like \textit{no} and \textit{never} often suggest \textit{contradiction} (Gururangan et al., 2018).

Models that capture this superficial pattern gain mirage advantages on the in-domain testing set and result in unreliable evaluation results.

Cross-datasets evaluation, \textit{e.g.}, training on SNLI while testing on other NLI datasets like SICK (Marelli et al., 2014), is an effective way to remove the impact of biases in the training data during evaluations. As the sources and preparations of datasets differ, they are less likely to suffer from the same kind of biases (Zhang et al., 2019a). Although different NLI datasets may be regarded as from different “domains”, \textit{they also all belong to a same general domain — the real world} (Torrralba and Efros, 2011), which is often witnessed in the domain generalization problems (Jiang and Zhai, 2007; Liang et al., 2019). Thus we argue that cross-datasets evaluation is a more reliable benchmark.

In this paper, we propose a new unified cross-dataset benchmark composed of 14 NLI datasets for models trained on SNLI in Section 2. We largely eliminate the inflated accuracy scores caused by the dataset bias of SNLI, and try not to let the evaluated methods rely heavily on any specific single dataset. Under the proposed scheme, we evaluate 9 widely-used neural network-based NLI models (Bowman et al., 2015; Conneau et al., 2017; Shen et al., 2018; Talman et al., 2019; Parikh et al., 2016; Wang et al., 2017; Chen et al., 2017; Gong et al., 2017; Devlin et al., 2019) in Section 3, and 5 existing debiasing methods for annotation artifacts (He et al., 2019; Belinkov et al., 2019; Zhang et al., 2019b; Clark et al., 2019) in Section 4.

The experimental results show that the cross-dataset generalization of NLI is still challenging. We hope our proposed evaluation scheme and experimental baselines could provide a basis to inspire the future development of reliable NLI research, which is discussed in Section 5.

\textsuperscript{1}https://nlp.stanford.edu/projects/snli/
2 Cross-dataset Evaluation Scheme

In this section, we present the details of the proposed cross-dataset benchmark. We first introduce the used datasets, then we propose the evaluation scheme.

2.1 Dataset Usage

In our experiments, we use SNLI (Bowman et al., 2015) as the training set, then validate and evaluate models on other 14 datasets with different creation protocols. The datasets used are listed in Table 1. Following Poliak et al. (2018), we divide the datasets into human elicited, human judged and automatically recast. Detailed introduction to the datasets is presented in Appendix A.

2.2 Settings for Evaluation

Up to 14 datasets are included in our cross dataset evaluation framework. For MultiNLI_{Matched}, we use the provided validation set as the testing set, and sample a validation set of the same size from the original training set. For MultiNLI_{Mismatched}, we split the original validation set equally for validation and testing. For CB, RTE and WNLI, we concatenate the original training set and the validation set, and randomly split them into two equally. For other datasets, we randomly split the whole dataset as validation set and testing set. Models will be trained on the training set of SNLI, hyper-parameters will be tuned based on the cross-dataset validation set, and final benchmark score will be the performance on the cross-dataset testing set.

For the final benchmark score, we collect the accuracy scores on all the testing sets, and report the average number of them. For those datasets with only two labels entailment and not_entailment, we add up the predicted scores of contradiction and neutral as the score for not_entailment. For dataset SciTail, since it only has entailment and neutral, we drop the scores of contradiction and normalize the rest as models’ predictions. Other datasets share the same definitions for the labels.

By averaging the performance on all the testing sets, we could obtain more robust and reliable evaluation results for models. The scores will not rely heavily on the property of any specific single dataset, and thus may better reflect the models’ performance in the real-world.

3 Evaluation Results for NLI Models

Based on the proposed cross-dataset evaluation scheme, we evaluated a wide range of NLI models. We first introduce the models, then present the results and our analyses.

3.1 Baselines

We chose three simple baselines, including:

- **Majority.** This method always outputs the label with the highest frequency in the validation set.
- **HOM** (Gururangan et al., 2018). The hypothesis-only model uses fastText (Joulin et al., 2017) only with the hypotheses to predict the labels.
- **RF** (Breiman, 2001). This is a simple baseline using Random Forest with 19 handcrafted features, including BLEU scores (Papineni et al., 2002), word mover’s distance (Kusner et al., 2015) and so on. Details are presented in Appendix B.1.

3.2 Evaluated Models

We evaluated several neural network-based models, which can be categorized into three kinds as,

- **Sentence Vector-based Models** They first map the premise and the hypothesis to vectors, then use the vectors to make final decisions. Their advantage is the ability to provide sentence vectors. We evaluated LSTM (Bowman et al., 2015), InferSent (Conneau et al., 2017), DiSAN (Shen et al., 2018), and HBMP (Talman et al., 2019).

- **Interaction-based Models** They compare the premise and the hypothesis at context level,

| Creation Protocol | Dataset                  |
|-------------------|--------------------------|
| Human Elicited    | MultiNLI_{Matched}       |
|                   | MultiNLI_{Mismatched}    |
| Human Judged      | SICK (Marelli et al., 2014) |
|                   | JOCI (Zhang et al., 2017) |
|                   | SciTail (Khot et al., 2018) |
|                   | MPE (Lai et al., 2017)   |
|                   | Diagnostic (Wang et al., 2018) |
|                   | Add-l (Pavlick and Callison-Burch, 2016) |
|                   | CB (Wang et al., 2019; de Marneffe et al., 2019) |
|                   | RTE (Wang et al., 2018)  |
| Automatically Recast | DPR (Rahman and Ng, 2012; White et al., 2017) |
|                   | SPR (Reisinger et al., 2015; White et al., 2017) |
|                   | FN+ (Pavlick et al., 2015; White et al., 2017) |
|                   | WNLI (Wang et al., 2018; Levesque et al., 2012) |

Table 1: The datasets used for the proposed cross-dataset evaluation scheme.
and usually yield superior performance compared with sentence vector-based models. We evaluated DecompAtt (Parikh et al., 2016), BiMPPM (Wang et al., 2017), DiIN (Gong et al., 2017), and ESIM (Chen et al., 2017).

Pretrained Models We evaluated BERT-base (Devlin et al., 2019), which is pretrained on large-scale corpus, and fine-tuned on the training set of SNLI.

A more detailed introduction to the evaluated models is in Appendix B.2.

### 3.3 Experiment Setup

When the models were evaluated, all models were retrained out of the box, i.e., we did not tune the hyper-parameters except that the cross-dataset validation set is used for early stopping, so the performance on the testing set of SNLI may be different with what was reported in the paper.

For all models, pre-trained GloVe 840B 300D word embeddings (Pennington et al., 2014) were used. Note that the vocabulary was built using SNLI together with the cross datasets, and the sequence length is set to 100 for all models.

### 3.4 Evaluation Results for NLI Models

The evaluation results are presented in Table 2, and the more detailed results for all the cross-datasets are presented in Appendix C.

From the table, we can get that the majority class accounts for about 47.1% in the cross-dataset testing set, and the hypothesis-only model, i.e., HOM, performed slightly worse compared with Majority, while HOM outperformed Majority significantly on SNLI’s testing set. This indicates that the inflated accuracy caused by SNLI’s annotation artifacts is successfully reduced in our cross-dataset evaluation setting. On the other hand, models like LSTM, InferSent, and DiSAN could not even beat RF with handcrafted features under the cross-dataset evaluation, although on the given testing set of SNLI they were far beyond RF. Such results show that these methods focus on SNLI’s specific patterns which may not contribute to but rather hurt generalization. These results raise a concern that whether future accuracy-increments on SNLI will be reliable or not. As a conclusion, a cross-dataset evaluation is necessary to demonstrate the generalization performance of any NLI method. Among all the evaluated models, only BERT could achieve more than 60% accuracy, suggesting that the cross-dataset generalization performances of NLI models are far below satisfactory.

In terms of the performance drop $\Delta$, the accuracy of RF was observed very consistently on both SNLI and cross-dataset. While all the neural network-based method suffered from significant drop. Among them, pretrained model BERT did enjoy the least drop, both absolute and relative, indicating that pretraining can help the model capture the true pattern of NLI better. Besides, it can be observed that the drop of interaction-based models is slightly better, compared with the (relatively strong) sentence vector-based models.

### 4 Evaluation Results for Debiasing Methods

Recently, debiasing methods (Belinkov et al., 2019; He et al., 2019; Zhang et al., 2019b; Clark et al., 2019) have been proposed to address the annotation artifacts in NLI. These methods can help the model avoid learning superficial patterns that happen to associate with the label on a particular dataset. In this section, we take stock of the proposed methods under the unified cross-dataset evaluation scheme to examine their effectiveness.

#### 4.1 Tested Methods

We test the following methods, including

- **ADV** (Belinkov et al., 2019). We evaluate the method 1 in the paper, which proposes to use adversarial training to remove the correlation between the label and the sentence encoding
Table 3: Evaluation Results for the debiasing methods. The column “Impr” is the relative improvement over the baseline. ’%’ is omitted for accuracy scores.

| Method         | SNLI | Impr | Cross | Impr |
|----------------|------|------|-------|------|
| BiLSTM         | 79.6 | -    | 49.4  | -    |
| +ADV           | 78.4 | -1.5%| 50.5  | +2.2%|
| +DRiFt         | 71.3 | -10.4%| 52.7  | +6.7%|
| +Learned-Mixin | 56.4 | -29.1%| 51.1  | +3.4%|
| +Learned-Mixin+H | 55.0 | -30.9%| 51.0  | +3.2%|
| +Weighting     | 75.4 | -5.3%| 49.9  | +1.0%|

of the hypothesis, and thus discouraging models from ignoring the premise.

• **DRiFt** (He et al., 2019). Focusing on the “hard” examples that the annotation artifacts cannot predict well, a robust model is trained to fit the residual of a hypothesis-only-model. The method is also referred as Bias Product by Clark et al. (2019).

• **Learned-Mixin** and **Learned-Mixin-H** (Clark et al., 2019). Based on DRiFt, a confidence factor is introduced to determine how much to trust the predictions of the hypothesis-only model in Learned-Mixin. An entropy penalty is added to the loss in Learned-Mixin+H in order to prevent the factor from degrading to zero.

• **Weighting** (Zhang et al., 2019b). The method manages to make models fit an artifact-neutral distribution by the instance weighting technique. The weights are generated from the predictions of the hypothesis-only model.

### 4.2 Evaluation Scheme

We implement a one-layer 300D BiLSTM-based siamese model with max pooling as the baseline and apply all the debiasing methods on it. All hyper-parameters are chosen by the performance on the proposed cross-dataset validation set. Details are in Appendix D.

### 4.3 Evaluation Results

The evaluation results are presented in Table 3. From the results, we can find that all debiasing methods can effectively improve models’ performances on the cross dataset evaluation, while the accuracies in the original SNLI testing set drop more or less. Among the results, we find that **DRiFt** brings the highest improvement in cross-dataset testing. The results conform that models are over-estimated on the in-domain evaluation because of the dataset biases, and demonstrate that the debiasing methods can help models gain better generalization ability to the real world.

### 5 Possible Directions for Future Research

Given that large-scale crowd-sourced datasets often suffer from significant biases, the following topics may be the possible directions for future research with the cross dataset evaluation.

**Robust NLI Models** The differences of sentence vector-based models and interaction-based models inspire us to develop robust NLI methods. We can make the model focus more on the semantic relationship between sentences with certain neural architectures, and thus better generalization performance could be achieved without explicit modeling for dataset biases.

**Debiasing NLI Methods** It is also encouraged to develop NLI methods with explicit modeling to handle dataset biases to boost generalization performance without extra training resources.

**Multi-task Learning for NLI** BERT demonstrate strong generalization performance in our experiments, which inspire us to the Multi-Task Learning (MTL) (Ruder, 2017; Liu et al., 2019) for NLI. With appropriate auxiliary tasks (e.g., text coherence (Nishida and Nakayama, 2018)) and effective MTL methods, models may focus more on useful generalizable patterns instead of overfit the dataset biases.

**Meta-learning for NLI** Finn et al. (2017) proposed the model-agnostic meta-learning method, whose idea can be summarized as “learning to learn.” We may borrow the idea and perform “learning on the biased dataset to learn on the (relatively) unbiased dataset”, thus we can utilize the large-scale human elicited datasets for training better models.

### 6 Conclusion

Dataset biases are challenging the NLI datasets and systems, not only when we are training the models, but also when the models are being evaluated. Models capturing the biases earn mirage advantages during the biased evaluations, while failing to perform well in the real-world. In this paper, we present a more trustworthy cross-dataset evaluation scheme, and re-evaluate 9 NLI models as well as 5 debiasing methods. We further discuss
the possible directions for future NLI research with the proposed cross-dataset evaluation scheme. We suggest that researchers could pay more attention to cross-dataset generalization benchmarks.

References

Roy Bar-Haim, Ido Dagan, Bill Dolan, Lisa Ferro, Danilo Giampiccolo, Bernardo Magnini, and Idan Szpektor. 2006. The second pascal recognising textual entailment challenge. In Proceedings of the second PASCAL challenges workshop on recognising textual entailment. Venice.

Yonatan Belinkov, Adam Poliak, Stuart M Shieber, Benjamin Van Durme, and Alexander M Rush. 2019. Don’t take the premise for granted: Mitigating artifacts in natural language inference. In Proceedings of the 57th Annual Meeting of the Association of Computational Linguistics, pages 877–891.

Luisa Bentivogli, Peter Clark, Ido Dagan, and Danilo Giampiccolo. 2009. The fifth pascal recognizing textual entailment challenge. In TAC.

Samuel R Bowman, Gabor Angeli, Christopher Potts, and Christopher D Manning. 2015. A large annotated corpus for learning natural language inference. In Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing, pages 632–642.

Leo Breiman. 2001. Random forests. Machine learning, 45(1):5–32.

Qian Chen, Xiaodan Zhu, Zhen-Hua Ling, Si Wei, Hui Jiang, and Diana Inkpen. 2017. Enhanced lstm for natural language inference. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1657–1668.

Christopher Clark, Mark Yatskar, and Luke Zettlemoyer. 2019. Don’t take the easy way out: Ensemble based methods for avoiding known dataset biases. 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 4060–4073.

Alexis Conneau, Douwe Kiela, Holger Schwenk, Loïc Barrault, and Antoine Bordes. 2017. Supervised learning of universal sentence representations from natural language inference data. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, pages 670–680.

Ido Dagan, Oren Glickman, and Bernardo Magnini. 2005. The pascal recognising textual entailment challenge. In Machine Learning Challenges Workshop, pages 177–190. Springer.

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.

David Dowty. 1991. Thematic proto-roles and argument selection. language, 67(3):547–619.

Chelsea Finn, Pieter Abbeel, and Sergey Levine. 2017. Model-agnostic meta-learning for fast adaptation of deep networks. In Proceedings of the 34th International Conference on Machine Learning-Volume 70, pages 1126–1135. JMLR. org.

Danilo Giampiccolo, Bernardo Magnini, Ido Dagan, and Bill Dolan. 2007. The third pascal recognizing textual entailment challenge. In Proceedings of the ACL-PASCAL workshop on textual entailment and paraphrasing, pages 1–9. Association for Computational Linguistics.

Yichen Gong, Heng Luo, and Jian Zhang. 2017. Natural language inference over interaction space. arXiv preprint arXiv:1709.04348.

Suchin Gururangan, Swabha Swayamdipta, Omer Levy, Roy Schwartz, Samuel Bowman, and Noah A Smith. 2018. Annotation artifacts in natural language inference data. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 2 (Short Papers), pages 107–112.

He He, Sheng Zha, and Haohan Wang. 2019. Unlearn dataset bias in natural language inference by fitting the residual. In Proceedings of the 2nd Workshop on Deep Learning Approaches for Low-Resource NLP (DeepLo 2019), pages 132–142.

Gao Huang, Zhuang Liu, Laurens Van Der Maaten, and Kilian Q Weinberger. 2017. Densely connected convolutional networks. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 4700–4708.

Jing Jiang and ChengXiang Zhai. 2007. Instance weighting for domain adaptation in nlp. In Proceedings of the 45th annual meeting of the association of computational linguistics, pages 264–271.

Armand Joulin, Edouard Grave, Piotr Bojanowski, and Tomas Mikolov. 2017. Bag of tricks for efficient text classification. In Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 2, Short Papers, pages 427–431. Association for Computational Linguistics.

Tushar Khot, Ashish Sabharwal, and Peter Clark. 2018. Scitail: A textual entailment dataset from science question answering. In Thirty-Second AAAI Conference on Artificial Intelligence.
Matt Kusner, Yu Sun, Nicholas Kolkin, and Kilian Weinberger. 2015. From word embeddings to document distances. In *International conference on machine learning*, pages 957–966.

Alice Lai, Yonatan Bisk, and Julia Hockenmaier. 2017. Natural language inference from multiple premises. In *Proceedings of the Eighth International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 100–109.

Hector Levesque, Ernest Davis, and Leora Morgenstern. 2012. The winograd schema challenge. In *Thirteenth International Conference on the Principles of Knowledge Representation and Reasoning*.

Jian Liang, Yuren Cao, Chenbin Zhang, Shiyu Chang, Kun Bai, and Zenglin Xu. 2019. Additive adversarial learning for unbiased authentication. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 11428–11437.

Xiaodong Liu, Pengcheng He, Weizhu Chen, and Jianfeng Gao. 2019. Multi-task deep neural networks for natural language understanding. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 4487–4496, Florence, Italy. Association for Computational Linguistics.

Marco Marelli, Stefano Menini, Marco Baroni, Luisa Bentivogli, Raffaella Bernardi, Roberto Zamparelli, et al. 2014. A sick cure for the evaluation of compositional distributional semantic models. In *LREC*, pages 216–223.

Marie-Catherine de Marneffe, Mandy Simons, and Judith Tonhauser. 2019. The commitmentbank: Investigating projection in naturally occurring discourse. In *Proceedings of Sinn und Bedeutung*, volume 23, pages 107–124.

Noriki Nishida and Hideki Nakayama. 2018. Coherence modeling improves implicit discourse relation recognition. In *Proceedings of the 19th Annual SIGDIAL Meeting on Discourse and Dialogue*, pages 344–349.

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 on association for computational linguistics*, pages 311–318. Association for Computational Linguistics.

Ankur Parikh, Oscar Täckström, Dipanjan Das, and Jakob Uszkoreit. 2016. A decomposable attention model for natural language inference. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, pages 2249–2255.

Ellie Pavlick and Chris Callison-Burch. 2016. Most “babies” are “little” and most “problems” are “huge”: Compositional entailment in adjective-nouns. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 2164–2173.

Ellie Pavlick, Travis Wolfe, Pushpendre Rastogi, Chris Callison-Burch, Mark Dredze, and Benjamin Van Durme. 2015. FrameNet+: Fast paraphrastic tripling of FrameNet. In *Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 2: Short Papers)*, pages 408–413.

Jeffrey Pennington, Richard Socher, and Christopher Manning. 2014. Glove: Global vectors for word representation. In *Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP)*, pages 1532–1543.

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.

Altaf Rahman and Vincent Ng. 2012. Resolving complex cases of definite pronouns: the winograd schema challenge. In *Proceedings of the 2012 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning*, pages 777–789. Association for Computational Linguistics.

Drew Reisinger, Rachel Rudinger, Francis Ferraro, Craig Harman, Kyle Rawlins, and Benjamin Van Durme. 2015. Semantic proto-roles. *Transactions of the Association for Computational Linguistics*, 3:475–488.

Sebastian Ruder. 2017. An overview of multi-task learning in deep neural networks. *arXiv preprint arXiv:1706.05098*.

Tao Shen, Tianyi Zhou, Guodong Long, Jing Jiang, Shirui Pan, and Chengqi Zhang. 2018. Disan: Directional self-attention network for rnn/cnn-free language understanding. In *Thirty-Second AAAI Conference on Artificial Intelligence*.

Aarne Talman, Anssi Ylijyra, and Jorg Tiedemann. 2019. Sentence embeddings in nli with iterative refinement encoders. *Natural Language Engineering*, 25(4):467–482.

Antonio Torralba and Alexei A Efros. 2011. Unbiased look at dataset bias. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 1521–1528.

Alex Wang, Yada Pruksachatkun, Nikita Nangia, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel R Bowman. 2019. Super-glue: A stickier benchmark for general-purpose language understanding systems. *arXiv preprint arXiv:1905.00537*.

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.

Zhiguo Wang, Wael Hamza, and Radu Florian. 2017. Bilateral multi-perspective matching for natural language sentences. In *Proceedings of the 26th International Joint Conference on Artificial Intelligence*, pages 4144–4150. AAAI Press.

Aaron Steven White, Pushpendre Rastogi, Kevin Duh, and Benjamin Van Durme. 2017. *Inference is everything: Recasting semantic resources into a unified evaluation framework*. In *Proceedings of the Eighth International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 996–1005, Taipei, Taiwan. Asian Federation of Natural Language Processing.

Adina Williams, Nikita Nangia, and Samuel Bowman. 2018. A broad-coverage challenge corpus for sentence understanding through inference. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, pages 1112–1122.

Guanhua Zhang, Bing Bai, Jian Liang, Kun Bai, Shiyu Chang, Mo Yu, Conghui Zhu, and Tiejun Zhao. 2019a. Selection bias explorations and debias methods for natural language sentence matching datasets. In *Proceedings of the 57th Annual Meeting of the Association of Computational Linguistics*, pages 4418–4429.

Guanhua Zhang, Bing Bai, Junqi Zhang, Kun Bai, Conghui Zhu, and Tiejun Zhao. 2019b. Mitigating annotation artifacts in natural language inference datasets to improve cross-dataset generalization ability. *arXiv preprint arXiv:1909.04242*.

Sheng Zhang, Rachel Rudinger, Kevin Duh, and Benjamin Van Durme. 2017. Ordinal common-sense inference. *Transactions of the Association for Computational Linguistics*, 5:379–395.
A Introduction to the Used Datasets

Here we introduce all the used cross datasets as follows.

- **MultiNLI** (Williams et al., 2018). MultiNLI is a human-elicted dataset. Compared with SNLI, it’s with a more diverse variety of text styles and topics. Two testing set are provided, i.e., Matched and Mismatched.

- **SICK** (Marelli et al., 2014). The Sentences Involving Compositional Knowledge (SICK) dataset is an English benchmark which include many examples of the lexical, syntactic and semantic phenomena that semantic models are expected to account for.

- **JOCI** (Zhang et al., 2017). JHU Ordinal Common-sense Inference (JOCI) is a collection of diverse common-sense inference examples. We convert the labels into NLI tags following Poliak et al. (2018).

- **SciTail** (Khot et al., 2018). SciTail is the first NLI dataset created solely from natural sentences that already exist independently in the wild, rather than sentences authored specifically for the entailment task. The hypotheses are from science questions and the corresponding answer candidates, and the premises are from relevant web sentences retrieved from a large corpus.

- **MPE** (Lai et al., 2017). This dataset requires inference over multiple premise sentences, and trivial lexical inferences are minimized.

- **Add-1** (Pavlick and Callison-Burch, 2016). The premise and the hypothesis in Add-1 differ only by the atomic insertion of an adjective, and only straight-forward examples are included.

- **DPR** (Rahman and Ng, 2012; White et al., 2017). The Definite Pronoun Resolution (DPR) dataset targets an NLI model’s ability to perform anaphora resolution.

- **SPR** (Reisinger et al., 2015; White et al., 2017). SPR is based on the seminal theory of proto-roles proposed by Dowty (1991).

- **FN+** (Pavlick et al., 2015; White et al., 2017). FrameNet+ (FN+) is an expanded version of FrameNet. It contains an additional 22K lexical units.

- **Diagnostic** Diagnostic is designed to for analysis on a series of linguistic phenomena by (Wang et al., 2018). The dataset is symmetrical, i.e., the premise and the hypothesis in every pair is compared conversely in another.

- **CB** The dataset is collected from the CommitmentBank (de Marneffe et al., 2019), and transferred into NLI dataset by (Wang et al., 2019).

- **RTE** The dataset is converted from four annual challenges for Recognizing Textual Entailment task (Dagan et al., 2005; Bar-Haim et al., 2006; Giampiccolo et al., 2007; Bentivogli et al., 2009) and we use the same setting with (Wang et al., 2018).

- **WNLI** The dataset is gathered from the Winograd Scheme Reading Comprehension Challenge (Levesque et al., 2012), in which the task is to determine the referent of the specific pronoun in each text. It is converted into a NLI dataset by replacing the ambiguous pronoun with each possible referent as hypotheses (Wang et al., 2018).

The size and the share of different labels are presented in Table 4.

B Details about the Tested Methods

B.1 Features used in Random Forest

We list the features we used in the baseline Random Forest. As mentioned above, we are using 19 hand-crafted features in total. The features are carefully chosen to compare the hypothesis and the premise, including:

- The BLEU score of the hypothesis to the premise, using n-gram length from 1 to 4, which are 4 features in total.

- The relative difference of the length between the hypothesis and the premise, in term of both words and characters, which are 2 features in total.

- The fuzzy string matching scores with FuzzyWuzzy, including fuzz QRatio, fuzz WRatio, fuzz token set ratio, fuzz token sort ratio, fuzz partial ratio, fuzz partial token set ratio, fuzz
### Table 4: The datasets used for the proposed evaluation scheme.

| Creation Protocol | Dataset | Validation Size | Test Size | Entailment | Not-Entailment | Contradiction | Neutral |
|-------------------|---------|-----------------|-----------|------------|----------------|---------------|--------|
| Human Elicited     | MultiNLI\textsubscript{Matched} | 9815 | 9815 | 32.8% | - | 32.4% | 34.8% |
|                   | MultiNLI\textsubscript{Mismatched} | 4916 | 4916 | 35.2% | - | 33.0% | 31.8% |
| Human Judged       | CB      | 4963 | 4964 | 28.8% | - | 14.7% | 56.5% |
|                   | JOCI    | 2327 | 2328 | 16.3% | - | 26.1% | 57.6% |
|                   | SciTail | 10000 | 17026 | 37.4% | - | 62.6% | - |
|                   | MPE     | 4999 | 5000 | 32.5% | - | 41.5% | 26.0% |
|                   | MMis    | 552  | 552  | 41.7% | - | 23.4% | 35.0% |
|                   | Add-I   | 1897 | 1897 | 15.7% | 84.3% | - | - |
|                   | CB      | 153  | 153  | 45.1% | - | 48.0% | 6.9% |
| Automatically Recast | DPR    | 1830 | 1831 | 50.0% | 50.0% | - | - |
|                   | SPR     | 10000 | 144607 | 34.8% | - | 65.2% | - |
|                   | FN+     | 10000 | 144604 | 43.4% | - | 56.6% | - |
|                   | RTE     | 2876 | 2876 | 50.4% | 49.6% | - | - |
|                   | SNLI    | 353  | 353  | 48.6% | 51.4% | - | - |

### Table 5: Detailed experimental results for NLI Models. “%” is omitted. “MM” stands for MultiNLI\textsubscript{Matched}, and “MMis” stands for MultiNLI\textsubscript{Mismatched}.

| Model       | MM | MMis | SICK | JOCI | SciTail | DPR | SPR | FN+ | MPE | Add-I | Diagnostic | CB | RTE | WNli | Acc Mean | SNLI |
|-------------|----|------|------|------|--------|-----|-----|-----|-----|-------|------------|----|-----|------|---------|------|
| Majority    | 31.8 | 31.8 | 56.8 | 58.4 | 62.9   | 48.4 | 65.2 | 56.6 | 26.1 | 83.8  | 34.1| 5.9 | 49.3 | 48.7   | 47.1 | 32.8 |
| HOM         | 43.7 | 44.2 | 34.3 | 36.3 | 56.0   | 48.3 | 53.0 | 56.2 | 35.9 | 83.2  | 34.0| 19.0 | 49.1 | 47.9   | 45.8 | 66.9 |
| RF          | 45.4 | 47.3 | 45.7 | 36.2 | 70.2   | 48.2 | 64.4 | 55.8 | 44.5 | 83.7  | 43.4| 48.5 | 60.3 | 51.3   | 53.2 | 54.0 |
| LSTM        | 45.0 | 44.9 | 42.0 | 40.7 | 60.8   | 49.7 | 61.7 | 53.1 | 46.9 | 66.9  | 39.4| 35.5 | 50.0 | 49.4   | 49.0 | 72.7 |
| InferSent   | 54.4 | 55.6 | 54.0 | 40.3 | 61.9   | 50.7 | 43.8 | 50.4 | 57.9 | 70.4  | 46.6| 44.1 | 57.7 | 50.0   | 52.7 | 83.7 |
| DiSAN       | 55.9 | 57.3 | 50.8 | 43.1 | 58.1   | 48.6 | 49.9 | 54.9 | 56.5 | 69.6  | 43.8| 34.3 | 54.7 | 51.6   | 52.1 | 84.3 |
| HBMP        | 57.0 | 58.2 | 51.5 | 44.4 | 62.0   | 48.4 | 46.6 | 54.7 | 58.2 | 79.8  | 44.2| 44.1 | 58.1 | 51.0   | 54.2 | 84.2 |
| DecompAtt   | 58.0 | 59.6 | 50.6 | 44.8 | 62.9   | 51.1 | 42.8 | 53.1 | 57.7 | 74.1  | 47.8| 43.8 | 60.8 | 51.6   | 54.2 | 83.1 |
| BiMPM       | 59.0 | 61.3 | 49.6 | 44.8 | 55.3   | 51.7 | 45.4 | 57.7 | 59.3 | 81.0  | 49.2| 45.9 | 60.6 | 51.6   | 55.2 | 84.3 |
| DIN         | 60.3 | 62.7 | 52.6 | 45.8 | 59.8   | 49.0 | 47.7 | 57.3 | 56.5 | 83.7  | 47.6| 37.7 | 61.8 | 51.9   | 55.3 | 86.1 |
| ESIM        | 62.2 | 64.6 | 57.0 | 45.0 | 53.7   | 51.8 | 45.4 | 55.6 | 62.9 | 74.7  | 50.5| 47.5 | 61.1 | 51.1   | 56.0 | 87.5 |
| BERT        | 73.7 | 73.9 | 56.4 | 48.8 | 64.2   | 51.8 | 59.6 | 56.1 | 65.8 | 83.7  | 51.9| 62.3 | 70.8 | 51.9   | 62.2 | 90.6 |

- Partial token sort ratio, which are 7 features in total.
- The word mover’s distance between the hypothesis and the premise, which is 1 feature.
- Difference type of distances between the vector representation of the hypothesis and the premise. The vector representation of a sentence is obtained by averaging the embeddings of the words. The distances include cosine distance, cityblock distance, canberra distance, euclidean distance and braycurtis distance, which are 5 features in total.

### B.2 Introduction to the Tested Models

The introduction to the models that we tested are listed below.

- **LSTM** (Bowman et al., 2015). We evaluated the 100D LSTM encoders for sentences.
- **InferSent** (Conneau et al., 2017). InferSent uses 4096D BiLSTM with max-pooling to encode sentences as vectors, then use the vectors to predict the NLI label.
- **DiSAN** (Shen et al., 2018). DiSAN is a 300D directional self-attention based sentence encoder.
- **HBMP** (Talmam et al., 2019). HBMP implements an iterative refinement strategy for sentence vectors with a hierarchy of 600D BiLSTM and max pooling layers.
- **DecompAtt** (Parikh et al., 2016). This model uses 200D attention to decompose the NLI problem into attend, compare and aggregate steps.
- **BiMPM** (Wang et al., 2017). BiMPM combines two sentence encoders and employs a bilateral multi-perspective matching mechanism.
- **ESIM** (Chen et al., 2017). ESIM is a carefully designing sequential inference models based on chain LSTM.
• **DIIN** *(Gong et al., 2017)*. DIIN is designed to hierarchically extracting semantic features from interaction space with DenseNet *(Huang et al., 2017)*.

• **BERT** *(Devlin et al., 2019)*. BERT is a pre-trained bidirectional encoder with transformers, and yield strong performance for many tasks. We use Bert-base in our experiments.

### C Detailed Evaluation Result

The detailed evaluation results are presented in Table 5. We report the accuracy scores of all the models on different cross-datasets.

### D Detailed Evaluation Scheme for Debiasing Methods

We use grid searching to find the best hyperparameters for debias methods. For **ADV** method, we search the hyper-parameters $\alpha$ and $\beta$ over $\{0.1, 0.2, 0.5, 1, 2\}$. For **Weighting** method, we sweep the smooth term smooth for weight generating over $\{0.1, 0.01, 0.02, 0.001, 0\}$. For **Learned Mixin+H** method, we search the entropy coefficient $w$ over $\{1, 0.5, 0.1, 0.05, 0.01, 0.005, 0.001\}$. 