Abstract

We investigate whether example forgetting, a recently introduced measure of hardness of examples, can be used to select training examples in order to increase robustness of natural language understanding models in a natural language inference task (MNLI). We analyze forgetting events for MNLI and provide evidence that forgettable examples under simpler models can be used to increase robustness of the recently proposed BERT model, measured by testing an MNLI trained model on HANS, a curated test set that exhibits a shift in distribution compared to the MNLI test set. Moreover, we show that, the “large” version of BERT is more robust than its “base” version but its robustness can still be improved with our approach.

1 Introduction

Neural network models have become ubiquitous in natural language processing applications, pushing the state-of-the-art in a large variety of tasks involving natural language understanding (NLU) and generation (Wu et al., 2016; Wang et al., 2019). In the past year, significant improvements have been obtained by training increasingly larger neural network language models on huge amounts of data openly available on the web and then fine-tuning those base models for each downstream task (Devlin et al., 2018; Peters et al., 2018; Liu et al., 2019).

In spite of their impressive performance, empirical evidence suggests that these models are far from forming human-like representations of natural language. In fact, their predictions have been shown to be brittle on examples that slightly deviate from the training distribution but are still syntactically and semantically valid (Jia and Liang, 2017; McCoy et al., 2019). In the context of natural language inference, evidence exists that they may not be robust when tested on examples obtained by applying simple meaning-preserving transformations such as passivization (Dasgupta et al., 2018). Increasing evidence supports the hypothesis that these models mainly tend to capture task- and dataset-specific biases such as shallow lexical word overlap features (Poliak et al., 2018; Dasgupta et al., 2018; McCoy et al., 2019; Clark et al., 2019), which seems to be at odds with the common belief that they form high-level semantic representations of the input data (Bengio et al., 2009). The reliance on highly predictive but brittle features is not confined to NLU tasks, it is also a perceived shortcoming of image classification models (Brendel and Bethge, 2019; Geirhos et al., 2018; Jacobsen et al., 2018). A relevant recent attempt at achieving robust learning when multiple “views” of the same training data are available can be found in Arjovsky et al. (2019).

Our general goal is to investigate whether it is possible to train more robust NLU models. In particular, we investigate the possibility to identify a set of “hard” or “atypical” examples, which would unlikely be explained by simple heuristics and, if identified correctly and up-weighted during training, could enable learning more robust features. In the past, dataset re-sampling and weighting techniques have been studied in order to solve class imbalance problem (Chawla et al., 2002) or co-variate shift (Sugiyama et al., 2007), notably by importance weighted empirical risk minimization. However, it has also been shown that up-weighting hard examples may be dangerous in the presence of outliers or noise (Chapelle, 2007; Kumar et al., 2010; Toneva et al., 2018).

Concurrently to our work, Clark et al. (2019) and Mahabadi and Henderson (2019) give evidence towards the effectiveness of reweighting examples in building more robust NLU models. The authors assume a priori knowledge of the heuristics in the
dataset and specifically weight examples that cannot be explained by those heuristics. In this work, we explore whether examples considered hard by “weak” or “simple” models (e.g. parametric models with a small number of parameters) naturally exclude the dataset heuristics without any prior knowledge of them. The underlying assumption is that weak models can more easily capture simple explanations of the training data but underfit more complex patterns.

We consider example forgetting (Toneva et al., 2018) as a model-dependent measure of “hardness” of an example. For a given task (e.g. image classification), example forgetting is defined as the number of times the neural network shifts from properly classifying an example to making a mistake on the same example at the next training epoch. Examples with a large number of forgetting events, the forgettable examples, are rather atypical compared to the unforgettable ones that contain very common features, prototypical of the class (e.g. an occluded gray plane versus a white plane centered on a bright blue sky). It is interesting to note that forgetting events capture the dynamics of example learning, and not solely their loss at the end of training (as considered in Clark et al. (2019)). We investigate whether up-weighting forgettable (hard) examples can help in training more robust models.

We first extend the results of Toneva et al. (2018) by computing forgetting events in MNLI (Williams et al., 2017), a natural language inference dataset, and by using different architectures of increasing capacity. The robustness of our models is verified by considering their performance on the recently proposed HANS test set (McCoy et al., 2019) which contains curated templates designed to test the robustness of a model against the following three heuristics for recognizing if a premise entails a hypothesis: lexical overlap (a premise entails any hypothesis built from of a subset of its words), subsequence (a premise entails any of its contiguous subsequences) and constituent (a premise entails all the complete subtrees in its parse tree). In particular, any model relying exclusively on those heuristics would not have a higher than chance classification accuracy on this test set.

McCoy et al. (2019) show that a variety of existing models – including BERT (Devlin et al., 2018), the state-of-the-art model at the time – perform, overall, worse than chance on classification accuracy of HANS evaluation data. This confirms the hypothesis that models trained on MNLI data tend to learn the three aforementioned heuristics rather than actually understanding the task. To test our methodology, we thus make use of the HANS evaluation dataset, which contains 30,000 examples equally split between the two labels: “entailment” and “non-entailment”.

2 Methodology
2.1 Datasets: MNLI and HANS
The MNLI corpus (Williams et al., 2017) is a popular NLU dataset containing premise/hypothesis pairs annotated with textual entailment information (neutral, entailment or contradiction). Multiple studies have hypothesized that deep learning models tend to capture simple heuristics from the MNLI training data, and do not build an actual understanding of the task. Over the years, a series of diagnostic datasets have been released to test these hypotheses. The very recent of these datasets, HANS (McCoy et al., 2019, Heuristic Analysis for NLI Systems), contains curated templates designed to test the robustness of a model against the following three heuristics for recognizing if a premise entails a hypothesis: lexical overlap (a premise entails any hypothesis built from of a subset of its words), subsequence (a premise entails any of its contiguous subsequences) and constituent (a premise entails all the complete subtrees in its parse tree). In particular, any model relying exclusively on those heuristics would not have a higher than chance classification accuracy on this test set.

We train two models, BoW and BiLSTM, as our weak baselines to compute forgetting statistics of different examples in the training set. We use the term weak to emphasize the fact that those models have fewer parameters than our base model BERT (we default to the “base” configuration of the BERT model). Our conjecture is that networks with lower capacity will discover the samples that support the various heuristics described in Section 2.1. In particular, forgettable examples for those models will correspond to sentences that do not verify said heuristics.

Both models are siamese networks, with similar input representations and classification layers. For the input layer, we lower case and tokenize the inputs into words and initialize their representations with Glove, a 300 dimensional pretrained
Table 1: Number of “forgettables” examples (those that are forgotten at least once or never learned) during five training epochs along with the accuracy on the MNLI matched development set.

| Model   | # Forg. | # Forg. (balanced) | MNLI |
|---------|---------|-------------------|------|
| BoW     | 100,345 | 63,390            | 64.0 |
| BiLSTM  | 76,270  | 46,740            | 69.6 |
| BERT    | 32,387  | 17,748            | 84.5 |

embedding (Pennington et al., 2014). For the classification task, from the premise and hypothesis vectors \( p \) and \( h \), we build the concatenated vector \( s = [p, h, |p - h|, p \odot h] \) and pass it to a two-layer perceptron classifier. To compute \( p \) or \( h \), the BoW model max-pools the bag of word embeddings, while the BiLSTM model max-pools the top-layer hidden states of a 2-layer bidirectional LSTM. The hidden size of the LSTMs is set to 200.

2.3 Computing forgetting events

For each of the three models (i.e., the two weak baselines and BERT) we train on all MNLI training examples for five epochs and calculate the number of times each example is forgotten, following the same procedure described in Toneva et al. (2018). In short, an example is forgotten if it goes from being correctly to incorrectly classified (because of multiple gradient updates performed on other examples).

If an example is forgotten at least once or is never learnt during training, we call it “forgettable”. In Table 1, the numbers of forgettable examples for BoW, BiLSTM and BERT models are shown. To remove the effect of bias in label distribution, we sample forgettable examples for each label to keep the label distribution the same as the original MNLI training data (i.e., 33% from each of the three label). The size of the balanced forgettables for each model is also shown in Table 1. We make use of the balanced forgettable sets in Section 3. It is worth noting that the larger the model, the fewer the forgettable examples. We also include the performance of the models on the development set of MNLI. Figure 1 shows the distribution of forgetting events.

2.4 Fine-tuning on forgettable examples

We adopt a simple strategy to exploit the sets of forgettables computed by one of our baselines or BERT itself: we first fine-tune BERT on all the MNLI examples in order to get a reasonable prior for the task. We then perform an additional stage of fine-tuning (3 epochs) only on the subset of selected forgettable examples from each of the considered models.

3 Evaluation

Our main results are presented in Table 2.

Training on Forgettables Lines 2 to 5 report results of fine-tuning BERT on different subsets of the MNLI dataset. This setting aligns with the setting presented in Toneva et al. (2018) where the authors show that, in multiple image classification tasks, the same generalization performance can be obtained by training a model initialized randomly on its own forgettable examples. Our results suggest that this behavior may be task and/or architecture dependent: in our setting, training only forgettable examples particularly affects generalization performance on MNLI. The most extreme drop in performance is observed when BERT is only fine-tuned on its own forgettable examples (line 2) achieving an accuracy of 38.9%. Training on BiLSTM (line 4) or BoW forgettables (line 6) examples causes a lesser drop in accuracy on MNLI although still noticeable. One of the possible reasons of the dramatic performance loss observed in line 2 is that BERT forgettables are significantly fewer than the counterparts from weaker baselines. In order to rule out this hypothesis, we train on a random subset of examples of the same size (17,748, line 3). These results suggest that there is an intrinsic difficulty in BERT forgettables that deserves to be
Table 2: Results of BERT\textsubscript{BASE} model trained on different sources of training examples. For each line, the accuracy of the corresponding model is shown on MNLI dev and HANS and the average of the two. Line 1 replicates the original BERT\textsubscript{BASE} result (Devlin et al., 2018). Lines from 2 to 7 correspond to finetuning only on subsets of MNLI data. The third block of results (lines from 8 to 11) corresponds to first finetuning BERT\textsubscript{BASE} on the entire MNLI data and then performing an additional finetuning stage on selected examples. We also compare performance to the recent baselines of Clark et al. (2019) (lines 12 to 14) and Mahabadi and Henderson (2019) (line 15). They obtain slightly higher results for their base model. All but our best model outperforms theirs.

| Train examples | HANS | MNLI | Avg. |
|----------------|------|------|------|
| 1 All          | 58.3 | 84.5 | 71.4 |
| 2 BERT\textsubscript{BASE} forgettables 17,748 | 48.8 | 38.9 | 43.9 |
| 3 Random 17,748 | 51.9 | 75.7 | 63.8 |
| 4 BiLSTM forgettables 46,740 | 54.0 | 66.8 | 60.4 |
| 5 Random 46,740 | 51.1 | 79.0 | 65.1 |
| 6 BoW forgettables 63,390 | 54.1 | 68.3 | 61.2 |
| 7 Random 63,390 | 53.9 | 79.6 | 66.8 |
| **Additional stage of finetuning** | | | |
| 8 All + finetuning on BERT\textsubscript{BASE} forgettables | 70.8 | 81.8 | 76.3 |
| 9 All + finetuning on BiLSTM forgettables | 74.0 | 82.5 | 78.3 |
| 10 All + finetuning on Random 46,740 | 60.9 | 84.4 | 72.7 |
| 11 All + finetuning on BoW forgettables | 73.7 | 82.4 | 78.1 |
| **From (Clark et al., 2019)** | | | |
| 12 All | 62.4 | 84.2 | 73.3 |
| 13 All (reweight) | 69.2 | 83.5 | 76.4 |
| 14 Learned Mixin | 64.0 | 84.3 | 74.2 |
| **From (Mahabadi and Henderson, 2019)** | | | |
| 15 Product of Experts | 66.5 | 84.0 | 75.3 |

Table 3: Results of BERT\textsubscript{LARGE} model trained on different sources of training examples.

| Train examples | HANS | MNLI | Avg. |
|----------------|------|------|------|
| All            | 72.3 | 86.4 | 79.3 |
| **Additional stage of finetuning** | | | |
| All + BoW forgettables | 77.3 | 85.5 | 81.4 |
| All + BiLSTM forgettables | 77.5 | 85.5 | 81.5 |

investigated in the future. To some extent, this is also the case for BiLSTM and BoW forgettables (lines 4 and 6), when comparing to random samples with the same size (lines 5 and 7).

**Additional Fine-Tuning** Lines 8-11 report the results obtained by fine-tuning a pretrained model on the set of forgettables, as described in Section 2.4. The results confirm that slightly biasing the model towards hard examples improves robustness at a slight (albeit noticeable) drop in MNLI accuracy. Our best model is obtained by using the BiLSTM forgettable examples (line 9) achieving an accuracy of 74.0% on HANS (max over 3 seeds, mean 73.7% ± 0.5%) which constitutes a +15.7% absolute improvement with respect to the base model in line 1 and +4.8% and +7.5% with respect to the concurrent models of Clark et al. (2019) and Mahabadi and Henderson (2019). Results on line 10 confirm that the forgettable subsets of examples identified by BiLSTM is responsible for the improvement. Fine-tuning on BoW forgettables (line 11) is also comparable to BiLSTM forgettables (line 9). An additional observation is that BERT forgettables provide less improvement in robustness than BiLSTM or BoW. We hypothesize that this is due to the smaller size of the BERT forgettables compared to BiLSTM or BoW.

We also show the detailed results of HANS based on its three different heuristics for our best performing model (line 9) in Appendix, Table 4. Further to give an insight, we retrieve the nearest neighbors a HANS example and show that in Appendix, Table 5.

**Robustness of larger models** A growing body of literature suggests that increasing the capacity of deep networks results in better generalization (Belkin et al., 2018). These results usually assume there is no distribution shift between train and test sets. We investigate whether robustness to the distribution shift studied in this paper may appear “for free” in models with a larger number of parameters. To that end, we apply our method to the “large” version of BERT, BERT\textsubscript{LARGE}, which achieves bet-
eter performance in the MNLI dataset (Devlin et al., 2018). Results are shown in Table 3. We see that BERT_{LARGE} generalizes on HANS significantly better than BERT_{BASE} (72.3% vs 58.3%), confirming – in this setting – that larger models seem more robust. We also observe a +5% increase in performance as a result of finetuning on fortablets from weaker models, supporting the applicability of the method to larger architectures.

4 Discussion and Conclusion

In this paper, we introduced a novel approach based on example forgetting to build more robust models for a natural language inference task. We finetuned a pre-trained model on a set of “hard” examples selected by measuring “example forgetting” (Toneva et al., 2018). We evaluated the robustness of our approach by training exclusively using the MNLI dataset and the evaluating the model on the out-of-distribution test set of HANS (McCoy et al., 2019). We improve BERT_{BASE} and BERT_{LARGE} performance on the challenging HANS test set by more than 15% and 5%, respectively. Although this paper focused on natural language inference, the method is widely applicable in other tasks and contexts. This constitutes one possible direction for future work. Moreover, we plan to analyze the forgettable examples more thoroughly to understand their special properties. Finally, we will study smoother re-weighting of the training examples and re-interpret the studied approach more formally in the context of importance weighted empirical risk minimization (Sugiyama et al., 2007).

References

Martin Arjovsky, Léon Bottou, Ishaan Gulrajani, and David Lopez-Paz. 2019. Invariant risk minimization. arXiv preprint arXiv:1907.02893.

Mikhail Belkin, Daniel Hsu, Siyuan Ma, and Soumik Mandal. 2018. Reconciling modern machine learning practice and the bias-variance trade-off. Cite arxiv:1812.11118.

Yoshua Bengio et al. 2009. Learning deep architectures for ai. Foundations and trends® in Machine Learning, 2(1):1–127.

Wieland Brendel and Matthias Bethge. 2019. Approximating cnns with bag-of-local-features models works surprisingly well on imagenet. arXiv preprint arXiv:1904.00760.

Olivier Chapelle. 2007. Training a support vector machine in the primal. Neural computation, 19(5):1155–1178.

Nitesh V Chawla, Kevin W Bowyer, Lawrence O Hall, and W Philip Kegelmeyer. 2002. Smote: synthetic minority over-sampling technique. Journal of artificial intelligence research, 16:321–357.

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

Ishita Dasgupta, Demi Guo, Andreas Stuhlmüller, Samuel J Gershman, and Noah D Goodman. 2018. Evaluating compositionality in sentence embeddings. arXiv preprint arXiv:1802.04302.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805.

Robert Geirhos, Patricia Rubisch, Claudio Michaelis, Matthias Bethge, Felix A Wichmann, and Wieland Brendel. 2018. Imagenet-trained cnns are biased towards texture; increasing shape bias improves accuracy and robustness. arXiv preprint arXiv:1811.12231.

Jörn-Henrik Jacobsen, Jens Behrmann, Richard Zemel, and Matthias Bethge. 2018. Excessive invariance causes adversarial vulnerability. arXiv preprint arXiv:1811.00401.

R. Jia and P. Liang. 2017. Adversarial examples for evaluating reading comprehension systems. In Empirical Methods in Natural Language Processing (EMNLP).

M Pawan Kumar, Benjamin Packer, and Daphne Koller. 2010. Self-Paced Learning for Latent Variable Models. In Proc. of NIPS, pages 1–9.

Xiaodong Liu, Pengcheng He, Weizhu Chen, and Jianfeng Gao. 2019. Multi-task deep neural networks for natural language understanding. arXiv preprint arXiv:1901.11504.

Rabeeh Karimi Mahabadi and James Henderson. 2019. Simple but effective techniques to reduce biases.

R. Thomas McCoy, Ellie Pavlick, and Tal Linzen. 2019. Right for the wrong reasons: Diagnosing syntactic heuristics in natural language inference. Proceedings of the ACL.

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.
Matthew E Peters, Mark Neumann, Mohit Iyyer, Matt Gardner, Christopher Clark, Kenton Lee, and Luke Zettlemoyer. 2018. Deep contextualized word representations. *arXiv preprint arXiv:1802.05365*.

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.

Masashi Sugiyama, Matthias Krauledat, and Klaus-Robert Müller. 2007. Covariate shift adaptation by importance weighted cross validation. *Journal of Machine Learning Research*, 8(May):985–1005.

Mariya Toneva, Alessandro Sordoni, Remi Tachet des Combes, Adam Trischler, Yoshua Bengio, and Geoffrey J Gordon. 2018. An empirical study of example forgetting during deep neural network learning. *arXiv preprint arXiv:1812.05159*.

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*.

Adina Williams, Nikita Nangia, and Samuel R Bowman. 2017. A broad-coverage challenge corpus for sentence understanding through inference. *arXiv preprint arXiv:1704.05426*.

Yonghui Wu, Mike Schuster, Zhifeng Chen, Quoc V Le, Mohammad Norouzi, Wolfgang Macherey, Maxim Krikun, Yuan Cao, Qin Gao, Klaus Macherey, et al. 2016. Google’s neural machine translation system: Bridging the gap between human and machine translation. *arXiv preprint arXiv:1609.08144*.
Table 4: Accuracy of the entailment ($E$) and non-entailment ($\neg E$) classes on HANS for three heuristics: lexical overlap (lexical), subsequence overlap (subseq), and constituent overlap (const).

| Training examples                                  | lexical | subseq | const |
|----------------------------------------------------|---------|--------|-------|
|                                                    | overall | $E$    | $\neg E$ | $E$    | $\neg E$ |
| All                                                | 58.3    | 96.3   | 38.4   | 99.6   | 4.7     | 99.7    | 10.6   |
| All + finetuning on BiLSTM forgettables            | 74.0    | 76.9   | 81.6   | 90.6   | 40.8    | 93.3    | 60.8   |
| Mahabadi and Henderson (2019)                       | 66.5    | 93.5   | 61.7   | 96.3   | 19.2    | 98.4    | 30.2   |
| Clark et al. (2019)                                | 69.2    | 67.9   | 77.4   | 84.3   | 44.9    | 81.0    | 59.6   |

Source HANS example

The banker thanked the tourist. $\rightarrow$ The tourist thanked the banker.

Nearest neighbors by BERT

The model simulates the size of the pool of exchangeable base cations in the soil.

$\rightarrow$ The model simulates the size of the pool of base cations in the dirt.

(Or click to read my summary of Wolfe’s and Rose’s positions.)

$\rightarrow$ To read my summary of Wolfe’s position, click.

Nearest neighbors by our Robust BERT

He sat patiently as she talked. $\rightarrow$ She sat patiently as he spoke

And Gates and Appiah would have to be thanked for opening the door.

$\rightarrow$ Gates and Appiah were thanked for opening the door.

Table 5: Two nearest neighbors for one HANS non-entailment ($\rightarrow \neg$) example show-casing how our robust model (line 5 in Table 2) pushes supporting $\rightarrow$ training data closer compared to standard BERT (MNLI). To compute nearest neighbors from the BERT models, the embedding of the special token (CLS) is assumed as the representation of an example and cosine is used as the similarity metric.