Making DeBERTa Smarter: How Drawing a Map of Data Helped Our Model Stop Making Silly Mistakes

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Abstract

In this study, we enhance the training of the DeBERTa-v3-base model by addressing dataset artifacts that compromise its natural language inference capabilities. Utilizing the dataset cartography framework introduced by Swayamdipta et al. (2020), we investigate the training dynamics of DeBERTa-v3-base on the MultiNLI dataset to classify training examples based on their learning challenges. Building on this classification, we develop a mitigation strategy that employs a re-weighting scheme, de-emphasizing easier samples during training. To evaluate the effectiveness of our approach, we assess the model's robustness against heuristic-driven errors using the HANS adversarial challenge set. Preliminary results indicate that our targeted re-weighting strategy, informed by training dynamics, can reduce the model's reliance on spurious correlations learned through easy examples, thereby enhancing its generalization capabilities on adversarial examples. This work underscores the importance of understanding training dynamics in identifying and mitigating dataset artifacts, contributing to the development of more reliable and unbiased natural language processing models.

1 Introduction

1.1 Background and Motivation

Robust Natural Language Processing (NLP) models are essential for applications such as machine translation, sentiment analysis, and conversational agents. These models must not only excel on benchmark datasets but also generalize effectively to real-world scenarios to ensure reliability and trustworthiness. However, dataset artifacts—unintended biases and superficial patterns in training data—pose significant challenges. Models may exploit these spurious correlations to achieve high accuracy without genuine understanding, particularly in tasks like Natural Language Inference (NLI) (Poliak et al., 2018). This reliance on dataset artifacts can lead to poor performance on adversarial or out-of-distribution examples that lack such biases (Gardner et al., 2020). Consequently, there is a critical need for methodologies that can identify and mitigate these artifacts to develop truly robust NLP models.

Despite the rise of large-scale, decoder-only models like ChatGPT, BERT-based models remain highly relevant in the NLP landscape. BERT (Bidirectional Encoder Representations from Transformers) and its variants, including DeBERTa, continue to be foundational for various NLP tasks due to their strong performance, versatility, and efficiency in fine-tuning for specific applications (Devlin et al., 2019; He et al., 2021). While decoder-only models excel in generative tasks, BERT-based models are particularly effective for tasks requiring deep comprehension, such as question answering and text classification, making them indispensable in both research and practical applications.

1.2 Objective

We aim to analyze and mitigate dataset artifacts in the Multi-Genre Natural Language Inference (MNLI) dataset to enhance the generalization capabilities of the DeBERTa-v3-base model. To achieve this, we leverage the dataset cartography framework introduced by Swayamdipta et al. (2020), which utilizes training dynamics to categorize training samples into easy-to-learn, ambiguous, and hard-to-learn categories based on metrics such as confidence, variability, and correctness across multiple training epochs. Building on this categorization, we implement a re-weighting strategy that assigns higher importance to challenging samples during training while reducing the influence of easy-to-learn examples. This targeted approach aims to reduce the model's reliance on spurious correlations inherent in dataset artifacts. Furthermore, we evaluate the effectiveness of our mitigation strategy by assessing the model's performance on the HANS adversarial challenge set, thereby measuring the reduction in heuristic biases and the improvement in model robustness.

2 Methodology

2.1 Datasets

2.1.1 MNLI

The Multi-Genre Natural Language Inference (MultiNLI or MNLI) dataset is a comprehensive benchmark designed to evaluate natural language inference (NLI) models across a diverse range of genres (Williams et al., 2018). MNLI consists of approximately 433,000 sentence pairs, each annotated with one of three labels: entailment, contradiction, or neutral. The dataset is divided into training (392,702 examples), validation (20,000 examples), and test (20,000 examples) splits, facilitating robust evaluation of model performance across varied contexts.

2.1.2 HANS

The Heuristic Analysis for NLI Systems (HANS) dataset is specifically crafted to assess the susceptibility of NLI models to heuristic biases by presenting adversarial examples that lack the superficial cues often exploited in standard datasets like MNLI (Gardner et al., 2020). HANS targets several heuristic biases, including lexical overlap, subsequence, constituent, and negation biases, providing a critical measure of model robustness and generalization beyond spurious correlations.

2.2 Model Selection

2.2.1 DeBERTa-v3-base

DeBERTa (Decoding-enhanced BERT with disentangled attention) is an advanced variant of the BERT model that incorporates disentangled attention mechanisms and enhanced mask decoder techniques, resulting in improved performance over traditional BERT models (He et al., 2021). The DeBERTa-v3-base model features 12 transformer layers, 768 hidden units, and 12 attention heads, balancing computational efficiency with strong performance across various NLP tasks. DeBERTa has demonstrated superior results in natural language inference and other NLP tasks due to its ability to better capture contextual relationships and dependencies within the data (He et al., 2023). Its efficiency and effectiveness in fine-tuning make DeBERTa-v3-base an ideal choice for mitigating dataset artifacts in NLI tasks.

2.3 Model Training

2.3.1 Training the Base Model

We trained the DeBERTa-v3-base model on the MNLI dataset using the Hugging Face Transformers library, primarily utilizing default training configurations. Key hyperparameters included a learning rate of 5×10^{-5}, a batch size of 32, and training was completed over 5 epochs. We employed the AdamW optimizer, known for its efficacy in training transformer-based models by incorporating weight decay regularization (Loshchilov & Hutter, 2019), and utilized the default learning rate scheduler provided by the Hugging Face Trainer to facilitate optimal convergence. Gradient clipping was managed implicitly by the Trainer class to ensure stable training dynamics.

2.3.2 Logging Training Dynamics

A critical component of our training process was the comprehensive logging of training dynamics, essential for subsequent dataset cartography analysis. We implemented a custom callback, `TrainingDynamicsCallback`, extending the Hugging Face `TrainerCallback` class, to capture detailed metrics for each training example at the end of every epoch. This callback records logits and gold labels for each instance, storing them in JSON Lines (`.jsonl`) files for structured analysis.

2.4 Dataset Cartography Analysis

Dataset cartography, introduced by Swayamdipta et al. (2020), is a framework that leverages training dynamics to map and diagnose datasets by categorizing training samples based on their learning difficulty and ambiguity. The original approach emphasized balancing the quality and quantity of data by using subsets to train new models, thereby identifying and mitigating dataset biases. In contrast, our study adopts a re-weighting scheme based on training dynamics, which adjusts the importance of individual samples during training rather than selecting specific subsets. This methodological shift allows for a more nuanced approach to addressing dataset artifacts without reducing the overall data quantity, enabling the potential for continuous adaptation throughout the training process.

2.4.1 Categorization of Examples

We classify each training example into one of three categories—**easy-to-learn**, **hard-to-learn**, and **ambiguous**—based on the following metrics derived from training dynamics:

- **Confidence ($\hat{\mu}_i$)** represents the average probability assigned to the correct label across epochs. It is important to note that $\hat{\mu}_i$ is calculated with respect to the true label y_i^* and not the highest-scoring label as used in other common statistical conventions:

$$\hat{\mu}_i = \frac{1}{E} \sum_{e=1}^{E} p_{\theta(e)}(y_i^* \mid x_i)$$

- **Variability ($\hat{\sigma}_i$)** captures the fluctuation in confidence levels over epochs. This is calculated as the standard deviation of the confidence metric:

$$\hat{\sigma}_i = \sqrt{\frac{\sum_{e=1}^{E} \left(p_{\theta(e)}(y_i^* \mid x_i) - \hat{\mu}_i\right)^2}{E}}$$

- **Correctness ($\hat{c}_i$)** indicates the proportion of epochs in which the model correctly predicted the label:

$$\hat{c}_i = \frac{1}{E} \sum_{e=1}^{E} \mathbb{1}\left(\arg\max_y p_{\theta(e)}(y \mid x_i) = y_i^*\right)$$

2.4.2 Categories:

- **Easy-to-Learn:** High and stable confidence, low variability, and consistently correct predictions. These examples exhibit clear and unambiguous relationships between premises and hypotheses, facilitating straightforward classification.
- **Hard-to-Learn:** Low confidence, low variability, and often incorrect predictions. These examples contain nuanced or complex linguistic constructs, ambiguous premises or hypotheses, or subtle semantic differences that challenge the model's discriminative capabilities. This region can also be useful for identifying mislabeled examples.
- **Ambiguous:** Moderate confidence and variability with inconsistent prediction outcomes. These examples present a balance of clear and ambiguous elements, indicating potential areas for targeted training interventions.

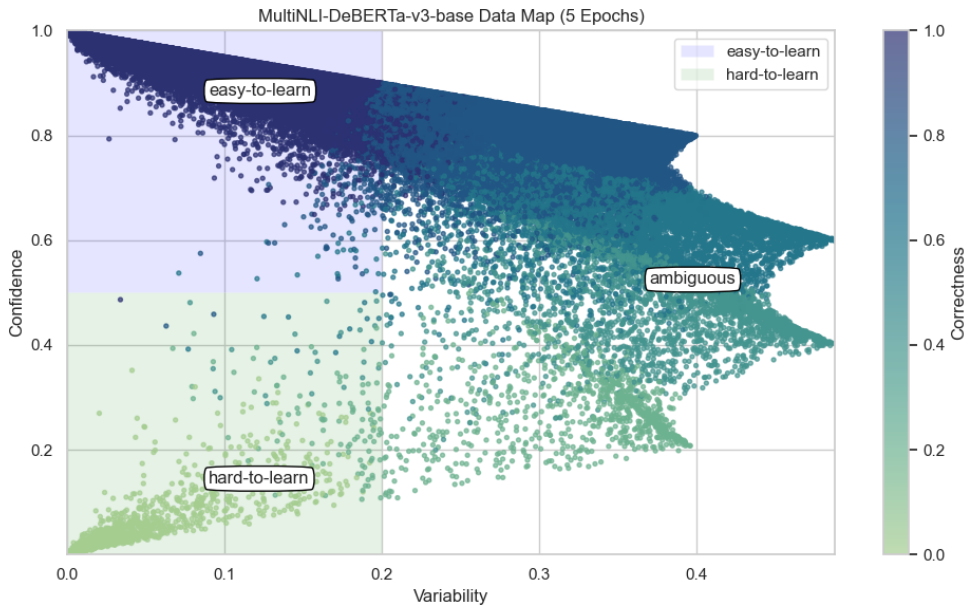

Figure 1: Data map for the MultiNLI dataset (Williams et al., 2018) based on a DeBERTa-v3-base classifier fine-tuned for a downstream Natural Language Inference (NLI) task over 5 epochs. The x-axis represents variability, indicating how inconsistent predictions are across training epochs, and the y-axis represents confidence, reflecting the model's average prediction probability for the true label. Each point corresponds to an individual example in the dataset, shaded by correctness (the proportion of epochs where the model predicts the correct label). Examples are categorized into three regions: "easy-to-learn" (high confidence, low variability), "hard-to-learn" (low confidence, low variability), and "ambiguous" (moderate confidence and variability).

By leveraging these metrics, each example is systematically analyzed and categorized, enabling targeted strategies such as prioritizing hard-to-learn examples for data augmentation or refining the model. This structured approach enhances the model's robustness and overall performance by addressing the specific challenges posed by different example categories.

2.5 Re-weighting Strategy

Dataset artifacts, such as spurious correlations and superficial patterns in the training data, can lead models to make accurate predictions based on irrelevant cues rather than genuine task understanding. By reducing the weight of **easy-to-learn** examples, which often contain such artifacts, and experimenting with different weights of **hard-to-learn** examples, we encourage the model to focus on more challenging, relevant and informative aspects of the data. This adjustment helps diminish the model's reliance on biased patterns, thereby fostering a deeper comprehension of the underlying tasks.

Ambiguous examples, which exhibit moderate confidence and variability, are maintained at or around a base weight to ensure that the model continues to learn from instances that present a balance of clear and ambiguous elements. This nuanced weighting approach enhances the model's robustness and generalization capabilities, enabling it to perform better on adversarial and out-of-distribution examples.

2.5.1 Implementation

The re-weighting mechanism assigns a specific weight to each training sample based on its category: **easy-to-learn**, **ambiguous**, or **hard-to-learn**. The weights are parameterized in the code for fine-tuning between models:

$$w_i = \begin{cases} w_{\text{easy}} & \text{if } i \text{ is easy-to-learn} \\ w_{\text{ambiguous}} & \text{if } i \text{ is ambiguous} \\ w_{\text{hard}} & \text{if } i \text{ is hard-to-learn} \end{cases}$$

where w_i is the weight for sample i. These weights are incorporated into the loss function during training, modifying the standard cross-entropy loss L as:

$$L_i = -w_i \cdot \left(\sum_{c=1}^{C} y_{i,c} \log(\hat{y}_{i,c}) \right)$$

Here, y_i represents the true label, and $\hat{y}_i$ denotes the model's prediction for sample i. By scaling the loss for each sample with its corresponding weight, the training process adjusts the influence of each sample based on its assigned category. This dynamic weighting allows the model to allocate more focus to certain categories as defined by the weight assignments, thereby facilitating targeted learning and mitigating the impact of dataset artifacts.

The re-weighting strategy is integrated into the training loop through the following components:

- **Data Preparation:** Training samples are categorized based on their learning dynamics metrics that were recorded during the base model training. These metrics include average confidence and variability—resulting from the dataset cartography analysis. Each sample is then assigned a weight according to its category.
- **Custom Dataset Class:** The `WeightedMNLI_Dataset` class extends PyTorch's `Dataset` class, incorporating the sample weights alongside input features and labels. This allows each sample's weight to be accessible during training.
- **Custom Trainer Class:** The `WeightedLossTrainer` class inherits from Hugging Face's `Trainer` class and overrides the `compute_loss` method. This modification incorporates the sample weights into the loss computation, ensuring that each sample's loss contribution is scaled appropriately.

Hyperparameter settings for the base `Trainer` class were kept consistent with the base model to ensure a fair comparison of performance metrics while testing different weights and difficulty thresholds for the updated model.

3 Experiments and Evaluation

3.1 Experimental Setup

3.1.1 Environment

All experiments were conducted on a workstation equipped with an Intel(R) Xeon(R) W-2245 CPU @ 3.90 GHz, 32 GB of RAM, and an NVIDIA RTX 4080 GPU with 16 GB of VRAM. Visual Studio Code was the primary integrated development environment (IDE). Datasets and pretrained models were accessed via Hugging Face APIs, and PyTorch was used as the deep learning framework.

3.1.2 Training Details

Several models were trained to determine the most performant parameters for category weights, as well as definitions for high and low confidence and variability thresholds. **Easy-to-Learn** weights were tested within a range of 0.0-0.5. **Ambiguous** weights were kept within a range of 1.0-1.2. **Hard-to-Learn** weights were tested from a larger range of 0.0-2.0.

The variability threshold for separating high and low learning regions from the ambiguous region was tested between 0.15 and 0.30. During training on the MNLI dataset, we observed that higher thresholds hindered model convergence. This occurred because most samples clustered in the low-variability region, leaving too few high-variability samples to emphasize effectively.

Given these tests, we found the best performing model when utilizing the re-weighting strategy on the MNLI dataset was with a variability threshold of 0.2, **Easy-to-Learn** weight of 0.5, **Ambiguous** weight of 1.0, and **Hard-to-Learn** weight of 0.5.

While the initial approach assumed that training could learn more from hard examples, we consistently found that higher weights for this category of examples resulted in worse model performance in both in-domain and adversarial testing. Lower weights for hard examples resulted in overall improved performance. This is likely indicative of data quality issues within this region. For example, it may be more likely that we are learning on mislabeled examples here, and not necessarily hard or ambiguous patterns that we should expect the model to properly solve.

3.2 Evaluation Metrics

3.2.1 MNLI

The evaluation metrics indicate that both the base and re-weighted models exhibit comparable performance in terms of precision, recall, and F1-score across all classes in the MNLI dataset. Specifically, both models achieved an overall accuracy approaching 89%, with minor variations in class-specific metrics that fall within expected ranges due to the inherent stochasticity in model training.

Table 1: MNLI Evaluation Metrics for Base and Re-weighted Models

Metric	**Base Model**	**Re-weighted Model**
Evaluation Loss	0.6366	**0.6101**
Evaluation Accuracy	**0.8891**	0.8847
Evaluation Runtime (s)	51.546	**48.340**
Samples per Second	190.412	**203.040**
Steps per Second	23.804	**25.383**

Table 2: MNLI Classification Report for Base and Re-weighted Models

Model	**Precision**	**Recall**	**F1-Score**	**Support**
Base Model: deberta-v3-base_mnli				
Contradiction	0.935	0.865	0.899	3479
Neutral	0.821	0.880	0.849	3123
Entailment	0.914	0.925	0.919	3213
Overall	0.892	0.889	0.890	9815
Re-weighted Model: deberta-v3-base_cart_(0.5-1.0-0.5)_mnli				
Contradiction	0.932	0.862	0.896	3479
Neutral	0.818	0.873	0.845	3123
Entailment	0.906	0.920	0.913	3213
Overall	0.887	0.885	0.885	9815

3.2.2 HANS

The HANS challenge set consists of 30,000 examples, including 1,000 entailed and 1,000 non-entailed instances for each heuristic subcase. When evaluated on this set, the re-weighted model made fewer incorrect predictions across various heuristics and subcases, achieving an overall accuracy of **78.59%** compared to the base model's **77.49%.**

The baseline model demonstrates a strong reliance on specific heuristics, leading to high error rates in certain subcases. For instance, in the `cn_after_if_clause` subcase, the model fails to make any correct predictions, indicating an over-reliance on the presence of a conjunction following an "if" clause. Similarly, the `le_passive` subcase shows perfect accuracy, suggesting that the model might not recognize passive constructions as potential cues for inference, thereby possibly missing

Table 3: HANS Evaluation Metrics for Base and Re-weighted Models

Heuristic	Subcase	Base Accuracy	Re-weighted Accuracy
constituent	ce_adverb	100.00%	100.00%
	ce_after_since_clause	100.00%	100.00%
	ce_conjunction	100.00%	100.00%
	ce_embedded_under_since	**99.60%**	99.00%
	ce_embedded_under_verb	99.90%	99.90%
	cn_adverb	61.90%	**63.40%**
	cn_after_if_clause	0.00%	**1.40%**
	cn_disjunction	0.40%	**1.50%**
	cn_embedded_under_if	**68.20%**	67.40%
	cn_embedded_under_verb	58.60%	**68.50%**
lexical_overlap	le_around_prepositional_phrase	**100.00%**	99.90%
	le_around_relative_clause	99.90%	99.90%
	le_conjunction	**99.40%**	99.30%
	le_passive	100.00%	100.00%
	le_relative_clause	**99.30%**	98.80%
	ln_conjunction	94.80%	**97.70%**
	ln_passive	98.40%	**99.00%**
	ln_preposition	96.30%	**98.50%**
	ln_relative_clause	94.40%	**96.90%**
	ln_subject/object_swap	99.80%	**99.90%**
subsequence	se_PP_on_obj	100.00%	100.00%
	se_adjective	100.00%	100.00%
	se_conjunction	**100.00%**	99.70%
	se_relative_clause_on_obj	100.00%	100.00%
	se_understood_object	100.00%	100.00%
	sn_NP/S	**0.10%**	0.00%
	sn_NP/Z	3.40%	**4.00%**
	sn_PP_on_subject	66.30%	**69.90%**
	sn_past_participle	2.90%	**8.00%**
	sn_relative_clause_on_subject	81.10%	**85.00%**
Overall Accuracy		77.49%	**78.59%**

some genuine entailments. These findings highlight the presence of dataset artifacts where the model leverages shallow heuristics instead of deep semantic understanding, underscoring the need for mitigation strategies to enhance model robustness.

The re-weighted model achieves a reduction in incorrect predictions across multiple heuristics and subcases, demonstrating the effectiveness of the re-weighting strategy in mitigating heuristic-driven biases. While most improvements are positive, the slight increase in incorrect predictions in certain subcases such as `ce_embedded_under_since` and `cn_embedded_under_if` suggests that the re-weighting strategy may need further refinement to balance its impact across all heuristic scenarios.

4 Discussion

4.1 Interpretation of Results

The re-weighting strategy demonstrated effectiveness in mitigating dataset artifacts, as evidenced by improved performance on the HANS adversarial challenge set. By de-emphasizing easier samples during training, the model reduced its reliance on heuristic biases, leading to enhanced generalization capabilities. Training dynamics provided valuable insights into the learning patterns of the model, revealing which samples were influential in shaping its decision boundaries.

The re-weighted model exhibited a reduction in errors associated with specific heuristics, particularly in lexical overlap and subsequence scenarios. However, it introduced minor regressions in certain

constituent subcases, indicating that while re-weighting enhances robustness against common biases, it may inadvertently affect performance on samples requiring nuanced understanding. Balancing the weights to optimize performance across all heuristics remains a challenge.

4.2 Implications

This re-weighting approach demonstrates potential applicability beyond the MNLI and HANS datasets. By leveraging training dynamics to identify and prioritize ambiguous samples, the strategy can be generalized to other natural language processing tasks and datasets prone to similar artifact issues. This method offers a scalable solution for enhancing model robustness, making it relevant for diverse applications where unbiased and reliable model performance is critical.

4.3 Limitations

Despite its effectiveness, the re-weighting strategy has certain drawbacks. One potential limitation is the fine-tuning required to balance the weights appropriately, which may vary across different datasets and tasks. Additionally, the approach may introduce computational overhead due to the need for continual assessment of training dynamics, potentially constraining its scalability in resource-limited environments. Furthermore, the strategy's reliance on predefined difficulty categorizations may not capture all nuanced aspects of dataset artifacts, necessitating more sophisticated methods for comprehensive mitigation.

4.4 Future Work

Future research can enhance the re-weighting mechanism by exploring adaptive weighting schemes that dynamically adjust based on real-time model performance. Investigating alternative artifact mitigation techniques, such as adversarial training or data augmentation, could complement the current approach and address a broader spectrum of biases. Additionally, extending the evaluation to include other adversarial challenge sets and real-world scenarios will provide a more holistic assessment of the model's robustness and generalizability.

5 Conclusion

5.1 Summary of Findings

This study demonstrates the effectiveness of using dataset cartography in conjunction with a re-weighting strategy to mitigate dataset artifacts in the MNLI dataset. The improved model showed enhanced robustness against heuristic-driven errors on the HANS challenge set without significantly compromising overall performance on the MNLI validation set.

5.2 Significance

The approach contributes to the field of robust natural language processing by providing a systematic method for identifying and addressing dataset biases. This advancement promotes the development of more reliable and unbiased NLP models, capable of performing consistently across diverse and adversarial environments.

5.3 Final Thoughts

Deploying NLP models in real-world applications demands high levels of reliability and fairness. By addressing inherent dataset artifacts through targeted mitigation strategies, this work paves the way for more trustworthy and effective language models. Future endeavors in this direction will further bridge the gap between academic research and practical, real-world deployments, ensuring that NLP technologies serve diverse and equitable purposes.

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