# Evaluating the fairness of task-adaptive pretraining on unlabeled test data before few-shot text classification

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## Abstract

Few-shot learning benchmarks are critical for evaluating modern NLP techniques. But it's possible that benchmarks favor methods which easily make use of unlabeled text, because researchers can pretrain their models on unlabeled text from the test set. Given the dearth of research on this potential problem, we run experiments to quantify the bias caused by pretraining on unlabeled test set text instead of on independently drawn unlabeled text. A controlled experiment varying the numbers of training and test observations for 25 classification tasks and 2 language models—BERT and GPT-2—does not find evidence of bias. Furthermore, we demonstrate the importance of repeated subsampling when studying few-shot text classification, and recommend that few-shot learning benchmarks include multiple training folds. Code and data are available here: `https://github.com` (currently omitted for anonymity).

## 1 Introduction

For NLP benchmarks, it's standard to release text from the test set. This allows researchers to submit a file of predictions instead of submitting code. A potential concern is that researchers can technically use this text during training. Consider the Real-world Annotated Few-shot Tasks (RAFT) benchmark (Alex et al., 2021), which contains "few-shot" text classification tasks—tasks where the training set contains a relatively small number of labeled examples. Below is an excerpt from the RAFT paper (emphasis added):

> For each task, we release a public training set with 50 examples and a larger unlabeled test set. *We encourage unsupervised pre-training on the unlabelled examples* and open-domain information retrieval.

In the RAFT competition, a model is evaluated by scoring its predictions on the same set of unlabeled text which the model may have been trained on (using an unsupervised training procedure).

It's wrong to train a model on test set features with their labels and then evaluate on the test set when one needs to estimate performance on out-of-sample data. Test set performance would be overoptimistic (Hastie et al., 2009). This fact is widely known. But what if, as encouraged by Alex et al. (2021), a model is trained on test set features *without* test set labels? This paper studies this question for the domain of few-shot text classification.

## 2 Motivation

NLP benchmarks for few-shot learning are widespread, as having only a handful of labeled examples is more common in practice. One consideration when designing these benchmarks is that some few-shot approaches can—at least theoretically—use unlabeled text from the test set. With Pattern-Exploiting Training (Schick and Schütze, 2021), for example, one can train the final classifier on test set text with soft labels predicted by an ensemble of supervised models. Or, with Pre-trained Prompt Tuning (Gu et al., 2022), one can pretrain the language model (LM) on unlabeled test set text before prompt-tuning on the labeled training set. A more classical approach would be to train a word2vec model (Mikolov et al., 2013) on unlabeled test set text, run this model on training text to get embeddings, and finally train a classifier on these embeddings with labels from the training set.

For other few-shot approaches, such as SetFit (Tunstall et al., 2022) and in-context learning with large LMs (as popularized by Brown et al., 2020), it's more common to only use labeled examples.

While the ability to exploit unlabeled text is useful, applying this ability to test set text could be substantively different than applying it to text which is statistically independent of the test set. This difference in methodology may be more concerning in the few-shot setting than in the many-shot setting. It's conceivable that differences between few-shot methods are as attributable to differences in how unlabeled text is used than how the few, labeled examples are used. This raises the question: can few-shot text classification benchmarks favor methods which exploited unlabeled text from the test set?

## 3 Related work

As indicated by the quote in §1, the RAFT benchmark implicitly assumes that the answer is no. It is not a fringe opinion that test set features may be used. The popular textbook by Hastie et al. (2009) contains the following passage without a reference or evidence (emphasis added):

> There is one qualification: *initial unsupervised screening steps can be done before samples are left out.* For example, we could select the 1000 predictors with highest variance across all 50 samples, before starting cross-validation. *Since this filtering does not involve the class labels, it does not give the predictors an unfair advantage.*

The opposite opinion—that exploiting unlabeled test set features is unfair—may be more popular. For example, Gururangan et al. (2020) contains the following criticism of another study when comparing performances on a popular text classification benchmark:

> Thongtan and Phienthrakul (2019) report a higher number (97.42) on IMDB, but they train their word vectors on the test set.

Moscovich and Rosset (2022) contains experiments and theory for unsupervised methods which are common to tasks involving tabular data. They find that estimators of out-of-sample performance which were subject to these methods may be biased positively or negatively, depending on all of the parameters of the problem. They recommend further research on this bias in more domains, particularly when dealing with small sample sizes and high-dimensional data.

## 4 Experimental design

In the absence of theory or experiments in NLP, this paper studies how much pretraining on unlabeled test set text biases test set performance for 25 diverse text classification tasks and two types of LMs: BERT (Devlin et al., 2019), and GPT-2 (Radford et al., 2019). Descriptions of the 25 classification tasks are included in Appendix A. The number of classes in each task ranges from 2 to 18.

At a high level, the goal of the experiment is to first establish that pretraining is beneficial, in line with Gururangan et al. (2020). Second, given that pretraining has a detectable benefit, the experiment measures the accuracy difference between using test set text for the pretraining stage—an arguably unfair methodology—versus using text which is independent of the test set—an inarguably fair methodology.

In more detail, the experiment starts by drawing three subsamples (without replacement) from the full sample of data for a given text classification task:

- `extra`: $n$ (either $50, 100, 200$ or $500$) unlabeled texts which are optionally used for pretraining
- `train`: $m$ (either 50 or 100) labeled texts for supervised classification training
- `test`: $n$ labeled texts to report accuracy.

Next, three accuracy estimators are computed. The procedures used to obtain them are described below.

### 4.1 $\mathrm{acc}_{\mathrm{extra}}$

1. Train a freshly loaded, pretrained LM on the $n$ unlabeled texts in `extra` using the LM's pretraining objective—masked language modeling loss for BERT, or autoregressive/causal language modeling loss for GPT-2.
2. Add a linear layer to this further-pretrained model. For BERT, the linear layer transforms the `[CLS]` token embedding. For GPT-2, the linear layer transforms the last token's embedding. The output dimension of the linear layer is the number of classes in the classification task. This layer, along with the rest of the weights in the LM, are finetuned to minimize classification cross entropy loss on `train`.
3. Compute the classification accuracy of this model on `test`.

Step 1 is task-adaptive pretraining—a procedure broadly recommended by Gururangan et al. (2020). Step 2 is the canonical way of training a transformer-based LM for a classification task, according to Section 2 of Zhang et al. (2021).

$\text{acc}_{\text{extra}}$ is clearly an unbiased estimator of out-of-sample accuracy, because it never trains on data from `test`.

### 4.2 $\text{acc}_{\text{test}}$

$\text{acc}_{\text{test}}$ is identical to $\text{acc}_{\text{extra}}$, except that pretraining is done on `test` instead of `extra` in step 1.

$\text{acc}_{\text{test}}$ represents what one might see in a competition like RAFT, where pretraining on unlabeled text from `test` is encouraged. It's unclear whether this accuracy estimator is unbiased, because it was (pre)trained and evaluated on the same set of test set text. A reasonable hypothesis is that it's overoptimistic, i.e., $\text{E}[\text{acc}_{\text{test}}] > \text{E}[\text{acc}_{\text{extra}}] =$ out-of-sample accuracy.

### 4.3 $\text{acc}_{\text{base}}$

$\text{acc}_{\text{base}}$ doesn't do pretraining; it doesn't make any use of unlabeled text. It simply trains a pretrained LM on `train` to do classification, and then computes this model's accuracy on `test`.

This score is a control. If there's no boost going from $\text{acc}_{\text{base}}$ to $\text{acc}_{\text{extra}}$, then it shouldn't be surprising that there's no boost going from $\text{acc}_{\text{extra}}$ to $\text{acc}_{\text{test}}$.

### 4.4 Repeated subsampling

The three accuracy estimators are paired, because their classification training and test sets are identical. The only difference is the source of unlabeled text for pretraining. For $\text{acc}_{\text{extra}}$, the source is independent of test set text. For $\text{acc}_{\text{test}}$, the source is exactly the test set text. For $\text{acc}_{\text{base}}$, no unlabeled text is used.

A potentially important source of variation in this experiment is the particular subsamples, i.e., the particular realizations of `extra`, `train`, and `test` for a given classification task. To expose this variation, the experiment procedure is repeated tens of times for each classification task.[1] For example, for $n = 200$, and for each of the 25 classification tasks, 50 ($\text{acc}_{\text{extra}}$, $\text{acc}_{\text{test}}$, $\text{acc}_{\text{base}}$) triples are computed.

[1] For $n = 50$ and $n = 100$, the experiment is repeated 100 times. For $n = 200$, the experiment is repeated 50 times. For $n = 500$, the experiment is repeated 20 times. In total, $81,000$ finetuned BERT and GPT-2 models were evaluated in this experiment.

Appendix B explains more experiment choices.

## 5 Results

Appendix D.2 visualizes the distributions of $\text{acc}_{\text{extra}} - \text{acc}_{\text{base}}$ and $\text{acc}_{\text{test}} - \text{acc}_{\text{extra}}$. $\text{acc}_{\text{extra}} - \text{acc}_{\text{base}}$ is a control: it's the accuracy boost from pretraining on unlabeled independent text versus not pretraining at all. $\text{acc}_{\text{test}} - \text{acc}_{\text{extra}}$ is the main quantity of interest: it's the accuracy boost from pretraining on unlabeled test set text instead of on unlabeled independent text, i.e., it's the evaluation bias.

Table 1 contains means of these differences for each configuration of the experiment. This table roughly suggests that while pretraining is consistently beneficial, pretraining on unlabeled test set text does not bias test set performance one way or the other.

A more complete analysis of this data is motivated and performed in the next section.

| | BERT | GPT-2 |
|---|---|---|
| $n = 50$ | 4.1% / 0.19% | 3.8% / 0.18% |
| $n = 100$ | 3.9% / 0.18% | 4.1% / 0.11% |
| $n = 200$ | 3.9% / -0.39% | 4.4% / -0.05% |
| $n = 500$ | 3.5% / 0.48% | 4.6% / -0.08% |

(a) $m = 50$

| | BERT | GPT-2 |
|---|---|---|
| $n = 50$ | 6.2% / -0.08% | 2.2% / -0.05% |
| $n = 100$ | 6.1% / -0.37% | 2.5% / 0.03% |
| $n = 200$ | 4.1% / 0.33% | 6.3% / -0.01% |
| $n = 500$ | 6.1% / -0.16% | 3.9% / -0.21% |

(b) $m = 100$

Table 1: Sample means of accuracy differences taken across all subsamples of the 25 text classification tasks. For each cell, the upper-left of the diagonal corresponds to the sample mean of $\text{acc}_{\text{extra}} - \text{acc}_{\text{base}}$, and the lower-right corresponds to the sample mean of $\text{acc}_{\text{test}} - \text{acc}_{\text{extra}}$.

## 6 Analysis

Reporting means is not enough, especially when studying few-shot learning. The figures in Appendix D.2 demonstrate that there is considerable variance, despite pairing.[2] And while these visualizations tell us about how raw accuracy differences vary, they do not tell us how the mean accuracy difference varies. We seek a neat answer to the core questions: on this benchmark of 25 classification tasks, how much does the average accuracy differ between two modeling techniques, and how much does this average difference vary?

One way to communicate the variance is to estimate the standard error of the mean difference across classification tasks. But the standard error statistic can be difficult to interpret (Morey et al., 2016). Furthermore, its computation is not completely trivial due to the data's hierarchical dependency structure: each triple, ($\text{acc}_{\text{extra}}$, $\text{acc}_{\text{test}}$, $\text{acc}_{\text{base}}$), is drawn from (`train`, `test`), which is itself drawn from the given classification dataset.

### 6.1 Model

This analysis does not aim to estimate standard errors. Instead, posterior distributions will be estimated by fitting a hierarchical model:

$$
\begin{aligned}
Y_{ijkl} &\sim \text{Binomial}(n, \lambda_{ijkl}) && (1)\\
\text{logit}(\lambda_{ijkl}) &= \mu + \alpha z_i + U_j + V_{jk} + \beta x_{ijkl} && (2)\\
\mu &\sim \text{Normal}(0, 1) && (3)\\
\alpha &\sim \text{Normal}(0, 5) && (4)\\
U_j &\sim \text{Normal}(0, \sigma_U) && (5)\\
V_{jk} &\sim \text{Normal}(0, \sigma_V) && (6)\\
\beta &\sim \text{Normal}(0, 1) && (7)\\
\sigma_U, \sigma_V &\sim \text{HalfNormal}(0, 1) && (8)
\end{aligned}
$$

(1) number of correct predictions

(2) logit link for accuracy rate, additive effects

(3) prior for the global intercept

(4) prior for the effect of the type of LM (BERT or GPT-2)—a control variable

(5) prior for the effect of the classification task (partial-pooled to reduce overfitting)

(6) prior for the nested effect of the task's subsampled dataset

(7) prior for the effect of interest ($x_{ijk1} = 1$ indicates the modeling intervention)

(8) prior for standard deviations.

The model is fit using Markov Chain Monte Carlo, using the interface provided by the `bambi` package (Capretto et al., 2022). 4,000 samples from the posterior were drawn for each effect. Appendix E.1 includes a simulation that demonstrates the model's ability to correctly recover null and non-null effects.

### 6.2 Posterior predictions

In NLP benchmarks, methods are assessed by taking their average performance across tasks. To place the analysis results in this context, samples from the posterior predictive distribution of $Y_{ijk1} - Y_{ijk0}$ (6.1) are taken, then averaged across $i$ (the 2 LM types—BERT and GPT-2), $j$ (the 25 classification tasks), and $k$ (their subsamples), and divided by $n$ to obtain the distribution of the average accuracy difference:

$$\frac{\bar{\hat{Y}}_{\cdots 1} - \bar{\hat{Y}}_{\cdots 0}}{n}.$$

These distributions are plotted in Figure 1. Each distribution is that of the marginal effect of the modeling intervention: pretraining versus not pretraining before classification training (the pretraining boost), or pretraining on unlabeled test set text instead of on unlabeled independent text before classification training (the evaluation bias).

## 7 Discussion

Figure 1 demonstrates that the average pretraining boost is significant in every configuration of the experiment, ranging from 2% to 6%. This finding replicates that from Gururangan et al. (2020). After averaging across settings for $m$, $n$, and the 2 LM types, only two of the 25 classification tasks had a pretraining boost less than 0, and both were greater than -1%.[3] Overall, pretraining is beneficial, so there may be a detectable evaluation bias.

As shown in Figure 1, the evaluation bias bounces inconsistently and insignificantly around 0. After averaging, 12 of the 25 classification tasks had a positive evaluation bias, and all tasks had an average evaluation bias less than 1% in absolute value. Given the lack of evidence for an evaluation bias in either direction, it's unlikely that a benchmark which releases unlabeled test set text can systematically promote models pretrained on it

[2] One source of variance is intentionally introduced: the subsamples/splits, as explained in §4.4. The other source of variance is inherent: the added linear layer to perform classification is initialized with random weights.

[3] The tasks were `blog_authorship_corpus` and `movie_rationales`.

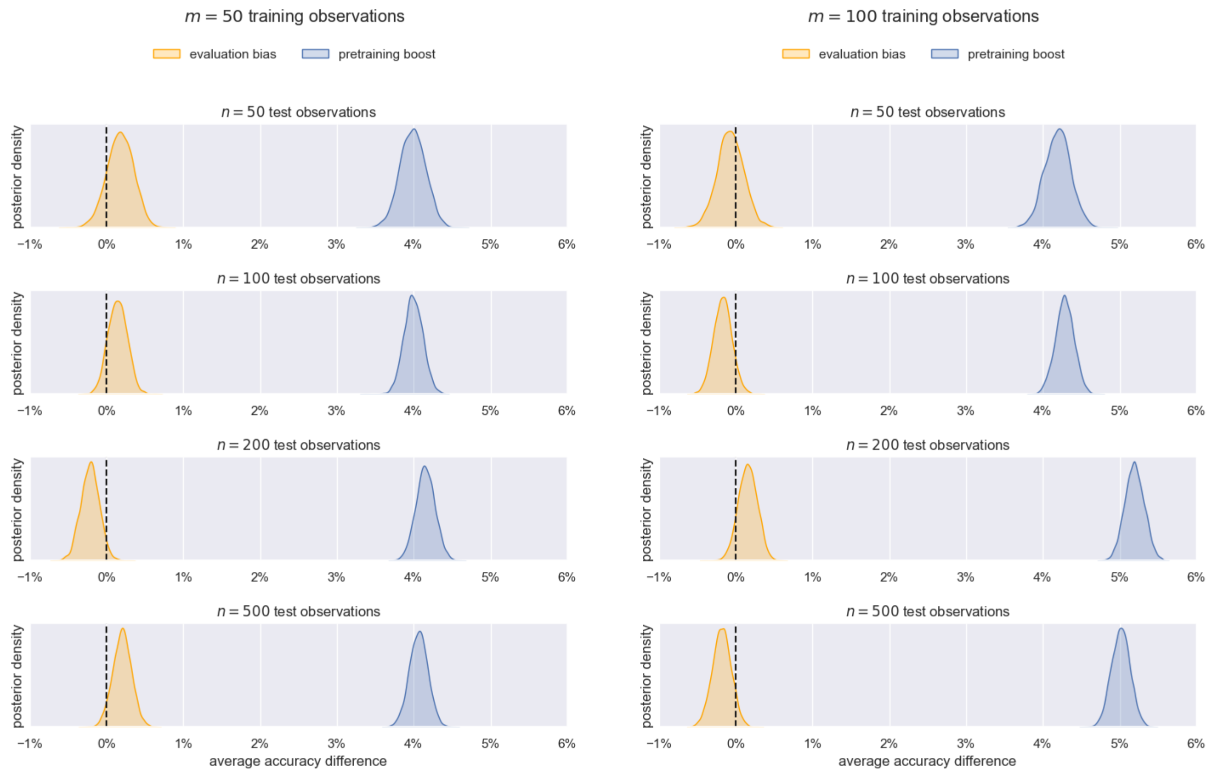


Figure 1: Distributions of average accuracy differences for $m = 50$ (left) and $m = 100$ (right). The evaluation bias is akin to $\text{acc}_{\text{test}} - \text{acc}_{\text{extra}}$. The pretraining boost is akin to $\text{acc}_{\text{extra}} - \text{acc}_{\text{base}}$.

over equally performant models which pretrained on unlabeled independent text.

Moscovich and Rosset (2022) found that the evaluation bias caused by certain unsupervised methods for tabular data gets closer to 0 as $n$ increases. This finding is not confirmed by this experiment. Figure 1 shows that for $m = 50$ and $m = 100$, the distribution of the evaluation bias consistently hovers around 0 across settings for $n$. But far more experiments varying $n$ are needed to thoroughly assess this insensitivity.

## 8 Meta-analysis

§4.4 briefly argues for subsampling multiple datasets from the full classification dataset. To assess this argument, the analysis was repeated on 500 random slices of the $m = 100, n = 500$ dataset of accuracies such that exactly 1 ($\text{acc}_{\text{extra}}$, $\text{acc}_{\text{test}}$, $\text{acc}_{\text{base}}$) triple per classification task (instead of 20) is included. This unreplicated data is often all you get from benchmarks.

Figure 2 (right) displays the cumulative distribution function of the posterior mean of the evaluation bias for $m = 100, n = 500$ under this unreplicated experimental design. The distribution is quite variant. There's a 47% chance that the posterior mean of $\beta$—the average increase in the log-odds of a correct prediction by pretraining on unlabeled test set text instead of on unlabeled independent text—is outside the interval $(-0.04, 0.04)$, which would indicate a significant negative or positive bias.[4] In other words, without subsampling, one may as well flip a coin to determine whether pretraining on unlabeled test set text is fair.

## 9 Conclusion

Across combinations for the number of classification training examples ($m = 50, 100$) and the number of pretraining or evaluation examples ($n = 50, 100, 200, 500$), pretraining on unlabeled test set text did not result in a consistent or significant bias compared to pretraining on unlabeled independent text. This is despite the almost universal benefit of pretraining.

One recommendation for designing few-shot benchmarks, which expands on the principle about robustness from Bragg et al. (2021) and recommendations from Madaan et al. (2024), is based on

[4] For 0.04, the odds ratio is $e^{0.04} \approx 1.04$. For context, the average odds ratio between adjacent submissions in the RAFT leaderboard is 1.03. For posterior means outside $(-0.04, 0.04)$, all of their 89% credible intervals exclude 0, which evidences a non-null effect.

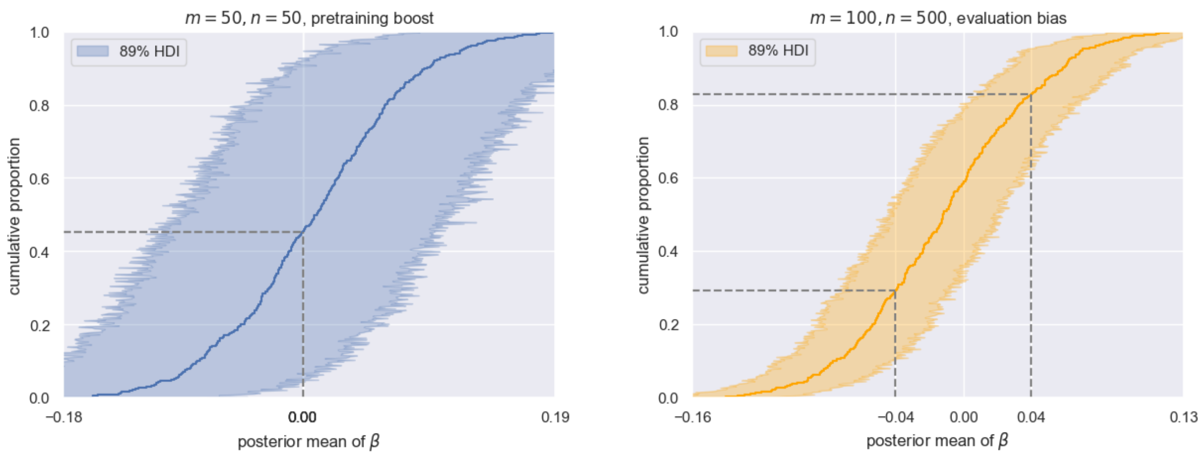


Figure 2: Distributions of this paper's conclusions for $m = 50, n = 50$ (left) and $m = 100, n = 500$ (right) had there been no technical replication. (left) $\beta$ is the average increase in the log-odds of a correct prediction by pretraining on unlabeled independent text versus not pretraining at all before classification training. (right) $\beta$ is the average increase in the log-odds of a correct prediction by pretraining on unlabeled text from the test set instead of on unlabeled independent text before classification training.

the meta-analysis in §8: empirical studies of few-shot learning should consider including multiple, independent subsamples of training data. While a single training set combined with a large test set is sufficient for precise, unbiased estimation of out-of-sample performance, this estimator is conditional on the training set. In few-shot learning, the training set is, by definition, minimal. The estimator hides two sources of variance—that from the randomly drawn training set, and that from randomness inherent in the training procedure. Figure 2 shows that this variance is large-enough to turn a methodology into a coin flip for a standard pretraining-and-training procedure. Benchmarks which require training on multiple, independent subsamples would expose training variance.

An important limitation of this paper is that it does not analyze semi-supervised methods like Pattern-Exploiting Training. This paper also doesn't study somewhat nefarious uses of the test set such as hand-inspecting the text and targeting interventions accordingly. This paper's conclusions are limited to task-adaptive pretraining of LMs.

A direction for future research is to further vary the amount of labeled training examples. Perhaps there's overoptimism for minimal training sets. Another empirical direction is to repeat the experiment for larger LMs trained via supervised finetuning, assuming data contamination can be accounted for.

A theoretical direction is to explore the role of causality. Jin et al. (2021) argue and demonstrate that the benefit of task-adaptive pretraining depends on the learning task's causal direction. Perhaps the principle of independent causal mechanisms is also relevant in assessing the fairness of pretraining on test set features.

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# A Classification tasks

The experiment was ran on 25 publicly available text classification tasks found in `https://huggingface.co/datasets`. Inclusion criteria:

1. All text is in English.
2. The number of classes is not greater than 25, because only 50 or 100 observations are used for training the classifier.
3. The task is to classify one text, not a pair as in, e.g., textual entailment tasks.
4. Texts aren't so long that too much useful signal is dropped when text is truncated to fit in BERT/GPT-2's context window, which is set to 256 tokens.
5. Based on our best judgment, it's likely that BERT/GPT-2 can do better than guessing, i.e., the task is not too niche.

Table 2 lists the exact tasks.

# B Other experiment choices

This section expands on §4.

For BERT, the number of epochs for pretraining was 2. For GPT-2, it was 1 because 2 epochs caused overfitting.

`train` is stratify-sampled by the class to ensure every class is represented, and to reduce the variance of accuracy estimators. `test` is not stratify-sampled. We're only interested in the *difference* between accuracies, which is a function of the difference between model likelihoods because the priors are uniform. So even if accuracies are worse than the majority vote, differences are still meaningful for the purposes of this experiment.

`train` text is not included during pretraining to minimize the overlap of pretraining between $\text{acc}_{\text{extra}}$ and $\text{acc}_{\text{test}}$. This choice was made in an effort to widen any gap between them. The experiment tries to go out of its way to provide evidence of a bias.

`train` contains $m = 50$ or $m = 100$ observations. $m = 50$ is inspired by the RAFT benchmark. $m = 100$ stretches the intention of "few" in few-shot learning, but was tested in an attempt to make lower-variance comparisons. BERT is quite sensitive—see Appendix D.2.

The experiment studies BERT and GPT-2 because their pretraining data is (likely) not already contaminated with text from the 25 text classification tasks. While modern finetuning usually involves instruction-finetuned large LMs, these models' pretraining data are opaque and more likely to include text from the 25 classification tasks (for example, from crawling the Dataset Viewer in HuggingFace's datasets web pages, which hosts the experiment's data). As a result, the comparisons—$\text{acc}_{\text{extra}}$ versus $\text{acc}_{\text{base}}$ and $\text{acc}_{\text{test}}$ versus $\text{acc}_{\text{extra}}$—would be less valid.

# C Hyperparameters and reproducibility

This paper's experiment and analysis code, and data, is available here: `https://github.com`.

`experiment.sh` lists hyperparameters used for each classification task and experiment configuration. Hyperparameters were pre-specified based on Zhang et al. (2021), and to obey memory limits. Run the script on a GPU with at least 15 GB VRAM to reproduce results in §5. It takes about 5 days on a T4 GPU. Training is performed using the `transformers` package (Wolf et al., 2020).

# D Results

## D.1 Individual analysis

The Jupyter notebook `analysis/dataset.ipynb` can be run to (1) produce visualizations of the distributions of $\text{acc}_{\text{extra}}$, $\text{acc}_{\text{test}}$, and $\text{acc}_{\text{base}}$ (for each classification task and experiment configuration), and (2) compute $p$-values for the following hypothesis test:

$$H_0 : \text{E}[\text{acc}_{\text{test}} - \text{acc}_{\text{extra}}] = 0$$
$$H_1 : \text{E}[\text{acc}_{\text{test}} - \text{acc}_{\text{extra}}] > 0.$$

The $p$-value is estimated via permutation testing. It's then adjusted to control the false discovery rate (Benjamini and Hochberg, 1995). No $p$-values were statistically significant at the $0.05$ level.

Care has to be taken when attempting to analyze or interpret $\text{acc}_{\text{extra}} - \text{acc}_{\text{base}}$ and $\text{acc}_{\text{test}} - \text{acc}_{\text{extra}}$ *together*. That's because these differences

| **Hugging Face dataset** | **Author(s)** | **Number of classes** | **Text length (25, 75) percentiles** |
|---|---|---|---|
| ag_news | Zhang et al. (2015) | 4 | (196, 266) |
| SetFit/amazon_counterfactual_en | O'Neill et al. (2021) | 2 | (60, 125) |
| app_reviews | Grano et al. (2017) | 5 | (10, 77) |
| blog_authorship_corpus | Schler et al. (2006) | 2 | (92, 556) |
| christinacdl/clickbait_notclickbait_dataset | | 2 | (46, 69) |
| climate_fever | Diggelmann et al. (2020) | 4 | (80, 156) |
| aladar/craigslist_bargains | He et al. (2018) | 6 | (346, 713) |
| disaster_response_messages | | 3 | (74, 178) |
| emo | Chatterjee et al. (2019) | 4 | (44, 83) |
| dair-ai/emotion | Saravia et al. (2018) | 6 | (53, 129) |
| SetFit/enron_spam | Metsis et al. (2006) | 2 | (342, 1553) |
| financial_phrasebank | Malo et al. (2014) | 3 | (79, 157) |
| classla/FRENK-hate-en | Ljubešić et al. (2019) | 2 | (34, 160) |
| hyperpartisan_news_detection | Kiesel et al. (2019) | 2 | (39, 63) |
| limit | Manotas et al. (2020) | 2 | (53, 123) |
| AmazonScience/massive | FitzGerald et al. (2023) | 18 | (24, 44) |
| movie_rationales | DeYoung et al. (2020) | 2 | (2721, 4659) |
| mteb/mtop_domain | Muennighoff et al. (2023) | 11 | (26, 44) |
| ccdv/patent-classification | Sharma et al. (2019) | 9 | (441, 775) |
| rotten_tomatoes | Pang and Lee (2005) | 2 | (76, 149) |
| silicone | Chapuis et al. (2020) | 4 | (29, 75) |
| trec | Wang et al. (2007) | 6 | (36, 61) |
| tweets_hate_speech_detection | Sharma (2019) | 2 | (62, 107) |
| yahoo_answers_topics | Huangzhao (2018) | 10 | (58, 213) |
| yelp_review_full | Zhang et al. (2015) | 5 | (287, 957) |

Table 2: Brief descriptions of the 25 classification tasks used in this experiment. Click the link in the cell to be taken to the dataset homepage in `https://huggingface.co/datasets`. The dataset subset (or config) and the chosen prediction task are specified in code in `src/pretrain_on_test/_load_data.py`.

are not independent: if $\text{acc}_{\text{extra}}$ is high, then $\text{acc}_{\text{extra}} - \text{acc}_{\text{base}}$ increases and $\text{acc}_{\text{test}} - \text{acc}_{\text{extra}}$ decreases. This paper does not analyze the scores together, per se. We care about $\text{acc}_{\text{test}} - \text{acc}_{\text{extra}}$. $\text{acc}_{\text{extra}} - \text{acc}_{\text{base}}$ only exists to sanity check that the pretraining code works; there may be an effect to detect.

### D.2 Difference distributions

Figures 5 - 12 visualize the distributions of the paired differences—$\text{acc}_{\text{extra}} - \text{acc}_{\text{base}}$ and $\text{acc}_{\text{test}} - \text{acc}_{\text{extra}}$–for each configuration of the experiment.

## E Analysis

The analysis in §6 can be reproduced by running all of the Jupyter notebooks in `analysis/fit_posteriors/`.

Posterior samples of $\beta$ (which were used to draw posterior predictive samples) were taken from four chains with 1,000 draws each, after 500 steps of tuning.

### E.1 Hierarchical model checks

Hierarchical models require some basic checks to have faith in their results (McElreath, 2018).

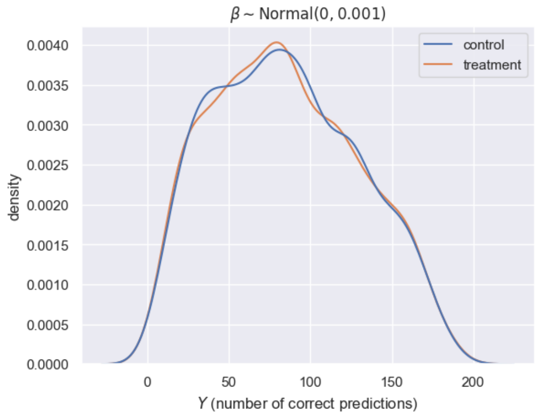
For each of the 16 hierarchical models (8 experiment configurations times 2 comparisons), no divergences were observed during the fitting procedure. All trace plots were healthy.

Figure 3 contains prior predictive distributions for $m = 100, n = 200$, demonstrating that priors are not unreasonable. Using default priors from the `bambi` package (Capretto et al., 2022), while scientifically unreasonable (because they result in wide, basin-like accuracy distributions), did not change the conclusions of this paper.

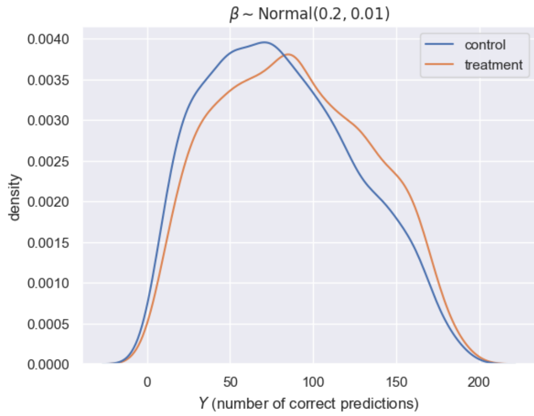
Figure 4 contains posterior distributions of $\beta$ for $m = 100, n = 200$, demonstrating the hierarchical model's ability to recover both null and non-null effects.

## F Meta-analysis

The meta-analysis in §8 can be reproduced by running the script, `analysis/meta/meta.py`, and then the Jupyter notebook `analysis/meta/meta.ipynb`. No divergences were observed.

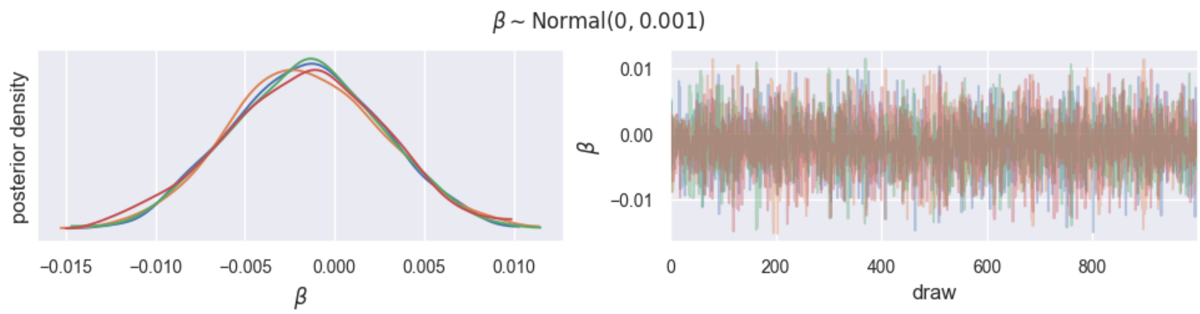



(a) Null effect

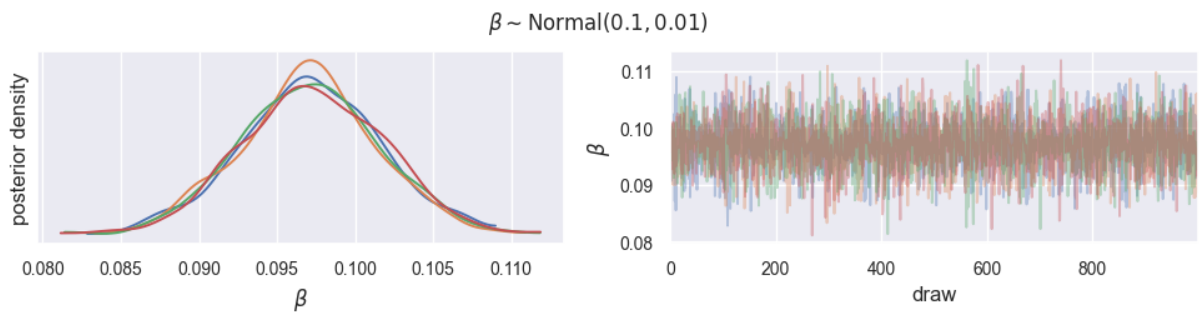



(b) Non-null, positive effect

Figure 3: Prior predictive distributions for $m = 100, n = 200$ from two different priors for $\beta$—the expected increase in the log-odds of a correct prediction resulting from an intervention/treatment.




(a) Null effect is recovered.




(b) Non-null, positive effect is recovered.

Figure 4: Posterior distributions and trace plots for null and non-null effects **from simulated data** where $m = 100, n = 200$, approximated by four chains with 1,000 draws each, after 500 steps of tuning. For each model, no divergences were observed during the fitting procedure. Visualizations were produced by the `arviz` package (Kumar et al., 2019).

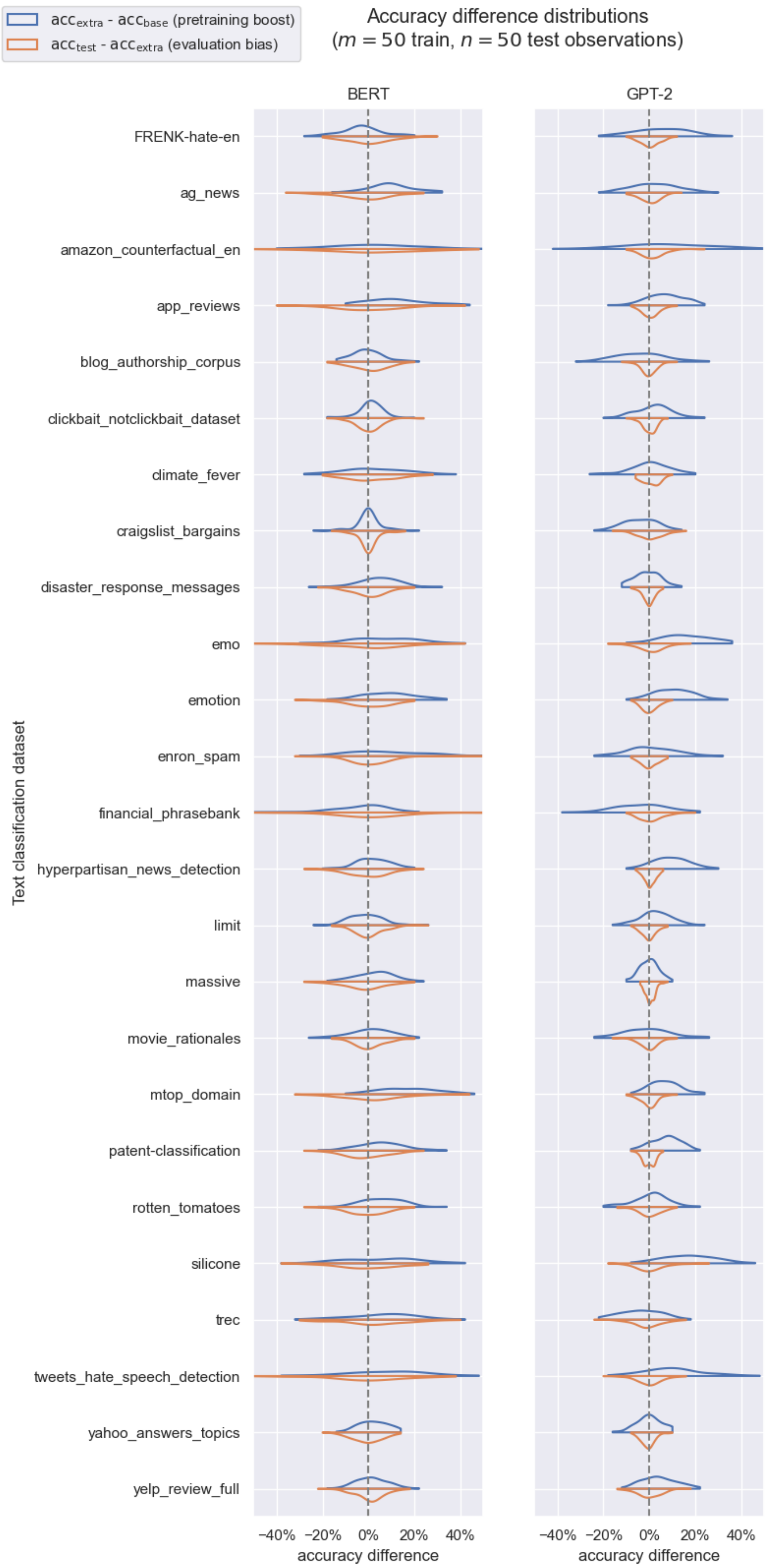
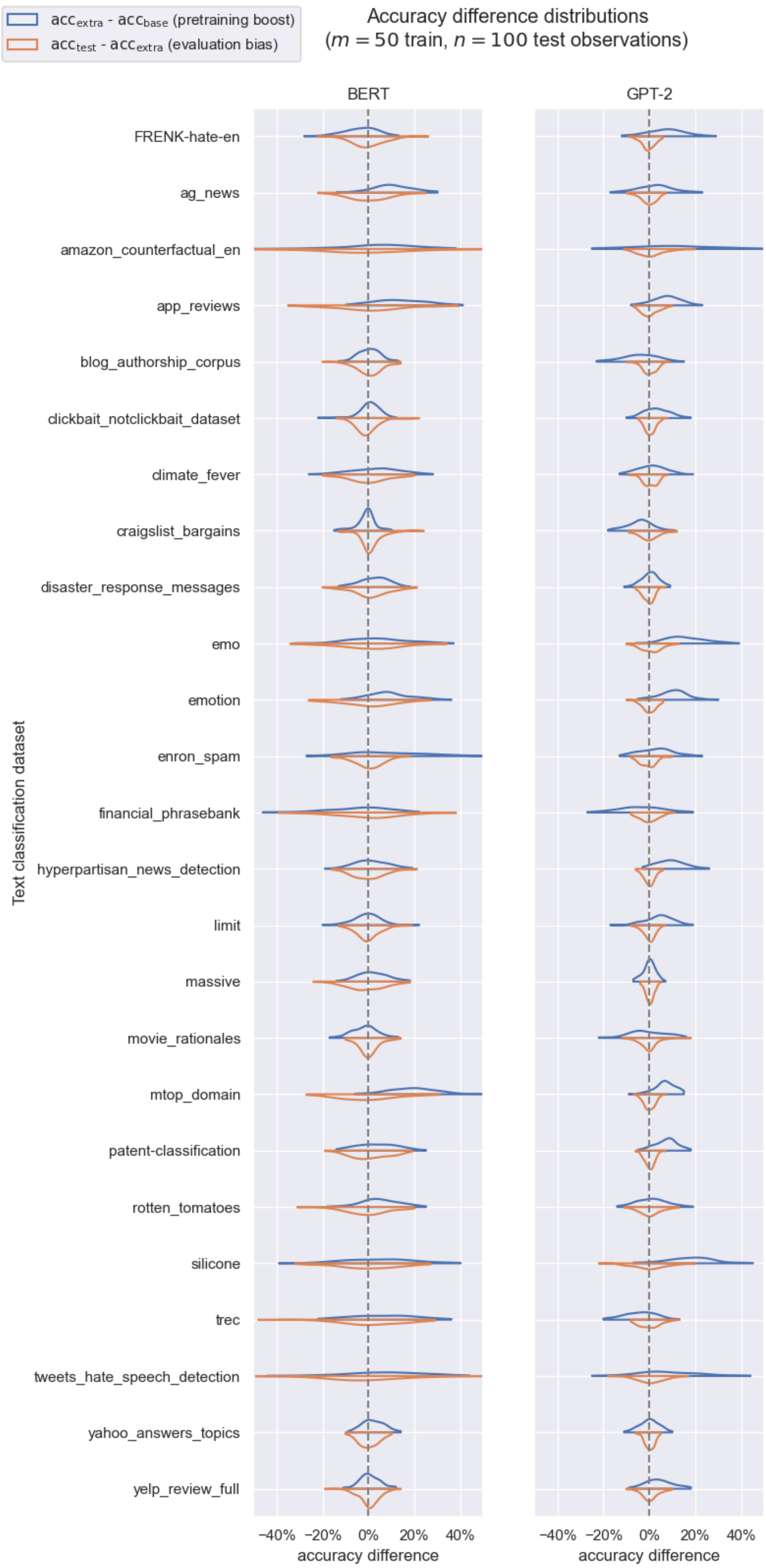
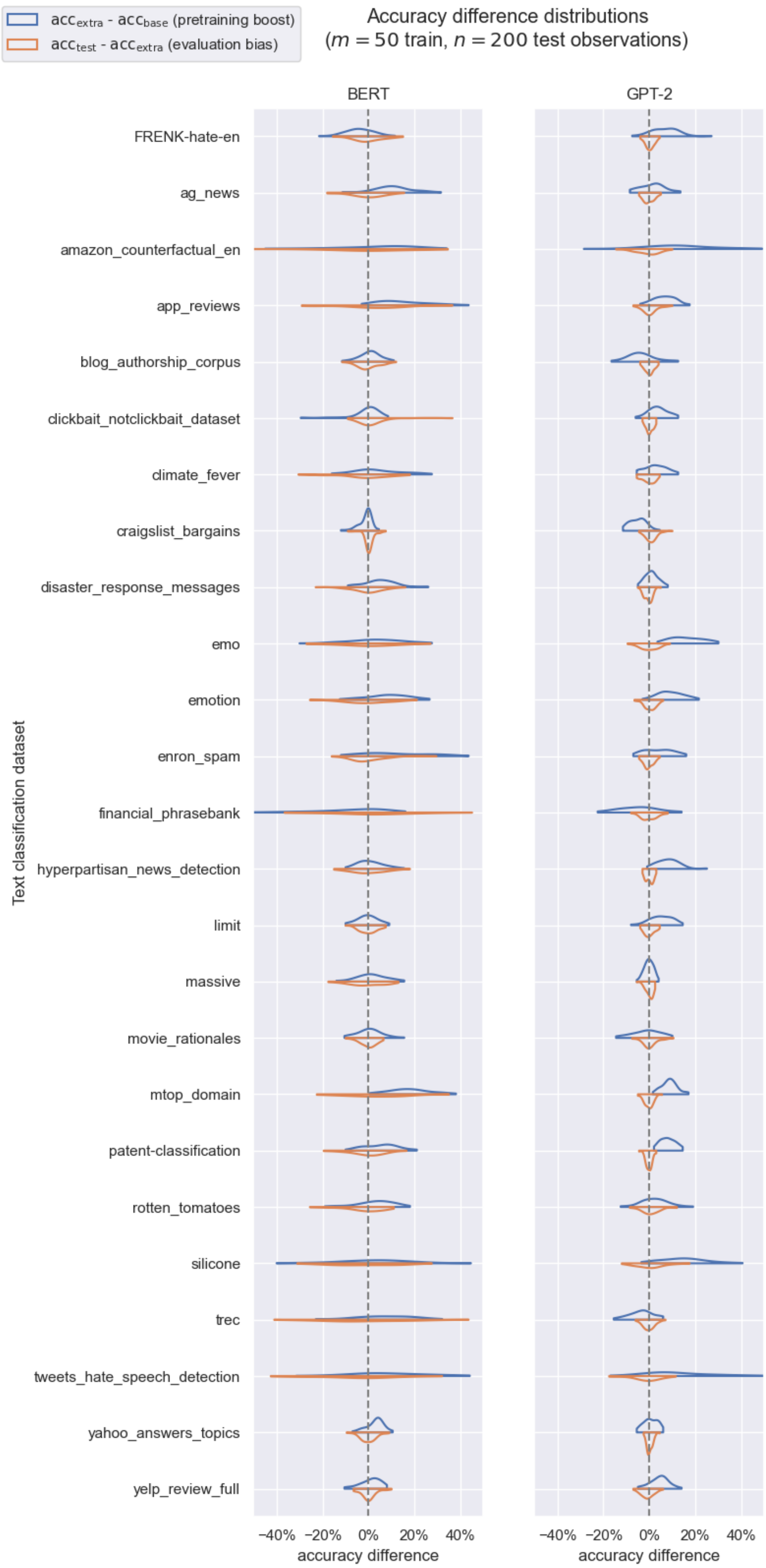

acc_extra - acc_base (pretraining boost)
acc_test - acc_extra (evaluation bias)
Accuracy difference distributions
(m = 50 train, n = 50 test observations)
BERT
GPT-2
Text classification dataset
FRENK-hate-en
ag_news
amazon_counterfactual_en
app_reviews
blog_authorship_corpus
clickbait_notclickbait_dataset
climate_fever
craigslist_bargains
disaster_response_messages
emo
emotion
enron_spam
financial_phrasebank
hyperpartisan_news_detection
limit
massive
movie_rationales
mtop_domain
patent-classification
rotten_tomatoes
silicone
trec
tweets_hate_speech_detection
yahoo_answers_topics
yelp_review_full
−40% −20% 0% 20% 40%
accuracy difference
−40% −20% 0% 20% 40%
accuracy difference

Figure 5



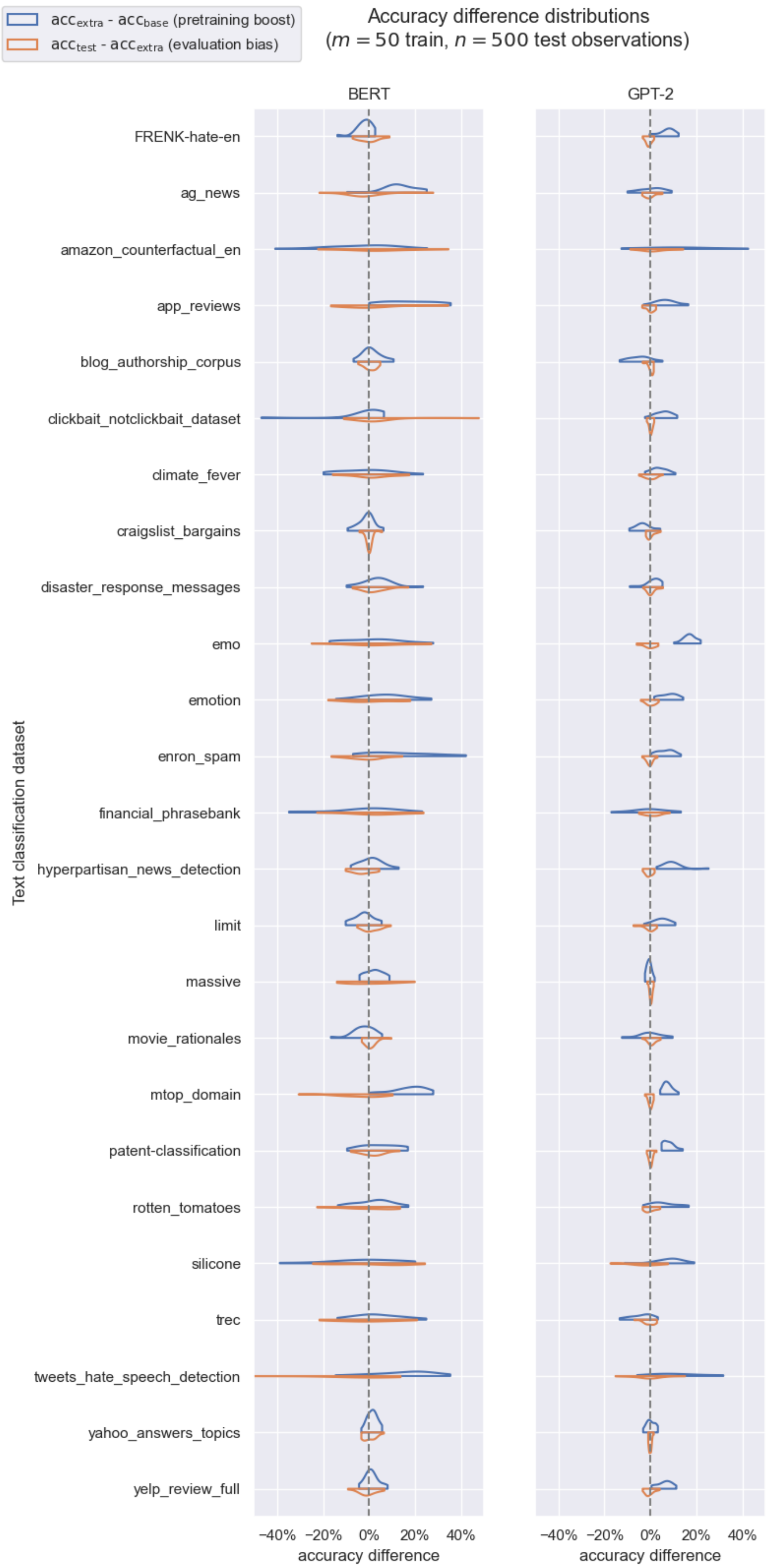
$acc_{extra}$ - $acc_{base}$ (pretraining boost)
$acc_{test}$ - $acc_{extra}$ (evaluation bias)
Accuracy difference distributions
($m = 50$ train, $n = 100$ test observations)
BERT
GPT-2
Text classification dataset
FRENK-hate-en
ag_news
amazon_counterfactual_en
app_reviews
blog_authorship_corpus
clickbait_notclickbait_dataset
climate_fever
craigslist_bargains
disaster_response_messages
emo
emotion
enron_spam
financial_phrasebank
hyperpartisan_news_detection
limit
massive
movie_rationales
mtop_domain
patent-classification
rotten_tomatoes
silicone
trec
tweets_hate_speech_detection
yahoo_answers_topics
yelp_review_full
−40% −20% 0% 20% 40%
accuracy difference


Figure 6



$acc_{extra}$ - $acc_{base}$ (pretraining boost)
$acc_{test}$ - $acc_{extra}$ (evaluation bias)
Accuracy difference distributions
($m = 50$ train, $n = 200$ test observations)
BERT
GPT-2
Text classification dataset
FRENK-hate-en
ag_news
amazon_counterfactual_en
app_reviews
blog_authorship_corpus
clickbait_notclickbait_dataset
climate_fever
craigslist_bargains
disaster_response_messages
emo
emotion
enron_spam
financial_phrasebank
hyperpartisan_news_detection
limit
massive
movie_rationales
mtop_domain
patent-classification
rotten_tomatoes
silicone
trec
tweets_hate_speech_detection
yahoo_answers_topics
yelp_review_full
−40% −20% 0% 20% 40%
accuracy difference


Figure 7


$acc_{extra}$ - $acc_{base}$ (pretraining boost)
$acc_{test}$ - $acc_{extra}$ (evaluation bias)
Accuracy difference distributions
($m = 50$ train, $n = 500$ test observations)
BERT
GPT-2
Text classification dataset
FRENK-hate-en
ag_news
amazon_counterfactual_en
app_reviews
blog_authorship_corpus
clickbait_notclickbait_dataset
climate_fever
craigslist_bargains
disaster_response_messages
emo
emotion
enron_spam
financial_phrasebank
hyperpartisan_news_detection
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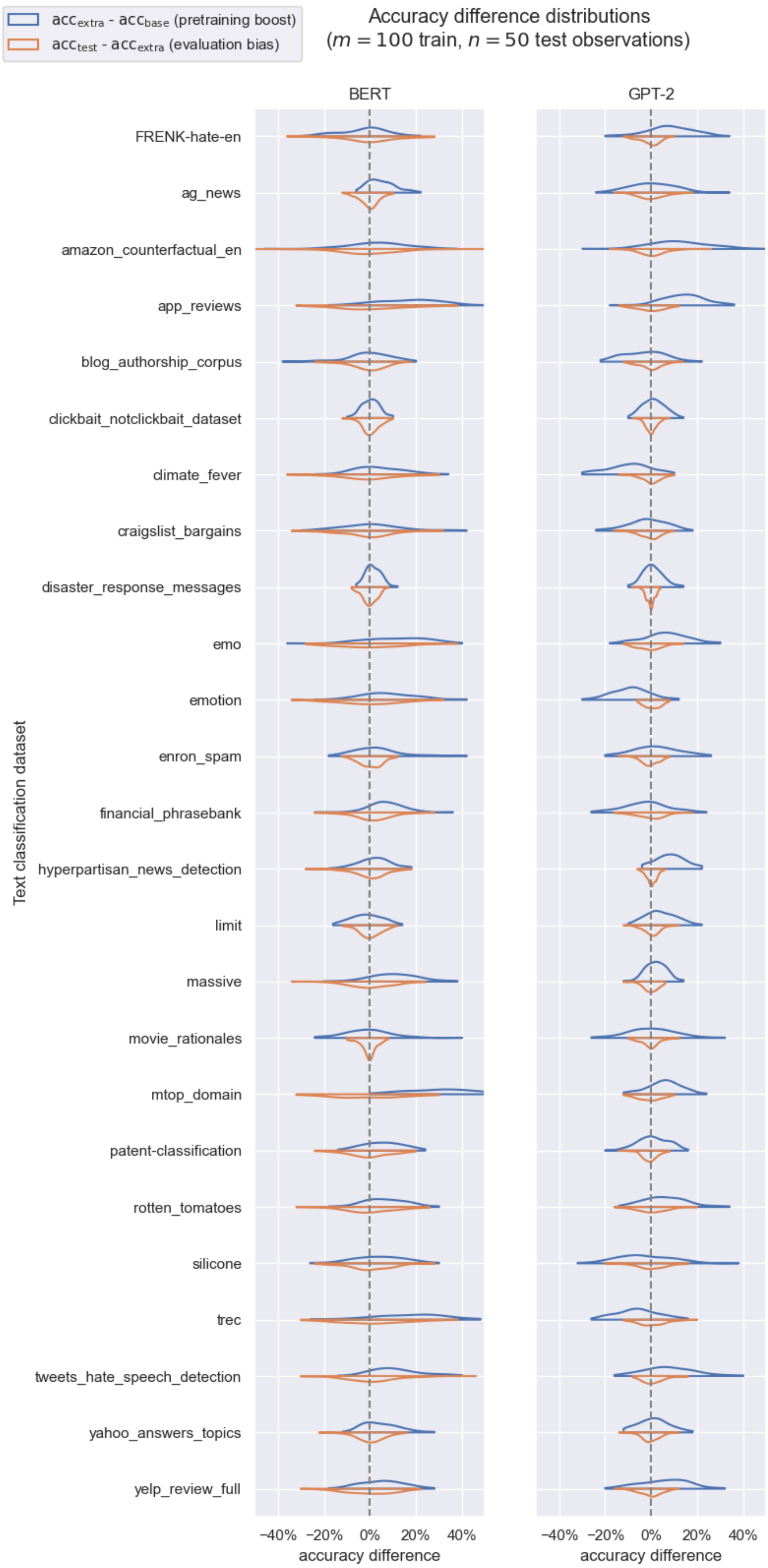
massive
movie_rationales
mtop_domain
patent-classification
rotten_tomatoes
silicone
trec
tweets_hate_speech_detection
yahoo_answers_topics
yelp_review_full
−40% −20% 0% 20% 40%
accuracy difference
−40% −20% 0% 20% 40%
accuracy difference

Figure 8



$acc_{extra}$ - $acc_{base}$ (pretraining boost)
$acc_{test}$ - $acc_{extra}$ (evaluation bias)
Accuracy difference distributions
($m = 100$ train, $n = 50$ test observations)
BERT
GPT-2
Text classification dataset
FRENK-hate-en
ag_news
amazon_counterfactual_en
app_reviews
blog_authorship_corpus
clickbait_notclickbait_dataset
climate_fever
craigslist_bargains
disaster_response_messages
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movie_rationales
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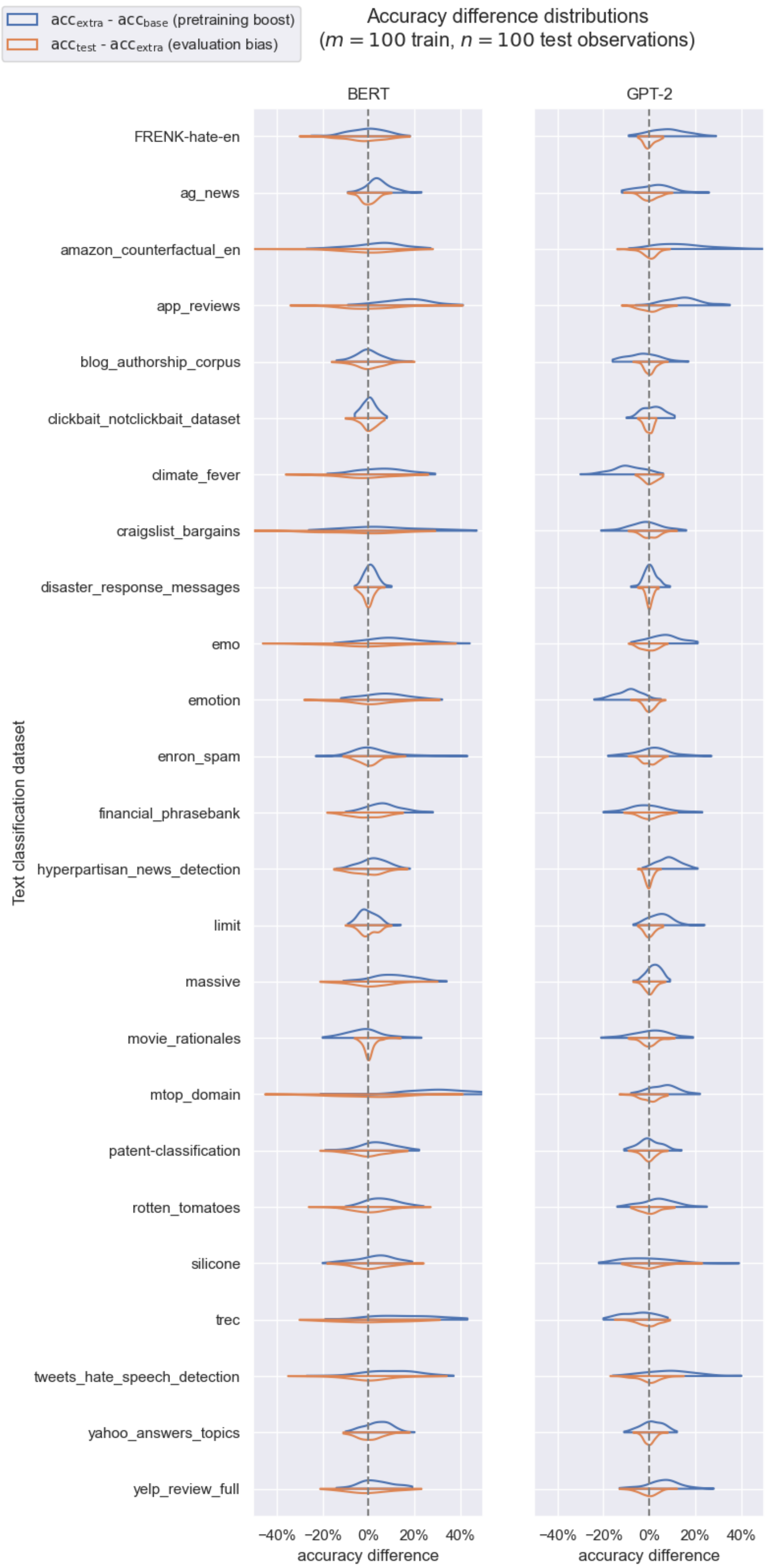
patent-classification
rotten_tomatoes
silicone
trec
tweets_hate_speech_detection
yahoo_answers_topics
yelp_review_full
−40% −20% 0% 20% 40%
accuracy difference


Figure 9


acc_extra - acc_base (pretraining boost)
acc_test - acc_extra (evaluation bias)
Accuracy difference distributions
(m = 100 train, n = 100 test observations)
BERT
GPT-2
Text classification dataset
FRENK-hate-en
ag_news
amazon_counterfactual_en
app_reviews
blog_authorship_corpus
clickbait_notclickbait_dataset
climate_fever
craigslist_bargains
disaster_response_messages
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emotion
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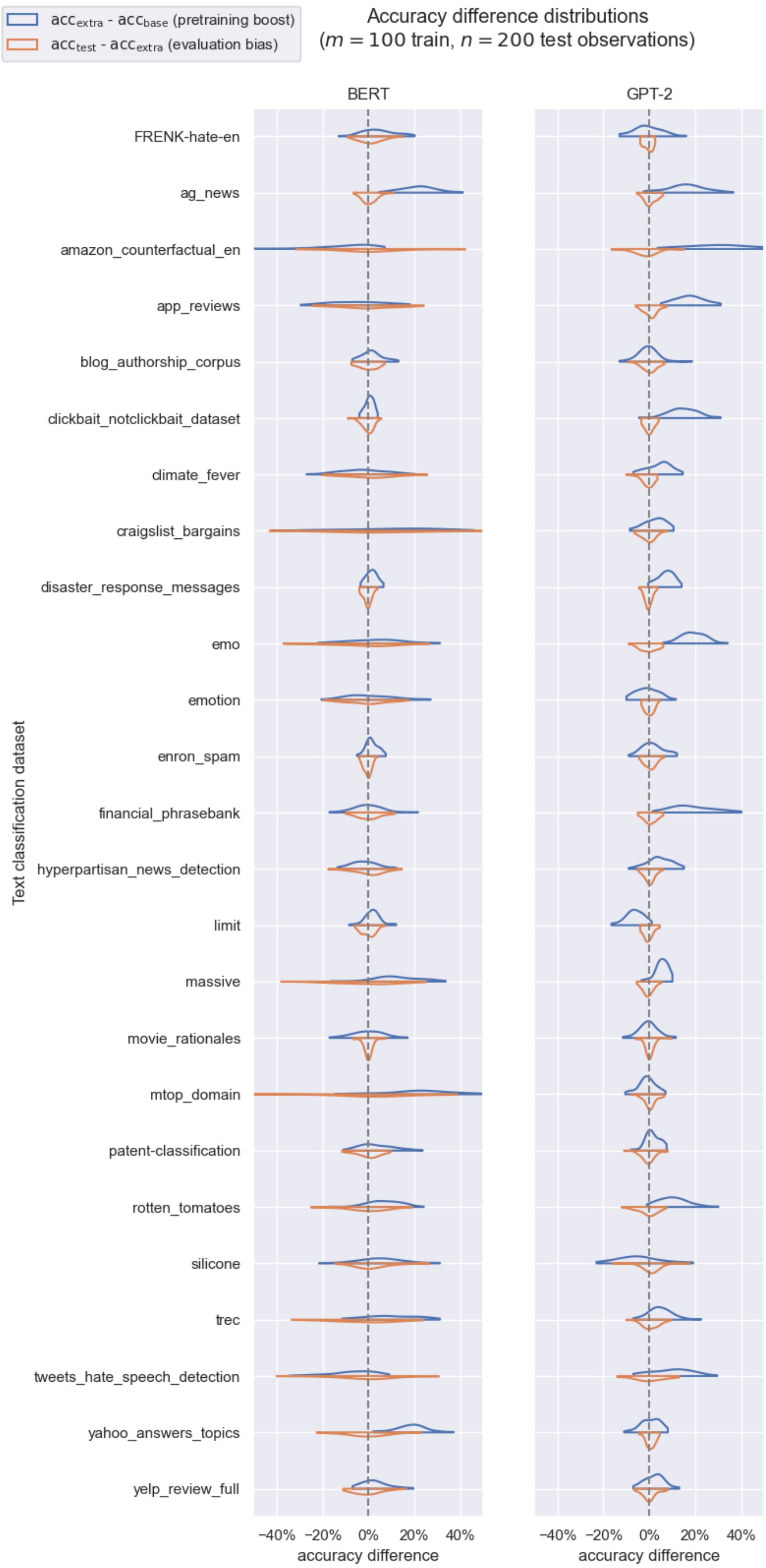
mtop_domain
patent-classification
rotten_tomatoes
silicone
trec
tweets_hate_speech_detection
yahoo_answers_topics
yelp_review_full
−40% −20% 0% 20% 40%
accuracy difference
−40% −20% 0% 20% 40%
accuracy difference

Figure 10



$acc_{extra}$ - $acc_{base}$ (pretraining boost)
$acc_{test}$ - $acc_{extra}$ (evaluation bias)
Accuracy difference distributions
($m = 100$ train, $n = 200$ test observations)
BERT
GPT-2
Text classification dataset
FRENK-hate-en
ag_news
amazon_counterfactual_en
app_reviews
blog_authorship_corpus
clickbait_notclickbait_dataset
climate_fever
craigslist_bargains
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patent-classification
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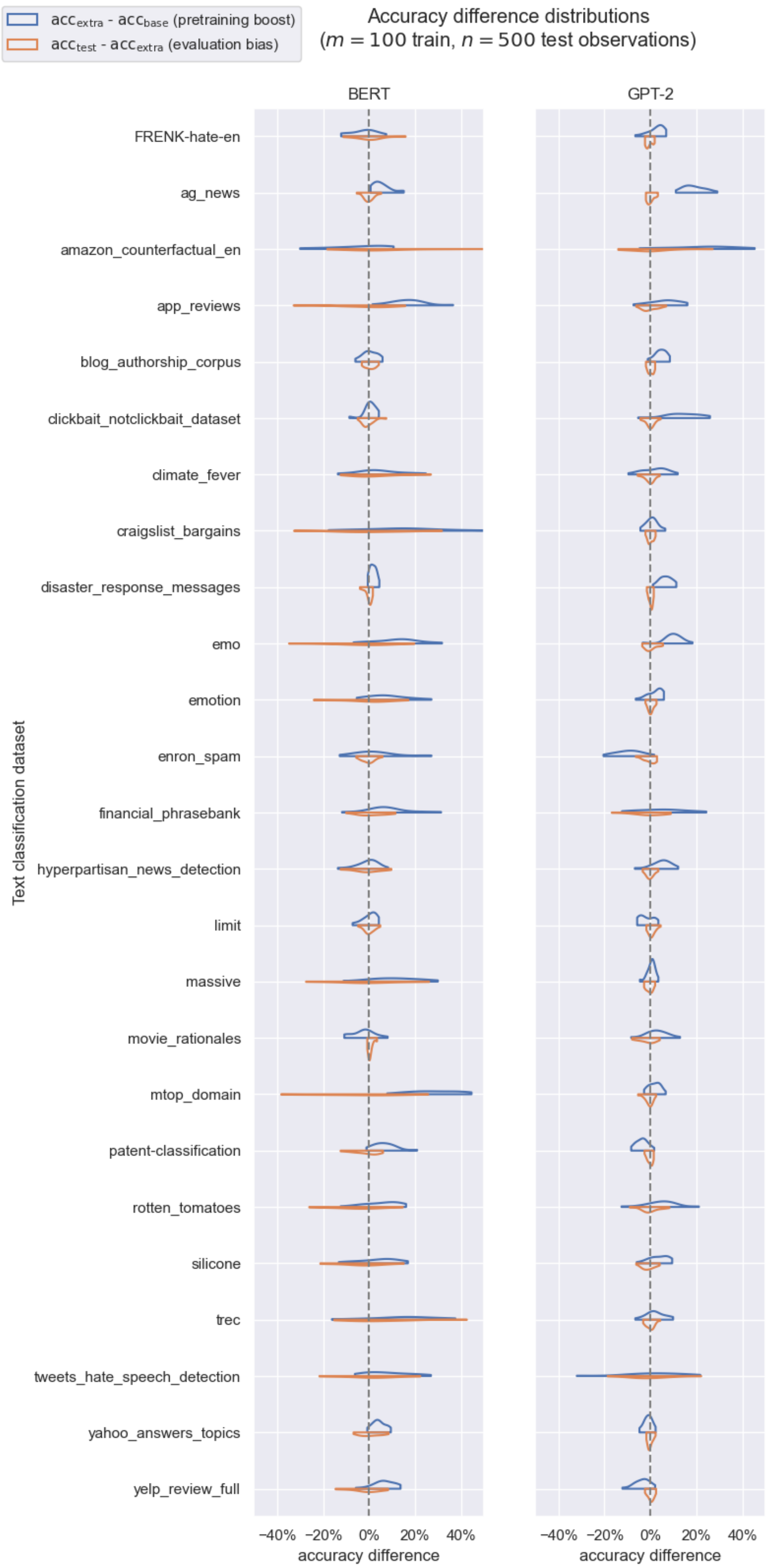
silicone
trec
tweets_hate_speech_detection
yahoo_answers_topics
yelp_review_full
−40% −20% 0% 20% 40%
accuracy difference
−40% −20% 0% 20% 40%
accuracy difference


Figure 11


acc_extra - acc_base (pretraining boost)
acc_test - acc_extra (evaluation bias)
Accuracy difference distributions
(m = 100 train, n = 500 test observations)
BERT
GPT-2
FRENK-hate-en
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clickbait_notclickbait_dataset
climate_fever
craigslist_bargains
disaster_response_messages
emo
emotion
enron_spam
financial_phrasebank
hyperpartisan_news_detection
limit
massive
movie_rationales
mtop_domain
patent-classification
rotten_tomatoes
silicone
trec
tweets_hate_speech_detection
yahoo_answers_topics
yelp_review_full
Text classification dataset
−40% −20% 0% 20% 40%
accuracy difference

Figure 12