Lost in Distillation: A Case Study in Toxicity Modeling

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Abstract

In an era of increasingly large pre-trained language models, knowledge distillation is a powerful tool for transferring information from a large model to a smaller one. In particular, distillation is of tremendous benefit when it comes to real-world constraints such as serving latency or serving at scale. However, a loss of robustness in language understanding may be hidden in the process and not immediately revealed when looking at high-level evaluation metrics. We investigate the hidden costs: what is "lost in distillation", especially in regards to identity-based model bias using the case study of toxicity modeling. With reproducible models using open source training sets, we investigate models distilled from a BERT teacher baseline. Using both open source and proprietary big data models, we investigate these hidden performance costs.

1 Introduction

The revolution in natural language processing brought on by transformers, which have now been employed in virtually all major text processing applications, also brought substantially higher computational costs. The typical BERT model (Devlin et al., 2019) has over 100M parameters and 12 layers. The prospect of using these models in production settings without special purpose hardware quickly led practitioners to seek techniques to reduce the computational costs.

An approach widely advocated is to employ the technique of knowledge distillation to improve the performance of a simpler student model by training on additional unsupervised data that has been labeled by the larger teacher model (Hinton et al., 2015).

The ability to draw upon the wellspring of nearly unlimited unsupervised data and to leverage the higher performance of a much larger model, while maintaining the lower serving costs of a smaller model, has led to rapid adoption of this practice. However, closer analysis of the performance of distilled models reveals that while they may be able to erect a facade of high accuracy, they fail to capture important aspects of the knowledge represented in the teacher models.

We present a particular method of using distillation that we used to improve the performance of our models through pseudo-labeling of unsupervised data, while retaining the model architecture and number of parameters. While, for some metrics we saw nearly asymptotic performance to the teacher model, using other metrics we discovered important differences. While we do not know if this problem will manifest across all differences in architecture and parameterization - we want to caution researchers who are exploring distillation as a potential quick fix.

2 Related Work

BERT models and transformer models in general have structures that are layered with computation units that limit the degrees that parallelism can be used. Focusing on task performance alone, as is often the case for benchmark tasks, has been criticized for failing to account for resource costs (Ethayarajh and Jurafsky, 2020). Knowledge distillation is one of many techniques authors have proposed schemes to reduce the size and complexity.
Models with unintended biases has received considerable attention with multiple survey papers both generally (Pessach and Shmueli, 2022) and for natural language in particular (Kurita et al., 2019; Czarnowska et al., 2021).

Two popular implementations of the distillation paradigm of creating a vast training set using large models to label unsupervised data are presented in Jiao et al. (2020) and Sanh et al. (2020). The primary goal of this work is producing a model with similar performance characteristics on the target task, but with lower a resource footprint. Turc et al. (2019) suggests pre-training and fine-tuning compact models as an alternative to traditional distillation. However, the effects on model bias were not reported in these studies.

Several other works explore this idea in modes similar to the work we present here, although often with a different array of model architectures. Wasserblat et al. (2020) and Mangalwedhekar (2021) both include CNNs as one of the target models. Tang et al. (2019); Chia et al. (2019); Adhikari et al. (2020) all present additional studies regarding distillation and the performance of the models in terms of fidelity to the teacher model.

Specifically regarding bias in the distillation or model compression setting, Xu and Hu (2022) report reduction in bias in contrast to our findings, although in a generation application. However, Gupta et al. (2022) makes clear that biases from the training data can also be preserved or exacerbated in a similar distillation setting.

Bender et al. (2021) raises several risks of large language models overall, including identity-based bias. We show that these risks can be magnified with the use of distillation, and that high-level accuracy metrics can hide nuances in performance, especially when large models are built to address a wide range of use cases.

3 Toxicity Modeling

We have chosen to use the problem of “toxic” comment classification to illustrate the difficulty that we observed in distillation. This is due to the ready availability of training resources for this task, the practical real-world need to address this problem, and the clear risks (Xu et al., 2021) of identity term bias and other modeling pitfalls.

Several diagnostic frameworks that were proposed to highlight the limitations of classification systems in general can also be used to highlight the problems with distillation in particular. Our primary framework is the method of measuring classifier unintended bias associated with neutral or ambiguous identity terms. This framework was introduced in Dixon et al. (2018) and expanded in Borkan et al. (2019) along with the Civil Comments dataset that is our primary source of supervised training data. In addition we use the diagnostic HateCheck test set (Röttger et al., 2021). Recently works that study implicitly abusive language (Wiegand et al., 2021; Lees et al., 2021), where careful attention to the context and implication of the comments is required. We include these evaluation challenges for our models.

4 Models

We found the bias effects of distillation to be remarkably persistent from a small to a very large scale. We created smaller, reproducible models entirely from publicly available resources, and duplicated the same findings on a very large model to show the generality of these findings. Table 1 provides a list of data sources and models described in the next sections.1

4.1 Teacher Models

We trained state of the art text classification models using both publicly available resources, and a larger model trained on resources that we are not authorized to release. Here, our intent is to show that the effects persist into the big data domain.

4.1.1 Civil Comments based Models

All of the models described in this section are based upon publicly available resources and data. The Civil Comments dataset introduced in Borkan et al. (2019) is a public domain corpus of 1.8M user comments labeled for toxicity by crowd raters. These comments originated from a distributed commenting platform that ceased operation in 2017. A subset of the data, ∼400K comments were additionally rated for specific identity subgroup associations such as gender, religion, or sexual orientation. The identity labels in the test set are used for bias evaluation.

Our Civil Comments based models were constructed both for the purposes of reproducibility and for experiments in distillation size. All of these

1A Python notebook demonstrating the ideas presented in this paper can be found at http://github.com/conversationai/Lost_in_Distillation.
were fine-tuned or trained only using the public domain Civil Comments training corpus. Also for the sake of reproducibility, all BERT model versions used open-source checkpoints. It should be noted that in addition to models listed below, we also experimented with distilling via alternate compact architectures. The results were worse in terms of performance and as such we omitted the results.

All CNN models are trained until convergence. For these models, no bias mitigation or data enhancement was employed. Some discrepancies between the big data models and the Civil Comments models, both in overall results metrics and bias, are due to these differences in data.

**CNN** A baseline CNN trained exclusively on Civil Comments data with a BERT-base checkpoint as initial embedding. With 5 layers (2-gram, 3-gram, 4-gram, 5-gram and 6-gram layers of 300) and a max pooling layer. The model hyperparameters were tuned on a held-out evaluation set. The final model employed batch size of 64, max token sequence length of 1536 and learning rate of $10^{-5}$. The hyper-tuned parameters were used for all of the distilled CNN student models below. The best model on the Civil Comments test set ($965$ AUC-ROC) was selected for evaluation. This baseline CNN model is used as a control to ascertain whether a distilled CNN has demonstrable improvements over a model without the benefits of teacher pre-training.

**BERT** A task-specific teacher model built from a BERT-base public checkpoint with 768 dimensions, 12 layers, 12 heads that was fine-tuned exclusively on the Civil Comments training data. The model used a batch size of 64, a learning rate of $10^{-5}$, max token length of 512 and Adam optimizer. The model was trained for $1M$ steps and the best performing checkpoint in terms of AUC-ROC was selected.

### 4.1.2 Big Data Models

Using a combination of publicly available datasets and our much larger proprietary datasets, we show the distillation bias effects in the toxicity space scale to big data. We start with a competitive teacher BERT model that is distilled using a compact CNN architecture. Both teacher and student incorporate the open-source Civil Comments training corpus as well as proprietary human-labeled data and bias mitigation data. We follow the best practices of data augmentation described in (Dixon et al., 2018) by including bias mitigation data to help mitigate discrepancies in identity subgroup metrics.

**PROPRIETARYBERT** A state-of-the-art BERT toxicity model that has been pre-trained on more than $1.5B$ user comments in English. This baseline was additionally fine-tuned on rater labeled comments. The model uses a custom sentence-piece vocabulary of size 200K. The teacher model is constructed with 768 dimensions, 12 layers, 12 heads, consistent with BERT-base (Devlin et al., 2019). The pre-training consists of MLM loss with uniform masking at $15\%$. Pretraining was conducted with batch size of 32 for over $100K$ steps. The model was fine-tuned on $3M$ user generated comments scored by raters for toxicity, bias mitigation data, and the Civil Comments training set with batch size of $512$ until convergence.

### 4.2 Distilled Models

Several models are used to examine distillation. For reference, knowledge distillation is defined as training a smaller neural network on a dataset called the transfer set. Using cross entropy as the loss function between the output of the smaller distilled model $y(x|t)$ and the output of the teacher model $\hat{y}(x|t)$, where $t$ is the temperature and for a standard softmax

$$E(x|t) = - \sum_i \hat{y}_i(x|t) \log y_i(x|t)$$

is normally set to 1.

**DISTILLEDCNN** The transfer data, scored by the above BERT model, is drawn from WikiConv (Hua et al., 2018), a corpus encompassing the history of conversations on Wikipedia Talk pages, and

### Table 1: Model Training Data Size

| Model                  | Data Sources                                                                 | Training Instances |
|------------------------|------------------------------------------------------------------------------|--------------------|
| CNN                    | Civil Comments                                                              | 1.8M               |
| Bert                   | Civil Comments                                                              | 1.8M               |
| ProprietaryBERT        | Civil Comments + Human Labeled Proprietary (3M) + Bias Mitigation (2M)     | 6.8M               |
| DistilledCNN           | Civil Comments + WikiConv (400K) + C4 (640k)                               | 21.8M              |
| DistilledCNNNoProprietary | Civil Comments + BERT-labeled proprietary (20M)                         | 21.8M              |
| DistilledSmDistilledBERTOnProprietary | Civil Comments + BERT-labeled proprietary (20M)             | 21.8M              |
| DistilledProprietaryCNN | proprietaryBERT data + ProprietaryBERT-labeled proprietary (20M) + Bias Mitigation (1.7M) | 36.5M              |
C4 (Raffel et al., 2019), a cleaned version of Common Crawl’s web crawl corpus. For both sources a large quantity of data was scored with BERT and then examples were dropped to ensure a 50/50 distribution of toxic and nontoxic examples using a 0.5 threshold. Since both sources are extremely non-toxic (0.004% and 0.00005% respectively), this process produced only 400k examples from WikiConv and 640k from C4.

**DISTILLEDCNNONProprietary** CNN model distilled on a much larger volume of unsupervised user comments as the transfer set labeled by BERT. As with DISTILLEDCNN, the architecture and training parameters replicate those used by CNN. The model was trained on the Civil Comments golden data and 20M teacher-labeled comments, including proprietary comments.

**DISTILLEDSBERTONProprietary** Small BERT model distilled on the same larger volume of unsupervised corpus of user-domain comments as DISTILLEDCNNONProprietary by using BERT as teacher. As with DISTILLEDCNNONProprietary the model uses Civil Comments golden data and 20M teacher-labeled comments from a proprietary dataset. The model is included to ascertain whether Small BERT for distillation yields improvements in bias over a CNN.

**DISTILLEDProprietaryCNN** A CNN student model distilled on 28M user comments scored with PROPRIETARYBERT. The model is also trained on the same golden data as the teacher model. In addition, the model training data also includes 1.7M bias mitigation examples added to the golden data to mitigate identity term bias. The model uses the same tokenizer as the teacher model and is initialized from the teacher word embeddings. The CNN is 5 layers: one layer of 300 bi-grams, one layer of 300 tri-grams, one layer of 300 quad-grams, one layer of 300 5-grams, one layer of 300 6-grams and a max pool of the entire sequence. The model is trained with an Adam optimizer (Kingma and Ba, 2017), learning rate of .1, a batch size of 128 and a maximum token sequence length of 1536 until convergence.

The distilled student model DISTILLEDProprietaryCNN achieves equivalent (if slightly better performance) to the teacher model PROPRIETARY-BERT on the Civil Comments test set, as shown in Table 3. The Short Synthetic test set is used to measure bias, as shown in Table 3, and further illustrates the similar performance of the two models.

![Figure 2: AUC-ROC performance of the BERT model distilled on proprietary data and evaluated on various test sets, broken down by distilled train set size.](image)

![Figure 3: AUC-PR performance of the BERT model distilled on proprietary data and evaluated on various test sets, broken down by distilled train set size.](image)

### 5 Evaluating Performance and Bias

Experiments are run on a variety of evaluation sets to assess the classification performance of the teacher, baseline and distilled models. In assessing both the Civil Comments based models and the big data models, we compare the distilled student and baseline models performance against the teacher models. Results are shown in Table 2 (Civil Comments based models) and Table 3 (big data models). The final column in each of these tables shows the difference in AUC-ROC between the student model and the teacher.

**Civil Comments** The test set from Civil Comments, drawn from the same distribution of comments as the training data, and is similar to the data distribution contained in the big data datasets.

Given the matched distribution between training and test, we expect this to be a best case result. All of the Civil Comments-based distilled and baseline models are within $\sim 1\%$ of BERT AUC-ROC.
In the big data case, in fact **DISTILLED PROPRIETARY CNN** yields better performance than **PROPRIETARY BERT** in Table 3. These results show the strong promise of distillation, which leverages unsupervised data and produces an improvement without additional model complexity.

**Short Synthetic** A synthetic test set created by substituting identity terms into toxic and non-toxic sentence templates (Dixon et al., 2018; Borkan et al., 2019).

The performance of **DISTILLED CNN** and **DISTILLED CNN NON PROPRIETARY** along with CNN begins to degrade (−3.5%) with respect to the teacher model BERT on this dataset. This yields some evidence that the distillation process, when used with CNN architectures, may increase identity term bias.

On the other hand, minimal degradation in performance occurred for **DISTILLED PROPRIETARY CNN** where carefully selected bias mitigation data was included as part of the teacher model training and distillation process.

**Long Synthetic** A dataset similar to Short Synthetic but with the addition of random filler text meant to be more confusing.

This more challenging dataset begins to show degradation for the **DISTILLED PROPRIETARY CNN** model, despite the addition of bias mitigation data. Table 3 shows almost a −5% fall in AUC-ROC performance with respect to the teacher **PROPRIETARY BERT**.

Likewise, larger drops in performance can be seen for the Civil Comments-based models in Table 2. Interestingly, **DISTILLED CNN NON PROPRIETARY** starts to slightly outperform the baseline CNN and **DISTILLED CNN** with only a −4% drop in AUC versus −6%+.

**Hate Check** A targeted diagnostic test for hate detection models from Röttger et al. (2021). This dataset explicitly attempts to probe the generalisability of a model, measuring systemic gaps and biases in other datasets using a suite of synthetically generated tests.

While the big data teacher model **PROPRIETARY BERT** begins to show slightly more robust performance than the smaller BERT model (.831 AUC vs .701), all distilled and baseline CNN models suffer significant falls in performance. **DISTILLED PROPRIETARY CNN** has nearly a −17% fall in AUC to .664. **Both DISTILLED CNN** and **DISTILLED CNN NON PROPRIETARY** models have ~10% or greater falls in AUC to (.575 and .595 respectively).

Examining the Hate Check functionalities, the categories with the largest differences where the teacher model outperforms the student model are in the non-hate comments that contain a negative term with negation (F14), followed by the comments that have a character swap (F25), and implicit derogation (F4). The teacher model, however, did not perform as well on abuse targeted against a non-protected object or individual (F22, F23). In 22 of the 29 categories, the student model performed worse than the teacher.

We continue our testing with a suite of more robust tests that demonstrate the limitations and weak-points in the distilled model versions.

**False Positives** A dataset inspired and derived from the work of Welbl et al. (2021), where authors trained a generative LM specifically to not produce toxic content. This dataset includes the sentences generated that had a large discrepancy in score between the publicly available toxicity model, Perspective API (Jigsaw, 2017), and human raters. Human annotations marked far fewer examples as toxic than the automated models, and the authors note a strong bias towards false positives in this set.

The False Positives dataset includes 50% auto-generated texts that had Perspective API scores > .75 but were marked by human raters as non-toxic and the rest as randomly selected auto-generated comments with corresponding human annotations.

Notably all models perform poorly on the challenging dataset with **PROPRIETARY BERT** and **BERT** yielding only .635 and .651 AUC-ROC respectively. However all distilled CNN models fared even worse when compared to the teacher models, varying between −11% and −15%.

**Identity Swaps** Inspired by the work in Prabhakaran et al. (2019), where Perturbation Sensitivity Analysis is used to detect unintended model bias related to named entities, we repeat a similar experiment in relation to curated swapped identity terms. A small subset of curated phrases with explicit identity terms meant to detect hard toxic and non-toxic instances. The phrases each have 23 identity terms which are swapped with correct associated grammar specifications. Examples from this data set appear in Table 8. The identity swaps sets shows similar drops in performance for all distilled model instances as compared to the teacher.
Covert Toxicity Detecting implicit abuse or covert toxicity, where clearly hateful or abusive words are not used in the comment, presents an especially hard challenge. Given the documented difficulty of toxicity models and hate models to identify such text, we included a representative set as a further baseline. Using a published test dataset (Lees et al., 2021) we select an output label that is defined as the max of the covert and overt toxic scores. Notably all models performed extremely poorly on this set with < .6 AUC. The effects of distillation were more mixed, suggesting that identifying covert toxicity or implicit abuse is a more nuanced and unsolved task and perhaps more reliant on training data.

Figure 4: Civil Comments Bias Metric Breakdowns for Identity Subtypes on Civil Comments-based Models

Figure 5: Civil Comments Eval Set Bias Metric Breakdowns for Identity Subtypes on Proprietary Big Data Models with bias mitigation implemented

6 Bias in Distilled Models

For evaluation of model bias, we employ a subset of the suite of metrics introduced in Borkan et al. (2019). In particular, we utilize the following metrics for identifying unintended bias along with averaging the differences in these metrics across a subsection of identity categories:

Subgroup AUC The AUC computed only for the data labeled as including a mention of a particular identity

Background Positive, Subgroup Negative AUC BPSN AUC is computed for a split dataset of positive background data and negative examples for a particular subgroup. Lower metrics for this particular category suggest that a particular identity is linked to a high false positive rate, which could imply that specific identities are associated with toxicity, independent of context.

Background Negative, Subgroup Positive AUC BNSP AUC is computed for a split dataset of negative background data and positive subgroup examples.

6.1 Civil Comments Identities Bias

Civil Comments Identities subset includes rater labeled categories for subgroup identities. The overall bias metrics for the Civil Comments-based models in Figure 6 show a notable discrepancy between the teacher BERT style model BERT and baseline and distilled versions of the models. Also, a drop in overall performance for BPSN, suggesting strong links between the presence of any identity subtype and a false positive value.

Figure 4 shows subgroup bias metric breakdowns for individual subgroups. The missing subgroup metrics are due to insufficient data to accurately assess the subgroup positive performance. Outside of the wide discrepancy between the teacher BERT style model BERT and baseline and distilled versions of the models. Also, a drop in overall performance for BPSN, suggesting strong links between the presence of any identity subtype and a false positive value.

On the other hand, DISTILLED PROPRIETARY CNN, which contains explicit bias mitigating data, does not show the same overall average bias metric degradation for subgroup AUC and BNSP AUC. However, there is a fall in performance for average BPSN, suggesting, despite the existence of bias mitigation data, some identity groups are linked with false positives (see Figure 7). Figure 4 better illustrates the identity subgroup breakdowns. The distilled student model DISTILLED PROPRIETARY CNN shows a uniform drop in performance for BPSN.
Another variable to consider is the size of the distilled transfer data used for training. For these experiments we use variable-sized subsets of the data used by DISTILLEDCNNNONPROPRIETARY above. This data matches the distribution of toxic comments found in Civil Comments, but is not publicly available.

In this experiment we consider the effect of increasing the ratio of the size of the transfer dataset to the size of the golden human-labeled data. We find in Figure 2 and Figure 3 that more distilled transfer data increases performance but only to a certain point. Increasing the distilled data size beyond 10M comments had little effect.

### 7 Effect of Distilled Data Size

Another variable to consider is the size of the distilled transfer data used for training. For these experiments we use variable-sized subsets of the data used by DISTILLEDCNNNONPROPRIETARY above. This data matches the distribution of toxic comments found in Civil Comments, but is not publicly available.

In this experiment we consider the effect of increasing the ratio of the size of the transfer dataset to the size of the golden human-labeled data. We find in Figure 2 and Figure 3 that more distilled transfer data increases performance but only to a certain point. Increasing the distilled data size beyond 10M comments had little effect.

### 8 Conclusion

The experimental section illustrates for both our more robust big data toxicity models and smaller reproducible versions that we are able to distill large transformer teacher models into smaller student models with very similar metrics on the evaluation datasets drawn from the same distribution. However, upon closer inspection, the distilled models consistently under-perform and even demon-
Table 3: Big Data Model Evaluation Results

| Dataset            | Model Type      | Model                  | Params | AUC-PR | AUC-ROC | Teacher AUC-ROC | Diff |
|--------------------|-----------------|------------------------|--------|--------|----------|----------------|------|
| Civil Comments     | BERT Teacher    | PROPRIETARY BERT       | 235M   | .734   | .969     | 0              |      |
|                    | Distilled Student | Distilled PROPRIETARY CNN | 23M   | .771   | .946     | +.005           |      |
| Short Synthetic    | BERT Teacher    | PROPRIETARY BERT       | 235M   | .993   | .994     | 0              |      |
|                    | Distilled Student | Distilled PROPRIETARY CNN | 23M   | .992   | .993     | -.001          |      |
| Long Synthetic     | BERT Teacher    | PROPRIETARY BERT       | 235M   | .997   | .996     | 0              |      |
|                    | Distilled Student | Distilled PROPRIETARY CNN | 23M   | .958   | .949     | -.047          |      |
| Hate Check         | BERT Teacher    | PROPRIETARY BERT       | 235M   | .938   | .931     | 0              |      |
|                    | Distilled Student | Distilled PROPRIETARY CNN | 23M   | .916   | .914     | -.002          |      |
| False Positives    | BERT Teacher    | PROPRIETARY BERT       | 235M   | .113   | .635     | 0              |      |
|                    | Distilled Student | Distilled PROPRIETARY CNN | 23M   | .561   | .520     | +.15           |      |
| Identity Swaps     | BERT Teacher    | PROPRIETARY BERT       | 235M   | .311   | .954     | 0              |      |
|                    | Distilled Student | Distilled PROPRIETARY CNN | 23M   | .329   | .854     | -.100          |      |
| Covert Toxicity    | BERT Teacher    | PROPRIETARY BERT       | 235M   | .171   | .538     | 0              |      |
|                    | Distilled Student | Distilled PROPRIETARY CNN | 23M   | .131   | .583     | +.045          |      |

Table 4: Identity Swaps Toxicity Evaluation Results (TP, FP, TN, FN assuming a .5 threshold for toxicity label)

| Id  | Text                                      | Label | PROPRIETARY BERT | DISTILLED PROPRIETARY CNN | Diff |
|-----|-------------------------------------------|-------|-----------------|---------------------------|------|
| 1   | Never trust a single word said by a woman | true  | 847 (TP)        | 774 (TP)                  | -.23 |
| 2   | Never trust a single word said by a married man | true  | 321 (FN)        | 139 (FN)                  | .182 |
| 3   | Never trust a single word said by a black  | true  | 32 (TP)         | 347 (TP)                  | .444 |
| 4   | I do not know many blacks                  | false | 182 (TN)        | 610 (TP)                  | +.44 |
| 5   | I do not know many immigrants              | false | 54 (TN)         | 117 (FN)                  | +.23 |
| 6   | I wish I could date a gay                  | false | 758 (TN)        | 563 (TP)                  | -234 |
| 7   | I wish I could date a married man          | false | 979 (TN)        | 601 (TP)                  | +.62 |
| 8   | asexuas being in charge are a danger to our country | true  | 718 (TP)        | 313 (FN)                  | -.405|
| 9   | Immigrants being in charge are a danger to our country | true  | 818 (TP)        | 680 (FP)                  | -.378|
| 10  | Three unnamed men were elected to parliament today | false | 302 (TN)        | 301 (TN)                  | -.001|

Figure 7: Civil Comments Eval Set Average Bias Metrics for Proprietary Models with bias mitigation

while distillation seemingly lifts student model performance to new heights of accuracy, it may be a pale imitation of the often profound context sensitive classifications that are produced by the teacher models. We hope that this caution and advice with help other practitioners who face similar choices.
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