When Chosen Wisely, More Data Is What You Need: A Universal Sample-Efficient Strategy For Data Augmentation

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Abstract

Data Augmentation (DA) is known to improve the generalizability of deep neural networks. Most existing DA techniques naively add a certain number of augmented samples without considering the quality and the added computational cost of these samples. To tackle this problem, a common strategy, adopted by several state-of-the-art DA methods, is to adaptively generate or re-weight augmented samples with respect to the task objective during training. However, these adaptive DA methods: (1) are computationally expensive and not sample-efficient, and (2) are designed merely for a specific setting. In this work, we present a universal DA technique, called Glitter, to overcome both issues. Glitter can be plugged into any DA method, making training sample-efficient without sacrificing performance. From a pre-generated pool of augmented samples, Glitter adaptively selects a subset of worst-case samples with maximal loss, analogous to adversarial DA. Without altering the training strategy, the task objective can be optimized on the selected subset. Our thorough experiments on the GLUE benchmark, SQuAD, and HellaSwag in three widely used training setups including consistency training, self-distillation and knowledge distillation reveal that Glitter is substantially faster to train and achieves a competitive performance, compared to strong baselines.

1 Introduction

The undeniable importance of data in deep learning (Sambasivan et al., 2021; Rogers, 2021) and the costly process of data annotation has propelled researchers into leveraging Data Augmentation (DA) in a broad range of applications from computer vision (Cubuk et al., 2019; Wang et al., 2020) to natural language processing (NLP) including machine translation (Sennrich et al., 2016; Shen et al., 2020), language understanding (Shen et al., 2020; Qu et al., 2021; Du et al., 2021; Kamalloo et al., 2021), and question answering (Alberti et al., 2019; Longpre et al., 2019; Shakeri et al., 2020). DA is shown to be effective in improving generalization of deep neural networks (DeVries and Taylor, 2017; Xie et al., 2020) and in increasing the number of training samples especially in low resource data regimes (Sennrich et al., 2016; Zhang et al., 2018). Nonetheless, in NLP, the discrete nature of text poses additional complexity to DA as generating semantically viable text from another text is challenging (Feng et al., 2021).

DA methods can be broadly categorized into task-aware and task-agnostic methods. Task-agnostic DA methods essentially generate augmented text regardless of the task at hand and often do not warrant additional training or fine-tuning. They can be based on some hand-crafted heuristics (Zhang et al., 2015; Wei and Zou, 2019), back-translation (Sennrich et al., 2016; Edunov et al., 2018), or token replacement from a pre-trained language model (Kobayashi, 2018; Wu et al., 2019; Ng et al., 2020). Even though deploying task-agnostic methods is straightforward, these methods do not take into account any task-specific information, and thus, their performance is usually limited. On the other hand, task-aware DA methods are capable of generating augmented samples, conditioned on the downstream task objective (Hu et al., 2019; Xie et al., 2020; Rashid et al., 2021). These methods adapt augmented examples specifically for a task in that they construct augmented examples, sometimes partly, during training. Despite their advantages, they often incur additional training costs, resulting in a prohibitively slow and a computationally expensive training.

In general, the central problems surrounding DA techniques in NLP can be summarized as follows:
First, DA methods are mostly not sample-efficient in that they add arbitrary number of augmented samples to the training data and naively incorporate all of them into training without investigating how many of augmented samples are actually needed. Second, although more effective, task-aware methods are notoriously time-consuming to train. This is especially problematic in large-scale datasets such as SQuAD (Rajpurkar et al., 2016) and MNLI (Williams et al., 2018). Third, most DA methods are not universal as they work solely with a particular setup—e.g., training a single-network (Xie et al., 2020), or training in teacher-student settings (Rashid et al., 2021). Overall, the importance of both sample efficiency and training efficiency for DA has been often overlooked.

Motivated by the above problems, in this work, we introduce a universal DA method, Glitter, which can be plugged into any DA method to make them sample-efficient, and task-aware without sacrificing performance. Specifically, given a pool of augmented samples that are generated offline, our proposed method follows a minimax approach (Farnia and Tse, 2016) to select a small subset with maximal expected loss during training. Without any further adjustments to the training algorithm, the task objective can be optimized for this selected subset.

Our key contributions in this paper can be summarized as follows:

1. Glitter is a universal method which can be effortlessly applied to any DA method to enforce sample efficiency while maintaining (or even boosting) their performance.

2. We devise strategies to adapt Glitter for a variety of widely used training setups including single-network, consistency training, self-distillation and knowledge distillation.

3. Through our empirical evaluations, we show that Glitter achieves superior performance over state-of-the-art DA methods on GLUE, SQuAD, and HellaSwag, while significantly speeding up the training.

2 Related Work

2.1 Task-agnostic DA in NLP

Contextual augmentation techniques (Kobayashi, 2018; Wu et al., 2019) use pre-trained language models for DA. Kobayashi (2018) propose bidirectional LSTM language models for word substitution conditioned on the label of their input text. SSMBA (Ng et al., 2020) and TinyBERT (Jiao et al., 2020) perturb the input by masking some of the tokens, and then, sample tokens from a BERT model to replace the masked tokens and generate augmented samples. Back-Translation (Sennrich et al., 2016) augments data using two consecutive translation models: the first model to translate the input into an arbitrary target language; then, a second model to translate the result back into its original language. Mixed-up (Guo et al., 2019) generates augmented samples based on interpolating word embedding and sentence embedding vectors. Shen et al. (2020) introduce a set of cut-off techniques that zero out contiguous spans of the embedding matrix at token level, feature level and span level. EDA (Wei and Zou, 2019) consists of simple word-level operations including synonym replacement, random deleting, random insertion and random swapping.

2.2 Task-aware DA in NLP

One approach to leverage task-specific information is to assign different weights to augmented samples based on their individual impacts on the model (Yi et al., 2021). Although effective, the re-weighting mechanism largely ignores sample efficiency. Wu et al. (2019) introduce a mask-and-reconstruct approach, namely c-BERT, that fine-tune a pre-trained BERT model to predict label-compatible tokens. CoDA (Qu et al., 2021) combines various label-preserving transformations with adversarial training jointly with a contrastive regularization objective. Unsupervised DA (UDA; Xie et al. 2020) uses off-the-shelf DA methods and adds an auxiliary consistency loss to the training objective. However, UDA is not sample-efficient and it is designed only for a single-network setup; how to deploy it in other training scenarios such as knowledge distillation is not clear. Hu et al. (2019) propose a reinforcement learning-based technique where the reward function is defined based on whether generated augmented samples are label-preserving or not.

2.3 DA for KD

KD (Buciluǎ et al., 2006; Hinton et al., 2015), initially proposed as a model compression technique, aims at transferring the knowledge of an already trained model, called teacher, to a smaller or a
same-size student model. Several studies found that DA can significantly boost KD’s performance in NLP. TinyBERT (Jiao et al., 2020) uses a task-agnostic DA technique for its task-specific fine-tuning. Kamalloo et al. (2021) and Rashid et al. (2021) showed that DA can also be tailored for KD. In particular, MATE-KD (Rashid et al., 2021) tunes a separate masked language model in order to generate augmented samples with maximum divergence. Kamalloo et al. (2021) and Du et al. (2021) employ kNN retrieval to fetch augmented samples from a massive sentence bank.

Glitter differs from previous work in that it simultaneously focuses on sample efficiency, and universality such that it can be freely used in any training setting.

3 Methodology

In this section, we introduce our task-aware DA method, Glitter, that aims at using an efficient number of augmented samples without sacrificing performance. Our proposed strategy is agnostic to DA methods; it can be seamlessly plugged into any DA method with any training setting to enforce sample efficiency.

Existing learning-based DA methods train a separate DA model and adapt its output for a particular objective function that is entirely task-dependent:

$$
\phi^{*} \leftarrow \min_{\phi} \ell_{DA}(M(\Omega(x; \phi)); \theta) \\
x^{*} = \Omega(x; \phi^{*})
$$

(1)

where $\ell_{DA}()$ is a loss function, geared towards the objective of the task, $\Omega(; \phi)$ is the DA model with trainable parameters $\phi$, and $M(\cdot; \theta)$ refers to the original model, parameterized by $\theta$.

In contrast to learning-based DA, we propose to generate many augmented candidates using any arbitrary DA method prior training, and adaptively select most suitable candidates during training. This procedure does not introduce additional trainable parameters into training, and more importantly, is capable of automatically ignoring unnecessary augmented examples. Let $(x_i, y_i)_{i=1}^{N} \in \{(X, Y)\}$ represent training data such that a pair $x_i \in X$ and $y_i \in Y$ are an input example and its corresponding label. Suppose a pool of $K$ augmented examples, $X′(i) = \{x′_j(i)\}_{j=1}^{K}$, are sampled from some DA model for each training example $(x_i, y_i) \in (X, Y)$. Note that Glitter imposes no restrictions on how to augment training data; augmented samples can be generated via a single or even multiple DA models.

Sample Selection. Given a pool of augmented samples, our approach is to adaptively select the best candidates according to particular defined criteria. Inspired by the minimax approach (Farnia and Tse, 2016; Volpi et al., 2018), our selection mechanism is based on finding top-$k_1$ (out of $K$) worst-case augmented samples from the $X′$ set. Minimizing the main model loss function on these worst-case augmented samples will help improving generalization of the model (Volpi et al., 2018).

In order to rank augmented samples, we evaluate $X′(i)$ based on a distance function with respect to the corresponding original training sample, $x_i$, within the model’s latent space:

$$
X′_k(i) \leftarrow \text{top}_{k_1}\left(\ell_{\text{eval}}(M(x_i; \theta), M(X′(i); \theta))\right) \\
X′_k(i) = \{x′_j(i)\}_{j=1}^{k_1} \subset X′(i)
$$

(2)

where $\text{top}_{k_1}()$ denotes returns top-$k_1$ indices based on the scores returned by $\ell_{\text{eval}}$. $X′_k(i)$ is the set of $k_1$ selected augmented samples for $x_i$; $\ell_{\text{eval}}()$ is the evaluation loss which is determined via the task objective.

Updating the Model Parameters. After obtaining the top-$k_1$ augmented samples, we group them with the original training samples, $\{x_i \cup X′_k(i)\}$, and subsequently, update the model parameters only based on this selected set of augmented samples on the original loss:

$$
\mathcal{L}(\theta) = \sum_{i=1}^{N} \ell_{\text{task}}(M(x_i; \theta), M(X′_k(i); \theta), y_i) \\
\theta_t \leftarrow \theta_{t-1} - \lambda \nabla_{\theta}(\mathcal{L}(\theta))|_{\theta_{t-1}}
$$

(3)

where $N$ is the number of training samples, $\lambda$ is the learning rate, and $\ell_{\text{task}}()$ is the final task loss—e.g., cross entropy (ce) for classification—that is computed over both original data and selected augmented data. In the remainder of this section, we discuss how Glitter can be applied to popular training settings including general DA for single networks, and DA for teacher-student (KD) setups. Note that Glitter is not restricted to these settings and may be adapted for other settings such as DAIR (Huang et al., 2022).

3.1 General DA for Single Networks

We consider three potential setups for the single network scenario: (1) General single network, (2)
Self-distillation, and (3) Consistency training.

**General Single Network.** In this setup, augmented samples are exploited in a semi-supervised manner where we can evaluate them based on the divergence of their predicted output $M(x'_k(i); \theta) = p(y|x'_k(i); \theta)$ from the ground-truth label or the prediction of the original corresponding training sample $M(x_i; \theta) = p(y|x_i; \theta)$ using the cross entropy loss, $\ell_{ce}$:

$$\ell_{eval} = \ell_{ce}(y_i, M(x'_k(i); \theta))$$

or

$$\ell_{eval} = \ell_{ce}(M(x_i; \theta), M(x'_k(i); \theta)).$$

The cross entropy criterion is not the only option here. Other choices for $\ell_{eval}$ include (but not limited to) focal loss (Lin et al., 2017), and tilted loss (Li et al., 2021).

For the final task loss, $\ell_{task}$ we can deploy a standard cross entropy loss over both training samples and their corresponding selected augmented samples:

$$\ell_{task} = \ell_{ce}(y_i, M(x_i; \theta)) + \frac{1}{k_1} \sum_{x \in X'_{k^*}} \ell_{ce}(y_i, M(x; \theta)).$$

**Consistency Training (CT; Xie et al. 2020).** In this configuration, we can employ the same $\ell_{eval}$ introduced in Eq. (4). As a result, our method naturally selects top-$k_1$ most inconsistent augmented samples for each training sample. Then, the network is optimized to make predictions for input augmented samples that are consistent with predictions of their corresponding original training samples:

$$\ell_{task} = \ell_{ce}(y_i, M(x_i; \theta)) + \frac{1}{k_1} \sum_{x \in X'_{k^*}} \ell_{ce}(y_i, M(x; \theta)).$$

As stated by Xie et al. (2020), the second term in Eq. (6) leverages the previous prediction of the network for each training example.

**Self-Distillation (Self-KD).** In Self-KD, we first train a model, and then, use it ($M(\theta^*)$) as a teacher to train an identical model but initialized from scratch using KD (Furlanello et al., 2018). How to adjust $\ell_{eval}$ and $\ell_{task}$ is detailed in §3.2.

### 3.2 DA for Teacher-Student (KD)

In this setup, we have a teacher model, $T(\psi^*)$ with parameters $\psi$ that is already trained on the training data, along with a student model, $M(\theta)$, which we aim to train. The selection criterion for augmented samples is to maximize divergence between the teacher and the student:

$$\ell_{eval} = KL(T(x'_k(i); \psi^*), M(x'_k(i); \theta))$$

where $\ell_{KL}$ refers to the KL divergence. After selecting the maximum divergence augmented samples, then we calculate the KD loss as following:

$$\ell_{task} = \alpha \ell_{ce}(y_i, M(x_i; \theta)) + (1 - \alpha) \times \frac{1}{k_1 + 1} \sum_{x \in \{x_i \cup X'_{k^*}\}} \ell_{KL}(T(x; \psi^*), M(x; \theta))$$

where $\alpha$ is a hyperparameter.
4 Experiments

4.1 Setup

To incorporate unlabelled augmented data into training, we adopt CT (Xie et al., 2020) and KD (Hinton et al., 2015). To this end, we conduct experiments under two settings:

**Standalone** where we train a single model on the augmented data. In this setting, we seek to answer two questions: (1) How much is DA capable of improving the model generalization? (2) Does sample efficiency of Glitter hurt performance? For this purpose, we fine-tune RoBERTa\textsubscript{base} (Liu et al., 2019) using CT and Self-KD on augmented data.

**Distilled** where we distill DistilRoBERTa (Sanh et al., 2019) (student) from RoBERTa\textsubscript{large} (Liu et al., 2019) (teacher) using the augmented data. Note that the teacher is already trained on the original data and DA comes into play only during distilling the student model. Our goal here is to investigate whether DA is an effective means in knowledge transfer to curb the capacity gap (Cho and Hariharan, 2019) between a large model and a small one.

In both settings, we take the best performing model on the development set and evaluate it on the test set (depicted by Test). Additionally, for the standalone model setting, we also report results on the development set when models are trained only for 5 epochs (depicted by Dev), similar to CoDA (Qu et al., 2021), to make a comparison with baselines. Our Dev results are an average of 10 runs with different seeds. The implementation details and hyperparameters are provided in §A.

4.1.1 DA Methods

We leverage three widely used textual augmentation methods:

1. **EDA** (Wei and Zou, 2019)\(^3\): We randomly replace 5% of the tokens with their synonyms and randomly delete up to 10%.

2. **Back-Translation** (BT; Sennrich et al. 2016): We use fairseq (Ott et al., 2019) to translate sentences into German and then back into English. We do nucleus sampling (Holtzman et al., 2020) with \(p = 0.9\) for both translations. We find that \(p = 0.6\) works better on sentiment classification.

3. **Mask-and-Reconstruct** (MR; Ng et al. 2020): We randomly mask 15% of the tokens and construct a new sentence by sampling from a pretrained BERT\textsubscript{large} for masked tokens. We adopt top-\(k\) sampling with \(k = 20\) to select new tokens. For MNLI, we obtain better results with top-10 sampling.

For each augmentation method, we generate 12 augmented examples per training instance for all datasets, except for large datasets—i.e., MNLI, QQP, and SQuAD—where the number of augmented examples are 8 per train example.

4.1.2 Baselines

Because the two environments—i.e., standalone and distilled—are different in nature, we compare Glitter with different baselines for each environment. For both, Vanilla-DA that takes all augmented data into account without reservation is the first baseline.

The baselines for the standalone setting are: CoDA (Qu et al., 2021), MMEL (Yi et al., 2021), and HiddenCut (Chen et al., 2021). And for distilled, we consider MATE-KD (Rashid et al., 2021).

4.2 GLUE

The GLUE benchmark (Wang et al., 2019) is a well-known suite of nine\(^4\) tasks that aim at evaluating natural language understanding models. We present test results in the distilled mode in Table 1. Glitter consistently outperforms Vanilla-DA, while it is faster to train. Specifically, Glitter achieves parity with Vanilla-DA for EDA in terms of the overall average score, while scoring +0.2% and +0.4% higher for BT and MR, respectively. We observe that only in few cases Vanilla-DA negligibly outperforms Glitter—e.g., on MRPC, and STS-B for BT. Nonetheless, Glitter \(8x/1x\) trains 50% faster than Vanilla-DA \(8x\) on average, and 30% faster for \(8x/2x\). Also, Glitter surpasses MATE-KD by +0.2% in the overall score. Unlike Glitter, MATE-KD introduces additional parameters to the model during training and it trains drastically slower because it generates augmented examples on-the-fly. Moreover, Table 1 illustrates that MR yields the best test results across the three DA methods except for SST where BT leads to better results. Based on this observation, we report results on MR augmented

\(^3\)https://github.com/makcedward/nlpaug

\(^4\)We excluded WNLI since our DA methods are not designed for this task.
Table 1: Test results of the distilled experiment on GLUE. (♣) denotes results are taken verbatim from: BERT_{Large} (Devlin et al., 2019), and MATE-KD (Rashid et al., 2021). **Bold** and **underlined** numbers indicate the best and the second best results across the DA methods.

| Method       | CoLA | SST | MRPC | STS-B | QQP  | MNLI-m/mm | QNLI | RTE | Avg. |
|--------------|------|-----|------|-------|------|-----------|------|-----|------|
|              | Mcc  | Acc | Acc/F | P/S   | Acc  | Acc/F     | Acc  | Acc |      |
| RoBERTa (teacher) | 63.8 | 96.8 | 90.6  | 92.4  | 81.5 | 90.3/89.8 | 94.8 | 88.3 | 87.3 |
| BERT_{Large}  | 60.5 | 94.9 | 87.4  | 87.1  | 80.7 | 86.7/85.9 | 92.7 | 70.1 | 82.5 |
| DistilRoB     | 55.2 | 93.9 | 85.9  | 86.0  | 80.3 | 84.0/83.1 | 90.6 | 73.6 | 81.1 |
| KD            | 54.9 | 94.0 | 86.8  | 87.3  | 80.5 | 85.1/83.7 | 91.9 | 73.5 | 81.7 |
| Task-Aware DA |      |     |       |       |      |           |      |     |      |
| MATE-KD       | 56.0 | 94.9 | **90.2** | 88.0  | **81.2** | 85.5/84.8 | **92.1** | **75.0** | **82.8** |
| Vanilla-DA (8x) | 55.5 | 94.8 | 87.6  | 86.1  | 80.7 | 85.3/84.7 | 92.0 | 72.8 | 81.8 |
| Glitter       | 54.5 | 95.1 | 87.5  | 86.5  | 80.4 | 85.4/84.8 | 92.1 | 73.2 | 81.8 |
|               | 8x/2x | 8x/1x | 8x/2x  | 8x/2x  | 8x/2x | 8x/2x     | 8x/2x | 8x/2x | 8x/2x |
| Back-Translation |      |     |       |       |      |           |      |     |      |
| Vanilla-DA (8x) | 53.4 | 95.1 | 88.5  | 87.5  | 80.9 | 85.9/85.9 | **92.2** | 73.5 | 82.1 |
| Glitter       | 54.9 | 95.1 | 88.4  | 87.3  | 80.9 | 86.2/85.3 | **92.2** | 73.7 | 82.3 |
|               | 8x/2x | 8x/1x | 8x/1x  | 8x/2x  | 8x/2x | 8x/2x     | 8x/2x | 8x/2x | 8x/2x |
| Mask-and-reconstruct |     |     |       |       |      |           |      |     |      |
| Vanilla-DA (8x) | 58.8 | 94.5 | 88.7  | 87.0  | 80.9 | 85.8/84.9 | 91.8 | 74.0 | 82.6 |
| Glitter       | 59.2 | 95.1 | 89.2  | 87.6  | 81.0 | **86.6/84.8** | **92.4** | 74.1 | **83.0** |
|               | 8x/1x | 8x/1x | 8x/2x  | 8x/1x  | 8x/2x | 8x/2x     | 8x/2x | 8x/2x | 8x/2x |

Table 2: Test result of the standalone experiments on GLUE using RoBERTa_{base}.

| Method       | CoLA | SST | MRPC | STS-B | QQP  | MNLI-m/mm | QNLI | RTE | Avg. |
|--------------|------|-----|------|-------|------|-----------|------|-----|------|
|              | Mcc  | Acc | Acc/F | P/S   | Acc  | Acc/F     | Acc  | Acc |      |
| RoBERTa      | 61.9 | 95.4 | 88.6  | 89.3  | 80.1 | 87.6      | 91.0 | 81.6 | 84.7 |
| Self-KD      | 61.7 | 95.7 | 89.0  | 89.0  | 80.8 | **88.3**  | 93.0 | 81.7 | 84.9 |
| + Vanilla-DA | 61.5 | **96.1** | 88.9  | **89.7** | 81.0 | 88.0      | 92.9 | 81.1 | 84.9 |
|               | 8x   | 8x   | 8x    | 8x    | 8x   | **8x**    | **8x** | **8x** | **12x** |
| + Glitter    | 62.5 | 96.0 | **89.8** | 89.5  | **81.1** | 88.1      | **93.5** | **82.3** | **85.4** |
|               | 8x/1x | 8x/2x | 8x/2x  | 8x/2x  | 8x/2x | 8x/2x     | 8x/2x | 12x/1x |      |
| CT + Vanilla-DA | 59.4 | 95.6 | 89.0  | 85.8  | 80.3 | 82.5      | 92.0 | 80.2 | 83.1 |
|               | 8x   | 8x   | 8x    | 10x   | 8x   | **8x**    | **8x** | **10x** |      |
| CT + Glitter | 62.7 | 95.8 | 89.2  | 87.9  | 80.9 | 84.1      | 92.9 | 81.8 | 84.4 |
|               | 8x/1x | 8x/1x | 8x/1x  | 10x/1x | 8x/2x | 8x/2x     | 8x/2x | 10x/1x |      |

For the standalone mode, Tables 2 and 3 present the results on test and dev, respectively. Similar to distilled, Glitter outperforms Vanilla-DA by +0.5% for both self-KD and CT. Self-KD yields better results than CT on all GLUE tasks except CoLA. CT falls short on most GLUE tasks, compared to no DA results—i.e., top-2 rows in Table 2. This is why, we only evaluated Glitter with self-KD on the dev data. Glitter achieves superior performance gains, compared to all three baselines on all datasets except QNLI. The key advantage of Glitter is that the training procedure remains intact.

### 4.2.1 Out-of-Domain Generalization

We also evaluate Glitter on OOD datasets. To this end, we test our models, already trained on GLUE tasks, on OOD datasets whose data distribution differs from the original data. In particular, here are our selected OOD datasets:

- **SST**: IMDb (Maas et al., 2011), IMDb-Cont. (Gardner et al., 2020), and IMDb-CAD (Kaushik et al., 2020), as done in Chen et al. (2021). Although both SST and IMDb datasets are collected on movie reviews, IMDb reviews tend to be substantially longer than SST sentences.

- **STS-B**: SICK (Marelli et al., 2014), a semantic relatedness dataset, created from image and video captions. SICK and STS-B are collected on roughly identical domains, but from different sources.

- **QQP**: PAWSQQP (Zhang et al., 2019), analogous to Chen et al. (2021), and MQP (McCreery et al., 2020), a medical question similarity dataset.
### Table 3: Dev results of the standalone experiment on GLUE using RoBERTa

| Method          | SST Acc | MRPC F1 | MNLI-m Acc | QNLI Acc | RTE Acc | IMDb-Con. Acc | A-NLI Acc | HANS Acc |
|-----------------|---------|---------|------------|----------|---------|---------------|-----------|----------|
| RoB             | 94.8    | 90.2    | 87.6       | 92.8     | 78.7    | -             | -         | -        |
| CoDA            | 95.3    | 91.7    | 88.1       | 93.6     | 82.0    | -             | -         | -        |
| HiddenCut       | 95.8    | 92.0    | 88.2       | 93.7     | 83.4    | 87.8          | 32.8      | 71.2     |
| MMEL            | 94.6±0.8| 91.9±0.4| 88.1±0.1   | 93.2±0.1 | 85.3±1.0| 90.5±0.7      | 31.4±0.6  | 74.5±0.6 |
| RoB†            | 94.3±0.1| 91.6±0.5| 87.7±0.1   | 92.8±0.2 | 84.5±0.8| 90.0±0.4      | 30.8±0.9  | 73.6±0.7 |
| Self-KD         | 94.3±0.2| 91.5±0.3| 87.9±0.1   | 92.9±0.2 | 84.0±0.6| 90.3±0.5      | 30.9±0.4  | 73.5±0.7 |
| + Vanilla-DA    | 95.4±0.5| 92.0±0.3| 88.2±0.1   | 93.4±0.1 | 84.4±0.7| 90.2±0.4      | 31.3±0.5  | 73.9±0.4 |
| + Glitter       | 95.7±0.2| 92.2±0.5| 88.2±0.1   | 93.4±0.1 | 85.6±0.7| 90.6±0.2      | 31.8±0.4  | 74.6±0.3 |

†: results verbatim from: RoB and CoDA (Qu et al., 2021), and HiddenCut (Chen et al., 2021). (†) indicates the results are obtained from our implementation of MMEL (Yi et al., 2021).

- MNLI: SciTail (Khot et al., 2018), collected from school-level science questions, and similar to Chen et al. (2021), A-NLI (Nie et al., 2020), and HANS (McCoy et al., 2019).

- RTE: HANS (McCoy et al., 2019).

Table 10 in §B.1 showcases the OOD results for the distilled mode. Glitter outperforms Vanilla-DA in all four domains.

### Table 4: Dev results of the distilled experiment on two downstream tasks

| Method     | SQuAD  | HellaSwag |
|------------|--------|-----------|
|            | EM/F1  |           |
| RoB_Large  | 88.9/94.6 | 85.2     |
| DistilRoB  | 80.9/87.9 | 42.9     |
| KD         | 81.1/88.2 | 42.5     |
| + Vanilla-DA (8x) | 81.8/89.1 | 41.8     |
| + Glitter  | 83.6/90.3 | 44.1     |

Table 4: Dev results of the distilled experiment on two downstream tasks.

results demonstrated in Table 4, Glitter comfortably surpasses Vanilla-DA by a +2.3% margin.

### 4.4 SQuAD

SQuAD (Rajpurkar et al., 2016) is a crowd-sourced reading comprehension benchmark that consists of more than 100K questions, derived from Wikipedia passages. The task objective is to extract an answer span from a given question/passage pair. We augment questions in SQuAD v1.1 using only BT to ensure that the answer can still be found in the given passage for the augmented questions. Analogous to HellaSwag, we report our results only in the distilled mode. As shown in Table 4, Glitter outperforms Vanilla-DA by +1.8% in exact-match accuracy on the development set.

We also evaluate our trained models under distribution shift by testing them on QA datasets from four different domains: Wikipedia, New York Times, Reddit, and Amazon product reviews (Miller et al., 2020). The OOD results are presented in Table 5. Glitter is consistently superior to Vanilla-DA in all four domains.

### 5 Ablation Study and Discussion

In this section, we aim to answer the following questions:
Method Wiki NYT Reddit Amzn
RoB 84.4 85.9 76.6 74.4
DistilRoB 76.6 78.1 66.2 62.9
KD 77.3 79.0 65.9 63.3
+ Vanilla-DA 79.3 80.7 68.1 64.7
+ Glitter β=0.7 95.8 92.8 93.4 85.9
β=0.9 95.0 92.5 93.5 85.2
LP 95.1 92.2 93.5 85.9
Glitter β=0.7 95.8 92.8 93.4 85.9
β=0.9 95.0 92.5 93.3 84.1
LP 95.1 92.2 93.5 85.9

Table 5: OOD results for models trained on SQuAD and tested on QA datasets from four different domains (Miller et al., 2020).

- How does training time of Glitter compare against Vanilla-DA?
- Instead of adaptively selecting augmented data during training, can we pre-process them to dispense with unnecessary examples prior to training?
- How many augmented examples are required for Glitter to work?
- Is our selection strategy based on sorting of $\ell_{\text{eval}}$ in Glitter important?

For this purpose, we conduct a detailed analysis on 4 GLUE tasks—i.e., SST, MRPC, QNLI, and RTE. We trained models based on Vanilla-DA and Glitter using Self-KD and tested them on the development set (the dev setting).

Runtime Analysis. Throughout our experiments in §4, we compare Glitter with Vanilla-DA when number of augmentations are similar for both methods—i.e., 8x. A natural question is: how would both DA methods behave with fewer augmented data? To this end, we vary augmentation size from 1x to 8x and train different Vanilla-DA models on each augmented dataset. We measure average the training time per epoch for all models. Figure 2 illustrates the dev accuracy as the training time increases. The training speed of Glitter 8x/2x is slightly faster than Vanilla-DA 6x on SST, MRPC, and QNLI and for Glitter 8x/1x, is faster than Vanilla-DA 4x on RTE. Glitter is superior of the two on all datasets.

Effect of Pre-processing Augmented Data. We conjecture that Glitter does not need any data engineering on augmented examples to obtain preferable performance gains. However, Vanilla-DA may require some pre-processing by weeding out potentially noisy data to become more effective. To investigate this, we exploit two pre-processing techniques: (1) Confidence-based filtering: Augmented examples for which the model’s confidence is below a minimum threshold $\beta$ are discarded, (2) Label-preserving augmentation (LP): Augmented examples for which the model predicts a different label than the original example are discarded. The results, reported in Table 6, show no meaningful performance gains by these pre-processing techniques. For Vanilla-DA, minimum confidence threshold of 0.7 performs slightly better as it brings minor improvements on MRPC (+0.3%) and QNLI (+0.1%), but is still lower than Glitter. On the other hand, applying these techniques slightly deteriorates the performance of Glitter in almost all cases. The only improvements are +0.1% on QNLI for LP and $\beta=0.7$.

Effect of Augmentation Size in Glitter. We explore how augmentation size affects the performance of Glitter. Throughout our experiments, we fix the augmentation size to 8x, but now, we reduce augmentation size $K$ to 6x and 4x, while retaining selection size $k_1$ as before—i.e., 1 for RTE, and 2 for the rest. Our results, shown in Table 7, reveal that when $K$ becomes close to $k_1$, Glitter’s performance declines. Nonetheless, for a sufficiently large augmentation, Glitter starts to shine. For SST, and MRPC, the magic number is 8x, whereas for QNLI, and RTE, Glitter performs best on 6x. Another parameter in Glitter is the selection size $k_1$. We find that for all tasks, the best value can be chosen from {1, 2} (2 by default). Using this method, tuning $k_1$ is straightforward and does not impose additional complexity to our method.

Effect of Selection Strategy in Glitter. In this section, our objective is to assess whether our proposed selection algorithm is crucial in Glitter. To
this end, we sample random augmented examples at each iteration, namely Glitter-Rnd, instead of selecting worst-case examples. As illustrated in Table 7 (the bottom two rows), the performance drops on all datasets—i.e., 0.2% on QNLI, and more than 1% on the rest, confirming the effectiveness of our selection algorithm.

6 Conclusion

In this work, we proposed a universal DA technique, namely Glitter, that can be freely applied to any DA technique to enforce sample efficiency without introducing additional parameters or changing the training procedure. We extensively evaluated Glitter on a broad range of NLU tasks and in various widely used settings including consistency training, self-distillation and knowledge distillation and demonstrated substantial efficiency gains without compromising effectiveness. Extending Glitter to auto-regressive models for machine translation and abstractive summarization is an interesting direction for future work.

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A Implementation Details

A.1 Fine-tuning details

We adopted the publicly available pre-trained RoBERTa (Liu et al., 2019) and DistilRoBERTa (Sanh et al., 2019)—using the Huggingface Transformers library (Wolf et al., 2020) and the Pytorch Lightning library⁵.

For the test settings, the model is evaluated on the development data once per epoch for small datasets and twice per epoch for large ones—i.e., SST-2, MNLI,QNLI, SQuAD, and HellaSwag. The best performing model is chosen for testing. Our learning rate schedule follows a linear decay scheduler with a warm-up, specified as a ratio of the total number of training steps. Maximum number of epochs is set to 20 for all tasks except SQuAD, following (Mosbach et al., 2021). For large datasets, we early stop with a patience of 10. The learning rate, and the batch size are tuned for each task separately. The details of hyperparameters are summarized in Table 9. We ran RoBERTa base experiments with the similar hyperparameters, but with these exceptions: On QNLI, learning rate, batch size, and weight decay are set to 3e-5, 64, and 0.1; warmup ratio is set to 0.06 on QQP.

For dev experiments, we follow CoDA (Qu et al., 2021) on the GLUE tasks. Specifically, we train the model for 5 epochs with a batch size of 32, learning rate 1e-5, warmup ratio 0.06, weight decay 0.1, and linear learning rate decay. For SQuAD, and HellaSwag, the hyperparameters are detailed in Table 8.

All experiments were conducted on two Nvidia Tesla V100 GPUs.

| Hyperparam.          | SQuAD | HellaSwag |
|----------------------|-------|-----------|
| Learning rate        | 1.5e-5| 1.5e-5    |
| Batch size           | 16    | 32        |
| Max length           | 512   | 512       |
| Max epochs           | 3     | 20        |
| Warmup ratio         | 0.06  | 0.06      |
| Grad. acc. steps     | 4     | 1         |
| Weight Decay         | 0.01  | 0.01      |
| temp. τ (for KD)     | 5.0   | 10.0      |

Table 8: Hyperparameters of DistilRoBERTa on two downstream tasks.

A.2 Knowledge distillation details

We implemented knowledge distillation by caching the teacher’s logits prior to training. We performed grid search to find the best softmax temperature $\tau$ from \{5.0, 10.0, 12.0, 20.0, 30.0\}. The value of $\tau$ used in our experiments are reported in Tables 8 and 9 for DistilRoBERTa and RoBERTa base; with the exception $\tau = 20.0$ on MRPC for RoBERTa base. Loss weight $\alpha$, in Eq. (8), is set to 0.5 for all tasks except CoLA in which $\alpha = 0.75$.

B OOD results

B.1 Distilled Mode

OOD results for models trained in the distilled mode are presented in Table 10.

B.2 Standalone Mode

Table 11 presents OOD results for models trained using test settings, and Table 12 (complementary to Table 3 in §4.2.1) presents OOD results for dev experiments.
| Hyperparam. | CoLA | SST | MRPC | STS-B | QQP | MNLI-m/mm | QNLI | RTE |
|------------|------|-----|------|-------|-----|-----------|------|-----|
| Learning rate | $10^{-5}$ | $10^{-5}$ | $10^{-5}$ | $10^{-5}$ | $10^{-5}$ | $10^{-5}$ | $10^{-5}$ | $10^{-5}$ |
| Batch size | 32 | 64 | 16 | 32 | 64 | 64 | 128 | 32 |
| Max length | 128 | 256 | 128 | 128 | 256 | 256 | 256 | 256 |
| Warmup ratio | 0.1 | 0.06 | 0.06 | 0.06 | 0.1 | 0.08/0.06 | 0.08 | 0.06 |
| Gradient acc. steps | 1 | 4 | 1 | 4 | 4 | 4 | 1 |
| Weight Decay | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.0/0.1 | 0.0 | 0.1 |
| Softmax temp. $\tau$ (for KD) | 30.0 | 20.0 | 12.0 | 12.0 | 20.0 | 12.0 | 12.0 | 12.0 |

Table 9: Hyperparameters of DistilRoBERTa on the GLUE benchmark. We used the same configuration for RoBERTa$_{base}$ albeit with a few exceptions marked by (*).

| Trained On -> Method | SST IMDb | SST IMDb-Con | SST IMDb-CAD | SICK | MRPQ | SciTail | MNLI | MNLI | RTE |
|----------------------|----------|--------------|-------------|------|------|---------|------|------|-----|
|                      | Acc      | Acc          | Acc         | P/S  | Acc/F1 | Acc     | Acc  | Acc  | Acc |
| RoB$_{base}$         | 93.7     | 92.0         | 94.0        | 84.3 | 71.6  | 43.6    | 82.0 | 45.9 | 81.8 |
| DistilRoB            | 90.2     | 87.6         | 92.5        | 79.6 | 67.3  | 36.3    | 74.8 | 27.8 | **71.3** |
| KD                   | 90.6     | 87.4         | 93.2        | 79.9 | 65.6  | 33.1    | 77.3 | 28.9 | 70.6 |
| EDA (Wei and Zou, 2019) |          |              |             |      |       |         |      |      |      |
| Vanilla-DA           | 91.8     | 87.2         | 92.9        | 80.0 | 59.9  | **38.0** | 75.8 | 27.3 | 66.6 |
| Glitter              | 91.2     | 87.1         | **94.0**    | 80.0 | 64.0  | 36.6    | 75.6 | 28.8 | 65.6 |
| Back-Translation     |          |              |             |      |       |         |      |      |      |
| Vanilla-DA           | 92.2     | 87.9         | 92.1        | 80.3 | **69.6** | 35.0    | 76.5 | 27.9 | 68.0 |
| Glitter              | **92.4** | 87.9         | 92.8        | **81.2** | 68.7  | 35.2    | 77.6 | **30.4** | 70.5 |
| Masked-and-reconstruct |          |              |             |      |       |         |      |      |      |
| Vanilla-DA           | 91.8     | **88.8**     | 92.9        | 80.4 | 68.5  | 33.7    | 77.4 | 28.5 | 69.3 |
| Glitter              | 92.0     | 88.0         | 92.5        | 80.7 | 68.8  | **78.2** | 29.9 | 70.9 |      |

Table 10: OOD results of models whose in-domain test results are reported in Table 1 for the distilled mode. **Bold** numbers indicate the best result across DistilRoB models.

| Trained On -> Method | SST IMDb | SST IMDb-Con | SST IMDb-CAD | SICK | MRPQ | PAWSQPP | SciTail | A-NLI | HANS |
|----------------------|----------|--------------|-------------|------|------|---------|---------|-------|------|
|                      | Acc      | Acc          | Acc         | P/S  | Acc/F1 | Acc     | Acc     | Acc   | Acc  |
| RoB$_{base}$         | 92.2     | 89.1         | 94.3        | 80.6 | 70.7  | 38.6    | 78.5    | 31.4  | 78.5 |
| Self-KD              | **92.6** | 89.1         | **95.0**    | 80.2 | 70.9  | 37.6    | **79.4** | 32.1  | 79.5 |
| + Vanilla-DA         | 91.8     | **88.8**     | 94.8        | 81.5 | 71.4  | 38.8    | 78.4    | 31.5  | 79.3 |
| + Glitter            | 92.0     | **89.6**     | 94.8        | **81.7** | **72.1** | **39.4** | 79.1    | **32.7** | 80.1 |
| CT + Vanilla-DA      | 90.6     | 88.1         | 92.1        | 76.6 | 70.6  | 38.3    | 76.6    | 30.3  | 78.4 |
| CT + Glitter         | 92.2     | 88.6         | 93.7        | 79.4 | 70.7  | 38.8    | 77.0    | 31.6  | **80.2** |

Table 11: OOD results of models whose in-domain test results are reported in Table 2 for the standalone experiment. **Bold** numbers indicate the best result.
| Trained On       | SST  | SST  | SST  | MNLI | MNLI | MNLI | RTE |
|------------------|------|------|------|------|------|------|-----|
| Method           | IMDb | IMDb-Con. | IMDb-CAD | SciTail | A-NLI | HANS | HANS |
| RoBBase          | 91.9 ± 0.3 | 90.0 ± 0.4 | 94.1 ± 0.4 | 80.1 ± 0.4 | 31.0 ± 0.6 | 73.7 ± 0.7 | 78.3 ± 0.4 |
| HiddenCut        | 87.8 | 90.4 | 94.5 ± 0.4 | 79.7 ± 0.3 | 31.4 ± 0.6 | 74.5 ± 0.6 | 78.3 ± 0.3 |
| MMEL             | 91.6 ± 0.1 | 90.5 ± 0.7 | 94.5 ± 0.4 | 79.9 ± 0.3 | 30.9 ± 0.4 | 73.5 ± 0.7 | 78.2 ± 0.4 |
| Self-KD          | 91.9 ± 0.3 | 90.3 ± 0.5 | 94.4 ± 0.4 | 79.3 ± 0.4 | 31.3 ± 0.5 | 73.9 ± 0.4 | 77.8 ± 0.3 |
| + Vanilla-DA     | 91.6 ± 0.4 | 90.2 ± 0.4 | 94.3 ± 0.3 | 79.3 ± 0.4 | 31.3 ± 0.4 | 74.3 ± 0.3 | 78.5 ± 0.4 |
| + Glitter        | 91.7 ± 0.2 | 90.6 ± 0.2 | 94.8 ± 0.2 | 79.4 ± 0.1 | 31.8 ± 0.4 | 74.6 ± 0.3 | 78.4 ± 0.2 |

Table 12: OOD results of models with dev settings in the standalone mode, same models whose results are reported in Table 3. (*) denotes results are taken verbatim from: HiddenCut (Chen et al., 2021). (†) indicates the results are obtained from our implementation of MMEL (Yi et al., 2021). **Bold** numbers indicate the best result.