Applicability of AUM on NLP datasets

Prachi Gupta **Varun Menon** **Arka Talukdar** **Monika Dagar**
New York University
{pg1647,vk2148,at4786,md4676}@nyu.edu

Abstract

The recent increase in dataset size has brought about significant advances in natural language understanding. These large datasets are usually collected through automation (search engines or web crawlers) or crowdsourcing which inherently introduces incorrectly labeled data. Training on these datasets leads to memorization and poor generalization. Thus, it is pertinent to develop techniques that help in the identification and isolation of mislabelled data. In this paper, we study the applicability of the Area Under the Margin (AUM) metric to identify and remove/rectify mislabelled examples in NLP datasets. We find that mislabelled samples can be filtered using the AUM metric in NLP datasets but it also removes a significant number of correctly labeled points and leads to the loss of a large amount of relevant language information. We provide empirical evidence that demonstrates that this is due to the nature of the data samples in NLP datasets. Our code is available at: https://github.com/mdagar6/AUM [1]

1 Introduction

Modern deep learning networks are becoming deeper and powerful, and have led to significant advances in Natural Language Processing (NLP) (Devlin et al., 2019), Computer Vision (He et al., 2015), and Speech Processing (Graves et al., 2013). However, these networks rely on large labeled datasets to be effective.

The creation of large labeled datasets has fueled the advances in NLP (Rajpurkar et al., 2016; Bowman et al., 2015). Abundant labeled data increases the likelihood of learning diverse phenomena, which in turn leads to models that generalize well (Linzen, 2020).

Curating expert annotated datasets is very time-consuming and costly (Malik and Bhardwaj, 2011) therefore large language datasets are usually collected through weakly supervised techniques like web crawling and crowd-sourcing or by hiring human annotators (Wang et al., 2019). Such methods inherently introduce label noise in the resulting data. Mislabelled training data is particularly problematic for deep neural networks with billions of parameters because they can over-fit on the mislabelled data and achieve zero training error even on randomly assigned labels (Zhang et al., 2016). Training models with noisy labels can also lead to misclassification on easy examples during test-time (Beigman and Beigman Klebanov, 2009).

It is prohibitively costly to manually inspect large datasets. Hence, the need arises to create an automated pipeline to analyze and clean datasets. Area Under the Margin (AUM) metric was designed to identify and eliminate noisy data. It can be used as a plug-and-play method within the training pipeline of any classification network with minimal overhead (Pleiss et al., 2020). AUM shows promising results in identifying mislabelled samples in image classification datasets.

Thus, in this paper, we investigate the applicability of the AUM metric on text classification datasets. We make the following contributions: (i) We show that the AUM metric has lower efficacy for filtering mislabelled data in NLP datasets than image datasets. (ii) We hypothesize that AUM does not work as expected in NLP datasets as it did in image datasets because of the intrinsic nature of the data samples. They have high intra-class and low inter-class feature similarity (Ho et al., 2021), which is usually not the case in NLP datasets. We show samples from NLP datasets to corroborate our hypothesis.

2 Related Work

Detecting mislabelled Instances. Pleiss et al. (2020) and Swayamdipta et al. (2020), both use model behavior on each sample over the training

[1] Repo is private; access invites have been sent to TAs and the Professor.

process, also known as training dynamics, to identify mislabelled instances in classification datasets but using different metrics. For each sample, Pleiss et al. (2020) finds the difference in logit value of the assigned class (gold label) and the highest other logit value among the non-assigned classes averaged over training epochs called the area under the margin (AUM) metric. They also introduce a fake class with samples having only mislabelled instances by definition to find a threshold AUM value. Samples with low AUM scores are likely to be mislabelled and the threshold AUM value is used to filter out such mislabelled instances. Swayamdipta et al. (2020) uses mean and standard deviation of the gold label probabilities over the training epochs, called confidence and variability scores, respectively, for each sample. They classify samples with low confidence and low variability as either mislabelled or "hard-to-learn" for the model.

Bhardwaj et al. (2010) uses statistical methods to find annotators whose annotations differ considerably from the remaining annotators and use manual inspection to decide the verdict for samples annotated by these annotators. Müller and Markert (2019) classifies training samples with the lowest gold label probabilities on a robust classifier as potentially mislabelled followed by their manual review for final decision. Zhang and Sugiyama (2021) detects samples with erroneous labels using an instance-dependent noise model along with instance-based embedding to capture instance-specific label corruption.

Learning in the Presence of Noisy Labels. Several efforts have been made to account for noise in the data and prevent the model from memorizing wrong examples without actually identifying and removing such examples from the training set. Li et al. (2020) replaces the last layer of models trained on noisy data with a linear layer trained on a small set of clean data, Jindal et al. (2019) adds a non-linear noise-modeling layer on top of the target text-classification model.

Other types of Noise in text data. Depending on the type of supervisory signal and data acquisition method, language datasets can have noise in the form other than labeling errors like spelling errors, grammatical errors (Subramaniam et al., 2009; Malik and Bhardwaj, 2011). Caswell et al. (2021) provides large-scale systematic quality analysis of various web-crawled multilingual datasets and found large amounts of samples with inconsistencies in language codes and mistranslations. Robust-to-noise word embeddings (Malykh, 2019), noisy data classifiers trained on clean data, and synthetically generated noisy data (Xu and Koehn, 2017) are some efforts to deal with non-label noise in language data. In this work, however, we only study label noise.

Percentile	Accuracy on Unfiltered Data	Accuracy on Filtered Data
1	87.91 ± 0.25	88.02 ± 0.79
10	87.79 ± 0.50	87.79 ± 0.61
50	87.87 ± 0.36	87.72 ± 0.48
90	87.79 ± 0.49	87.72 ± 0.48

Table 1: Accuracy on real-world Dataset: SST-2; Sieving

Relation to annotator disagreement. The work on dealing with noisy labels in classification datasets can also be related to the work on studying annotator disagreements. Previous work (Beigman and Beigman Klebanov, 2009; Beigman Klebanov et al., 2008; Pavlick and Kwiatkowski, 2019) shows that there can be two reasons for disagreements in annotator labels in crowdsourced datasets: difference of opinion and attention slip. Former generally occurs when different groups of people agree with a different assigned label for a sample based on their understanding of the text. Latter generally occurs due to attention slip or genuine mistake during annotation. As a direction of future work, comparing samples identified as mislabelled using the AUM method with samples that get relatively low agreement among crowd worker annotators can provide meaningful insights.

3 Implementation Details

3.1 Filtering data with AUM

We use the AUM metric and methodology from Pleiss et al. (2020) to identify training samples with AUM values below a threshold value as mislabelled. To calculate this threshold, original training data is distributed to make a fake class with equal samples from all the original classes. The classification model is trained on this new dataset configuration to generate the AUM values for all the data points. Samples in fake class are by definition mislabelled hence AUM values of fake class samples can be used as a threshold for the samples in the original classes. This method is repeated to find the mislabelled samples among the samples which were in fake class initially. In the second run, a fake class is created such that it does not have any samples which were in the fake class in the first run.

As discussed in Section 5, we observed that the heuristic-based thresholding technique suggested in Pleiss et al. (2020), wherein they used the AUM value of the 99th percentile threshold sample as the threshold to filter the data, does not show major improvement in NLP datasets. We thus consider the AUM threshold value as a hyperparameter and fine-tune it. We also propose a method to rectify the labels and reuse the data for training (discussed in Section 4).

3.2 Experimental Setup

We finetuned a distillBERT-base model on SST-2 (Socher et al., 2013) and CoLA (Warstadt et al., 2019), pretrained using a masked language modeling (MLM) objective (Sanh et al., 2019) with a default AdamW optimizer (Loshchilov and Hutter, 2017). We selected distillBERT for our experimentation because it is small and fast while preserving over 95% of BERT's performance measured on GLUE benchmark (Sanh et al., 2019).

4 Experiments

Following the recommendations from Pleiss et al. (2020), we test the efficacy of AUM on synthetic-noisy and real-world NLP datasets to identify mislabelled samples. We run two experiments on both types of datasets. First, we discard the samples classified by AUM as mislabelled; we will refer to this process as Sieving. Second, instead of discarding samples, we rectify the label and reuse them for training; we will refer to this process as Flipping. Since we train on binary-classification tasks, we flip the label of the samples which are classified as mislabelled.

As noted in Pleiss et al. (2020), the AUM threshold for filtration is dataset dependent. The authors provide a simple heuristic for classifying samples as mislabelled; samples with AUM lower than the 99th percentile threshold sample's AUM will be classified as mislabelled. Further, they also note that the filtration performance is robust to this hyperparameter (percentile threshold). In our experiments with CoLA and SST-2, we observed that this does not translate well to NLP datasets. Indiscriminately removing samples with AUM less than the 99th percentile threshold consistently had poor performance compared to the unfiltered dataset. As the percentile threshold was reduced, the validation accuracy increases as seen in Figure 1 for CoLA and Table 1 for SST-2. It is because that samples with AUM lower than a high percentile threshold could be a hard-to-learn sample which helps generalization (Swayamdipta et al., 2020). To support this hypothesis, we classified data points using the method (refer to Section 2 for details) suggested by Swayamdipta et al. (2020). We observed significant overlap in samples identified as mislabelled using AUM and samples identified as hard-to-learn using Swayamdipta et al. (2020) which can be seen in Figure 2. As we reduce the percentile threshold, we proportionately filter a larger fraction of truly mislabelled data than hard-to-learn samples. Overfitting is another issue that is facilitated by indiscriminately removing samples with low AUM as the proportion of easy-to-learn samples is increased in the filtered dataset (Swayamdipta et al., 2020).

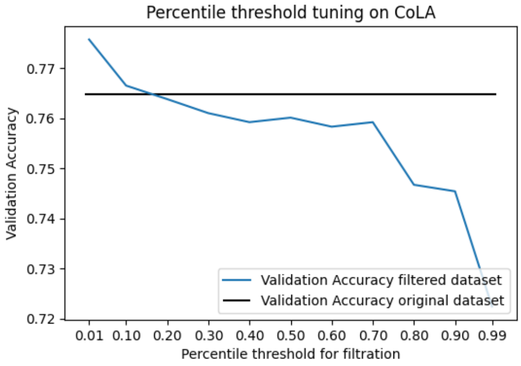

Figure 1: CoLA: Percentile threshold vs Validation accuracy

5 Results & Analysis

Table 1 shows the results for Sieving on the real-world dataset (SST-2). This experiment also shows how increasing the percentile threshold decreases the increase in performance, hinting at the fact that large amounts of relevant language information might be getting filtered. Table 3 shows the result for sieving and flipping on synthetic mislabelled samples (SST-2). We expected to observe a drastic dip in performance with noise injection and a relatively large gain once filtered, but we only observed a marginal dip after injecting noise and a marginal increase after filtering in performance. For the Flipping experiment, we only saw ~1% increase after flipping 68 samples (<0.1st percentile threshold) with the lowest aum. We considered such a low threshold in an attempt to flip only the truly mislabelled data. Investigating further, we saw that

Sample Id	Text	Target Class	AUM
1432	I disliked the boy's playing the piano loudly.	0	-0.501698
1433	The boy whose loud playing of the piano I disliked was a student.	1	0.163168
1434	The piano which I disliked the boy's playing loudly was badly out of tune.	0	-0.349795
1435	The boy's loud playing of the piano drove everyone crazy.	1	0.99208
1436	The boy's playing the piano loudly drove everyone crazy.	1	0.521766
1437	That piano, the boy's loud playing of which drove everyone crazy, was badly out of tune.	1	0.49058
1438	That piano, the boy's playing which loudly drove everyone crazy, was badly out of tune.	0	-0.333451
1439	That piano, which the boy's playing loudly drove everyone crazy, was badly out of tune.	0	-0.628104
1440	Did that he played the piano surprise you?	0	-0.290151
1441	Would for him to have played the piano have surprised you?	0	-0.430419
1442	Is whether he played the piano known?	0	-0.292625
1443	Did his having played the piano surprise you?	1	0.332026

Table 2: Cluster of data points in CoLA with high inter-class similarity; Dominant class - class with samples that have high structural and vocab similarity; Class 0 is the major class in this example but the high structural and vocab similarity within class 1 reinforces the modeling process to present it as the dominant class

Noise %	Accuracy on Unfiltered Data	Accuracy on Filtered Data(Sieving)	Accuracy on Filtered Data(Flipping)
20	85.38	**85.94**	85.83
40	82.70	84.26	**85.96**

Table 3: Accuracy on Synthetic mislabelled Samples (SST-2); Seed: 100; Threshold Percentile: 90

about 60-65% of the noise samples were filtered from our experiments. Figure 3 shows the distribution of AUM values of the synthetic noise and clean samples. The graphs clearly show that AUM does help in identifying the mislabelled samples to some extent (Table 4 and Table 5 show the mislabelled samples we detected in SST-2 and CoLA with low AUM values) but a lot of correctly labeled samples also get filtered depending on how noisy the dataset is. Although there is a high correlation between noise and correctly labeled samples being filtered, the amount of noise alone does not explain this behavior. This leads us to question the efficacy of the AUM metric in NLP datasets.

On manual inspection of the CoLA dataset, we found multiple clusters with high feature similarities. Table 2, 6, 7, 8 and 9 show different examples of such clusters. We observed that the model is relying on superficial features like word co-occurrence statistics (Sinha et al., 2021), within these clusters and builds a bias for the dominant class label in a particular cluster. Thus the non-dominant class samples (which usually are correctly labeled) get low AUM values instead of the synthetic noise samples. This does not go hand in hand with our previous observations where Figure 3 shows that synthetic noise samples have low AUM, but it is important to note that synthetic noise samples also happen to be a part of the non-dominant class in most cases (noise in an acceptable dataset is non-dominant). Again, we emphasize correlation does not imply causation.

In Table 2, the synthetically introduced noise (marked in red) and members of class 0 (marked in yellow) are both parts of the non-dominant class which gives these samples a negative AUM. While the red labeled samples are legitimate candidates for removal, the removal of yellow samples causes loss of correctly labeled data points. We observed the same pattern through all clusters, and Table 9 shows another cluster in CoLA with this pattern.

6 Conclusion

We report on the applicability of AUM on NLP datasets. AUM does help in identifying mislabelled samples available to some extent, but sieving these samples indiscriminately removes large amounts of relevant language information. We hypothesize that the reason AUM works well in image datasets is because of the intrinsic nature of the data samples, i.e., data samples in image datasets have high intra-class and less inter-class feature similarity whereas in NLP datasets, data samples have high inter-class feature similarity as seen in Table 2 and this coupled with the model dependency on superficial features results in low AUM values for the non-dominant class samples instead of the mislabelled class samples consequently reducing the efficacy of the AUM metric in NLP datasets.

Ethical Consideration

Various techniques, like AUM, used to detect mislabelled samples, are evaluated against their performance on the test set. However, as we have shown, AUM removes a significant amount of correctly labeled data points in non-dominant classes along with the mislabelled data points in NLP datasets. Reckless filtering poses a risk of eliminating correctly labeled rare/corner cases from the training dataset. While there might be an increase in accuracy on the test set, this might cause machine learning-based applications built on filtered datasets to be more biased to over-represented data points. This could be a hindrance in developing fair AI systems. For example, if non-dominant class data points represent minority race or gender, AUM will filter these data points out which will reinforce the bias in the model (Sanh et al., 2021). Thus machine learning practitioners must use AUM-like filtering techniques with caution.

Collaboration Statement

1. **Arka** : Designed the end to end data pipeline for the experiments and ran baseline models. Performed qualitative analysis. Contributed in writing the paper and presentation, reviewed relevant literature.

2. **Varun**: Implemented training pipeline and ran extensive experiments on various datasets and helped in data collection and hyperparameter tuning. Contributed to writing of the paper and presentation.

3. **Monika**: Implemented training pipeline and ran extensive experiments on various datasets and helped in data collection and hyperparameter tuning. Contributed to writing of the paper and presentation.

4. **Prachi**: Performed qualitative analysis and implemented the pipeline to generate results from Swayamdipta et al. (2020). Performed extensive literature survey and wrote related work (Section 2). Also contributed in writing introduction and presentation.

   Everyone participated in discussing the results and planning the execution and writing of paper and presentation.

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Appendix A Data Points Identified by AUM Metric

Index	Sentence	Label	Guess
390	He I often sees Mary.	acceptable	unacceptable
5766	Heidi believes any description of herself.	acceptable	unacceptable
2801	Paula hit the sticks.	unacceptable	acceptable
1522	That the sun is out was obvious.	unacceptable	acceptable
8332	I wanted Jimmy for to come with me.	acceptable	unacceptable

Table 4: Filtered examples from CoLA dataset

Index	Senetence	Label
41767	a damn fine and a truly distinctive and a deeply pertinent film	Negative
42407	guts and	Negative
62237	as original and insightful as last week 's episode of behind the music .	Negative
6886	loves the members of the upper class almost as much as they love themselves	Negative
19153	of how horrible we are to ourselves and each other	Positive
19159	he script is n't up to the level of the direction	Positive
62178	though it runs 163 minutes , safe conduct is anything but languorous .	Positive

Table 5: Filtered examples from Stanford Sentiment Treebank (SST2)

Appendix B Comparison with Data Cartography

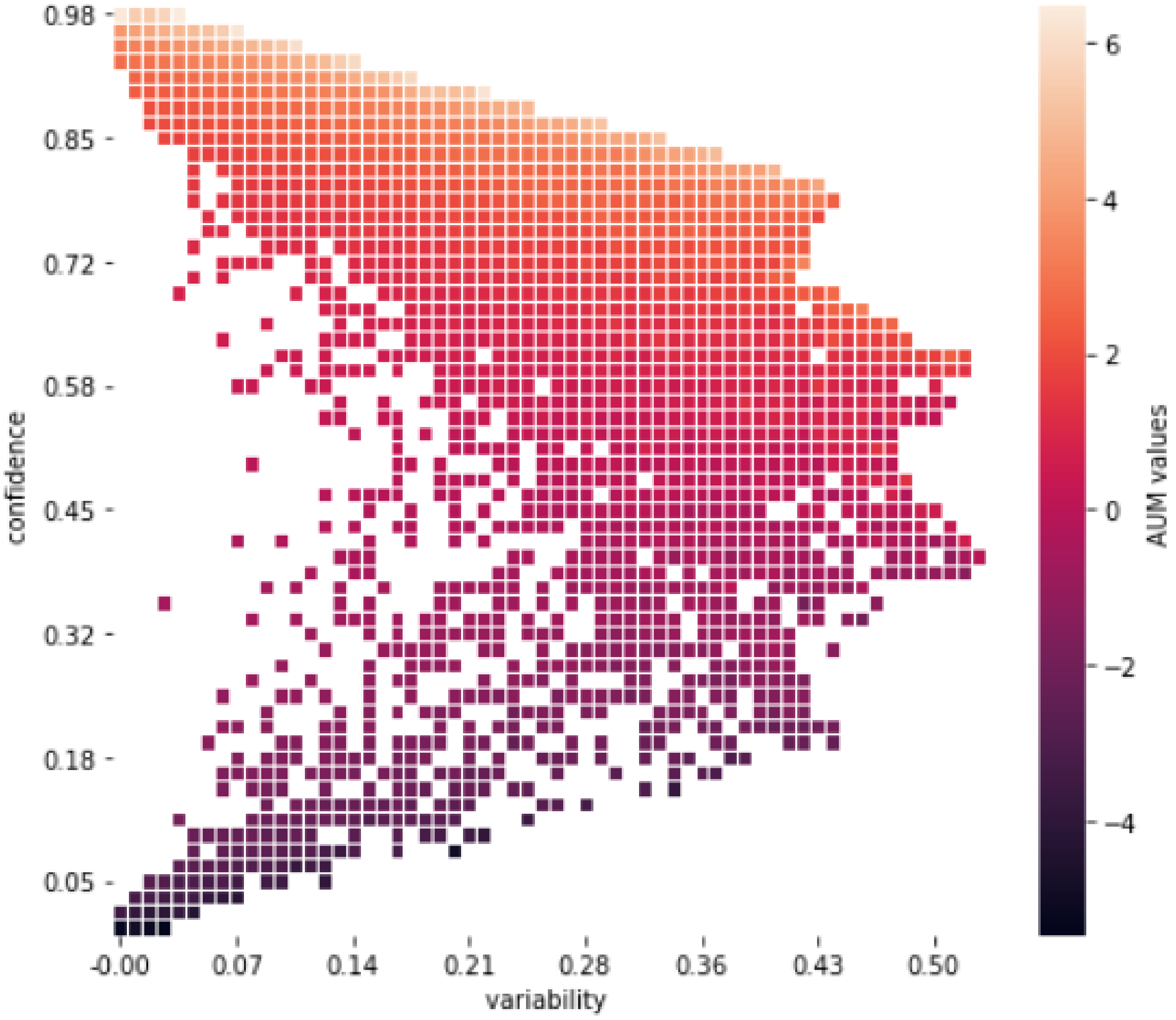


Figure 2: Visualizing AUM values of SST-2 samples along with their Data Map plotted as per Swayamdipta et al. (2020) shows considerable overlap in samples with low AUM values and samples identified as hard-to-learn/mislabelled as per Data map (sampled with low confidence and low variability scores).

Appendix C Clusters in CoLA

Sample Id	Text	Target Class
3100	Cynthia ate at the peach.	1
3101	Cynthia ate on the peach.	0
3102	Cynthia ate the peach with a fork.	1
3103	Cynthia nibbled the carrot .	1
3104	Cynthia nibbled .	1
3105	Cynthia nibbled at the carrot .	1
3106	Cynthia gobbled the pizza .	1
3107	Cynthia gobbled the pizza down .	1
3108	Cynthia gobbled .	0
3109	Cynthia gobbled at the pizza .	0
3110	Cynthia gobbled on the pizza .	0
3111	Cynthia devoured the pizza .	1
3112	Cynthia devoured .	0
3113	Cynthia devoured at the pizza .	0
3114	Cynthia devoured on the pizza .	0
3115	Cynthia lunched.	1
3116	Cynthia lunched on peaches.	1
3117	Cynthia lunched peaches.	0
3118	Cynthia lunched at peaches.	0
3119	Cynthia munched.	0
3120	Cynthia munched on peaches.	1
3121	Cynthia munched peaches.	0
3122	Cynthia munched at peaches.	0

Table 6: Cluster of data points in CoLA with high inter-class similarity

Sample Id	Text	Target Class
5606	I expect soon to see the results.	1
5607	I expect to see the results soon.	1
5608	I expect to soon see the results.	1
5609	I expect more than to double my profits.	0
5610	I expect to double more than my profits.	0
5611	I expect to double my profits more than.	0
5612	I expect to more than double my profits.	1

Table 7: Cluster of data points in CoLA with high inter-class similarity

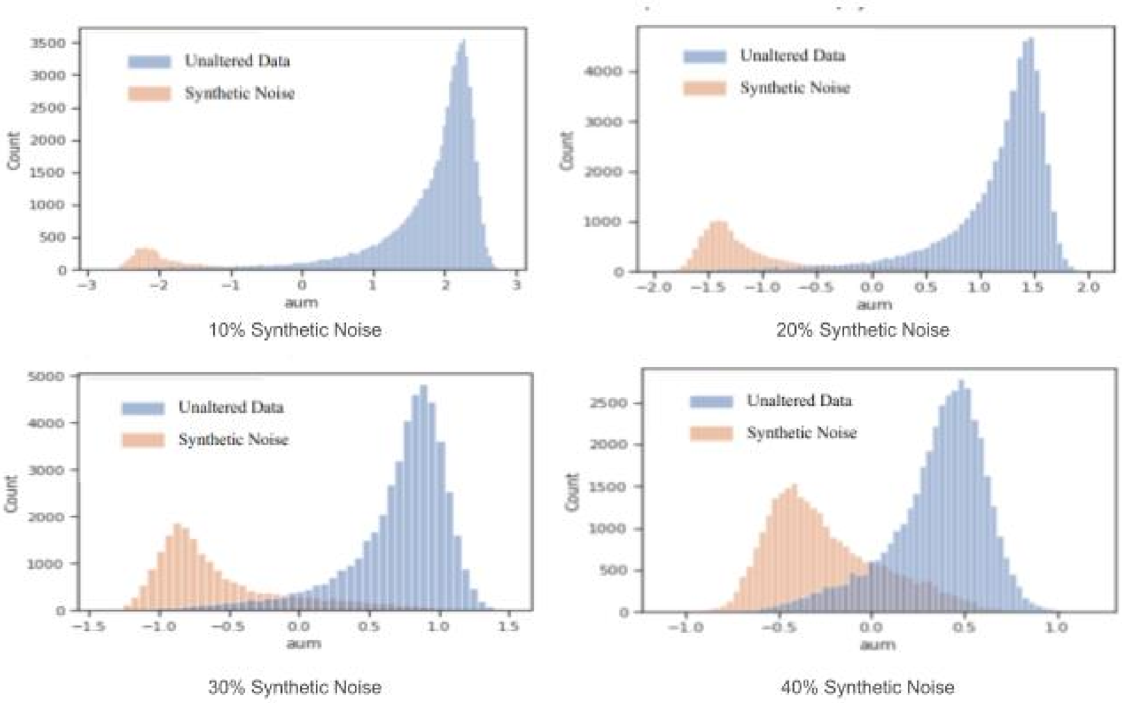
Sample Id	Text	Target Class
1201	Phineas knows a girl who is jealous of Maxime.	1
1202	Phineas knows a girl who is behind Maxime.	1
1203	Phineas knows a girl who is working with Maxime.	1
1204	Who does Phineas know a girl who is jealous of?.	0
1205	Who does Phineas know a girl who is behind?	0
1206	Who does Phineas know a girl who is working with?	0
1207	Who does Phineas know a girl jealous of?	0
1208	Who does Phineas know a girl behind?	0
1209	Who does Phineas know a girl working with?	0

Table 8: Cluster of data points in CoLA with high inter-class similarity

Sample Id	Text	Target Class	AUM
6504	Any cat doesn't like mice.	1	0.387194
6505	Every cat doesn't like mice.	0	-0.006255
6506	Every cat doesn't like mice, for example Felix doesn't.	0	-0.435432
6507	Almost every cat likes mice, but Felix doesn't.	1	0.850877
6508	Every cat doesn't like mice, but Felix doesn't.	1	0.608173
6509	Almost every cat likes mice, for example Felix doesn't.	1	0.727123

Table 9: : Cluster of datapoints in CoLA with high inter-class similarity

Appendix D Synthetic Data AUM Values



10% Synthetic Noise

20% Synthetic Noise

30% Synthetic Noise

40% Synthetic Noise

Figure 3: AUM distribution of synthetic noise and unaltered data.