Polarized Opinion Detection Improves the Detection of Toxic Language

Anonymous EACL submission

Abstract

Distance from unimodality (DFU) has been found to correlate well with human judgment for the assessment of polarized opinions. However, its un-normalized nature makes it less intuitive and somewhat difficult to exploit in machine learning (e.g., as a supervised signal). In this work a normalized version of this measure, called nDFU, is proposed that leads to better assessment of the degree of polarization. Then, we propose a methodology for K-class text classification, based on nDFU, that exploits polarized texts in the dataset. Such polarized instances are assigned to a separate K+1 class, so that a K+1-class classifier is trained. An empirical analysis on three datasets for abusive language detection, shows that nDFU can be used to model polarized annotations and prevent them from harming the classification performance. Finally, we further exploit nDFU to specify conditions that could explain polarization given a dimension and present text examples that polarized the annotators when the dimension was gender and race.

1 Introduction

Annotations for subjective tasks are often aggregated, to form ground truth labels and allow supervised learning algorithms to be trained for these tasks. Given a text, for example, annotations are averaged to yield binary labels reflecting whether the text is misogynous or not (Kirk et al., 2023). These annotations, however, are not always described by a single mode. Specific data items may lead to non-unimodal annotations, increasing the inter-annotator disagreement. This point is clearer if we consider a post that is classified as -1 by half of the annotators and as 1 by the other half, assuming a 3-point scale. No point is suitable to represent this item, since two polarized ratings co-exist.

Current machine learning conventions reduce the annotations for a given text into a single label (most often, the mode) and consider the inter-annotator agreement an an indicator of the quality of the ground truth, or the task difficulty. In this work, we argue that polarized annotations may be beneficial in machine learning for subjective tasks and that inter-annotator agreement is not necessarily reflective of the quality of the ground truth. The negative impact of the information loss due to such aggregations can be higher when the annotators come from different social groups. Language that is offensive to specific groups at risk for discrimination will be obscured in datasets with aggregated annotations and consequently be ignored by algorithms trained on those datasets.

In this work, we focus on polarized opinions of annotators about the label to be assigned,[1] suggesting their detection prior to supervised learning, to remove ambiguous annotations and improve classification performance. Recently, the measure of the distance from unimodality (DFU) has been found to be correlating well with human judgment as an index of polarization (Pavlopoulos and Likas, 2022). Although effective, this measure is un-normalized, a fact that limits the measure's interpretability. To this end, we propose a normalization which directly improves the measure. By employing the normalized measure, we propose a classification methodology where we introduce a new class comprising data with polarised annotations.. Despite the fact that, in principle, a new class increases the task's difficulty, our approach outperforms the binary baseline in three datasets for abusive language classification. Furthermore, the computed probability for the added class serves as an estimation of the annotation polarization of a text input.

The contribution of this work is threefold. First, we introduce a normalized variant of the DFU measure of polarized opinions, called nDFU, that also

[1] The same post may be classified quite differently depending, for example, on the cultural background of the annotator. Tables 4 and 6 (Appendix) show examples in the domain of toxic language detection, where this is a realistic scenario.

correlates well with human judgment and allows for better interpretation. Second, we propose unpolarized learning, an approach that introduces and exploits a new class that contains polarized data. Experimenting on the subjective and of high social impact task of toxic language detection,[2] we show that our approach outperforms the baseline in three datasets. Third, we present conditions based on nDFU, which can be used to detect polarized items that are unimodally-annotated by specific groups of annotators. Using gender and race, we present texts that satisfy those conditions, attempting to explore the roots of polarization.

2 Related Work

For many NLP tasks, a diversity of valid beliefs exist about what the correct data labels should be (Röttger et al., 2021). Such tasks comprise the detection of toxic language (Sap et al., 2021; Salminen et al., 2019), harassment (Al Kuwatly et al., 2020), and stance (Luo et al., 2020). Due to the lack of measures assessing polarized opinions, however, no published work to date aimed at detecting and classifying polarized annotations, which is the goal of this study. Instead, current approaches either reduce the number of classification labels (Campagner et al., 2021; Thierry et al., 2019), or model the distribution of annotations using a Gaussian distribution (Wan and Chan, 2020; Chang et al., 2020), or learn the histogram of annotations (Fornaciari et al., 2021; Prabhakaran et al., 2021).

Reducing the number of class labels Campagner et al. (2021) showed that the quality of the ground truth (e.g., the inter-annotator agreement) impacts the performance of machine learning models and should not be taken for granted. The authors studied different ways to yield a single target label from multi-rater settings, which is a common approach in supervised learning for NLP. The standard reduction method is majority voting from crowdsourced opinions or the fraction of raters who said yes (in a yes/no question), binarized. Although common, this approach fails to encode uncertainty (Thierry et al., 2019).

Uncertain ground truth Uncertainty can be tackled by considering the annotations for a data item as noisy observations that can be modeled by a Gaussian distribution (Wan and Chan, 2020). Chang et al. (2020) attempt to learn simultaneously the mean and the variance of the normal distribution showing that this approach outperforms ground-truthing methods that disregard uncertainty. Although encoding uncertainty is useful, the use of a unimodal distribution (e.g., a Gaussian) imposes severe limitations, since it disregards the possibility of polarized opinions (multiple modes). Such an assumption may be harmful in tasks with subjective opinions, such as sentiment analysis and toxic language detection, where annotators with different personal, cultural, or demographic backgrounds may perceive differently commonsense knowledge (what they will assign as target label) of the same item (Akhtar et al., 2021).

Soft labels Instead of a noisy unidimensional target label, one may attempt to learn a multivariate probability density function (i.e., the normalized histogram). Such a ground truth model allows the maintenance of polarized annotated opinions in the supervised signal when using machine learning algorithms. Peterson et al. (2019), for example, showed that predicting the whole distribution of the class annotations improves robustness in image classification. Gordon et al. (2021) encoded human disagreement to improve the quality of the social computing datasets. This work builds on prior findings showing that annotators' disagreement is not noise (Chung et al., 2019; Kairam and Heer, 2016). These studies treat polarized opinions as a special case of disagreement (Prabhakaran et al., 2021).

3 Assessing Opinion Polarization

3.1 The DFU Measure

DFU for an opinion histogram has been defined by Pavlopoulos and Likas (2022) as the deviation from unimodality. Let a set $X = \{x_1, ..., x_n\}$ of n opinions, each of which can take K ordinal ratings: $x_i \in \{O^1, ..., O^K\}$. We assume that $f = (f_1, ..., f_K)$ are the relative frequencies of the K ratings defining the opinion distribution (histogram) of X. The discrete opinion distribution f is unimodal if it has a single mode, which means that there exists a maximum value f_m and that the values f_i monotonically decrease while moving away from m. More formally, $f_{i-1} \leq f_i$ for $i < m$ and $f_{i+1} \leq f_i$ for $i > m$. DFU is defined as the maximum of the differences d_i between successive

[2] We use this term universally, to cover what researchers refer to as 'abusive', 'offensive', 'hateful' or otherwise harmful. Besides the social impact of this task, texts with polarised annotations (Tables 4 and 6) and unaggregated annotations exist in this domain, making it an ideal ground for our study.

f_i values that are computed as:

$$d_i = \begin{cases} f_i - f_{i-1} & m < i < K \\ f_i - f_{i+1} & 2 < i < m \\ 0 & i = m. \end{cases} \quad (1)$$

$$DFU = max(d) \quad (2)$$

3.2 The Normalized DFU Measure

As shown in Equation 2, DFU is defined as the maximum d_i value. This is also shown in line 9 of Algorithm 1. It can be observed that $d_i \leq f_m$, which means that DFU, which is the maximum d_i, is always smaller than the highest peak of the histogram (the mode). Therefore, we can produce a normalized variant by dividing DFU with the mode f_m (line 10 of Algorithm 1).

Algorithm 1: Calculation of nDFU

Data: Opinions X: $x \in \{O_1, ..., O_K\}$
Result: A score $nDFU \in [0, 1]$
1 **for** $i = 1$ *to* K **do**
2 $\quad f_i = \frac{\sum_{x=1}^{|X|} 1^{O_i = x}}{N}$;
3 $m = \underset{i}{\text{argmax}} f$;
4 $d_m = 0$;
5 **for** $i = m$ *to* K **do**
6 $\quad d_i = f_i - f_{i-1}$;
7 **for** $i = 2$ *to* m **do**
8 $\quad d_i = f_i - f_{i+1}$;
9 $DFU = max(d)$;
10 $nDFU = \frac{DFU}{f_m}$;
11 **return** $nDFU$

It should be noted that the special case $f_m = max(d)$ (i.e., $nDFU = 1$) occurs when at least two non-consecutive bins are of equal height (e.g., in uniform distributions). In a simple 3-point Likert scale (e.g., agree and disagree at the poles, neutral in the middle), this case regards equal height for agree and disagree bins while the neutral bin is zero. As can be seen in Figure 1, both DFU variants, normalized or not, yield a zero score for the unimodal Gaussian. The scores of the normalized variant (nDFU), however, are considerably higher, close to 1, for the multimodal Gaussian mixtures. On the contrary, the un-normalized score (DFU) is neither intuitive nor interpretable.

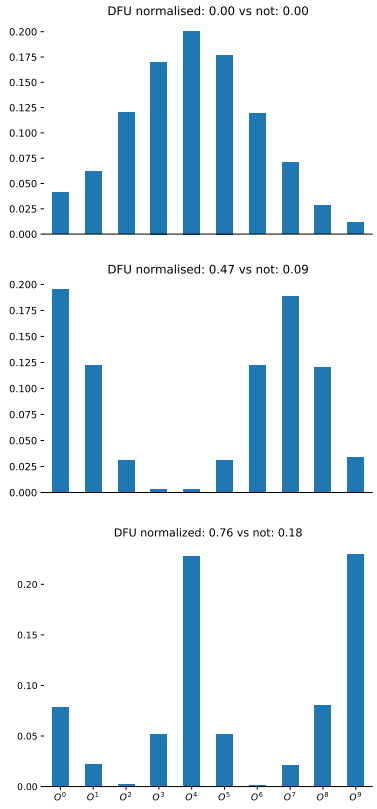


Figure 1: Histograms of synthetic data (from top) of a unimodal, bimodal, and trimodal Gaussian mixture and the corresponding DFU and nDFU values.

4 Unpolarized Learning

Supervised learning is often applied to subjective tasks, such as toxic language classification, by transforming the set of ordinal annotations $X = \{x_1, ..., x_n\}$, $x_i \in \{O^1, ..., O^K\}$ into a binary label. Such a binarization is implemented by first thresholding each annotation x_i and then applying majority voting. In other words, a threshold h ($O_1 \leq h \leq O_K$) is defined that is used to binarize x_i:

$$x_i = \begin{cases} 0, & x_i < h \\ 1, & x_i \geq h. \end{cases} \quad (3)$$

A probability is then computed, as the fraction of positive ratings, rounded (or thresholded) to produce the final binary label assigned to the instance.

The assumption of binarized thresholded ratings is problematic, because items with polarized ratings will get a noisy signal. For example, assume the case where annotators rate a post's toxicity from 1 (clearly civil) to 5 (very toxic). A post that is rated as 5 by 49% of the raters and as 1 by the rest will be assigned a binary label of 0, meaning civil. Therefore, similar posts (i.e., causing polarized ratings)

may end up in both binary classes, introducing noise to the dataset. We argue that introducing a K+1 class (e.g., a 3rd class in binary classification), comprising data with polarized annotations, is advantageous in a supervised learning setting. That is because only unimodal data will be used to learn the original K-class task while polarized items will form a class on their own. We call this strategy *unpolarized learning* because only unpolarized data (i.e., data with unimodal annotations) are used to learn the original K classes.

4.1 Training with $K+1$ Classes

In the following, without of loss of generality, we assume K=2, classifying an instance either to the negative (0) or the positive (1) class, and we provide more details of the proposed strategy.

First, we detect polarized items, which are the items that have an nDFU value that is greater than a threshold.[3] Unpolarized items, which are characterized by a single mode, are classified to the positive or the negative class, normally, based on majority voting. The rest, on the other hand, are not. Instead, we introduce a third $(K+1)$ class label which we assign to all polarized instances. Next, we train the network for the 3-class classification task. The resulted network will learn to classify an item as positive, negative, or to the 3rd class with the polarized annotations.

In principle, training the classifier becomes harder when a class is added, reducing the accuracy of a random baseline from $\frac{1}{K}$ to $\frac{1}{K+1}$. At the same time, however, the supervised signal with which the network is learning the task becomes clearer, because each actual class is learned using items with unpolarized (unimodal) annotations. Therefore, a more accurate K-class classification is expected.

4.2 Class Reduction at Inference

It should be noted that during inference, it is possible to exploit the $K+1$ classifier outputs in two ways. The first possibility is not to assign class labels to items that are estimated as polarized (i.e., with high $K+1$ output value). The other possibility (considered in this work) is to ignore the $K+1$ output value and always classify an item to one of the original K classes, i.e., to the one with the highest output value.

[3] A natural choice for this threshold is 0, but this is tunable.

5 Datasets

We investigated one resource comprising what human experts perceive as polarized and three datasets comprising annotations for toxic language, a subjective task with high social impact. Regarding the latter, we limited our search to datasets whose annotations are provided without any aggregation, i.e., one label per annotator.

5.1 Opinion Polarization Ground Truth

The (OPGT) dataset was introduced by Koudenburg et al. (2021) to approximate what humans perceive as a distribution of polarized opinions. Sixty researchers of opinion polarization judged with a five-point scale the extent of polarization of fifteen opinion distributions. The average judgment per distribution was then used by Pavlopoulos and Likas (2022) to build the ground truth regarding the extent to which the participants thought the respective histogram represented a polarized state.

5.2 Toxicity Detection

Several datasets exist for toxic language detection but the vast majority of them has only released an aggregated label (e.g., toxic) or score (e.g., 70% for being perceived as toxic) of the annotations. In this study, we opt for the two publicly available datasets that provide access to their raw annotations, viz. the Civil Comments (CCTK) and the Ex-Machina (XMACH) datasets. Also, we were granted access to another dataset (Attitudes) by Sap et al. (2021).

CCTK comprises comments posted from 2015 to 2017 on several English-language news sites. Multiple annotators from several countries rated each post with a 4-point Likert scale, from non-toxic (68.7%), to "hard to say" (0.5%), to "toxic" (29.4%), and "very toxic" (1.5%). Pavlopoulos and Likas (2022) used this dataset to predict the not-normalized DFU score. They found that posts with high (not-normalized) DFU were annotated by people coming from more countries compared to ones with low DFU, revealing cultural context as a possible reason behind polarized opinions. We followed the authors' suggested split and we yielded a binary ground truth (when needed) by forming a single class of toxic and very toxic posts (17%).

Attitudes was introduced to study how the annotators' identities affect their text toxicity annotations (Sap et al., 2021).[4] The authors studied the anno-

[4] Only participants from the U.S.A. were considered to restrict the perceptions of race and political attitudes.

tators' race, gender, and political leaning. A small dataset was formed by giving fifteen posts to 641 participants and asking for their toxicity ratings, combined with their identities and their attitudes. The participants led to different proportions regarding their race (13% Black, 85% White), political (29% conservative, 59% liberal), and gender identities (54% women, 45% men, 1% non-binary). A 5-point Likert scale was used for the rating, from 1 (civil) to 5 (very toxic).[5] We formed the toxic class in a binary setting using posts assumed by the majority of the voters as very toxic (23%).

XMACH was developed by Wulczyn et al. (2017) who crowd-annotated 100k comments focusing on personal attacks or harassment. This was a subset of 63M Wikipedia comments from discussions relating to user pages and articles dating from 2004 to 2015. To address the imbalance of the toxic class (1%), the authors extended their resource by sampling and adding comments which were made by users who were blocked or violating Wikipedia's policy. Five comments per user were sampled around each block event, leading to an increased balance for this resource (17%) and overall (12%). A 5-point Likert scale was used for the rating, from -2 (very toxic) to 2. A binary toxic class was formed by merging toxic and very toxic posts (32%).

5.2.1 Exploratory Analysis

In Table 1, we summarise the statistics about the texts of the datasets, computed on the training subsets. In all three datasets, we assume an equal train/test split. CCTK posts are the lengthier on average, followed by XMACH, and Attitudes. The latter, not only has the shortest posts, but also the fewer instances and the fewer annotations per text. XMACH, on the other hand is the dataset with the more annotations per text on average.

	LENGTH	SIZE	CODES (#)
CCTK	309.3 (276.6)	10k	6.1 (2.8)
ATTIT.	125.4 (85.9)	313	5.6 (0.8)
XMACH	194 (128.3)	2k	8.4 (1.3)

Table 1: The average text length in characters (st. deviation), the number of train instances, and the average number of annotations (st. deviation) per dataset.

Figure 2 shows that for all three datasets the number of posts with zero nDFU is significantly greater than that of the rest. This means that the majority of posts comprise unimodal annotations.

[5]Two criteria were used, toxic according to the annotator or to any. We used the former.

We also observe that for the two smaller datasets, there are nDFU zones for which there are no posts, as for example: $0.8 \leq nDFU \leq 0.9$.

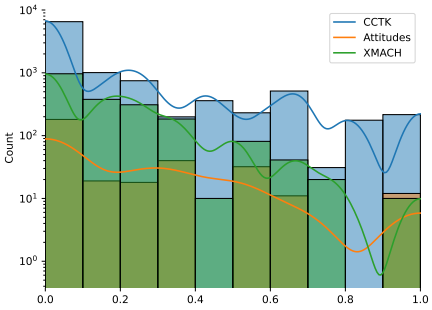


Figure 2: The number of instances (vertically, in log scale) per dataset per nDFU score (horizontally).

6 Experiments

Using OGDT, we measured the correlation between our proposed nDFU and human judgment. Then, we used nDFU to introduce the additional class of polarized opinions in three toxicity datasets, and we compare the performance in toxicity detection with and without the polarized class.

6.1 Correlation with Human Judgment

We computed the correlation between our nDFU measure and what humans perceive as a distribution of polarized opinions using OGDT (§5.1). Figure 3 shows the average judgment of each of these fifteen histograms, along with their nDFU score. The Pearson correlation between the score and human judgment is 0.90, which is on par with what has been reported in (Pavlopoulos and Likas, 2022) using the un-normalized DFU (0.89). By being limited in [0,1], the proposed measure facilitates also the tuning process, which is not straight-forward with the unconstrained (in upper limit) DFU.

In Figure 4, we sampled participants from three (left) to fifty (right) and re-computed the correlation between nDFU and human judgment. We can observe that a high correlation, yet less stable, is established with fewer participants in the survey (§5.1). This finding shows that nDFU is able to capture a polarized state even when only ten or fewer annotations are provided for a data item, which is most often the case in subjective machine-actionable datasets (Leonardelli et al., 2023).

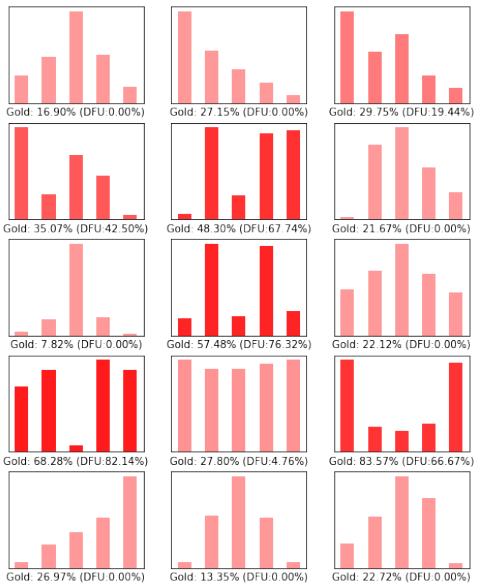


Figure 3: Histograms of fifteen opinion distributions. The average judgment of the extent to which sixty polarization experts (§5.1) thought the respective histogram represented a polarized state (Koudenburg et al., 2021) is shown in the horizontal axis (Gold). Transparency is reversely related to the respective normalized DFU score (shown in parentheses) per histogram.

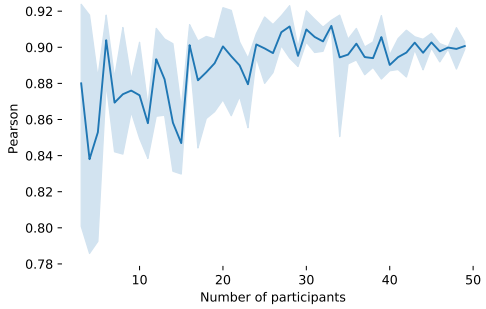


Figure 4: Pearson correlation between nDFU and subgroups of polarisation experts of varying size.

6.2 Benchmarking Unpolarized Learning

We opted for BERT features (Devlin et al., 2019), using the uncased base model, and training a logistic regression model on top of the [CLS] pseudo token.[6] Class weights were set according to the class balance of the dataset. By yielding binary toxicity labels per dataset (§5), and by introducing the class of polarized opinions, we trained and assessed this classifier. The results are shown in Table 2. The prediction of the toxic class is the most difficult task, especially in the heavily-imbalanced

[6]This is a decent approach for classification tasks (Reimers and Gurevych, 2019, Table 5). We also experimented with fine-tuning, but that was time-consuming, especially for the two largest datasets.

	F1			AUC
	CIVIL	TOXIC	POLARIZED	
CCTK	0.82	0.13	0.58	0.80
ATTITUDES	0.49	0.35	0.54	0.65
XMACH	0.49	0.37	0.46	0.62

Table 2: Macro-averaged F1 per class, along with one vs. rest AUC, of a BERT-based unimodal learning classifier.

	Test subset	P+	R+	F1	AUC
CCTK	nDFU=0	0.59	0.33	**0.71**	**0.92**
	nDFU>0	0.63	0.18	0.54	0.71
ATTIT.	nDFU=0	0.45	0.39	0.62	**0.75**
	nDFU>0	0.50	0.43	0.62	0.73
XMACH	nDFU=0	0.63	0.67	**0.76**	**0.84**
	nDFU>0	0.58	0.62	0.71	0.79

Table 3: Precision and Recall of the toxic class, macro-F1, AUC in binary toxicity classification of a BERT baseline assessed on data with zero (unimodal) and non-zero (non-unimodal) nDFU.

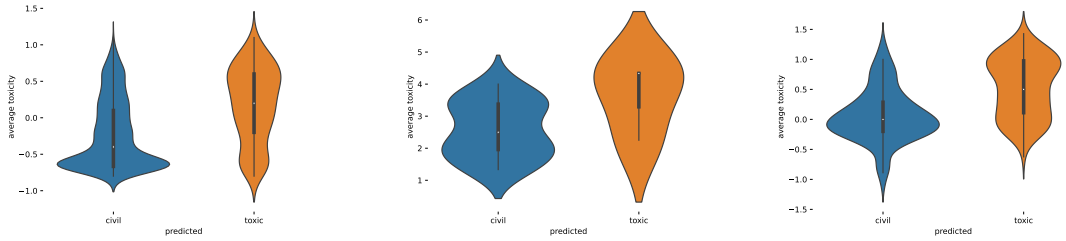
CCTK. The performance of predicting the polarized (K+1) class ranged from 0.46 (XMACH), to 0.54 (ATTITUDES), to 0.58 (CCTK) and the K+1 class was the easiest (ATTITUDES) or the second easiest (CCTK, XMACH) to predict among the three. In order to better understand the benefits of adding the polarized class, we experimented with a hypothesis where we ignore the predictions for the polarized class during inference, which we describe next.

6.3 Polarized Class Reduction

As discussed in §4, class reduction allows for a $K+1$-class classifier to be evaluated in the K-class setting. Hence, we used it to compare our 3-class classifier discussed above with a binary classification baseline.

The baseline is a binary classification model, that is the same BERT-based logistic regression classifier we used for unpolarized learning, but trained to classify a text as civil or toxic, which is a typical approach in this field (Hartvigsen et al., 2022; Zhou et al., 2023). To assess this classifier, we focused on evaluation posts with both, zero and non-zero nDFU and we present the results in Table 3. In all datasets, the classifier performs equally or better with unpolarized data, with a more clear difference in CCTK. The performance drop on polarized data shows that they set a harder classification target, probably explained by the fact that their ground truth is formed by aggregating polarized opinions, i.e., far away from the two edges.[7]

[7]In Appendix B, we discuss an alternative nDFU-based binary classification method that may perform on par while significantly reducing training time.



(a) CCTK (b) ATTITUDES (c) XMACH

Figure 5: Violin plots of the non-binarized average toxicity (vertically, higher means more toxic) of the K+1 class ($nDFU > 0$) that were predicted as civil (left, in blue) or toxic (right, in orange).

The reduced predictions of our unpolarized learning method were compared to those of the binary baseline, but we tuned the threshold above which a text is classified to the polarized (K+1) class.[8] We opted for a development set per dataset to select the optimum threshold, based on the macro-averaged F1 when performing the class reduction step for the binary evaluation (Appendix A.2). Then, we sampled randomly test texts, comparing the predictions of the binary baseline with the reduced ones provided by our tuned model. A one-sided Mann-Whitney test (Mann and Whitney, 1947) showed that the latter had a better performance with a statistically significant difference across datasets ($p < 0.05$).[9] On average, the macro-averaged F1 score increased from 0.58 to 0.64 for Attitudes (+6 percent units), from 0.77 to 0.78 for XMACH (+1), and from 0.71 to 0.72 for CCTK (+1). Putting this result in a wider context, unpolarized learning has led to a better binary classification outcome.

7 Polarized Class Prediction Analysis

As shown with the reduced class hypothesis (§6.3), unpolarized learning can lead to a performance improvement in binary toxicity classification. Networks trained using the unpolarized learning strategy, also provide an additional benefit, which is the ability to estimate the probability for the K+1 class. In other words, for a new text input the K+1 output estimates the *probability the text is going to receive polarized annotations*. In order to better assess the ability of the model to provide such predictions, we used the polarized class probability along with the model-agnostic explainability framework of Ribeiro et al. (2016), which has been found to be the best option for text classification tasks (Jeyakumar et al., 2020).

The words suggested as explanations were not always easy to interpret or distinguish from the other two classes. One example from the CCTK dataset is "I'm not black, but there's a whole lotta times I wish I could say I'm not white - frank zappa", where the words 'black' and 'white' contribute toward the decision for the K+1 class while the surname of Frank Zappa contributed reversely.

To gain more insights into the K+1 class of polarized annotations, we used error analysis as a proxy. A common mistake of models trained with unpolarized learning (i.e., using posts with non-zero nDFU to define the K+1 class) concerns the misclassification of K+1 to the civil class (confusion matrices in Appendix A.3). This information, however, is not useful on its own. Therefore, we focused solely on these posts, exploring their average toxicity without the step of binarization. As is shown in Fig 5, K+1 posts that are misclassified as civil (in blue, on the left) are often annotated as civil by the annotators. On the other hand, K+1 posts that are misclassified as toxic (in orange, on the right) are annotated more often as toxic. In other words, the annotations of these posts were considered polarized (hence, the K+1 class) but the mode of the annotations was aligned with the model's prediction. This explains why unpolarized learning has led to a well-performing model in binary toxicity classification despite the burden of an added class.

8 A Posteriori Unimodality Explanations

Polarization may be due to various reasons, such as political beliefs, social dimensions, gender, age,

[8] We did not tune the classification threshold neither for the binary nor the K+1 classifiers. We only tuned the number of high nDFU posts removed from the training data. Doing a sanity check with the (small) Attitudes dataset and a Random Forest binary classifier, tuned from 0 to 0.9 with step 0.1, yielded 0.5 as the best threshold.

[9] https://docs.scipy.org/doc/scipy/reference/generated/scipy.stats.mannwhitneyu.html

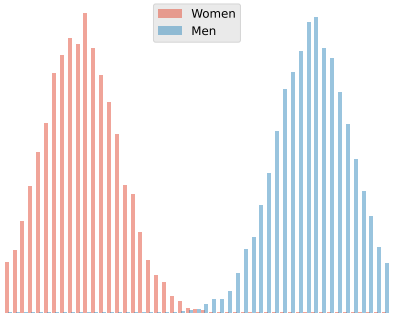


Figure 6: Synthetic bimodal histogram of annotations, where annotators agree only conditioned on their gender.

etc. Although nDFU estimates polarization (§3.2), it does not suggest its cause. As an example, a bimodal annotation histogram is shown in Figure 6, where the colour reflects the gender of the annotator. Although polarization is easily estimated in this histogram, its root cause (here, gender) is not revealed. To address this important issue, we next propose an approach that could possibly explain polarization given a dimension.

Let the set of opinions X of Algorithm 1 for a non-zero nDFU post, and let G be the values for a dimension D that characterizes the opinion holder i, that is $D_i \in \{d^1, ..., d^G\}$.[10] Based on the value of D corresponding to each annotator, the set X can be partitioned into G subsets X^k $(k = 1, ..., G)$. This means that each subset X^k contains the annotations of the annotators with value d_k. Then, we consider that D explains the polarization of X ($nDFU(X) > 0$), if the following *a posteriori unimodality* conditions hold:

$$nDFU(X^k) = 0, \forall k = 1, \ldots, G \qquad (4)$$

In the simple case of Figure 6, where only male and female annotators are considered, let X^1 denote the set of annotations from men (red histogram) and X^2 the set of annotations from women (blue histogram). It is obvious that $nDFU(X^1) = 0$ and $nDFU(X^2) = 0$ since each of them forms a unimodal histogram. Consequently, it can be inferred that gender constitutes the source of polarization observed for the whole dataset X.

We explored CCTK posts that satisfy Equation 4 regarding two dimensions, viz. gender and race.[11]

[10]We assume a single dimension for simplicity, but a combination of dimensions could be used as well.

[11]We used the richer re-annotation of Goyal et al. (2022), who collected annotations for posts from three groups of annotators: African American, LGBTQ, and a control group.

Source	Toxic	Civil	Text
CCTK	LGBTQ	CNTRL	Homosexuality, transgender sex-all are deviations from normal human behavior as well.
CCTK	CNTRL	AA	In other words, he's not brown enough for ya to be labeled a terrorist.

Table 4: Posts satisfying Equation 4 found as toxic (civil) only by LGBTQ, African American (AA), or control-group (CNTRL) annotators.

Table 4 presents two posts resulted from this exploration. The first claims that homosexuality deviates from normality. LGBTQ annotators considered this post toxic, but annotators from the control-group did not. The second post, touched on a racist stereotype, considered as civil by African American annotators, but not from the control group. A more thorough analysis of the detected posts and beyond (more examples are shown in Table 6 of the Appendix) is left for future work.

9 Conclusions

In this study we have focused on DFU, a measure that correlates well with human judgment for the assessment of polarized opinions. We have presented a normalised version, called nDFU, which not only correlates well with human judgment but is also more intuitive and interpretable that is important for tuning purposes. Using nDFU, we suggested the unpolarized learning method for text classification, which introduces a new class that contains the items detected as polarized. In this way the original classes are trained using unimodal (unpolarized items) and classification performance is improved. Experimenting with toxic language detection, an important and challenging due to the subjective annotations task, we showed that it outperforms the baseline with a statistically significant difference.

Finally, besides estimating polarization, we have shown that nDFU can also be used to trace the possible cause of polarization, by checking aposteriori unimodality conditions. Putting gender and race under the microscope, we presented texts per feature for which annotators were polarized only in an inter-dimension setting. Future work aims to apply aposteriori unimodality to more datasets, developing a corpus of polarized texts and facilitating the study of polarization. Also, extensions of unpolarized learning will be investigated exploring further the path towards more accurate and fair NLP.

Limitations

- The proposed approach is potentially applicable to any classification task with subjective annotations (e.g., sentiment analysis). The experiments of this study, however, were limited regarding the modality (text input), the language (English), and the domain (toxicity). Future work will investigate such extensions.

- Aposteriori unimodality (§8) has already revealed posts with polarized annotations (Tables 4 and 6), but their analysis is limited in this study. A thorough investigation of each such post should follow, by also taking into consideration the post's context (e.g., conversational) in order to draw more robust conclusions regarding the roots of polarization.

- The application of unpolarized learning and aposteriori unimodality requires datasets with un-aggregated annotations. Such datasets, however, are scarce. In future work, we will investigate whether the ATTITUDES dataset can also become publicly available, assisting towards that end with one more dataset.

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Appendix

A Unpolarized learning

A.1 Benchmark

Table 5 presents the Precision and Recall of the binary baseline, assessed on unimodal and non-unimodal evaluation data.

	P(uni/non)	R(uni/non)
CCTK	0.59/0.63	0.33/0.18
ATTITUDES	0.45/0.50	0.39/0.43
XMACH	0.63/0.58	0.67/0.62

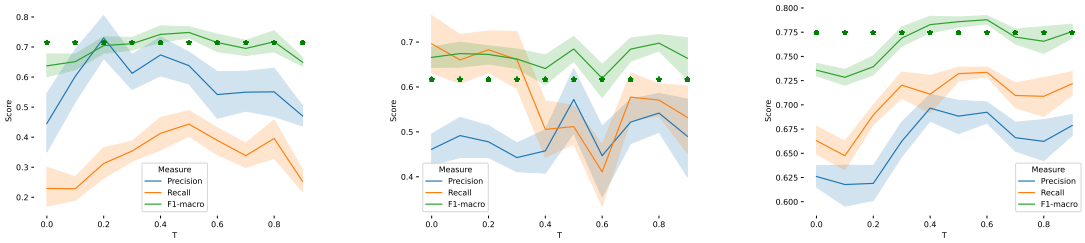
Table 5: Precision and Recall in binary classification of the BERT baseline, assessed on evaluation data with zero (unimodal) and non-zero (non-unimodal) nDFU.

A.2 Tuning

We sampled 500 posts per threshold for CCTK and XMACH and 50 for the smaller ATTITUDES. We repeated the experiment ten times to compute 95% confidence intervals. We only used zero nDFU posts, which are clearly correct. Similar results but on a smaller scale were observed for multimodal data. The green solid line in Figure 7 depicts the F1 of the model trained with unpolarized learning for the different thresholds when we ignored the predictions to the K+1 class during inference (i.e., class reduction). The optimum threshold in our study was between 0.4 and 0.5, but this depends on the fraction of posts with polarized annotations and is expected to vary across datasets and depend on the annotators.

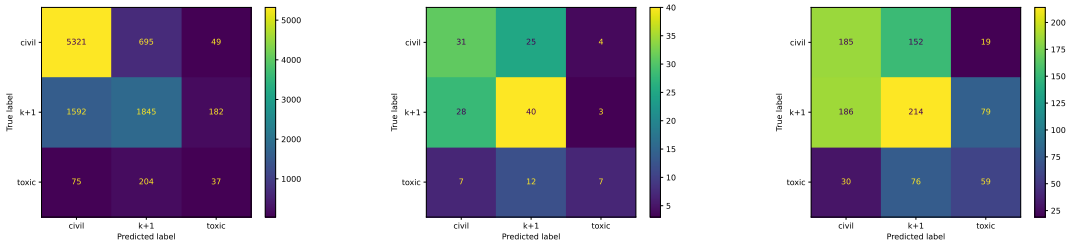
A.3 Confusion

By focusing on the second row of each confusion matrix in Figure 8, we observe that K+1 posts are often (mis)classified as civil.



(a) CCTK (b) ATTITUDES (c) XMACH

Figure 7: Precision, Recall, and macro-averaged F1 (in green) of a text classifier trained with the unpolarized learning approach for different thresholds T (horizontally). Predictions to the K+1 class ($nDFU > T$) are ignored during inference. The F1 score of a binary text toxicity classifier (ignoring the K+1 class) is shown in stars.



(a) CCTK (b) ATTITUDES (c) XMACH

Figure 8: Confusion matrix for our BERT-based text toxicity classifier trained with unimodal learning where the K+1 class is defined for posts for which $nDFU > 0$.

B Binary Classification with nDFU

The current binary classification formulation uses all the data, inferring a label for polarised annotations. Discarding high nDFU posts from the binary classifier's training data, however, sets another possible nDFU-based method. Our experiments in this direction showed that high-nDFU posts confuse the binary classifier. That is, by removing from 35% (CCTK) or 50% (Attitudes, XMACH) of the training instances (speeding up considerably training time), the performance remains the same in two out of three datasets (i.e., Attitudes, XMACH). Further investigation of this method is left for future work.

C Aposteri unimodal CCTK posts

Table 6 presents CCTK posts (§5) using the re-annotations provided by (Goyal et al., 2022) which come from three groups of annotators. Five annotators were African American, five were from the LGBTQ community, and five were selected beyond these groups to act as a control group.

Source	Toxic	Civil	Text
CCTK	CNTRL	AA	Nothing in the Bible about Jesus saying anything about immigration rights. [...] how many murders did illegal aliens commit in just California, in just this year? Just California. How many murders by illegal aliens? You answer that.
CCTK	CNTRL	AA	Are you high??? Selling someone a cake? Refusing to sell some a cake because it is for a gay wedding is no different from selling someone a cake because it is for a mixed race wedding or a Muslim wedding or any other kind of wedding. IT IS DISCRIMINATION! Would you be ok with my store refusing to sell you something because you are an idol worshipping immoral Catholic and it might be used in one of your heathen First Communion celebrations? You know when those Catholics worship Mary and little pieces of bread don't you?
CCTK	AA	CNTRL	How do you know he is not proud of his cakes? Artists do not take pride in their work? Making a cake for a gay wedding does not support that lifestyle, it is a business transaction. Period. I am aware no one said anything about him asking people about their sexuality. I am sorry that was hard for you to understand. Is he going to ask everyone that comes in if the cake is for a gay wedding? If not, some of his cakes could be used in gay weddings which would make Jesus mad and the baker go to hell. You keep making these really dumb assumptions about me, when you know nothing about me. I am not confused, you are rude. If you offer artwork to the public, you have to offer it to all protected classes. Why would black people be discriminated against? Precedent. Ridiculous? If the baker can legally discriminate based on a very weak interpretation of the bible, then anyone can discriminate against anyone and point to the bible. Satanists can discriminate against Christians...
CCTK	AA/LGBTQ	cntrl	well thats a no brainer hillary clinton gave huma abdein a security clearance when she has ties to a known terrorist group the muslim brotherhood, and her mother runs an anti american news paper in the middle east, debbie washed up crook shultz got the awan famaily security clearances and they were recent immigrants, had absolutely no IT experience and possible ties to terrorist groups in pakistan. its pretty clear our liberal ran government is a complete and total failure when it comes to national security. 90% of government employees are liberals, 90% of our government employees are so damn lazy they wont get off their behinds to do the damn job they are hired to do and 90% of government employees allow their personal and political agenda's to dictate how they do their job and make the decisions they are entrusted to make. our government needs a douche and all public employees sent to the unemployment line union contracts negated and the whole thing started over again with out union
CCTK	LGBTQ	cntrl	All men are sex offenders? Really? A sexual predator is a person who attacks a victim. Typical men don't rape or use force on women. You are obviously a person who hates men and or healthy, normal sex.

Table 6: CCTK posts from Goyal et al. (2022) that satisfied Equation 4 and which were found as toxic (civil) only by LGBTQ, African American (AA), or control-group (CNTRL) annotators.