Platt-Bin: Efficient Posterior Calibrated Training for NLP Classifiers

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Abstract

Modern NLP classifiers are known to return uncalibrated estimations of class posteriors. Existing methods for posterior calibration rescale the predicted probabilities but often have an adverse impact on final classification accuracy, thus leading to poorer generalization. We propose an end-to-end trained calibrator, Platt-Binning, that directly optimizes the objective while minimizing the difference between the predicted and empirical posterior probabilities. Our method leverages the sample efficiency of Platt scaling and the verification guarantees of histogram binning, thus not only reducing the calibration error but also improving task performance. In contrast to existing calibrators, we perform this efficient calibration during training. Empirical evaluation of benchmark NLP classification tasks echoes the efficacy of our proposal.

1 Introduction

Deep learning has proven to be tremendously attractive for researchers in fields such as physics, biology, and manufacturing, to name a few (Baldi et al., 2014; Anjos et al., 2015; Bergmann et al., 2014). However, these are fields in which representing model uncertainty is of crucial importance (Gal and Ghahramani, 2016). A common way to incorporate DNNs in other fields is to use the predictions of a trained classifier for decision making in a downstream task. In some cases the effectiveness of the decisions depends on a utility function and it is not enough to simply predict the most likely label for each example. What is needed instead is to quantify model uncertainty about the predictions. Despite promising performance in supervised learning benchmarks in terms of accuracy, DNNs are poor at quantifying predictive uncertainty, and tend to produce overconfident predictions. Overconfident incorrect predictions can be harmful or offensive in NLP applications (Amodei et al., 2016), hence proper uncertainty quantification is crucial in practice. Probabilistic uncertainty in machine learning translates to estimation of the probability mass function \( p(y|x) \) by the model, where \( x \) is the input sample and \( y \) is a class label. Recent works have shown that state-of-the-art structured prediction models are poorly calibrated. Therefore, blindly using the output of the softmax function output as the model uncertainty is misleading (Kumar and Sarawagi, 2019; Dong et al., 2018; Nguyen and O’Connor, 2015).

We are interested in calibrating the posterior estimates, i.e. we wish to get posterior probability estimations that reflect the true probability of the classes. The probability that a system outputs for an event should reflect the true frequency of that event: if an automated diagnosis system says 1,000 patients have cancer with probability 0.1, approximately 100 of them should indeed have cancer (Kumar et al., 2019). Even if the actual mechanism might be difficult to interpret, a calibrated model at least gives us a signal that it “knows what it doesn’t know,” thereby making these models easier to deploy in practice (Jiang et al., 2012). We define perfect calibration as follows.

\[
P(y|f(x)) = f(x)
\]

where \( f : \mathcal{X} \rightarrow \Delta_{K-1} \) is the probabilistic classifier that maps the samples \( x \in \mathcal{X} \) to the \( K \)-dimensional simplex. As majority of the current state-of-the-art structured prediction models, such as DNNs, do not output calibrated probabilities out of the box (Kuleshov et al., 2018), existing works rely on re-calibration methods that take the output of an uncalibrated model, and transform it into a calibrated probability. One way of addressing this is to use Scaling approaches for re-calibration such as Platt scaling (Platt et al., 1999), isotonic regression (Zadrozny and Elkan, 2002), and temperature scaling (Guo et al., 2017). These methods are widely used and require very few samples,
however it is challenging to calibrate posterior estimates with sub-optimal binning schemes (Kumar et al., 2019). An alternative approach, histogram binning (Zadrozny and Elkan, 2001), outputs probabilities from a finite set. Histogram binning can produce a model that is calibrated, and unlike scaling methods we can measure its calibration error, but it is sample inefficient. In particular, the number of samples required for calibration scales linearly with the number of classes for which probability estimates need to be generated.

Irrespective of the choice of the calibration method, existing works generally calibrate the posterior distribution predicted from the classifier after training. These post-processing calibration methods re-learn an appropriate distribution from a held-out validation set and then apply it to an unseen test set. The fixed split of the data sets and insufficient number of samples for training the calibration function adversely affects the generalization of post-hoc calibrated classifiers and reduce their accuracy. In this paper we try to address some of the existing challenges in achieving apt calibration. In particular our contributions are:

- We propose a training technique that optimizes a classification objective for an NLP task by calibrating the posterior distribution while training.
- We leverage the advantages of both scaling and binning methods and propose a calibration method for NLP classification task which is both sample efficient and verifiable.
- We demonstrate how the proposed method not only calibrates but also improves the performance of benchmark NLP classification tasks.

2 Related Works

Model uncertainty estimation and posterior calibration is a topic of continued interest not only in the fields of machine learning and statistics, but also in meteorology (Bröcker, 2009), fairness (Liu et al., 2019), healthcare (Jiang et al., 2012), reinforcement learning (Malik et al., 2019), natural language processing (Card and Smith, 2018), speech recognition (Yu et al., 2011) and economics (Gneiting et al., 2007). In probabilistic models, the principal goal of estimation of the posterior \( p(y|x) \) given a sample \( x \in \mathcal{X} \) and a label \( y \in [K] \), is to assign low confidence to samples that were not explained well by the training data. One common way to calibrate multi-class posteriors after training the classifier \( f : \mathcal{X} \rightarrow \mathbb{R} \) is to treat the problem as \( K \) one-vs-all binary problems. In this case, model uncertainty is quantified by normalizing the estimation of \( p(y = k|f(x)_k) \) where \( f(x)_k \) is the output score of the classifier for sample \( x \) and class \( k \). Generalization of calibration tests with kernel methods can be found in (Widmann et al., 2019). Various binary calibration methods can be used to estimate the marginal posterior over a calibration dataset, ranging from parametric approaches (e.g. Platt scaling, temperature scaling, vector scaling (Platt et al., 1999; Guo et al., 2017), to non-parametric methods (e.g. quantile or bayesian binning (Zadrozny and Elkan, 2001; Naeini et al., 2015), and isotonic regression (Zadrozny and Elkan, 2002).

Another way to reduce the problem to binary calibration is by estimating model accuracy conditioned on its confidence, \( p(y = \hat{y} | \max_{k \in [K]} f(x)_k) \). Multi-class calibration aims to estimate the distribution of class labels conditioned on the estimated probability vector, \( p(y | f(x)) \). In this case the sample complexity is exponential in the number of classes and therefore with large number of classes, the main challenge is to constrain the hypothesis space with regularization. Some of the proposed methods for this purpose are matrix scaling and Dirichlet scaling which both use linear models for estimation of \( p(y = k | f(x)) \) (Guo et al., 2017; Kull et al., 2019), and MLP and order preserving functions (Rahimi et al., 2020a,b).

Another approach is to account for model uncertainty via bayesian models. In Bayesian Neural Networks (BNNs) the predictive uncertainty will naturally be high in regions where training data is scarce (MacKay, 1992). However, the marginalization of the weights in BNN is intractable in general. Consequently, following papers propose various approximations such as variational inference (VI) (Graves, 2011; Blundell et al., 2015). Although BNNs are theoretically proven to control the overconfidence of the model in unseen regions of data space (Krstiadi et al., 2020), they require expensive approximations which limit their application in most modern NLP architectures. For instance, in (Joo et al., 2020) the authors model the distribution on posterior probability using a Dirichlet prior distribution and variational inference. MCDropout is
a variational approximation of Gaussian processes that avoids explicit modeling of the posterior distribution (Gal and Ghahramani, 2016). Both of these methods require modification of training of the network.

In NLP, tasks with structured outputs posterior calibration are particularly challenging. This is because the number of classes is exponentially large and estimation of every posterior density or marginal posterior density is not possible. Previous works such as (Jung et al., 2020; Nguyen and O’Connor, 2015) propose to use the downstream task with small number of classes to perform calibration and estimation of the calibration error. In structured prediction models, calibration is also important for the generation of the structured outputs as the decoding algorithm relies on the posterior estimates to efficiently search through the space of sequences. However, estimation of the sequence calibration error and its correction is intractable. To cope with this problem, approximate calibration methods using a set of interesting events and feature based calibration are proposed in (Kuleshov and Liang, 2015; Jagannatha and Yu, 2020) and an alternative calibration error estimator was proposed using sequence precision scoring function BLEU in (Kumar and Sarawagi, 2019). We are considering the first class of problems and leave the structured calibration to future work.

3 Method

In general, NLP classifiers work by first predicting a posterior probability distribution over all classes and then selecting the class with the largest estimated probability. However, these models are often poorly calibrated. Existing calibration methods re-learn an appropriate distribution from a held-out validation set and then apply it to an unseen test set which degrades the model performance. Alternatively, we can dynamically estimate the required statistics for calibration from the train set during training iterations, thereby minimizing cross-entropy as well as the calibration error as a multi-task setup (Jung et al., 2020). Given a training set $D = \{(x_1,y_1),\ldots,(x_n,y_n)\}$, where $x_i$ is an $n$-dimensional vector of input features and $y_i$ is a $K$-dimensional one-hot vector corresponding to its true label (with $K$ classes), we minimize the loss $L_{train}$:

$$L_{train} = L_{class} + \lambda L_{cal}$$

Here $L_{class}$ is the classification loss (for eg. cross-entropy) based on the predicted probability $p_{ik}$ updated during training for sample $i$ and class $k$:

$$L_{class} = -\sum_{i=1}^{N} \sum_{k=1}^{K} y_{ik}\log(p_{ik})$$

$L_{cal}$ is the calibration loss which acts as a regularizer. It essentially tries to minimize the difference between the updated probability $p$ and true posterior probabilities $q$ via a distance function $d$ (eg. mean squared error, KL-divergence, etc.):

$$L_{cal} = \sum_{i=1}^{N} \sum_{k=1}^{K} d(q_{ik}, p_{ik})$$

One crucial step here is to estimate the empirical probability $q$, which can be done by histogram binning method. Here, we measure the ratio of true labels for each bin split by the predicted posterior $p$ from each update. This refers to CalEmpProb() function in algorithm 1. We store the results in Empirical Probability Matrix $Q \in \mathbb{R}^{B \times K}$, where $B$ is the number of bins used for each posterior dimension. Histogram binning outputs probabilities from a finite set. Unlike scaling methods, it can produce a model that is calibrated and measure its calibration error. However, the number of samples required to calibrate scales linearly with the number of distinct probabilities $B$ the model can output which can be large in the multi-class setting (Naeini et al., 2014).

In this work, we propose an adaptive binning method that circumvents this bottleneck. We leverage the sample efficiency of Platt scaling (Platt et al., 1999) and the verification guarantees of histogram binning (Zadrozny and Elkan, 2001) by defining the Platt-Binning Calibrator. The problem with scaling methods is we cannot estimate their calibration error. The upside of scaling methods is that if the function family has at least one function that can achieve calibration error $\epsilon$ they require $O(1/\epsilon^2)$ samples to reach calibration error $\epsilon$, while histogram binning requires $O(B/\epsilon^2)$ samples. Platt-Binning Calibrator facilitates estimation of calibration error while being sample-efficient at the same time.

**Platt scaling calibrator**: Since most modern deep learning classifiers do not output calibrated probabilities out of the box, recalibration methods take
the output of an uncalibrated model, and transform it into a calibrated probability. That is, given a trained model \( f : \mathcal{X} \rightarrow [0, 1] \), let \( z = f(x) \). We are given recalibration data \( T = \{(z_i, y_i)\}_{i=1}^n \) corresponding to model logits and the labels, and we wish to learn a calibrator \( g : [0, 1] \rightarrow [0, 1] \) such that \( g \circ f \) is well-calibrated. Conventional Scoring methods, for example Platt scaling, output a function \( g \):

\[
g = \arg\min_{g \in G} \sum_{(z,y) \in T} l(g(z), y)
\]

where \( G \) is the hypothesis class, \( g \in G \) is differentiable, and \( l \) is a loss function, for example the log-loss or mean-squared error. The advantage of such methods is that they converge very quickly since they only fit a small number of parameters.

**Histogram binning calibrator**, on the other hand, constructs a set of bins that partitions \([0, 1]\) via a binning scheme. A binning scheme \( \hat{B} \) of size \( B \) is a set of \( B \) intervals \( I_1, ..., I_B \) that partitions \([0, 1]\). We use the notation \( \sigma \) to denote the softmax function. Given \( p = \sigma(z)_k \in [0, 1] \), let \( \beta(z) = j \), where \( j \) is the interval that \( p \) lands in \((p \in I_j)\). The binning scheme, \( \hat{B} \) typically corresponds to choosing bins of equal widths (called equal width binning) or so that each bin contains an equal number of \( z \) values in the calibration dataset (called uniform mass binning). Histogram binning then outputs the average \( y_i \) value in each bin.

**Platt-Binning Calibrator** builds at the intersection of the above two methods. Given a recalibration data \( T \) of size \( n \), Platt-Binning Calibrator outputs \( \hat{g}_\beta \) such that \( \hat{g}_\beta \circ f \) has a low calibration error by using the following procedure:

**Step 1:** Select \( g \):

\[
g = \arg\min_{g \in G} \sum_{(z,y) \in T} (y - g(z))^2 \tag{2}
\]

**Step 2:** Choose the bins so that an equal number of \( g(z)_i \) in \( T \) land in each bin \( b_j \) for each \( j = 1, ..., B \)

\[
\text{ECE} = \frac{1}{K} \sum_{k=1}^K \sum_{b=1}^B \frac{N_{kb}}{N_k} |Q_{bk} - \bar{p}_{bk}|
\]

where \( \bar{p}_{bk} \) is the average posterior estimate for class \( k \) for samples in \( b \)-th bin. \( N_{kb} \) and \( N_k \) are the number of samples of class \( k \) assigned to bin \( b \) and in total, respectively. Contrary to equal-width binning, uniform-mass binning is a well-balanced binning scheme with guarantees on error bounds of estimated Expected Calibration Error, \( ECE \) (Kumar et al., 2019).

**Step 3:** Discretize \( g \), by outputting the average \( g \) value in each bin. Let \( \mu(S) = \frac{1}{|S|} \sum_{x \in S} x \) denote the mean of a set of values \( S \). We set \( \hat{g}_\beta(z) = \mu((\beta(g(z))) \) - we output the mean value of the bins that \( g(z) \) falls in.

The motivation behind our method is that the \( g \) values in each bin are in a narrower range than the label values \( y_i \), so when we take the average we incur lower estimation error. If \( G \) is well chosen, our method requires \( O(\frac{1}{\epsilon^2} + B) \) samples to achieve calibration error \( \epsilon \) instead of \( O(\frac{B}{\epsilon^2}) \) samples for histogram binning. All these steps are performed during training as explained in the pseudo-code in Algorithm 1. To the best of our knowledge, such a formulation is novel among existing calibrators that tackle the problem during training. Also, the whole approach is the first to be utilised to calibrate classifiers in the NLP domain. In the following section we prove the efficacy of our method by carrying out extensive evaluation of the performance of pre-trained transformer models such as BERT (Devlin et al., 2019) on simple multi-class text classification tasks. Our motivation comes from the analysis in (Desai and Durrett, 2020) which shows that pre-trained models are significantly better calibrated when used out-of-the-box.

### 4 Experiments

In the experiments we fine-tune the parameters on pre-trained BERT classifier using the regularized loss in equation (1). We compare our method to the following baselines:

- **MLE** is the baseline with maximum likelihood training without calibration where we simply report the results of vanilla BERT classifier on the chosen tasks.
- **Platt scaling** (posPS) is a post-hoc calibration method where we calibrate the posterior estimations of MLE classifier using Platt scaling (Platt et al., 1999). Formally, the parameters of the calibration functions \( g(z; W, b) = NN(W \cdot \sigma(z) + b) \) is fit to the validation dataset. Here, \( NN \) refers to a neural network with the component-wise logistic function. Model is fit using one-vs-all binarization of the classification task. Instead of the estimated posterior-
Algorithm 1 Platt-Binning Calibrated Training

Input: Train set $D$, $j^{th}$ bin $b_j$, Set of all bins $b$, Number of Classes $K$, Number of epochs $e$, Learning rate $\eta$, Update period $u$

Output: Model Parameters $\Theta$

Let $Q$ : Empirical Probability Matrix $\in \mathbb{R}^{B \times K}$
Random initialization of $\Theta$

for $i \in \{1,2,3, \ldots , e\}$ do
Break $D$ into random mini-batches $m$

for $m$ from $D$ do

if $i \mod u == 0$ then

$\hat{p}(x) = \max_k \sigma(\Theta, D)_k$, $\forall x \in D$.

$\hat{y} = \arg \max_k \sigma(\Theta, D)_k$, $\forall x \in D$.

Select $q$ using equation 2.

Uniform-mass binning over $g(p_k)$.

Discretize $g$: $\hat{g}_\beta(p_k) = \mu[\beta(g(p_k))]$

$Q \leftarrow \text{CalEmpProb}(\hat{p};b_j)$

$\Theta \leftarrow \Theta - \eta \nabla_\Theta L_{\text{train}}(\Theta, \hat{g}_\beta(p_k), b)$

end

end

end

$\sigma(f(x))_k$ for class $k$ - we return the calibrated value $g(f(x))$ as the class probability. Despite its simplicity this method is competitive with the more complex methods when implemented post-hoc (Guo et al., 2017).

- **PosCal** end-to-end training calibration using histogram binning (Jung et al., 2020). In this method we have a nested training procedure where in the outer loop we fit a histogram binning scheme with fix widths to each dimension of the posterior estimates of the BERT model. We use $Q_{bk}$ - the ratio of samples of $k^{th}$ class that were assigned to $b^{th}$ bin-as the empirical probability distribution $q$. In the inner loop we perform the ordinary training iterations over mini-batches of training dataset with cross-entropy loss and regularization term in equation (1) using KL-divergence between softmax output and the estimated empirical distribution.

$$L_{\text{cal}} = \sum_{i=1}^{N} \sum_{k=1}^{K} \log \frac{\sigma(z_i)_k}{Q_{\text{bin}(z_i)_k}^k}$$

where $\text{bin}(\cdot)$ returns the index of bin assigned to its input. In the experiments we used $\lambda = 1.0$, 10 bin for discretisation of $q$ and we update $Q$ after every training epoch.

We test the baselines and our method on the benchmark on NLP classification tasks: xSLUE (Kang and Hovy, 2019). xSLUE contains classification benchmark on different types of styles such as a level of humor, formality and even demographics of authors. We train our method with two types of calibrators: in the first calibration task we train a calibrator for the most confident prediction of the classifier and call this version plattbintop (PBtop).

The pseudocode of this version is illustrated in algorithm (1). In the second version we train a separate Platt scaler and histogram binning for each class in a one-vs-all manner and we call this version of calibration plattbin (PB). While this version is exactly the same as plattbintop for binary tasks, it results in a very different solution for tasks with $K > 2$. The pseudocode of this version is omitted due to being mainly similar to the other version with one additional loop over the classes at line 7 of algorithm (1) and conversion of label $y$ and $\hat{y}$ to one-vs-all binary labels. We report task accuracy, F1 score and ECE as the evaluation metrics.

5 Results and Discussion

Table 1 shows task performance and calibration error on xSLUE benchmark datasets. In general, our method outperforms MLE, Poscal and posPS on more than 50% of the datasets, in terms of both model performance and calibration error. For the rest of the datasets, our method gives competitive results. In seven out of nine cases, we reduce the calibration error ECE as compared to PosCal. In cases such as DailyDialog, SentiTreeBank and ShortHumor, the achieved reduction in ECE as compared to all baselines is significant. Note that this reduction has not compromised the model performance. In fact, cases like SentiTreeBank and ShortRomance even witness a significant improvement in the performance of the model when ECE is reduced. These observations prove the efficacy of our method in maintaining a perfect balance between model performance and model uncertainty-a testimony of an ideal calibrator. Post-hoc methods such as posPS might achieve lower calibration error on a couple of datasets, but they fail to attain competitive performance in terms of accuracy. Similarly, in-training methods like PosCal tend to achieve higher accuracy but fail to be consistent in
Table 1: Comparison of Model performance and Calibration error on different benchmark datasets. MLE: Maximum Likelihood; PosCal: Posterior Calibrated Training with Histogram Binning; posPS: post-hoc calibration with Platt scaling; PB: Platt-Binning Method; PBtop: PB over max(softmax(logits)). Our method (PB or PBtop) achieves better balance among the three metrics reported.

| Dataset          | Accuracy | F1 score | ECE |
|------------------|----------|----------|-----|
| DailyDialog      | 84.8     | 84.9     | 84.9|
| HateOffensive    | 91.5     | 95.9     | 95.9|
| SarcasmGhosh     | 54.4     | 54.5     | 54.5|
| SentTreeBank     | 94.6     | 95.8     | 95.8|
| ShortRomance     | 99.9     | 99.9     | 99.9|
| StanfordPoliteness | 67.9  | 68.1     | 68.1|
| TroFi            | 77.5     | 77.7     | 77.7|
| VUA              | 80.6     | 81.7     | 81.7|

Figure 1: Calibration plots: (top) accuracy vs average confidence, (bottom) number of samples per bin vs average confidence. Our proposed method (PB or PBtop) hits the sweet-spot between the two extremes and is shown to achieve better results than baselines: highest accuracy except for TroFi, highest F1 score except for TroFi and VUA and lowest ECE except for TroFi and stanfordpoliteness (Table 1).

We now analyse how our method behaves in comparison to MLE at sample level during test time. Table 2 shows a detailed analysis of misclassification made by MLE and Platt-Binning (PB). We see that both the methods have almost comparable performance in columns A1 and A2, with A2 being slightly higher. As such, the number of samples for which MLE and PB gave different predictions (column M) is actually a small fraction of the total number of test samples used of evaluation of the methods (column Test). We further analyse the number of samples where MLE gave correct predictions while PB failed to do so (column P1) and vice-versa (column P2). In 8 out of 9 datasets, PB demonstrates superior or similar performance (P2 ≥ P1). The difference is insignificant compared...
to the total size of the test set for the reverse scenario. This quantitative analysis reinstates that our method, PB, has better model performance at test time, thereby establishing that it generalizes well while reducing calibration error.

We extend the discussion above by analysing qualitative results in Table 3. We consider three datasets: a two-class classification task StanfordPoliteness, a three-class classification task HateOffensive and a multi-class classification task \( K > 3 \) DailyDialog, and include few test samples where MLE and PB disagreed on the predictions. The corresponding \( \hat{p} \) along with the true label is also depicted.

In the first two cases from StanfordPoliteness dataset, the level of politeness (e.g., “Hey!” in S1) or arrogance (e.g., “What?” in S2) indicated on phrases is not captured well by MLE, so it predicts the incorrect label while PB gives a correct prediction. However, for the rest two cases, MLE gives confident correct predictions taking into account phrases such as "like" in S1 or a slightly difficult example in S2 but PB fails (only slightly in S2 though) to give correct predictions. Arguing on similar lines for the multi-class case, we witness cases where MLE fails to classify correctly (e.g. S1 and S2 in HateOffensive) but PB gives highly confident predictions and vice-versa. From our manual investigation above, we find that statistical knowledge about posterior probability helps correct \( \hat{p} \) while training PB, so making \( \hat{p} \) switch its prediction. For further analysis, we provide more examples in Appendix ??.

Table 2: Comparison of model performance at test time between MLE and PB. Test: Number of test samples, M: No. of test samples for which MLE and Platt-Binning (PB) gave different predictions, P1: No. of samples correctly classified by MLE but misclassified by PB, P2: No. of samples correctly classified by PB but misclassified by MLE, A1: Accuracy of MLE, A2: Accuracy of PB

| Data              | Test | M  | P1  | P2  | A1  | A2  |
|-------------------|------|----|-----|-----|-----|-----|
| DailyDialog       | 7740 | 475| 244 | 292 | 84.7| 84.9|
| HateOffensive     | 1255 | 93 | 32  | 50  | 91.4| 92.9|
| SarcasmGhosh      | 2000 | 0  | 0   | 0   | 54.4| 54.4|
| SentiTreeBank     | 1749 | 73 | 29  | 44  | 94.5| 95.4|
| ShortHumor        | 2256 | 93 | 44  | 49  | 95.4| 95.6|
| ShortRomance      | 100  | 0  | 0   | 0   | 99.9| 99.9|
| StanfordPoliteness| 567  | 37 | 38  | 67.9| 68.1|
| TroFi             | 227  | 41 | 23  | 18  | 77.5| 75.3|
| VUA               | 5873 | 958| 472 | 486 | 80.6| 80.9|

In Figure 1 we show the calibration plots for three datasets: DailyDialog, HateOffensive, and StanfordPoliteness. We divide test samples according to the most confident estimated posterior into 10 bins. We plot the accuracy of the classifier versus the average classification confidence in each one of the bins in the top row. We also plot the number of samples in each calibration bin versus the classification confidence in the bottom row. Ideally, a calibrated classifier would assign a probability to the top class that is equivalent to its accuracy. Therefore, the accuracy-confidence curve of a calibrated classifier is close to the dashed grey curve in the top row. When Platt-bin and Platt-bin-top are further away from the calibration line it is because the number of samples in corresponding bins are low or even 0 in some cases. The bins with 0 samples in them can be ignored as they don’t play a role in the classifier predictions.

However, the distance of the curves is not enough to determine model calibration as most of the samples are assigned to the bin with highest estimated posterior. Thus, correcting the calibration error in the bins with more samples is more effective in improving the expected calibration error. Platt-Binning and Platt-Binning-Top algorithms increase the number of samples with lower classification confidence in all three of the illustrated tasks, while in comparison to MLE with no regularization they only reduce classification accuracy by a negligible amount and even increase the accuracy for HateOffensive task. Although, the classifier become visibly underconfident in HateOffensive task where post-hoc Platt scaling has a more calibrated output. While the ECE doesn’t improve in StanfordPoliteness, Platt-Binning algorithm doesn’t increase the ECE as much as PosCal regularization. We conjecture that such a behavior is demonstrated due to better sample efficiency of our algorithm.

We conclude our analysis by observing the effect of two important parameters to this discussion- \( B \): number of histogram bins used for calibration, and \( \lambda \): strength of the regularization. Figure 2 shows how calibration error (ECE) vary when the number of bins \( B \) is varied as \( \{10, \ldots, 100\} \). We see that the calibration error of all the methods have an increasing trend as \( B \) is increased. One plausible
### Table 3: Predicted $\hat{p}$ of true label from MLE and PB with corresponding sentences in D-Dialog, H-Offensive and S-Polite dataset. Provided examples contrast the predictions between MLE and PB for qualitative analysis.

| Data       | Sentence                              | True Label | $\hat{p}$ (MLE) | $\hat{p}$ (PB) | MLE $\rightarrow$ PB |
|------------|---------------------------------------|------------|-----------------|----------------|----------------------|
| DailyDialog| S1: Really ? What did you get one for ? | surprise   | 0.17            | 0.60           | INCOR $\rightarrow$ COR |
|            | S2: To hell with you . The accident was your fault | anger      | 0.14            | 0.41           | INCOR $\rightarrow$ COR |
|            | S1: I might just ! Enjoy your stupid game ! | anger      | 0.41            | 0.36           | COR $\rightarrow$ INCOR |
|            | S2: Yeah . We rolled out the red carpet to welcome him home . | noemotion  | 0.96            | 0.37           | COR $\rightarrow$ INCOR |
| HateOffensive| S1: @HBergHattie @snkscoyote I wonder if the progs didn’t relegate young black men to the ghettos to keep them away from harry reid’s friends. | neither    | 0.02            | 0.91           | INCOR $\rightarrow$ COR |
|            | S2: Every spic cop in #LosAngeles is loyal to the #LatinKin | hate       | 0.002           | 0.65           | INCOR $\rightarrow$ COR |
|            | S1:’Our people”. Now is the time for the Aryan race to stand up and say "no more”. Before the mongerls turn the world into a ghetto slum. | hate       | 0.95            | 0.37           | COR $\rightarrow$ INCOR |
|            | S2: #RebelScience .....is using an ACTUAL WOMAN as a genetic engineering lab for “all natural clones”..... or something..... #faggot #fro | hate       | 0.98            | 0.04           | COR $\rightarrow$ INCOR |
| S-Polite   | S1: Hey, long time no seeing! How’s stuff? | polite     | 0.16            | 0.63           | INCOR $\rightarrow$ COR |
|            | S2: What user list? The one I linked to? | impolite   | 0.34            | 0.52           | INCOR $\rightarrow$ COR |
|            | S1: I like the first shot. Are those doghouses? | polite     | 0.68            | 0.24           | COR $\rightarrow$ INCOR |
|            | S2: I usually just boil water and then drink but I think it won’t help here. Does it? | impolite   | 0.68            | 0.48           | COR $\rightarrow$ INCOR |

### Figure 2: Effect of number of histogram bins used for calibration on the calibration error

Explanation can be that as we increase the number of bins, we don’t have enough samples per bin to estimate the empirical probabilities accurately. Since calibrated probabilities are used as an estimation of the true probabilities of the classes in case of PosCal and PB, it adds to the error if they are estimated wrongly. Thus, smaller number of bins is preferred, and as evident in Fig. 2, PB achieves lower ECE than PosCal when number of bins is low. The accuracy and F1 scores do not vary much with the number of the bins. Similarly, the performance is not impacted significantly by variations in the value of $\lambda$ (see Appendix ??)

### 6 Conclusion

In this work we proposed a simple yet effective method called Platt-Binning calibrator for better posterior calibration. Our method has theoretically lower sample complexity than histogram binning, giving us the best of scaling and binning methods. And unlike the existing post-processing calibration methods, Platt-Binning directly penalizes the difference between the predicted and the true (empirical) posterior probabilities dynamically over the training steps. Our empirical analysis corroborates that Platt-Binning can not only reduce the calibration error but also increase the task performance on the classification benchmarks. For tasks where the reduction in calibration error is low, our method maintains the performance of the model instead of degrading it as seen for other existing calibrators. Moreover, our method can be extended to any classification model as an additional component in the loss function, thus jointly optimised during training. There are many exciting avenues for future works in this regard. It will be interesting to assess how our method can provide advantages in the scenarios of domain adaptation and transfer learning. Moreover, exploring alternatives to the model family $G$ from which estimate $\hat{g}$ is considered can be a direction of improvement. Lastly, optimizing the overall method for huge datasets can be
an essential extension. Our method may also assist in analysing the bias and fairness aspects of the predictions made by NLP classifiers. This can facilitate ethical deployment of NLP models for real-world applications.

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Figure 3: Effect of Bin-size (upper row) and regularization (lower row) on model accuracy and F1 score

| True Label | MLE → PB | MLE $\hat{p}$ | PB $\hat{p}$ | Sentence |
|------------|----------|---------------|--------------|-----------|
| happiness  | INCOR → COR | 0.32          | 0.70         | Our pleasure. Please fill out this form, leaving your address and telephone number. |
| noemotion  | INCOR → COR | 0.30          | 0.55         | sounds good. What are you going to have for your main course? |
| surprise   | INCOR → COR | 0.17          | 0.60         | Really? What did you get one for? |
| happiness  | INCOR → COR | 0.13          | 0.82         | I’m glad to help you. What’s wrong? |
| anger      | INCOR → COR | 0.12          | 0.36         | Damn it! I’m injured here. We could wait all day for the police. |
| anger      | INCOR → COR | 0.14          | 0.41         | To hell with you. The accident was your fault. |
| noemotion  | INCOR → COR | 0.11          | 0.39         | To hell with you. |
| noemotion  | COR → INCOR | 0.73          | 0.43         | No problem. |
| noemotion  | COR → INCOR | 0.99          | 0.31         | Of course. The fitting room is right over there. |
| happiness  | COR → INCOR | 0.61          | 0.46         | Great, thanks. |
| noemotion  | COR → INCOR | 0.78          | 0.34         | Hello! |
| happiness  | COR → INCOR | 0.64          | 0.15         | Sure thing, follow me. This here is the. |
| noemotion  | COR → INCOR | 0.90          | 0.36         | Well, if you ever want to visit Korea, I would be happy to show you around. |
| anger      | COR → INCOR | 0.41          | 0.36         | I might just! Enjoy your stupid game! |
| noemotion  | COR → INCOR | 0.81          | 0.40         | But he seems to be very happy with Rose. |
| happiness  | COR → INCOR | 0.53          | 0.08         | So sorry. Next time we’ll go, thanks anyway. |
| disgust    | COR → INCOR | 0.49          | 0.28         | I dislike it most. |
| noemotion  | COR → INCOR | 0.98          | 0.42         | It was a real red letter day for you. |
| noemotion  | COR → INCOR | 0.96          | 0.37         | Yeah. We rolled out the red carpet to welcome him home. |

Table 4: Additional examples for predicted $\hat{p}$ of true label from MLE and PB with corresponding sentences in DailyDialog
| True Label | MLE → PB | MLE \hat{p} | PB \hat{p} | Sentence |
|------------|----------|-------------|-------------|----------|
| offensive  | INCOR → COR | 0.02 | 0.56 | @aschops absolutely agree with that statement. It’s just so amusing how angry it makes all these teabagger scumbags. That alone is worth i |
| neither    | INCOR → COR | 0.02 | 0.91 | @H1bagHat1e @unномые I wonder if the prog’s didn’t relegate young black men to the ghettos to keep them away from Harry Reid’s friends, |
| offensive  | INCOR → COR | 0.03 | 0.49 | kieffer_jason i swear u a fuck nigga u a scary little bitch u think this a game bun |
| hate       | INCOR → COR | 0.32 | 0.60 | @InToBlame you a fatherless wallet carrying ass video game playing ass negro bich. You lill. No way you can afford to date a #TwitterHome |
| offensive  | INCOR → COR | 0.09 | 0.74 | I hate a don’t get shit done ass nig |
| hate       | INCOR → COR | 0.002 | 0.65 | Every single cop in LA is loyal to the #LatinoKin |
| offensive  | COR → INCOR | 0.99 | 0.06 | "@KingCali @16standronvs so i alt record bu time us pt bahuahahah lol anythinguany bu |
| hate       | COR → INCOR | 0.98 | 0.04 | @RebelScience .... is using an ACTUAL WOMAN as a genetic engineering lab for "all natural clones" ... or something ... #waggitbvs |
| offensive  | COR → INCOR | 0.99 | 0.38 | "Let’s do nips shoy and spank me maybe |
| hate       | COR → INCOR | 0.95 | 0.37 | “Our people”. Now is the time for the Aryan race 2 stand up and say “no more”. Before the mongrels turn the world into a ghetto slum. 14 |
| offensive  | COR → INCOR | 0.68 | 0.47 | \#1253530 RT @SexSince81: niggers RT @VonsheyB Before any moves are made... my black ass must take a na |
| TRUE LABEL | MLE → PB | MLE \hat{p} | PB \hat{p} | Sentence |
| impolite   | INCOR → COR | 0.34 | 0.52 | What user list? The one I linked to? |
| polite     | INCOR → COR | 0.35 | 0.60 | As I wrote above, at first I thought lets keep it, but after I heard some arguments, and when I made analysis of my own, I got to my conclusion. What’s yours? |
| impolite   | INCOR → COR | 0.47 | 0.74 | You and <url> are getting quite close to an edit war. Perhaps you should talk it out? |
| polite     | INCOR → COR | 0.16 | 0.61 | Hey, long time no seeing! How’s stuff? |
| impolite   | COR → INCOR | 0.59 | 0.36 | I am not sure of the question. Do you want problems that are obviously in one of the classes but not the other? |
| polite     | COR → INCOR | 0.62 | 0.43 | 02/2011 Try adding 'ServerAlias mystic.com' after 'ServerName' line. Also, do you have a DNS entry for mystic.com – same as www.mystic.com? |
| polite     | COR → INCOR | 0.68 | 0.24 | I like the first shot. Are those poisonous? |
| impolite   | COR → INCOR | 0.51 | 0.44 | Hmmmm, Apple software on Windows question. I guess the "Apple Software" part defines the fact that you posted it here? |
| polite     | COR → INCOR | 0.61 | 0.49 | how do you import the csv into the spreadsheet? (importable?) |
| impolite   | COR → INCOR | 0.68 | 0.68 | I usually just boil water and then drink it but I think it won’t help here. Does it? |
| impolite   | COR → INCOR | 0.78 | 0.27 | What’s the benefit of the horizontal dropout? Is it safety? Is it just a style? Is it ease of maintenance? |
| impolite   | COR → INCOR | 0.51 | 0.32 | Maybe it’s necessary to phrase this another way: is there any food that "everybody" can eat? |

Table 5: Additional examples for predicted \( \hat{p} \) of true label from MLE and PB with corresponding sentences in HateOffensive

| True Label | MLE → PB | MLE \hat{p} | PB \hat{p} | Sentence |
|------------|----------|-------------|-------------|----------|
| impolite   | INCOR → COR | 0.34 | 0.52 | What user list? The one I linked to? |
| polite     | INCOR → COR | 0.35 | 0.60 | As I wrote above, at first I thought lets keep it, but after I heard some arguments, and when I made analysis of my own, I got to my conclusion. What’s yours? |
| impolite   | INCOR → COR | 0.47 | 0.74 | You and <url> are getting quite close to an edit war. Perhaps you should talk it out? |
| polite     | INCOR → COR | 0.16 | 0.61 | Hey, long time no seeing! How’s stuff? |
| impolite   | COR → INCOR | 0.59 | 0.36 | I am not sure of the question. Do you want problems that are obviously in one of the classes but not the other? |
| polite     | COR → INCOR | 0.62 | 0.43 | 02/2011 Try adding 'ServerAlias mystic.com' after 'ServerName' line. Also, do you have a DNS entry for mystic.com – same as www.mystic.com? |
| polite     | COR → INCOR | 0.68 | 0.24 | I like the first shot. Are those poisonous? |
| impolite   | COR → INCOR | 0.51 | 0.44 | Hmmmm, Apple software on Windows question. I guess the "Apple Software" part defines the fact that you posted it here? |
| polite     | COR → INCOR | 0.61 | 0.49 | how do you import the csv into the spreadsheet? (importable?) |
| impolite   | COR → INCOR | 0.68 | 0.68 | I usually just boil water and then drink it but I think it won’t help here. Does it? |
| impolite   | COR → INCOR | 0.78 | 0.27 | What’s the benefit of the horizontal dropout? Is it safety? Is it just a style? Is it ease of maintenance? |
| impolite   | COR → INCOR | 0.51 | 0.32 | Maybe it’s necessary to phrase this another way: is there any food that "everybody" can eat? |

Table 6: Additional examples for predicted \( \hat{p} \) of true label from MLE and PB with corresponding sentences in StanfordPoliteness