Revisiting Calibration for Question Answering

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Abstract

Model calibration aims to adjust (calibrate) models’ confidence so that they match expected accuracy. We argue that the traditional evaluation of calibration (expected calibration error; ECE) does not reflect usefulness of the model confidence. For example, after conventional temperature scaling, confidence scores become similar for all predictions, which makes it hard for users to distinguish correct predictions from wrong ones, even though it achieves low ECE. Building on those observations, we propose a new calibration metric, MacroCE, that better captures whether the model assigns low confidence to wrong predictions and high confidence to correct predictions. We examine various conventional calibration methods including temperature scaling, feature-based classifier, neural answer reranking, and label smoothing, all of which do not bring significant gains under our new MacroCE metric. Towards more effective calibration, we propose a new calibration method based on the model’s prediction consistency along the training trajectory. This new method, which we name as consistency calibration, shows promise for better calibration.

1 Introduction

Large pre-trained language models (LMs) have shown impressive results on multiple NLP benchmarks. However, the predictions from these models are still far from perfect. When deploying into real-world applications such as search engines or digital assistants, we need to avoid presenting wrong predictions to users, which could misinform user decisions. Therefore, models should reliably provide the corresponding confidence estimation so that predictions with low confidence can be abstained. This problem is often defined as Model Calibration: making the confidence of the prediction represent the actual likelihood of it being correct.

While past work has proposed post-hoc approaches to calibrate model predictions, such as temperature scaling (Guo et al., 2017), they are designed only for multi-class classification tasks. In this paper, we revisit calibration and apply it on a more complex task with real-world applications: open-domain question answering (ODQA). The task takes an input question, retrieves evidence passages from a large knowledge base such as Wikipedia, and then returns an answer string.

We focus on ODQA because it is a real-world example of a user forced to evaluate whether or not to trust a computer’s prediction. From a user’s perspective, a better confidence score could help
a user understand whether to accept an answer or to dig deeper and verify an answer. From a provider’s perspective, better calibration could prevent embarrassing wrong answers like answering how many legs a horse has with “six”. From an engineering perspective, ODQA has two components (which we review in detail in section 3.1): a passage retriever, and a reader model for selecting the answer span. This makes the task format drastically unlike simple multi-class classification, and makes adapting existing calibration techniques a non-trivial challenge.

In this work, we re-examine calibration of retriever-reader style ODQA models on both in-domain and out-of-domain (OOD) settings. We start with the conventionally used calibration metric, expected calibration error (ECE), which bucketets the model predictions into confidence intervals and computes weighted average of the discrepancy between each bin’s expected accuracy and confidence. After adapting and applying temperature scaling on ODQA, models get very low ECE scores (Section 3). However, by taking a closer look at the actual bucket distribution, we find that all “calibrated” predictions have similar level of low confidence (close to the average answer accuracy), which results in a misleadingly low ECE. Such result has little practical utility to inform user decisions since all predictions have similar confidence values. Further, as large number of predictions are clustered in the same buckets, it causes cancellation effects as over-confident and under-confident predictions are averaged out, hiding away the instance-level calibration errors.

To address these issues, we provide an alternative view of calibration where the goal is to make correct and wrong predictions distinguishable, and propose a new metric, category-Macro-average Calibration Error (MacroCE), which sums calibration error at the instance level, and takes equal weight on both correct and wrong predictions. On the same experiment setting, temperature scaling approach that works well under ECE evaluation, fails under MacroCE (Section 4).

Apart from temperature scaling, we also benchmark a series of other existing calibration methods, including feature-based classifier, neural answer reranker, and label smoothing. We find that none of these existing methods brings significant gains under our new MacroCE metric, indicating that calibration is much more challenging than previously thought (Section 5).

Furthermore, we develop a new calibration method that is actually effective. We leverage the intuition that the prediction consistency throughout the model’s training trajectory could serve as a strong cue for the prediction confidence. We experiment this consistency calibration method and find that it works better than all the aforementioned existing calibration methods (Section 6).

2 Background

In this section, we review the existing bucketing-based calibration framework and the associated ECE metric. We also introduce a commonly used temperature scaling method that is designed to optimize the ECE metric.

2.1 Bucketing-based Calibration and ECE

Under the existing bucketing-based calibration framework, a model is defined as perfectly calibrated if the prediction probability (i.e., confidence) reflects the ground truth likelihood (Guo et al., 2017; Nixon et al., 2019; Minderer et al., 2021). Specifically, given the input \( x \), the ground truth \( y \) and the prediction \( \hat{y} \), the perfectly calibrated confidence \( \text{Conf}(x, \hat{y}) \) will satisfy:

\[
\forall p \in [0, 1], P(\hat{y} = y | \text{Conf}(x, \hat{y}) = p) = p.
\]

Under this framework, most prior works use Expected Calibration Error (ECE) to measure how well the model is calibrated. Specifically, we bucket all model predictions into \( M \) bins according to the confidence scores. Let \( B_m \) be the \( m \)-th bin consisting of \( (x, y, \hat{y}) \) triples, ECE is defined as:

\[
\text{Acc}(B_m) = \frac{1}{|B_m|} \sum_{i=1}^{B_m} \mathbb{I}(y = \hat{y}),
\]

\[
\text{Conf}(B_m) = \frac{1}{|B_m|} \sum_{i=1}^{B_m} \text{Conf}(x, \hat{y}),
\]

\[
\text{ECE} = \sum_{m=1}^{M} \frac{|B_m|}{N} |\text{Acc}(B_m) - \text{Conf}(B_m)|,
\]

where \( N \) is the total number of examples and \( |B_m| \) denotes the number of examples in the \( m \)-th bin.

Most work uses equal-width binning for defining buckets (interval-based ECE): a triple \( (x, y, \hat{y}) \) with \( \frac{m}{M} \leq \text{Conf}(x, \hat{y}) \leq \frac{m+1}{M} \) is assigned to the \( m \)-th bin. Minderer et al. (2021) also used equal-mass binning (density-based ECE): predictions
are sorted by their confidence values and exactly \( \frac{N}{M} \) number of triples are assigned to each bin.\(^1\)

### 2.2 Temperature Scaling

One of the most widely-used calibration methods is **temperature scaling** due to its simplicity and empirical effectiveness shown in a range of prior works (Guo et al., 2017; Desai and Durrett, 2020; Jiang et al., 2021). Temperature scaling is the multi-class extension of Platt scaling (Platt et al., 1999) that uses a single scalar parameter \( \tau \) chosen based on the development set. More precisely, given \( C \) that is the set of all candidate outputs and the logit value \( z \in \mathbb{R}^{|C|} \) associated with the prediction \( y \), the confidence for the prediction \( y \) that is the \( j \)-th candidate in \( C \) is computed as:

\[
\text{Softmax} \left( \frac{z_j}{\tau} \right)
\]

The temperature scalar \( \tau \) is tuned to optimize negative log likelihood (NLL) on the development set for multi-class classification, while for open-domain question answering, the number of correct answers in the candidate set \( C \) varies (zero, one, or more). Hence, we optimize development set ECE instead of NLL. Notably, performing temperature scaling only impacts the confidence without changing the predictions, therefore preserving the original accuracy.

### 3 Calibration in Open-Domain Question Answering

In this section, we adapt the bucketing-based calibration framework designed for multi-class classification tasks on open-domain question answering, and we experiment temperature scaling on multiple QA benchmarks, both in- and out-of-domain.

#### 3.1 The ODQA Model

We use the model from Karpukhin et al. (2020), which we call DPR-BERT. The model consists of both retrieval and reader components following the retrieve-and-read pipeline (Chen et al., 2017). The retrieval model is a dual encoder that computes the vector representation of the question and each Wikipedia passage, and returns the top-\( K \) passages with the highest inner product scores between the question vector and the passage vector. The reader model is a BERT-based (Devlin et al., 2019) span extraction model. It is given as input the concatenation of the question and each retrieved passage, and returns three logit values, representing the passage selection score, the start position score and the end position score respectively. These three logits are produced by three different classification heads on top of the final BERT representations. More precisely,

\[
H_i = \text{BERT}(q, p_i) \in \mathbb{R}^{h \times L},
\]

\[
z_{\text{psg}}(i) = (H_i)_{[\text{CLS}]} w_{\text{psg}} \in \mathbb{R},
\]

\[
z_{\text{start}}(i, s) = (H_i w_{\text{start}})_s \in \mathbb{R},
\]

\[
z_{\text{end}}(i, e) = (H_i w_{\text{end}})_e \in \mathbb{R},
\]

where \( w_{\text{psg}}, w_{\text{start}}, w_{\text{end}} \in \mathbb{R}^{h} \) are trainable parameters.

#### 3.2 Temperature Scaling For ODQA

To adapt temperature scaling on ODQA, we first compute the raw score for each candidate span, then apply softmax over the candidate set \( C \) to convert the raw span scores into probabilistic confidence values. We explore two possible implementations:

- **Joint Calibration** We perform inference on top \( k = 10 \) retrieved passages for each question, and for each passage we obtain the top \( n = 10 \) spans. This results in an answer set of \( n \times k = 100 \) spans per question. We score each candidate span as:

\[
z_{\text{start}}(\hat{i}, s) + z_{\text{end}}(\hat{i}, e) + z_{\text{psg}}(i).
\]

After temperature scaling the confidence value is computed as:

\[
\text{Softmax}_{(i,s,e)\in C} \left( \frac{z_{\text{psg}}(i) + z_{\text{start}}(i, s) + z_{\text{end}}(i, e)}{\tau} \right).
\]

- **Pipeline Calibration** We choose the passage with the highest passage selection score \( i_{\text{max}} = \arg\max_{1 \leq i \leq K} z_{\text{psg}}(i) \) and then define the span score \( S(s, e, i) \) as

\[
(z_{\text{start}}(\hat{i}, s) + z_{\text{end}}(\hat{i}, e)) \mathbb{1}[i = i_{\text{max}}].
\]

In this case, we only keep the top \( n = 10 \) spans from the top passage for each question. After temperature scaling, the confidence is computed as

\[
\text{Softmax}_{(i,s,e)\in C} \left( \frac{z_{\text{start}}(i, s) + z_{\text{end}}(i, e)}{\tau} \right).
\]

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\(^1\)In practice we find that there is little difference between interval- and density-based ECE results and so we mostly only report interval-based ECE.
| Model       | Section 3 | Section 4 |
|-------------|-----------|-----------|
|             | EM$^1$    | ECE$^2$   | ICE$^3$   | MacroCE$^4$ |
| *NQ*        |           |           |           |             |
| Joint - No Calibration | 32.85    | 27.09    | 47.76    | 43.60 |
| Joint - Temp Scaling   | 32.85    | 4.04     | 37.40    | 42.53 |
| Pipeline - No Calibration | 34.07    | 48.18    | 55.07    | 44.21 |
| Pipeline - Temp Scaling | 34.07    | 2.69     | 39.65    | 44.41 |
| *NQ → HotpotQA*       |           |           |           |             |
| Joint - No Calibration | 24.89    | 40.99    | 54.73    | 45.66 |
| Joint - Temp Scaling   | 24.89    | 12.51    | 40.29    | 45.48 |
| Pipeline - No Calibration | 22.55    | 59.60    | 65.85    | 47.43 |
| Pipeline - Temp Scaling | 22.55    | 8.37     | 37.93    | 47.72 |
| *NQ → TriviaQA*       |           |           |           |             |
| Joint - No Calibration | 33.63    | 25.44    | 48.61    | 45.12 |
| Joint - Temp Scaling   | 33.63    | 6.38     | 38.43    | 44.27 |
| Pipeline - No Calibration | 34.21    | 48.15    | 54.54    | 43.69 |
| Pipeline - Temp Scaling | 34.21    | 6.10     | 39.23    | 44.64 |
| *NQ → SQuAD*          |           |           |           |             |
| Joint - No Calibration | 12.35    | 41.72    | 48.50    | 39.45 |
| Joint - Temp Scaling   | 12.35    | 12.44    | 26.57    | 39.74 |
| Pipeline - No Calibration | 12.24    | 62.72    | 65.14    | 41.37 |
| Pipeline - Temp Scaling | 12.24    | 13.52    | 29.09    | 43.94 |

Table 1: In-domain and OOD calibration results. *Joint* and *Pipeline* refer to whether the candidate set consists of top answer candidates from all top-10 retrieved passages or just the top-1 retrieved passage (and with corresponding scoring functions as described in section 3.2). For the “*No Calibration*” baseline, it is equivalent to using a temperature value of 1. All numbers are multiplied by 100 for better readability throughout the paper. EM: higher is better. Calibration errors: lower is better.

### 3.3 Experiments

We experiment the above temperature scaling method on both in-domain and OOD settings, since Desai and Durrett (2020); Jiang et al. (2021) mentioned that OOD calibration is more challenging than in-domain calibration. We use four QA datasets as follows.

**Natural Questions (NQ)** (Kwiatkowski et al., 2019) consists of questions mined from Google search queries. We use the open version of NQ where each question has answers with up to five tokens found from Wikipedia (Lee et al., 2019). We use NQ for training and in-distribution evaluation.

**SQuAD** (Rajpurkar et al., 2016) contains a set of questions written by crowdworkers given a Wikipedia paragraph. We use the open version of SQuAD following Chen et al. (2017). We use SQuAD for out-of-distribution evaluation.

**TriviaQA** (Joshi et al., 2017) includes trivia questions scraped from the web. We use the unfiltered version for out-of-distribution evaluation.

**HotpotQA** (Yang et al., 2018) is a multi-hop question answering dataset written by crowdworkers given a pair of Wikipedia paragraphs. We take the full-wiki version of HotpotQA and use it for out-of-distribution evaluation.

For temperature scaling, we tune the temperature scalar on the NQ development set but evaluate on NQ test set (in-domain) three other QA datasets (OOD). We report exact match (EM) score to measure the answer accuracy (note that temperature scaling does not impact the EM score), and ECE for calibration results.

According to Table 1, we observe that without calibration, both joint and pipeline approaches have high ECE scores. Applying temperature scaling significantly lowers ECE in all cases, including both in-domain and OOD settings. As expected, OOD settings incur higher ECE than the in-domain setting even after calibration. However, in the next section, we challenge this “success” by re-examining the bucketing mechanism in ECE computation.

### 4 Flaws in ECE and Better Alternatives

In this section, we use case studies to illustrate the flaws of ECE and correspondingly propose new calibration metrics to remedy these flaws and provide complementary views of calibration.

#### 4.1 What’s Wrong With ECE?

We begin with a case study analysis on an OOD setting where we train a DPR-BERT model on NQ and evaluate on HotpotQA. According to Figure 2, we observe that the uncalibrated model is overconfident since the confidence is higher than the accuracy for all buckets. After temperature scaling, as shown in Figure 3, the accuracy and confidence are close each other, resulting in a significant ECE reduction. However, we argue that this result misleadingly over-estimated the effectiveness of temperature scaling. The reasons are the following:

1. **All predictions have similar confidence.** After calibration, all predictions have low confidence (which match the relatively low accuracy). This is essentially conveying the message that all predictions are not confident, even for correct ones. An ideal calibration metric should penalize such scenario and encourage the calibrator to differentiate between correct and wrong predictions by assigning high and low confidence scores respectively.

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1We illustrate the problem with a case study on HotpotQA, the same issues hold true on other datasets as well, for both in-domain and OOD calibration.
2) **Bucketing causes cancellation effects, thus underestimating the true calibration error.** A large number of predictions are clustered in the same buckets (in the [0.1, 0.4] range in Figure 3). As a result, there exists many over-confident and under-confident predictions in the same bucket, causing a cancellation effect where over- and under-confidence values are averaged to become closer to the average accuracy, despite the over- and under-confidence issues remain. A better calibration metric should avoid such cancellation effects caused by bucketing.

### 4.2 The Alternative View of Calibration

The dominant calibration framework as evaluated by ECE follows an expectation point of view: the goal is for the confidence to match the expected accuracy. However, this goal can be trivially achieved by simply outputting the similar confidence for all predictions that match the expected accuracy, as in the case of temperature scaling. In practical settings, such calibration results are not particularly useful because users cannot differentiate correct and wrong predictions based on such clustered confidence values. Hence, we propose the alternative view of calibration where the goal is to **differentiate between correct and wrong predictions**. We argue that achieving this goal would bring better practical values for real use cases of calibration. Towards this end, we propose new evaluation metrics of calibration that align closely with our new calibration objective.

### 4.3 New Metric: MacroCE

One straightforward solution to avoid the cancellation effect is to remove bucketing and accumulates the calibrator error of each individual prediction. We refer to this method as the **Instance-level Calibration Error (ICE)**:

\[
ICE = \frac{1}{n} \sum_{i=1}^{n} |I(y_i = \hat{y}_i) - \text{Conf}(x_i, \hat{y}_i)|.
\]

Note that this is also equivalent to ECE with equal-mass binning under the condition that \(M = N\) (i.e., the bucket size is always 1).

However, the ICE metric has another important flaw: it is highly sensitive to the model accuracy. For instance, if most predictions are correct, applying a small temperature scalar to boost all confidence scores lowers the ICE score, but not penalizing the wrong predictions with high confidence scores, as the small proportion of wrong predictions would not contribute much to the overall metric.

To overcome this issue, we propose to take equal consideration of both correct and wrong predic-
Figure 4: Calibration errors after temperature scaling. x-axis represents different temperature values; lines with different colors represent different metrics. MacroCE stays relatively constant while ECE varies largely at different temperature values.

We conduct the same experiment as Section 3, evaluated by ICE and MacroCE. According to Table 1 (rightmost two columns), we find the stark contrast that while temperature scaling brings significant improvement on ECE and ICE, it has no improvement on MacroCE. In the following subsection, we provide a series of controlled experiments to highlight why MacroCE is more informative.

### 4.4 Comparing Different Metrics Through Controlled Experiments

We design three controlled experiments (NQ in-domain evaluation) to compare ECE and MacroCE.

**Temperature Scaling with Different Temperature Scalars** We apply temperature scaling with varying temperature scalar $\tau$. According to Figure 4, as we increase the temperature value, the confidence scores decrease, and consequently $\text{ICE}_{\text{pos}}$ increases and $\text{ICE}_{\text{neg}}$ decreases. Meanwhile, MacroCE stays constant while ECE changes drastically, which reflects the flaw of temperature scaling: a single temperature value cannot improve calibration for both correct and wrong predictions simultaneously. Such flaw is only captured by MacroCE.

**Temperature Scaling at Different Accuracy Levels** We re-sample the data to control the model accuracy, and examine the effect of temperature scaling at different accuracy levels. According to Table 2, before calibration, the ECE score decreases with higher model model accuracy, since higher accuracy matches the over-confidence predictions and gets rewarded by low ECE score. Such finding also applies to ICE, since the majority of predictions are correct, the impact of negative predictions with over-confidence is marginal. MacroCE results remain stable across all accuracy levels. As model accuracy increases, $\text{ICE}_{\text{pos}}$ decreases and $\text{ICE}_{\text{neg}}$ increases. MacroCE captures the trade-off and implies the model remains poorly calibrated.

**Temperature Scaling under Subpopulation Shift** We consider the subpopulation shift setting, where the development and test set accuracy differs largely. In particular, we consider the cases where we: 1) tune temperature on a development set with 90% accuracy and evaluate on a test set with 10% accuracy; and 2) tune temperature on a development set with 10% accuracy and evaluate on a test set with 90% accuracy. According to Table 3, we observe that ECE and ICE are sensitive to the model accuracy but not MacroCE. Temperature scaling selects a low temperature on the highly accurate development set which does not transfer to the test set with low accuracy, which indicates that

| Temp   | ECE | ICE | MacroCE |
|--------|-----|-----|---------|
| Before Calibration | 1.00 | 69.97 | 71.93 | 44.32 |
| After Temp Scaling  | 10.00 | 11.49 | 26.08 | 46.90 |
| Before Calibration | 1.00 | 34.15 | 44.50 | 44.50 |
| After Temp Scaling  | 4.27 | 5.60 | 42.42 | 42.42 |
| Before Calibration | 1.00 | 7.96 | 8.08 | 45.33 |
| After Temp Scaling  | 0.47 | 9.08 | 13.18 | 47.77 |

Table 2: Calibration results where we re-sample the predictions to control the model accuracy (10%, 50%, 90%; same for both dev and test sets). We also report the tuned temperature values along with the calibration results under different metrics.
Table 3: Calibration results under subpopulation shift. In the first case, we tune the temperature value on a development set with only 10% correct predictions but evaluate on a test set with 90% correct predictions. We reverse the setup in the second case. Temperature scaling fails under such settings. ECE misleadingly tells that the model is well calibrated on the development set while MacroCE stays poor on both development and test sets.

All three experiments indicate that MacroCE is a more reliable calibration evaluation metric. We thus prioritize MacroCE evaluation throughout the rest of the paper.

5 Re-Evaluating Other Calibration Methods

Given the above criticisms against ECE and the conclusion that temperature scaling does not help MacroCE, we examine several other calibration methods to see if they are effective under MacroCE. These methods include: feature-based classifier, neural reranker, and label smoothing. All experiments are conducted on NQ in-domain data.

5.1 Feature Based Classifier

One widely-used calibration method is to train a feature-based classifier to predict the correctness of predictions (Kamath et al., 2020; Zhang et al., 2021; Ye and Durrett, 2022). In our experiments, we include the following features based on previous work and domain knowledge (Kamath et al., 2020; Rodriguez et al., 2019): the length of the question, passage and predicted answer; raw and softmax logits of passage, span start and end selection; softmax logits of other predicted answers among the top 100 answer candidates; the number of times that the predicted answer appears in the passage and the question; the number of times the predicted answer appears in the top 100 predictions; and the difference between the current and the next most confident prediction. To train the classifier, we use the QA model’s predictions on the NQ dev set as the training data. We hold out 10% predictions as the validation set and we apply early stopping based on the validation loss. During inference, we directly use the predicted probability as the confidence value. We train multiple binary classifiers with these features and compare the calibration performance on the NQ test set.

According to Table 4, all classifiers improve the EM score due to better answer reranking, however they suffer from over-confidence as shown by the large calibrator error on negative predictions (ICE<sub>neg</sub>), and as a result, there is no improvement on MacroCE. We conclude that the feature-based classification approach does not work well for calibration as it still assigns high confidence for negative predictions.

5.2 Neural Reranker

Instead of using manual features, an alternative approach is to train a neural answer reranker for post-hoc calibration. We adopt ReConsider (Iyer et al., 2021) as our neural answer reranker, where we train a BERT-large classifier by feeding in the
concatenation of the question, passage, and answer span. During training, for each question we include one randomly chosen positive and \( M-1 (M=10) \) randomly chosen hard negatives. We use DPR-BERT’s predictions on NQ training set for reranker training. During inference, we use the trained reranker to rerank the top five predictions. We explore two ways of obtaining the confidence value of the top reranked answer prediction: 1) we compute softmax over the top \( M=5 \) predictions; 2) we compute sigmoid of the raw logit score.

According to Table 4, we find that the sigmoid scoring works better for calibration than softmax, but neural reranking is generally ineffective for improving MacroCE.

5.3 Label Smoothing

Besides the post-hoc calibration approaches above, another way of calibration is to train models that are inherently calibrated, and a representative approach is label smoothing (Pereyra et al., 2017; Desai and Durrett, 2020).

In label smoothing, we assign the gold label with probability mass \( \alpha \), and the rest classes \( \frac{1-\alpha}{|Y|-1} \). We apply label smoothing on all three components of the ODQA pipeline: passage selection (where the first passage is gold, the rest \( K-1 \) are false); span start and end position selection, both of which the gold class is the gold position, and false classes are the rest of the positions in the passage. We use \( \alpha = 0.1 \) in our experiments, and we find that the calibration results are largely insensitive to the choice of \( \alpha \). We change the loss function from cross entropy to KL divergence with the label smoothed gold probability distribution.

We compare the calibration results of the model trained without and with label smoothing, and we also explore applying temperature scaling on top of the model trained with label smoothing. According to Table 4, contrary to previous conclusion that label smoothing helps calibration measured by ECE (Desai and Durrett, 2020), label smoothing is ineffective for calibration measured by MacroCE.

6 New Calibration Method: Consistency Calibration

The failure of approaches in Section 5 under MacroCE suggests that directly relying on the outputs from QA model is not sufficient for calibration. This calls for additional cues that can expose the model’s confidence. We take inspiration from training dynamics (Swayamdipta et al., 2020), which tracks whether the model makes consistent and correct predictions across the training process. While Swayamdipta et al. (2020) aim to measure the difficulty of the examples, we leverage similar intuition but focus on the calibration perspective.\(^3\)

Specifically, we propose a new simple calibration method called consistency calibration. The idea is that if the same answer prediction is consistent throughout the training trajectory, then it could serve as a strong sign that the model is confident about that prediction, and vice versa.

To implement this idea, we save a total of eight checkpoints throughout training. We take the final checkpoint as the QA model for evaluation. For each question, we check how many times the predicted answer string also appears from the previous seven checkpoints (\( n \in [0, 7] \)). For calibration, we set a threshold \( n_0 \) and for all predictions with \( n \geq n_0 \), we assign a confidence value of 1, otherwise 0. We iterate through all possible threshold values on the NQ development set and select the best \( n_0 \) that minimizes the MacroCE.

We compare two ways of obtaining the top prediction of each checkpoint - joint (considering top predictions from all top-10 retrieved passages) and pipeline (only considering the top predictions from top-1 retrieved passage). We also compare with the following other simple baselines to ensure that our claimed improvement on MacroCE is indeed meaningful:

- Binary baseline: We assign the top \( p\% \) (\( p\% \) is the model accuracy on the development set) confident predictions in the test set with confidence value of 1, and others 0.
- Average baseline: We assign all predictions in the test set with the confidence value equal to the average accuracy on the development set.
- Random confidence baseline: For each test prediction, we assign the prediction with a random confidence value drawn uniformly from the range \([0, 1]\).

According to Table 5, our consistency calibration achieves the best MacroCE compared to all other baseline calibration methods. We believe that it is

\(^3\)Note that in Swayamdipta et al. (2020), confidence is defined as the mean probability of the true label across epochs; our confidence scoring will be different from their definition. Moreover, our definition of consistency is similar to they called ‘variability’.
Table 5: Calibration results of baseline calibration methods as well as our new consistency calibration. We highlight the best result in bold. Our new consistency calibration method outperforms all other baselines on MacroCE. Note that different metrics give different ranking of these methods, which further highlights the importance of using a reliable and informative metric.

| Calibrator                  | EM | ECE$_{interval}$ | ECE$_{density}$ | ICE | ICE$_{pos}$ | ICE$_{neg}$ | MacroCE |
|-----------------------------|----|------------------|-----------------|-----|-------------|-------------|---------|
| **No Calibration**          |    |                  |                 |     |             |             |         |
| Joint                       | 36.45 | 31.63            | 31.62           | 36.88 | 93.96     | 4.14        | 49.05   |
| Pipeline                    | 37.17 | 51.72            | 51.72           | 55.69 | 5.33       | 85.48       | 45.41   |
| **Binary Baseline**         |    |                  |                 |     |             |             |         |
| Joint                       | 36.45 | 40.06            | 37.67           | 40.06 | 55.78     | 31.04       | 43.41   |
| Pipeline                    | 37.17 | 32.85            | 31.14           | 32.85 | 45.08     | 25.62       | 35.35   |
| **Average Baseline**        |    |                  |                 |     |             |             |         |
| Joint                       | 36.45 | 1.45             | 2.11            | 45.94 | 65.00     | 35.00       | 50.00   |
| Pipeline                    | 37.17 | 0.68             | 2.16            | 46.53 | 63.51     | 36.49       | 50.00   |
| **Random Confidence Baseline** |   |                  |                 |     |             |             |         |
| Joint                       | 36.45 | 27.68            | 27.50           | 50.31 | 50.70     | 50.09       | 50.40   |
| Pipeline                    | 37.17 | 27.96            | 27.77           | 50.68 | 51.19     | 50.39       | 50.79   |
| **Temperature Scaling**     |    |                  |                 |     |             |             |         |
| Joint                       | 36.45 | 6.33             | 6.39            | 39.59 | 56.12     | 30.11       | 43.12   |
| Pipeline                    | 37.17 | 4.37             | 4.73            | 41.10 | 58.35     | 30.89       | 44.62   |
| **Consistency Calibration** |    |                  |                 |     |             |             |         |
| Joint                       | 36.45 | 32.35            | 30.03           | 32.35 | 32.52     | 32.26       | 32.39   |
| Pipeline                    | 37.17 | 31.83            | 30.11           | 31.83 | 30.77     | 32.45       | 31.61   |

possible to develop more sophisticated calibration methods based on our consistency idea to further improve the calibration performance, and we leave it to future work.

7 Related Work

Model calibration is a long-standing concept in statistical machine learning. Guo et al. (2017) experimented various post-hoc calibration methods including temperature scaling with the ECE metric. Nixon et al. (2019) focused on image classification and claimed that different calibration metrics influence calibration methods. Thulasidasan et al. (2019) find that for image classification, using mixup training improves calibration evaluated by the ECE metric.

Within NLP domain, previous works have explored calibration on various tasks, including classification (Desai and Durrett, 2020) and tagging (Nguyen and O’Connor, 2015). In question answering, Kamath et al. (2020) proposed the selective question answering setting that measures the accuracy of the QA model when abstaining the least confident questions. Follow-up works added more features in training a binary classifier for deciding what questions to abstain (Zhang et al., 2021; Ye and Durrett, 2022). In a similar vein, Rodriguez et al. (2019) explored optimal buzzing strategy in the setting of incremental QA (Quizbowl). While selective question answering offers a way of measuring calibration, the scale of confidence values are not considered since abstention can be effective as long as correct predictions have higher confidence than wrong ones, regardless of the absolute scales. A recent work (Dhuliawala et al., 2022) also explored calibration for retriever-reader style ODQA setup, mainly focusing on how to combine information from the retriever and reader components. While in this paper we only focused on span-extraction QA, Jiang et al. (2021) focused on generation-style QA. However, both approaches are evaluated by the ECE metric that we claim has major flaws.

8 Conclusion

In this paper we re-examine calibration in the context of ODQA. We start by adapting the conventional temperature scaling approach on ODQA, and find that it significantly improves the widely-used metric, ECE. We look beyond the numbers and identify the flaws of ECE due to the bucketing mechanism, and propose a new MacroCE metric to remedy the flaws. Our controlled experiments demonstrate the advantage of MacroCE over ECE, and we find that existing calibration methods including temperature scaling, feature based classi-
fier, neural answer reranking and label smoothing fail on our MacroCE metric. To improve calibration, we develop a simple but effective new method called consistency calibration, which leverages prediction consistency through training trajectories of the QA model. We believe that our work sheds new insights on how to evaluate utility-centric calibration through the MacroCE metric, and the proposed consistency calibration method is a promising direction towards better calibration.

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