ON THE IMPORTANCE OF FIRTH BIAS REDUCTION IN FEW-SHOT CLASSIFICATION

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ABSTRACT

Learning accurate classifiers for novel categories from very few examples, known as few-shot image classification, is a challenging task in statistical machine learning and computer vision. The performance in few-shot classification suffers from the bias in the estimation of classifier parameters; however, an effective underlying bias reduction technique that could alleviate this issue in training few-shot classifiers has been overlooked. In this work, we demonstrate the effectiveness of Firth bias reduction in few-shot classification. Theoretically, Firth bias reduction removes the $O(N^{-1})$ first order term from the small-sample bias of the Maximum Likelihood Estimator. Here we show that the general Firth bias reduction technique simplifies to encouraging uniform class assignment probabilities for multinomial logistic classification, and almost has the same effect in cosine classifiers. We derive an easy-to-implement optimization objective for Firth penalized multinomial logistic and cosine classifiers, which is equivalent to penalizing the cross-entropy loss with a KL-divergence between the predictions and the uniform label distribution. Then, we empirically evaluate that it is *consistently effective across the board* for few-shot image classification, regardless of (1) the feature representations from different backbones, (2) the number of samples per class, and (3) the number of classes. Finally, we show the robustness of Firth bias reduction, in the case of imbalanced data distribution. Our implementation is available at https://github.com/ehsansaleh/firth_bias_reduction.

1 INTRODUCTION

Few-shot image classification is the practice of learning accurate classifiers using a small number of labeled samples (Fei-Fei et al., 2006; Vinyals et al., 2016; Wang and Hebert, 2016; Finn et al., 2017; Snell et al., 2017; Wang et al., 2020). It has a wide range of applications from face and gesture recognition (Pfister et al., 2014) to visual navigation in robotics (Finn et al., 2017). Essentially, modern few-shot classification methods can be viewed as a combination of learning (1) a strong feature representation through a backbone network (e.g., Verma et al. (2019); Gidaris et al. (2019); Tian et al. (2020)), and (2) an accurate small-sample classifier (e.g., Wang and Hebert (2016); Chen et al. (2019)). Therefore, two key questions arise in few-shot image classification: (1) *How can we obtain a strong feature representation?* and (2) *How can we train accurate classifiers using a small number of samples?* There have been many existing methods addressing the former question using a host of different techniques (Snell et al., 2017; Rusu et al., 2019; Verma et al., 2019; Mangla et al., 2020). Here we focus on the less-explored second question. For our purposes, we will use standard feature representations and methods for training the backbone model for few-shot classification. That still leaves us with a severe classifier problem than most people realize.

There is a substantial difficulty with training a classifier using a small number of samples. In particular, with very few samples, standard classification machinery is biased. In other words, although the Maximum Likelihood Estimators (MLEs) are statistically consistent and asymptotically normal (Fahrmeir and Kaufmann, 1985), it is well-established that **MLEs are biased** for a small number of N samples, with bias of $O(N^{-1})$ (Cox and Snell, 1968; Box, 1971; Whitehead, 1986; Firth, 1993). Since common logistic regression models are a type of MLEs, they are also *biased* (Schaefer,

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1983; Cordeiro and McCullagh, 1991; Firth, 1993; Steyerberg et al., 1999). Such biases increase the error rate of the few-shot trained classifiers, and so are important in few-shot learning.

In fact, there is a standard solution for bias prevention by modifying the ordinary MLEs – known as **Firth's Penalized Maximum Likelihood Estimator (PMLE)** (Firth, 1993). In the case of the exponential family of distributions, Firth has a simplified form that penalizes the likelihood by Jeffrey's invariant prior (Firth, 1993; Poirier, 1994), which is proportional to the determinant of the Fisher Information Matrix F. For logistic and cosine classifiers (Chen et al., 2019) which are widely used in few-shot classification, since they belong to the exponential family, Firth bias reduction can be further cast as adding a log-determinant penalty ($\log(\det(F))$) to the cross-entropy loss. While such standard strategies can control the bias in classifiers trained with very few samples, they have not been utilized in few-shot image classification tasks.

In this paper, we show that using Firth bias reduction produces *reliable improvements in a wide range of circumstances*. We achieve this by deriving a simplified yet effective Firth formulation that penalizes the KL-divergence between the predicted distribution and the uniform distribution of classes, for both *multinomial* logistic regression models and cosine classifiers. Note that common regularization techniques (such as L2-regularization and label smoothing (Szegedy et al., 2016)) cannot reduce the estimation bias of *classifier weights in small-sample regimes* (Liu et al., 2020) as Firth's penalty does; these regularization techniques are mainly used to control model complexity of deep neural networks for training *feature extractor backbones in large-sample regimes*.

More concretely, our results indicate that the improvements produced by Firth bias reduction for few-shot image classification tasks are *consistent* across the board (1) on a wide range of feature representations, (2) with both balanced and imbalanced data, (3) for both single-layer and multi-layer classifiers, (4) for both logistic and cosine classifiers, and (5) over multiple datasets and problems. Importantly, we found Firth bias reduction to consistently yield *statistically significant and positive improvements*, and we did not observe any performance penalty for utilizing it. Such improvements are on the order of 0.5-2.5% and up to 3% in challenging tasks with large number of classes.

Our main contributions include (1) deriving a *generalized* expression for Firth bias reduction in few-shot *multinomial* logistic regression models, and providing geometrical insight into its effect on the classification probability space; (2) evaluating the efficacy of the Firth penalized multinomial logistic model in few-shot scenarios, both with balanced and imbalanced data distributions; (3) showing that Firth bias reduction can be extended beyond typical logistic models, and can be successfully adopted in cosine classifiers; and (4) providing an empirical comparison of Firth bias reduction with common regularizers such as L2 and label smoothing.

2 Background

Mathematical Notations: In this work, we assume a multinomial logistic regression model for the classifier, with a total of $J+1$ classes $\{0, 1, 2, \cdots, J\}$. The logistic regression weights for class j is denoted as β_j ($1 \leq j \leq J$). The class $j = 0$ is the base class with zero logistic regression weights. We assume to have a total number of N samples $\mathcal{D} = \{(x_1, y_1), \cdots, (x_N, y_N)\}$. The ith target $\mathbf{y}_i$ is the one-hot encoding of the ith label. The assignment probability of the ith sample to class j is denoted as $\mathrm{P}_{i,j}$:

$$\mathrm{P}_{i,j} := \Pr(y_i = j | x_i) = \frac{e^{\beta_j^\intercal x_i}}{1 + \sum_{j'=1}^{J} e^{\beta_{j'}^\intercal x_i}}. \tag{1}$$

The likelihood of the sample set $\mathcal{D}$ given the weights β is denoted as $\Pr(y|x;\beta)$:

$$\Pr(y|x;\beta) = \prod_{i=1}^{N} \sum_{j=1}^{J} \mathbf{1}[y_i = j] \cdot \mathrm{P}_{i,j}, \tag{2}$$

where $\mathbf{1}[\cdot]$ denotes the binary indicator function. We may abuse the notation and use $\Pr(y|x)$ instead of $\Pr(y|x;\beta)$ in the derivation processes. Therefore, the logistic log-likelihood function $\mathcal{L}_{\text{logistic}}$ is defined as

$$\mathcal{L}_{\text{logistic}} := \sum_{i=1}^{N} \sum_{j=0}^{J} \mathbf{1}[y_i = j] \cdot \log(\mathrm{P}_{i,j}). \tag{3}$$

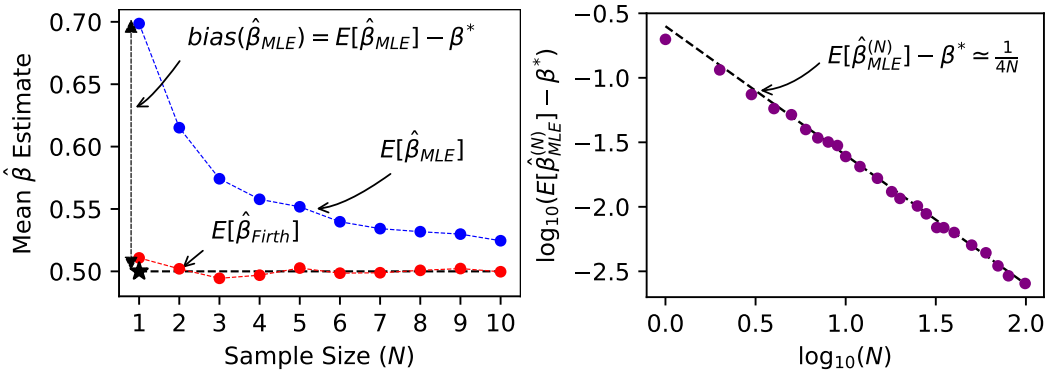

Figure 1: **The MLE bias and Firth's bias reduction visualized in a geometric experiment**. Here, the task is to estimate the coin flip probability based upon the number of tosses until the first head shows up. **(left)** The average MLE (shown in blue) and Firth's bias-reduced estimator (shown in red) against increasing number of samples. The true generative parameter $\beta^* = 0.5$ is annotated with a star, and the MLE bias is also visualized. Firth's bias-reduced estimator removes the leading $O(N^{-1})$ term from the MLE even with small N. **(right)** To show that the MLE bias is asymptotically of $O(N^{-1})$, MLE bias is plotted against the sample size N in the log-log scale.

The Fisher Information Matrix (FIM) is defined as the Hessian of the negative log-likelihood function $\mathcal{L}_{\text{logistic}}$:

$$F := -\text{Hess}_\beta(\mathcal{L}_{\text{logistic}}) = \mathbb{E}_y[\nabla_\beta \mathcal{L}_{\text{logistic}} \cdot \nabla_\beta \mathcal{L}_{\text{logistic}}^\intercal]. \tag{4}$$

The Maximum Likelihood Estimator (MLE) for logistic regression is defined as

$$\hat{\beta}_{\text{MLE}} := \arg\max_\beta \Pr(y|x;\beta). \tag{5}$$

The dimension of the feature space is denoted as d in the derivations. $U_{[a,b]}$ denotes the (discrete) uniform distribution in the $[a, b]$ interval. The cross-entropy and the KL-divergence of distributions p, q are defined as

$$\text{CE}(p\|q) := -\sum_x p(x) \cdot \log(q(x)), \qquad D_{\text{KL}}(p\|q) := \sum_x p(x) \cdot \log\left(\frac{p(x)}{q(x)}\right). \tag{6}$$

Table A2 in the Appendix summarizes these notations.

Small-Sample Bias of MLE: Assume β^* is the true generative parameter. When the sample size N is small, it is shown that the MLE bias $b(\hat{\beta}_{\text{MLE}}) := \mathbb{E}[\hat{\beta}_{\text{MLE}} - \beta^*]$ is non-zero and of $O(N^{-1})$ (Cox and Snell, 1968). Therefore, while MLE is unbiased as $N \to \infty$, it is inaccurate for few-shot learning.

Firth Bias Reduction for MLE: Firth's Penalized Maximum Likelihood Estimator (PMLE) (Firth, 1993) is a modification to the ordinary MLE, which removes the $O(N^{-1})$ term from the small-sample bias. In particular, **Firth has a simplified form for the exponential family**. When $\Pr(y|x;\beta)$ belongs to the exponential family of distributions, the effect is to penalize the likelihood by Jeffrey's invariant prior (Poirier, 1994), which is proportional to the determinant of F ($\det(F)$). Logistic and cosine classifiers (Chen et al., 2019) – the widely-used classification models in few-shot learning – belong to the exponential family; so for them, Firth bias reduction simplifies to adding a penalty ($\log(\det(F))$) to the cross-entropy loss. In what follows, we will derive a further simplified yet effective Firth formulation for logistic and cosine classifiers, which is computationally more efficient, deals with the case when $\det(F) = 0$, and generalizes to multinomial distributions.

MLE vs. Firth's PMLE for a Simple Case: To demonstrate the extent of the MLE bias and how Firth's PMLE removes the leading $O(N^{-1})$ bias term, we simulated data from the geometric distribution with probability of success $\beta = 0.5$ as its only parameter. The geometric experiment was chosen since a closed-form solution for the MLE and Firth's PMLE can be derived. Given the samples $(y_1, \cdots, y_N)$ from the geometric distribution, the sample mean is $\bar{y} = \frac{1}{N}\sum y_i$ and we have $\hat{\beta}_{\text{MLE}} = \frac{1}{\bar{y}}$ and $\hat{\beta}_{\text{Firth}} = \frac{N-1}{N\bar{y}-1}$. Note that since the sample mean is noisy, the MLE suffers from a

noisy denominator, making it biased. Figure 1 shows that $\hat{\beta}_{\text{Firth}}$ is close to the true parameter β^* for all sample sizes, whereas $\hat{\beta}_{\text{MLE}}$ has a significant bias away from β^* for small N. To further validate that the MLE bias is indeed of $O(N^{-1})$, we plotted the MLE bias against the sample size in the log-log scale in Figure1, which shows that it is closely following a line with a negative unit slope.

3 Firth Bias Reduction in Logistic and Cosine Classifiers

In logistic models, the penalized likelihood function proposed by Firth is equivalent to imposing Jeffreys' prior (Poirier, 1994) on the parameters and making a maximum a posteriori estimation. In particular, Firth bias reduction encourages models with "*large*" F by multiplying the likelihood by $\det(F)$. This penalty degenerates when $\det(F) = 0$. We work in the highest dimensional subspace where F has full rank, and use $\det(F|r)$ to denote the product of all r non-zero eigenvalues of F, obtaining

$$\Pr(\beta|x, y) = \frac{1}{Z} \cdot \Pr(y|x; \beta) \cdot \det(F|r)^{1/2}, \tag{7}$$

where Z is a normalization constant and $\det(F|r)^{1/2}$ is the Jeffery's prior. Taking the log of both sides yields the log-posterior as a sum of the logistic log-likelihood function and the Firth bias reduction term:

$$\mathcal{L} := \log(\Pr(\beta|x, y)) = \mathcal{L}_{\text{logistic}} + \mathcal{L}_{\text{Firth}}, \tag{8}$$

where we have

$$\mathcal{L}_{\text{Firth}} := \frac{\lambda}{2} \log(\det(F|r)) + \text{cte}. \tag{9}$$

The definition of $\mathcal{L}_{\text{Firth}}$ was left ambiguous up to a constant with respect to β to facilitate the Firth bias reduction term's interpretation and avoid the definition of similar terms. Furthermore, λ controls for the impact of the Firth term on the outcome relative to $\mathcal{L}_{\text{logistic}}$. We then apply a series of derivation steps to simplify Equation (9), which are left to Section A in the Appendix. Finally, the Firth bias reduction term can be expressed as

$$\mathcal{L}_{\text{Firth}} = \lambda \cdot \frac{1}{N} \sum_{i=1}^{N} \left[\sum_{j=0}^{J} \left(\beta_j^\intercal x_i - \log \sum_{j'=0}^{J} e^{\beta_{j'}^\intercal x_i} \right) \right] = \lambda \cdot \frac{1}{N} \sum_{i=1}^{N} \left[\sum_{j=0}^{J} \log(\mathrm{P}_{i,j}) \right]. \tag{10}$$

For the cosine classifier, the proof that $\log(\det(F))$ simplifies to Equation (10) involves straightforward manipulation of the proof for the logistic classifier, and is left to Section B in the Appendix. The normalization of the β_j weights in the cosine classifier turns into a pure scale term in the optimization, and for a cosine classifier, scaling of the β_j weights does not affect predictions. Therefore, this term should be ignored, and the bias reduction term effectively becomes the same as Equation (10).

Interpreting the Firth Bias Reduction for Logistic Models: It is well known that Jeffery's prior shrinks the parameter estimates towards zero, which is equivalent to encouraging uniform class assignment probabilities (Firth, 1993; Bull et al., 2002). We take an alternative approach to reach the same conclusion in the following. By re-arranging Equation (10), one can see the $\sum_{j=0}^{J} \log(\mathrm{P}_{i,j})$ term as a scaled average over a uniform distribution of classes:

$$\mathcal{L}_{\text{Firth}} \propto \frac{1}{N} \sum_{i=1}^{N} \left[\sum_{j=0}^{J} \frac{1}{J+1} \cdot \log(\mathrm{P}_{i,j}) \right] = \frac{-1}{N} \sum_{i=1}^{N} \left[\mathrm{CE}\big(\mathrm{U}_{[0,J]} \| \mathrm{P}_i\big) \right]. \tag{11}$$

Therefore, we can abuse the notation, and redefine the coefficient λ and the constant to have

$$\mathcal{L}_{\text{Firth}} = \lambda \cdot \frac{-1}{N} \sum_{i=1}^{N} D_{\mathrm{KL}}(\mathrm{U}_{[0,J]} \| \mathrm{P}_i) + \text{cte}. \tag{12}$$

This means that by dropping the constants, the optimization objective $\mathcal{L}$ can be rewritten as

$$\mathcal{L} = \frac{-1}{N} \sum_{i=1}^{N} \left[\mathrm{CE}(\mathbf{y}_i \| \mathrm{P}_i) + \lambda \cdot D_{\mathrm{KL}}(\mathrm{U}_{[0,J]} \| \mathrm{P}_i) \right]. \tag{13}$$

Since the KL-divergence and the FIM define an information geometry and a Riemanian metric on probabilistic measure spaces (Nielsen, 2020), a geometrical insight into Equation (13) is provided in Figure A8 in the Appendix as well.

Firth Bias Reduction vs. Common Regularization: While this insight brings Firth bias reduction closer to the common regularization techniques (e.g., L2-regularization), it is worth noting that (1) common regularization techniques mainly focus on controling model complexity, instead of reducing small-sample estimation bias; (2) Firth bias reduction operates on a much lower-dimensional *target* distribution space, unlike L2 which operates in the high-dimensional *parameter* space; (3) Firth uses the same kind of metric as the logistic loss; and (4) Firth bias reduction is dimensionally consistent like the Natural Gradients (Amari, 1998; Pascanu and Bengio, 2013), whereas L2 is not.

Firth Bias Reduction vs. Label Smoothing: Notice that the original form of label smoothing used for training in large-sample regimes (Szegedy et al., 2016) has the same formulation as the simplified Firth penalty term in Equation (12) *for multinomial logistic classifiers*. However, Firth bias reduction is inherently different in that it reduces the classifier estimation bias in the small-sample regimes, whereas label smoothing penalizes over-confident predictions when training deep neural networks with large amounts of samples. Generally, the Firth bias reduction term (i.e., $\log(\det(F))$) is not the same as the label smoothing penalty (i.e., $D_{\mathrm{KL}}(\mathrm{U}\|\mathrm{P}_i)$) for deep neural networks. Additional analysis and empirical comparisons are provided in Section 4.4 and Section F in the Appendix.

4 Experimental Results

Here we show that for a wide range of experiments, Firth bias reduction is a reliable source of small yet useful improvements in the performance. Since we report improvements for a wide range of methods and settings, the absolute accuracy improvements were reported. These absolute improvements sometimes constitute significantly to the baseline accuracy in terms of relative importance.

Datasets: We perform experiments on four widely-used and publicly available benchmarks: mini-ImageNet (Vinyals et al., 2016), CIFAR-FS (Bertinetto et al., 2019), tiered-ImageNet (Ren et al., 2018), and CUB (Welinder et al., 2010). Each dataset consists of non-overlapping base, validation, and novel classes. The detailed class splits are described in Section D in the Appendix. Following the standard practice (Chen et al., 2019), we train feature backbones on base classes, cross-validate bias reduction coefficients on validation classes, and train classifiers and measure test accuracy over multiple trials on novel classes.

Implementation Details: Details regarding the setup, implementation, statistical significance, and reducing the effect of randomized factors are covered in Appendix Section D.

Baselines and Evaluation Metric: Non-penalized classifiers are used as the baseline in all experiments to compare Firth bias reduction and L2-regularization. *Absolute* accuracy improvements over the baseline averaged across multiple trials are used as the evaluation metric in all experiments. *Relative* improvements are also shown in the Appendix, which demonstrate similar behaviors.

Summary of Results: Section 4.1 shows the efficacy of Firth bias reduction on standard feature backbones (ResNets with varying depth) and single-layer logistic classifiers. Section 4.2 shows and argues that Firth bias reduction outperforms L2-regularization on few-shot classification tasks. Next, we investigate the driving factor in Firth's improvement in Section 4.3, and show evidence for the efficacy of Firth's bias suppression property. We also show that Firth bias reduction can be effectively, and without any modifications, applied to imbalanced data distribution settings. Section 4.4 compares Firth bias reduction against label smoothing variants, and shows that Firth outperforms label smoothing. In Section 4.5 Firth bias reduction is applied to modern few-shot methods with advanced feature backbones (i.e., WideResNet trained with strong regularization (Mangla et al., 2020)) and cosine classifiers. Experiments with additional feature backbones (DenseNet and MobileNet (Wang et al., 2019)) are included in Appendix Section G. Finally, Section 4.6 demonstrates that Firth bias reduction produces reliable improvements over the state-of-the-art feature calibration method (Yang et al., 2021). Our collective results clearly indicate a consistent pattern of improvements over a large array of (1) feature representations, (2) datasets, (3) classification ways, (4) number of shots, (5) types of classifiers, and (6) with both balanced and imbalanced data distributions.

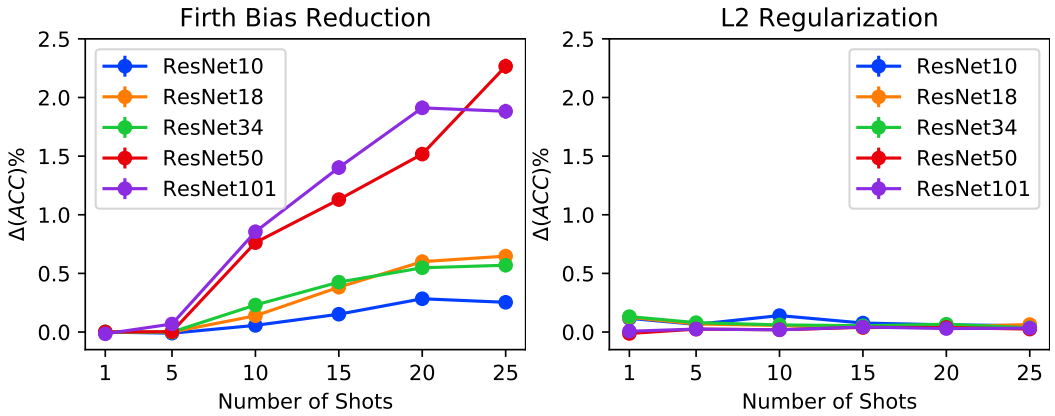

Figure 2: **Firth bias reduction produces statistically significant improvements over a wide range of backbone architectures and number of shots, whereas the common L2-regularization cannot**. Firth bias reduction **(left)** delivers a novel class accuracy improvement over the baseline classifier with an order of around 0.5-2.5%. By contrast, L2-regularization **(right)** is mostly statistically insignificant in the same setting. **16-way** logistic classification on the mini-ImageNet dataset was conducted in this experiment, with over **400 randomized and matching trials** for each combination of method, backbone, and number of samples, and the confidence intervals are covered by the blobs. Absolute and delta accuracies are provided in Table A9. The same experiments were repeated with a 3-layer classifier instead of a 1-layer classifier in Figure A5 in the Appendix and show similar results.

4.1 Firth Bias Reduction Improves the Accuracy of Logistic Classifiers

Figure 2 summarizes the results. For all the k-shot tasks and backbones, the average absolute test accuracy improvement is significant and it increases as k increases. Also, Firth bias reduction does not hurt the 1 and 5-shot performance, with slight improvements for some backbones. Extra experiments are included in Appendix Section E.1.

4.2 L2-Regularization is not as Effective as Firth Bias Reduction

To explore whether the performance improvement pattern for Firth bias reduction can be reproduced by common regularization techniques such as L2, the same experiments were repeated with L2-regularized logistic classifiers. For almost all the k-shot tasks and feature backbones, the average absolute test accuracy improvement is close to zero, as shown in Figure 2. This suggests that the bias reduction property of Firth plays a significant part in improving the classifier's performance in the few-shot regime which cannot be achieved by L2- regularization.

4.3 Bias or Prior?

Firth bias reduction clearly helps. It may be doing so because it is an effective way of suppressing bias. Alternatively, reinforcing the prior information might be helping. This section offers evidence that bias suppression is what is important. We consider data where the class frequencies are imbalanced. We apply a variant of Firth bias reduction that uses class prior frequencies to this data. This variant is not as successful as routine Firth bias reduction, suggesting that bias correction is what is important. One might consider replacing the uniform distribution in the Firth prior with a class probability distribution. That is, replacing $\mathcal{L}_{\text{Firth}} = -\lambda \cdot D_{\text{KL}}(\text{U}_{[0,J]} \| \text{P}_i)$ by $\mathcal{L}_{\text{Firth}} = -\lambda \cdot D_{\text{KL}}(A \| \text{P}_i)$ with A being the imbalanced class distribution, when training a Firth penalized few-shot logistic classifier.

To test this, we designed two schemes to generate imbalanced datasets. These schemes differ in the imbalanced count vectors used to create the few-shot dataset in validation and novel splits. The increments in the counts per class were designed to result in two different average counts of 7.5 (Scheme 1), and 15 (Scheme 2) over the classes (experimental details are left to Section D in the Appendix). For each scheme, the experiments were carried out similar to the "balanced few-shot" case on mini-ImageNet, except that in each trial three classifiers – (1) baseline (not penalized), (2) Firth penalized (KL with the uniform prior), and (3) modified Firth penalized (KL with the imbalanced

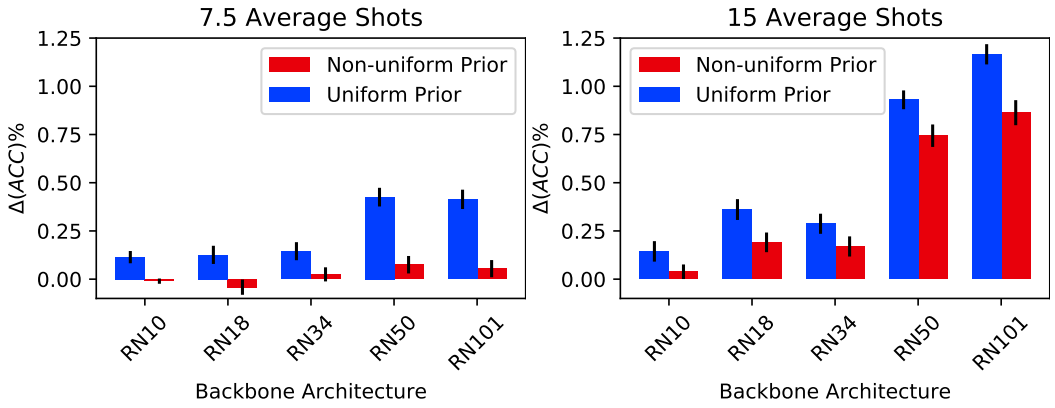

Figure 3: **Penalizing KL to the imbalanced class distribution is worse than using the Firth bias reduction.** The accuracy improvement is compared (1) when $D_{\mathrm{KL}}(U\|\mathrm{P}_i)$ is penalized (i.e., the blue bars with the uniform prior label) vs. (2) when the KL divergence to the imbalanced class distribution A (i.e., $D_{\mathrm{KL}}(A\|\mathrm{P}_i)$) is penalized (i.e., the red bars with the non-uniform prior label). The left and right plots use a class distribution with an average of 7.5 and 15 shots, respectively. The range of shots vary from 2- to 16-shots in the left plot, and from 1- to 29-shots in the right plot. The difference of accuracy improvements between the uniform and the non-uniform priors is more striking for the 7.5-average-shot case, which suffers from a greater deal of estimation bias than the 15-average-shot scenario. **This shows that the improvements of Firth bias reduction are driven by its bias suppression property, and are not a mere consequence of imposing a uniform class prior.** The same experiments were repeated with a 3-layer classifier in Figure A10 in the Appendix.

prior) – were trained. In both schemes, the improvement achieved by the Firth penalized classifier is *higher* than that of the modified Firth penalized classifier over the baseline for all backbones, as shown in Figure 3. The difference between the two improvements is more substantial in Scheme 1, where the average of samples per class is less than Scheme 2. This implies that the Firth penalized classifier is indeed reducing the bias and should not be naively considered as if a prior is simply defined over the class assignment probabilities.

4.4 Firth Bias Reduction Improves Over Label Smoothing

Even though the original version of label smoothing (Szegedy et al., 2016) has the same formulation as the Firth bias reduction term in Equation (13), there is a family of label smoothing techniques that aim to reduce overfitting and over-confident predictions (Pereyra et al., 2017). Namely, the confidence penalty (i.e., regularizing $D_{\mathrm{KL}}(\mathrm{P}_i\|\mathrm{U})$) and unigram label smoothing (i.e., regluarizing the KL-divergence with class priors) are two label smoothing variants, which are shown to outperform the original label smoothing, when training complex networks with large amounts of samples (Pereyra et al., 2017). Figure 3 shows that Firth bias reduction outperforms unigram label smoothing, and Table A4 in the Appendix shows that Firth bias reduction yields better results than applying confidence penalties and entropy regularization. This further suggests that the improvements obtained by Firth are the result of its bias reduction property.

4.5 Firth Bias Reduction Improves the Performance of Cosine Classifiers

As cosine classifiers have recently proven to be useful for few-shot classification (Gidaris and Komodakis, 2018; Chen et al., 2019), we investigated the impact of Firth bias reduction on them. The difference between a logistic and cosine classifier parameter space is that the parameter space of the cosine classifier is constrained to a unit sphere, therefore it is likely for the Firth bias reduction to improve cosine classifier performance as well. To test this, we based our experiments on the implementation of the S2M2$_R$ method (Mangla et al., 2020), and used their pre-trained WideResNet-28-10 (Zagoruyko and Komodakis, 2016) on the base classes as a strong feature extractor. We trained Firth penalized and non-penalized cosine classifiers on the mini-ImageNet, tiered-ImageNet, and CIFAR-FS datasets. Few-shot classifiers were trained for varying number of classes, depending on

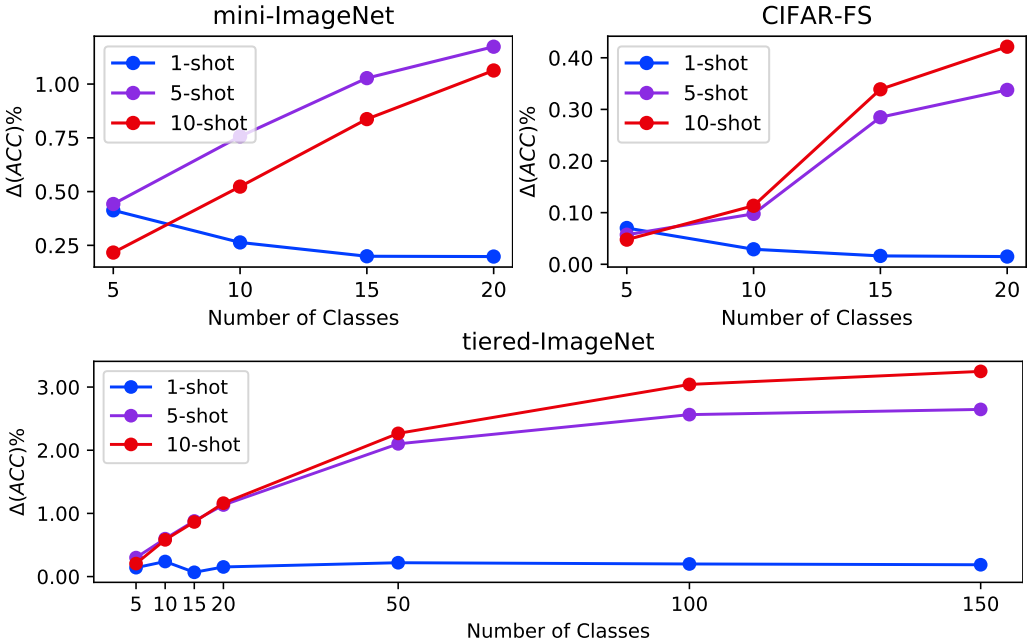

Figure 4: **Firth bias reduction consistently improves the accuracy of the cosine classifier (a better few-shot classifier) in the presence of strong backbone features regardless of (1) the type of dataset, and (2) the number of classes in few-shot classification.** For each dataset, an advanced backbone architecture (WideResNet-28-10) with strong mixup regularization and self-supervision was trained. The error bars are almost non-existent (i.e., less than 0.02%), since over 10,000 trials with **matching randomization factors** were performed for each point. **Firth bias reduction improvements are always positive, and it never hurts to use the Firth bias reduction technique.** Absolute and delta accuracies are provided in Tables A6, A7, and A8 in the Appendix.

the dataset, and varying number of samples per class. We followed the same scheme as Mangla et al. (2020) to generate the k-shot support and query datasets for training and testing, respectively.

As shown in Figure 4, in all datasets, Firth bias reduction improves the performance of 5-, and 10-shot tasks in a monotonically increasing fashion with respect to the number of classes. This behavior is well represented for tiered-ImageNet, as increasing 5-way to 150-way classification results in more than 2.5% improvement of the average test accuracy. In the 1-shot task, the improvement by Firth bias reduction is monotonically decreasing with the number of classes in all the datasets except tiered-ImageNet, but it does not hurt the performance. The improvement almost falls within (0.1%-0.5%), (0-0.1%), and (0-0.2%), for mini-ImageNet, CIFAR-FS, and tiered-ImageNet, respectively.

This experiment suggests that not only is Firth bias reduction effective for cosine classifiers, but it also could help with the performance even when strong features are used. This is well justified as Firth bias reduction targets the bias introduced in the classifier parameters not the features.

4.6 Comparison with Additional State-of-the-Art Method

We further applied the Firth bias reduction term to the recent state-of-the-art method in few-shot classification (Yang et al., 2021), called Distribution Calibration (DC). DC computes the closest base classes to each sample in the feature space, and samples artificial examples from a Gaussian distribution centered around the mean of the closest base class features. To make the setup challenging, we consider data where the base classes are categorically different from the novel classes: i.e., by performing *cross-dataset* few-shot classification, where the features are trained on the base classes of mini-ImageNet and tiered-ImageNet, and the novel sets are instead sampled from the CUB dataset. The results are shown in Table 1, and indicate that the Firth bias reduction improves over Yang et al. (2021). We also show the Firth bias reduction improvements on the tiered-ImageNet dataset in

Appendix Section H and Table A5. This further supports the observation that Firth bias reduction yields small but reliable improvements under different methods.

		mini-ImageNet → CUB			tiered-ImageNet → CUB		
Way	Shot	Before	After	Improvement	Before	After	Improvement
10	1	37.14	37.40 ± 0.13	0.26 ± 0.03	64.36	64.52 ± 0.16	0.15 ± 0.04
10	5	59.77	60.77 ± 0.12	1.00 ± 0.04	86.23	86.66 ± 0.10	0.43 ± 0.02
15	1	30.22	30.37 ± 0.09	0.15 ± 0.03	57.73	57.74 ± 0.13	0.01 ± 0.01
15	5	52.73	53.84 ± 0.10	1.12 ± 0.03	82.16	83.05 ± 0.09	0.90 ± 0.02

Table 1: **The cross-domain experiments for the DC method with and without Firth bias reduction.** The columns containing the novel set accuracy obtained by DC and Firth penalized DC methods are tagged *Before* and *After*, respectively. Each setting (a combination of way, shot, and method) was tested with and without data augmentation (addition of 750 samples), and the maximum accuracy was reported. Note that the confidence intervals are much smaller for the improvement column thanks to the random-effect matching procedure we used in this study. The *Before* confidence intervals were similar to the *After* confidence intervals, and thus not repeated due to space constraints.

5 Related Work

Bias Reduction of the MLE: A myriad of statistical work has been proposed to mitigate the small-sample bias of the MLE under different settings (Anderson and Richardson, 1979; Kenward and Roger, 1997; Bull et al., 2002; Kosmidis and Firth, 2009). Originally, the asymptotic bias of MLE was shown to be of $O(N^{-1})$, with N being the sample size (Firth, 1993). To counter such an estimation bias, many approaches have existed. To name a few, (1) additive penalization terms to the main logistic loss were proposed to reduce the MLE's bias (Firth, 1993; Bull et al., 2002; Greenland and Mansournia, 2015), and (2) some methods have been proposed to directly approximate and remove such a small sample bias (Cox and Hinkley, 1979). While the latter approach may sound appealing, estimating the MLE's bias can be impractical. For instance, in few-shot scenarios, a perfect separation of the classes may be achievable, causing the logistic MLE to be unbounded (Heinze and Schemper, 2002). On the other hand, the penalization methods do not modify the estimated parameters directly, and instead gently push for a preference towards less biased estimates. Such penalization methods can be generally applicable to a vast array of models.

Theoretically, Firth's PMLE reduces the bias by removing the leading $O(N^{-1})$ term from the MLE's bias (Firth, 1993) – a property that does not exist in common regularization techniques such as L2-regularization. Furthermore, PMLE of the logistic model has been shown to have smaller variance than MLE as well (Copas, 1988; Kosmidis and Firth, 2009). Firth's PMLE has been well studied for binomial logistic regression (Firth, 1993), and applied and tested against other penalization techniques in other fields (Rainey and McCaskey, 2015; Muchlinski et al., 2016; Rahman and Sultana, 2017).

Additional related work on **few-shot image classification** was left to Appendix Section C.

6 Conclusion

We show that Firth bias reduction consistently improves the accuracy across the board in few-shot classification regardless of (1) the employed feature backbone, (2) the number of classes and samples, and (3) the dataset and problem setting. Furthermore, our experiments show that Firth bias reduction can improve the performance of the cosine classifiers, and is applicable to imbalanced few-shot settings without any necessary modifications. Overall, our evaluations suggest that Firth bias reduction is a useful and general bias reduction tool that has been missing in few-shot classification, and should be incorporated in few-shot classification tasks for accuracy improvements.

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A FIRTH BIAS REDUCTION FOR FEW-SHOT MULTINOMIAL LOGISTIC REGRESSION

Table A2 summarizes the notations used throughout the main paper and here. Given a dataset of N samples $\mathcal{D} = \{(x_1, y_1), (x_2, y_2), \cdots, (x_N, y_N)\}$, the multinomial logistic model for a total of $J+1$ classes can be formulated as

$$\log\left[\frac{\Pr(y=j|x_i)}{\Pr(y=0|x_i)}\right] = \beta_j^\intercal x_i, \qquad j \in \{1, 2, \cdots, J\}, \tag{A14}$$

where class $j = 0$ was chosen as the base class in the log odds ratio. In other words, w.l.o.g. we assume $\beta_0 = 0$ in this formulation. Given the decision rule in Equation (A14), we can write

$$\mathrm{P}_{i,0} = \frac{1}{1 + \sum_{j'=1}^{J} e^{\beta_{j'}^\intercal x_i}}, \qquad \mathrm{P}_{i,j} = \frac{e^{\beta_j^\intercal x_i}}{1 + \sum_{j'=1}^{J} e^{\beta_{j'}^\intercal x_i}} \qquad \forall 1 \leq j \leq J. \tag{A15}$$

Under this notation, the log-likelihood would be $\mathcal{L}_{\text{logistic}} = \sum_{i=1}^{N} \sum_{j=0}^{J} \mathbf{1}[y_i = j] \cdot \log(\mathrm{P}_{i,j})$. The data matrix X_D is given as

$$X_D := [x_1 \quad x_2 \quad \cdots \quad x_N]_{d \times N} \tag{A16}$$

Also, $X := X_D \otimes I_J$ where the $\otimes$ operator denotes the Kronecker matrix product, and the J-dimensional identity matrix is denoted as I_J.

Firth (1993) has established that the bias of logistic regression can be removed by maximizing the sum of (1) the log-likelihood $\mathcal{L}_{\text{logistic}}$ and (2) the log-determinant of the Fisher Information Matrix (FIM). For our purposes, this presents some challenges: we have a few number of samples and the FIM determinant is zero. Instead, we use the product of all non-zero eigenvalues of the FIM as its "*amended determinant*". To obtain this efficiently, we need to know the specific structure of the FIM.

It is important in what follows that the FIM can be defined as the matrix product

$$F_{(dJ)\times(dJ)} = X^\intercal_{(dJ)\times(NJ)} \cdot M_{(NJ)\times(NJ)} \cdot X_{(NJ)\times(dJ)}, \tag{A17}$$

where M is a block-diagonal matrix whose i^{th} diagonal block is denoted as M_i. We leave the definition of X and M_i to the "*FIM Formulation for Logistic Regression*" subsection. Next, we focus on:

- *Determinant Amendment and Constant Dropping*: Generically, we show that

$$\log(\det(F|NJ)) = \sum_{i=1}^{N} \log(\det(M_i)) + \text{cte}, \tag{A18}$$

  where $\det(F|NJ)$ is an amended version of $\det(F)$.
- *Efficient Computation of* $\log(\det(M_i))$: Next, we show that

$$\log(\det(M_i)) = \sum_{j=0}^{J} \log(\mathrm{P}_{i,j}). \tag{A19}$$

Combining these two points will lead us to the simplified Firth bias reduction objective:

$$\mathcal{L}_{\text{Firth}} = \lambda \cdot \frac{1}{N} \sum_{i=1}^{N} \sum_{j=0}^{J} \log(\mathrm{P}_{i,j}). \tag{A20}$$

Determinant Amendment and Constant Dropping: Having $F = X^\intercal \cdot M \cdot X$ prompts us to utilize the SVD of X as

$$X_{NJ\times dJ} = U_{NJ\times NJ} \cdot S_{NJ\times dJ} \cdot V^\intercal_{dJ\times dJ}. \tag{A21}$$

Therefore, the FIM can be written as $F = V \cdot \left(S^\intercal \cdot K \cdot S\right) \cdot V^\intercal$, where $K := U^\intercal \cdot M \cdot U$. Since V and U are rotation matrices, we can write $\det(F) = \det(S^\intercal \cdot K \cdot S)$, and

$$\det(K) = \det(M) = \prod_{i=1}^{N} \det(M_i). \tag{A22}$$

Notation	Description
$J+1$	Total Number of Classes in Multinomial Logistic Regression
β_j	The Logistic Regression Weights for Class j ($j \in \{1, 2, \cdots, J\}$)
$\mathrm{P}_{i,j}$	Classification Probability of Sample i Belonging to Class j
P_i	The ith Sample's Soft Classification Probabilities
N	Number of Samples
$\mathcal{D} = \{(x_i, y_i)\}_{i=1}^N$	Logistic Regression Samples Dataset
$\mathbf{y}_i$	The One-Hot Encoding of the Label y_i
$\mathbf{1}[a=b]$	The Binary Indicator Function (i.e., 1 when $a=b$ and 0 otherwise)
F	The Fisher Information Matrix
d	Dimension of the Features
I_J	The $J \times J$ Identity Matrix
$A \otimes B$	The Kronecker Product of Matrix A by Matrix B
$\mathbf{1}_{r \times c}$	The All Ones Matrix with r Rows and c Columns by Matrix B
$\hat{\beta}_{\text{MLE}}$	The Maximum Likelihood Estimator (MLE)
$\mathcal{L}_{\text{logistic}}$	The Logistic Log-Likelihood Function
$\mathcal{L}_{\text{Firth}}$	The Firth Bias Reduction Function
λ	The Firth Bias Reduction Coefficient
$\mathrm{CE}(p\|q)$	The Cross-Entropy of p and q (See Equation (6) of the main paper)
$D_{\mathrm{KL}}(p\|q)$	The KL Divergence of p and q (See Equation (6) of the main paper)
$\mathrm{U}_{[0,J]}$	The Uniform Class Assignment Probabilities
$\det(A\|r)$	The Amended Determinant of the Degenerate Matrix A with at most r Non-zero Eigenvalues (See Section A of the Appendix).

Table A2: The mathematical notations used throughout the paper.

As we have $d > N$ for most few-shot tasks, the matrix S can be viewed in the following form:

$$S_{NJ \times dJ} = \begin{bmatrix} \hat{S}_{NJ \times NJ} & 0 \end{bmatrix}, \tag{A23}$$

where $\hat{S}$ is a diagonal square matrix. Since $\hat{S}^\intercal = \hat{S}$, we have

$$S^\intercal \cdot K \cdot S = \begin{bmatrix} \left(\hat{S} \cdot K \cdot \hat{S}\right)_{NJ \times NJ} & 0 \\ 0 & 0 \end{bmatrix}. \tag{A24}$$

Equation (A24) and $\det(F) = \det(S^\intercal \cdot K \cdot S)$ show why $\det(F)$ is zero. For mitigation, we replace $\det(F)$ with the product of the non-zero eigenvalues of F, namely $\det(F|NJ)$, and call it the "*amended determinant*" of F. Thanks to $F = V \cdot \left(S^\intercal \cdot K \cdot S\right) \cdot V^\intercal$, even the amended determinants $\det(F|NJ)$ and $\det(S^\intercal \cdot K \cdot S|NJ)$ are the same:

$$\det(F|NJ) = \det(S^\intercal \cdot K \cdot S|NJ) = \det(\hat{S} \cdot K \cdot \hat{S}) = \det(M) \cdot \det(\hat{S}^2). \tag{A25}$$

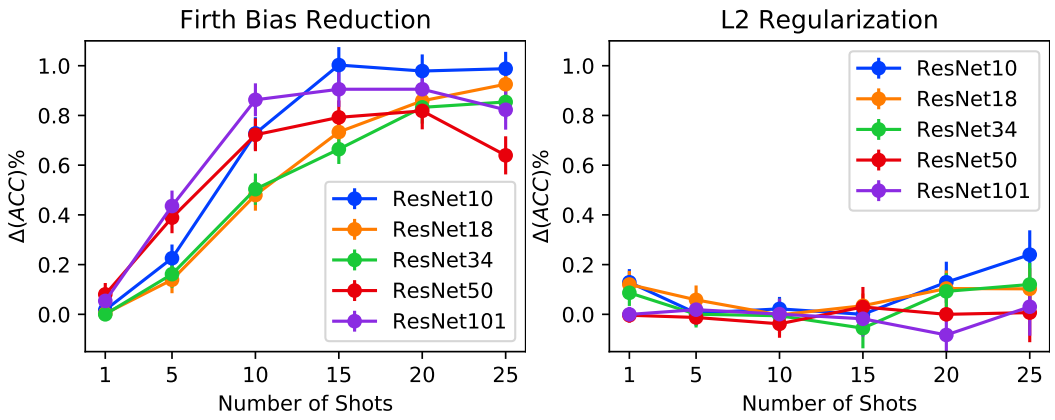

Figure A5: **Same experiment as Figure 2 of the main paper but with a 3-layer logistic classifierlogistic classifier instead of a single-layer logistic classifier (in the main paper)**. Again, Firth bias reduction improves the accuracy for different backbones and number of samples (left panel), whereas L2-regularization is not effective at all (right panel). In the very hard cases, i.e. 1- and 5-shots, there is a mild improvement by Firth and no deterioration. The error bars, representing the 95% confidence interval, are covered by the blobs.

Could $\det(F|NJ)$ *be zero?* The answer is "*not*" generically; $\det(M)$ is generically positive as we will show $\det(M_i) = \prod_{j=0}^{J} \mathrm{P}_{i,j}$ later in Equation (A28). Also, $\det(\hat{S}^2) > 0$ holds with probability 1 for continuous data distributions. In fact, $\det(\hat{S}^2)$ can only be zero when the data contains linearly dependant samples, which happens with zero probability for non-atomic data distributions. Therefore, we have

$$\log(\det(F|NJ)) = \sum_{i=1}^{N} \log(\det(M_i)) + \log(\det(\hat{S}^2)). \tag{A26}$$

This is the same as Equation (A18): since the $\log(\det(\hat{S}^2))$ term is independent of the model's parameters, we can treat it as an optimization constant and drop it.

The FIM Formulation for Logistic Regression: Elementary methods established that the FIM of the logistic classifier is composed of $J \times J$ block matrices, each with a dimension of $d \times d$ (where d is the dimension of the features). These block matrices can be expressed as

$$\begin{aligned} F_{j,j} &= \sum_{i=1}^{N} \mathrm{P}_{i,j} \cdot (1 - \mathrm{P}_{i,j}) \cdot x_i \cdot x_i^\intercal & \forall \quad 1 \leq j \leq J, \\ F_{j,k} &= -\sum_{i=1}^{N} \mathrm{P}_{i,j} \cdot \mathrm{P}_{i,k} \cdot x_i \cdot x_i^\intercal & \forall \quad 1 \leq j \neq k \leq J. \end{aligned} \tag{A27}$$

This facilitates the expression of the FIM as shown in Equation (A17): We can define X as the Kronecker product of (1) the data matrix X_D and (2) the J-dimensional identity matrix I_J:

$$X_D := \begin{bmatrix} x_1^\intercal \\ \hline x_2^\intercal \\ \hline \vdots \\ \hline x_N^\intercal \end{bmatrix}_{N \times d}, \qquad X := X_D \otimes I_J. \tag{A28}$$

M would then be a block-diagonal matrix whose i^{th} block is defined as

$$\begin{aligned} (M_i)_{j,j} &= \mathrm{P}_{i,j}(1 - \mathrm{P}_{i,j}) & \forall \quad 1 \leq j \leq J, \\ (M_i)_{j,k} &= -\mathrm{P}_{i,j}\mathrm{P}_{i,k} & \forall \quad 1 \leq j \neq k \leq J. \end{aligned} \tag{A29}$$

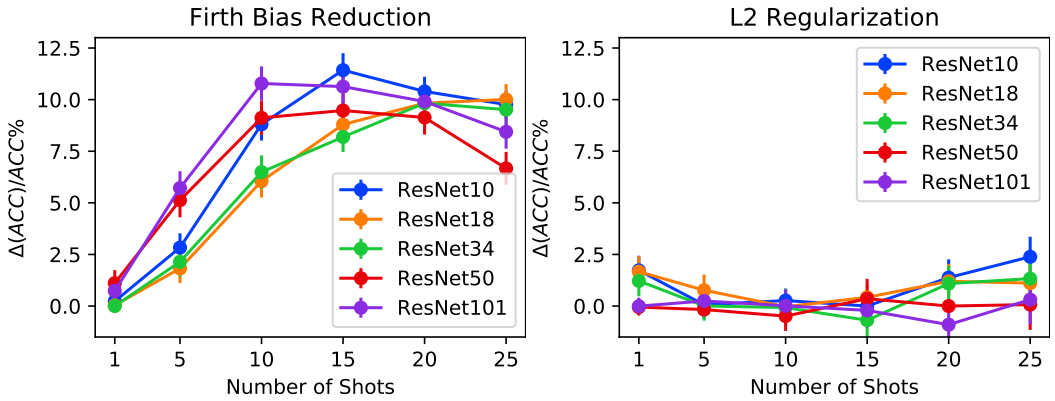

Figure A6: **Relative accuracy improvements corresponding to Figure A5 with the 3-layer logistic classifier**. The behavior of the relative accuracy improvements are similar to the absolute accuracy improvements for all the backbones in both techniques.

Efficient Computation of $\log(\det(M_i))$**:** We define the soft predictions of the ith sample (excluding the base class) as $\mathrm{P}_{i,1:J} := \begin{bmatrix}\mathrm{P}_{i,1} & \cdots & \mathrm{P}_{i,J}\end{bmatrix}^\intercal$. Given M_i's definition in Equation (A29), we can write

$$M_i = \mathrm{Diag}(\mathrm{P}_{i,1:J}) - \mathrm{P}_{i,1:J} \cdot \mathrm{P}_{i,1:J}^\intercal. \tag{A30}$$

Next, we use the Matrix-Determinant Lemma (David, 1998) to compute $\det(M_i)$:

$$\begin{aligned}\det(M_i) &= \det(\mathrm{Diag}(\mathrm{P}_{i,1:J})) \cdot (1 - \mathrm{P}_{i,1:J}^\intercal \cdot \mathrm{Diag}(\mathrm{P}_{i,1:J}) \cdot \mathrm{P}_{i,1:J}) \\ &= (\prod_{j=1}^{J} \mathrm{P}_{i,j}) \cdot (1 - \mathrm{P}_{i,1:J}^\intercal \mathbf{1}_{J\times 1}) = (\prod_{j=1}^{J} \mathrm{P}_{i,j}) \cdot \mathrm{P}_{i,0} = \prod_{j=0}^{J} \mathrm{P}_{i,j}.\end{aligned} \tag{A31}$$

Taking the log will give us Equation (A19).

B Firth Bias Reduction for Cosine Classifiers

Section A derived the Firth bias reduction term for the logistic classifier as $D_{\mathrm{KL}}(\mathrm{U}\|\mathrm{P}_i)$. Here, we generalize this observation to cosine classifiers, and prove that the Firth bias reduction for cosine classifiers reduces down to the same form as the one obtained for logistic classifiers.

By defining the normalization transformation

$$T(\beta) = \left[\frac{\beta_0^\intercal}{\|\beta_0\|}, \cdots, \frac{\beta_J^\intercal}{\|\beta_J\|}\right]^T, \qquad T(x) = \left[\frac{x_1^\intercal}{\|x_1\|}, \cdots, \frac{x_N^\intercal}{\|x_N\|}\right]^T, \tag{A32}$$

we have the log-likelihood relation between the cosine classifier and the logistic model:

$$\mathcal{L}_{\text{cosine}}(\beta; x, y) = \mathcal{L}_{\text{logistic}}(T(\beta); T(x), y). \tag{A33}$$

According to Equation (4) of the main paper and the chain rule, we can write

$$F_{\text{cosine}}(\beta, x, y) = A \cdot F_{\text{logistic}}(T(\beta), T(x), y) \cdot A^\intercal, \tag{A34}$$

where $A_{d(J+1)\times d(J+1)}$ is the Jacobian matrix of $T(\beta)$ with respect to β. It can be shown that A is a symmetric block-diagonal matrix, whose j^{th} diagonal block is

$$A_{j,j} = \frac{1}{\|\beta_j\|}\left(I_{d\times d} - \frac{\beta_j \beta_j^\intercal}{\beta_j^\intercal \beta_j}\right). \tag{A35}$$

Therefore,

$$\begin{aligned}\log(\det(F_{\text{cosine}})) &= \log(\det(F_{\text{logistic}})) + 2\log(\det(A)) \\ &= \log(\det(F_{\text{logistic}})) + 2\sum_{j=0}^{J} \log(\det(A_{j,j})).\end{aligned} \tag{A36}$$

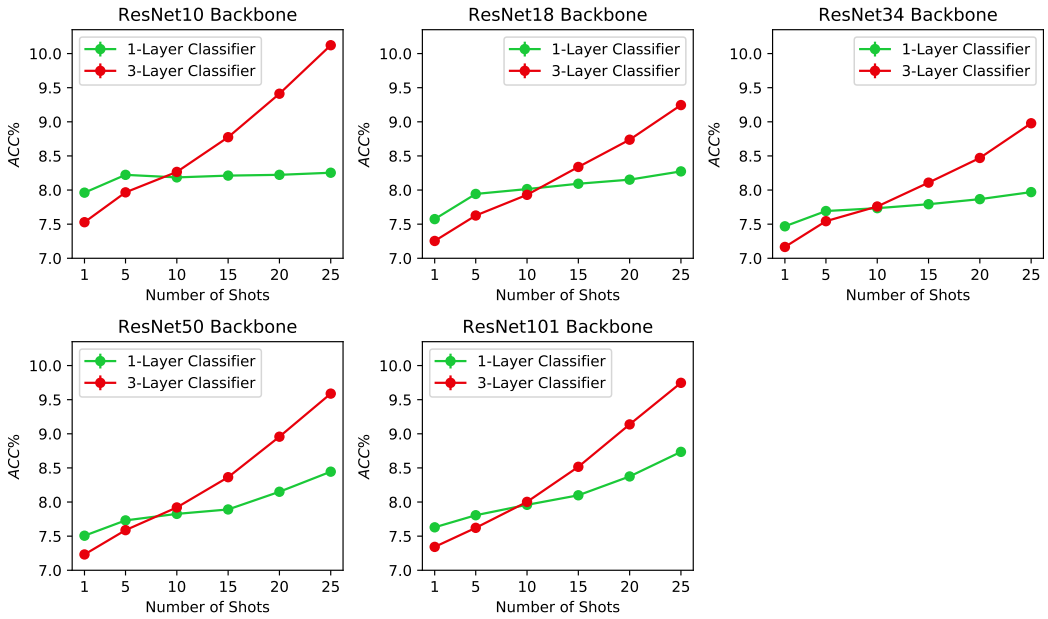

Figure A7: **Absolute test accuracy values of 16-way classification for the non-penalized 3-layer and single-layer logistic classifiers on the novel set of mini-ImageNet for different backbones and varying number of samples.** 3-layer logistic classifier works better than the single-layer logistic classifier in most of the regimes. This justifies the choice of the 3-layer logistic classifier for the experiments carried out in the main paper.

It is obvious that

$$A_{j,j} \cdot v = \begin{cases} 0 & v \parallel \beta_j \\ \frac{v}{\|\beta_j\|} & v \perp \beta_j. \end{cases} \tag{A37}$$

Therefore, $A_{j,j}$ can be thought as an identity-proportional matrix in the sub-space perpendicular to β_j. Therefore, its amended determinant is

$$\log(\det(A_{j,j}; d-1)) = -(d-1) \cdot \log(\|\beta_j\|). \tag{A38}$$

For the plain logistic model, the Firth penalized optimization problem is:

$$\max_{\beta} \Big[\mathcal{L}_{\text{logistic}}(\beta; x, y) + \lambda \cdot \log(\det(F_{\text{logistic}}(\beta, x, y))) \Big]. \tag{A39}$$

For the cosine classifiers, the Firth penalized optimization problem is:

$$\max_{\beta} \Big[\mathcal{L}_{\text{logistic}}(T(\beta); T(x), y) + \lambda \cdot \log(\det(F_{\text{logistic}}(T(\beta), T(x), y))) - C \sum_{j=0}^{J} \log(\|\beta_j\|) \Big], \tag{A40}$$

where we have $C := 2\lambda(d-1)$. By re-parameterizing $\beta = (u_\beta, s_\beta)$ with $u_\beta := T(\beta)$ and $s_\beta := \big[\|\beta_0\|, \cdots, \|\beta_J\|\big]$, we have

$$\max_{u_\beta, s_\beta} \Big[\mathcal{L}_{\text{logistic}}(u_\beta; T(x), y) + \lambda \cdot \log(\det(F_{\text{logistic}}(u_\beta, T(x), y))) - C \sum_{j=0}^{J} \log(s_{\beta_j}) \Big]. \tag{A41}$$

Since u_β and s_β are independent optimization parameters, this problem can be restated as

$$\max_{u_\beta} \Big[\mathcal{L}_{\text{logistic}}(u_\beta; T(x), y) + \lambda \cdot \log(\det(F_{\text{logistic}}(u_\beta, T(x), y))) \Big] + \max_{s_\beta} \Big[-C \sum_{j=0}^{J} \log(s_{\beta_j}) \Big]. \tag{A42}$$

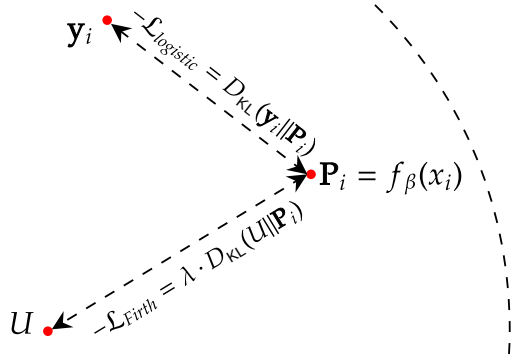

Figure A8: **Firth bias reduction is effectively the same as minimizing the KL divergence to the uniform class probabilities for logistic regression**. Here, P_i denotes the predicted distribution of classes for the sample x_i, and U denotes the uniform distribution of classes. The logistic objective minimizes the KL-divergence between P_i and the true label $\mathbf{y}_i$, while Firth bias reduction $\mathcal{L}_{\text{Firth}}$ tries to tie P_i with a *KL divergence rope* to the uniform distribution over the classes.

Since s_β has no effect on the predictions of the model, it can be ignored. Therefore, we end up with the optimization problem

$$\max_{u_\beta} \left[\mathcal{L}_{\text{logistic}}(u_\beta; T(x), y) + \lambda \cdot \log(\det(F_{\text{logistic}}(u_\beta, T(x), y))) \right]. \tag{A43}$$

Essentially, this suggests applying the same bias reduction form to cosine classifiers as the one used for logistic classifiers; $\log(\det(F_{\text{logistic}}(u_\beta, T(x), y)))$ reduces down to $D_{\text{KL}}(\mathrm{U} \| \mathrm{P}_i)$ as proven in Section A, and $\mathcal{L}_{\text{logistic}}(u_\beta; T(x), y)$ is the cross-entropy loss with the true labels.

C Additional Related Work on Few-Shot Image Classification

As one of the unsolved problems in machine learning, few-shot learning (Miller et al., 2000; Fei-Fei et al., 2006) has attracted growing interest in the deep learning era (Lake et al., 2015; Santoro et al., 2016; Wang and Hebert, 2016; Vinyals et al., 2016; Snell et al., 2017; Finn et al., 2017; Hariharan and Girshick, 2017; George et al., 2017; Triantafillou et al., 2017; Edwards and Storkey, 2017; Mishra et al., 2018; Douze et al., 2018; Wang et al., 2018; Chen et al., 2019; Dvornik et al., 2019; Allen et al., 2019; Li et al., 2019a; Yoon et al., 2019; Lifchitz et al., 2019; Li et al., 2019b; Zhang et al., 2020; Ye et al., 2020; Dhillon et al., 2020; Triantafillou et al., 2020; Tian et al., 2020; Dvornik et al., 2020; Yang et al., 2021; Phoo and Hariharan, 2021; Liu et al., 2021; Zhang et al., 2021). Successful generalization from few training samples requires "inductive biases" or shared knowledge from related tasks (Baxter, 1997), which is commonly acquired through transfer learning, and more recently, meta-learning (Thrun, 1998; Schmidhuber, 1987; Schmidhuber et al., 1997; Bengio et al., 2013). By explicitly "learning-to-learn" over a series of few-shot learning tasks (i.e., episodes), which are simulated from base classes, meta-learning exploits accumulated task-agnostic knowledge to few-shot learning problems of novel classes. Within this paradigm, various types of meta-knowledge has been explored, including (1) a generic feature embedding or metric space, in which images are easy to classify using a distance-based classifier such as cosine similarity or nearest neighbor (Koch et al., 2015; Vinyals et al., 2016; Snell et al., 2017; Sung et al., 2018; Ren et al., 2018; Oreshkin et al., 2018); (2) a common initialization of network parameters (Finn et al., 2017; Nichol and Schulman, 2018; Finn et al., 2018) or learned update rules (Andrychowicz et al., 2016; Ravi and Larochelle, 2017; Munkhdalai and Yu, 2017; Li et al., 2017; Rusu et al., 2019); (3) a transferable strategy to estimate model parameters based on few class examples (Bertinetto et al., 2016; Qiao et al., 2018; Qi et al., 2018; Gidaris and Komodakis, 2018), or from an initial small dataset model (Wang and Hebert, 2016; Wang et al., 2017). Some most recent work (Gidaris and Komodakis, 2018; Chen et al., 2019; Tian et al., 2020) also showed that the performance of these complex models can be matched by simple representation learning on base classes and classifier fine-tuning on novel classes.

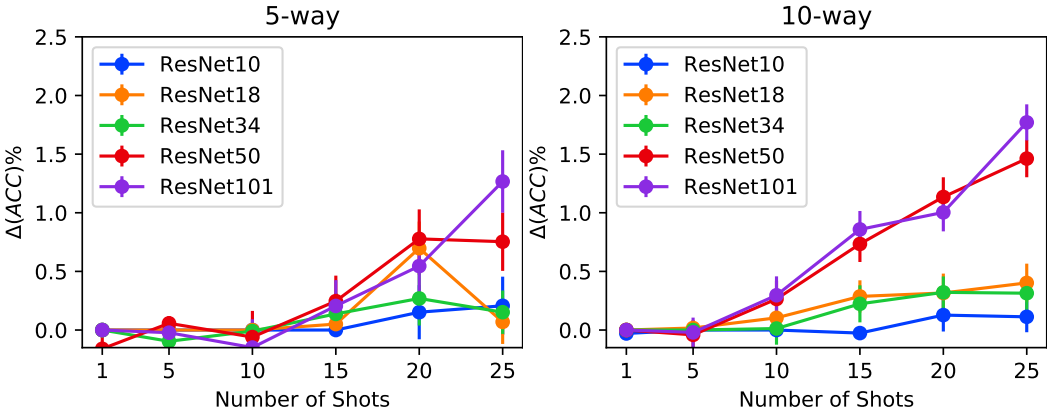

Figure A9: **Improvements of Firth-penalized logistic classifier over the baseline on mini-ImageNet with 5 and 10 number of classes.** Except for the number of classes, the experiments were performed in the same setting as Figure 2 experiments.

D Datasets and Additional Experiment Details

Datasets: mini-ImageNet consists of 64, 16, and 20 classes from ImageNet for base, validation, and novel sets, respectively. Each class contains 600 images of size 84×84. **tiered-ImageNet** consists of 351, 97, and 160 classes from ImageNet for base, validation, and novel sets, respectively. Unlike mini-ImageNet, the classes could have varying number of samples in tiered-ImageNet but the images are of the same size. **CIFAR-FS** is a random split of CIFAR-100 (Krizhevsky et al., 2009) with images of size 32×32 into 64, 16, and 20 classes for base, validation, and novel sets, respectively.

Setups and Implementation Details: Our experiments fall into two main categories: (1) the standard ResNet (He et al., 2016) feature experiments for logistic classifiers, and (2) more powerful, state-of-the-art WideResNet (Zagoruyko and Komodakis, 2016) features trained with strong regularization techniques (manifold mixup) and additional self-supervision (Mangla et al., 2020), or further calibrated via feature transformations (Yang et al., 2021), for logistic and cosine classifiers. For the first category of experiments, we averaged our results over 400 random trials for both methods. An array of 5 different ResNet architectures with varying depths were used in this category: ResNet10, 18, 34, 50, and 101. The mini-ImageNet dataset was used for these experiments, and 16-way classification was performed on both the validation and novel classes. For this purpose, 16 out of 20 novel classes were chosen at random once and fixed for all the evaluations. We split the validation and novel classes into 90% training and 10% held-out for accuracy evaluation. The imbalanced data settings were chosen to either have 7.5 or 15 average number of shots per class. For the second category of experiments, we used the WideResNet-28-10 pre-trained feature backbones from Mangla et al. (2020); Yang et al. (2021). These experiments were conducted on all three benchmarks, and each hyper-parameter configuration was averaged over 10,000 random trials. Additional details and hyper-parameters are covered in the subsequent sections.

Additional Implementation Details for Sections 4.1 and 4.2 of the Main Paper: In all the experiments, a 3-layer logistic classifier with 100 and 50 hidden units and ReLU activation was used. The L2-regularization coefficient was chosen for the mean-squared value of all classifier parameters, and the Firth bias reduction coefficient was chosen for Equation (13) of the main paper.

Statistical Significance and Reducing the Effect of Randomized Factor: Our study investigates improvements over the baseline. Random effects (random number seed; batch ordering; parameter initialization; and so on) complicate the study by creating variance in the measured improvement. We used a matching procedure (so that the baseline and the Firth penalized models share the same values of all random effects) to control this variance. As long as one does not search for random effects that yield a good improvement (we did not), this yields an unbiased estimate of the improvement. Each experiment is repeated multiple times to obtain confidence intervals. Note that (1) confidence intervals are small; and (2) improvements occur over a large range of feature backbones and datasets.

Setting	Hyper-parameter	Value
All Standard Backbone Experiments	Learning Rate	0.005
	Mini-batch Size	10
	Number of Classes	16
	Optimizer	SGD
	Train-Heldout Shares	90%-10%
	Backbones	ResNet 10, 18, 34, 50, 101
Balanced Data Experiments of Sections 4.1 and 4.2 of the Main Paper	Number of Shots	1, 5, 10, 15, 20, 25
	Firth Coefficients Set*	0, 0.01, 0.03, 0.1, 0.3, 1, 3, 10
	L2 Coefficients Set**	0, 1, 3, 10, 30, 100, 300, 1000
Imbalanced Data Experiments of Section 4.3 of the Main Paper	7.5-Shots Class Distribution	2, 2, 2, 2, 4, 4, 4, 4, 8, 8, 8, 8, 16, 16, 16, 16
	15-Shots Class Distribution	1, 1, 5, 5, 9, 9, 13, 13, 17, 17, 21, 21, 25, 25, 29, 29
Experiments of Sections 4.1, 4.2, and 4.3 of the Main Paper with 1-Layer Logistic Classifier	Number of Epochs	100
	Classifier Architecture	Features→100→ReLU→50 →ReLU →Classes→Softmax
	Number of Trials	More than 400
Experiments of Section E.2 with 3-Layer Logistic Classifier	Number of Epochs	400
	Classifier Architecture	Features→Classes→Softmax
	Number of Trials	More than 800

Table A3: Experimental settings used for the standard backbone experiments. The table is partitioned into 5 sections, where the first section shows the global hyper-parameters used in all standard backbone experiments. The same set of Firth bias reduction and L2 regularization coefficients were used for all validation experiments. *The Firth regularization coefficients were chosen for Equation (13) of the main paper. **We defined the L2-regularization as the **mean** squared value of all classifier parameters, which is why the normalized set of coefficients seems large. The typical unnormalized regularization coefficients can be obtained by dividing these normalized coefficients by the number of classifier parameters.

It is safe to conclude that Firth bias reduction reliably offers a small but useful improvement in accuracy for few-shot classifiers.

Additional Implementation Details for Section 4.3 of the Main Paper: We used two non-uniform count vectors with different average counts, 7.5 (scheme 1) and 15 (scheme 2), to generate the datasets in both validation and novel sets. The count vector with the average of 7.5-shots had 4 classes for each count from the geometric sequence $\{2, 4, 8, 16\}$, and the count vector with the average of 15-shots had 2 classes for each count from the arithmetic sequence $\{1, 5, 9, 13, 17, 21, 25, 29\}$. The same 1-layer logistic classifier of Sections 4.1 and 4.2 was used in Section 4.3 of the main paper.

Table A3 summarizes the hyper-parameters used in all the standard backbone experiments. Also, Figure A6 shows the *relative* accuracy improvements corresponding to Figure A5. Figure A12 contains the validation accuracy versus Firth coefficient λ for the experiments of Figure 2, and Figure A5.

Additional Implementation Details for Section 4.5 of the Main Paper: In the experiments carried out in Section 4.5 of the main paper, a 1-layer cosine classifier was used. Also, for the Firth bias-reduced cosine classifier, the regularization coefficient was tuned for each (N, J) pair, with N representing the number of samples per class and J being the number of classes. For J-way

Number of Shots	Confidence Penalty Improvements	Firth Improvements
5	0.13 ± 0.13 %	0.23 ± 0.06 %
10	0.52 ± 0.14 %	0.73 ± 0.07 %
15	0.57 ± 0.18 %	1 ± 0.07 %

Table A4: **Comparing Firth bias reduction against the confidence penalty label smoothing technique.** The confidence penalty is defined as a $D_{\mathrm{KL}}(\mathrm{P}_i \| \mathrm{U})$ regularization term, whereas Firth bias reduction for logistic and cosine classifiers reduces to a $D_{\mathrm{KL}}(\mathrm{U} \| \mathrm{P}_i)$ penalty. The experimental setting is the same as Figure 2 with the ResNet-10 backbone. This suggests that the improvements obtained by Firth are the result of its bias suppression property, and Firth cannot be replaced by standard label smoothing techniques.

classification on the novel set when J happened to be larger than the number of classes in the validation set (J_{val}) the coefficient tuned for J_{val}-way classification was adopted.

Computational Resources: For the standard backbone experiments, we trained more than 384,000 3-layer and 768,000 1-layer logistic classifiers for the balanced data settings. For the imbalanced settings, we trained more than 64,000 3-layer and 128,000 1-layer logistic classifiers. All classifiers were trained on CPUs, and these experiments alone consumed more than 16 CPU years. The 5 backbones were trained once using an Nvidia-V100 GPU and took 3-days for training.

For the cosine classifier experiments, we trained over 1.92, 1.92, and 3.36 million classifiers for mini-ImageNet, CIFAR-FS, and tiered-ImageNet datasets, respectively. These experiments used more than 5 CPU years in total.

		No Artificial Samples			750-Artificial Samples		
Way	Shot	Before	After Firth	Improvement	Before	After Firth	Improvement
10	1	59.44	60.07 ± 0.16	0.63 ± 0.04	61.85	61.90 ± 0.17	0.05 ± 0.02
10	5	80.52	80.85 ± 0.12	0.33 ± 0.03	79.66	80.07 ± 0.13	0.42 ± 0.04
15	1	52.68	53.35 ± 0.13	0.67 ± 0.03	54.57	54.62 ± 0.14	0.05 ± 0.02
15	5	75.18	75.64 ± 0.11	0.46 ± 0.03	73.88	74.40 ± 0.11	0.53 ± 0.04

Table A5: **The Firth bias reduction accuracy improvements on the tiered-Imagenet dataset when 0 or 750 artificial samples were generated from the calibrated normal distribution in Yang et al. (2021).**

E Additional Experiments on the Standard Backbones

E.1 Additional Logistic Classifier Experiments

The experiments of Figure 2 were repeated to perform 16-way classification using a logistic classifier on tiered-ImageNet and CIFAR-FS Figure A13. Moreover, 5-way and 10-way classification was tested for mini-ImageNet in Figure A9 in the same setting as Figure 2. The results show that Firth improvements always exist and it is even more effective as the number of classes increases.

E.2 3-Layer Logistic Classifiers for the Standard Backbones

We conducted the same experiments as in Sections 4.1 and 4.2 of the main paper but with a 3-layer logistic classifier. Again, we see consistent accuracy improvements for the Firth bias-reduced classifier over the non-penalized (baseline) classifier in Figure A5. This further supports the idea that *Firth bias reduction boosts the performance of any reasonable classifier*. Needless to say, L2-regularization is not effective as shown in Figure A5.

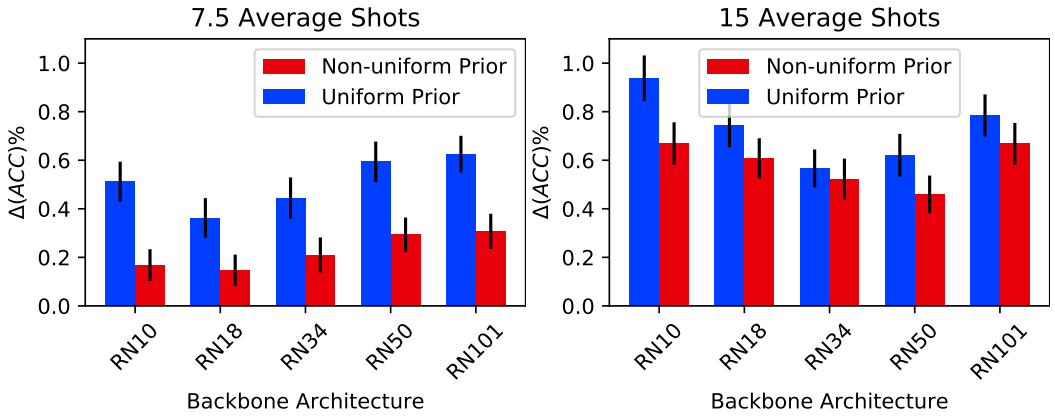

Figure A10: **Same experiment as Figure 3 of the main paper but with a 3-layer logistic classifier instead of a single-layer (in the main paper).** Again, in both schemes (7.5 and 15 average shots), the Firth penalized classifier results in more accuracy improvements than the classifier penalized with KL-divergence to the non-uniform prior. This further suggests that Firth bias reduction is indeed reducing the bias and is not simply imposing a uniform prior. Also, it reaffirms that plain Firth bias reduction can safely be used on imbalanced data.

	5-way			10-way		
	Before	After	Improvement	Before	After	Improvement
1-shot	74.96	75.03 ± 0.19	0.07 ± 0.01	61.46	61.49 ± 0.13	0.03 ± 0.00
5-shot	87.43	87.48 ± 0.13	0.06 ± 0.00	77.73	77.83 ± 0.10	0.10 ± 0.00
10-shot	89.83	89.88 ± 0.11	0.05 ± 0.00	81.52	81.64 ± 0.09	0.11 ± 0.00

	15-way			20-way		
	Before	After	Improvement	Before	After	Improvement
1-shot	53.45	53.47 ± 0.10	0.02 ± 0.00	47.78	47.79 ± 0.07	0.01 ± 0.00
5-shot	70.70	70.99 ± 0.07	0.28 ± 0.00	65.26	65.60 ± 0.03	0.34 ± 0.00
10-shot	75.37	75.71 ± 0.06	0.34 ± 0.00	70.57	70.99 ± 0.02	0.42 ± 0.00

Table A6: **The Firth bias reduction improvements on the CIFAR-FS dataset shown in Figure 4 of the main paper.** "Before" stands for the novel set accuracy without having any Firth bias reduction, and "After" stands for the novel set accuracy after applying Firth bias reduction. Note that the confidence intervals are much smaller for the improvement column thanks to the random-effect matching procedure we used in this study. The "Before" confidence intervals were similar to the "After" confidence intervals, and thus not repeated due to space constraints.

Furthermore, the imbalanced few-shot classification in Section 4.3 of the main paper was repeated with the 3-layer logistic classifier in Figure A10. Again for both schemes, the Firth penalized classifier has larger accuracy improvement than the classifier penalized with the KL-divergence to the non-uniform prior over the class probabilities. This further validates the effectiveness of Firth bias reduction in reducing the parameter estimation bias present in the few-shot setting.

F Comparing Firth Bias Reduction Against Standard Label Smoothing Techniques

To demonstrate that Firth bias reduction cannot simply be replaced with label smoothing, we tested two advanced variants of label smoothing that are superior to the original version as proposed

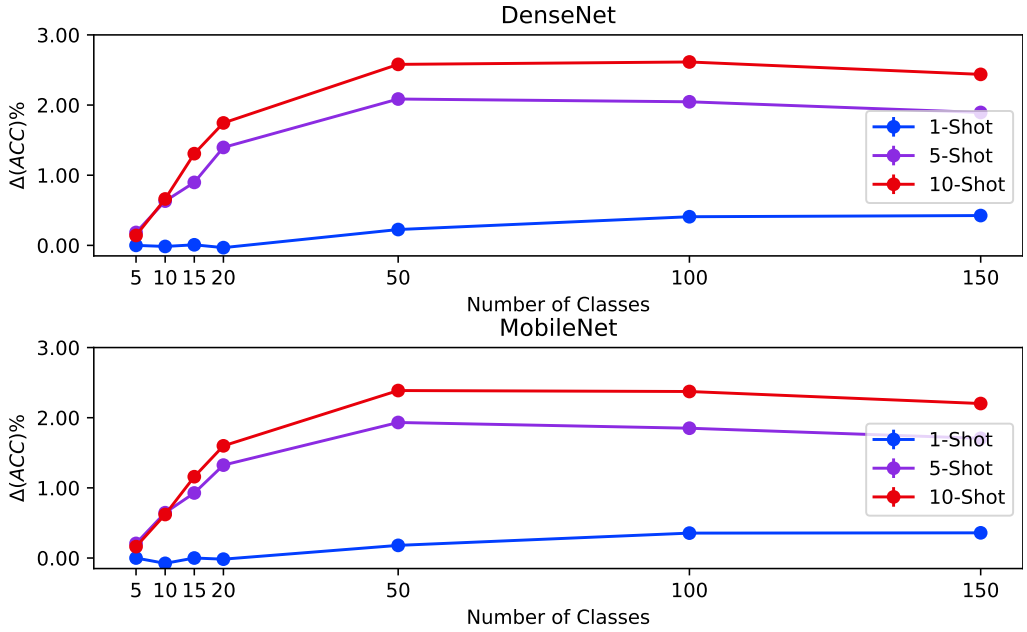

Figure A11: Firth bias reduction improves the accuracy of the logistic classifier on tieredImageNet for both DenseNet (top) and MobileNet (bottom) as backbone architectures. The improvement is consistent over the number of classes in few-shot classification.The error bars are almost non-existent (i.e., less than 0.02%) since over 10,000 trials with matching randomization factors were used for obtaining each single point. Firth bias reduction improvements are always positive, and it never hurts to use it.

	5-way			10-way		
	Before	After	Improvement	Before	After	Improvement
1-shot	65.17	65.59 $\pm$ 0.18	0.41 $\pm$ 0.02	50.38	50.64 $\pm$ 0.11	0.26 $\pm$ 0.01
5-shot	82.60	83.04 $\pm$ 0.12	0.44 $\pm$ 0.01	71.15	71.91 $\pm$ 0.10	0.76 $\pm$ 0.02
10-shot	86.82	87.04 $\pm$ 0.09	0.22 $\pm$ 0.01	77.34	77.87 $\pm$ 0.08	0.52 $\pm$ 0.01
	15-way			20-way		
	Before	After	Improvement	Before	After	Improvement
1-shot	42.65	42.85 $\pm$ 0.08	0.20 $\pm$ 0.01	37.56	37.76 $\pm$ 0.07	0.20 $\pm$ 0.00
5-shot	63.73	64.76 $\pm$ 0.07	1.03 $\pm$ 0.01	58.35	59.52 $\pm$ 0.04	1.17 $\pm$ 0.01
10-shot	70.87	71.71 $\pm$ 0.05	0.84 $\pm$ 0.01	66.06	67.12 $\pm$ 0.03	1.06 $\pm$ 0.01

Table A7: **The Firth bias reduction improvements on the mini-ImageNet dataset shown in Figure 4 of the main paper.** "Before" stands for the novel set accuracy without having any Firth bias reduction, and "After" stands for the novel set accuracy after applying Firth bias reduction. Note that the confidence intervals are much smaller for the improvement column thanks to the random-effect matching procedure we used in this study. The "Before" confidence intervals were similar to the "After" confidence intervals, and thus not repeated due to space constraints.

by Pereyra et al. (2017). The first variant, called confidence penalty, uses the entropy of the classifier's output (or equivalently, reverses the direction of the KL divergence in the original version of label smoothing (Szegedy et al., 2016)); and the second variant, called unigram label smoothing, uses prior distribution over the classes instead of uniform, which has been shown to be advantageous when the output labels' distribution is imbalanced in Pereyra et al. (2017). Note that both the variants were

	5-way			10-way		
	Before	After	Improvement	Before	After	Improvement
1-shot	73.50	73.64 $\pm$ 0.25	0.14 $\pm$ 0.03	61.20	61.44 $\pm$ 0.16	0.24 $\pm$ 0.01
5-shot	88.00	88.31 $\pm$ 0.12	0.30 $\pm$ 0.01	79.41	80.01 $\pm$ 0.11	0.60 $\pm$ 0.01
10-shot	90.94	91.14 $\pm$ 0.10	0.21 $\pm$ 0.01	83.88	84.47 $\pm$ 0.09	0.58 $\pm$ 0.01

	15-way			20-way		
	Before	After	Improvement	Before	After	Improvement
1-shot	53.90	53.97 $\pm$ 0.15	0.07 $\pm$ 0.01	48.81	48.96 $\pm$ 0.11	0.15 $\pm$ 0.01
5-shot	73.33	74.21 $\pm$ 0.09	0.88 $\pm$ 0.01	68.58	69.71 $\pm$ 0.08	1.13 $\pm$ 0.01
10-shot	78.70	79.57 $\pm$ 0.08	0.86 $\pm$ 0.01	74.58	75.74 $\pm$ 0.07	1.16 $\pm$ 0.01

	50-way			100-way		
	Before	After	Improvement	Before	After	Improvement
1-shot	33.91	34.13 $\pm$ 0.06	0.22 $\pm$ 0.01	24.80	25.00 $\pm$ 0.03	0.20 $\pm$ 0.00
5-shot	52.60	54.71 $\pm$ 0.05	2.10 $\pm$ 0.01	41.03	43.59 $\pm$ 0.03	2.56 $\pm$ 0.01
10-shot	59.67	61.94 $\pm$ 0.04	2.27 $\pm$ 0.01	47.77	50.81 $\pm$ 0.02	3.04 $\pm$ 0.01

	150-way		
	Before	After	Improvement
1-shot	20.37	20.56 $\pm$ 0.02	0.19 $\pm$ 0.00
5-shot	34.89	37.54 $\pm$ 0.01	2.65 $\pm$ 0.01
10-shot	41.04	44.28 $\pm$ 0.01	3.25 $\pm$ 0.01

Table A8: **The Firth bias reduction improvements on the tiered-ImageNet dataset shown in Figure 4 of the main paper.** "Before" stands for the novel set accuracy without having any Firth bias reduction, and "After" stands for the novel set accuracy after applying Firth bias reduction. Note that the confidence intervals are much smaller for the improvement column thanks to the random-effect matching procedure we used in this study. The "Before" confidence intervals were similar to the "After" confidence intervals, and thus not repeated due to space constraints.

investigated for training a full deep neural network with a feature extractor backbone in large-sample regimes in Pereyra et al. (2017). Surprisingly, our evaluation of these two variants for training only classifiers on novel classes in few-shot regimes indicates that they are not as helpful as Firth bias reduction.

Our experiments in Figure 3 show that, in imbalanced few-shot classification tasks, the improvements achieved by unigram label smoothing is significantly less than the Firth penalized classifier. This validates the bias suppression effect of Firth – a property that cannot be achieved by unigram label smoothing.

We also performed more experiments in the same setting to compare Firth bias reduction against confidence penalty regularization. As summarized in Table A4, in all the settings Firth bias reduction has larger significant improvements than the confidence penalty technique. This further supports the value of using Firth bias reduction and the fact that its impact on few-shot classification cannot be reproduced with well-known and widely-used label smoothing techniques.

	ResNet10			ResNet18		
	Before	After	Improvement	Before	After	Improvement
1-shot	7.96	7.97 $\pm$ 0.06	0.01 $\pm$ 0.01	7.57	7.58 $\pm$ 0.05	0.01 $\pm$ 0.01
5-shot	8.22	8.23 $\pm$ 0.06	0.01 $\pm$ 0.01	7.94	7.95 $\pm$ 0.06	0.01 $\pm$ 0.01
10-shot	8.19	8.24 $\pm$ 0.05	0.06 $\pm$ 0.05	8.01	8.15 $\pm$ 0.05	0.14 $\pm$ 0.06
15-shot	8.21	8.36 $\pm$ 0.05	0.15 $\pm$ 0.06	8.09	8.47 $\pm$ 0.05	0.38 $\pm$ 0.06
20-shot	8.22	8.51 $\pm$ 0.05	0.28 $\pm$ 0.06	8.15	8.75 $\pm$ 0.06	0.60 $\pm$ 0.06
25-shot	8.25	8.51 $\pm$ 0.05	0.25 $\pm$ 0.06	8.27	8.92 $\pm$ 0.05	0.65 $\pm$ 0.06

	ResNet34			ResNet50		
	Before	After	Improvement	Before	After	Improvement
1-shot	7.47	7.48 $\pm$ 0.05	0.01 $\pm$ 0.01	7.51	7.52 $\pm$ 0.05	0.01 $\pm$ 0.01
5-shot	7.69	7.70 $\pm$ 0.05	0.01 $\pm$ 0.01	7.73	7.78 $\pm$ 0.05	0.05 $\pm$ 0.05
10-shot	7.73	7.96 $\pm$ 0.05	0.23 $\pm$ 0.05	7.83	8.59 $\pm$ 0.05	0.76 $\pm$ 0.06
15-shot	7.79	8.22 $\pm$ 0.05	0.43 $\pm$ 0.06	7.89	9.02 $\pm$ 0.05	1.13 $\pm$ 0.06
20-shot	7.87	8.41 $\pm$ 0.05	0.55 $\pm$ 0.06	8.15	9.67 $\pm$ 0.06	1.52 $\pm$ 0.06
25-shot	7.97	8.54 $\pm$ 0.05	0.57 $\pm$ 0.06	8.44	10.71 $\pm$ 0.06	2.27 $\pm$ 0.06

	ResNet101		
	Before	After	Improvement
1-shot	7.63	7.65 $\pm$ 0.05	0.02 $\pm$ 0.02
5-shot	7.81	7.88 $\pm$ 0.05	0.07 $\pm$ 0.05
10-shot	7.96	8.81 $\pm$ 0.05	0.86 $\pm$ 0.06
15-shot	8.10	9.50 $\pm$ 0.05	1.40 $\pm$ 0.06
20-shot	8.37	10.29 $\pm$ 0.06	1.91 $\pm$ 0.06
25-shot	8.74	10.62 $\pm$ 0.06	1.88 $\pm$ 0.06

Table A9: **The Firth bias reduction improvements on the mini-ImageNet dataset shown in Figure 2 of the main paper.** "Before" stands for the novel set accuracy without having any Firth bias reduction, and "After" stands for the novel set accuracy after applying Firth bias reduction. Note that the confidence intervals are much smaller for the improvement column thanks to the random-effect matching procedure we used in this study. The "Before" confidence intervals were similar to the "After" confidence intervals, and thus not repeated due to space constraints.

G Additional Feature Backbones

To test the Firth bias reduction technique for additional backbones, we used pretrained DenseNet and MobileNet backbones on tiered-ImageNet from (Wang et al., 2019). The accuracy improvements of Firth penalized logistic classifier over the baseline averaged over 10,000 trials are plotted in Figure A11. Regardless of the number of classes, the improvements are always positive.

H Comparison with Additional State of the Art Method

Table A5 summarizes the accuracy improvements obtained by integrating Firth bias reduction with the distribution calibration method (Yang et al., 2021) under different shots and ways on the tiered-ImageNet dataset. This method calibrates the features to follow a normal distribution, and generates

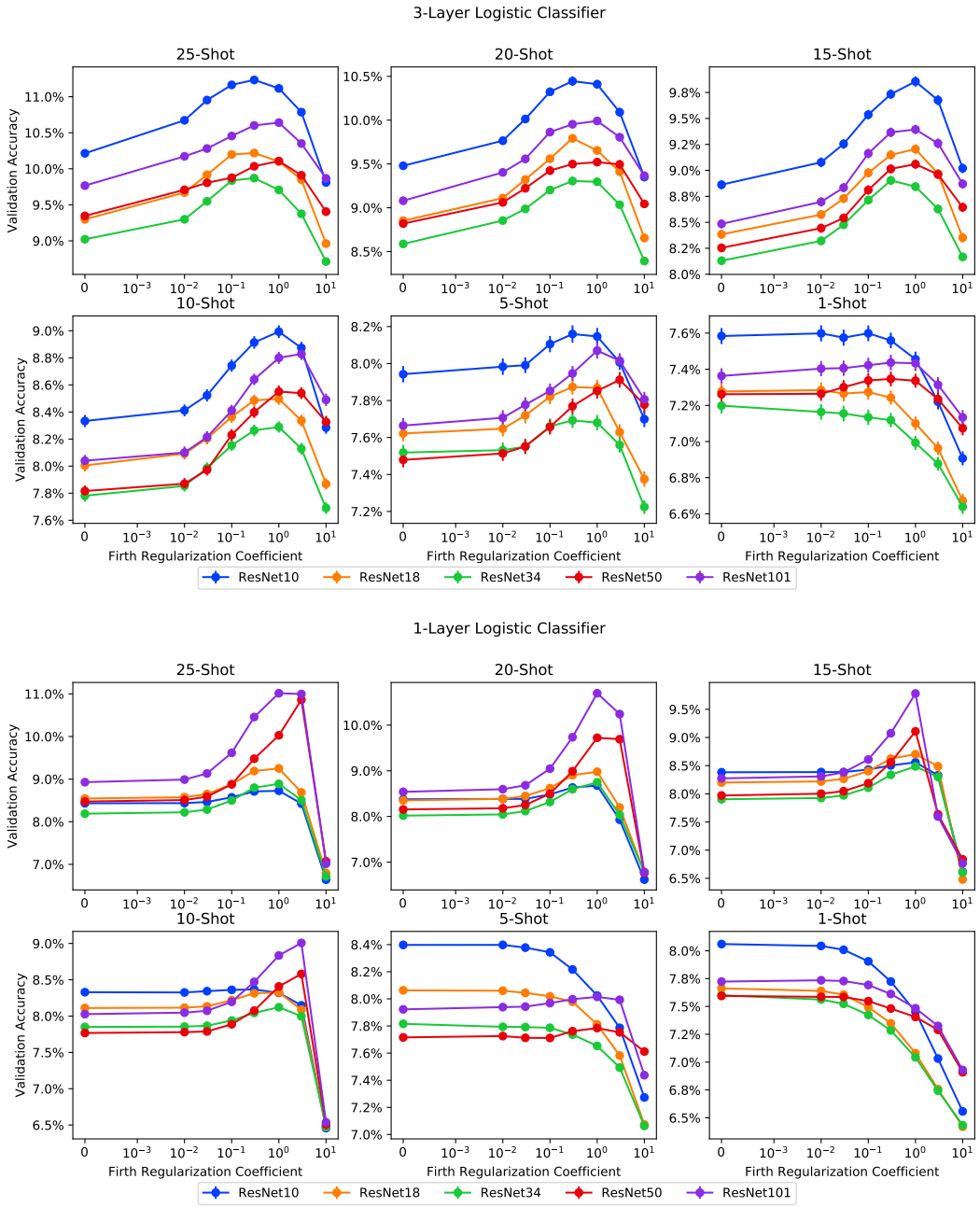

Figure A12: **The effect of the validation coefficient λ on the validation accuracy for different number of shots and backbone architectures.** The top two rows belong to the 3-layer logistic classifier of Figure A5 of the Appendix, and the bottom two rows belong to the 1-layer logistic classifier of Figure 2 of the main paper.

artificial samples from the estimated normal distribution as data augmentation to aid the few-shot classification. In its state-of-the-art setting, the features are transformed using Tukey transformations, 750 artificial samples are generated per class, and a logistic classifier is used. We tested Firth bias reduction in two scenarios: (i) state-of-the-art setting without generating artificial samples from the calibrated distribution; and (ii) state-of-the-art setting with 750 artificial samples generated per class, as shown in Table A5. The 95% confidence intervals for the accuracy improvements are reported in both cases.

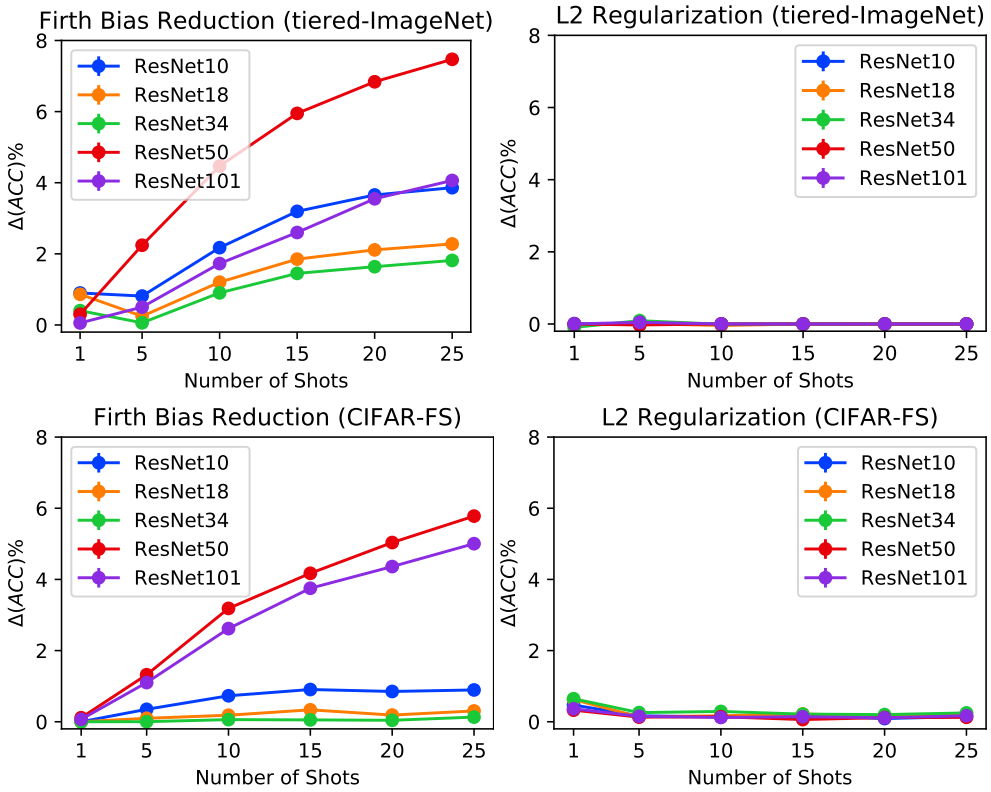

Figure A13: **Comparing the effect of Firth bias reduction against L2-regularization on the novel set classification accuracy over the tiered-Imagenet and CIFAR-FS datasets**. Firth bias reduction (left) delivers a novel class accuracy improvement over the baseline classifier up to 8.0%. By contrast, L2-regularization (right) is mostly statistically insignificant in the same few-shot setting. **16-way** logistic classification was conducted in this experiment, with over 1000 randomized and matching trials for each combination of method, backbone, and number of samples.

As shown in Table A5, Firth bias reduction produces positive improvements in all cases, which are statistically significant in all the cases. As expected, Firth bias reduction produces larger improvements when artificial sample generation is disabled and thus there is a larger maximum likelihood estimation bias on the linear classifier (despite the use of Tukey transformation). In the case that artificial samples are added and they are tuned to follow the original normal distribution, having 750 of them can to some extent alleviate the bias in the estimation of the logistic classifier's weights in the few-shot regime. However, the results show that even in the presence of more data (artificial samples), Firth bias reduction is still effective. This suggests that producing artificial samples to augment data cannot resolve the estimation bias issue, as they are more likely to be similar to the limited real samples available. We suspect this will become an even more severe problem in the cross-domain few-shot setting; producing artificial samples will be significantly less effective than Firth bias reduction, due to the domain shift (see Section 4.6).