Long-Tailed Recognition Using Class-Balanced Experts

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Abstract. Classic deep learning methods achieve impressive results in image recognition over large-scale artificially-balanced datasets. However, real-world datasets exhibit highly class-imbalanced distributions. In this work we address the problem of long tail recognition wherein the training set is highly imbalanced and the test set is kept balanced. The key challenges faced by any long tail recognition technique are relative imbalance amongst the classes and data scarcity or unseen concepts for mediumshot or fewshot classes. Existing techniques rely on data-resampling, cost sensitive learning, online hard example mining, reshaping the loss objective and complex memory based models to address this problem. We instead propose an ensemble of experts technique that decomposes the imbalanced problem into multiple balanced classification problems which are more tractable. Our ensemble of experts reaches close to state-of-the-art results and an extended ensemble establishes new state-of-the-art on two benchmarks for long tail recognition. We conduct numerous experiments to analyse the performance of the ensemble, and show that in modern datasets relative imbalance is a harder problem than data scarcity.

1 Introduction

In recent years, deep learning has boosted success in image recognition to a new stage. The availability of large-scale datasets with thousands of images in each class has been a major factor in this revolution. However, these datasets are manually curated and artificially balanced, as opposed to real-world datasets that exhibit a highly skewed and class-imbalanced distribution in a long-tailed shape: a few common classes and many more rare classes. Class imbalance is a persistent problem that pops up in essentially all problems such as face verification, object detection, image defect detection, and in safety-critical applications such as the biomedical industry and autonomous driving, to name a few.

Researchers have tried to attack this problem from various angles, particularly zero-shot learning, fewshot learning, imbalanced classification, and more recently long-tailed recognition.
In this work, we focus on the problem of long-tailed recognition, wherein datasets exhibit a natural power law distribution, allowing us to assess model performance on four folds, Manyshot classes (≥ 100 samples), Mediumshot classes (20 ∼ 100 samples), Fewshot classes (< 20 samples), and All classes. In this problem, the training data contains a highly class-imbalanced distribution, and the testing data is kept balanced so that performing equally well on all classes is crucial.

The key issues for any classification model dealing with long-tailed datasets are relative imbalance amongst the classes, and data scarcity or unobservable data modes. Existing techniques for imbalanced classification have focused on data re-sampling or cost-sensitive learning, and hard example mining to re-weigh the loss objective and counter relative imbalance, while techniques for fewshot learning have employed data augmentation, predicting classifier weights and prototype-based non-parametric methods to primarily deal with data scarcity.

We instead take the simple and classic approach of an ensemble of experts, and decompose the imbalanced classification problem into balanced classification problems that are more tractable. Thereby, we train experts on balanced subsets of classes, that is, Manyshot, Mediumshot, or Fewshot data, with out-of-distribution detection for samples from outside an expert’s class-balanced subset. This explicitly tackles the issue of relative imbalance, and prevents competition between Manyshot and Fewshot classes during training. We initialise the feature extractor of each expert using a Baseline model trained on the entire dataset to use all available data for learning feature representations and to transfer knowledge from Manyshot to Mediumshot and Fewshot classes. For inference, the partial posteriors from the experts are fused through a module that scales and shifts posteriors to jointly calibrate the experts’ predictions, and then sums them up into a full posterior from which the final prediction is taken. This simple and effective approach reaches close to state-of-the-art results without involving more complex models or sophisticated loss objectives. Moreover, our experiments with an Oracle upper bound allow us to match Fewshot and Mediumshot accuracy with Manyshot accuracy, which reveals that in modern datasets the data scarcity for Mediumshot and Fewshot classes can be effectively handled using knowledge transfer from Manyshot classes. Therefore, relative imbalance is the more severe problem that must be addressed by the community.

We also leverage the flexibility and modularity of the ensemble framework to create larger and diverse ensembles using existing solutions for long-tailed recognition. Specifically, we involve the following methods in the solution space: (1) A Baseline model without any bells or whistles. (2) Feature learning followed by classifier finetuning with uniform class sampling. (3) Data augmentation using feature generation networks, employed in zero-shot and fewshot learning. (4) Knowledge transfer through prototype-based memory representation, used for fewshot learning and long-tailed recognition. This is easy to accomplish as the ensemble framework is agnostic to the kind of model or training strategy used by each individual method. The larger ensemble consist-
Fig. 1: Our pipeline for long-tailed recognition, consisting of an ensemble of experts trained on Manyshot, Mediumshot and Fewshot subsets of data that are intrinsically balanced. We transfer knowledge from Manyshot to Mediumshot and Fewshot classes by initialising experts with a baseline model trained on all the data. Expert models classify samples outside their subset as out-of-distribution and output partial posteriors that are fused together into a full posterior to obtain the final prediction.

Our contributions in this work can be summarised as:

1. We propose a simple and effective ensemble of experts framework for long tail recognition that decomposes the imbalanced classification problem into multiple balanced classification problems that are tractable. Our framework utilises all available data for learning feature representations and transfers this knowledge from Manyshot to Mediumshot and Fewshot classes. Our proposed pipeline reaches close to state-of-the-art performance on two benchmark long tail datasets, ImageNet-LT and Places-LT [42].

2. We complement our ensemble with a diverse set of existing solutions for long-tailed recognition, namely data re-sampling, data augmentation using synthesized features, and prototype-based classification, and set a new state-of-the-art for long tail recognition.

3. We analyse the upper bound performance of our approach with Oracle access to the expert containing the test sample’s ground truth class in its class-balanced subset, and find that data scarcity for rare classes is not a severe issue in modern day datasets, and relative imbalance is the main bottleneck.

2 Related work

Imbalanced classification and long-tailed recognition. There is a long history of research in imbalanced classification [21, 2, 55], in binary and more generally multi-class classification problems. Classic problems that naturally encounter class imbalance are face attribute detection [11, 22, 45, 29], object detec-
tion [72, 49, 71, 40], and image defect detection [66]. Recent work on image classification [66, 61] deals with long-tailed datasets, but only recently a benchmark for the problem on the ImageNet and Places dataset was proposed by [42]. They also propose splits for open world classification, but in this work we only consider long-tailed recognition and we report the performance of our methods on the proposed ImageNet-LT and Places-LT. We summarize below the existing solutions for imbalanced classification and long-tailed recognition.

**Data re-sampling heuristics and cost-sensitive learning.** These are classic ways to tackle long-tailed recognition. A more balanced data distribution is achieved by randomly over-sampling fewshot classes or randomly under-sampling of manyshot classes [38, 10, 21]. However, over-sampling suffers from overfitting on fewshot classes while under-sampling cannot take full benefit of available data for generalization on manyshot classes. Other work has focused on hard example mining [8] or cost-sensitive learning [9, 40] reasoned from class frequencies. Instead, to augment our ensemble of experts, we use a uniform class sampling procedure in mini-batch training for fine-tuning the classifier after a representation learning phase, which has the advantage that all data is used to learn representations while decision boundary learning takes class imbalance into account. This has also been employed before in related zero-shot learning [64] and fewshot learning [53] work.

**Synthetic data augmentation.** Synthetic minority data augmentation [3, 19] is a classic technique that synthesizes features for minority classes based on feature space similarities. More recently, generative models have been employed in zero-shot [11, 63, 64] and fewshot learning [59] literature to automatically generate images or feature embeddings for data-starved classes. In this work, we use the f-VAEGAN-D2 model from [64] that generates feature embeddings conditioned on available class embeddings using a VAE-GAN model, and integrate it into our ensemble of experts framework.

**Prototype-based models and knowledge transfer.** Another paradigm of long-tailed recognition approaches focuses on building feature representations that are compact within one class and discriminative across classes. Contrastive loss functions [18] were proposed to pull examples from the same class closer and push farther away samples from different classes. Prototype-based networks [24, 50] maintain a memory module for all the classes such that each class is equally represented regardless of sample frequency. In particular, Liu et al. [42] learn prototype-based features on-the-fly to effectively transfer knowledge from manyshot classes to fewshot classes. We integrate their model into our ensemble due to its ability to perform consistently well across the entire class spectrum. Transfer learning [46] addresses data imbalance by transferring abundant features of manyshot classes to those of fewshot classes. Recent work includes transferring the intra-class variance [65] and transferring semantic deep features [69, 42]. We instead transfer knowledge across the dataset by initialising our expert models with a baseline model pre-trained on the entire dataset.

**Ensemble learning.** Ensemble methods are a well-studied topic in machine learning literature. In particular, a variety of ensemble-based methods using
boosting \cite{12,31,10,67}, bagging \cite{25,13,32}, stacking \cite{02,68,1}, and evolutionary selection of classifiers \cite{35} have been employed for imbalanced datasets. However, they all consider ensembles with the same kind of model and task. Our approach is related to the work of Hinton et al. \cite{26} who train an ensemble of experts over disjoint semantically-close subsets of classes, thereby each expert effectively deals with a different classification task. We instead train our experts on subsets of classes that are intrinsically balanced to counter relative imbalance and prevent competition between manyshot and fewshot classes during training. Moreover, differently from prior work, we integrate a diverse set of models for long-tailed recognition into our ensemble of experts.

**Out-of-distribution detection and confidence calibration.** Modern neural networks can function both as classification models and detectors for out-of-distribution examples \cite{23}. Recent works focus on adding small perturbations in input space and applying temperature scaling \cite{39}, and adding loss terms to push out-of-distribution examples towards uniform confidence \cite{24}. Related work on confidence calibration tries to fix overconfident predictions on in-distribution data using temperature scaling \cite{15}. We instead focus on learning an ensemble of experts for long tail recognition, where the problem of out-of-distribution detection arises when dealing with samples from outside an expert’s subset, and jointly calibrate the confidences from the experts to fuse their partial posteriors.

## 3 Method

We propose an ensemble of experts for solving the problem of long-tailed recognition. We split the long-tailed dataset into (approximately) class-balanced subsets, and a separate classification model, or expert, is trained for each subset. The partitioning of the long-tailed dataset into class-balanced subsets leads to balanced classification problems that are more tractable. Expert models identify samples belonging to classes outside their subset as out-of-distribution; therefore we train them to produce low confidence predictions on these samples. During inference, each classification model yields a partial posterior distribution for test samples, that are fused together to form a complete posterior distribution. Our entire pipeline is depicted in Fig. 1. The rest of this section is structured as follows: in Sec. 3.1 we detail our ensemble of experts framework for long-tailed recognition, in Sec. 3.2 we describe out-of-distribution detection mechanisms for training experts, and finally in Sec. 3.3 we list our strategies for fusing expert posteriors.

### 3.1 Long-tailed recognition using class-balanced experts

The task of long-tailed visual recognition is as follows: given class-imbalanced training set $D_{\text{Train}} = \{(x_i, y_i)\}_{i=1}^n$ and class-balanced validation set $D_{\text{Val}}$ and class-balanced test set $D_{\text{Test}}$, the objective is to maximise test accuracy on four folds,
Manyshot classes (≥ 100 samples), Mediumshot classes (20 ∼ 100 samples), Fewshot classes (< 20 samples), and All classes. This is a hard problem, since any high performing model must deal with the two problems of relative imbalance and data scarcity. Relative imbalance leads to biased classification boundaries wherein accuracy on fewshot samples is compromised in favor of manyshot samples that dominate the training objective. Data scarcity leads to representations that do not model unobserved data modes and is more severe. To tackle both these issues, we sort the class-imbalanced training set $\mathcal{D}_{\text{Train}}$ according to class frequencies and partition it into contiguous class-balanced subsets $\mathcal{D}_{\text{Manyshot}}$, $\mathcal{D}_{\text{Mediumshot}}$ and $\mathcal{D}_{\text{Fewshot}}$. This is visualised in Fig. 2. For each subset, we train separate classification models or experts, that are initialised using a model pre-trained on the entire dataset. Formally,

$$\mathcal{D}_{\text{Train}} = \mathcal{D}_{\text{Manyshot}} \cup \mathcal{D}_{\text{Mediumshot}} \cup \mathcal{D}_{\text{Fewshot}}, \text{ where}$$

$$\mathcal{D}_{\text{Manyshot}} \cap \mathcal{D}_{\text{Mediumshot}} = \mathcal{D}_{\text{Mediumshot}} \cap \mathcal{D}_{\text{Fewshot}} = \mathcal{D}_{\text{Fewshot}} \cap \mathcal{D}_{\text{Manyshot}} = \emptyset$$

and consequently we obtain the expert models $\mathcal{E}_{\text{Manyshot}}$, $\mathcal{E}_{\text{Mediumshot}}$ and $\mathcal{E}_{\text{Fewshot}}$ corresponding to each class-balanced subset. The feature extractor part of each expert model $\mathcal{E}$ is initialised using the Baseline model pre-trained on the entire training set $\mathcal{D}_{\text{Train}}$. This enables knowledge transfer from Manyshot to Mediumshot and Fewshot classes. In this work, the expert models $\mathcal{E}$, and the Baseline model are deep fully convolutional neural networks with softmax classifiers.

3.2 Out-of-distribution detection for experts

The expert models identify samples from classes outside their class-balanced subset as out-of-distribution or OOD for short, therefore we train them using out-of-distribution detection mechanisms. Observe that this is a hard problem, since here OOD examples come from within the same distribution albeit from extra classes within the dataset, as opposed to standard out-of-distribution detection wherein OOD samples come from an entirely different dataset. Below we describe the two out-of-distribution mechanisms we employed while training our experts.

3.2.1 Training with reject class. We add a reject class to the softmax classifier of each expert. For instance, $\mathcal{E}_{\text{Manyshot}}$ treats samples from $\mathcal{D}_{\text{Mediumshot}} \cup \mathcal{D}_{\text{Fewshot}}$ as a single reject class. This introduces imbalance since the reject
class has far more samples than any other class, therefore we undersample reject class samples appropriately during training. We correct for the statistical bias introduced during training by incrementing the logit score by the log of the undersampling ratio. Also note that samples in the reject class have very high variance and are therefore hard to fit.

3.2.2 Outlier exposure training. For each expert, we add a cross entropy loss term to the objective that penalizes deviation of the predicted class posterior from the uniform distribution for its OOD samples [24]. For instance, the $\mathcal{E}_{\text{Manyshot}}$ has the following objective:

$$
\mathbb{E}_{(x,y) \sim \mathcal{D}_{\text{Manyshot}}} \left[ - \log \mathbb{E}_{\mathcal{y}_{\text{Manyshot}}} (x) \right] + \lambda \mathbb{E}_{x \sim \mathcal{D}_{\text{Mediumshot}} \cup \mathcal{D}_{\text{Fewshot}}} \left[ H(U; \mathcal{E}_{\text{Manyshot}}(x)) \right],
$$

where $\lambda$ is a hyperparameter.

3.3 Fusing expert posteriors
We consider various baseline strategies and propose our own joint calibration module to fuse expert posteriors $\mathcal{E}_x$ into a complete posterior distribution. The final prediction and confidence scores are taken from this posterior, denoted as $q(x)$, using the argmax operation.

3.3.1 KL-divergence minimisation. We find the full posterior distribution for each sample, by minimising its KL-divergence with all the partial posterior distributions predicted by the experts [26], that is,

$$
\min_{q(x)} \sum_{\mathcal{E}_x} KL(\mathcal{E}_x(x) || q(x))
$$

where $q(x)$ is parameterised using logits $z$ and a softmax function as $q(x) = \text{softmax}(z)$. Note that probabilities corresponding to out-of-distribution classes for the expert $\mathcal{E}_x$ are summed up into one probability score in $q(x)$ to align the two distributions.

3.3.2 Soft-voting. We find the full posterior by summing up the partial posteriors directly and normalising the sum to 1,

$$
q(x) = \frac{\sum_{\mathcal{E}_x} g(x)}{\sum_{\mathcal{E}_x} 1}
$$

Here $g(.)$ is a function that converts an expert’s partial posterior into a full posterior. For experts trained with the reject class, $g(.)$ averages the reject class probability score across the out-of-distribution classes corresponding to expert $\mathcal{E}_x$. For experts trained using the outlier exposure loss term, $g(.)$ simply pads zero probability scores for out-of-distribution classes corresponding to expert $\mathcal{E}_x$. 

3.3.3 Expert selection. We train a 3-way classifier on the validation set, taking the partial posterior vectors $E(x)$ of each expert $E$ as input, to predict for a sample $x$ the expert model $E$ that contains the sample’s ground truth class in its class-balanced subset. Thus, for instance, the classifier learns to predict that a manyshot sample lies in the class-balanced subset of the manyshot expert $E_{Manyshot}$. The full posterior $q(x)$ is then given by $g(E_{E}(x))$ for the predicted expert $E_{E}$, where $g(.)$ is defined similarly as before.

3.3.4 Model stacking. We train a single layer linear softmax classifier to predict the full posterior $q(x)$ from the partial posterior vectors $E(x)$ of each expert $E$. The vectors $E(x)$ are concatenated to form a feature embedding for the softmax classifier which is trained by optimising the cross entropy loss on the validation set. This is a standard way for ensemble fusion known as model stacking [62].

3.3.5 Joint calibration. We calibrate the partial posteriors $E(x)$ by learning scaling and shift parameters before adding up the posteriors similarly to soft-voting,

$$q(x) = \frac{\sum g(\sigma_{SM}(w_{E} \odot z_{E}(x) + b_{E})))}{Z}$$

where $\sigma_{SM}$ denotes the softmax operation, $w_{E}$ and $b_{E}$ are scale and shift parameters respectively, $z_{E}(x)$ denotes the logit scores of expert $E$ for sample $x$, $\odot$ denotes elementwise multiplication of two vectors, $Z$ is a normalisation factor, and $g(.)$ is defined as before. We learn the scale and shift parameters by minimising the cross entropy loss on the validation set. This module effectively learns the right alignment for the experts’ partial posteriors before performing the soft-voting operation.

4 Experiments

Datasets. We use the object-centric ImageNet-LT and scene-centric Places-LT datasets for long-tailed recognition, released by Liu et al. [42]. The training set statistics are depicted in Table 1. ImageNet-LT has an imbalanced training set with 115,846 images for 1,000 classes from ImageNet-1K [6]. The class frequencies follow a natural power law distribution [55] with a maximum number of 1,280 images per class and a minimum number of 5 images per class. The validation and testing sets are balanced and contain 20 and 50 images per class respectively. Places-LT has an imbalanced training set with 62,500 images for 365 classes from Places-2 [70]. The class frequencies follow a natural power law distribution [55] with a maximum number of 4,980 images per class and a minimum number of 5 images per class. The validation and testing sets are balanced and contain 20 and 100 images per class respectively.
Table 1: Statistics for training sets in ImageNet-LT and Places-LT.

| Datasets     | Attributes | Many | Medium | Few | All     |
|--------------|------------|------|--------|-----|---------|
| ImageNet-LT  | Classes    | 391  | 473    | 136 | 1,000   |
|              | Samples    | 89,293 | 24,910 | 1,643 | 115,846 |
| Places-LT    | Classes    | 132  | 162    | 71  | 365     |
|              | Samples    | 52,862 | 8,834  | 804  | 62,500  |

Evaluation metrics. We report average top-1 accuracy across the four folds, Manyshot classes (≥ 100 samples), Mediumshot classes (20 ~ 100 samples), Fewshot classes (< 20 samples), and All classes. These four metrics are important for fair evaluation since high accuracy on All classes does not imply high accuracy on Fewshot classes or Mediumshot classes.

Implementation Details. For the Baseline model, we take a Resnet-10 backbone for ImageNet-LT, following [42]. We initialize the model with Gaussian weights, use an initial learning rate of 0.2 and train for 100 epochs with a cosine learning rate schedule [43]. For Places-LT, we take a Resnet-152 ImageNet pre-trained model, and finetune it with an initial learning rate of 0.01 for 30 epochs with exponential learning rate decay of 0.1 every 10 epochs. To train expert models, we initialise the feature extractor of each expert $E$ from the Baseline model, and finetune it on its class-balanced subset. For $E_{Mediumshot}$ and $E_{Fewshot}$, we freeze the lower layers of the feature extractor and only learn the top few layers. The number of learnable layers is a hyperparameter that is fixed by measuring performance on the validation set. To train experts with the reject class, we fix the undersampling ratio for samples from the reject class by measuring performance on the validation set. For outlier exposure training we set $\lambda = 0.5$. Note that the classifier for each expert $E$ is smaller than the Baseline model; it equals the number of classes in the expert’s class-balanced subset, plus additional reject class when training with a reject class.

4.1 Effect of out-of-distribution detection strategy

In this section we compare our two strategies for training the experts with out-of-distribution detection. We fuse expert posteriors using our joint calibration module and compare the results in Table 2 and Table 3. We observe that reject class training does slightly better than outlier exposure training. We therefore use experts trained with the reject class in the rest of our experiments.

| Method            | Many | Medium | Few | All     |
|-------------------|------|--------|-----|---------|
| Outlier exposure  | 43.1 | 31.1   | 18.4| 34.1    |
| Reject class      | 43.2 | 34.3   | 18.9| 35.7    |

| Method            | Many | Medium | Few | All     |
|-------------------|------|--------|-----|---------|
| Outlier exposure  | 38.4 | 34.2   | 21.3| 33.2    |
| Reject class      | 37.2 | 35.3   | 26.3| 34.2    |

4.2 Oracle Performance

To estimate the upper bound of our approach, we consider the performance with Oracle access to expert selection information, that is, with apriori knowledge of
the expert $E_i$ that contains the ground-truth class of a test sample in its class-balanced subset. Here we take experts trained with the reject class, the results are depicted in Table 4 and Table 5. The Oracle outperforms the Baseline by a significant margin on Mediumshot, Fewshot and All accuracy. Moreover, it is interesting to note that the Oracle accuracies on Manyshot, Mediumshot and Fewshot classes are at par with other. This suggests that the reason for drop in performance on Mediumshot and Fewshot classes is relative imbalance and not data scarcity, therefore in theory it is possible for a classification model to match Fewshot accuracy and Mediumshot accuracy with Manyshot accuracy. It is also interesting to see that the Manyshot accuracy does not improve much by using an Oracle, suggesting that Manyshot accuracy is already saturated in the Baseline model.

Table 4: Performance of Oracle vs Baseline on ImageNet-LT.

| Method       | Many | Medium | Few  | All  |
|--------------|------|--------|------|------|
| Baseline     | 54.3 | 26.2   | 5.8  | 34.4 |
| Experts (Oracle) | 54.2 | 43.3   | 45.7 | 47.9 |

Table 5: Performance of Oracle vs Baseline on Places-LT.

| Method       | Many | Medium | Few  | All  |
|--------------|------|--------|------|------|
| Baseline     | 45.4 | 25.6   | 9.0  | 29.5 |
| Experts (Oracle) | 47.3 | 46.1   | 46.5 | 46.6 |

4.3 Effect of joint calibration module

We apply the methods outlined in Sec. 3.3 for fusing expert posteriors to experts trained using the reject class and compare their performance on ImageNet-LT and Places-LT. The results are depicted in Table 6 and Table 7. KL-div minimisation and Soft-voting yield the highest Fewshot accuracy, however All accuracy is much lower than the other methods. Expert selection and Stacking are better than KL-div minimisation and Soft-voting on Manyshot, Mediumshot and All accuracy, but worse on Fewshot accuracy. The Joint-calibration module obtains the best Manyshot, Mediumshot and All accuracy, even though Fewshot accuracy suffers.

Table 6: Effect of joint calibration module for ImageNet-LT.

| Module         | Many | Medium | Few  | All  |
|----------------|------|--------|------|------|
| KL-div min.    | 25.3 | 20.5   | 39.1 | 21.9 |
| Soft-Voting    | 26.3 | 21.3   | 38.9 | 25.6 |
| Expert Selection | 38.3 | 32.6   | 17.2 | 32.8 |
| Stacking       | 28.1 | 27.5   | 33.8 | 28.6 |
| Joint Calibration | 43.2 | 34.3   | 18.9 | 35.7 |

Table 7: Effect of joint calibration module for Places-LT.

| Module         | Many | Medium | Few  | All  |
|----------------|------|--------|------|------|
| KL-div min.    | 30.2 | 31.7   | 28.9 | 30.4 |
| Soft-Voting    | 30.0 | 31.8   | 28.9 | 30.6 |
| Expert Selection | 32.6 | 31.8   | 24.5 | 30.7 |
| Stacking       | 28.2 | 36.0   | 26.2 | 31.3 |
| Joint Calibration | 37.2 | 35.3   | 26.3 | 34.2 |

4.4 Diverse ensembles with experts

The formulation of our framework for long-tailed recognition as an ensemble of experts allows us to add existing solutions to increase the diversity and performance of the ensemble. In this section, we analyse the performance of various
combinations of models in the ensemble. We experiment with the following models: (i) The Baseline model, (ii) The three expert models, $E_{\text{Manyshot}}, E_{\text{Mediumshot}}$ and $E_{\text{Fewshot}}$ fused using Soft-voting, collectively referred to as Experts, (iii) Classifier finetuning with uniform class sampling, wherein we freeze the feature extractor of the Baseline model and finetune the classifier with uniform class sampling. This is referred to as Uniform class sampling or Uniform, (iv) Data augmentation for Mediumshot and Fewshot classes using a conditional generative model from class embeddings to feature embeddings, denoted as GAN based augmentation or simply GAN, (v) Knowledge transfer from Manyshot to Fewshot classes using a learned convex combination of class prototypes from [42], denoted as Liu et. al. The performances of these base models are depicted in Fig. 3a and Fig. 3c. Notice how the performance of the Baseline model degrades from Manyshot to Mediumshot to Fewshot accuracy. The Expert models give the highest accuracy on the Fewshot classes, but are worse on Manyshot accuracy.

We combine all these models into a single ensemble, take one model out and see the effect on the performance. To keep the analysis simple, we use Soft-
Table 8: Results on ImageNet-LT, using backbone net Resnet-10. *Results obtained from the author’s code. ‡Results taken directly from [42].

| Methods                | Manyshot | Mediumshot | Fewshot | All   |
|------------------------|----------|------------|---------|-------|
| Lifted Loss† [45]      | 35.8     | 30.4       | 17.9    | 30.8  |
| Focal Loss† [40]       | 36.4     | 29.9       | 16      | 30.5  |
| Range Loss† [68]       | 35.8     | 30.3       | 17.6    | 30.7  |
| FSLwF† [14]           | 40.9     | 22.1       | 15      | 28.4  |
| Liu et al.‡ [42]       | 43.2     | 35.1       | 18.5    | 35.6  |
| Baseline               | 54.3     | 26.2       | 5.7     | 34.4  |
| Uniform Class Sampling |          |            |         |       |
| GAN-based Augmentation |          |            |         |       |
| Liu et al.* [42]       | 40.8     | 33.3       | 16.6    | 33.9  |
| Ours (Experts)         | 43.2     | 34.3       | 18.9    | 35.7  |
| Ours (All)             | 48.2     | 37.0       | 21.5    | 39.2  |

Table 9: Results on Places-LT, using backbone net Resnet-152. *Results obtained from the author’s code. ‡Results taken directly from [42].

| Methods                | Manyshot | Mediumshot | Fewshot | All   |
|------------------------|----------|------------|---------|-------|
| Lifted Loss† [45]      | 41.1     | 35.4       | 24.0    | 35.2  |
| Focal Loss† [40]       | 41.1     | 34.8       | 22.4    | 34.6  |
| Range Loss† [68]       | 41.1     | 35.4       | 23.2    | 35.1  |
| FSLwF† [14]           | 43.9     | 29.9       | 29.5    | 34.9  |
| Liu et al.‡ [42]       | 44.7     | 37.0       | 25.3    | 35.9  |
| Baseline               | 45.4     | 25.6       | 9.0     | 29.5  |
| Uniform Class Sampling |          |            |         |       |
| GAN-based Augmentation |          |            |         |       |
| Liu et al.* [42]       | 41.4     | 37.1       | 19.2    | 35.2  |
| Ours (Experts)         | 37.2     | 35.3       | 26.3    | 34.2  |
| Ours (All)             | 43.6     | 39.9       | 27.7    | 38.9  |

voting for fusing posteriors from all the models, since it doesn’t require learning of additional parameters. This ablation is depicted in Fig. 3b and Fig. 3d. As expected, the diverse ensembles give higher All accuracy than the base models. Taking Experts out causes performance drop on Mediumshot, Fewshot and All accuracy, and increase in accuracy on Manyshot classes. This suggests that the Experts are important in the ensemble for high Mediumshot and Fewshot accuracy. On the other hand, taking the Baseline model out of the ensemble causes an increase in Fewshot accuracy while Manyshot accuracy drops. The ablation also reveals the inherent trade-off between Manyshot and Fewshot accuracy; an
appropriate combination of models can be chosen to tilt accuracy in favor of Manyshot or Fewshot classes.

4.5 Comparison to state-of-the-art

We now compare our ensemble of experts and the diverse ensemble described in the previous section to state-of-the-art on the test set of ImageNet-LT and Places-LT. All ensemble combinations use the joint calibration module to fuse model posteriors as it gives us the highest average accuracy. The results are depicted in Table 8 and Table 9. We observe that Ours (Experts) gives us comparable results to the state-of-the-art, and Ours (All) establishes a new state-of-the-art on both the benchmark datasets. This validates our hypothesis that an ensemble of expert models is a simple and effective strategy for dealing with long-tailed datasets.

4.6 Discussion

There is a significant difference between the results depicted in Table 8 and Table 9, and Table 8 and Table 9. This shows that the various strategies used for fusing expert posteriors are sub-optimal. To analyse the reason behind this, we take our ensemble of experts and plot a confusion matrix, where each entry shows the percentage of samples from a dataset that are classified by an expert model. Note that for ease of analysis we again use Soft-voting for fusing expert posteriors. The result for Places-LT is shown in Fig. 4. The plot shows there is significant confusion between the experts, experts aren’t selected optimally for the classes to which a test sample belongs. We term this phenomenon as Expert collision.

The reason for this becomes clear if we consider the confidence assigned to its predictions by an expert model. We take the confidence or the maximum softmax probability (MSP) from the expert posteriors and plot confidence histograms to visualise how confident the model is on average. We do this for Manyshot on
its class-balanced subset $\mathcal{D}_{\text{Manyshot}}$, for samples from the test set it can correctly classify, and for $\mathcal{E}_{\text{Fewshot}}$ on the same test samples from $\mathcal{D}_{\text{Manyshot}}$. This is depicted in Fig. 5. The plots show that the manyshot expert $\mathcal{E}_{\text{Manyshot}}$ has high confidence predictions while the fewshot expert $\mathcal{E}_{\text{Fewshot}}$ has low confidence predictions on samples in $\mathcal{D}_{\text{Manyshot}}$ that $\mathcal{E}_{\text{Manyshot}}$ can correctly classify. However to avoid Expert collision both the confidence histograms should have a reasonable margin in between and not overlap. We tried to fix this by using temperature scaling to calibrate confidences [15] for each expert before Soft-voting, and it does decrease Expert collision. Going one step further, learning scale and shift parameters for partial posteriors from each expert before fusing the posteriors together yields the best results. However, they are still far behind the Oracle performance. Moreover, the comparison to state-of-the-art in Table 8 and Table 9 shows that no approach including ours is able to match the Fewshot accuracy to the Manyshot accuracy of the Baseline model, leaving a lot of room for improvement. We hope our results encourage further research into this hard problem.

5 Conclusion

This article presented a simple and effective ensemble of experts framework for long tail recognition. We decompose the imbalanced classification problem into balanced classification problems that are more tractable, and train separate expert models for Manyshot, Mediumshot and Fewshot subsets of the data with out-of-distribution detection for samples lying outside an expert’s class-balanced subset. We explore different ways to train and fuse the expert models, and our best ensemble of experts reaches close to state-of-the-art performance on two long tail benchmarks, without the need for sophisticated loss objectives or complex memory models. We also extend our ensemble with diverse existing solutions for long tail recognition and establish a new state-of-the-art on the benchmark datasets. Lastly, our experiments with an Oracle upper bound reveal that data scarcity for rare classes is not a major problem in modern day datasets, and relative imbalance is the primary bottleneck.
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