

Low-shot Visual Recognition by Shrinking and Hallucinating Features

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Abstract

Low-shot visual learning—the ability to recognize novel object categories from very few examples—is a hallmark of human visual intelligence. Existing machine learning approaches fail to generalize in the same way. To make progress on this foundational problem, we present a low-shot learning benchmark on complex images that mimics challenges faced by recognition systems in the wild. We then propose a) representation regularization techniques, and b) techniques to hallucinate additional training examples for data-starved classes. Together, our methods improve the effectiveness of convolutional networks in low-shot learning, improving the one-shot accuracy on novel classes by $2.5\times$ on the challenging ImageNet dataset.

1. Introduction

Recently, error rates on benchmarks like ImageNet [9] have been halved, and then halved again. These gains come from deep convolutional networks (ConvNets) that learn rich feature representations [23]. It is now clear that if an application has an a priori fixed set of visual concepts and thousands of examples per concept, an effective way to build an object recognition system is to train a deep ConvNet. But what if these assumptions are not satisfied and the network must learn novel categories from very few examples?

The ability to perform *low-shot learning*—learning novel concepts from very few examples—is a hallmark of the human visual system. We are able to do this not only for natural object categories such as different kinds of animals, but also for synthetic objects that are unlike anything we’ve seen before [37]. In contrast, in spite of significant improvements in recognition performance, computational recognition approaches fail to generalize well from few examples [24]. Our goal in this paper is to make progress towards imparting this human ability to modern recognition systems.

Our first contribution is a low-shot learning benchmark based on the challenging ImageNet1k dataset. As shown in Figure 1, our benchmark is implemented in two phases. In the *representation learning phase*, the learner tunes its

feature representation on a set of base classes that have many training instances. In the *low-shot learning phase*, the learner is exposed to a set of novel classes with only a few examples per class and must learn a classifier over the *joint* label space of base and novel classes. This benchmark simulates a scenario in which the learner is deployed in the wild and has to quickly learn novel concepts it encounters from very little training data. Unlike previous low-shot learning tests (e.g., [13, 24]) we measure the learner’s accuracy on both the base and novel classes. This provides a sanity check that accuracy gains on novel classes do not come at the expense of a large loss in performance on the base classes. This evaluation protocol follows the standard way that image classifiers are evaluated on popular benchmarks like ImageNet, thus easing the comparison of progress on low-shot learning to the typical data-rich scenario.

Next, we investigate how to improve the learner’s performance on the benchmark. First, we show that the feature representation learnt in the first phase has a large impact on low-shot generalization ability. Specifically, we formulate a loss function that penalizes the difference between classifiers learnt on large and small datasets, and then draw connections between this loss and regularization of *feature activations*. We show that simply regularizing feature activations can increase one-shot, top-5 accuracy on novel classes by *11 points* (absolute) without harming base class performance.

Finally, we propose improvements to the low-shot learning phase. Our intuition is that certain modes of intra-class variation generalize across categories (e.g., pose transformations). We present a way of “hallucinating” additional examples for novel classes by transferring modes of variation from the base classes. These additional examples further improve the one-shot performance on novel classes by *9 points* while also maintaining accuracy on the base classes.

2. Related work

One-shot and low-shot learning. One class of approaches to one-shot learning uses generative models of appearance. The benefit of such approaches is that they can tap into a global [13] or a supercategory-level [36] prior. For restricted domains such as hand-written characters [27, 24],

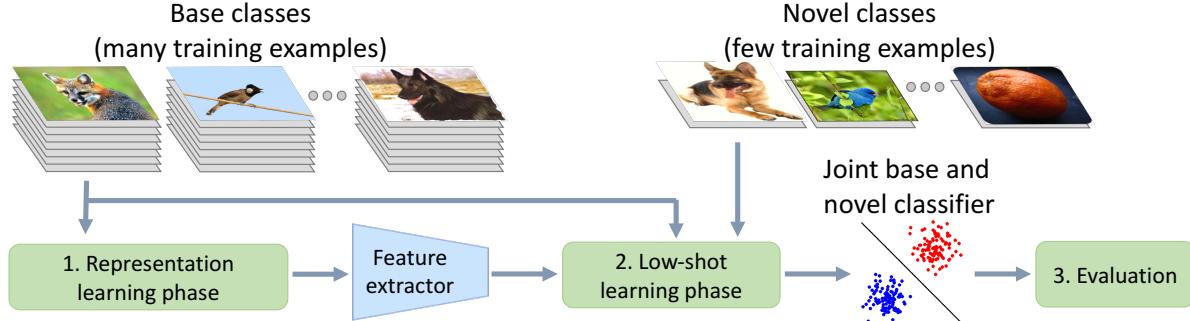


Figure 1. We propose a low-shot learning benchmark that mimics real world scenarios (see Section 1). In the *representation learning phase*, the learner trains its feature extractor on a set of base classes that have many training examples. In the *low-shot learning phase*, the learner is presented with a set of novel classes for which only a few training samples are available. The learner must then train a classifier over the joint label space of base and novel classes. The final evaluation is based on its accuracy on both base and novel classes.

there exist powerful generative models that compose characters from a dictionary of parts [45] or strokes [25]. Such generative models have shown promise on datasets without much intra-class variation or clutter, such as Caltech 101 [13]. We also propose a way to generate additional examples, but unlike prior work, our model is non-parametric and directly generates feature vectors. Jia *et al.* [21] present a promising alternative to generation using Bayesian reasoning to infer an object category from a few examples; however, in [21] the full, large-scale training set is available during training.

Among discriminative approaches, early work attempted to use a single image of the novel class to adapt classifiers from similar base classes [4, 31] using simple hand-crafted features. Bertinetto *et al.* [5] regress from a single example to a classifier. Wang and Herbert [44] propose a more general approach, regressing from classifiers trained on small datasets to classifiers trained on large datasets. Vinyals *et al.* [43] attempt to directly learn a function that maps training sets and test examples to classification outputs. We compare favorably with these approaches in our experiments.

Amongst representation learning approaches, metric learning, such as the triplet loss [41, 38, 14] or siamese networks [22, 17], has been used to automatically learn feature representations where objects of the same class are closer together. Such approaches have shown benefits in face identification [41]. On benchmarks involving more general Internet imagery, such as ImageNet [9], these methods perform worse than simple classification baselines [34], and it is unclear if they can benefit low-shot learning.

Zero-shot learning. Zero-shot recognition uses textual or attribute-level descriptions of object classes to train classifiers. While this problem is different than ours, the motivation is the same: to reduce the amount of data required to learn classifiers. One line of work uses hand-designed attribute descriptions that are provided to the system for the novel categories [35, 26, 12]. Another class of approaches embeds images into word embedding spaces learnt using

large text corpora, so that classifiers for novel concepts can be obtained simply from the word embedding of the concept [15, 40, 30, 46]. A final class of approaches attempts to directly regress to image classifiers from textual descriptions [11, 28] or from prototypical images of the category [20]. Similar to our benchmark, Chao *et al.* [6] propose that zero-shot learning evaluation should also include the training categories that do have examples. We believe this evaluation style is good for both zero and low-shot learning.

Transfer learning. The ability to learn novel classes quickly is one of the main motivations for multitask and transfer learning. Thrun’s classic paper convincingly argues that “learning the n -th task should be easier than learning the first,” with ease referring to sample complexity [42]. However, recent transfer learning research has mostly focussed on the scenario where large amounts of training data are available for novel classes. For that situation, the efficacy of pre-trained ConvNets for extracting features is well known [10, 32, 39]. There is also some analysis on what aspects of ImageNet training aid this transfer [2, 3]. For faces, Taigman *et al.* [41] find that low-dimensional feature representations transfer better on faces and Galanti *et al.* [16] provide some theoretical justification for this finding. This work hints at a link between the complexity of the feature representation and its generalizability, a link which we also observe in this paper. We find that stronger base classifiers generalize better than weaker classifiers (*e.g.* comparing ResNet-10 to ResNet-50 [18]). There have also been novel losses proposed explicitly to aid transfer, such as the multi-verse loss of Littwin and Wolf [29]. Our paper also proposes novel losses designed specifically for low-shot learning.

3. A low-shot learning benchmark

Our goal is to build a benchmark for low-shot learning that mimics situations that arise in practice. Current recognition systems require days or even weeks of training on expensive hardware to develop good feature representations.

The trained recognition systems may then be deployed as a service to be used by downstream applications. These downstream applications may need the ability to recognize novel categories, but they may have neither the training data required, nor the infrastructure needed to retrain the models. Thus, there are two natural phases: in the first phase, we have the data and resources to train sophisticated feature extractors on large labelled datasets, and in the second phase, we want to add additional categories to our repertoire at minimal computational and data cost.

Our low-shot learning benchmark implements a similar setup. It employs a learner, two training phases, and one testing phase. The learner is assumed to be composed of a feature extractor and a multi-class classifier. The benchmark is agnostic to the specific form of each component.

During *representation learning* (training phase one), the learner receives a fixed set of base categories C_{base} , and a dataset D_{base} containing a large number of examples for each category in C_{base} . The learner uses D_{base} to set the parameters of its feature extractor.

In the second phase, which we call *low-shot learning*, the learner is provided with a set of categories C^l that it needs to learn to distinguish. C^l is a mix of base categories, and some novel categories that the learner has not seen before. That is, $C^l = C_{base} \cup C_{novel}$. For each novel category, the learner has access to only n positive examples, where $n \in \{1, 2, 5, 10, 20\}$. For the base categories, the learner still has access to D_{base} . The learner may then use these examples and its feature extractor to set the parameters of its multi-class classifier while also optionally modifying the feature extractor.

In the testing phase, the learnt model predicts labels from the combined label space $C_{base} \cup C_{novel}$ on a set of previously unseen test images. To measure the variability in low-shot learning accuracy, we repeat the low-shot learning and testing phases for 5 trials, each time with a random draw of examples for the novel classes. We report the mean accuracy and the standard deviation over these trials.

The simplest and most obvious baseline approach is to train a ConvNet with label cross-entropy loss in the representation learning phase and then train a new linear classifier head in the low-shot learning phase. We now show how this baseline can be significantly improved, first by learning a better representation (Section 4) and then by automatically generating additional training data (Section 5).

4. Better representations for low-shot learning

Our goal is to modify the representation learning phase to yield better generalization from low-shot learning. We first describe a proposal that encodes the goal of low-shot learning in a loss that can be minimized during representation learning. Then, we draw connections to several alternatives.

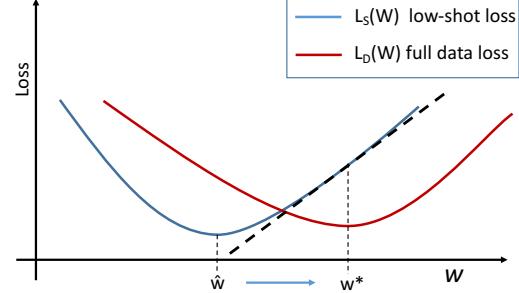


Figure 2. Motivation for the SGM loss. We want to learn a representation ϕ such that the classifier \hat{W} trained on a small dataset S is the same as the classifier W^* trained on a large dataset D .

4.1. Squared gradient magnitude loss (SGM)

Intuitively, our goal is to reduce the difference between classifiers trained on large datasets and classifiers trained on small datasets so that those trained on small datasets generalize better. Given a large dataset D and a representation ϕ , the classifier weights W^* are obtained by minimizing

$$L_D(W) = \frac{1}{|D|} \sum_{(x,y) \in D} L_{cls}(W, \phi(x), y), \quad (1)$$

where $L_{cls}(W, x, y)$ is the multiclass logistic loss on an example x with label y for a linear classifier with weights W :

$$L_{cls}(W, x, y) = -\log p_y(x) \quad (2)$$

$$p_k(x) = \frac{\exp(w_k^T x)}{\sum_j \exp(w_j^T x)}. \quad (3)$$

Similarly, given a small dataset $S \subset D$, $|S| \ll |D|$, we can train the classifier weights \hat{W} by minimizing

$$L_S(W) = \frac{1}{|S|} \sum_{(x,y) \in S} L_{cls}(W, \phi(x), y). \quad (4)$$

We want W^* and \hat{W} to be the same. In other words, we want W^* to be the *minimizer* of $L_S(W)$. Because $L_S(W)$ is convex in W , a necessary and sufficient condition for this is that $\nabla_W L_S(W^*) = 0$. We therefore propose to minimize $\tilde{L}_S(W^*) = \|\nabla_W L_S(W^*)\|^2$ as an additional loss term. Figure 2 shows a schematic of this idea.

Therefore when learning the representation on the large dataset D , we can simultaneously sample small datasets S from D and minimize \tilde{L}_S , in addition to the standard multiclass logistic loss on each example. We can make things simple by noting that S can be as small as a *single example* (x, y) . In this case, the loss is simply:

$$\begin{aligned} \tilde{L}_{\{(x,y)\}}(W) &= \|\nabla_W L_{\{(x,y)\}}(W)\|^2 \\ &= \|\nabla_W L_{cls}(W, \phi(x), y)\|^2 \end{aligned} \quad (5)$$

Our final loss is thus the combination of the total multinomial logistic loss over the entire dataset: $\sum_{(x,y) \in D} L_{cls}(W, \phi(x), y)$, and the total SGM loss corresponding to every possible choice of singleton set S : $\sum_{(x,y) \in D} \|\nabla_W L_{cls}(W, \phi(x), y)\|^2$. Therefore training solves the following minimization problem:

$$\min_{W, \phi} \sum_{(x,y) \in D} L_{cls}(W, \phi(x), y) + \lambda \|\nabla_W L_{cls}(W, \phi(x), y)\|^2 \quad (6)$$

Note that the two terms are not equivalent: L_{cls} can be low even when $\nabla_W L_{cls}$ is high, and vice versa. We call the second term above the SGM loss (Squared Gradient Magnitude).

It can be shown that the second term has a simple form:

$$\begin{aligned} \|\nabla_W L_{cls}(W, \phi(x), y)\|^2 &= \sum_k \|\nabla_{w_k} L_{cls}(W, \phi(x), y)\|^2 \\ &= \sum_k \|(p_k(x) - \delta_{yk})\phi(x)\|^2 = \alpha(W, x)\|\phi(x)\|^2 \end{aligned} \quad (7)$$

where $\|\phi(x)\|^2$ is the squared L_2 norm of the feature representation, δ_{yk} is 1 when $y == k$ and 0 otherwise, and $\alpha(W, x) = \sum_k (p_k(x) - \delta_{yk})^2$ is an example dependent weight that is higher for data points that are misclassified.

Batch SGM. Above, the small datasets S that we used to define the loss consisted of single examples. However, in the low-shot learning phase, we may reasonably expect to have a small number of examples that is greater than 1 and indeed we evaluate over the range of $n \in \{1, 2, 5, 10, 20\}$. We therefore consider an extension of SGM that we call “batch SGM.” Here, instead of choosing S to be singleton sets, we consider the *entire mini-batch* B in an SGD iteration as S . Hence, we penalize the squared gradient magnitude of the average loss over B , yielding the loss term: $\lambda \left\| \nabla_W \left(\frac{1}{|B|} \sum_{(x,y) \in B} L_{cls}(W, \phi^*(x), y) \right) \right\|^2$. In each SGD iteration, our total loss is thus the sum of this loss term and the standard classification loss. Note that because this loss is defined on mini-batches the number of examples per class in each mini-batch is a random variable. Thus batch SGM optimizes for an expected loss over a distribution of possible low-shot values n .

4.2. Feature regularization-based alternatives

One can ask if the weights $\alpha(W, x)$ in Equation (7) are necessary. We can therefore consider a simplification of Equation (6) in which we use a simple squared L_2 norm:

$$\min_{W, \phi} \sum_{(x,y) \in D} L_{cls}(W, \phi(x), y) + \lambda \|\phi(x)\|^2. \quad (8)$$

While L_2 regularization is a common technique, note that here we are regularizing the *feature representation*, as opposed to regularizing the *weight vector*.

We can also consider other ways of regularizing the representation, such as an L_1 regularization:

$$\min_{W, \phi} \sum_{(x,y) \in D} L_{cls}(W, \phi(x), y) + \lambda \|\phi(x)\|_1. \quad (9)$$

While regularizing the feature vector norm has been a staple of unsupervised learning approaches to prevent degenerate solutions [33], to the best of our knowledge it hasn’t been considered in supervised classification.

We also evaluate other forms of feature regularization that have been proposed in the literature. The first of these is dropout [19], which were used in earlier ConvNet architectures [23], but has been eschewed by recent architectures such as ResNets [18]. Another form of feature regularization involves minimizing the correlation between the features [7, 8]. As a final baseline, we also consider the multi-versus loss [29] which was shown to improve transfer learning performance.

4.3. Metric-learning based approaches

Distance metric learning is a common approach in the one-shot learning literature. Intuitively, the distance metric should generalize to novel classes. There are many metric learning approaches. We train a ConvNet with the triplet loss as a representative method. The triplet loss takes as input a triplet of examples (x, x_+, x_-) , where x and x_+ belong to the same category while x_- does not:

$$\begin{aligned} L_{triplet}(\phi(x), \phi(x_+), \phi(x_-)) &= \\ \max(\|\phi(x_+) - \phi(x)\| - \|\phi(x_-) - \phi(x)\| + \gamma, 0). \end{aligned} \quad (10)$$

Here, γ is a margin and intuitively the loss is zero if x_- is at least γ farther away from x than x_+ is. Otherwise the loss increases the closer x_- is to x or the farther x_+ is from x .

5. Better low-shot learning through generation

We now assume that we have a well-trained feature representation, and turn to the low-shot learning phase. In this phase we are given only a few examples for each novel category and we want to make the best use of them. Intuitively, the challenge is that these examples capture only a tiny fraction of the category’s intra-class variation. For instance, if one novel category is a particular bird species, then the examples available may only show the bird perched on a branch, and we may have no examples of the bird in flight. From only what is seen, our classifier might erroneously conclude that this novel category only consists of perched birds.

However, our base classes include several other bird species, and these base classes would include examples of both perched birds and birds in flight. From these base classes, if we could figure out what different kinds of perched birds look like in flight, then we can “hallucinate” what our

novel bird species will look like in flight, and feed these hallucinations as additional examples to the classifier.

In other words, all bird species share the transformation that relates the image of a perched bird to an image of the same bird in flight. If we were given the set of all such category-independent transformations, then we can hallucinate as many new examples for each novel category example as there are transformations.

However, we do not have a pre-defined set of transformations that we can apply. But we can take a non-parametric approach. Any two examples z_1 and z_2 belonging to the same category represent a plausible transformation. Then, given a novel category example x , we want to apply to x the transformation that sent z_1 to z_2 . That is, we want to complete the transformation “analogy” $z_1 : z_2 :: x : ?$.

We will do this by training a function G that takes the tuple (x, z_1, z_2) as input and produces a generated example by applying the $z_1 \rightarrow z_2$ transformation to x . G operates on top of the learnt feature representation ϕ . It takes as input the concatenated feature vectors of the three examples $[\phi(x), \phi(z_1), \phi(z_2)]$ and outputs a new “hallucinated” feature vector of the same dimensionality as $\phi(x)$. In our experiments we use an MLP with three fully connected layers for G .

We first describe how we train the function G , and then show how we can use the generated examples in the low-shot learning phase.

5.1. Learning to generate new examples

We set up the training problem for G as a fully supervised regression problem. Therefore, to train G , we first need completed analogies from our base classes that we can use as supervision. To do this we first cluster the feature vectors of the examples in each base category into a fixed number of clusters (100). This is to keep computational complexity manageable. Next, for each pair of centroids c_1^a, c_2^a in one category a , we search for another pair of centroids c_1^b, c_2^b from another category b , such that the cosine distance between $c_1^a - c_2^a$ and $c_1^b - c_2^b$ is minimized. We collect all such quadruplets $(c_1^a, c_2^a, c_1^b, c_2^b)$ with cosine similarity greater than zero into a dataset D_G . See Figure 3 for example transformation analogies.

We now use the dataset D_G to train G . For each quadruplet $(c_1^a, c_2^a, c_1^b, c_2^b)$, we feed (c_1^a, c_1^b, c_2^b) to the generator. Let $\hat{c}_2^a = G([c_1^a, c_1^b, c_2^b])$ be the output of the generator. We then minimize the weighted sum of two losses:

1. The mean squared error $L_{mse}(\hat{c}_2^a, c_2^a)$ between the generator’s output and the true target of the analogy c_2^a .
2. The classification loss $L_{cls}(W, \hat{c}_2^a, a)$, where W is the fixed linear classifier on the base classes learnt during representation learning, and $L_{cls}(W, x, y)$ is, as before, the log loss of the classifier W on the example (x, y) .

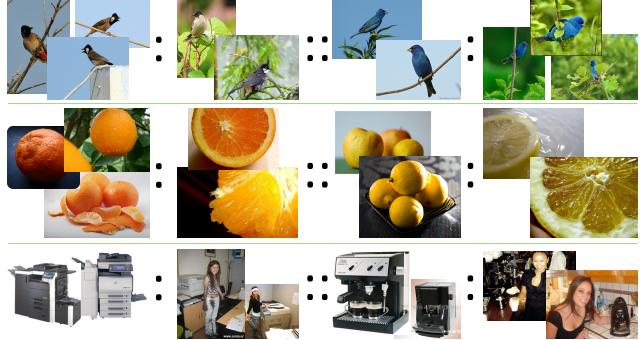


Figure 3. Example mined analogies. Each row shows the four clusters of images that form the four elements in the analogy. **Row 1:** transformation from a bird with a sky backdrop to a bird with greenery in the background. **Row 2:** transformation from whole fruit into cut fruit. **Row 3:** transformation from a machine (printer, coffee making) in isolation to the same machine operated by a human.

Our loss is thus $\lambda L_{mse}(\hat{c}_2^a, c_2^a) + L_{cls}(W, \hat{c}_2^a, a)$.

5.2. Using generated examples for low-shot learning

We do not expect our generated examples to be as good as real examples. However, we expect them to provide a useful bias to the classifier when only a few real examples are present. Therefore we want to rely on generated examples only when the number of real examples is low, and then discard them when enough real examples are available.

Concretely, we have a hyperparameter k (set through cross-validation), which is the minimum number of examples per novel category that we want to have. If the actual number of real examples for a novel category, n , is less than k , then we additionally generate $k - n$ hallucinated examples. To generate a synthetic example for a novel category l , we sample the feature vector of a “seed” example $\phi(x)$ from one of the n real examples for this category, and a pair of cluster centroids c_1^a, c_2^a from a base category a chosen uniformly at random. We then pass this triplet through G , and add the hallucinated feature vector $G([\phi(x), c_1^a, c_2^a])$ to our training set with label l . We then train the logistic regression classifier on this mix of real and generated data in the usual manner.

6. Experiments and discussion

6.1. Low-shot learning setup

We conduct the low-shot evaluation using classes and images from the ImageNet1k challenge dataset. We use ImageNet because it has a wide array of classes with significant intra-class variation. We divided the 1000 ImageNet categories randomly into 389 base categories and 611 novel categories (listed in the supplementary material [1]).

Many of the methods we evaluate have hyperparameters that need to be cross-validated. Since we are interested in

generalization to novel classes, we did not want to cross-validate on the same set of classes that we test on. We therefore constructed two disjoint sets of classes by dividing the base categories into two subsets C_{base}^1 (193 classes) and C_{base}^2 (196 classes) and the novel categories into C_{novel}^1 (300 classes) and C_{novel}^2 (311 classes). Then, for cross-validating hyperparameters, we provided the learner with $C^{cv} = C_{base}^1 \cup C_{novel}^1$ in the low-shot learning and testing phase, and evaluated its top-5 accuracy on the combined label set C^{cv} . The hyperparameter setting that gave the highest top-5 accuracy was then frozen. We then conducted our final experiments using these hyperparameter settings by providing the learner with $C^{fin} = C_{base}^2 \cup C_{novel}^2$. All reported numbers in this paper are on C^{fin} .

Our test images are a subset of the ImageNet1k validation set: we simply restricted it to only include examples from the classes of interest (C^{cv} or C^{fin}). Performance is measured by top-1 and top-5 accuracy on the test images for each value of n (number of novel examples per category). We report the mean and standard deviation from 5 runs each using a different random sample of novel examples during the low-shot training phase.

To break down the final performance metrics, we report separately the average accuracy on the test samples from the novel classes and on all test samples. While our focus is on the novel classes, we nevertheless need to ensure that good performance on novel classes doesn't come at the cost of lower accuracy on the base classes.

6.2. Network architecture and training details

For most of our experiments, we use a small ten-layer ResNet architecture [18] as our feature extractor ϕ (details in supplementary material [1]). When trained on all 1000 categories of ImageNet, it gives a validation top-5 error rate of 16.7% (center crop), making it similar to AlexNet [23]. We use this architecture because it's relatively fast to train (2 days on 4 GPUs) and resembles state-of-the-art architectures. Note that ResNet architectures, as described in [18], do not use dropout. Later, we show some experiments using the larger and deeper ResNet-50 architecture.

For all experiments on representation learning, except the triplet embedding, the networks are trained from scratch for 90 epochs on the base classes.¹ The learning rate starts at 0.1 and is divided by 10 every 30 epochs. The weight decay is fixed at 0.0001. For the triplet embedding, we first pretrain the network using a softmax classifier and log loss for 90 epochs, and then train the network further using the triplet loss and starting with a learning rate of 0.001. We stop training when the loss stops decreasing (55 epochs). This schedule is used because, as described in [34], triplet networks train slowly from scratch.

¹Random initialization with the same RNG seed for all experiments.

For methods that introduce a new loss, there is a hyperparameter that controls how much we weigh the new loss. Dropout also has a similar hyperparameter that governs what fraction of activations are dropped. We set these hyperparameters by cross-validation.

For our generator G , we use a three layer MLP. All hidden layers have a dimensionality of 512. We use ReLU as the activation function between the hidden layers, and also add a ReLU at the end, since ϕ is known to be non-negative.

In the low-shot learning phase, we train the linear classifier using SGD for 5000 iterations with a mini-batch size of 1000. We cross-validate for the learning rate.

6.3. Training with class imbalance

The low-shot benchmark creates a heavily imbalanced classification problem. During low-shot learning the base classes may have thousands of examples, while each novel class has only a few examples. We use two simple strategies to mitigate this issue. One, we oversample the novel classes when training the classifier by sampling uniformly over classes and then uniformly within each chosen class. Two, we L_2 regularize the multi-class logistic classifier's weights by adding weight decay during low-shot learning. We find that the weight of the classifier's L_2 regularization term has a large impact and needs to be cross-validated.

6.4. Results

Impact of representation learning. We plot a subset of the methods² in Figure 4, and show the full set of numbers in Tables 1 and 2. The plots show the mean top-5 accuracy, averaged over 5 low-shot learning trials, for the novel classes, and over the combined set of novel and base classes. The standard deviations are low (generally less than 0.5%, see supplementary material [1]) and are too small to display clearly as error bars. Top-1 accuracy and numerical values are in the supplementary material. We observe that:

- When tested just on base classes, many methods perform similarly (not shown, see supplementary material), but their performance differs drastically in the low-shot scenarios, especially for small n . Thus, *accuracy on base classes does not generalize to novel classes, especially when novel classes have very few training examples*.
- For representation learning, Batch SGM, SGM, and L_2 perform similarly and are top performers overall. They improve novel class accuracy by more than 10 points for small n (1 or 2). The gains become smaller as n increases, but still persist (about 3 points) even for $n = 20$. L_1 also improves low-shot performance, but the gains are much smaller.

²The subset reduces clutter, making the plots more readable. We omit results for Batch SGM, Dropout and L_1 because Batch SGM performs similarly to SGM and L_2 , while L_1 and Dropout performs worse.

- Dropout is on par with SGM for small n . However, its accuracy falls with increasing n : for $n = 20$ it is 1 point worse than the baseline and 4 points worse than SGM in terms of all class accuracy. Empirically, dropout also reduces feature norm, suggesting that implicit L_2 feature regularization might explain some of these gains.
- Triplet loss improves accuracy for small n but is 5 points worse than the baseline for $n = 20$ in terms of all class accuracy. Note that more sophisticated variants of the triplet loss may improve performance [34]. However, it seems clear that feature regularization alternatives are not only competitive, but also simpler.
- The DeCov loss provides marginal gains for higher values of n but is outperformed by the feature regularization alternatives.

As an additional experiment, we also attempted to finetune the baseline representation on all the base class examples and the small set of novel class examples. We found that this did not improve performance over the frozen representation (see Baseline-ft in Tables 1 and 2). This indicates that finetuning the representation is not only expensive, but also does not help in the low-shot learning scenario.

Impact of generation. Figure 5 shows the top-5 accuracies on novel classes and on base+novel classes for our generation method applied on top of the baseline representation and the SGM feature representation. The numbers are in Tables 1 and 2. Note that we only generate examples when $n < k$, with $k = 20$ for baseline representations and 5 for SGM (see Section 5.2). We observe that the generated examples provide a large gain of over 10 points for $n = 1, 2$ on the novel classes for the baseline representation. When using the SGM representation, the gains are much smaller, but still significant.

Comparison to other low-shot methods. We also compared to two recently proposed low-shot learning methods: Matching networks [43] and Model regression [44]. **Model regression** trains a small MLP to regress from the classifier trained on a small dataset to the classifier trained on the full dataset. It then uses the output from this regressor to regularize the classifier learnt in the low-shot learning phase. **Matching networks** proposes an end-to-end model that takes a training set and a test example as input, and produces classification scores as output. We apply both these techniques on our baseline representation.

For both these methods, the respective papers evaluated on the novel classes only. As discussed before, this is not realistic since real-world recognition systems will need to discriminate between novel concepts with little data, and the base classes that have lots of data. We adapt these methods to work with both base and novel classes as follows. For model regression, we only use the model regressor on the novel classes, and so only the classifier for the novel classes is

Representation	Lowshot phase	n=1	2	5	10	20
<i>ResNet-10</i>						
Baseline	Classifier	12.7	31.9	55.3	66.0	71.3
Baseline	Generation* + Classifier	30.2	43.6	58.2	66.3	71.0
SGM*	Classifier	23.9	42.8	61.9	69.8	73.9
SGM*	Generation* + Classifier	<i>33.0</i>	47.3	61.9	69.8	73.9
Batch SGM*	Classifier	24.6	43.2	61.6	69.6	73.8
L1*	Classifier	20.8	40.8	59.8	67.5	71.6
L2*	Classifier	25.5	45.9	63.3	69.2	72.2
Triplets	Classifier	24.5	41.8	56.0	61.3	64.2
Dropout [19]	Classifier	26.8	43.9	59.6	66.2	69.5
Decov [8]	Classifier	13.0	33.9	59.3	68.9	73.4
Multiverse [29]	Classifier	13.7	30.6	52.5	63.8	71.1
Baseline	Model Regression [44]	20.7	39.4	59.6	68.5	73.5
Baseline	Matching Network [43]	33.1	46.5	60.6	67.7	72.0
Baseline-ft	Classifier	12.5	29.5	53.1	64.6	70.4
<i>ResNet-50</i>						
Baseline	Classifier	23.3	45.8	67.1	75.0	79.3
Baseline	Generation* + Classifier	<i>40.5</i>	54.3	67.8	74.5	79.3
SGM*	Classifier	33.7	53.0	69.7	75.9	79.3
SGM*	Generation* + Classifier	40.9	55.7	69.7	75.9	79.3

Table 1. Top-5 accuracy on only novel classes. Best are bolded and blue; the second best are italicized and red. *Our methods.

regularized in this way. The other classifiers are regularized using standard weight decay. We use one-vs-all classifiers instead of a multiclass logistic, to match the original work.

Matching networks require the entire training dataset to be kept in memory during test time. To make this tractable, we use 100 examples per base class. To balance classes, we oversample the examples from the novel classes so there are 100 examples per novel class.

Comparisons between these methods and our generation approach on the same representation is shown in Figure 6. We find that model regression improves significantly over the baseline, but our generation strategy works better for low n . Model regression also hurts overall accuracy for high n .

Matching networks work very well and are slightly better than our generation approach. However, note that while our approach results in a lightweight linear classifier that is trivial to apply at test time, matching networks require the training data to be kept in memory at test time and have to run over the training set multiple times at test time, which makes them much less scalable.

Deeper networks. We also evaluated our approach on the ResNet-50 network architecture to test if our conclusions extend to deeper convnets that are now in use (Tables 1 and 2). First, even with the baseline representation and without any generation we find that the deeper architecture also leads to improved performance in all low-shot scenarios. However, our SGM loss and our generation strategy further improve this performance. Our final top-5 accuracy on novel classes is still more than 10 points higher for $n = 1, 2$, and our overall accuracy is more than 4 points higher, indicating that our contributions generalize to deeper and better models.

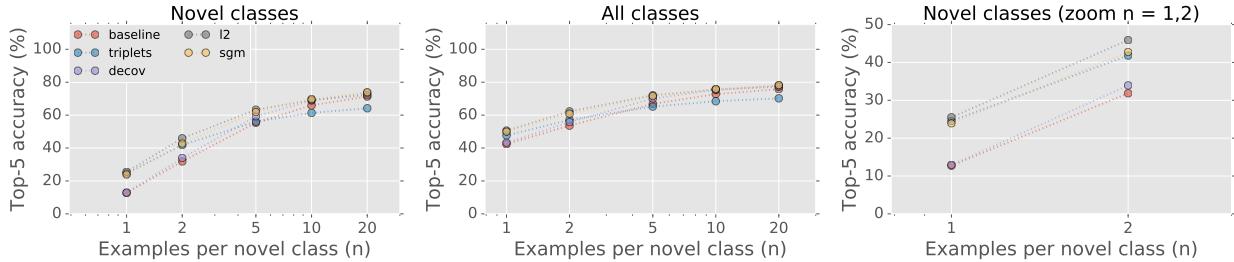


Figure 4. **Representation learning comparison.** Top-5 accuracy on ImageNet1k val. Top-performing feature regularization methods reduce the training samples needed to match the baseline accuracy by 2x.

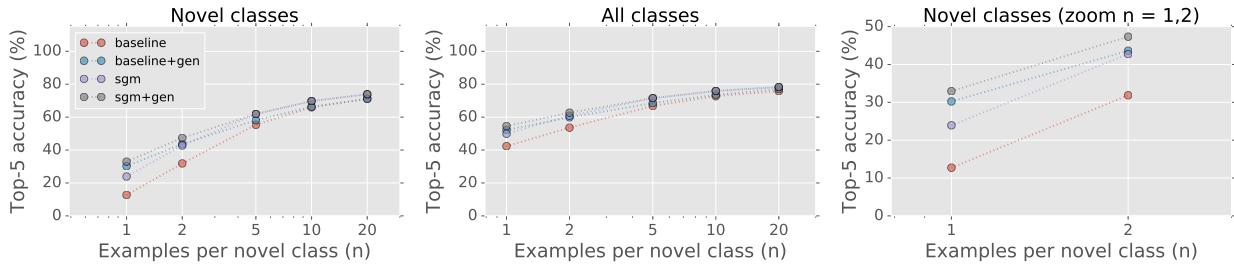


Figure 5. **Comparisons with and without example generation.** Top-5 accuracy on ImageNet1k val.

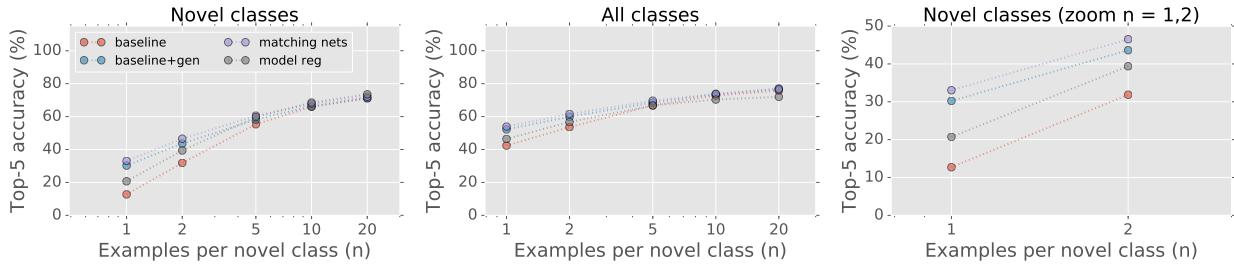


Figure 6. **Comparison of example generation to recently proposed methods.** Top-5 accuracy on ImageNet1k val.

Representation	Lowshot phase	n=1	2	5	10	20
<i>ResNet-10</i>						
Baseline	Classifier	42.4	53.6	66.8	72.7	75.8
Baseline	Generation* + Classifier	52.2	59.9	68.5	73.6	77.0
SGM*	Classifier	49.9	60.8	71.5	75.9	78.3
SGM*	Generation* + Classifier	54.6	62.7	71.5	75.9	78.3
Batch SGM*	Classifier	50.3	61.0	71.2	75.7	78.1
L1*	Classifier	47.1	58.5	69.2	73.7	76.1
L2*	Classifier	50.6	62.3	72.0	75.5	77.26
Triplets	Classifier	47.6	57.1	65.2	68.4	70.2
Dropout [19]	Classifier	50.1	59.7	68.8	72.7	74.7
Decov [8]	Classifier	43.3	55.7	70.1	75.4	77.9
Multiverse [29]	Classifier	44.1	54.2	67.0	73.2	76.9
Baseline	Model Regression [44]	46.4	56.7	66.8	70.4	72.0
Baseline	Matching Network [43]	53.9	61.6	69.7	73.8	76.6
Baseline-ft	Classifier	41.7	51.7	65.0	71.2	74.5
<i>ResNet-50</i>						
Baseline	Classifier	50.7	64.0	76.2	80.6	83.0
Baseline	Generation* + Classifier	60.1	68.0	76.0	80.1	83.0
SGM*	Classifier	57.0	68.2	77.3	80.6	82.5
SGM*	Generation* + Classifier	60.6	68.9	77.3	80.6	82.5

Table 2. Top-5 accuracy on base and novel classes. Best are bolded and blue; the second best are italicized and red. *Our methods.

7. Conclusion

This paper (1) proposes a benchmark for low-shot recognition that evaluates methods on a large set of both base and novel classes of realistic complexity, and (2) proposes improvements to representation learning and low-shot learning that significantly improve the low-shot generalization abilities of ConvNet features. Our novel feature regularization method, called squared gradient magnitude (SGM), is derived by encoding the end-goal of low-shot learning as a soft constraint during ConvNet training. We also show how one can transfer modes of variation from base classes to hallucinate additional training examples for novel classes. We compare these methods and find that they dramatically increase accuracy in low-shot settings. Source code for our methods as well as our low-shot benchmark will be released.

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