

Self-training with Noisy Student improves ImageNet classification

Qizhe Xie^{*1}, Minh-Thang Luong¹, Eduard Hovy², Quoc V. Le¹

¹Google Research, Brain Team, ²Carnegie Mellon University

{qizhex, thangluong, qvl}@google.com, hovy@cmu.edu

Abstract

We present a simple self-training method that achieves 88.4% top-1 accuracy on ImageNet, which is 2.0% better than the state-of-the-art model that requires 3.5B weakly labeled Instagram images. On robustness test sets, it improves ImageNet-A top-1 accuracy from 61.0% to 83.7%, reduces ImageNet-C mean corruption error from 45.7 to 28.3, and reduces ImageNet-P mean flip rate from 27.8 to 12.2.

*To achieve this result, we first train an EfficientNet model on labeled ImageNet images and use it as a teacher to generate pseudo labels on 300M unlabeled images. We then train a larger EfficientNet as a student model on the combination of labeled and pseudo labeled images. We iterate this process by putting back the student as the teacher. During the generation of the pseudo labels, the teacher is not noised so that the pseudo labels are as accurate as possible. However, during the learning of the student, we inject noise such as dropout, stochastic depth and data augmentation via RandAugment to the student so that the student generalizes better than the teacher.*¹

1. Introduction

Deep learning has shown remarkable successes in image recognition in recent years [45, 79, 74, 30, 82]. However state-of-the-art (SOTA) vision models are still trained with supervised learning which requires a large corpus of labeled images to work well. By showing the models only labeled images, we limit ourselves from making use of unlabeled images available in much larger quantities to improve accuracy and robustness of SOTA models.

Here we use unlabeled images to improve the SOTA ImageNet accuracy and show that the accuracy gain has an outsized impact on robustness (out-of-distribution generalization). For this purpose, we use a much larger corpus of un-

labeled images, where a large fraction of images do not belong to ImageNet training set distribution (i.e., they do not belong to any category in ImageNet). We train our model using the self-training framework [70] which has three main steps: 1) train a teacher model on labeled images, 2) use the teacher to generate pseudo labels on unlabeled images, and 3) train a student model on the combination of labeled images and pseudo labeled images. We iterate this algorithm a few times by treating the student as a teacher to relabel the unlabeled data and training a new student.

Our experiments show that an important element for this method to work well at scale is that the student model should be noised during its training while the teacher should not be noised during the generation of pseudo labels. This way, the pseudo labels are as accurate as possible, and the noised student is forced to learn harder from the pseudo labels. To noise the student, we use RandAugment data augmentation [18], dropout [75] and stochastic depth [37] during its training. We call the method NoisyStudent to emphasize the role that noise plays in the method and results.

Using NoisyStudent, together with 300M unlabeled images, we improve EfficientNet’s [82] ImageNet top-1 accuracy to 88.4%. This accuracy is 2.0% better than the previous SOTA ImageNet accuracy which requires 3.5B weakly labeled Instagram images. Not only our method improves standard ImageNet accuracy, it also improves classification robustness on much harder test sets by large margins: ImageNet-A [32] top-1 accuracy from 61.0% to 83.7%, ImageNet-C [31] mean corruption error (mCE) from 45.7 to 28.3 and ImageNet-P [31] mean flip rate (mFR) from 27.8 to 12.2. Our main results are shown in Table 1.

	ImageNet top-1 acc.	ImageNet-A top-1 acc.	ImageNet-C mCE	ImageNet-P mFR
Prev. SOTA	86.4%	61.0%	45.7	27.8
NoisyStudent	88.4%	83.7%	28.3	12.2

Table 1: Summary of key results compared to previous state-of-the-art models [84, 55]. Lower is better for mean corruption error (mCE) and mean flip rate (mFR).

^{*} This work was conducted at Google.

¹Models are available at <https://github.com/tensorflow/tpu/tree/master/models/official/efficientnet>. Code is available at <https://github.com/google-research/noisystudent>.

2. NoisyStudent: Iterative Self-training with Noise

Algorithm 1 gives an overview of NoisyStudent. The inputs to the algorithm are both labeled and unlabeled images. We use the labeled images to train a teacher model using the standard cross entropy loss. We then use the teacher model to generate pseudo labels on unlabeled images. The pseudo labels can be soft (a continuous distribution) or hard (a one-hot distribution). We then train a student model which minimizes the combined cross entropy loss on both labeled images and unlabeled images. Finally, we iterate the process by putting back the student as a teacher to generate new pseudo labels and train a new student. The algorithm is also illustrated in Figure 1.

Require: Labeled images $\{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\}$ and unlabeled images $\{\tilde{x}_1, \tilde{x}_2, \dots, \tilde{x}_m\}$.

- 1: Learn teacher model θ^t which minimizes the cross entropy loss on labeled images

$$\frac{1}{n} \sum_{i=1}^n \ell(y_i, f^{noised}(x_i, \theta^t))$$

- 2: Use an unnoised teacher model to generate soft or hard pseudo labels for unlabeled images

$$\tilde{y}_i = f(\tilde{x}_i, \theta^t), \forall i = 1, \dots, m$$

- 3: Learn an **equal-or-larger** student model θ^s which minimizes the cross entropy loss on labeled images and unlabeled images with **noise** added to the student model

$$\frac{1}{n} \sum_{i=1}^n \ell(y_i, f^{noised}(x_i, \theta^s)) + \frac{1}{m} \sum_{i=1}^m \ell(\tilde{y}_i, f^{noised}(\tilde{x}_i, \theta^s))$$

- 4: Iterative training: Use the student as a teacher and go back to step 2.

Algorithm 1: NoisyStudent method.

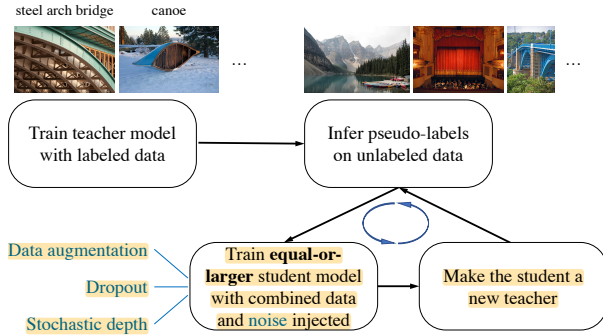


Figure 1: Illustration of the NoisyStudent method. (All shown images are from ImageNet.)

The algorithm is fundamentally self-training, a standard method in semi-supervised learning (e.g., [70, 94]). More discussions on how our method is related to prior works are included in Section 5. Our key differences lie in adding more sources of noise to the student and using student models that are as large as (if not larger than) the teacher. This makes our method different from Knowledge Distillation [33] where adding noise is not the core concern and a small model is often used as a student to be faster than the teacher. One can think of our method as Knowledge Expansion in which we want the student to be better than the teacher by giving the student model more capacity and difficult environments in terms of noise to learn through.

Noising Student – When the student is deliberately noised it is actually trained to be consistent to the more powerful teacher that is not noised when it generates pseudo labels. In our experiments, we use two types of noise: input noise and model noise. For input noise, we use data augmentation with RandAugment [18]. For model noise, we use dropout [75] and stochastic depth [37].

When applied to unlabeled data, noise has a compound benefit of enforcing local smoothness in the decision function on both labeled and unlabeled data. Different kinds of noise have different effects. With data augmentation noise, the student must ensure that an image, when translated for example, should have the same category as a non-translated image. This invariant constraint encourages the student model to learn beyond the teacher to make predictions with more difficult images. When dropout and stochastic depth function are used as noise, the teacher behaves like an ensemble at inference time (during which it generates pseudo labels), whereas the student behaves like a single model. In other words, the student is forced to mimic a more powerful ensemble model. We present an ablation study on the effects of noise in Section 4.

Other Techniques – NoisyStudent also works better with an additional trick: data filtering and balancing. Specifically, we filter images that the teacher model has low confidences on since they are usually out-of-domain images. To ensure that the distribution of the unlabeled images match that of the training set, we also need to balance the number of unlabeled images for each class, as all classes in ImageNet have a similar number of labeled images. For this purpose, we duplicate images in classes where there are not enough images. For classes where we have too many images, we take the images with the highest confidence.²

Finally, in the above, we say that the pseudo labels can be soft or hard. We observe that both soft and hard pseudo labels work well in our experiments. In particular, soft pseudo labels work slightly better for out of domain unlabeled data.

²The benefits of data balancing is significant for small models while less significant for larger models. See Study #5 in Appendix A.3 for more details.

Thus in the following, for consistency, we report results with soft pseudo labels unless otherwise indicated.

3. Experiments

In this section, we will first describe our experiment details. We will then present our ImageNet results compared with those of state-of-the-art models. Lastly, we demonstrate the surprising improvements of our models on robustness datasets (such as ImageNet-A, C and P) as well as under adversarial attacks.

3.1. Experiment Details

Labeled dataset. We conduct experiments on ImageNet 2012 ILSVRC challenge prediction task since it has been considered one of the most heavily benchmarked datasets in computer vision and that improvements on ImageNet transfer to other datasets [44, 66].

Unlabeled dataset. We obtain unlabeled images from the JFT dataset [33, 15], which has around 300M images. Although the images in the dataset have labels, we ignore the labels and treat them as unlabeled data. We filter the ImageNet validation set images from the dataset (see [58]).

We then perform data filtering and balancing on this corpus. First, we run an EfficientNet-B0 trained on ImageNet [82] over the JFT dataset [33, 15] to predict a label for each image. We then select images that have confidence of the label higher than 0.3. For each class, we select at most 130K images that have the highest confidence. Finally, for classes that have less than 130K images, we duplicate some images at random so that each class can have 130K images. Hence the total number of images that we use for training a student model is 130M (with some duplicated images). Due to duplications, there are only 81M unique images among these 130M images. We do not tune these hyperparameters extensively since our method is highly robust to them.

Architecture. We use EfficientNets [82] as our baseline models because they provide better capacity for more data. In our experiments, we also further scale up EfficientNet-B7 and obtain EfficientNet-L2. EfficientNet-L2 is wider and deeper than EfficientNet-B7 but uses a lower resolution, which gives it more parameters to fit a large number of unlabeled images. Due to the large model size, the training time of EfficientNet-L2 is approximately five times the training time of EfficientNet-B7. For more information about EfficientNet-L2, please refer to Table 7 in Appendix A.1.

Training details. For labeled images, we use a batch size of 2048 by default and reduce the batch size when we could not fit the model into the memory. We find that using a batch size of 512, 1024, and 2048 leads to the same performance.

We determine the number of training steps and the learning rate schedule by the batch size for labeled images. Specifically, we train the student model for 350 epochs for models larger than EfficientNet-B4, including EfficientNet-L2 and train smaller student models for 700 epochs. The learning rate starts at 0.128 for labeled batch size 2048 and decays by 0.97 every 2.4 epochs if trained for 350 epochs or every 4.8 epochs if trained for 700 epochs.

We use a large batch size for unlabeled images, especially for large models, to make full use of large quantities of available unlabeled images. Labeled images and unlabeled images are concatenated together to compute the average cross entropy loss.

Lastly, we apply the recently proposed technique to fix train-test resolution discrepancy [84] for EfficientNet-L2. We first perform normal training with a smaller resolution for 350 epochs. Then we finetune the model with a larger resolution for 1.5 epochs on unaugmented labeled images. Similar to [84], we fix the shallow layers during finetuning.

Our largest model, EfficientNet-L2, needs to be trained for 6 days on a Cloud TPU v3 Pod, which has 2048 cores, if the unlabeled batch size is 14x the labeled batch size.

Noise. We use stochastic depth [37], dropout [75], and RandAugment [18] to noise the student. The hyperparameters for these noise functions are the same for EfficientNet-B7 and L2. In particular, we set the survival probability in stochastic depth to 0.8 for the final layer and follow the linear decay rule for other layers. We apply dropout to the final layer with a dropout rate of 0.5. For RandAugment, we apply two random operations with magnitude set to 27.

Iterative training. The best model in our experiments is a result of three iterations of putting back the student as the new teacher. We first trained an EfficientNet-B7 on ImageNet as the teacher model. Then by using the B7 model as the teacher, we trained an EfficientNet-L2 model with the unlabeled batch size set to 14 times the labeled batch size. Then, we trained a new EfficientNet-L2 model with the EfficientNet-L2 model as the teacher. Lastly, we iterated again and used an unlabeled batch size of 28 times the labeled batch size. The detailed results of the three iterations are available in Section A.2.

3.2. ImageNet Results

We first report the validation set accuracy on the ImageNet 2012 ILSVRC challenge prediction task as commonly done in literature [45, 79, 30, 82] (see also [66]). As shown in Table 2, NoisyStudent with EfficientNet-L2 achieves 88.4% top-1 accuracy which is significantly better than the best reported accuracy on EfficientNet of 85.0%. The total gain of 3.4% comes from two sources: by making the model larger (+0.5%) and by NoisyStudent (+2.9%). In

Method	# Params	Extra Data	Top-1 Acc.	Top-5 Acc.
ResNet-50 [30]	26M	-	76.0%	93.0%
ResNet-152 [30]	60M	-	77.8%	93.8%
DenseNet-264 [36]	34M	-	77.9%	93.9%
Inception-v3 [80]	24M	-	78.8%	94.4%
Xception [15]	23M	-	79.0%	94.5%
Inception-v4 [78]	48M	-	80.0%	95.0%
Inception-resnet-v2 [78]	56M	-	80.1%	95.1%
ResNeXt-101 [90]	84M	-	80.9%	95.6%
PolyNet [98]	92M	-	81.3%	95.8%
SENet [35]	146M	-	82.7%	96.2%
NASNet-A [102]	89M	-	82.7%	96.2%
AmoebaNet-A [65]	87M	-	82.8%	96.1%
PNASNet [50]	86M	-	82.9%	96.2%
AmoebaNet-C [17]	155M	-	83.5%	96.5%
GPipe [38]	557M	-	84.3%	97.0%
EfficientNet-B7 [82]	66M	-	85.0%	97.2%
EfficientNet-L2 [82]	480M	-	85.5%	97.5%
ResNet-50 Billion-scale [91]	26M	3.5B images labeled with tags	81.2%	96.0%
ResNeXt-101 Billion-scale [91]	193M		84.8%	-
ResNeXt-101 WSL [55]	829M		85.4%	97.6%
FixRes ResNeXt-101 WSL [84]	829M		86.4%	98.0%
Big Transfer (BiT-L) [43] [†]	928M	300M weakly labeled images from JFT	87.5%	98.5%
NoisyStudent (EfficientNet-L2)	480M	300M unlabeled images from JFT	88.4%	98.7%

Table 2: Top-1 and Top-5 Accuracy of NoisyStudent and previous state-of-the-art methods on ImageNet. EfficientNets trained with NoisyStudent have better tradeoff in terms of accuracy and model size compared to previous state-of-the-art models. NoisyStudent (EfficientNet-L2) is the result of iterative training for multiple iterations. [†]: Big Transfer is a concurrent work that performs transfer learning from the JFT dataset.

other words, using NoisyStudent makes a much larger impact on the accuracy than changing the architecture.

Further, NoisyStudent outperforms the state-of-the-art accuracy of 86.4% by FixRes ResNeXt-101 WSL [55, 84] that requires 3.5 Billion Instagram images labeled with tags. As a comparison, our method only requires 300M unlabeled images, which is perhaps more easy to collect. Our model is also approximately twice as small in the number of parameters compared to FixRes ResNeXt-101 WSL.

Model size study: NoisyStudent for EfficientNet B0-B7 without Iterative Training.

In addition to improving state-of-the-art results, we conduct experiments to verify if NoisyStudent can benefit other EfficientNet models. In previous experiments, iterative training was used to optimize the accuracy of EfficientNet-L2 but here we skip it as it is difficult to use iterative training for many experiments. We vary the model size from EfficientNet-B0 to EfficientNet-B7 [82] and use the same model as both the teacher and the student. We apply RandAugment to all EfficientNet baselines, leading to more competitive baselines. We set the unlabeled batch size to be three times the

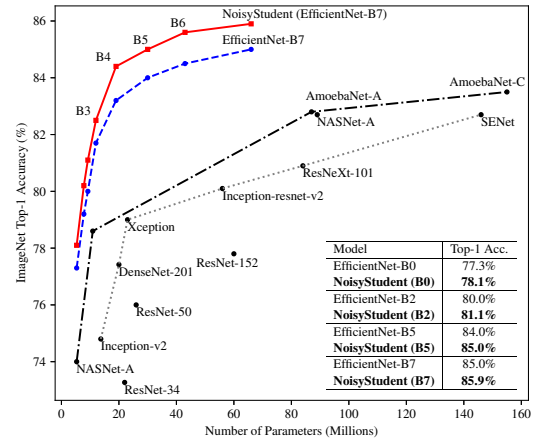


Figure 2: NoisyStudent leads to significant improvements across all model sizes for EfficientNet. We use the same architecture for the teacher and the student and do not perform iterative training.

batch size of labeled images for all model sizes except for EfficientNet-B0. For EfficientNet-B0, we set the unlabeled

batch size to be the same as the batch size of labeled images. As shown in Figure 2, NoisyStudent leads to a consistent improvement of around 0.8% for all model sizes. Overall, EfficientNets with NoisyStudent provide a much better tradeoff between model size and accuracy than prior works. The results also confirm that vision models can benefit from NoisyStudent even without iterative training.

3.3. Robustness Results on ImageNet-A, ImageNet-C and ImageNet-P

Method	Top-1 Acc.	Top-5 Acc.
ResNet-101 [32]	4.7%	-
ResNeXt-101 [32] (32x4d)	5.9%	-
ResNet-152 [32]	6.1%	-
ResNeXt-101 [32] (64x4d)	7.3%	-
DPN-98 [32]	9.4%	-
ResNeXt-101+SE [32] (32x4d)	14.2%	-
ResNeXt-101 WSL [55, 59]	61.0%	-
EfficientNet-L2	49.6%	78.6%
NoisyStudent (L2)	83.7%	95.2%

Table 3: Robustness results on ImageNet-A.

Method	Res.	Top-1 Acc.	mCE
ResNet-50 [31]	224	39.0%	76.7
SIN [23]	224	45.2%	69.3
Patch Gaussian [51]	299	52.3%	60.4
ResNeXt-101 WSL [55, 59]	224	-	45.7
EfficientNet-L2	224	62.6%	47.5
NoisyStudent (L2)	224	76.5%	30.0
EfficientNet-L2	299	66.6%	42.5
NoisyStudent (L2)	299	77.8%	28.3

Table 4: Robustness results on ImageNet-C. mCE is the weighted average of error rate on different corruptions, with AlexNet’s error rate as a baseline (lower is better).

Method	Res.	Top-1 Acc.	mFR
ResNet-50 [31]	224	-	58.0
Low Pass Filter Pooling [97]	224	-	51.2
ResNeXt-101 WSL [55, 59]	224	-	27.8
EfficientNet-L2	224	80.4%	27.2
NoisyStudent (L2)	224	85.2%	14.2
EfficientNet-L2	299	81.6%	23.7
NoisyStudent (L2)	299	86.4%	12.2

Table 5: Robustness results on ImageNet-P, where images are generated with a sequence of perturbations. mFR measures the model’s probability of flipping predictions under perturbations with AlexNet as a baseline (lower is better).

We evaluate the best model, that achieves 88.4% top-1 accuracy, on three robustness test sets: ImageNet-A, ImageNet-C and ImageNet-P. ImageNet-C and P test sets [31] include images with common corruptions and perturbations such as blurring, fogging, rotation and scaling. ImageNet-A test set [32] consists of difficult images that cause significant drops in accuracy to state-of-the-art models. These test sets are considered as “robustness” benchmarks because the test images are either much harder, for ImageNet-A, or the test images are different from the training images, for ImageNet-C and P.

For ImageNet-C and ImageNet-P, we evaluate models on two released versions with resolution 224x224 and 299x299 and resize images to the resolution EfficientNet trained on. As shown in Table 3, 4 and 5, NoisyStudent yields substantial gains on robustness datasets compared to the previous state-of-the-art model ResNeXt-101 WSL [55, 59] trained on 3.5B weakly labeled images. On ImageNet-A, it improves the top-1 accuracy from 61.0% to 83.7%. On ImageNet-C, it reduces mean corruption error (mCE) from 45.7 to 28.3. On ImageNet-P, it leads to a mean flip rate (mFR) of 14.2 if we use a resolution of 224x224 (direct comparison) and 12.2 if we use a resolution of 299x299.³ These significant gains in robustness in ImageNet-C and ImageNet-P are surprising because our method was not deliberately optimized for robustness.⁴

Qualitative Analysis. To intuitively understand the significant improvements on the three robustness benchmarks, we show several images in Figure 3 where the predictions of the standard model are incorrect while the predictions of the NoisyStudent model are correct.

Figure 3a shows example images from ImageNet-A and the predictions of our models. The model with NoisyStudent can successfully predict the correct labels of these highly difficult images. For example, without NoisyStudent, the model predicts *bullfrog* for the image shown on the left of the second row, which might be resulted from the black lotus leaf on the water. With NoisyStudent, the model correctly predicts *dragonfly* for the image. At the top-left image, the model without NoisyStudent ignores the *sea lions* and mistakenly recognizes a buoy as a lighthouse, while the NoisyStudent model can recognize the *sea lions*.

Figure 3b shows images from ImageNet-C and the corresponding predictions. As can be seen from the figure,

³For EfficientNet-L2, we use the model without finetuning with a larger test time resolution, since a larger resolution results in a discrepancy with the resolution of data and leads to degraded performance on ImageNet-C and ImageNet-P.

⁴Note that both our model and ResNeXt-101 WSL use augmentations that have a small overlap with corruptions in ImageNet-C, which might result in better performance. Specifically, RandAugment includes augmentation Brightness, Contrast and Sharpness. ResNeXt-101 WSL uses augmentation of Brightness and Contrast.

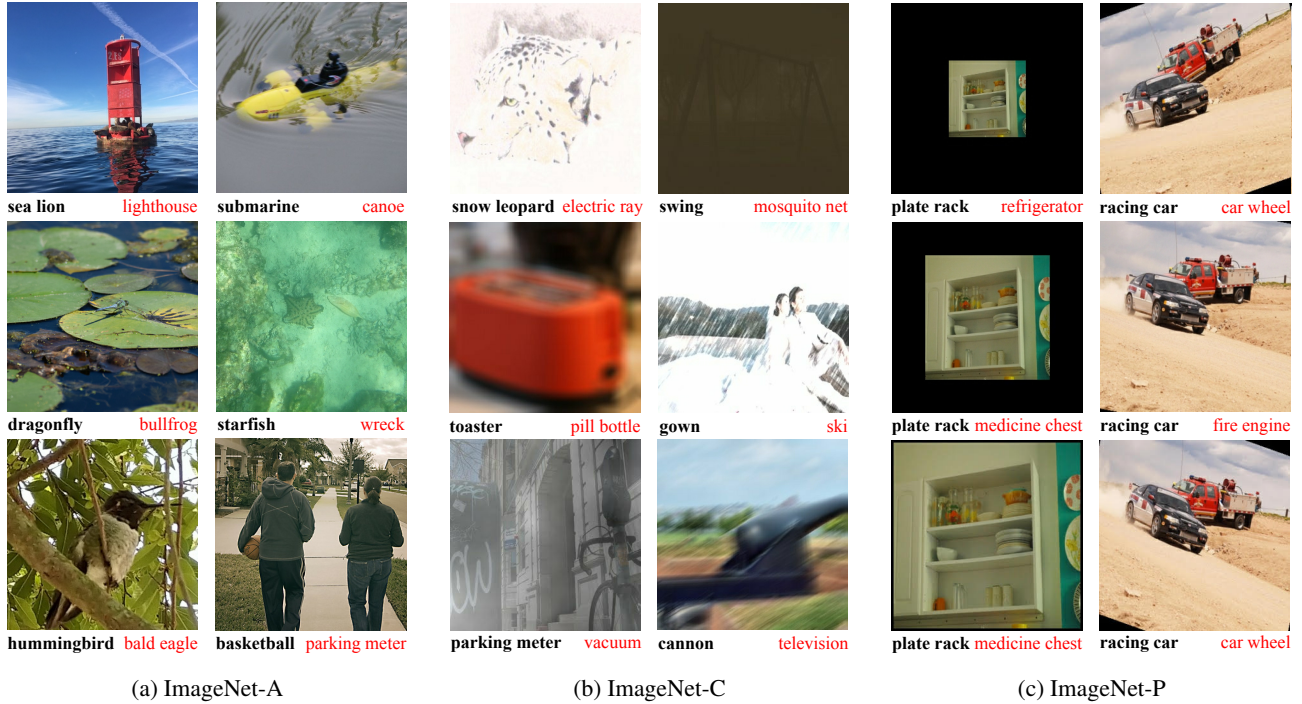


Figure 3: Selected images from robustness benchmarks ImageNet-A, C and P. Test images from ImageNet-C underwent artificial transformations (also known as common corruptions) that cannot be found on the ImageNet training set. Test images on ImageNet-P underwent different scales of perturbations. On ImageNet-A, C, EfficientNet with NoisyStudent produces correct top-1 predictions (shown in **bold black** texts) and EfficientNet without NoisyStudent produces incorrect top-1 predictions (shown in **red** texts). On ImageNet-P, EfficientNet without NoisyStudent flips predictions frequently.

our model with NoisyStudent makes correct predictions for images under severe corruptions and perturbations such as snow, motion blur and fog, while the model without NoisyStudent suffers greatly under these conditions. The most interesting image is shown on the right of the first row. The *swing* in the picture is barely recognizable by human while the NoisyStudent model still makes the correct prediction.

Figure 3c shows images from ImageNet-P and the corresponding predictions. As can be seen, our model with NoisyStudent makes correct and consistent predictions as images undergone different perturbations while the model without NoisyStudent flips predictions frequently.

3.4. Adversarial Robustness Results

After testing our model’s robustness to common corruptions and perturbations, we also study its performance on adversarial perturbations. We evaluate our EfficientNet-L2 models with and without NoisyStudent against an FGSM attack. This attack performs one gradient descent step on the input image [25] with the update on each pixel set to ϵ . As shown in Figure 4, NoisyStudent leads to very significant improvements in accuracy even though the model is

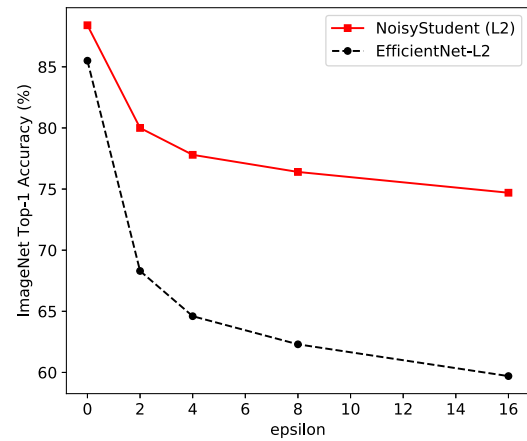


Figure 4: NoisyStudent improves adversarial robustness against an FGSM attack though the model is not optimized for adversarial robustness. The accuracy is improved by 11% at $\epsilon = 2$ and gets better as ϵ gets larger.

not optimized for adversarial robustness. Under a stronger attack PGD with 10 iterations [54], at $\epsilon = 16$, NoisyStudent improves EfficientNet-L2’s accuracy from 1.1% to 4.4%.

Note that these adversarial robustness results are not directly comparable to prior works since we use a large input resolution of 800x800 and adversarial vulnerability can scale with the input dimension [22, 25, 24, 73].

4. Ablation Study: The Importance of Noise in Self-training

In this section, we study the importance of noise. The ablation for iterative training and other components of our method are available in Appendix A.2 and A.3.

Since we use soft pseudo labels generated from the teacher model, when the student is trained to be exactly the same as the teacher model, the cross entropy loss on unlabeled data would be zero and the training signal would vanish. Hence, a question that naturally arises is why the student can outperform the teacher with soft pseudo labels. As stated earlier, we hypothesize that noising the student is needed so that it does not merely learn the teacher’s knowledge. We investigate the importance of noising in two scenarios with different amounts of unlabeled data and different teacher model accuracies. In both cases, we gradually remove augmentation, stochastic depth and dropout for unlabeled images when training the student model, while keeping them for labeled images. This way, we can isolate the influence of noising on unlabeled images from the influence of preventing overfitting for labeled images. In addition, we compare using a noised teacher and an unnoised teacher to study if it is necessary to disable noise when generating pseudo labels.

Model / Unlabeled Set Size	1.3M	130M
EfficientNet-B5	83.3%	84.0%
NoisyStudent (B5)	83.9%	84.9%
student w/o Aug	83.6%	84.6%
student w/o Aug, SD, Dropout	83.2%	84.3%
teacher w. Aug, SD, Dropout	83.7%	84.4%

Table 6: Ablation study of noising. We use EfficientNet-B5 as the teacher model and study two cases with different numbers of unlabeled images and different augmentations. For the experiment with 1.3M unlabeled images, we use the standard augmentation including random translation and flipping for both the teacher and the student. For the experiment with 130M unlabeled images, we use RandAugment. Aug and SD denote data augmentation and stochastic depth respectively. We remove the noise for unlabeled images while keeping them for labeled images. Here, iterative training is not used and unlabeled batch size is set to be the same as the labeled batch size to save training time.

Here, we show the evidence in Table 6, noise such as stochastic depth, dropout and data augmentation plays an

important role in enabling the student model to perform better than the teacher. The performance consistently drops with noise function removed. However, in the case with 130M unlabeled images, when compared to the supervised baseline, the performance is still improved to 84.3% from 84.0% with noise function removed. We hypothesize that the improvement can be attributed to SGD, which introduces stochasticity into the training process.

One might argue that the improvements from using noise can be resulted from preventing overfitting the pseudo labels on the unlabeled images. We verify that this is not the case when we use 130M unlabeled images since the model does not overfit the unlabeled set from the training loss. While removing noise leads to a much lower training loss for labeled images, removing noise leads to a smaller drop in training loss for unlabeled images. This is probably because it is harder to overfit the large unlabeled dataset.

Lastly, adding noise to the teacher model that generates pseudo labels leads to lower accuracy, which shows the importance of having a powerful unnoised teacher model.

5. Related works

Self-training. Our work is based on self-training (e.g., [70, 94, 67]). Self-training first uses labeled data to train a good teacher model, then use the teacher model to label unlabeled data and finally use the labeled data and unlabeled data to jointly train a student model. In typical self-training with the teacher-student framework, noise injection to the student is not used by default, or the role of noise is not fully understood or justified. The main difference between our work and prior works is that we identify the importance of noise, and aggressively inject noise to make the student better.

Self-training was previously used to improve ResNet-50 from 76.4% to 81.2% top-1 accuracy [91] which is still far from the state-of-the-art accuracy. Yalniz *et al.* [91] also did not show significant improvements in terms of robustness on ImageNet-A, C and P as we did. In terms of methodology, they proposed to first only train on unlabeled images and then finetune their model on labeled images as the final stage. In NoisyStudent, we combine these two steps into one because it simplifies the algorithm and leads to better performance in our experiments.

Data Distillation [63], which ensembles predictions for an image with different transformations to strengthen the teacher, is the opposite of our approach of weakening the student. Parthasarathi *et al.* [61] find a small and fast speech recognition model for deployment via knowledge distillation on unlabeled data. As noise is not used and the student is also small, it is difficult to make the student better than teacher. The domain adaptation framework in [68] is related but highly optimized for videos, e.g., prediction on which frame to use in a video. The method in [99] en-

sembles predictions from multiple teacher models, which is more expensive than our method.

Co-training [9] divides features into two disjoint partitions and trains two models with the two sets of features using labeled data. Their source of “noise” is the feature partitioning such that two models do not always agree on unlabeled data. Our method of injecting noise to the student model also enables the teacher and the student to make different predictions and is more suitable for ImageNet than partitioning features.

Self-training / co-training has also been shown to work well for a variety of other tasks including leveraging noisy data [85], semantic segmentation [4], text classification [40, 77]. Back translation and self-training have led to significant improvements in machine translation [71, 20, 28, 14, 88, 29].

Semi-supervised Learning. Apart from self-training, another important line of work in semi-supervised learning [12, 101] is based on consistency training [5, 64, 47, 83, 56, 52, 62, 13, 16, 60, 2, 49, 86, 89, 8, 96, 46, 7]. These works constrain model predictions to be invariant to noise injected to the input, hidden states or model parameters. Although they have produced promising results, in our preliminary experiments, consistency regularization works less well on ImageNet because consistency regularization in the early phase of ImageNet training regularizes the model towards high entropy predictions, and prevents it from achieving good accuracy. A common workaround is to use entropy minimization or to ramp up the consistency loss. However, the additional hyperparameters introduced by the ramping up schedule and the entropy minimization make them more difficult to use at scale. Compared to consistency training [56, 8, 89], the self-training / teacher-student framework is better suited for ImageNet because we can train a good teacher on ImageNet using labeled data.

Works based on pseudo label [48, 39, 72, 1] are similar to self-training, but also suffer the same problem with consistency training, since they rely on a model being trained instead of a converged model with high accuracy to generate pseudo labels. Finally, frameworks in semi-supervised learning also include graph-based methods [100, 87, 92, 42], methods that make use of latent variables as target variables [41, 53, 93] and methods based on low-density separation [26, 69, 19], which might provide complementary benefits to our method.

Knowledge Distillation. As we use soft targets, our work is also related to methods in Knowledge Distillation [10, 3, 33, 21, 6]. The main use of knowledge distillation is model compression by making the student model smaller. The main difference between our method and knowledge dis-

tillation is that knowledge distillation does not consider unlabeled data and does not aim to improve the student model.

Robustness. A number of studies, *e.g.* [81, 31, 66, 27], have shown that vision models lack robustness. Addressing the lack of robustness has become an important research direction in machine learning and computer vision in recent years. Our study shows that using unlabeled data improves accuracy and general robustness. Our finding is consistent with arguments that using unlabeled data can improve *adversarial* robustness [11, 76, 57, 95]. The main difference between our work and these works is that they directly optimize adversarial robustness on unlabeled data, whereas we show that NoisyStudent improves robustness greatly even without directly optimizing robustness.

6. Conclusion

Prior works on weakly-supervised learning required billions of weakly labeled data to improve state-of-the-art ImageNet models. In this work, we showed that it is possible to use unlabeled images to significantly advance both accuracy and robustness of state-of-the-art ImageNet models. We found that self-training is a simple and effective algorithm to leverage unlabeled data at scale. We improved it by adding noise to the student, hence the name NoisyStudent, to learn beyond the teacher’s knowledge.

Our experiments showed that NoisyStudent and EfficientNet can achieve an accuracy of 88.4% which is 2.9% higher than without NoisyStudent. This result is also a new state-of-the-art and 2.0% better than the previous best method that used an order of magnitude more weakly labeled data [55, 84].

An important contribution of our work was to show that NoisyStudent boosts robustness in computer vision models. Our experiments showed that our model significantly improves performances on ImageNet-A, C and P.

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