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# LSUN: Construction of a Large-Scale Image Dataset using Deep Learning with Humans in the Loop

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## Abstract

While there has been remarkable progress in the performance of visual recognition algorithms, the state-of-the-art models tend to be exceptionally data-hungry. Large labeled training datasets, expensive and tedious to produce, are required to optimize millions of parameters in deep network models. Lagging behind the growth in model capacity, the available datasets are quickly becoming outdated in terms of size and density. To circumvent this bottleneck, we propose to amplify human effort through a partially automated labeling scheme, leveraging deep learning with humans in the loop. Starting from a large set of candidate images for each category, we iteratively sample a subset, ask people to label them, classify the others with a trained model, split the set into positives, negatives, and unlabeled based on the classification confidence, and then iterate with the unlabeled set. To assess the effectiveness of this cascading procedure and enable further progress in visual recognition research, we construct a new image dataset, LSUN. It contains around one million labeled images for each of 10 scene categories and 20 object categories. We experiment with training popular convolutional networks and find that they achieve substantial performance gains when trained on this dataset.

## 1 Introduction

High capacity supervised learning algorithms, such as deep convolutional neural networks [10, 9], have led to a discontinuity in visual recognition over the past four years and continue to push the state-of-the-art performance (e.g. [7, 22, 8]). These models usually have millions of parameters, resulting in two consequences. On the one hand, the many degrees of freedom of the models allow for extremely impressive description power; they can learn to represent complex functions and transformations automatically from the data. On the other hand, to search for the optimal settings for a large number of parameters, these data-hungry algorithms require a massive amount of training data with human initialized labels [4, 6, 23, 24].

Although there has been remarkable progress in improving deep learning algorithms (e.g. [7, 16]) and developing high performance training systems (e.g. [22]), advancements are lacking in dataset construction. The ImageNet dataset [4], used by most of these algorithms, is 7 years old and has been heavily over-fitted [1]. The recently released Places [24] dataset is not much larger. The number of parameters in many deep models now exceeds the number of images in these datasets. While the models are getting deeper (e.g. [15, 16]) and the accessible computation power is increasing, the size of the datasets for training and evaluation is not increasing by much, but rather lagging behind and hindering further progress in large-scale visual recognition.

Moreover, the density of examples in current datasets is quite low. Although they have several million images, they are spread across many categories, and so there are not very many images in each category (e.g., 1000 in ImageNet). As a result, deep networks trained on them often learn features that are noisy and/or unstable [17, 11]. To address this problem, researchers have used techniques

that augment the training sets with perturbations of the original images [22]. Those methods add to the stability and generalizability to trained models, but without increasing the actual density of novel examples. We propose an alternative: an image dataset with high density. We aim for a dataset with  $\sim 10^6$  images per category, which is around 10 times denser than PLACES [24] and 100 times denser than ImageNet [4].

Although the amount of available image data on the Internet is increasing constantly, it is nontrivial to build a supervised dataset that dense because of the high costs of manual labeling. Clever methods have been proposed to improve the efficiency of human-in-the-loop annotation (e.g., [2, 5, 13, 20, 21]). However, manual effort is still the bottleneck – the construction of ImageNet and Places both required more than a year of human effort via Amazon Mechanical Turk (AMT), the largest crowd-sourcing platform available on the Internet. If we desire a  $N$ -times bigger/denser dataset, it will require more than  $N$  years of human annotation. This will not scale quickly enough to support advancements in deep visual learning. Clearly, we must introduce a certain amount of automation into this process in order to let data annotation maintain pace with the growth of deep models.

In this paper, we introduce an integrated framework using deep learning with humans in the loop to annotate a large-scale image dataset. The key new idea is a labeling propagation system that automatically amplifies manual human effort. We study strategies for selecting images for people to label, interfaces for acquiring labels quickly, procedures for verifying the labels acquired, and methods for amplifying the labels by propagating them to other images in the dataset. We have used the system to construct a large scale image database, “LSUN”, with 10 million labeled images in 10 scene categories and 59 million labeled images in 20 object categories.<sup>1</sup>.

One of the main challenges for a semi-automatic approach is achieving high precision in the final labeled dataset. Our procedure uses statistical tests to ensure labeling quality, providing more than 90% precision on average according to verification tests. This is slightly lower than manual annotation, but still good enough to train high performance classification models. During experiments with popular deep learning models, we observe substantial classifier performance gains when using our larger training set. Although the LSUN training labels may contain some noise, it seems that training on a larger, noisy dataset produces better models than training on smaller, noise-free datasets.

## 2 Overview

An overview of our labeling pipeline is shown in Figure 1. For each category, we start by collecting a large set of candidate images using keyword search (usually  $\sim 10^7 - 10^8$  images). Then, we iterate between asking people to label a small subset, training a classifier on that subset, asking the classifier to predict labels and confidences, and then selecting a small candidate set for further consideration.

In many ways, this process is similar to active learning [14, 18, 3, 20]. However, there is a key difference: we aim to get correct labels for all examples in a specific set of images rather than learning a generalizable classifier. The main implication of this difference is that it is acceptable for our system to over-fit a model to adapt locally to its target set, without considering generalizability outside the set.

Our iterative method learns a cascade of over-fit classifiers, each of which splits a set of images into positive, negative, and unlabeled subsets. The positive examples are added to our dataset; the negative examples are discarded; and the unlabeled subset is passed to the next iteration for further processing. The cascade terminates when the unlabeled subset is small enough that all images can be labeled manually. If the unlabeled subset shrinks by a significant factor at each iteration, the process can label a very large data set with a practical amount of human effort.

The following sections describe the main components of our system, with detailed descriptions of how we collect data, learn a deep network classifier for each iteration, design an interface for manual labeling, and control for label quality. These descriptions are followed by results of experiments designed to test whether the collected dataset is helpful for image classification.

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<sup>1</sup>We are continuing to collect and annotate data through our platform at a rate of 5 million images and 2 categories per week

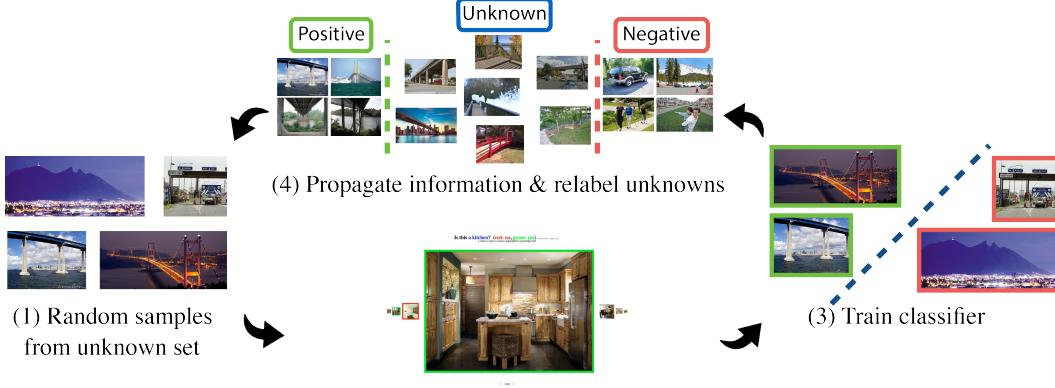


Figure 1: An overview of our pipeline. To annotate a large number of images, we first randomly sample a small subset (1) and label them through crowdsourcing using our Amazon Mechanical Turk interface(2). This small labeled subset is then utilized to train a binary classifier with deep learning feature (3). Then, we run the binary classifier on the unlabeled images. The images with high or low scores are labeled as positive or negative automatically, while the images ambiguous to the classifier are fed into the next iteration as the unlabeled images (4). The pipeline runs iteratively until the number of images remaining in the unknown set is amenable to exhaustive labeling.

### 3 Data Collection

The first step in constructing a large-scale image database is collecting the images themselves. As in previous work, we leverage existing image search engines to gather image URLs. Here, we use Google Images search. By querying with appropriate adjectives and synonyms, we can bypass the usual limit on search results and obtain nearly 100 million relevant URLs for each category.

Similar to SUN and MS COCO, our target database will contain images from both scene and object categories. To generate queries for scene categories, 696 common adjectives relevant to scenes (messy, spare, sunny, desolate, etc.), manually selected from a list of popular adjectives in English (obtained by [24]), are combined with each scene category name. Adding adjectives to the queries allows us to both download a larger number of images than what is available in previous datasets and increase the diversity of visual appearances. To further increase the number of search results per category, we set the time span for each query to three days and query all three-day time spans since 2009. We find that a shorter time span seldom returns more useful results. We then remove duplicate URLs and download all accessible images (some URLs may be invalid or the images not properly encoded). These same methods are used to collect image URLs for object categories, except the queries use a different set of object-relevant adjectives. As an example of our querying results, we obtain more than 111 million unique URLs for images relevant to “dog”.

To date, more than 1 billion images have been downloaded. An initial quality check is performed before labeling these images. Only images with smaller dimension greater than 256 are kept. After the check, around 60% of the images are kept. Unlike previous systems [23, 24], we don’t remove duplicates (in terms of image content) in this initial pool of images as it is very expensive to remove duplicates while avoiding overkill on tens of millions of non-duplicate images. In addition, our pipeline requires only a small subset of this pool (with rare duplicates) to be manually labeled. Therefore leaving duplicates in the original image pool does not increase the cost of manual labeling. The duplicate images usually exhibit various compression qualities, sizes, and even croppings. They augment our dataset naturally, and it will be up to algorithm designers how to utilize the duplication. All images from this initial pool will be released for unsupervised image analysis.

### 4 Deep Learning with Humans in the Loop

Although we can collect around 100 million relevant images for each category, the time and human effort required for manual labeling is prohibitive. We observe that existing methods for image classification tasks obtain impressive results, as shown in the recent ImageNet challenges [12]. We therefore propose to use image classification algorithms in combination with humans to label the images semi-automatically, amplifying human effort.

We treat the labeling process for each category as a binary classification problem – i.e., every image downloaded for the category is labeled as either positive or negative.

Starting with the large pool of unlabeled images. We randomly sample a small subset of images from this pool and acquire labels for them from AMT workers (see section 5 for details). This labeled set is then randomly split into a training and testing set. We train a classifier on the training set and then run it on both the labeled testing set and the full unlabeled pool. By examining the scores output by the classifier on the labeled testing set, we can determine score ranges which delineate either confident scores corresponding to easy images or weaker scores corresponding to more difficult or ambiguous images.

To define these score ranges, we compute two thresholds: the score above which 95% of the images are ground truth positives and the score below which there are only 1% of the total positive images. Both in the labeled subset and the unlabeled pool, images scoring above or below this threshold are labeled as positive or negative, respectively. All images scoring in between these two thresholds, i.e., the more challenging images, are sent to the next iteration. Thus, during each iteration, we label a portion of images with confident scores as positive and also remove highly probable negative images while maintaining a good recall for the final labeled set.

This process is repeated identically for each iteration except that, beginning with the second iteration, the randomly sampled subset for manual labeling will be combined with the ambiguous portion of the previous iteration’s labeled subset. Therefore, because later iterations have a larger number of difficult training examples, the later classifiers can outperform previous classifiers, confidently assigning labels to some of the images in the unlabeled pool. Then, the images still lacking confident labels are passed to the next iteration. This process is illustrated in Figure 1. The next two sections will discuss details regarding performing classification and sampling images in each iteration.

**Classification:** We encounter a tradeoff between computation time and performance when selecting classification models for our pipeline. Although the most accurate classification model will limit the number of iterations necessary to label the entire image pool, we may not be able to afford its running time on tens of millions of images. Also, the current successful classification models are all based on convolutional networks. Better models are usually deeper and of higher capacity, requiring more training images.

To make the tradeoff, we assess several different classification models. We find that, for the initial image set, the image representation from the last fully connected layer in AlexNet can be used to separate the images effectively. By using a multi-layer perceptron (MLP) with two hidden layers, we can remove more than half of the images from the initial set. However, after two iterations with a MLP, this feature space is no longer effective. So we then adapt pre-trained GoogLeNet [16] by fine-tuning, which can continuously benefit from the additional training images sampled at each iteration. The learning rate of fine-tuning starts with 0.001 and drops to 0.0001 after 40,000 iterations. The total number of iteration is 60,000. The mini batch size is 80. In the testing phase during early iterations, we only pass the central crop of each image to the model. After 10 labeling iterations, we train the network for the labeling iterations divided by 10 more training iterations. Also, we pass 10 crops to the network and average the score output. Although evaluating with 10 crops is 10 times more expensive, far fewer images remain after 10 labeling iterations.

To select the best models from the training process, we evaluate the models on a validation set and compare the models by accuracy. Because the validation set has a low ratio of positive to negative images we must carefully select the accuracy metric. Given a set of images for validation, we measure two scores of accuracy by assigning different weights to the images. For one score, all the images have the same weight. In the second score, the sums of the weights of positive and negative images are equal, with the set of positive images and the set of negative images each being weighted uniformly. We select the model that removes more images in the testing set.

**Image Sampling:** To improve the classifier at each iteration, we sample 40 thousand images uniformly randomly from the unlabeled pool. 10 thousand are reserved for testing the classifier confidence. 5 thousand are used for validation to pick the best models from the training procedure. The remaining images are used for training. At the end of each iteration, after the classifier labels the positive images and removes negative images, the labels of all the images in the remaining set are kept for training in the next iteration. We have also experimented with sampling 80 or 120 thousand images per iteration but it did not improve the classifier results significantly during the initial stages.

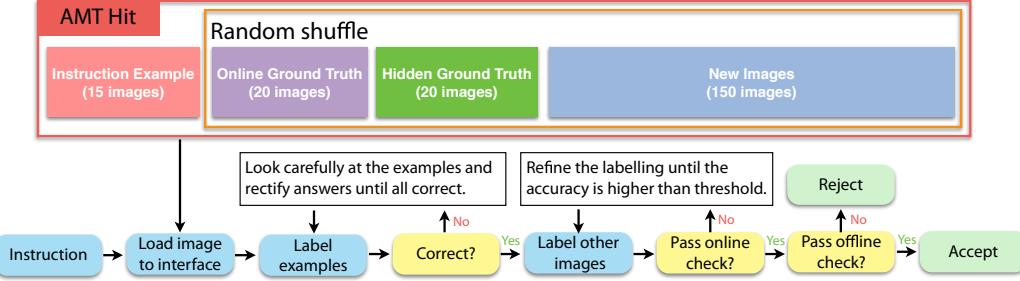


Figure 2: Life time of a HIT on AMT.

## 5 Crowd Sourcing

A critical part of our pipeline is obtaining high quality manual annotations (from humans in the loop). Of necessity is the ability to obtain many labels, quickly and at minimal cost. To this end, we use Amazon Mechanical Turk (AMT), the largest crowdsourcing platform available. However, annotations obtained from AMT can vary in quality. Here we present a series of mechanisms and measures to ensure high quality annotations.

**Interface Design:** Built on the labeling interface from [24], our interface allows human annotators to go through the images one by one. As shown in the supplemental material, a single image is displayed on the screen at a time along with a question asking if the image content fits a particular category (e.g., “Is this a kitchen”). A definition of the category is also provided. Small thumbnails are shown for the previous three images to the left and upcoming three images to the right. By pressing the arrow keys, a worker can navigate through the images, with the default answer of each image set to “No”. The worker can press the space bar to toggle the current answer (encoded by the color of the boundary box).

We observe that scene images can be complicated, and a larger view of the images is often helpful for comprehension. Likewise we display one image at a time, maximizing the image size to fill the window. To make sure the window can fully utilize the worker’s screen, we provide a simple button that forces the labeling window to enter fullscreen mode.

**Labeling Instructions:** There is some ambiguity inherent to the task of assigning scene and object categories to images. For example, how much of a person’s body must be visible for an image to be considered positive for the category “person”? If only a face is shown, does this count? What if only an arm is shown? This ambiguity can be amplified by the fact that AMT workers come from a variety of countries and cultural backgrounds; their preconceived notions of particular categories may differ from ours. In order to thoroughly clarify the range of image content we desire for each scene and object, we include an instructions page displaying example images, their ground truth labels, and explanations for the labels.

To gather effective examples for each category, we first address obvious corner cases. For example, for the “car” category, we would like trucks and buses to be excluded as these will later form separate categories. Therefore, we specify that trucks and buses should be marked as negative on the “car” instruction page. In addition, for each object category, we decide which parts of the object are significant enough that when visible, they make the object’s identity clear. For example, when only one wheel is visible in an image, there is not enough information to confidently assert the presence of a bicycle. While we acknowledge that these decisions are ultimately subjective, by keeping these instructions consistent for all the workers we can build a dataset that cleanly abides by these class definitions.

After addressing corner cases, we run some test hits on AMT to discover any other possible sources of confusion. For each category, we sample 30,000 images from all the images and label each image by 3 people on the AMT and check the images with conflicting labels. We manually select a subset of them to seed a pool of example corner cases, from which we randomly sample 15 to show the AMT worker before each hit.

In addition to category-specific examples, we also provide the workers with examples of general types of images we do not want to include in our dataset. For example, as we wish to build a natural image dataset, we advise the workers to mark as negative any computer-generated or cartoon imagery.

Images with obtrusive text overlay (where solid font text occludes the object of interest) and photo collages are similarly marked as negative. If an object of interest is printed on a magazine/book/TV screen within an image, we consider this to be negative. In these cases it is actually the magazine/book/TV screen that is physically present within the scene, not the object of interest.

**Quality Control:** In any crowdsourcing platform like AMT, the quality of work can vary from worker to worker. We take the approach of redundant labeling and enforced instruction. For each image, we gather labels from two workers and only keep doubly confirmed labels.

Given a set of images that need to be labeled, we divide them into groups of 150 images. In each AMT HIT, we have the human annotator label 205 images. 150 of these are the actual images we are interested in and the remaining 55 are included for quality control purposes. The workers normally finish the hits within 5 minutes. Having tested a variety of hit lengths, we found this to be a good trade-off between efficiency and quality control.

Figure 2 shows the steps for the life time of a HIT. First, we show an instruction page to explain the task and questions with positive and negative examples. Although it is useful and necessary, we find that some workers may not actually read through the instruction very carefully, especially the detailed definition and the positive and negative examples. They may also forget about the subtlety for some categories. Therefore, we set the first 15 images in each HIT to test whether the workers understand the instruction. The images are from a set of examples representing typical category images and common mistakes. If a worker gives a wrong label to one of the example image, a pop window will show up and block the labeling interface until the worker fixes the label to that image. After the 15 tutorial images, they will go on to label without immediate feedback per image.

We embed 40 images sampled from hundreds with known ground truth in each HIT to measure the labeling quality. 20 of them are online, meaning that their quality is checked before the HIT result is submitted to the server. If the worker can't pass the online check, they are not allowed to submit the labeling results and advised to revise their labeling results until they can pass the online check. The other 20 of those images are checked after the HIT is submitted. They are used to check whether the worker hack our Javascript code to pass the online check to make sure they exhaustively look for online ground truth to pass the submission test. The labels of these images are not sent to the worker's browser, so they can't hack our interface to submit bad results. The labeling accuracy threshold for ground truth is 90% for the online and 85% for the hidden.

## 6 Results

We are running this labeling pipeline continuously and have now collected enough data to evaluate how well it is performing and study its potential impact on visual recognition.

**Dataset Statistics:** So far, we have collected 59 million images for 20 object categories selected from PASCAL VOC 2012 and 10 million images for 10 scene categories selected from the SUN database. Figure 3 shows the statistics of object categories. The number of images used in ImageNet classification challenge is about 1.4 million, which is used to train recent convolutional networks. Most of our object categories have more images than the whole challenge. Even if we only consider the basic level categories in ImageNet such as putting all the dogs together, our dataset is still much denser.

**Label Precision:** We have run a series of experiments to test the labeling precision of this dataset. We sampled 2000 images from 11 object categories and label them with completely manual pipeline using trained experts (AMT labeling is not reliable enough for this test). The final precision of those categories is shown in Figure 4aa. We observe that normally, the precision is around 90%, but it varies across different categories. The major mistakes in our labels are caused by toys, computer rendered images, photo collages, and human edited photos. The inclusion of computer-rendered images is the most serious for the person category. Although we have tests for classifier confidence, there are lots of confusing cases for human labelers on these images, which subsequently confuse the statistical tests.

**Effort Amplification:** We next checked how much our pipeline amplifies human labeling effort – i.e., the ratio between the number of images put into a positive or negative set versus the number of images labeled by people. The result is shown in Figure 4b. It shows that our pipeline amplifies

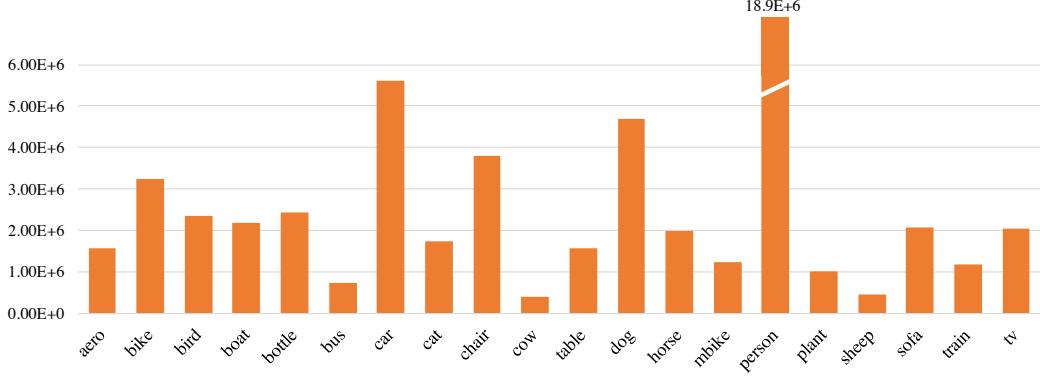


Figure 3: Number of images in our object categories. Compared to ImageNet dataset, we have more images in each category, even comparing only basic level categories.

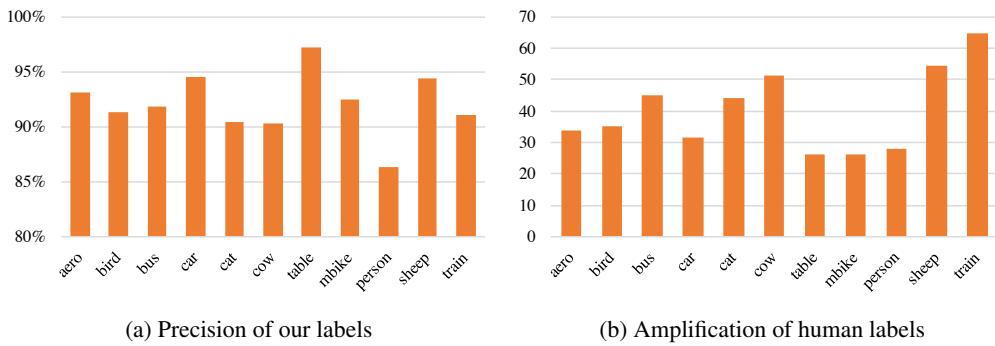


Figure 4: Labeling precision and reduced labeling efforts of our pipeline. (a) shows the precision of labels from 11 object categories. The precision is normally around 90%. (b) shows how much labeling effort is saved with our pipeline. On average the ratio between all images and the number of human-provided labels is around 40:1.

human efforts by 40 times on average. In the case of the train category, people labeled less than 1/60th of the images.

**Impact on Model Performance:** We next investigate whether the new dataset can help current models achieve better classification performance. As a first test, we use the standard AlexNet [9] trained on PLACES and compare the model fine-tuned by the PLACES data [24] with the same model fine-tuned by both PLACES and LSUN, in both cases fine-tuning on only the 10 categories in LSUN. As a simple measure to balance the dataset, we only take at most 200 thousand images from each LSUN category. Then we test the classification results on this 10 categories in PLACES testing set. The error percentage comparison is shown in Figure 5. The overall detection error percentage is 28.6% with only PLACES and 22.2% with both PLACES and LSUN, which yields a 22.37% improvement on testing error. Although the testing is unfavorable to LSUN due to potential dataset bias issues [19], we can see that the additional of more data can improve the classification accuracy on PLACES testing set for 8 of the 10 categories.

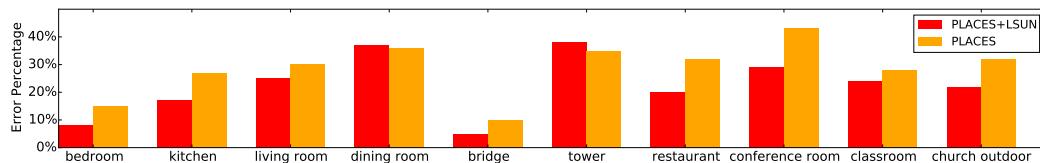


Figure 5: Comparison of classification error by training AlexNet with PLACES vs. LSUN and PLACES. Lower errors are better.

We then use the pre-trained model to fine-tune on PASCAL VOC 2012 classification training images with Hinge loss and evaluate the learned representation. We use two pre-trained models for comparison. One is AlexNet trained by our object data from scratch. The other is VGG trained by our object data but initialized by ImageNet. We sample 300 thousand images from each of the 20 object categories and use them as training data from LSUN. To get classification score for testing images, we sample 10 crops from each testing image at center and four corners with mirroring and take the average. The results are evaluated on the validation set for each ablation study. As a comparison, we go through the same procedure with model pre-trained on ImageNet. The results are shown in Table 1. The table shows that the model pre-trained on our data performs significantly better. It indicates that it is better to have more images in relevant categories than more categories.

Together with the results on scene categories, it is interesting to observe that although AlexNet is small compared to other image classification models developed in recent years, even it can benefit from more training data.

Model	Pre-train	aero	bike	bird	boat	bottle	bus	car	cat	chair	cow	table	dog	horse	mbike	person	plant	sheep	sofa	train	tv	mAP
AlexNet	ImageNet	0.96	0.86	0.88	0.85	0.49	0.94	0.75	0.89	0.62	0.86	0.65	0.87	0.92	0.9	0.85	0.53	0.91	0.68	0.92	0.77	0.8
AlexNet	LSUN	0.98	0.93	0.94	0.9	0.64	0.95	0.78	0.97	0.74	0.96	0.72	0.96	0.98	0.94	0.85	0.59	0.96	0.76	0.97	0.82	0.87
VGG	ImageNet	0.95	0.85	0.92	0.86	0.65	0.92	0.8	0.93	0.68	0.77	0.66	0.9	0.85	0.86	0.94	0.56	0.89	0.6	0.94	0.85	0.82
VGG	LSUN	0.98	0.92	0.94	0.9	0.69	0.96	0.82	0.96	0.75	0.97	0.78	0.93	0.97	0.92	0.95	0.67	0.96	0.73	0.97	0.84	0.88

Table 1: Comparison of pre-training on ImageNet and LSUN. We pre-train AlexNet and VGGnet with ImageNet and our data to compare the learned representation. We fine tune the networks after removing the last layer on PASCAL VOC 2012 images and compare the results. The table shows that pre-training with more images in related categories is better than that with more categories.

**Learned Image Representation:** As a final test, we study the image representation learned by our object categories and compare it to ImageNet to understand the tradeoff between number of images and categories. We compare AlexNet trained by ImageNet and our training data used in the last section. Then we check the response in the first layer. As shown in Figure 6, we find that the filters in the first level present cleaner patterns than those learned on ImageNet data.

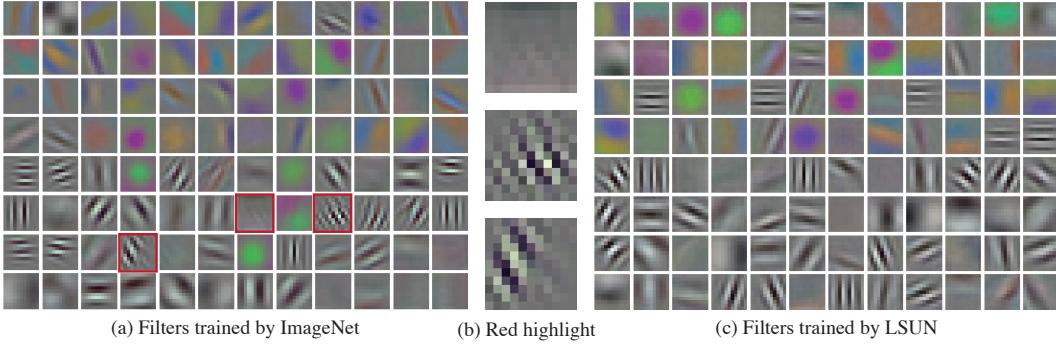


Figure 6: Comparison of learned filters. We train AlexNet with our object images and compare the first level filter with ImageNet. We observe that the filter pattern learned with our data is cleaner, while the filters from ImageNet are noisier, as highlighted in (b).

## 7 Conclusion

This paper proposes a working pipeline to acquire large image datasets with category labels using deep learning with humans in the loop. We have constructed an initial version of “LSUN” database, a database with around a million labeled images in each scene category and more than a million in each of 20 object categories. Experiments with this dataset have already demonstrated the great potential of denser training data for visual recognition. We will continue to grow the dataset indefinitely, making it freely available to the community for further experimentation.

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