We present a simple yet powerful approach to exploit web data for learning CNNs. Specifically, inspired by curriculum learning algorithms, we present a two-step approach for learning CNNs. First, we use simple, easy images to train an initial visual representation. We then use this initial CNN and adapt it to harder Flickr style scene images by exploiting the structure of data and categories (using a relationship graph). We demonstrate that our two-stage CNN performs very competitively to the ImageNet pretrained network architecture for object detection without even using a single ImageNet training label. We also demonstrate the strength of webly supervised learning by localizing objects in web images and training a R-CNN style [19] detector. To the best of our knowledge, we show the best performance on VOC 2007 where no VOC training data is used.

1. Introduction

With an enormous amount of visual data online, web and social media are among the most important sources of data for vision research. Vision datasets such as ImageNet [43], PASCAL-VOC [13] and MS-COCO [30] have been created from Google or Flickr by harnessing human intelligence to filter out the noisy images returned by search engines. The resulting clean data has helped significantly advance performance on relevant tasks [15, 25, 19, 62]. For example, training a neural network on ImageNet followed by fine-tuning on PASCAL-VOC has led to the state-of-the-art performance on the object detection challenge [25, 19]. But human supervision comes with a cost and its own problems (e.g., inconsistency, incompleteness and bias [55]). Therefore, an alternative, and more appealing way is to learn visual representations from the web data directly, without using any manual labeling. But the big question is, can we actually use millions of images online without using any human supervision?

In fact, researchers have pushed hard to realize this dream of learning visual representations from web data.
These efforts have looked at different aspects of weakly supervised learning such as:

- **What are the good sources of data?** Researchers have tried various search engines ranging from text/image search engines [4] to Flickr images [35].
- **What types of data can be exploited?** Researchers have tried to explore different types of data, like images-only [28, 9], images-with-text [4, 45] or even images-with-n-grams [12].
- **How do we exploit the data?** Extensive algorithms (e.g. probabilistic models [16, 28], exemplar based models [9], deformable part models [12], self organizing map [20] etc) have been developed.
- **What should we learn from Web data?** There has been lot of effort ranging from just cleaning data [14, 60, 35] to training visual models [28, 56, 29], to even discovering common-sense relationships [9].

Nevertheless, to the best of our knowledge, while many of these systems have seen orders of magnitudes larger number of images, their performance has never shown to match up against contemporary methods that receive extensive supervision from humans. Why is that?

Of course the biggest issue is the data itself: 1) it contains noise, and 2) it has bias - image search engines like Google usually operate in the high-precision low-recall regime and tend to be biased toward images where a single object is centered with a clean background and a canonical viewpoint [31, 3, 30]. But is it just the data? We argue that it is not just the data, but also the ability of algorithms to learn from large data sources and generalize. For example, traditional approaches which use hand-crafted features (e.g. HOG [9] and classifiers like support vector machines [12] have very few parameters (less capacity to memorize) and are therefore unlikely to effectively use large-scale training data. On the other hand, memory based nearest neighbors classifier can better capture the distribution given a sufficient amount of data, but are less robust to the noise. Fortunately, Convolutional Neural Networks (CNNs) [25] have resurfaced as a powerful tool for learning from large-scale data: when trained with ImageNet [43] (~1M images), it is not only able to achieve state-of-the-art performance for the same image classification task, but the learned representation can be readily applied to other relevant tasks [19, 62].

Attracted by its amazing capability to harness large-scale data, in this paper, we investigate webly supervised learning for CNNs (See Figure 1). Specifically, 1) we present a two-stage webly supervised approach to learning CNNs. First we show that CNNs can be readily trained for easy categories with images retrieved by search engines with no bells or whistles. We then adapt this network to hard (Flickr style) web images using the relationships discovered in easy images; 2) we show webly supervised CNNs also generalize well to relevant vision tasks, giving state-of-the-art performance compared to ImageNet pretrained CNNs if there is enough data; 3) we show state-of-the-art performance on VOC data for the scenario where not a single VOC training image is used - just the images from the web. 4) We also show competitive results on scene classification. To the best of our knowledge, our paper is one of the first papers to achieve competitive or even better object detection performance than ImageNet trained CNNs for the same model architecture. We believe this paper opens up avenues for exploitation of Web data to achieve next cycle of performance gain in vision tasks (and at no human labeling costs!).

### 1.1. Why Webly Supervised?

Driven by CNNs, the field of object detection has seen a dramatic churning in the past two years, which has resulted in a significant improvement in the state-of-the-art performance. But as we move forward, how do we further improve performance of CNN-based approaches? We believe there are two directions. The first and already explored area is designing deeper networks [48, 53]. We believe a more juicier direction is to feed more data into these networks (in fact, deeper networks would often need more data to train). But more data needs more human labeling efforts. Therefore, if we can exploit web data for training CNNs, it would help us move from million to billion image datasets in the future. In this paper, we take the first step in demonstrating that it is indeed possible to have competitive or even better performance to ImageNet pretrained CNNs by just exploiting web data at much larger scales.

### 2. Related Work

Mining high-quality visual data and learning good visual representation for recognition from the Web naturally form two aspects of a typical chicken-and-egg problem in vision. On one hand, clean and representative seed images can help build better and more powerful models; but on the other hand, models that recognize concepts well are crucial for indexing and retrieving image sets that contain the concept of interest. How to attack this problem has long been attractive to both industry and academia.

**From models to data:** Image retrieval [50, 49] is a classical problem in this setting. It is not only an active research topic, but also fascinating to commercial image search engines and photo-sharing websites since they would like to better capture data streams on the Internet and thus better serve user’s information need. Over the years, various techniques (e.g. click-through data) have been integrated to improve search engine results. Note that, using pretrained models (e.g. CNN [60]) to clean up Web data also falls
into this category, since extensive human supervision has already been used.

**From data to models:** A more interesting and challenging direction is the opposite - can models automatically discover the hidden structures in the data and be trained directly from Web data? Many people have pushed hard in this line of research. For example, earlier work focused on jointly modeling images and text and used text based search engines for gathering the data [4, 45, 44]. This tends to offer less biased training pairs, but unfortunately such an association is often too weak and hard to capture, since visual knowledge is usually regarded as common sense knowledge and too obvious to be mentioned in the text [9]. As the image search engines became mature, recent work focused on using them to filter out the noise when learning visual models [17, 59, 57, 56, 29, 12, 20]. But using image search engines added more bias to the gathered data [6, 31, 30]. To combat both noise and data bias, recent approaches have taken a more semi-supervised approach. In particular, [28, 9] proposed iterative approaches to jointly learn models and find clean examples, hoping that simple examples learned first can help the model learn harder, more complex examples [2, 26]. However, to the best of our knowledge, human supervision is still a clear winner in performance, regardless of orders of magnitude more data seen by many of these Web learners.

Our work is also closely related to another trend in computer vision: learning and exploiting visual representation via CNNs [25, 19, 54, 21]. However, learning these CNNs from noisy labeled data [52, 42] is still an open challenge. Following the recent success of convolutional networks and curriculum learning [2, 26, 27], we demonstrate that, while directly training CNNs with high-level or fine-grained queries (e.g. random proper nouns, abstract concepts) and noisy labels (e.g. Flickr tags) can still be challenging, a more learning approach might provide us the right solution. Specifically, one can bootstrap CNN training with easy examples first, followed by a more extensive and comprehensive learning procedure with similarity constraints to learn visual representations. We demonstrate that visual representations learned by our algorithm performs very competitively as compared to ImageNet trained CNNs.

Finally, our paper is also related to learning from weak or noisy labels [10, 36, 11, 51, 58]. There are some recent works showcasing that CNNs trained in a weakly-supervised setting can also develop detailed information about the object intrinsically [47, 34, 38, 5, 37]. However, different from the assumptions in most weakly-supervised approaches, here our model is deprived of clean human supervision altogether (instead of only removing the location or segmentation). Most recently, novel loss layers have also been introduced in CNNs to deal with noisy labels [52, 42]. On the other hand, we assume a vanilla CNN is robust to noise when trained with simple examples, from which a relationship graph can be learned, and this relationship graph provides powerful constraints when the network is faced with more challenging and noisier data.

### 3. Approach

Our goal is to learn deep representations directly from the massive amount of data online. While it seems that CNNs are data-guzzlers - small datasets plus millions of parameters can easily lead to over-fitting, we found it is still hard to train a CNN naively with random image-text/tag pairs. For example, most Flickr tags correspond to meta information and specific locations, which usually results in extremely high intra-tag variation. One possibility is to use commercial text-based image search engine to increase di-
versity in the training data. But if thousands of query strings are used some of them might not correspond to a visualizable concept or some of the query strings might be too fine grained (e.g., random names of a person or abstract concepts). These non-visualizable concepts and fine-grained categories incur unexpected noise during the training process.

One can use specifically designed techniques [9][12] and loss layers [52][52] to alleviate some of these problems. But these approaches are based on estimating the empirical noise distribution which is non-trivial. Learning the noise distribution is non-trivial since it is heavily dependent on the representation, and weak features (e.g., HOG or when the network is being trained from scratch) often lead to incorrect estimates. On the other hand, for many basic categories commonly used in the vision community, the top results returned by Google image search are pretty clean. In fact, they are so clean that they are biased towards iconic images where a single object is centered with a clean background in a canonical viewpoint [31][40][3][30]. This is good news for learning algorithms to quickly grasp the appearance of a certain concept, but a representation learned from such data is likely biased and less generalizable. So, what we want is an approach that can learn visual representation from Flickr-like images.

Inspired by the philosophy of curriculum learning [2][26][27], we take a two-step approach to train CNNs from the Web. In curriculum learning, the model is designed to learn the easy examples first, and gradually adapt itself to harder examples. In a similar manner, we first train our CNN model from scratch using easy images downloaded from Google Image Search. Once we have this representation learned we try to feed harder Flickr images for training. Note that training with Flickr images is still difficult because of noise in the labels. Therefore, we apply constraints during fine-tuning with Flickr images. These constraints are based on similarity relationships across different categories. Specifically, we propose to learn a relationship graph and initial visual representation from the easy examples first, and later during fine-tuning, the error can backpropagate through the graph and get properly regularized. To demonstrate the effectiveness of our representation, we do two experiments: (a) First, we use our final trained network using both Google and Flickr images to test on VOC 2007 and 2012 dataset. We use R-CNN pipeline for testing our representations; (b) We train object detectors from the cleaned out web data and perform localization. These detectors are tested on standard VOC 2007 dataset. The outline of our approach is shown in Figure 2.

3.1. Initial Network

As noted above, common categories used in vision nowadays are well-studied and search engines give relatively clean results. Therefore, instead of using random noun phrases, we obtained three lists of categories from ImageNet Challenge [43], SUN database [61] and NEIL knowledge base [9]. ImageNet syn-sets are transformed to its surface forms by just taking the first explanation, with most of them focusing on object categories. To better assist querying and reducing noise, we remove the suffix (usually correspond to attributes, e.g., indoor/outdoor) of the SUN categories. Since NEIL is designed to query search engines, its list is comprehensive and favorable, we collected the list for objects and attributes and removed the duplicate queries with ImageNet. The category names are directly used to query Google for images. Apart from removing unreadable images, no pre-processing is performed. This leave us with ~600 images for each query. All the images are then fed directly into the CNN as training data.

For fair comparison, we use the same architecture (besides the output layer) as the BLVC reference network [24], which is a slight variant of of the original network proposed by [45]. The architecture has five convolutional layers followed by two fully connected layers. After seventh layer, another fully connected layer is used to predict class labels.

3.2. Representation Adaptation with Graph

After converging, the initial network has already learned favorable low-level filters to represent the “visual world” outlined by Google Image Search. However, as mentioned before, this “visual world” is biased toward clean and simple images. For example, it was found that more than 40% of the cars returned by Google are viewed from a 45 degree angle, and horses rarely occur lying on the ground [31]. Moreover, when a concept is a product, lots of the images are wallpapers and advertisements with artificial background and the concept of interest centered (and of course, viewed from the best selling view). On the other hand, photo-sharing websites like Flickr have more realistic images since the users upload their own pics. Though photographic bias still exist, most of the images are closer-looking to the visual world we experience everyday. Datasets constructed from them are shown to generalize better [55][30]. Therefore, as a next step, we aim to narrow the gap by fine-tuning our representation on Flickr images.

For fine-tuning the network with hard Flickr images, we again feed these images as-is for training, with the query words acting as class labels. While we are getting more realistic images, we did notice that the data becomes noisier. Powerful and generalizable as CNNs are, they are still likely

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1We tried to train a network with search engine results of ~7000 entities randomly sampled from Web noun phrases but the network does not converge.

2Flickr images are downloaded using tag search. We use the same query strings as used in Google Image Search.
to be diluted by the noisy examples over the fine-tuning process. In an noisy open-domain environment, mistakes are unavoidable. But humans are more intelligent: we not only learn to recognize concepts independently, but also build up interconnections and develop theories to help themselves better understand the world [7]. Inspired by this, we want to train CNNs with such relationships - with their simplest form being pair-wise look-alike relationships [46, 9, 12].

One way to obtain relationships is through extra knowledge sources like WordNet [33] or Word2Vec [32]. However, they are not developed for the visual domain we are interested in. Instead, we take a data-driven approach to discover such relationships in our data: we assume the network will intrinsically develop connections between different categories when clean examples are offered, and all we have to do is to distill the knowledge out.

We take a simple approach by just testing our network on the training set, and take the confusion matrix as the relationships. Mathematically, for any pair of concepts $i$ and $j$, the relationship $R_{ij}$ is defined as:

$$R_{ij} = P(i|j) = \frac{\sum_{k \in C_i}CNN(j|I_k)}{|C_i|}, \quad (1)$$

where $C_i$ is the set of indexes for images that belong to concept $i$, $|\cdot|$ is the cardinality function, and given pixel values $I_k$, $CNN(j|I_k)$ is the network’s belief on how likely image $k$ belongs to concept $i$. We want our graph to be sparse, therefore we just used the top $K$ ($K = 5$ in our experiments) and re-normalized the probability mass.

After constructing the relationship graph, we put this graph (represented as a matrix) on top of the seventh layer of the network, so that now the soft-max loss function becomes:

$$L = \sum_k \sum_i R_{ij} \log(CNN(i|I_k)). \quad (2)$$

In this way, the network is trained to predict the context of a category (in terms of relationships to other categories), and the error is back-propagated through the relationship graph to lower layers. Note that, this extra layer is similar to [52], in which $R_{ij}$ is used to characterize the label-flip noise. Different from them, we do not assume all the categories are mutually exclusive, but instead inter related. For example, “cat” is a hyper-class of “Siamese cat”, and its reasonable if the model believes some examples of “Siamese cat” are more close to the average image of a “cat” than that of the “Siamese cat” and vice versa. Please see experimental section for our empirical validation of this assumption. For fear of semantic drift, in this paper we keep the initially learned graph structure fixed, but it would be interesting to see how updating the relationship graph performs (like [9]).

### 3.3. Localizing Objects

To show the effectiveness of our representation, after fine-tuning we go back to the problem of organizing the data on the web: that is, clean up the data by removing noise and localizing objects in the images. But shouldn’t the CNN have learned intrinsically the salient regions in an image for the concepts of interest [47, 5, 37]? Isn’t getting clean data as simple as ranking the initial set of images based on the soft-max output? We argue that, while the network has already learned to model the positive examples when solving the multi-way classification problem, it has not yet learned the distribution of negative data, e.g. background clutter. While scenes and attributes are more “stuff-like” and thus finding clean full images might be enough, it is important for objects to be localized well, particularly when they are small in the original image. In fact, since the network is optimized for a classification loss, the representation is learned to be spatially invariant (e.g., the network should output “orange” regardless of where it exists in the image, and how many there are), precisely localizing the object is a very challenging task.

To overcome the difficulty, we developed a subcategory discovery based approach similar to [9] to localize the object given a collection of search engine results. It is based on Google’s bias toward images with a single centered object, so we can use them as seeds to locate similar examples in other images of the collection. Apart from the exemplar based pipeline, there are some significant differences:

- Instead of sliding window based detection framework, we used object proposals from EdgeBox [63], so that for each image, only a few hundred of patches are examined.

- Given the proposals, we compute the seventh layer output ($fc7$) to represent each patch, instead of HOG. The original alignment is lost, but the feature has better generalization power (See qualitative results from Figure 4).

- For Exemplar-LDA [22], we extracted random patches from all the downloaded Web data to build the negative correlation matrix.

- Affinity propagation [18] is used in [9] for subcategories, whereas we just merged the initial clusters (formed by top detections) from bottom up to get the final subcategories, which works well and takes less time.

Finally after getting the clean examples, we train detectors following the R-CNN [19] approach. In the first trial,
we simply used the positive examples as-is, and negative patches are randomly sampled from YFCC dataset. Typically, hundreds of positive instances per category are available for training. While this number is comparable to the PASCAL VOC 2007 trainval set (except car, chair and person), one big advantage of Internet is its nearly infinite limit on data. Therefore, we tried two augmentation strategies:

**Data augmentation** We followed [19] and did data augmentation on the positive training examples. We again used EdgeBox [63] to propose regions of interest on images where the positive example lies in. And whenever a proposal has a higher than 0.5 overlapping (measured by IoU, intersection over union) with any of the positive bounding box, we add it to the pool of our training data.

**Category expansion** Here we again used the relationship graph to look for synonyms and similar categories in our list of objects for more training examples. After semantic verification, we add the examples into training dataset. We believe adding the examples from these categories should allow better generalization.

4. Experimental Results

We now describe our experimental results. Our goal is to demonstrate that the visual representation learned using two-step webly supervised learning is meaningful. For this, we will do four experiments: 1) First, we will show that our learned CNN can be used for object detection. Here, we use the approach similar to R-CNN [19] where we will fine-tune our learned CNN using VOC data. This is followed by learning SVM-detectors using CNN features. 2) We will also show that our CNN can be used to clean up the Web data: that is, discover subcategories and localize the objects in Web images. 3) We will train detectors using the cleaned up web data and evaluate them on VOC data. Note in this case, we will not use any VOC training images. We will only use web images to train both the CNN and the subsequent SVMs. 4) Finally, we will show scene classification results to further showcase the usefulness of the trained representation.

All the networks are trained with the Caffe Toolbox [24]. In total we have 2,240 objects, 89 attributes, and 874 scenes. Two networks are trained: 1) The object-attribute network (GoogleO), where the output dimension is 2,329, and 2) All included network (GoogleA), where the output dimension is 3,203. For the first network, ~1.5 million images are downloaded from Google Image Search. Combining scene images, ~2.1 million images are used in the second network. The first network is then fine-tuned with ~1.2 million Flickr images (Flickr). We set the batch size to be 256 and start with a learning rate of 0.01. The learning rate is reduced by a factor of 10 after every 150K iterations, and we
stop training at 450K iterations. For fine-tuning, we choose a step size of 30K and train the network for a total of 100K iterations.

### Is Confusion Matrix Informative for Relationships?
Before we delve into the results, we want to first show if the following assumption holds: whether the network has learned to discover the look-alike relationships between concepts in the confusion matrix. To verify the quality of the network, we take the GoogleO net and visualize the top-5 most confusing concepts (including self) to some of the categories. To ensure our selection has a good coverage, we first rank the diagonal of the confusing matrix (accuracy) in the descending order. Then we randomly sample 3 categories from the top-100, bottom-100, and middle-100 from the list. The visualization can be seen in Figure 3.

#### 4.1. PASCAL VOC Object Detection
Next, we test our webly trained CNN model for the task of object detection. We run our experiments on VOC 2007 and VOC 2012 datasets. We follow the R-CNN pipeline: given our trained CNN, we first fine-tune the network using trainval images. We then learn a SVM using trainval fine-tuned \( fc \ell \) features. For VOC 2007, we used a step size of 20K and 100K iterations of fine-tuning. For VOC 2012, since the number of trainval images is doubled, we use 200K iterations of fine-tuning with a step size of 50K. For fair comparison, since we did not tune any parameters in R-CNN, the settings for SVM training are kept identical to those for ImageNet. Since we trained three different networks with different types of training data, we report three different numbers (GoogleO-FT, GoogleA-FT, Flickr-FT).

Note that Flickr-FT network corresponds to learning both on Google and Flickr data using two step process and is initialized with GoogleO network.

As baselines we compare against R-CNN trained using CNN-Scratch features [1] (VOC-Scratch), R-CNN trained on ImageNet features without fine-tuning (ImageNet-NFT), R-CNN trained on ImageNet features with fine-tuning on VOC trainval (ImageNet-FT) and our webly trained CNN without fine-tuning (GoogleO-NFT, GoogleA-NFT and Flickr-NFT). The results on VOC 2007 are indicated in Table 1. As the results show, all our networks outperform VOC-Scratch by a huge margin. When it comes to results without fine-tuning on VOC, our Flickr-FT performs exactly similar to Imagenet-NFT (mAP = 44.7). This indicates that the webly supervised CNN learns visual representation comparable to ImageNet pretrained CNN. After fine-tuning, all of our webly supervised CNN perform comparably to ImageNet pretrained CNN.

The results on VOC 2012 are reported in Table 2. In this case, our two-stage CNN with fine-tuning (Flickr-FT) outperforms the ImageNet pretrained network. Both in case of VOC 2007 and 2012, our webly supervised CNN seems to work better for vehicles since we have lots of data for cars and other vehicles (∼500). On the other hand, ImageNet CNN seems to outperform our network on animals such as cat and dog. This is probably because ImageNet has a lot more data for animals. This indicates that the performance of our network might increase further if more query strings for animals are added. Note that the original R-CNN paper fine-tuned the ImageNet network using train data alone and therefore reports lower performance. For fair comparison, we fine-tuned both ImageNet network and our webly supervised network on combined trainval images.
Table 3. Webly supervised VOC 2007 detection results (No VOC training data used).

| VOC 2007 test | aero | bike | bird | boat | bottle | bus | car | cat | chair | cow | table | dog | horse | mbike | person | plant | sheep | sofa | train | tv | mAP |
|---------------|------|------|------|------|--------|-----|-----|-----|------|-----|-------|-----|-------|-------|--------|-------|-------|------|-------|---|-----|
| LEVAN         | 14.0 | 36.2 | 12.5 | 10.3 | 9.2    | 35.0| 35.9| 8.4 | 10.0 | 17.5| 6.5   | 12.9| 30.6  | 27.5  | 6.0    | 1.5   | 18.8  | 10.3 | 23.5  | 16.4| 17.1 |
| GoogleO      | 30.2 | 34.3 | 16.7 | 13.3 | 6.1    | 43.6| 27.4| 22.6| 6.9  | 16.4| 10.0  | 21.3| 25.0  | 35.9  | 7.6    | 9.3   | 21.8  | 17.3 | 31.0  | 18.1| 20.7 |
| GoogleA      | 29.5 | 38.3 | 15.1 | 14.0 | 9.1    | 44.3| 28.3| 24.9| 6.9  | 15.8| 9.7   | 22.6| 23.5  | 34.3  | 9.7    | 12.1  | 21.4  | 15.8 | 33.4  | 19.4| 21.5 |
| Flickr        | 32.6 | 42.8 | 19.3 | 13.9 | 9.2    | 46.6| 29.6| 20.6| 6.8  | 17.8| 10.2  | 22.4| 26.7  | 40.8  | 11.7   | 14.0  | 19.0  | 19.0 | 34.0  | 21.9| 22.9 |
| Flickr-M      | 32.7 | 44.3 | 17.9 | 14.0 | 9.3    | 47.1| 26.6| 19.2| 8.2  | 18.3| 10.0  | 22.7| 25.0  | 42.5  | 12.0   | 12.7  | 22.2  | 20.9 | 35.6  | 18.2| 23.0 |
| Flickr-C      | 30.2 | 41.3 | 21.7 | 18.3 | 9.2    | 44.3| 25.5| 22.6| 9.8  | 21.5| 10.4  | 26.7| 27.3  | 42.8  | 12.6   | 13.3  | 20.4  | 20.9 | 36.2  | 22.8| 24.4 |

4.2. Object Localization

In this subsection, we are interested to see if we can detect objects without using a single PASCAL training image. We believe this is possible since we can localize objects automatically in web images with our proposed approach (see Section 3.3). Please refer to Figure 4 for the qualitative results on the training localization we can get with fc7 features. Compared to [9], the subcategories we get are less homogeneous (e.g., people are not well-aligned, objects in different view points are clustered together). But just because of this more powerful representation (and thus better distance metric), we are able to dig out more signal from the training set - since semantically related images can form clusters and won’t be purged as noise when an image is evaluated by its nearest neighbors.

Using localized objects, we train R-CNN based detectors to detect objects on the PASCAL VOC 2007 test set. We compare our results against [12], who used Google N-grams to expand the categories (e.g., “horse” is expanded to “jumping horse”, “racing horse” etc.) and the models were also directly trained from the web. The results are shown in Table 3. For our approach, we try five different settings: a) GoogleO: Features are based on GoogleO CNN and the bounding boxes are also extracted only on easy Google Images; b) GoogleA: Features are based on GoogleA CNN and the bounding boxes are extracted on easy images alone; c) Flickr: Features are based on final two-stage CNN and the bounding boxes are extracted on easy images; d) Flickr-M: Features are based on final two-stage CNN and the bounding boxes are extracted on easy and hard images; e) Flickr-C: Features are based on final two-stage CNN and the positive data includes bounding box of original and related categories. From the results, we can see that in all cases the CNN based detector boosts the performance a lot.

This demonstrates that our framework could be a powerful way to learn detectors on the fly without labeling any training images that still yields respectable results. We plan to release this as a service for everyone to train R-CNN detectors on the fly.

4.3. Failure Modes for Webly Trained Detectors

In this section, we would like to gain more insights about the potential issues of our webly supervised object detection pipeline. We took the results from our best model (Flickr-C) and fed them to the publicly available diagnosis tool [23]. Figure 5 and 6 highlight some of the interesting observations we found.

Firstly, localization error accounts for a majority of the false positives. Since Google Image Search do not provide precise location information, the background is inevitably included when the detector is trained (e.g., aeroplane, dining table). Multiple instances of an object can also occur in the image, but the algorithm has no clue that they should be treated as separate pieces (e.g., bottle). Moreover, since our CNN is directly trained on full images, the objective function also biases the representation to be invariant (to spatial locations, etc.). All these factors caused localization issues.

Second, we did observe some interesting semantic drift between PASCAL categories and Google categories. For example, bicycle can also mean motorcycle on Google. Sense disambiguation for this polysemous word [44,8] is
needed here. Also note that our person detector is confused with cars, we suspect it is because “caprice” was added as a related category but it can also mean a car (“chevy caprice”). How to handle such issues is a future research topic by itself.

### 4.4. Scene Classification

To further demonstrate the usage of CNN features directly learned from the web, we also conducted scene classification experiments on the MIT Indoor-67 dataset [39]. For each image, we simply computed the fc7 feature vector, which has 4096 dimensions. We did not use any data augmentation or spatial pooling technique, with the only pre-processing step normalizing the feature vector to unit $\ell_2$ length [41]. The default SVM parameters ($C=1$) were fixed throughout the experiments.

Table 4 summarizes the results on the default train/test split. We can see our web based CNNs achieved very competitive performances: all the three networks achieved an accuracy at least on par with ImageNet pretrained models. Fine-tuning on hard images enhanced the features, but adding scene-related categories gave a huge boost to 66.5 (comparable to the CNN trained on Places database [62], 68.2). This indicates CNN features learned directly from the web are indeed generic.

Moreover, since we can easily get images for semantic labels (e.g. actions, N-grams, etc.) other than objects or scenes from the web, webly supervised CNN bears a great potential to perform well on many relevant tasks - with the cost as low as providing a category list to query for that domain.

| Indoor-67 | Accuracy |
|-----------|----------|
| ImageNet  | 62       |
| OverFeat  | 58.4     |
| GoogleO   | 58.1     |
| GoogleA   | 66.5     |
| Flickr    | 59.2     |

Table 4. Scene Classification Results on MIT Indoor-67 Dataset.

### 5. Conclusion

We have presented an approach to train CNNs using noisy web data. Specifically, we have presented a two-stage approach. In the first stage we train CNN with easy images downloaded from Google Image Search. This network is then used to discover structure in the data in terms of similarity relationships. Finally, we fine-tune the original network on hard (but realistic) Flickr images using the relationship graph. We demonstrate that our two-stage CNN comes close to ImageNet pretrained architecture on VOC 2007, and outperforms on VOC 2012. We would like to emphasize that our CNN was trained with zero explicit human labels. We even show that our representation is so powerful that we can use it to organize the web data and learn category detectors directly from web data. To the best of our knowledge, we show the best performance on VOC 2007 where no VOC training data is used. Additional results on scene understanding further demonstrate the effectiveness of our webly learned representation.

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Figure 6. Top false positives for selected categories on PASCAL VOC 2007 detection with Flickr-C. From top down: aeroplane, bicycle, bottle, dinning table, and person.

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