Object-centric Sampling for Fine-grained Image Classification

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Abstract

This paper proposes to go beyond the state-of-the-art deep convolutional neural network (CNN) by incorporating the information from object detection, focusing on dealing with fine-grained image classification. Unfortunately, CNN suffers from over-fitting when it is trained on existing fine-grained image classification benchmarks, which typically only consist of less than a few tens of thousands training images. Therefore, we first construct a large-scale fine-grained car recognition dataset that consists of 333 car classes with more than 150 thousand training images. With this large-scale dataset, we are able to build a strong baseline for CNN with top-1 classification accuracy of 81.6%. One major challenge in fine-grained image classification is that many classes are very similar to each other while having large within-class variation. One contributing factor to the within-class variation is cluttered image background. However, the existing CNN training takes uniform window sampling over the image, acting as blind on the location of the object of interest. In contrast, this paper proposes an object-centric sampling (OCS) scheme that samples image windows based on the object location information. The challenge in using the location information lies in how to design powerful object detector and how to handle the imperfectness of detection results. To that end, we design a saliency-aware object detection approach specific for the setting of fine-grained image classification, and the uncertainty of detection results are naturally handled in our OCS scheme. Our framework is demonstrated to be very effective, improving top-1 accuracy to 89.3% (from 81.6%) on the large-scale fine-grained car classification dataset.

1. Introduction

Large-scale image classification has been undergoing amazing progress since the seminal work of Krizhevsky et al. [7] in 2012, which trained deep convolutional neural networks (CNN) to produce dramatic classification accuracy on the ImageNet Large Scale Visual Recognition Challenge (ILSVRC2012). In contrast, the success of deep CNN on fine-grained image classification has not been so overwhelming. One reason for this slackness is that CNN often requires large-scale training data to avoid over-fitting but fine-grained image labels are expensive to obtain. For
example, Amazon Mechanical Turkers may be easy to tell whether an image contains a car, but it would be very difficult for them to tell whether an image contains a Chevrolet Equinox 2010–2013. In fact, most existing fine-grained image classification benchmark datasets only consist of a few tens of thousands (or less) of training images. For example, the Stanford car dataset [6] only consists of 8,144 training images. As a result, training CNN on this dataset only obtains 68% top-1 classification accuracy (compared to 69.5% top-1 accuracy using conventional LLC features with SPM and SVM [6]).

To build a strong baseline for CNN so that we can study any further improvement on CNN, we construct a large-scale fine-grained car classification dataset. Our car dataset consists of 157,023 training images and 7,840 testing images from 333 categories, each of which is described as “which brand, which model and which year blanket”. A year blanket means the year range that a car model does not change its outlook design (so that the cars in the same year blanket are not visually distinguishable). The training set of this dataset is more than one magnitude larger than the Stanford car dataset [6]. This enables us to build a strong baseline performance using CNN, achieving 81.6% top-1 classification accuracy (compared to 52.8% top-1 accuracy using conventional LLC features with SPM and SVM according to our own experiment).

One major challenge in fine-grained image classification is to distinguish subtle between-class differences while each class often has large within-class variation in the image level. One contributing factor to the within-class variation is cluttered image background. The existing CNN training uniformly samples image windows from a target image, acting as blind on where is the foreground (namely, the object of interest) and where is background in the image. While background portion sometimes benefits base-class image classification by providing context cues, it is less likely to help fine-grained image classification because all the categories belong to the same base class (like the car class in this case). Figure 1 shows our proposed pipeline for fine-grained image classification. In contrast to the uniform sampling as used in most existing CNN training approaches, we first apply detection on a target image to derive the location of the object of interest and then use the location information to enable an object-centric sampling (OCS) scheme. The OCS tends to sample more image windows around the detected object for CNN training.

In fact, it is an obvious idea to use object detection to help fine-grained image classification to down-weight cluttered background, but there has not been much success in the literature in this direction. To our view, there are two critical requirements for object detection to help: 1) accurate object detection, and 2) a robust mechanism to handle imperfectness in detection results. To address the first requirement, we introduce a saliency-aware object detection, which consists of the efforts in both constructing a saliency-oriented dataset and training a saliency-aware detector. For dataset construction, we only label the most salient object as the ground truth for an image while both the background and less salient objects (like smaller objects or occluded objects) in the image are labeled as negative samples. We adopt the Regionlet object detection framework [18] to learn our object detector because of its unique characteristics that it operates on original images and has the capability of implying object scales through detection response, as discussed in Sec. 4.1.2. Indeed, we exploit the specific property in the fine-grained image classification setting – that is, the object of interest is always the most salient object in an image to achieve high accuracy in object detection. To address the second requirement, we propose the OCS to be a multinomial sampling with a soft emphasis over the detection output. The training samples which have larger overlap with the detection or closer to the original image would have a higher probability to be sampled during CNN training. On one hand, the OCS incorporates detections to implicitly down-weight noisy samples from irrelevant background; on the other hand, it is robust to imperfect detections because of soft sampling scheme.

The major contributions of this paper lie in three folds: 1) we introduce a large-scale fine-grained car classification dataset to achieve strong baseline performance using CNN, enabling the study of the approaches for further improving CNN; 2) based on the Regionlet framework, we propose a saliency-aware object detection method that is specifically tailored for detection in a fine-grained image classification setting; 3) we propose an object-centric sampling (OCS) scheme to replace uniform sampling in CNN training, and the OCS is a multinomial sampling for handling the imperfectness in detection results. Our proposed overall approach achieves significant performance improvement, improving the top-1 classification accuracy of 81.6% by the state-of-the-art CNN to 89.3% on the large-scale car dataset.

The rest of this paper is organized as following: Sec. 2 describes the related work. Sec. 3 introduces the large-scale fine-grained car classification dataset. Sec. 4 presents our saliency-aware object detection method and the OCS scheme for CNN training. Sec. 5 discusses the experiment results, followed with conclusion.

2. Related Work

Deep convolutional neural network for image classification. Deep convolutional neural network (CNN) [8] has become the dominant approach for large-scale image classification. Since Krizhevsky et al. [7] overwhelmingly won the ImageNet Large Scale Visual Recognition Challenge using a deep CNN, CNN has been widely used for large-scale image classification tasks. There are efforts to improve
CNN architecture, for example, recent works of using more layers [14], to achieve even better performance. The effort of this work is orthogonal to those efforts. Rather, we will use the CNN proposed in [7] as the example, and we show how to incorporate object detection results to improve classification accuracy. The approach proposed in this paper, object-centric pooling (OSC), is expected to be applicable to CNNs with deeper architectures [14, 13].

Fine-grained image classification datasets. CNN has been known to work well on large-scale classification datasets, but it is often suffered in the case of small training data due to over-fitting. Unfortunately, in the research community, most of the existing fine-grained image classification benchmark datasets are fairly small. This is because fine-grained labels are often difficult to obtain. Table 1 lists the sizes of some popular fine-grained image classification benchmark datasets. To enable applying CNN for fine-grained image classification, we construct a large-scale fine-grained car classification dataset. The dataset consists of 333 car classes with 157,023 training images and 7,840 testing images. With this large-scale dataset, CNN is able to achieve 81.6% top-1 classification accuracy, which serves as a strong baseline for us to further study the possible approaches that could go beyond the current CNN.

Fine-grained image classification. Fine-grained image classification has been an active research topic in recent years. Compared to base-class image classification, fine-grained image classification needs to distinguish many similar classes with only subtle differences among the classes. There has been much work [20, 2, 19] aiming at localizing salient part of fine-grained classes. To ease the challenge, many of them even assume that the ground-truth bounding boxes of the objects of interest are given. This work is different in two aspects. First, rather than using ground-truth bounding boxes, we make attempts to train a good object detector by proposing a saliency-aware detection approach based on the Regionlet framework. Second, we build a mechanism to handle imperfect detection results.

Object centric classification. Object centric classification means using object location information for image classification. It is different from popular approaches like spatial pyramid matching (SPM) where an image is blindly divided into SPM blocks for feature pooling. Apparently, if the accurate information about object location could be obtained, object centric classification should be a better choice than SPM based classification. This is especially the case for fine-grained image classification where the key is to distinguish subtle differences from similar classes and removing cluttered background is helpful. This work is conceptually similar to object centric pooling (OCP) as in [12], but it is different in the way that we designed a much more powerful detector to achieve higher detection accuracy. This is done by exploiting some specific properties that exist in fine-grained image classification. And, the detector here is trained in a supervised manner. In contrast, in OCP, the detectors were trained in an unsupervised manner, and the resulting detectors were fairly weak.

Detection with Regionlets. There is a rich literature in object detection research. Deformable part model (DPM) [3] has been a popular approach for generic object detection in the past years. Recently, regions with CNN (R-CNN) approach [4] achieves excellent performance on benchmark datasets. Both approaches require to scale images (so that the object is fit into a fixed-size sliding window) or warp candidate bounding boxes (to the same size to be input into CNN). Such treatments enable scale-invariant property. However, in the case of object detection for fine-grained image recognition, scale is an important saliency cue that we hope to exploit, as explained in more details in Section 4.1.2. Regionlet approach [18] is a good choice because it operates on the candidate bounding boxes proposed on original images, and it has the capability to utilize scale as an important saliency cue. This work also makes some important modifications to the original Regionlet approach, namely, saliency-aware object detection, which exploits the special property in the setting of fine-grained image classification where the object of interests is always the most salient (e.g., not occluded, occupying a big portion of image, etc) object in an image.

### Table 1: The size of our car dataset in comparison with the sizes of existing fine-grained image classification benchmark datasets. In term of the number of training images, our car dataset is more than one magnitude larger than existing datasets.

| Datasets            | Classes | # of Images (Train/Test) |
|---------------------|---------|--------------------------|
| Caltech-USCD Bird   | 200     | 5,994/5,794              |
| Oxford Flower 102   | 102     | 2,040/6,149              |
| Stanford Dog        | 120     | 12,000/8,580             |
| Oxford Cat&Dog      | 37      | 3,680/3,669              |
| Stanford Car        | 196     | 8144/8041                |
| Our car dataset     | 333     | 157,023/7,840            |

3. A Large Scale Car Dataset

To construct a large-scale fine-grained car classification dataset, we crawled images from Internet and hired car experts to provide a label for each image. We first tried to use Amazon Mechanical Turk to label the images, but the
Figure 2: Some sample images from our large-scale fine-grained car classification dataset. Each image is labeled as maker, model and year blanket, for example, Chevrolet Equinox 2010–2013. The use of year blanket is because the cars within the range of the same year blanket do not change their designs on outlook and thus they are visually not distinguishable. All images are naturally taken images. The objects of interest are mostly centered in images, and they have fairly arbitrary poses.

returned fine-grained labels were too noisy to be useful. Therefore, we ended up hiring car experts to label the images in-house. We also purposely discarded artificially synthesized images and only kept the natural images directly taken by cameras. We also paid more attention to images where a car of interest is the most salient object in an image. After 8 months of efforts of 4 full-time labelers, we have obtained 157,023 training images and 7,840 testing images from totally 333 fine-grained car categories. We made efforts of cross-checking among different labeler to ensure high-quality labels, and the images in the testing set was ensured to have no overlapping with the images in the training set.

The dataset currently covers most car types from 5 brands (or makers), Chevrolet, Ford, Honda, Nissan and Toyota. Figure 2 shows some sample car images from the dataset. There are totally 140 different car models with years ranging from 1962 to 2013. Each of the car images is labeled to be one (and only one) of the 333 fine-grained car categories. Table 2 describes the divides of the dataset with respect to car makers. Figure 3 shows some statistics of the dataset.

It is important to realize that the images for fine-grained classification are very different from the images for generic base-class classification (like PASCAL VOC). This is because, when a user takes an image for the purpose of fine-grained image classification, the user is more or less in a collaborative mode to take a close-up photo. This is particularly the case when we are thinking of the scenario of search by image where an user tries to take a photo by a smartphone and then search for relevant information on Internet (for example, the price of the same type of car on Craigslist). Figure 4 shows the histogram of the relative sizes of the objects of interest in the images from the fine-grained car dataset, and it is contrast by the case of PASCAL VOC 2007. For the fine-grained car dataset, it is hard to label bounding boxes on all images. As a result, we sampled about 11,000 images from the dataset and manually labeled bounding boxes on the objects of interest in those images. From Figure 4, it is evident that, for fine-grained image classification, an object of interest often occupies a significant portion of an image, reflecting its strong saliency in an image; but it is not the case for base-class classification as in PASCAL VOC.

While we are using our available dataset for this work, we continue to grow our car dataset, both covering more car categories and enriching the existing classes that currently

| Manufacturer | total # | # of models | # of years | # of categories |
|--------------|---------|-------------|------------|-----------------|
| Chevrolet    | 47909   | 25          | 52         | 66              |
| Ford         | 13542   | 31          | 38         | 69              |
| Honda        | 41264   | 24          | 24         | 61              |
| Nissan       | 24611   | 37          | 44         | 76              |
| Toyota       | 37537   | 23          | 49         | 61              |
4. Object-centric Sampling for Fine-grained Image Classification

4.1. Saliency-aware Object Detection

The term “saliency” is usually referred as the saliency map which describes how salient a pixel is in the image. Without any confusion, here we borrow the term “saliency” to describe the importance of an object in an image for fine-grained image classification. Thus the “saliency” is defined in object level in contrast to pixel level.

The target of object detection for fine-grained image classification is different to that of general object detection. In later case, we aimed at localizing all the objects of interest. While in fine-grained image classification, usually there is only one object that represents the fine-grained label of the image. As shown in Fig 5, the most salient object generally corresponds to the fine-grained label if multiple objects exist. Thus small detections are less likely to be the required detection compared to bigger detections. If two detections have the same scale, completely visible objects are more likely to be of interest than significantly occluded objects. These fundamental differences put specific requirements on the object detector and the training strategy. The object detector should be aware of object scales and occlusions, etc. Ideally, small detection responses should be linked to relatively small or occluded objects, or false alarms. We resolve the challenge by constructing a saliency-aware dataset and using a scale-aware object detector. The occlusion awareness is implicitly achieved by training the detector with visible objects.

4.1.1 Construct training/testing set for detection

We construct a saliency-aware training set for our object detector. As aforementioned, traditional detection labeling encourages to detect all objects appearing in an image, which may not comply with the task of fine-grained image classification. To facilitate saliency-aware detection, we only label the salient object in one image and surely it should be consistent with the fine-grained category label, i.e. the labeled object should belong to the fine-grained category. For each image, we label one and only one object as the detection ground truth. When multiple instances are available, the selection is done based on a mixed criteria of saliency:

- The bigger object is preferred over smaller objects.
- The visible object is preferred over occluded objects.
- An object in the center is preferred over objects around the corner.
- The object’s fine-grained category label is consistent with the image label.

Typically only one object satisfies one or more of these criteria. In any case multiple instances equally meet these criteria, which is not likely to happen, a random object is selected for the ground truth labeling.

Note that there might be small cars, occluded cars, cars off the center that are given negative labels. We delicately apply this labeling protocol to enhance the saliency-aware training. As a consequence, the smaller or occluded cars are likely to have relatively smaller detection response because they have higher chance being put into the negative set. For middle scale objects which could appear in positive samples for some images and in negative samples for others, we rely on the object detector to produce a “middle” high score.

Labeling all the images in the large-scale dataset is very expensive and not necessary. We totally labeled 13,745 images, in which 11,000 images are used for training and 2,745 images are used for testing. It corresponds to slightly more than 8% of the entire fine-grained car dataset.

A detector trained on the constructed dataset is not necessarily capable of detecting the salient object. For example, the most import saliency factor, scale of the object, is not distinguishable based on detection responses for most
object detectors. Because only one detection can be used for our fine-grained image classification, we have to struggle with the option between a bigger size detection with lower response and a smaller size detection with higher detection response if the detector does not imply the object scale by detection scores.

4.1.2 Train the scale-aware detector: Regionlet

Most of the popular object detectors [17, 1, 3, 4] are learned with a fixed scale template. For example, Dalal et al. [1] and Wang et al. [17] trained the human detector using a 96 × 160 HOG template. The root filter and part filters in deformable part-based model [3] also use fixed resolution HOG templates. Deep convolutional neural network based object detectors such as [4] are learned entirely from a fixed input resolution such as 224 × 224 or 227 × 227. Although multiple scale object detection can be achieved by operating the learned models on different scales of the image, these detectors cannot distinguish object scales. In other words, they give the same response to two objects only differed in scales, because these two objects will be resized to the same scale and fed to the detector.

The Regionlet detector introduced by Wang et al. [18] directly deals with the original object scale. It supports training and testing on arbitrary detection windows generated from low-level segmentation cues. In contrast to warping positive samples to a fixed resolution, the Regionlet approach takes the original positive samples as the input, thus preserving the scale information during training. The Regionlet classifier is a boosting classifier composed of thousands of weak classifiers:

\[
H(x) = \sum_{t=1}^{T} h_t(x),
\]

where \( T \) is the total number of training stages, \( h_t(x) \) is the weak classifier learned at stage \( t \) in training, \( x \) is the input image. The weak classifier \( h_t(x) \) can be written as a function of several parameters: the spatial location of Regionlets in \( h_t \), and the feature used for \( h_t \), as following:

\[
h_t(x) = G(p_t, f_t, x),
\]

where \( p_t \) is a set of Regionlet locations, \( f_t \) is the feature extracted in these regions. The feature extraction locations \( p \) are defined to be proportional to the resolution of the detection window. Because feature extraction regions are automatically adapted to accommodate the detection window size, the Regionlet detector operate on the original object scale. Thus we use the Regionlet detector for our fine-grained image classification.

In testing phase, we apply the Regionlet detector to all the object proposals. We extend the conventional non-max suppression by only taking the object proposal which gives the maximum detection response. This operation is done over the whole image, regardless of the overlap between two detections.

4.2. Object-centric sampling for CNN training

With the detected bounding boxes, our next question is how to utilize these bounding boxes to train an accurate deep CNN for fine-grained classification. Most previous studies [20] exploit the bounding box annotations simply crop the image patch within a bounding box and use the cropped image (probably resized) as the input to a learning system. However, this method suffers from a crucial deficiency: the detected bounding boxes might not be hundred percent correct. Therefore cropping the image according to the detected bounding boxes may lose a lot of useful information. On the other hand, translation is an effective technique for data augmentation for preventing over-fitting of the deep CNN. Therefore, we do not crop out a single image but rather generate multiple patches guided by detection.

The sampling based approach has been exploited to generate multiple image patches from an image for data augmentation. The common practice is to generate an image patch\(^1\) by random sampling over a valid range, which is also implemented by the popular Cuda-convnet\(^2\). However, uniform sampling has innocently ignored the position

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\(^1\)A fix sized image patch is full determined by its starting coordinates in the left upper corner.

\(^2\)https://code.google.com/p/cuda-convnet/
of the interesting object and it could end up with many sampled patches with small overlap with the interesting object, consequently confusing the learning of CNN. To be more effective in utilizing the detected bounding boxes, we propose in the paper a non-uniform sampling approach based on the detected position of the interesting object. The assumption of the non-uniform sampling is that the detected bounding box provides a good estimation of the true position of the interesting object. The further of an image patch from the detected region, the less likely it will contain the interesting object. To this end, we generate multiple image patches with a given size according to how much they overlap with the detected region.

Let \( s \times s \) denote the size of the input image to CNN, which is also the size of the sampled image patch. Given a training image \( I \) with size \( w \times h \), we let \((x_o, y_o)\) denote the coordinate of the detected object, i.e., the center of the bounding box that includes the interesting object and let \( R_o \) denote the region of the detected bounding box. Similarly, let \((x, y)\) denote a position in the image and it is associated with a fixed size \( s \times s \) region \( R_{x,y} \) that is centered at \((x, y)\). The sampling space is given by \( S = \{(x,y) : R_{x,y} \subset I, |R_{x,y} \cap R_o| \geq \tau\} \), where \( \tau \) is an overlapping threshold and \(|R_{x,y} \cap R_o|\) denotes the size of overlap between the image patch defined by \((x, y)\) and the bounding box. We set \( \tau \) to be 0 and sample \((x, y) \in S\) following a multinomial distribution, with a probability proportional to \(|R_{x,y} \cap R_o|\). Thus, a region with a large overlap with the bounding box has a high probability to be sampled and used as a training example to the CNN. This is illustrate in Figure 6.

In order to efficiently implement the multinomial sampling of image patches, we can first compute a cumulative probability map for each training image according to the detected bounding box and then sample a coordinate by uniform sampling from the probability quantiles. The prediction on a testing image are averaged probability over five crops from the original image and their flipped copies, as well as five crops around the detection and their flipped copies.

5. Experiments

5.1. Dataset

We carried out experiments on our large-scale car dataset. For the evaluation of object detection performance, we follow the PASCAL VOC evaluation criterion, but increase the requirement of overlap with ground truth to be 80%. We view 50% overlap as too much offset from the ground truth for fine-grained image classification.

5.2. Car Detection

We use selective search \([15]\) to generate object proposals for detector training and testing. In the training, object proposals which have more than 70% overlap with the ground truth are selected as positive samples. Object proposals which have less than 30% overlap with the ground truth are used as negative training samples. To further polish the localization precision, we use the Regionlet Re-localization method \([9]\) to learn a support vector regression model to predict the actual object location.

We use 11,000 images to train our car detector. Our training procedure follows \([18]\). The final car detection model has 8 cascades with around 10 thousand weak classifiers in total. As aforementioned, we replace the non-max...
suppression post processing scheme with a max-operation over the whole image. Our detector achieves 85.8% detection average precision. Our experiment demonstrates that detection for fine-grained image classification is doable if the training dataset and the detector are carefully designed. Figure 7 shows sample detector responses on the detection testing dataset.

To validate whether the detector is able to produce more confidence detection for relative large objects, which is crucial for the following image classification process, we plot the average detection score versus object size in Figure 8. It shows that the detection confidence for relatively bigger objects is consistently higher.

5.3. Fine-grained Image Classification

We directly utilize the neural network structure for image-net classification as in [7] except that we have 333 object categories. The fine-grained image classification experiment is carried out using three different configurations:

- **Uniform sampling**: the input image is resized to 256 × y or x × 256. The 224 × 224 training samples are uniformly sampled from the entire image.

- **Multinomial sampling**: the input image is resized to 256 × y or x × 256. The 224 × 224 training samples are sampled from the entire image with a preference to the location of the maximum detection response.

The classification accuracy is shown in Table 3. The classification accuracy is significantly boosted by enforcing multinomial sampling based on detection outputs, i.e.

### Table 3: Fine-grained car classification accuracy (%) with different sampling strategies.

| Sampling method | Top 1 | Top 5 |
|-----------------|-------|-------|
| Uniform         | 81.6% | 92.8% |
| Multinomial     | 89.3% | 96.6% |

The top 1 accuracy is improved from 81.6% to 89.3%, the top 5 accuracy is improved from 92.8% to 96.6%. Sample prediction results are shown in Figure 9.

Figure 9: Sample detection output as well as prediction results obtained from our object-centric sampling based neural network training. False predictions are colored red.

6. Conclusion

In this paper, we identify the unique properties of fine-grained image classification and delicately designed an effective pipeline for the challenging task. It includes two techniques: 1) saliency-aware object detection and multinomial object-centric sampling for deep CNN training. The first component is achieved by constructing saliency-aware training data construction and training an adapted Regionlet detector. Compared to traditional detection approaches, our detector yields higher response on salient objects. The resulting detections are used in an object-centric sampling scheme to guide the sampling procedure in deep CNN training. The effectiveness of our fine-grained image classification framework was shown to be dramatic, improving the top-1 classification accuracy from 81.6% to 89.3%. In order
to study the effectiveness of the object-centric sampling, we also constructed a large-scale fine-grained car classification dataset.

Our feature work includes staying the object-centric sampling in CNN with more layers. And we also continue to build even larger fine-gained car dataset. We are also interested in applying the proposed framework to other types of objects than fine-grained cars.

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