Abstract—Currently, the state-of-the-art image classification algorithms outperform the best available object detector by a big margin in terms of average precision. We, therefore, propose a simple yet principled approach that allows us to leverage object detection through image classification on supporting regions specified by a preliminary object detector. Using a simple bag-of-words model based image classification algorithm, we leveraged the performance of the deformable model objector from 35.9% to 39.5% in average precision over 20 categories on standard PASCAL VOC 2007 detection dataset.

I. INTRODUCTION

To achieve the goal of automatic image understanding, computers should be able to recognize what objects are in an image and to locate where they are. Image classification is to predict existence of target objects in given images, whereas object detection is to locate each object of a specific class. The location of an object is represented as a bounding box, according to the prestigious and influential PASCAL Visual Object Challenge (VOC) [1]. Object detection is regarded as more difficult than image classification because object detection requires predicting not only the presence of each object category but also the location of each instance. The results of the most recent PASCAL VOC results support this argument: In terms of average precision (AP), the winner of the image classification task [2], [3] achieved a mean AP of 81%; the winner of object detection task [4]–[7] achieved a mean AP below 40% [8]. This big performance gap forces us to speculate: Can we take advantage of the much better performed image classification algorithm to improve the object detection performance?

Furthermore, available labeled training image data are quite unbalanced for image classification and object detection. Since most of state-of-the-art image classification and object detection algorithms are supervised learning based, the quantity and the quality of the labeled data affect the performance heavily. This is another reason why we can achieve acceptable performance for image classification but not for object detection. Besides, we can easily determine the labor difference between annotating an image for image classification and annotating an image for object detection: For image classification, annotators only need to check a list of Yes or No check boxes of relevant object categories; for object detection, annotators have to label every instance of each object category with bounding boxes of various scales and aspect ratios. This labor difference is more salient for large-scale image dataset: In the standard large scale ImageNet dataset [9], there are 14,197,122 images of 21,841 synsets (object categories) labeled for the image classification task. Among these large numbers of images with categorical labels, bounding box labels are only available for around 3,000 popular synsets, of which the average number of bounding-box labeled images is merely 150 image per category [9]. We can save a huge amount of human labor if we can train or improve an object detector with image data labeled for image classification. Therefore, building an image classification leveraged object detector is quite desirable from the perspective of performance as well as practical application cost.

However, there are several factors we need to consider in order to apply the available image classification algorithms to object detection. First, simply applying the state-of-the-art image classification algorithms [2], [10]–[17] to each scanning window is not feasible due to the speed issue. Most of the aforementioned image classification algorithms [2], [10], [11], [14]–[16] use one or several key classic components including the Bag of Words (BOW) model of a large size codebook, Spatial Pyramid Matching (SPM), and feature pooling, which makes feature extraction very slow compared with the modern sliding-window-based detectors [3], [18]–[20]. Usually a sliding-window-based object detector will scan hundreds of thousands of sliding windows in order to detect every instances in the image. If we directly apply image classification algorithms to each scanning window, object detection in an
image is equivalent to classifying hundreds of thousands of images. Second, if we apply image classification to selected candidate regions as in [7], i.e., the selective search on oversegmented superpixels, the image classification algorithm should be robust to region cropping and clipping and should remain discriminative.

We propose a simple yet principled approach to leveraging object detection through image classification on supporting regions specified by a preliminary object detector. Using a simple bag-of-words model based image classification algorithm, we leveraged the performance of the deformable model objector from 35.9% to 39.5% in average precision, which led to the state-of-the-art performance on the standard PASCAL VOC 2007 detection dataset.

II. CLASSIFICATION LEVERAGED OBJECT DETECTOR

A Classification Leveraged Object Detector (CLOD) mainly contains three components: detection algorithm, classification algorithm and supporting regions for classification. We will first discuss the details about the supporting regions in section II-A, then CLOD will be proposed to incorporate supporting regions, detection algorithm and classification algorithm into a cascade style framework in section II-B.

A. Supporting Regions

Object detection can be formulated as a classification algorithm if given the possible bounding boxes, which indicates the possible object locations. However, directly applying the classification algorithm to bounding boxes will result in bad performance, because the multiple detection boxes of the same object in an image will considered false detections. Therefore, we are going to introduce supporting regions concept for classification algorithm. Some supporting regions examples are illustrated in Figure 1. Some possible locations are predicted by a preliminary object detector, then the supporting regions are generated based on the predicted bounding boxes according the formulation below:

Let $D_i$ be the detection candidate boxes, $i$ is from 1 to $N$ for a single image. We sort the boxes so that the detection score of $D_i$ is larger than $D_j$, if $i < j$. Let $B$ be the background region, which can be expressed as
\[ B = \bigcap_{i=1}^{N} D_i \]  

If there are no missing detections, the classification score of \( B \) would satisfy
\[ f_c(B) < 0 \]  

Then \( i \) is from 1 to \( N \), that is, the boxes we want to classify are from high detection score to low detection score.
\[ S_k = B \cup \left( \bigcup_{i>k} (D_k \cap D_i) \right) \]  
\[ = B \cup (D_k - \bigcup_{i>k} (D_k \cap D_i)) \]

This equation means the classification region for detection box \( k \) will only be affected by the the boxes whose detections scores are higher.

As previously mentioned, there may be mis-detections in the image, which will affect our results a lot. So we define a background region as follows:
\[ B_i = D_i^c \cap \left( \bigcap_{i=1}^{N} \overline{D}_i \right) - D_i \]

In this equation, \( D_i^c \) is the box \( D_i \) with an extra margin.

### B. Workflow for Classification Leveraged Object Detector

Our detection algorithm is a enhanced deformable part models, where we developed a new feature called PCA-reduced-HOG-LBP feature. First, each input region is split into \( 16 \times 16 \) blocks. Both HOG and LBP features are extracted from all the blocks. Then we concatenate the HOG and LBP feature for each block and apply pca on them. The final concatenated PCA-reduced-HOG-LBP is incorporated into deformable part models framework.

Our classification algorithm has following steps: feature extraction, coding , pooling and classification. In this paper, we use dense SIFT and LBP features, and adopt Locality-constrained Linear coding(LLC) to enhance the feature representation. Then Spatial Pyramid Matching(SPM) is applied to make the feature more robust. The final feature representation is sent to linear SVM to predict the presence of the target object in an image.

Given detection algorithm, classification algorithm and supporting regions, the workflow for our classification leveraged object detector is described in Figure 2. First, we apply detection approach. The we could get some predicted bounding boxes. Then, the supporting regions are generated according to the rules in Section II-A. We train one classification classifier using those supporting regions from training data and apply the classification model to these supporting regions from testing data.

We implemented a simple but powerful procedure to boost the performance based on the detection results and classification scores: Let \( (D_1, ..., D_k) \) be a set of detections obtained using \( k \) different object categories in an image \( I \). Each detection \( D_i = (B_i, s_i) \) is defined by a bounding box \( B_i = (x_1, y_1, x_2, y_2) \) and a confidence score \( s_i \). Detection score information \( f_1(I) = \langle \alpha(s_1), ..., \alpha(s_k) \rangle \) where \( \alpha(s) \) is the score of the highest scoring detection in \( D_i \), and \( \alpha(x) = 1/(1 + \exp(2x)) \) is a logistic function for renormalizing the scores. Classification score information \( f_2(I) \) is defined in similar procedure. So the final combined feature for each box is a \( 2k + 6 \) dimensional feature: \( \langle \alpha(c_1), \alpha(c_2), x_1, y_1, x_2, y_2, f_1(I), f_2(I) \rangle \). Finally, SVM with RBF kernel is applied to rescore the preliminary detection confidence scores.

### III. Experiments and Discussion

To demonstrate the advantage of our approach, we test the CLOD on the very challenging PASCAL Visual Object Challenge 2007 (VOC2007) datasets [1]. First, we give a detailed description of VOC2007 dataset and the cropped dataset for our CLOD framework. Then, we evaluate our classification algorithm on PASCAL VOC2007 classification dataset. After that we compare the CLOD performance with the state the art detection performance on PASCAL VOC2007 detection dataset.

#### A. Datasets and Metrics

1) Datasets: PASCAL VOC2007 datasets [1] has 20 categories, containing 9,963 images and 24,640 objects. This dataset is divided into “train”, “val”and “test” subsets, which contains 2501, 2510 and 4592 images respectively. Parameters of the algorithm are tuned via training on “train” set and evaluating on “val” set. The final model is trained on “train” + “val” sets and is applied on the “test” set to obtain the final results. The dataset is extremely challenging since the objects vary significantly in size, view angle, illumination, appearance and pose.

Notice the the classification is applied on the supporting regions instead of the the whole image as it is shown in Section II-A, so a region level (achieved by cropping the bounding boxes from the dataset) seems necessary for a satisfactory classification classifier in CLOD. We prepare a region-level dataset by cropping the detection ground truth boxes according to the detection annotations. This cropped dataset contains “train” and “val”. The positive examples are the ground truth bounding boxes, while the negative examples are the ground truth bounding boxes from other categories. “test” subset is not used to for region-level classification classifier. We refer this region-level dataset as pure ground-truth-box set.

There is another way to get classification classifiers: We can use detection false alarm boxes as the negative and the ground truth boxes as the positive. Notice that the false alarms boxes here are applied to the supporting region technique, so that the false alarms do not have any part of the ground truth. In this way, each category has a different kmeans codebook, while features from other categories are not taken into consideration. For this task, the positive examples are the sum of ground truth in “train” and “val”, and negative examples are a random
TABLE I  
CLASSIFICATION PERFORMANCE ON PASCAL VOC 2007 CLASSIFICATION DATASET.

|     | plane | bike | bird | boat | bottle | car | cat | chair | cow |
|-----|-------|------|------|------|--------|-----|-----|-------|-----|
| INRIA Genetic [21] | 77.5  | 63.6 | 56.1 | 71.9  | 33.1  | 60.6 | 78.0 | 58.8  | 53.5 | 42.6 |
| SuperVec [22]       | 79.4  | 72.5 | 55.6 | 73.8  | 34.0  | 72.4 | 83.4 | 63.6  | 56.6 | 52.8 |
| INRIA 2009 [23]     | 77.2  | 69.3 | 56.2 | 66.6  | 45.5  | 68.1 | 83.4 | 53.6  | 58.3 | 51.1 |
| TagModal [24]       | 87.9  | 85.5 | 76.3 | 75.6  | 61.5  | 71.3 | 77.9 | 79.2  | 46.2 | 62.7 |
| CODE [25]           | 82.5  | 79.6 | 64.8 | 73.4  | 54.2  | 75.0 | 87.5 | 65.6  | 62.9 | 36.4 |
| SIFT+LBP            | 71.1  | 61.2 | 49.1 | 65.5  | 26.0  | 55.0 | 75.7 | 56.9  | 51.1 | 36.1 |
| LBP+LLC             | 74.8  | 54.3 | 40.7 | 65.1  | 20.9  | 53.0 | 69.9 | 54.8  | 50.7 | 31.8 |
| SIFT+LBP+LLC        | 77.2  | 64.3 | 52.7 | 70.4  | 27.2  | 60.3 | 77.3 | 61.0  | 54.6 | 40.2 |

TABLE II  
COMPARISON OF DIFFERENT TYPES OF CLASSIFICATION CLASSIFIERS.

|     | Det | bird | horse | motor | person | plant | sheep | sofa | train | tv | mAP |
|-----|-----|------|-------|-------|--------|-------|-------|------|-------|----|-----|
| INRIA Genetic [21] | 54.9 | 45.8 | 77.5 | 64.0  | 85.9  | 36.3 | 44.7 | 50.6 | 79.2  | 53.2 | 59.4 |
| SuperVec [22]       | 63.2 | 49.5 | 80.9 | 71.9  | 85.1  | 36.4 | 46.5 | 59.8 | 83.3  | 58.9 | 64.0 |
| INRIA 2009 [23]     | 62.2 | 45.2 | 78.4 | 69.7  | 86.1  | 32.8 | 54.4 | 54.3 | 75.8  | 62.1 | 63.5 |
| TagModal [24]       | 41.4 | 74.6 | 84.6 | 76.2  | 84.0  | 48.0 | 67.7 | 44.3 | 86.1  | 32.7 | 66.7 |
| CODE [25]           | 66.0 | 55.5 | 85.0 | 76.8  | 91.1  | 53.9 | 61.0 | 67.5 | 83.6  | 70.6 | 70.5 |
| SIFT+LLC            | 46.6 | 39.5 | 76.1 | 61.9  | 81.6  | 25.5 | 42.2 | 52.2 | 73.9  | 50.2 | 55  |
| SIFT+LLC            | 40.8 | 42.6 | 72.9 | 46.8  | 80.3  | 22.2 | 34.8 | 43.7 | 72.7  | 39.0 | 50.6 |
| SIFT+LBP+LLC        | 33.8 | 46.9 | 77.2 | 62.4  | 84.0  | 26.8 | 44.1 | 54.2 | 77.2  | 51.4 | 58.2 |

selection from the false alarms from the detection boxes in the “trainval” dataset. We refer this region-level dataset as ground-truth-false-alarms set.

2) Metrics: Average Precision (AP) For the VOC2007 Challenge, the interpolated average precision [30] was used to evaluate both classification and detection.

For a given task and class, the precision/recall curve is computed from a methods ranked output. Recall is defined as the proportion of all positive examples ranked above a given rank. Precision is the proportion of all examples above that rank which are from the positive class. The AP summarizes the shape of the precision/recall curve, and is defined as the mean precision at a set of eleven equally spaced recall levels \([0, 0.1, ..., 1]\):

\[
AP = \frac{1}{11} \sum_{r \in [0,0.1,...,1]} P_{\text{interp}}(r)
\]

(6)

The precision at each recall level \(r\) is interpolated by taking the maximum precision measured for a method for which the corresponding recall exceeds \(r\):

\[
P_{\text{interp}}(r) = \max_{\hat{r} \geq r} p(\hat{r})
\]

(7)

Where \(p(\hat{r})\) is the measured precision at recall \(\hat{r}\).

Bounding Box Evaluation As noted, for the detection task, participants submitted a list of bounding boxes with associated score (rank). Detections were assigned to ground truth objects and judged to be true/false positives by measuring bounding box overlap. To be considered a correct detection, the overlap ratio \(a_o\) between the predicted bounding box \(B_p\) and ground truth bounding box \(B_g\) must exceed 0.5 (50\%) by the formula,

\[
a_o = \frac{B_p \cap B_g}{B_p \cup B_g}
\]

(8)

where \(B_p \cap B_g\) denotes the intersection of the predicted and ground truth bounding boxes and \(B_p \cup B_g\) their union.

B. Classification Classifier

In this section, we first tune the parameters of our classification algorithm using the image-level dataset and compare the performance with other state-of-the-art classification algorithms. Then we fix those parameters and apply the classification algorithm in our CLOD framework to compare the image-level classifier and region-level classifier.

1) Image-level classification: For our classification method, we choose dense SIFT and LBP as features and BoF+SPM+LLC system. For both dense SIFT and LBP, we adopt a multi-scale technique, in which the patch size for dense SIFT is 8 \(\times\) 8, 16 \(\times\) 16, 25 \(\times\) 25, 36 \(\times\) 36 and the patch size for LBP is 12 \(\times\) 12, 16 \(\times\) 16, 20 \(\times\) 20, 24 \(\times\) 24. The stride for dense SIFT is 4 and LBP is 50\% overlap stride. After extracting the dense SIFT and LBP features, a codebook is trained separately by kmeans. The codebook
size for each feature is 10,240 and the spatial pyramid matching is using $1 \times 1, 1 \times 2$, and $2 \times 3$. Therefore, each image would have a 184,320-dimension feature. We can see the performance of our classification classifier from PASCAL VOC 2007 and compare it with the other state-of-the-art classification algorithms in Table I.

From Table I, we could see that our classifier is not the best one, but later we will prove that even with this below-average classification classifier, our CLOD approach would still be able to boost the detection a lot.

2) Region-level Classification: From Section II-A1 there are two kinds of region-level dataset. With the exact same experiment setup, we train our region-level classifier on the “train” + “val” subsets of the cropped ground truth dataset and support-region dataset. We evaluate it on the “test” subset, the performance is listed in Table I. In Table I only the LBP feature is used due to the speed issue. CLS is adding classification score to the original detection score instead of the complex rescore scheme in Section II-B. Det means the performance of preliminary detection results. CLS-I means CLS using classification classifiers trained on image-level set. CLS-Rg means CLS using classification classifiers trained on region-level pure ground-truth-box set.

We can see that the image-level classifier is the worst and the region-level classifier from the pure ground-truth-box set is the best. Since our CLOD actually applied the classification on the supporting regions instead of the whole images, it is reasonable that the image-level classifier does not work well. But it is quite interesting that the classifier from the pure ground-truth-box dataset is better than the classifier from ground-truth-false-alarms set. The reason behind this results is that negative examples from ground truth of other categories carry more discriminative information than the negative examples from false alarms of detector. Therefore, by taking all of the above into consideration, we choose the classification classifier from the pure-ground-truth dataset as our classification classifier in our CLOD framework.

C. Leverage Detection with Classification

Now, we have already discussed the datasets and details for the CLOD framework. We have showed that each box has a detection score and classification score. Notice that the classification score is not achieved by the whole bounding box region but the supporting region.

From Section II-A, the supporting regions are defined as the subtractions of bounding boxes from detection classifiers. In fact given different detection threshold, there will be different number of detection bounding boxes. To reduce the candidate boxes for each class, we set threshold to -0.95 for all the categories, which will lead most categories to contain less than 2,000 candidate boxes.

Table III compares the CLOD with other state-of-the-art performance on PASCAL VOC 2007 detection dataset. The bold fond represents the first rank in related categories. Our methods achieved first place in 9 out of 20 categories, and rank first in mean average precision. The Figure 3 shows detailed precision-recall curve of CLOD and original detection algorithm over 20 categories in PASCAL VOC 2007 detection dataset. The CLOD significantly improve the preliminary results for all categories.

IV. Conclusion

In this paper, we have proposed a simple but powerful object detector called Classification Leveraged Object Detector. This detector needs a detection model and a classification model for each class. Extensive experiments on PASCAL2007 has shown the advantage of our approach. We achieved the state-of-the-art performance.
REFERENCES

[1] M. Everingham, L. Van Gool, C. Williams, J. Winn, and A. Zisserman, “The pascal visual object classes challenge,” 2010.
[2] Z. Song, Q. Chen, Z. Huang, Y. Hua, and S. Yan, “Contextualizing object detection and classification,” in CVPR, 2011.
[3] F. S. Khan, J. van de Weijer, and M. Vanrell, “Modulating shape features by color attention for object recognition,” International Journal of Computer Vision, vol. 98, no. 1, pp. 49–64, 2012.
[4] P. F. Felzenszwalb, D. A. McAllester, and D. Ramanan, “A discriminatively trained, multiscale, deformable part model,” in CVPR, 2008.
[5] L. Zhu, Y. Chen, A. L. Yuille, and W. T. Freeman, “Latent hierarchical structural learning for object detection,” in CVPR, 2010.
[6] A. Vedaldi, V. Gulshan, M. Varma, and A. Zisserman, “Multiple kernels for object detection,” in ICCV, 2009.
[7] K. E. A. van de Sande, J. R. R. Uijlings, T. Gevers, and A. W. M. Smeulders, “Segmentation as selective search for object recognition,” in ICCV, 2011.
[8] M. Everingham, L. Van Gool, C. Williams, J. Winn, and A. Zisserman, “The PASCAL Visual Object Classes Challenge 2012 (VOC2012) Results,” http://www.pascal-network.org/challenges/VOC/voc2012/workshop/index.html.
[9] J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, and L. Fei-Fei, “ImageNet: A Large-Scale Hierarchical Image Database,” in CVPR09, 2009.
[10] K. Grauman and T. Darrell, “The pyramid match kernel: Discriminative classification with sets of image features,” in In ICCV, 2005, pp. 1458–1465.
[11] S. Lazebnik, C. Schmid, and J. Ponce, “Beyond bags of features: Spatial pyramid matching for recognizing natural scene categories,” in Proceedings of Computer Vision and Pattern Recognition. Washington, DC, USA: IEEE Computer Society, 2006, pp. 2169–2178.
[12] O. Boiman, E. Shechtman, and M. Irani, “In defense of nearest-neighbor based image classification,” in CVPR, 2008.
[13] A. Bosch, A. Zisserman, and X. Muñoz, “Scene classification using a hybrid generative/discriminative approach,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 30, no. 4, pp. 712–727, 2008.
[14] X. Zhou, N. Cui, Z. Li, F. Liang, and T. S. Huang, “Hierarchical gaussianization for image classification,” in ICCV, 2009, pp. 1971–1977.
[15] J. Wang, J. Yang, K. Yu, F. Lv, T. S. Huang, and Y. Gong, “Locality-constrained linear coding for image classification,” in CVPR, 2010, pp. 3360–3367.
[16] Y. Yang and S. Newsam, “Spatial pyramid co-occurrence for image classification,” in ICCV, 2011.
[17] H. Zhang, A. C. Berg, M. Maire, and J. Malik, “Svm-knn: Discriminative nearest neighbor classification for visual category recognition,” ser. CVPR ’06. Washington, DC, USA: IEEE Computer Society, 2006, pp. 2126–2136.
[18] N. Dalal and B. Triggs, “Histograms of oriented gradients for human detection,” in CVPR, 2005.
[19] P. F. Felzenszwalb, R. B. Girshick, D. A. McAllester, and D. Ramanan,
“Object detection with discriminatively trained part-based models,” IEEE Trans. Pattern Anal. Mach. Intell., 2010.

[20] C. Desai, D. Ramanan, and C. C. Fowlkes, “Discriminative models for multi-class object layout,” International Journal of Computer Vision, vol. 95, no. 1, pp. 1–12, 2011.

[21] H. M. Marszalek, C. Schmid and J. van de Weijer, “Learning object representations for visual object class recognition,” in In Visual Recognition Challenge workshop, ICCV, 2007.

[22] T. Z. Zhou, K. Yu and T. Huang, “Image classification using supervector coding of local image descriptors,” in ECCV, 2010.

[23] F. H. Harzallah and C. Schmid, “Combining efficient object localization and image classification,” in ICCV, 2009.

[24] S. Kumar and M. Hebert, “Multimodal semi-supervised learning for image classification,” in CVPR, 2010.

[25] J. D. Z. H. Y. H. S. Y. Qiang Chen, Zheng Song, “Contextualizing object detection and classification,” in Pattern Analysis and Machine Intelligence, IEEE Transactions on, 2014.

[26] C. Li, D. Parikh, and T. Chen, “Extracting adaptive contextual cues from unlabeled regions,” in ICCV, 2011.

[27] J. Zhang, K. Huang, Y. Yu, and T. Tan, “Boosted local structured hog-lbp for object localization,” in CVPR, 2010.

[28] R. B. Girshick, P. F. Felzenszwalb, and D. McAllester, “Discriminatively trained deformable part models, release 5,” http://people.cs.uchicago.edu/~rbg/latent-release5/.

[29] J. X. Guang Chen, Yuanzun Ding and T. X. Han, “Detection evolution with multi-order contextual co-occurrence,” in CVPR, 2013.

[30] M. M. J. Salton, G., “Introduction to modern information retrieval,” McGraw-Hill., 1986.