Combining Local and Global Hypotheses in Deep Neural Network for Multi-label Image Classification

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Abstract

Multi-label image classification is a challenging problem in computer vision. Motivated by the recent development in image classification performance using Deep Neural Networks, in this work, we propose a flexible deep Convolutional Neural Network (CNN) framework, called Local-Global-CNN (LGC), to improve multi-label image classification performance. LGC consists of firstly a local level multi-label classifier which takes object segment hypotheses as inputs to a local CNN. The output results of these local hypotheses are aggregated together with max-pooling and then re-weighted to consider the label co-occurrence or interdependencies information by using a graphical model in the label space. LGC also utilizes a global CNN that is trained by multi-label images to directly predict the multiple labels from the input. The predictions of local and global level classifiers are finally fused together to obtain MAP estimation of the final multi-label prediction. The above LGC framework could benefit from a pre-train process with a large-scale single-label image dataset, e.g., ImageNet. Experimental results have shown that the proposed framework could achieves promising performance on Pascal VOC2007 and VOC2012 multi-label image dataset.

Keywords: Deep Learning, Convolutional Neural Network, Multi-label Classification

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1. Introduction

With the development of Internet and digital camera equipment, the amount of digital images is drastically increasing in recent years. Image annotation is an important task to automate the processing of such huge image data. Image annotation requires identifying a set of objects presented in each image from a given set of desired object concepts, and usually such prediction process is relevant to multi-label image classification. Many existing image classification works [1, 2, 3] focus on single-label problems, with the most recent advances being reported on the large-scale ImageNet database [1]. Compared with designing handcrafted visual features, e.g., SIFT [4], Fisher Vector [5] and combining with classic classifier such as Support Vector Machine (SVM) [6], deep Convolutional Neural Network (CNN) has demonstrated promising results for single-label image classification tasks due to its ability to discover representative and abstract features automatically [7].

Multi-label image classification task is more complicated than single-label image classification due to the following challenges. Firstly, foreground objects in multi-label images are not as aligned as in single-label images. In some multi-label images, objects are located at various positions with different scales and poses. Even worse, some foreground objects are occluded by others. For example, in a living room scene, the chairs are located at various positions, and may be occluded by tables. Secondly, in most single-label images, a foreground object occupy a larger portion of entire image, and the remaining local regions are often clean and semantically very different from the object. However, there are more than one objects in most of multi-label images, and the foreground object may only occupy a very small local region of the entire image.

Despite the challenges, there are also additional cues that could be utilized to assist multi-label image classification. Co-occurrence and interdependencies exist among multiple class labels, and capturing the co-occurrence information among class labels is useful to improve performance. For example, chair and dining table usually appear together, while the former is unlikely to co-appearance with sheep. Typically, many parts of the chairs could be invisible, but the dining table is easy to recognize and could help recognizing the chairs. Similarly, classes such as cow and sheep which are

almost impossible to appear together with dining table could be lower ranked. Besides, advantages of deep CNN are also beneficial for multi-label image classification. For instance, Gong *et al.* [8] compared several conventional visual features, such as SIFT [4] and HOG [9], with features based on deep neural networks for the multi-label
35 annotation problem, and it is observed that the latter outperforms the former.

In this paper, we are most interested at combining the local and global hypotheses to improve multi-label image classification performance. Local region pays attention to a single object, while global multi-label image emphasizes the global level information. Local regions and global multi-label image consist of different information
40 from different perspective and are both important for multi-label classification task. Motivated by these observations, in this paper, we propose a flexible deep CNN framework for multi-label image classifier, called Local-Global-CNN (LGC). LGC consists of firstly a local level multi-label classifier which takes object segment hypotheses as inputs to a local CNN model, and the output results of different hypotheses are then
45 aggregated with max-pooling and then re-weighted to consider the label co-occurrence information by using a graphical model in the label space. The local CNN model is indeed a single-label classifier to predict over a set of local object segment hypotheses [10], and the goal of using a graph to refine the local prediction is to find the relevant (co-occurred) and irrelevant (uncorrelated) labels, because most of irrelevant labels we
50 found are true negative labels in the multi-label image, and therefore we could significantly reduce prediction from irrelevant labels and reduce the effects of those noise hypotheses. LGC also consists of a second CNN model as the global level multi-label classifier, where images are directly fed into the CNN and generate multi-label prediction. Finally, we integrate predictions of local and global level classifier together as
55 the ultimate multi-label prediction. In this way, the local level classifier and the global level classifier compensate the shortcomings of each other. The proposed LGC framework nicely integrates these two aspects by taking advantage of local level, global level and label co-occurrence information and achieves very promising performance on Pascal VOC 2007 and VOC 2012 [11] multi-label image dataset. The rest of the paper
60 is organized as follows. In Section 2, we briefly review the related work. Section 3 and section 4 present details of local level multi-label classification and global level

Figure 1: An illustration of the proposed LGC framework

multi-label classification respectively, and Section 5 combines the two and presents the complete LGN framework. Finally, experimental results and conclusions are provided in section 6 and section 7 respectively.

65 2. Related Work

A considerable amount of research has been devoted to multi-label classification problems. Over the past decade, many traditional methods are based on bag-of-words (BoW). Some complex methods exploit label correlations to improve multi-label image classification performance. In recent years, Deep Neural Networks have demonstrated
70 promising performance in image classification. In this section, we will provide a brief review over the most related work to multi-label classification.

The Bag-of-features (BoF) model as a traditional approach has been very popular in image classification. The BoF method represents an image as a histogram of its local features. Hand-crafted features, such as SIFT [4], Histogram of Oriented Gra-
75 dients [12] and Local Binary Patterns [13] are firstly extracted from local patches, quantized into discrete visual words, and then converted into a compact histogram as the image representations. Taking information about the spatial layout of features into consideration, the SPM [14] method partitions the image into increasingly finer spa-

tial subregions and computes histograms of local features from each sub-region. The
80 resulted spatial pyramid is a computationally efficient extension of the orderless BoF
representation, and has shown very promising performance on many image classifica-
tion tasks. Some coding schemes, e.g., Sparse Coding [15] and Locality-constrained
Linear Coding (LLC) [16], replace the VQ coding in traditional SPM to further im-
prove performance in image classification. In addition, some methods [17, 18, 19] focus
85 on image data representation by subspace learning and feature selection. The method
in [17] propose a novel Robust Structured Subspace Learning (RSSL) algorithm by
integrating image understanding and feature learning into a joint learning framework.
The learned subspace is adopted as an intermediate space to reduce the semantic gap
between the low-level visual features and the high-level semantics.

90 In contrast to traditional methods that focus on feature representation, the labels
co-occurrence information is very important in multi-label classification. Many works
explore correlation between labels to improve multi-label classification performance.
One group of works is the ranking based methods [20, 21, 22], where the relevant label-
s are ranked higher than irrelevant ones in considering the label correlations. Another
95 group of works is the graph-based methods that incorporate the label correlations into
label propagation algorithms as part of the graph weights [23, 24]. Others have used the
label correlations as additional constraints [25, 26]. The method in [27] explore label
combinations to enrich the label space and improve the label identification capacity in
the original label space by generating many label combination pairs in a tree-structured
100 graph for the label space, according to the label co-occurrence information in the train-
ing data, which naturally forms a conditional random field.

Recently, features based on deep neural networks have demonstrated promising
performance in image classification. Deep Neural Networks has achieved promising
performance in many computer vision tasks. Specifically, deep CNN has achieved
105 state-of-the-art performance [28, 29, 7, 30] in many single-label dataset, such as CIFAR-
10/100 [31] and ImageNet [1]. Many researchers have therefore adopted the CNN ar-
chitectures to address multi-label classification problems. Gong *et al.* [8] use a similar
network structure to [7] for the multi-label annotation problem. He compared sever-
al multi-label loss functions, and found that the weighted approximated-ranking loss

110 (WARP) [32] can achieve promising performance for multi-label annotation problems. Yun *et al.* [33] also proposed a novel CNN structure, called Hypotheses-CNN-Pooling (HCP). Object segment hypotheses are taken as the inputs. Output results of these hypotheses from a shared CNN are aggregated with max pooling to produce the ultimate multi-label predictions. The proposed HCP infrastructure has achieved promising
 115 performance on Pascal VOC2007 and VOC2012 multi-label image dataset. Some studies [34, 35, 36] have shown that CNN features are suitable for images classifications.

3. Local Level Multi-label Classification

Local level multi-label classifier takes object segment hypotheses as inputs, and aggregate the output results of different hypotheses with max-pooling. The aggregated
 120 result will be re-weighted to consider the label co-occurrence information by using a graphical model in the label space. In this section, we will introduce training stage and test stage of local level multi-label classification.

3.1. Training Stage

Local CNN is a single-label classifier. The architecture of the local CNN is similar
 125 to the network described in [7], which contains five convolutional layers and three fully-connected layers with about 60 million parameters. To obtain an effective CNN model, we need enough training dataset. Local CNN training dataset is provided by ground-truth bounding box information of multi-label images training dataset. We crop out the ground-truth bounding box as the training dataset. However, large-scale
 130 multi-label dataset is not affordable and difficult to annotate. What's more, we also need the object's bounding box ground-truth and corresponding label ground-truth in multi-label dataset. Bounding box and label annotation will cost a lot of manpower and resources. Fortunately, the CNN can be pre-trained by a large-scale single-label image dataset for parameter initialization. To obtain an optimal CNN model for our
 135 task, fine-tuning is enforced to adjust the parameters.

3.1.1. Pre-training On A Large-scale Single-label Image Dataset

We pre-train the local CNN on ImageNet [1]. Before the start of training, we first resize images to 256×256 . Next, random 227×227 patches from the image are fed to convolutional layers. We set convolution filter sizes to squares of size 11, 5, and 3 respectively for the different convolutional layers. Max pooling layers are used in some of convolutional layers. Each of the densely connected layers are followed by a dropout layers with a dropout ratio of 0.6. The output of the last fully-connected layer is fed to a 1000-way softmax layer with multinomial logistic regression as the loss function. The rectified linear units (ReLU) is chose as the nonlinear activation function for all layers. The whole network is optimized by stochastic gradient descent with a momentum of 0.9 and weight decay of 0.0005. The global learning rate for the all layers is set to 0.01 at the beginning, and a staircase weight decay is applied after a few epochs.

3.1.2. Fine-tuning

Fine-tuning process is enforced to adapt the model for our classification task. Firstly, we need prepare the single-label images from a multi-label dataset, e.g., Pascal VOC [11]. And object boundingbox annotations are required for multi-label image dataset. We generate some windows around the ground-truth boundingbox and select several windows where overlapping rate between the ground-truth boundingbox and the window is more than 70%. We crop out the selected window as the training image and annotate it with the same label with ground-truth boundingbox. In addition, we add a negative class. The negative class images are selected from windows whose overlapping rate is less than 10%. Each training image is resized into 230×230 . Random 227×227 patches extracted from the given image are fed to network. Fine-tuning process is different from pre-training in some details. Since the category number of Pascal VOC is not equal to ImageNet, the output of the last fully-connected layer is fed into a $(c + 1)$ -way softmax which produces a probability distribution over the $(c + 1)$ class labels. c is category number of Pascal VOC and 1 refers to the negative class. The loss function is still multinomial logistic regression. During fine-tuning process, the parameters of layers except the last fully-connected layer are initialized by the pa-

rameters pre-trained on ImageNet. The parameters of the last fully-connected layer are initialed with a Gaussian distribution $G(\mu, \sigma)(\mu = 0, \sigma = 0.01)$. We set much higher learning rate for the last fully-connected layer to guarantee a fast convergence to the new optimum on the new target dataset.

170 3.2. Test Stage

In the test stage, object segment hypotheses are taken as the inputs to local CNN trained by single-label images, and the CNN output results of different hypotheses are aggregated with max pooling, then we take the label co-occurrence information into account to improve classification accuracy by using graphs in the label space.

175 3.2.1. Hypotheses Extraction

The quality of the extracted hypotheses have a great impact on the performance of local level multi-label classifier. An effective hypotheses extraction approach must satisfy several requirements below. Hypotheses extraction approach can achieve high detection recall rate and the extracted hypotheses can cover all the single objects of the multi-label image. What’s more, computational efficiency of hypotheses extraction
180 also significantly influences the performance of the whole framework.

During the past few years, many methods [37, 38, 39, 40] have been proposed to tackle the hypotheses detection problem. [37, 38, 40] are based on hypothesis, which generate a set of hypotheses to cover all independent objects in a given image. But
185 these methods are not applicable to local level multi-label classification, since quite time-consuming when extract a large number of hypotheses.

Most recently, Cheng *et al.* [10] proposed a simple and efficient hypotheses extraction approach called binarized normed gradients(BING). BING can be used for efficient objectness estimation, which requires only a few atomic operations. This method
190 is faster (300fps on a single laptop CPU) than most popular alternatives [37, 38, 40] and yielding 96.2% object detection rate (DR) with 1,000 proposals. In the experiment, we choose BING as our hypotheses extraction method.

3.2.2. Max Pooling

n hypotheses of a multi-label image are fed into local CNN and $n(c+1)$ -dimensional vectors are computed as the output of the CNN. Some hypotheses may contain one object or more. Others may contain none of object. To suppress the noisy hypotheses, we fuse the outputs into one integrative prediction with a cross-hypothesis max-pooling method, and remove negative class output. As for hypothesis which contains an object, the output vector will have a high response on the j_{th} component, meaning a high confidence for the appearance of j_{th} category in multi-label image. As for hypothesis which contains none object, the output vector will have a high response on the negative class component and have low response on the remaining class component. In this way, we suppress the influence of noisy hypotheses. Suppose $\mathbf{v}_i (i = 1, \dots, n)$ is the output vector of the i_{th} hypothesis from the local CNN and $\mathbf{v}_i^j$ is the j_{th} component of $\mathbf{v}_i$. And we remove negative class component. The cross-hypothesis max-pooling on the n output vectors can be formulated as,

$$\mathbf{v}^j = \max(\mathbf{v}_1^j, \mathbf{v}_2^j, \dots, \mathbf{v}_n^j) \quad (1)$$

where $\mathbf{v}^j$ can be considered as the predicted value for the j_{th} category of the given image. With cross-hypothesis max-pooling, large predicted values corresponding to objects of interest will be reserved, while the values from the noisy hypotheses will be ignored.

3.2.3. Label Co-occurrence Information

Capturing the dependencies among class labels during classification is useful to improve classification performance. We construct a simple graph to find the related labels and irrelated labels of the given multi-label image. A fully connected directed graph $G = (V, E)$ is constructed over the label space. Each vertex of V represents a label variable, and a set of directed edges $(s, t) \in E$ represents the dependency between the label variables. We measure co-presence empirical probabilities of each label pair as the weight of the corresponding edge. We propose a simple new measure to compute co-presence empirical conditional probabilities from the training data. For

two label variables V_i and V_j , the weight of the directed edge $W(\overrightarrow{V_i, V_j})$ is defined as,

$$W(\overrightarrow{V_i, V_j}) = \frac{\text{count}(V_i, V_j)}{\text{count}(V_i)} \quad (2)$$

where $\text{count}(V_i, V_j)$ is the number of co-occurrence of the two labels in the training data, such that,

$$\text{count}(V_i, V_j) = \sum_{\ell=0}^n I[V_i^\ell = 1, V_j^\ell = 1] \quad (3)$$

and $I[\bullet]$ denotes an indicator function. Similarly, $\text{count}(V_i)$ and $\text{count}(V_j)$ are the numbers of occurrences of single labels in the training data.

For example, there are totally 100 people images, 80 dog images and 15 images containing people and dogs. Assume label variables V_i and V_j represent person and dog respectively. The weight of the directed edge $W(\overrightarrow{V_i, V_j})$ is 15/100, and $W(\overrightarrow{V_j, V_i})$ is 15/80.

Our task is to find the related labels and irrelated labels of the given multi-label images. This problems can be formulated in terms of energy minimization. The energy function is defined as,

$$E = \sum_{i=1}^c [\alpha(L_i - S_i)^2 + \sum_{j=1}^c (L_i - L_j)^2 * W(\overrightarrow{V_i, V_j})] \quad (4)$$

where L_i represents whether the i_{th} category is the related label of multi-label image or not. At the beginning, L_i will be random assigned a label 1 or 0, which represent related label and irrelated label respectively. S_i is the prediction value of the multi-label image on the i_{th} category. $(L_i - S_i)^2$ is the data item which measures the disagreement between L and the observed data S . $\sum_{j=1}^c (L_i - L_j)^2 * W(\overrightarrow{V_i, V_j})$ is the smooth data, which measures the extent of piecewise smooth. α is a ratio adjustment factor. Some methods (e.g. graph cut and simulated annealing), can find a local minimum of the energy minimization. From the result of L , we get the related labels and irrelated labels of the given multi-label images.

According to the above results, the amount of the related labels we found is usually more than the ground-truth. But most of the irrelated labels we found are true negative labels of the multi-label image. We reduce prediction values of irrelated labels by half to reduce impact of noise hypotheses and remain unchanged for related labels. In the way, we further improve the accuracy of multi-label classification.

4. Global Level Multi-label Classification

Global CNN is a multi-label classifier. The architecture of the global CNN is similar to the network described in [7], which contains five convolutional layers and three fully-connected layers with about 60 million parameters. Therefore, without enough training images, it is very difficult to obtain an effective CNN model for multi-label classification. The same as the local CNN, we use the a large-scale single-label image dataset, i.e., ImageNet [1], to pre-train global CNN. To obtain an optimal CNN model for our task, the entire images from a multi-label image set, e.g., Pascal VOC [11], are then utilized to fine-tune the CNN model.

In the fine-tuning process, parameters pre-trained on ImageNet are directly transferred for fine-tuning except for the last fully-connected layer. Each image is resized into 227×227 pixels without cropping. Since the category number of Pascal VOC is not equal to that of ImageNet, the output of the last fully-connected layer is fed into a c -way softmax which produces a probability distribution over the c class labels. The loss function is softmax loss. The softmax loss function is defined as follows.

Assuming that each image has multiple labels, and we can form a label vector $\mathbf{y} \in R^{1 \times c}$ where $\mathbf{y}_j = 1$ means the presence of a label and $\mathbf{y}_j = 0$ means absence of a label for an image. We can obtain ground-truth probability by normalizing $\mathbf{y}$ as $\mathbf{y}/\|\mathbf{y}\|^2$. If the ground-truth and prediction probability for image i and class j is defined as $\bar{p}_{ij}$ and p_{ij} respectively, the cost function to be minimized is,

$$J = -\frac{1}{m} \sum_{i=1}^n \sum_{j=1}^c \bar{p}_{ij} \log(p_{ij}) = -\frac{1}{m} \sum_{i=1}^n \sum_{j \in \mathcal{L}_i} \frac{1}{c_+} \log(p_{ij}) \quad (5)$$

where $\mathcal{L}_i$ denotes the positive label set of the i^{th} image and c_+ denotes the number of positive labels for each image.

we also adopt a discriminating learning rate scheme for different layers. The parameters of the last fully-connected layer are initialed with a Gaussian distribution $G(\mu, \sigma)(\mu = 0, \sigma = 0.01)$. We set a much higher learning rate for the last fully-connected layer to guarantee a fast convergence to the new optimum on the new target dataset.

5. Combination of Local and Global Level Multi-label Classification

Finally, we add predictions of local level multi-label classification and global level multi-label classification together as the ultimate multi-label predictions. From different perspective, local level multi-label classification and global level multi-label classification make up for the shortcomings of each other. Our deep CNN infrastructure
245 nicely integrates these two aspects by taking advantage of local level, global level and label co-occurrence information and achieves very promising performance on Pascal VOC2007 and VOC2012 multi-label image dataset.

Based on the trained LGC model, the multi-label classification of a given image
250 can be summarized as follows. We firstly generate the input hypotheses of the given image based on BING [10] method. The object segment hypotheses are taken as inputs to local CNN. Predictions of different hypotheses are aggregated with max pooling. Then we take the label co-occurrence or interdependencies information into account to improve classification accuracy by using graphs in the label space. As for global
255 level multi-label classifier, the global multi-label images are taken as inputs to global CNN. Finally, we add predictions of local level multi-label classifier and global level multi-label classifier together as the ultimate multi-label prediction. As shown in Fig 2, the left part is local level classification. For each object independent hypothesis, there is a high response on the corresponding category (i.e., cow, person) after classification
260 of local CNN. Some categories (e.g., horse, sheep) are similar to cow and also have high response. Taking the co-occurrence information into account, we find the unrelated labels (e.g., cat) and reduce their prediction values by half. The right part is global level classification. The entire image is taken as input to global CNN. The response is high on several categories. Finally, we add predictions of local level multi-label classifier
265 and global level multi-label classifier together as the ultimate multi-label prediction.

6. Experimental Results

6.1. Dataset

We performed experiments on the PASCAL Visual Object Classes Challenge (VOC) dataset [11]. Pascal is one of the most well-known image datasets for classification and

Figure 2: An illustration of the proposed LGC for a VOC 2007 test image. The left part is local level classification. Firstly, object independent hypothesis are taken as inputs to local CNN. Secondly, taking the co-occurrence information into account, we reduce irrelevant labels prediction values by half. The right part is global level classification. The entire image is taken as input to global CNN. Finally, we add predictions of local level multi-label classifier and global level multi-label classifier together as the ultimate multi-label prediction.

270 detection. It contains 20 different object classes and is widely used as a benchmark for
multi-label classification. In this paper, we conducted experiments on PASCAL VOC
2007 and VOC 2012 dataset. These two dataset, which contain 9,963 and 22,531 im-
ages respectively, are divided into training, validation and testing subsets. We followed
the suggested data partition and evaluation metric which is the Average Precision (AP)
275 measure and mean AP (mAP) to comply with the PASCAL challenge protocols.

6.2. Benchmark Methods

We compare our method with several state-of-the-art approaches as listed below.
The deep learning methods are all pre-trained on the original ImageNet dataset [1]
with 1000 categories and the network is similar to [7]. In addition, we also compared
280 with global level classification (Global-CIs) and local level classification (Local-CIs).
To validate the effectiveness of graph model in local level classification, we present the
result of local level classification without using graph model. In other words, we only
use the combination of local CNN and cross-hypothesis max-pooling, which is named
as Local-CNN-Max.

- 285 • INRIA [41]: Harzallah *et al.* proposed a contextual combination method of local-
ization and classification to improve the performance for both. Specifically, for
classification, image representation is built on the traditional feature extraction-
coding-pooling pipeline, and object localization is built on sliding-widow ap-
proaches. Furthermore, the localization is employed to enhance the classification
290 performance.
- FV [5]: The Fisher Vector representation of images can be considered as an
extension of the bag-of-words. Some well-motivated strategies, e.g., $L2$ normal-
ization, power normalization and spatial pyramids, are adopted over the original
Fisher Vector to boost the classification accuracy.
- 295 • CNN-SVM [36]: OverFeat [42], which obtained very competitive performance
in the image classification task of ILSVRC 2013, was released by Sermanet *et*
al. as a feature extractor. Razavian *et al.* [36] employed OverFeat, which is
pre-trained on ImageNet, to get CNN activations as the off-the-shelf features.

300 The state-of-the-art classification result on PASCAL VOC 2007 was achieved by using linear SVM classifiers over the 4,096 dimensional feature representation extracted from the 22nd layer of OverFeat.

- PRE-1000C [43]: Oquab *et al.* proposed to transfer image representations learned with CNN on ImageNet to other visual recognition tasks with limited training data. The network has exactly the same architecture as in [7]. Firstly, the network is pre-trained on ImageNet. Then the first seven layers of CNN are fixed with the pre-trained parameters and the last fully-connected layer is replaced by two adaptation layers. Finally, the adaptation layers are trained with images from the target PASCAL VOC dataset. PRE-1000C means the transferred parameters are pre-trained on the original ImageNet dataset with 1000 categories.
- 310 • HCP-1000 [33] Yun *et al.* proposed a novel CNN infrastructure, called Hypotheses-CNN-Pooling (HCP). Object segment hypotheses are taken as the inputs to shared CNN. Output results of these hypotheses from a shared CNN are aggregated with max pooling to produce the ultimate multi-label predictions. The proposed HCP infrastructure has achieved state-of-the-art performance on Pascal VOC2007 and VOC2012 multi-label image dataset. HCP-1000C means the transferred parameters are pre-trained on the original ImageNet dataset with 1000 categories.

6.3. Classification Performance

Table 1 reports our comparison results on VOC 2007. From the experimental results, we see that methods based on LGC have a large improvement over those based on hand-crafted features. Comparing Local-CNN-Max with Local-Cls, we see that label co-occurrence information based on a simple graph model in label space could help improve classification accuracy. Our method integrates local and global level multi-label classification and have a 0.8% improvement compared with HCP-1000C [33].

Table 2 reports our comparison results on VOC 2012. One additional benchmark included is from [44] (denoted as LeCun-ICML). Similar to the previous experiment, our method outperforms other methods except that the score is slight lower than HCP-1000C [33] on 9 categories AP. These results demonstrated the effectiveness of the

Table 1: Comparison of classification results (AP in %) on VOC 2007 (trainval/test). * indicates methods using external data (e.g. ImageNet) for training.

	plane	bike	bird	boat	bottle	bus	car	cat	chair	cow	table	dog	horse	motor	person	plant	sheep	sofa	train	tv	mAP
INRIA [41]	77.2	69.3	56.2	66.6	45.5	68.1	83.4	53.6	58.3	51.1	62.2	45.2	78.4	69.7	86.1	52.4	54.4	54.3	75.8	62.1	63.5
FV [5]	75.7	64.8	52.8	70.6	30.0	64.1	77.5	55.5	55.6	41.8	56.3	41.7	76.3	64.4	82.7	28.3	39.7	56.6	79.7	51.5	58.3
CNN-SVM* [36]	88.5	81.0	83.5	82.0	42.0	72.5	85.3	81.6	59.9	58.5	66.5	77.8	81.8	78.8	90.2	54.8	71.1	62.6	87.4	71.8	73.9
PRE-1000C* [43]	88.5	81.5	87.9	82.0	47.5	75.5	90.1	87.2	61.6	75.7	67.3	85.5	83.5	80.0	95.6	60.8	76.8	58.0	90.4	77.9	77.7
HCP-1000* [33]	95.1	90.1	92.8	89.9	51.5	80.0	91.7	91.6	57.7	77.8	70.9	89.3	89.3	85.2	93.0	64.0	85.7	62.7	94.4	78.3	81.5
Global-ClS*	91.6	84.9	89.2	84.9	41.9	75.1	88.8	86.1	60.6	66.0	74.4	83.1	86.3	83.2	91.6	58.6	74.7	59.4	91.5	73.1	77.3
Local-CNN-Max*	86.3	84.7	83.9	77.0	57.2	77.8	91.7	84.5	54.7	63.6	65.4	84.6	84.7	86.7	96.5	68.5	71.4	64.6	89.7	70.7	77.2
Local-ClS*	90.8	87.7	87.3	80.3	57.9	79.9	92.7	87.7	58.3	68.3	66.9	86.6	85.3	88.6	95.8	73.0	76.0	65.1	92.0	74.7	79.8
LGC*	92.8	90.8	90.8	85.3	56.3	81.4	93.1	89.5	65.3	71.5	76.3	88.1	88.6	89.7	96.0	70.6	78.8	68.9	93.9	77.8	82.3

Table 2: Comparison of classification results (AP in %) on VOC 2012 (trainval/test). * indicates methods using external data (e.g. ImageNet) for training.

	plane	bike	bird	boat	bottle	bus	car	cat	chair	cow	table	dog	horse	motor	person	plant	sheep	sofa	train	tv	mAP
LeCun-ICML* [44]	96.0	77.1	88.4	85.5	55.8	85.8	78.6	91.2	65.0	74.4	67.7	87.8	86.0	85.1	90.9	52.2	83.6	61.1	91.8	76.1	79.0
PRE-1000C* [43]	93.5	78.4	87.7	80.9	57.3	85.0	81.6	89.4	66.9	73.8	62.0	89.5	83.2	87.6	95.8	61.4	79.0	54.3	88.0	78.3	78.7
HCP-1000* [33]	97.7	83.0	93.2	87.2	59.6	88.2	81.9	94.7	66.9	81.6	68.0	93.0	88.2	87.7	92.7	59.0	85.1	55.4	93.0	77.2	81.7
LGC*	95.8	83.3	89.6	87.2	63.4	89.3	84.4	91.6	69.5	74.9	67.6	91.1	85.3	89.3	94.6	64.6	79.4	61.1	90.8	76.7	81.5

proposed LGC framework for multi-label image classification problems.

6.4. Sensitivity to Hypothesis Parameters

330 The object segmentation hypothesis is critical to the local classifier. While the performance of the object segmentation generator is beyond the scope of this paper, and we could always adopt generator of better performance without touching the structure of the proposed LGC framework, we are still interested in investigating the multi-label classification performance with respect to the number of hypotheses. Figure 3 shows
335 changes in mAP values when we select different number of top hypotheses. The hypotheses are sorted based on the predicted objectness scores [10]. Starting from a small number of hypothesis, object recall rate rise as the number of hypotheses increases, and the mAP score of both local level classification and Local-Global-CNN rise. And the mAP value saturate when top 500 hypotheses are selected (i.e., LGC,82.3% and Local-
340 Cls,79.8%). When we continue increase the number of hypotheses, the mAP score began to decline. The reason is that more and more noisy hypotheses would influence the accuracy even the recall rate continue rise.

Figure 3: An illustration of changes in mAP values when we select different number of top hypotheses. The hypotheses are sorted based on the predicted objectness scores. At the beginning, as the number of hypotheses increases, mAP values of both local level classification and Local-Global-CNN rise. And the mAP value achieve the highest at selected top 500 hypotheses (i.e., LGC, 82.3%; Local-Cls, 79.8%). When we continue increase the number of hypotheses, the mAP values began to decline.

7. Conclusions

In this paper we propose a flexible deep CNN infrastructure, called Local-Global-
 CNN (LGC). This infrastructure can be divided into local level multi-label classifica-
 tion and global level multi-label classification. Local level multi-label classifica-
 tion pays attention to local region or single object. Global level multi-label classifica-
 tion emphasizes the global level information. In Local level multi-label classification, we
 take the label co-occurrence information into account to improve classification accu-
 racy by using graphs in the label space. Finally, we integrate predictions of local lev-
 el multi-label classifier and global level multi-label classifier together as the ultimate
 multi-label prediction. Experimental results on Pascal VOC2007 and VOC2012 multi-
 label image dataset show that the proposed method achieves very promising perfor-
 mance in multi-label classification.

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