Modular network for high accuracy object detection.

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Abstract
We present a novel modular object detection convolutional neural network that significantly improves the accuracy of computer vision object detection. The network consists of two stages in a hierarchical structure. The first stage is a network that detects general classes. The second stage consists of separate networks to refine the classification and localization of each of the general classes objects. Compared to a state-of-the-art object detection networks the classification error in the modular network is improved by approximately 3-5 times, from 12 percent to 2.5-4.5 percent. The modular network achieved a very high score in object detection of 0.94 mAP. The network is easy to implement, it can be a platform to improve the accuracy of widespread state of the art object detection networks and other kinds of deep learning networks.

1 Introduction
In this paper, we present a novel highly accurate deep learning network for computer vision object detection. In particular, for fine-grained object detection. There is constant effort to increase the accuracy of deep learning object detection networks. A major topic in object detection is fine-grained object detection objects for detecting differences between similar object classes.

The main principles that guide the building of our network are modularity and hierarchy. Our object detection network denoted as modular network, consists of two stages, the first stage is an object detection network for detecting multi classes objects where the classes are general. The second stage consists of separate object detection networks, each one of them trained to detect only similar and related classes that belong to one of the general classes of the first stage network. Images with objects that belong to one of the general classes detected in the first stage are passed on to the second stage networks for detailed identification of the object’s kind and location. We compared the detection results of our modular network to a state of the art multi class object detection network which was trained to detect the same classes as the modular network. The experiments showed that our modular network has significantly higher accuracy.

Our contributions in this paper are: 1) A simple to implement highly accurate, modular and hierarchical architecture for fine-grained object detection. 2) We show both experimentally and theoretically that that a deep learning network designed to detect a small number of classes and initially trained by transfer learning is more accurate than a network trained on more classes.

Each of the building blocks networks inside our modular network designated to detect less classes than a regular multi class network that designated to detect the same number of classes as the whole modular network. This make the building blocks networks and the whole modular network more accurate than a regular multi class network. The modular network architecture suggested in this paper can be used to increase the accuracy of state of the art object detection networks by integrating them as parts of the building blocks of this network and without changing the intensive optimizations carried out on them.

Other types of networks can improve their accuracy by inserting them into this modular network platform.

2 Related Work
2.1 Object detection
Notable convolutional neural networks for object detection are [1; 2; 3]. Faster R-CNN [4] that consists of: a classification network, a region proposal network which divides the image into rectangular regions, followed by a regression for additional accuracy in classification and location. RetinaNet [5] is a one stage detector based on densenet and uses focal loss to handle class imbalance. Most of the state of the art object detection networks include a core image classification network such as Alexnet [6], VGG [7] or Resnet [8] these networks use transfer learning based on the training on a large image data set such as Imagenet [9] and Coco [10].

2.2 Hierarchical structures
Hierarchical structures appear in many forms in computer vision, Fukushima [11] and Jarrett et al [12] proposed a neural network for visual pattern recognition based on a hierarchical network. Du et al, designed a hierarchical network where on the first stage identified sub classes integrated to a single class on the last stage [13]. Kowsari et al proposed hierarchical deep learning network for text classification, [14]
2.3 Fine grained

Computer vision fine grained neural networks for recognizing similar classes were presented by Kraus et al [15] who suggested a method based on generating parts using co-segmentation and alignment, combined in a discriminative mixture to get precise identification in classification and location. Hariharan et al [16] define the hyper-column, a pixel as the vector of activation of all CNN units above that pixel. Using hypercolumns as pixel descriptors. Singh et al [17] present a fine-grained action detector for video on a recurrent neural network. Howard et al [18] proposed a streamlined network architecture that uses depth-wise separable convolutions.

3 The modular network

3.1 Modular network architecture

We present in this paper a new modular and hierarchical object detection network. The network consists of two stages, the first stage consists of a deep learning object detection network trained to detect predetermined general classes and the second stage consists of several deep learning object detection networks each trained on more fine grained classes belong to the same single general class of the first stage network. All the building blocks networks inside the modular network trained on negative images too.

Each independent deep learning network in the modular network goes through complete object detection process of training, test and inference. The full input image data set for inference is inserted to the first stage network, if an object in an image is detected to belong to one of this network classes the image is passed to inference by the second stage network trained to detect sub classes of this class. The purpose of the second stage network is to distinguish between objects of similar classes making more detailed classification and more accurate location of the object in the image. Each sub network in the modular network was initialized by transfer learning weights trained on ImageNet data base.

![Diagram of modular network](image)

Figure 1: A modular network whose first stage is trained to detect 3 general classes. Its second stage networks, consist of 3 separate networks each trained to detect one of the sub classes of the three general classes.

An additional suggested network that is based on the modular network is a network consisting of multiply modular networks in parallel each train to detect different classes, all have the same input images data. This network has the accuracy of a single modular network but can detect multiple number of different objects classes and can be operating in parallel. The modular network can consist of more than two hierarchical stages of object detection.

3.2 Algorithm and deep learning network construction

a. To detect multiple classes use an object detection network trained by transfer learning. Merge similar classes labels to a general class label

b. Train the network, denotes as the first stage network, to detect the new general classes and additional negative images with no labels that don’t belong to any of these classes.

c. For each of the general classes \( C_i \), train additional network, denoted as a second stage network, on fine grained classes all belong this general class together with negative images.

d. Input images for inference into the first stage network. Images with objects detected to belong to a general class are transferred to the second stage network dedicated to this class.

e. Input the transferred images for inference in to the appropriate second stage network for fine grained object classification and location.

3.3 Advantages and risk of the modular network

In each of the convolutional neural network inside the modular network there are less classes than regular network designated to detect the same number of classes as the whole modular network. Thus there are more filters dedicated for each class object detection, result in better accuracy in object detection. Small number of features to identify a class cussing less distinction in detection of similar classes and errors in detection of rare class objects too, since features are formed to identify objects types that appear in many images in the training. When there are a few features available to identify each class more features are formed to detect multiple classes this cause errors in fine grained object detection.

Fewer classes in object detection network mean potentially less bounding boxes of detected objects in the image, which gives fewer errors in identifying the objects and finding their locations.

In the modular network training there are less images in the input data set for each of the second stage networks because the training images are distributed over several networks. This results in less parameters and features dilution of each image or object.

The advantage of the hierarchical structure of the modular network compared to detection by many few class networks with no connection to each other is the hierarchical structure drastically cuts down the number required inferences as the inferences are arranged in a tree structure.

The modular deep learning network in this research has some similarities to recurrent neural network [19; 20] as both networks relate to the previous stage in the network, the difference is RNN use the previous stage network weights while the modular network doesn’t. This able the modular network to avoid problems of vanishing gradients or exploding gradients in the gradient back prorogation process that RNN has.

The accuracy of the modular network will be better than a multi class network when
\[ a < (a + \Delta_1)(a + \Delta_2) \] (1)

\( a \) - the multi-label network accuracy, \( \Delta_1 \) - the improvement in accuracy of the first stage of the modular network compared to the multi class network accuracy and \( \Delta_2 \) - the improvement in accuracy of the second stage compared to the multi class network accuracy.

Assuming we use for the building block network of the modular networks the same type of object detection network as the multi class network. If the multi class network has low accuracy then the multi class network is preferred since the building blocks networks inside the modular network should give a very large accuracy improvement compared to the multi-class network accuracy. For most state of the art object detection networks, their accuracy is large enough to use them as the building block network for the modular network and obtaining a modular network with higher accuracy compared to a single same state of the art object detection network.

A risk of the modular network is detection of false negatives in the network first stage may reduce accuracy as these objects will not be included as input for the second stage. This problem is solved for input sequence of images where the same object is assumed to appear in more than image. After inference of all the images sequence in the first stage of the modular network. The entire image sequence is sent for inference to networks in the second stage whose fine grained classes matched the general classes of the objects detected in the first stage. In this way there is no loss of accuracy due to false negative detection in the first stage. This method is denoted as modular network v2.

4 MathematicalDescriptions of the results

4.1 Convolutional neural network features distribution due to fine tuning.

Most state of the art deep learning networks initialized their network weights by transfer learning [21; 22; 23; 24; 25] from large data base of images and classes. The network then is fine-tuning by training on objects images belongs to classes the network is designated to detect [25]. The features for detecting a designated class in this network are divided to two types, features that formed when training the network on objects belong to this class and features that formed by training the network by other classes. \( N_c \) is the number of features that formed when training the network on objects belong to a specific class denoted as c. \( N_c \) is function of \( I \) - the total number images the deep learning network trained on, \( I_c \) - the number of training images with objects of class c. \( n \) - the number of classes the network designated to detect, \( g \) - the class’s objects complexity, \( N_{ctot} \) is the total number of the features in all the classes formed by fine tuning. We approximate \( N_c \sim \frac{N_{ctot} I_c}{\eta f} \) where \( g = 1 \). The features for detection of c formed by training on other classes are divided to: features from the transfer learning and feature formed in the fine tuning for other designated classes. The number of the later is negligible in most networks compared to the features based on the transfer learning. Because the number of classes in the transfer learning is much larger than the number of classes in a regular network and the number of features for c formed initially for other classes is related to the number of classes the network trained on. For example in our experiments the transfer learning has 1000 classes compared to the 9 other classes in the multi class network. The two major factors determine the number of features detecting class c is \( N_c \) which in this approximation is inversely proportional to \( n \), the number of designated classes for detection by the network. The smaller the number of features are designated to class c making class c object detection more accurate. The second major factor is features formed in the transfer learning which is correlated to the number of classes in the transfer learning.

4.2 Convolutional neural network classification error estimation by Bayes error.

For probing the images classification error we use a statistical approach based on Bayes error and Bayesian decision theory[26; 27; 28; 29]. Instead of features vector, we use filters vector since filters detect features and filters can be located precisely in the convolutional neural network, while identifying features in an image is more ambiguous. Filters can be identified for example by their known place in the activation layer features map, a filter that is activated is identified by high value pixels in its features map. We approximate that each of the features detected by the same filter belongs to the same classes. The reason for our approximation is based on the convolution method in convolutional neural networks where convolutions of all the channels in the filters are added together. A filter with channels that present features that don’t belong to the same class may lead to false identifications by adding values in the convolution that do not belong to the object, result in errors in object detection or classification. Let \( x=x_1...x_f \) be the filters vector, the number of filters in a network is constant. Let c be a set of classes \( c=c_0,...,c_n \). Every detection of an object in an image is defined by a set of active filters, i.e filters that identify features in this object, for example, the filters set \( x_{c_0},...,x_{c_n} \) identify objects belong to class \( C_1 \). To describe the error in the objects classifications we use Bayes error which estimates the probability for error in classification. According to Bayes error estimation when there are probabilities the feature and in our case the filter, classifies both classes \( C_0 \) and \( C_1 \), the error in the classification by filter \( x_i \) is the smallest probability density between the probability density of classifying class \( C_0 \) by filter \( x_i \) and classifying class \( C_1 \) by filter \( x_i \). As an example of estimating the classification error or accuracy of the networks in this research, we analyze a theoretical example of two fine grained classes detection \( C_0 \) and \( C_1 \). Assuming for each of the filters in the network the probability density for classifying classes \( C_1 \) and \( C_0 \) is known. We estimate the Bayes error by the filters of the last layer because their probability density for classifying classes \( C_1 \) and \( C_0 \) includes the influence of all the filters in the previous layers. This is more mathematically accurate since there are no duplication in including the previous layers filters influence on the class’s classification. In the estimation we approximate that the probabilities densities of identifying classes \( C_1 \) or \( C_0 \) by, filters that have probabilities densities to identify other classes, is negligible. In this approximation the number of filters dedicated to detect negative images is
we assume the total number of filters in the basic network was trained to detect in addition there are basic filters that are common to several classes. There is a large overlap area between the filters of classes \( C_0 \) and \( C_1 \) compared to the total areas of classes \( C_0 \) and \( C_1 \) filters. Which according to the Bayes error estimation indicates a large error in the classification.

Graph 2 illustrates the first stage network in the modular network the general classes network. This network detect objects of five general classes and additional negative category. The region of the filters that active by classes \( C_0 \) and \( C_1 \) is presented in discrete values we approximate as a continuous graph. Graphs 1-3 illustrates the filters activation in the modular and multi-class networks by classes \( C_0 \) and \( C_1 \). The X-axis in the graph will be the filter space. We assume the total number of filters in the basic network \( N_f \) is the same for all the networks inside the modular network. The Y axis is the probability density that a filter is activated by class \( C_0 \) or \( C_1 \). The filters in the graph are set that all filters with probability of matching a particular class are in the same region on the x axis. Filters that have a probability of matching the two classes will be displayed in the graph in a common area of both classes. The error in classification between classes \( C_0 \) and \( C_1 \) defined by Bayes error approximation as a sum of areas of minimal probability density belongs to classes \( C_0 \) and \( C_1 \), which is the overlapping area in classes \( C_0 \) and \( C_1 \) graphs.

Graph 3 presents the networks of the second stage in the modular network. This network trained to detect only two classes and negative images. The filters in this network are distributed between classes \( C_0 \) and \( C_1 \). The overlap region area of the two classes is small compared to the classes total areas, this indicate the classification error is small. Additional reason for small probability for miss classification is since the number of filters for each class is large the filters are trained to detect more detailed features, which reduce the error probability for miss classification.
5 Implementation

The image data set contains 522 images for training augmented to 46,044 images by mirroring, sharpness, brightness and contrast augmentations. The test data set contained 125 original images. Most of the original images were taken from the Caltech 101 image database and the rest randomly from the internet. The size of each of the original images in the data is up to 800*800 pixels. The size of the output images of the network is 800*800 pixels. For the multi-class network and the building blocks networks of the modular network we used the state of art object detection network Faster R-CNN with backbone classification network VGG 16. The Faster R-CNN network is initialized by training on ImageNet 2012 data base contained contained 1.2 million images for training and 50k validation images in 1,000 categories.

6 Experiments

In the experiments the sub networks inside the modular network and the multi-class network all have the same hyperparameters values previously optimized on different classes than the classes the networks trained to detect to make the comparison between a multi class network and the modular network unbiased. Both networks were trained to detect the same 10 classes. All the networks trained for 40 epochs, with learning rates of: 0.001 on the first 10 epochs, 0.0001 on the next 10 epochs and 0.000001 on the last 20 epochs. We test the networks on four classes: two dog species Pekinese and Spaniel and two planets Mars and Saturn. Each of these classes has about 30 original images for testing.

6.1 Networks training

Modular network

The modular network has two stages. We evaluate the first stage network by training the object detection network on five general classes dog, planet, bike, boat, bird each of the classes is a unification of a couple of similar classes out of the ten classes. The training loss as defined in Faster RCNN paper [4],is 0.0216. The training images are the same as in the multi class network. The test data set contained 125 images of two general class labels, dog and planet. Images that were detected with dogs and planets were sent for inference to the second stage networks.

We evaluated the second stage of the modular network by training two separate object detection networks, each network trained on two similar classes. One network trained on the two dog’s species classes Pekinese and Spaniel and negative category images, with 0.0151 loss. The training image data set contain only the images of these two classes and the negative images from the initial training image data set used in stage one. Another object detection network in the second stage was trained to detect two solar planets; Mars, Saturn and negative category. The training loss is 0.0170. The network was trained only on the images from the training data set of these classes and the negative images. The full second stage contains five separate networks each network detects two fine grained classes belonging to one of the general classes of the first stage.

multi-class network

The multi class object detection network was trained to detect ten classes with training loss of 0.0229. The training image data set is the same as in the first stage of the modular network but with 10 labels as opposed to 5 in the first stage of the modular. The test data set contained the same 125 images as in the test data of the modular network.

6.2 Experiments results

The training results indicate that as the number of classes trained to be detected by the network become smaller the training loss become smaller too.

Table 1 shows the mean average precision, mAP, of the networks, tested on the same images. The modular network v1 mAP 0.94 is significantly better than the multi-class network mAP 0.87 and on almost every class. The mAP of the modular network v2 0.95, which is mAP of a network trained to detect to detect two fine grained classes is better than the mAP 0.87 of the multi class network who trained to detect 10 classes.

The modular network v1 AP is calculated by taking into account the images detected as false negative on the first state of the modular network thereby do not appear on the mAP calculation of the second stage, each added as zero AP to the calculation and their weight is 1 divided by the total number of the modular network input images. For example, in table 1, the AP of Saturn in the modular network v1 is 0.91 but the AP of Saturn in the second stage network is 0.94.

Table 1: Object detection average precision

| Network            | dogs | planets | Spaniel | pekinese | Mars | Saturn | mAP |
|--------------------|------|---------|---------|----------|------|--------|-----|
| Modular net v1     | 0.97 | 0.90    | 0.97    | 0.91     | 0.94 |
| Modular net v2     | 0.97 | 0.90    | 0.97    | 0.94     | 0.95 |
| Multi-class        | 0.93 | 0.74    | 0.84    | 0.94     | 0.87 |
| General classes    | 0.93 | 0.92    | 0.93    |          |      |

Table 2: Classification Error

| Network            | Error-dogs | Error-planets | Error-Avg |
|--------------------|------------|---------------|-----------|
| Modular network v1 | 6%         | 3%            | 4.5%      |
| Modular network v2 | 5%         | 0%            | 2.5%      |
| Multi-class network| 14%        | 10%           | 12%       |
| General classes Mod| 1.5%       | 3%            | 2.25%     |

Table 2 shows the networks classification errors. The modular network error was significantly reduced to 6% and 3% error for dogs and planets compared to 14% and 10% respectively in the multi class network.

In figure 5 in the first column where the images detected by the multi class network, in the first three rows there are errors in classification. While the general classes network and the fine grained network detected the same objects correctly. It is
shows in second raw images that the detection of the object location is more accurate in the right image detected by the fine grained network compared to the object location in the left image detected by the multi class network.

Figure 5: Left column are object detection images by the multi class network, center column are detected images by the general classes network and right column are images detected by fine grained networks.

7 Comparison with state of the art object detection network.

Table 3 shows the mAP of the modular network and state of the art object detection networks[5].

| Two stage method          | Backbone         | mAP  |
|---------------------------|------------------|------|
| Faster RCNN++             | ResNet-101-C4    | 55.7 |
| Faster RCNN W FPN         | ResNet-101-FPN   | 59.1 |
| Faster RCNN by G-RMI      | Inception-ResNet-v2 | 55.5 |
| Faster RCNN w TDM         | Inception-TDM    | 55.5 |
| One stage method          |                  |      |
| Yolo v2                   | DarkNet-19       | 44.0 |
| SSD513                    | ResNet-101-SSD   | 50.4 |
| DSSD513                   | ResNet-101-DSSD  | 53.3 |
| RetinaNet                 | ResNet-101-FPN   | 59.1 |
| RetinaNet                 | ResNet-101-FPN   | 61.1 |
| Our method                |                  |      |
| Modular network v1        | VGG-16           | 93.8 |
| Modular network v2        | VGG-16           | 94.6 |

Table 3: Object detection networks mAP in percents

1 and version 2 accuracy is higher by additional 7.5% to 9.5% compared to the multi-class network respectively. Which is reduction of the classification error by 2.7 and 4.8 times respectively. We obtained that network with less classes is more accurate, the accuracy of a network that detect only two similar objects is 9.5% higher in compared to the multi-class network that detect 10 classes. In some of the images in the experiments the identification of the object location was improved by the modular network. The error in the second stage network that designated to detect two similar classes and the error of the whole modular network is smaller for planets classes than dogs classes. The planet classes are less similar to each other compared to the similarity between the dogs classes. Thus the classification error is smaller if the fine grained classes are less similar.

The accuracy our modular network achieved is higher than the accuracy of any widespread state of the art object detection network and should significantly improve the accuracy of any state of the art object detection network by implementing it as building blocks of the modular network. For maintaining the same high accuracy of the modular network in large number of classes (hundreds or more) we suggest adding together several modular networks in parallel, each designated to detect part of the classes.

8 Discussion

Most of the classification errors in the multi class network were between similar classes. The modular network version

9 Conclusion

The modular network presented in this paper significantly improves object detection performances in both classification and location. This is true especially for detection require differentiating between similar classes. This modular network improves state of the art deep learning object detection networks without requiring a change to those networks architecture and hyper-parameters. We found that reducing the number of classes a convolutional neural network is trained to detect increases the network accuracy. This modular network
could be a platform for other kinds of networks for example, recurrent neural networks, improving their accuracy by implementing them as building blocks of the modular network.

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