# **Cross-Domain Object Detection with YOLO**

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**Abstract**

*There are some papers about cross-domain classification, but only few of them are about object detection. In this paper, we present the results obtained and the methodologies adopted for cross-domain supervised object detection, basing ourselves on the paper by Inoue, Furuta, Yamasaki, Aizawa. For this paper, we have access to images with instance-level annotations in multiple source domains and images with only image-level annotations in a target domain. The classes to be detected in the target domain are all or a subset of those in the source domains. We start from a YOLO implementation using a pre-trained Darknet, and then we apply a two-step progressive domain adaptation technique by fine-tuning the Darknet on two types of artificially and automatically generated samples. Finally, we test our YOLO network on a subset of the Comic dataset, achieving… (and achieve an improvement of approximately 5 to 20 percentage points in terms of mean average precision (mAP) compared to the best-performing baselines.)*

# **Introduction**

The idea behind this paper is to train a network implementing the YOLO algorithm to detect objects in real-time in a target domain, which has only information about objects in the images, but no information about where they are placed. So, our goal is to use instance-level annotations of other domains and try to generate them on the target one. To make this possible, we have used the Darknet as implemented by [reference to pjreedie] with no pre-trained weights applied. Object detection is the process of autonomously recognizing objects (e.g. people, animals, cars etc.) in an image or video not only classifying those objects correctly deciding what they are, but also recognizing their positions and sizes in the input image. In fact, object detection is about assigning the right label (i.e. the class) and the right bounding box (i.e. a rectangular shaped frame) to an object. So, we define as image-level annotation of an image the set of classes coupled with the objects contained in that image, without knowing where objects are. The knowledge of the class and the position of objects in an image defines the instance-level annotation of the image. The position of an object is defined with a bounding box **b**, defined as *(x, y, width, height)*, where *x* and *y* are the coordinates in pixel of the upper left vertex of the box.

Right now, most object detection networks and researches focus on images from the real world­­­­­­­ obtaining great results, but object detection can be very useful also in other domains than just real-world one. The methods explained in this paper aim for detect objects in domains covered by few datasets with lack of annotations, i.e. painting or comic, and this is very useful to improve performances on them and transfer knowledge from a well-known domain. For example, an automated museum guide will exploit the knowledge obtained from these techniques to recognize objects in form of statues, paintings, etc.

We start from a Darknet pretrained on images with instance-level annotations from a source domain, then we fine-tune it in the target domain. This approach seems the best one, but there are no instance-level annotations available in the target domain. To generate this information, we use the same methods applied in the paper made by Inoue, that are *Domain Transfer* and *Pseudo Labeling*, that will be explained later. To perform *Domain Transfer*, we use a CycleGAN implemented by [AMICO FRIZZ], in order to transform data from source domains in the target one. Once the annotations are automatically created, we fine-tune the Darknet on them. The results obtained by the original paper applying this task achieve an improvement of 5 to 20 percentage points in terms of mean average precision, but the domain adaptation was made starting from a single source domain to a target one. The source was always Pascal VOC, which contains real-world images, and three networks were created to transfer instance-level knowledge to three different domains, that are Clipart, Comic and Watercolor. In our implementation, we want to know how much the results change if we use several sources and transfer all their information to the target one. All the sources have instance-level annotations, meanwhile the target one has only information about the objects in the images, so image-level annotations. The domains we take as source domains are Pascal VOC 2007 and 2012, Watercolor and Clipart. Comic, instead, is used as target domain.

# **Related Work**

## Supervised Detection: YOLOv3

Many methods can be used to realize object detection in images and video, such as Fast R-CNN, Faster R-CNN, YOLO. The first two use a similar approach: they first define some region of interest in the image, then they try to classify the objects into them. These two approaches are more accurate than YOLO, but they are slower. In fact, YOLO is faster and able to detect objects in real time, without a big latency between the request and the response. The approach of YOLO in the detection is quite different, and this is because YOLO splits the image in a grid and creates a set of bounding boxes in each of them. Then it regresses from each box to a box made by *(x,y,width,height,confidence)*, where the first four values have the same meaning explained before, and the confidence says the probability of having a correct prediction. Once this is done for each box, it predicts scores for the classes in the dataset, including the background class, and outputs them. YOLOv3 is able to learn instance-level annotations from a training dataset and then to detect objects in an image in about 40 milliseconds, which makes it suitable for real-time detection.

## Cross-Domain Object Detection

The target domains may have few or zero information about the position of the objects in the images. This may lead to an unfeasible detection. The idea is to take instance-level annotations from a source domain and use them in the target one as starting point. So, the network learns from a well-known domain, that has big and several datasets of images coupled with instance-level annotations. But if it tries to predict objects in other domains’ images, the results significantly worsen, because the features in the images are different and the network is not able to understand them. In order to increase performance, the network has to use knowledge of the source domain and to extract patterns from target one, and this will make the prediction more reliable. As we said before, we use the same approach, in terms of methods, of [Inoue]. The [Inoue] one takes a real-world dataset as source and adapts it to a target one, which has only image-level annotations. In our implementation, instead, we use multi-domain source and one target domain. The domains used as source have all the instance-level annotations. We also have instance-level annotations of the target one, but we use them only for testing, in order to get the prediction precision. We want to know if the results get worse with multiple domains or if they can be used to make the network more robust.

## Domain Adaptation

There are lots of methods to perform the domain adaptation task. The one proposed here is the CycleGAN, that is an unsupervised method able to translate images from a source to a target domain and vice versa. It uses two GANs, which are unsupervised generative models able to generate images similar to the set used as training. The GAN uses an implicit density distribution to generate data and uses a two-player approach. There are a generator and a discriminator in each of the GAN that tries to fool the generator creating real-like images and to distinguish between real and fake images respectively. The CycleGAN generates a fake image from source to target and tries to reconstruct the image to the source from the target. The cycle-consistency losses are used to update the parameters in the network in order to create images from source to target like the real target ones.

# **Dataset**

In our implementation, four datasets have been used. The source ones are Pascal VOC [2007][2012], Clipart [] and Watercolor. The target one is Comic. Comic and Watercolor datasets belong to BAM! dataset [], which contains several domains, but some of them are not suitable for the detection, because they contain just one object placed in the center in most of the images, so the detection is not so challenging. All these datasets have instance-level annotations, but only the source domains’ ones are used in the training.

## Pascal VOC

Pascal VOC is the biggest dataset among the used ones, and it is composed of images from real world. The dataset consists of two subparts made in different years, which are 2007 and 2012. The first one contains 9963 images, whereas the second one has 17125 images. Both datasets address 20 classes. This set is used to pre-train the Darknet and to transform the contained images in the target domain for the domain transfer.

## Clipart

Clipart is a dataset made by drawings and pictures. It contains 1000 images belonging to 20 classes, that are the same of Pascal VOC.

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...

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5. Actual Author Name. Frobnication tutorial, 2014. Some URL al tr.pdf.

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