UnseenNet: Fast Training Detector for Any Unseen Concept with No Bounding Boxes

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Abstract

Training of object detection models using less data is currently the focus of existing N-shot learning models in computer vision. Such methods use object-level labels and takes hours to train on unseen classes. There are many cases where we have large amount of image-level labels available for training but cannot be utilized by few shot object detection models for training. There is a need for a machine learning framework that can be used for training any unseen class and can become useful in real-time situations. In this paper, we proposed an “Unseen Class Detector” that can be trained within a very short time for any possible unseen class without bounding boxes with competitive accuracy. We build our approach on “Strong” and “Weak” baseline detectors, which we trained on existing object detection and image classification datasets, respectively. Unseen concepts are fine-tuned on the strong baseline detector using only image-level labels and further adapted by transferring the classifier-detector knowledge between baselines. We use semantic as well as visual similarities to identify the source class (i.e. Sheep) for the fine-tuning and adaptation of unseen class (i.e. Goat). Our model (UnseenNet) is trained on the ImageNet classification dataset for unseen classes and tested on an object detection dataset (OpenImages). UnseenNet improves the mean average precision (mAP) by 10% to 30% over existing baselines of object detection on different unseen class splits. Moreover, training time of our model is < 10 min for each unseen class. Qualitative results demonstrate that UnseenNet is suitable not only for few classes of Pascal VOC but for unseen classes of any dataset or web. Code is available at https://github.com/Asra-Aslam/UnseenNet.

1. Introduction

Detection of objects is one of the significant challenges in computer vision. Multiple object detection models have been proposed to date, including R-CNN (Girshick et al., 2014), Fast R-CNN (Girshick, 2015), Faster R-CNN (Ren et al., 2015), SSD (Liu et al., 2016), RetinaNet (Lin et al., 2017), and YOLO (Redmon et al., 2016). The conventional trend is to train such high-performance models on images with bounding box annotations for weeks and detect objects only for certain classes present in object detection datasets (like Pascal VOC (Everingham et al., 2010): 20 classes, MCOCO (Lin et al., 2014): 80 classes, OpenImages (OID) (Krasin et al., 2017): 600 classes). Recently we started calling such trained classes as “Seen” classes, and the remaining classes of the whole world are “Unseen” to object detection models. This problem persists not only because we are highly dependent on annotated object bounding boxes based datasets but also we ignore the classification data available on the web, which can be accumulated on request using labels of classes. Research focus is mainly on increasing the accuracy by giving few shots (Chen et al., 2018; Kang et al., 2019; Yan et al., 2019; Wang et al., 2019; Wu et al., 2020; Wang et al., 2020; Sun et al., 2021; Li et al., 2021), and where existing image-level labels cannot be utilized. Moreover training time of such approaches is increasing to days while struggling to provide competitive performance. Thus, such approaches are not suitable for real-time applications. Clearly, no settings are available for delivering competitive performance with reduced training time for unseen categories.

Several works (Hoffman et al., 2014; Tang et al., 2016; Uijlings et al., 2018; Li et al., 2018) are bringing a lot of potential in the area of unseen concepts by converting classifiers to detectors using image-level labels. These models are trained for a finite number of classes with an adaptation of classifiers into detectors, not for the adaptation to any number of domains. Moreover, they are lagging behind in terms of achieving good accuracy on unseen classes. In this work, we attempt to make detectors using classification data while providing better accuracy and responding to unseen classes in real-time.

Our work aims to answer the question: Can we train detec-
tors for any possible unseen concept (with only image-level labels) within a limited amount of time while providing competitive accuracy?

We divide the proposed framework “UnseenNet†” into two parts; first, we train two detectors “Strong Baseline” and “Weak Baseline” on 100 classes for weeks (~300 epochs). Here, we train strong baseline on object detection datasets (MCOCO and OID), and weak baseline on image classification dataset (ILSVRC (Russakovsky et al., 2015)). We use pipeline of YOLO (Redmon & Farhadi, 2018) with MobileNet (Howard et al., 2017) backbone to train detectors for fast detection and classification.

The second part is designated for the training of unseen classes. Here, we collect images (with no bounding boxes) from the web using only unseen class names. Then we choose a class (i.e., seen class) from strong baseline detector similar to unseen class and fine-tune it on collected classification data. We conduct extensive experiments to evaluate the performance of proposed framework (shown in Figure 1) in low response time for unseen concepts. We show that UnseenNet improves the mean average precision (mAP) by 10 to 30% over baselines in 10 min of training time, where existing models takes hours (or days) to attain a similar mAP.

2. Task Definition

In the case of our training detector for unseen concepts without bounding boxes, we assume that we have access to the object detection datasets (i.e., training images with bounding box annotations for the small number of classes) and image classification datasets (i.e., training images with only image-level labels for the large but finite number of classes). Our objective is to train detectors for any possible unseen concept (i.e., an infinite number of classes) without bounding box annotations within a short time to make them useful for real-time applications.

3. Related Work

Training of Object Detection Models: Existing object detection models (YOLO (Redmon et al., 2016), RetinaNet (Lin et al., 2017), SSD (Liu et al., 2016), Faster R-CNN (Ren et al., 2015)) require images with bounding box annotations for training, thus falls in the category of fully-supervised models. Such models require training for weeks, even for a limited number of classes, thus cannot process any new/unseen class. We attempt to overcome this limitation by providing training on unseen concepts without bounding boxes in a short training time.

Use of Datasets: Most popular object detection datasets in-clude Pascal VOC (Everingham et al., 2010), MCOCO(Lin et al., 2014), OID (Krasin et al., 2017), and ILSVRC detection challenge (Russakovsky et al., 2015). Though these datasets show promising results on the training of object detection models, indeed fail to fulfill the data requirements of object detection models that could process numerous classes. On the other side, image classification datasets (ImageNet (Deng et al., 2009); 1000, MNIST (LeCun et al., 2010); 10, CIFAR-10 (Krizhevsky et al., 2009); 10 classes) could be useful for training weak detectors regardless of having only image-level labels and iconic images. Presently, the significance of detection/classification datasets only appears in the comparison of deep learning models. We propose settings of utilizing all existing (object-detection, domain-specific, image-classification) datasets to train detectors for unseen classes of real-world scenarios.

Weakly Supervised Detection of Unseen Objects:

Weakly supervised learning (Zhu et al., 2017; Oquab et al., 2015; Bilen & Vedaldi, 2016; Kolesnikov & Lampert, 2016) is an emerging solution for large-scale unseen concepts. Weakly supervised learning also formulated as a Multiple Instance Learning (MIL) problem. wSOD" (Zeng et al., 2019) uses bottom-up object evidences and top-down classification output with an adaptive training mechanism. Multiple MIL based methods appear in literature (Tang et al., 2017a; 2018; Cinbis et al., 2016; Gokberk Cinbis et al., 2014) for the weakly supervised object localization. Most of these methods use pre-trained ImageNet (Deng et al., 2009) for initialization. However, our model uses the fastest MobileNetv3 (Howard et al., 2017) as backbone and own trained “Strong Baseline Detector” for the initialization. Such methods are evaluated on Pascal VOC (Everingham et al., 2010), and Pascal VOC is known in computer vision for a long time; its classes shouldn’t be considered unseen.

Another area of related work includes the knowledge transfer from source to target domain. Large Scale Detection through Adaptation (LSDA) (Hoffman et al., 2014) abased approaches transforms classifiers into object detectors using only image-level labels. Tang et al. (Tang et al., 2016) improve LSDA by incorporating informed visual knowledge and semantic similarities. Uijlings et al. (Uijlings et al., 2018) proposed a revisit knowledge transfer for detectors training in the weakly supervised settings and outperformed all the baselines. We utilize the concept of transferring knowledge between classifier and detector in our work. Some of the significant advantages of our work includes better accuracy, short training time, flexibility for training any possible unseen (new) concept and no requirement of bounding boxes.

N-Shot Learning: N-Shot learning is a branch of machine learning which handles the challenge of training a model with only a small amount of data. In terms of terminology,
UnseenNet: Fast Training Detector for Any Unseen Concept

Figure 1: An illustration of our “UnseenNet” model. We make use of existing object detection datasets (have bounding box annotations) and image classification datasets (have only image-level labels) and train two separate detectors “Strong Baseline Detector (0)” and “Weak Baseline Detector (0’)” respectively, in advance. (1) On request of any unseen concept, (2) we download images using only image-level labels (like goat). (3) Strong baseline detector is then fine-tuned on collected images of unseen concepts by labeling the most semantically similar class (like sheep) with the unseen class name (like a goat). (4) At this stage, we also compute the visual similarity of the constructed unseen class detector (trained on classification data) with seen classes of weak baseline detector, combine it with semantic similarities, and select top-k classes ranked on comprehensive similarities. (5) Finally, we transfer the knowledge of classifier-detector differences of top classes to the constructed unseen class detector, adapt it into the stronger detector without further training, and (6) return detection results. Note: Baseline detectors (0, 0’) are trained offline while other parts (1-6) gets train on unseen class request.

we refer to it as N-way K-Shot-classification, where N is the number of classes and K is the number of labeled training samples from each class. Recently few-shot learning based approaches (Chen et al., 2018; Kang et al., 2019; Yan et al., 2019; Wang et al., 2019; Wu et al., 2020; Wang et al., 2020; Sun et al., 2021; Li et al., 2021) are achieving promising results for the task of object detection. Such approaches requires multiple stages of training and thus more training time. Moreover, these approaches does not utilize image-level labels which can be easily acquired rather than object-level labels.

4. UnseenNet

We propose an “UnseenNet” detector (shown in Figure 1) which allow user to construct detectors for unseen classes without the need for detection data (no bounding boxes) within the short training time. Our model is based on making use of existing object detection datasets of bounded vocabulary (consists of seen concepts) to construct detectors for unseen concepts (i.e., unbounded vocabulary) by using the differences between a weak detector (trained on image classification dataset) and a strong detector (trained on object detection datasets). We describe below the construction of our strong and weak baseline detectors offline for seen concepts and training of detectors online for unseen concepts while investigating the object detection model’s training time, which we are referring to as the response-time of our model on unseen concepts.

4.1. Training Baseline Detector Offline for Seen Concept (with Bounded Vocabulary)

First, we setup an architecture of YOLO with MobileNet backbone and construct two baseline detectors as follows:

Strong Baseline Detector ($D_S$) is a $|K|$ class detector trained on existing object detection datasets. It is a detector that is trained on strong labels (i.e., bounding box annotations). Presently we have taken 100 classes (like LSDA) by considering all classes of MCOCO (80 classes (Lin et al., 2014)) and 20 classes of OID (Krasin et al., 2017). Please note that 20 classes of Pascal VOC (Everingham et al., 2010) are also present in MCOCO.

Weak Baseline Detector ($D_W$) is another $|K|$ class detector trained on image classification dataset. We trained it on weak labels (i.e., images-level labels). In this detector, we consider the same classes on which we trained the previous Strong Baseline Detector, but we use the ILSVRC (Russakovsky et al., 2015) classification data. The value of $|K|$ is 100 in both cases.
4.2. Training Online Detector for Unseen Concept (for Unbounded Vocabulary)

On request of an unseen class (u), say goat, first our model provides an environment to collect images for “goat” from the Web using Google Images\(^2\), Flickr\(^3\), or Bing Image\(^4\) search. Second, it use the “Strong Baseline Detector”, and set up a new detector by labeling the most similar seen class (like sheep) with unseen class (i.e. goat). It is important to note that a similar class (like sheep for goat) can be chosen only using semantic similarity at this stage as visual features of an unseen class cannot be computed before training. Next, we fine-tune the detector on images collected for “goat”. Now we have a new detector having |K| classes that can detect goat. Since goat class is trained only on image-level labels, we call it a weak detector or simply a classifier “C\(_u\)” for unseen class. At this point, our model’s response time for unseen concepts is equal to the time for fine-tuning.

We presume that fine-tuning induce a specific category bias transformation in the detection network towards goal “goat” (which is positive from the viewpoint of detecting a class (i.e. goat). Moreover, this network already encodes a generic “background” category due to previously trained on detection data (because of strong baseline), which is another positive perspective, as this will automatically make the new detector much more effective in localizing the new class without detection data. Finally, the previous classifier C\(_u\) adapts into a corresponding detector D\(_u\). This assumes that “difference between classification and detection of a target object category has a positive correlation with similar categories” detailed in large scale detection approaches (Hoffman et al., 2014; Tang et al., 2016).

Suppose weights of the output layer of D\(_S\) (Strong Baseline Detector) and D\(_W\) (Weak Baseline Detector) are w\(_D^S\) and w\(_D^W\) respectively. We know that for any seen category i ∈ K, final detection weights should be computed as w\(_D^S\) = w\(_D^W\) + δ\(_K\)\(_i\), where δ\(_K\)\(_i\) is the difference in weights for the seen category.

By using this knowledge difference and denoting the k\(_i\) nearest neighbor in set K of category u as \(N\(_K\)(u, k)\), we adapt the final output detection weights for categories u as:

\[
w^D_u = w^C_u + \sum_{i=1}^{k} s(u, i)\delta K_{N\(_K\)(u, i)}
\]

where \(k \leq |K|\), and s\((u, i)\) denotes the similarity of seen class (i) with unseen class (u).

Eq.1 uses the weighted nearest neighbor scheme ((Tang et al., 2016; 2017b), where weights are assigned to seen categories based on how similar they are to the unseen category. We select top-k weighted nearest neighbor categories (\(s(u, i)\)) using Eq.2. Other than the semantic similarity, we also compute the visual similarity at this stage by using the minimal Euclidean distance between the detection parameters of the last layers of detectors D\(_W\) and C\(_u\). Suppose \(K\)\(_v\) is the set of visually similar \(s\(_v\)\) categories and \(K\)\(_s\) is the set of semantically similar \(s\(_s\)\) categories, then comprehensive similarity \(s(u, i)\) for unseen category with seen categories is evaluated as:

\[
s(u, i) = \alpha s_v(u, i) + (1 - \alpha)s_s(u, i), \quad i \in \{K_v \cap K_s\}
\]

where \(\alpha \in [0, 1]\) is a parameter introduced in literature (Tang et al., 2016; 2017b) to control the influence of the two similarity measures. We use minimal Euclidean distance between feature distributions of the last layers as visual similarity (Hoffman, 2016) and naive path-based semantic similarity measure of WordNet (Pedersen et al., 2004) along with a weighted average scheme to compute the comprehensive similarity \(s(u, i)\) scores. We verify the value \(\alpha = 0.6\) on simplified similarity measures by analyzing the performance.

Finally, we call this adapted detector “D\(_u\)” a strong detector for unseen class. We analyze the response-time of our model in Section–5 from the stage of no detector to weak detector (C\(_u\)), and eventually to a strong detector (D\(_u\)).

5. Experiments

5.1. Implementation Details

Data Preparation We trained Strong and Weak Baseline Detectors on seen classes offline and performed experiments on unseen classes while having training time constraints.

Seen Classes

Strong Baseline Detector Training: In this case, We consider all 80 classes of Microsoft COCO (Lin et al., 2014) and 20 classes of Open Images OID (Krasin et al., 2017) to train a strong baseline detector with bounding box annotations. We select 20 classes from OID by sorting its 600 classes on the basis number of images per class and considering the top 20 with the highest number of images available for training.

Weak Baseline Detector Training: Here, We take the same 100 seen classes, retrieve images with labels from the ISLVR (Russakovsky et al., 2015) dataset (i.e., images have no bounding boxes), and train weak baseline detector by giving full image size in place of annotations.

Unseen Classes

We chose classes from the ILSVRC (Russakovsky et al., 2015) that are also present in Open Images OID (Krasin et al., 2017) (consist of 600 classes) and consist of reason-
able number of testing images (>100). So that we can evaluate the model on an object detection dataset, which gets trained on image classification dataset. That is, we use the testing dataset of OID for unseen classes to serve as groundtruth in the evaluations.

We also perform qualitative evaluations on additional 16 unseen classes that we downloaded from the web using Google Images API. Such classes are not present in any dataset (Pascal VOC, ImageNet etc.) to-date. This clearly proves our model’s significance for unseen concepts (known or unknown).

In our experiments, we consider the pipeline of YOLOv3 (Redmon et al., 2016; Redmon & Farhadi, 2018) and MobileNetv3 (Howard et al., 2017; 2019) for fast detection and classification. Specifically, we used the three layers (38, 117, 165) from the MobileNetv3 (Small) within YOLO to make the prediction.

We trained our baseline detectors first on learning rate of $10^{-3}$ till 100 epochs, then we used the decay type exponential till 200 epochs; finally, we used the $10^{-4}$ till 300 epochs as validation loss stopped decreasing near this point. However, for the training of our unseen classes, we used the constant learning rate of $10^{-4}$, which could be increased in future experiments for faster results. We kept the slowest possible learning rate, as our model should serve as the base-work for handling dynamic unseen concepts in short training time. Finally, we utilize the benchmark object detection metrics project to evaluate our detections with IOU=0.5.

We assume it is essential to specify that ImageNet and Object detection datasets use different name for the same classes, so we are using the vocabulary of WordNet to give a single name to each class and also provide mappings of different datasets with our model.

We used the path vector of WordNet for the semantic similarity measure. Visual similarity is simply computed using the minimal Euclidean distance of weights of the unseen class detector (trained on classification data) and weights of weak baseline detector, which is the same as described in LSDA. Here we use a degree of similarity measure to compute the comprehensive similarity between seen and unseen classes

**Degree of Similarity Parameter ($\alpha$)**

To complete the weighted average scheme’s evaluations over the simplified (visual and semantic) similarity measures, we also analyzed the value of parameter $\alpha$, which is responsible for computation of the degree of similarity of the unseen category with seen categories. Figure 2 shows the impact of $\alpha$ on mAP, and its possible peak values could be 0.5, 0.6, and 0.7.

### Estimation of Number of Epochs

We estimated the total number of epochs required to train the model for the designated training time by considering the batch size, number of available training images, and speed of our GPU for the completion of one step. The total number of epochs computed as:

$$\text{epochs} = \frac{\text{ResponseTime}}{(\text{Num of Images/Batch Size}) \times t} \quad (3)$$

where, “response time” denotes the total training time allowed, “Num of Images” is the number of available training images, and $t$ is time GPU takes to complete one step, which is 0.465 sec in our case. Here, “Num of Images/Batch-Size” is the number of steps. We used default batch-size 16. We conducted experiments on NVIDIA TITAN Xp GPU (8 Core Processor x 16), Driver 440.1 with CUDA 10.2.

#### 5.2. Quantitative Evaluation on Unseen Categories

##### 5.2.1. Comparative Analysis with Existing Models

We compare the performance of the UnseenNet in Table 1 against weakly supervised object detection models. We show mean average precision (mAP) for unseen categories along with required training time. We evaluate our model by considering different number (5, 10, and 100) of nearest neighbors of “unseen” categories with “seen” categories while using weighted average nearest neighbor scheme (Eq 1).

The first 4 rows show the results of existing approaches including LSDA (Hoffman et al., 2014), its improved version with visual knowledge transfer (Tang et al., 2016), zero shot learning ZSDTR (Zheng & Cui, 2021) (as we are also not giving any shots of bounding boxes), and revisiting knowledge transfer MI based approach (Uijlings et al., 2018). We can observe that mean Average Precision (mAP) of existing weakly supervised approaches are low while there training
## Table 1: The mean average precision (mAP) while using ILSVRC for Weak Level labels and MCOCO & OID for Strong Level labels. First, we show the performance for existing weakly-supervised methods. We also include the performance of semi-supervised LSDA. Row 5–7 shows our model's results on classification network, class invariant adaptation while fine-tuning specific class, then including Classifier to Detector Adaptation. We show the training time (10 min) our model takes to provide similar detection mAP. It is important to note that, inference time of UnseenNet is 9.2fps.

| Method                                | "Unseen" Categories | mAP       | Response-Time |
|----------------------------------------|----------------------|-----------|---------------|
| LSDA (Hoffman et al., 2014)            |                      | 16.33     | 5.5 hours     |
| Visual knowledge transfer (Tang et al., 2016) |                      | 20.03     | > 5.5 hours   |
| ZSDTR (Zheng & Cui, 2021)              |                      | 20.16     | –             |
| Knowledge Transfer MI (Uijlings et al., 2018) |          | 23.3      | –             |
| (Classification Network with No Adapt) |                      | 22.82     | 5 min         |
|                                        |                      | 27.92     | 10 min        |
|                                        |                      | 27.04     | 50 min        |
| (Class Invariant Adapt & Specific Class Fine-Tuning) |          | 33.36     | 5 min         |
|                                        |                      | 42.03     | 10 min        |
|                                        |                      | 39.77     | 50 min        |
| UnseenNet                               |                      |           |               |
| (Class Invariant Adapt, Specific Class Fine-Tuning, & Adapt) |          | 36.17     | 5 min         |
|                                        | Weighted Avg NN - 5  | 42.24     | 10 min        |
|                                        |                      | 39.79     | 50 min        |
|                                        | Weighted Avg NN - 10 | 42.36     | 10 min        |
|                                        |                      | 39.80     | 50 min        |
|                                        | Weighted Avg NN-100  | 43.07     | 10 min        |
|                                        |                      | 39.88     | 50 min        |

time is very high (>5.5 hours) or days and weeks in existing scenarios.

It is necessary to evaluate our model first by training only on classification data because we are using YOLOv3–MobileNetv3 (Redmon & Farhadi, 2018; Howard et al., 2019) in contrast to R-CNN–AlexNet (Girshick et al., 2014; Krizhevsky et al., 2012). We show that this amendment improves the performance from 16.33 to 22.82. Here we show the mAP for different response time (5 min, 10 min, 50 min). We choose these response times using testing and training (shown in Figure 3) detail in Section–5.2.2.

Second, we show the mAP using Class Invariant Adapt (Strong Baseline Detector) and fine-tuning the nearest “seen” class on target “unseen” class classification data. Finally, we apply the specific class adaptation by using the weighted average of “N” nearest neighbor classes, where N could be 5, 10, and 100. This step does not require training. We show the final detection performance (average on 100 classes) by indicating our model’s total time.

Best results indicate that we can reach from stage of no detector for unseen concepts to weak detector (mAP 42.03) and strong detector (mAP 43.07) within 10 min of training.

In present case, UnseenNet does not require any shots of bounding box based annotations, and use only image-level labels for finetuning. However, existing few-shot object detection models are showing great promise by providing competitive performance with only few shots of annotated bounding boxes. Thus, we compared our model performance with recent few-shot detection approaches (Chen et al., 2018; Kang et al., 2019; Yan et al., 2019; Wang et al., 2019; Wu et al., 2020; Wang et al., 2020; Sun et al., 2021; Li et al., 2021). Presently these models perform experiments by considering base classes of Pascal VOC for training and then novel classes also of Pascal VOC; and also in case of Microsoft COCO, base and novel classes belongs to same dataset. However, in our case we used Pascal VOC and Microsoft COCO classes in our strong baseline detector, thus we chose novel classes from OID dataset and still we get better performance than existing few-shot detection methods. Existing approaches used 5-class and 20-class novel splits, so we randomly generated 5-class pairs and 20-class pairs in our dataset of unseen classes. We can observe in Table 2 for case of 5-class splits we are getting mAP 68.78 which is >10% improvement over existing models. Similarly in case of 20 class splits our performance is mAP 51.09 which is greatest among existing approaches. Again, we trained on classification dataset (ImageNet) and tested on images Open Images dataset which consist of multiple objects in single image. It is important to note that we consider here
| Method                  | mAP on Splits |   |   |
|------------------------|---------------|---|---|
| LSTD (Chen et al., 2018) | 35.27         | 3.2 |   |
| FSRW (Kang et al., 2019) | 44.53         | 5.6 |   |
| Meta-RCNN (Yan et al., 2019) | 48.33         | 8.7 |   |
| MetaDet (Wang et al., 2019) | 44.4          | 7.1 |   |
| MPSR (Wang et al., 2020) | 53.1          | 9.8 |   |
| TFA (Wang et al., 2020) | 48.73         | 10.0 |   |
| FSCE (Sun et al., 2021) | 57.37         | 11.9 |   |
| cos-FSOD (Li et al., 2021) | 54.77         | 20.3 |   |
| UnseenNet               | 68.78         | 51.29 |   |

Table 2: Comparison with Few-Shot Detection methods

5.2.2. EXPERIMENTAL RESULTS WITH RESPONSE-TIME

To retrieve the range of response-time effective in our model, we train each category until the point testing accuracy starts to decrease (to avoid over-fitting). We show average performance of all unseen concepts with training time in Figure 3. Please note here we compute the total number of epochs for varying the training time (detail in Section 5.1). We first train our model on weak level labels (i.e., without bounding boxes) and then test on strong labels (i.e., with bounding boxes). Here weak labels are taken from ImageNet classification data and strong labels are taken from OID dataset. We observe that the maximum mAP of each class could be achieved within 10 min of training. After that, mAP decreases and remain constant. However, we recommend 10 min of training to attain maximum mAP 43.07 to avoid any unexpected reduction in mAP due to over-fitting.

5.2.3. EXPERIMENTAL RESULTS WITH UNSEEN CONCEPTS

We present an analysis mAP with similarities of unseen categories with seen categories (top-10) for few examples of our unseen classes. The simple average similarity score:

$$s_j = \frac{\sum_{i=1}^{m} s(j, i)}{m}$$

where m is 10 presently and $s(j, i)$ is the comprehensive similarity (shown in Eq. 2) between unseen (j) and seen (i) category computed using $\alpha=0.6$. It shows if we have unseen classes (like building, pasta, salad) more similar to seen classes, then our model have high probability of giving high performance with the exception for small size objects or availability of less training data.

5.3. Qualitative Evaluation on Unseen Categories

We show visual examples of our model detections in Figure 5. Examples of correct detections of our model on “Unseen” categories shown in red color and groundtruth (taken from OID) in green. Here Figure 5 (a) – (h) includes classes of ILSVRC, and Figure 5 (i) – (p) consist of additional unseen classes that not present in any object detection or image classification dataset to date. Correct detections of unseen concepts verify that UnseenNet can be trained on any class within a 10 min of training. It also reduces the need to create large object detection datasets.

Some examples of incorrect detections are shown in Figure 6, where Figure 5 (a) – (h) includes classes of ILSVRC, and Figure 5 (i) – (p) consist of additional unseen classes that our model downloaded online and are not present in any object detection dataset to date. This demonstrates that if we have “unseen” classes less similar to “seen” classes, then UnseenNet could label them correctly because of the
training on classification data with incorrect localization due to absence of detection data.

6. Conclusion and Future Work

We presented an “UnseenNet” model that has the ability to construct a detector for any unseen concept without bounding boxes while training in a short time and providing competitive accuracy. We found that starting from a “strong baseline detector” trained on existing object detection datasets speed up the training rather than using only ImageNet (Russakovsky et al., 2015) pre-trained model to train unseen concepts. Moreover, in conjunction with semantic and visual similarity measures, classifier-detector conversion methods make our model more robust. Our evaluations demonstrate that UnseenNet outperforms the baseline approaches in terms of training time for any unseen class and improves the mAP from 10% to 30% over existing detection based methods.

In the future, UnseenNet could be improved with more effective detectors and classifiers. Presently, we provided the size of images as bounding boxes for training weak baseline detector. This could be improved by background extraction or segmentation approaches and provide better annotations for training. Lastly, Strong and Weak baseline detectors could include large number of seen classes to obtain more similar classes.

References

Bilen, H. and Vedaldi, A. Weakly supervised deep detection networks. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 2846–2854, 2016.

Bilen, H., Pedersoli, M., and Tuytelaars, T. Weakly supervised object detection with posterior regularization. Proceedings BMVC 2014, pp. 1–12, 2014.

Bilen, H., Pedersoli, M., and Tuytelaars, T. Weakly supervised object detection with convex clustering. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 1081–1089, 2015.

Chen, H., Wang, Y., Wang, G., and Qiao, Y. Lstd: A low-shot transfer detector for object detection. In Proceedings of the AAAI conference on artificial intelligence, volume 32, 2018.

Cinbis, R. G., Verbeek, J., and Schmid, C. Weakly supervised object localization with multi-fold multiple instance
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Deng, J., Dong, W., Socher, R., Li, L.-J., Li, K., and Fei-Fei, L. Imagenet: A large-scale hierarchical image database. In Computer Vision and Pattern Recognition, 2009. CVPR 2009. IEEE Conference on, pp. 248–255. IEEE, 2009.

Everingham, M., Van Gool, L., Williams, C. K. I., Winn, J., and Zisserman, A. The pascal visual object classes (voc) challenge. International Journal of Computer Vision, 88(2):303–338, June 2010.

Fei-Fei, L., Fergus, R., and Perona, P. One-shot learning of object categories. IEEE transactions on pattern analysis and machine intelligence, 28(4):594–611, 2006.

Girshick, R. Fast r-cnn. In Proceedings of the IEEE international conference on computer vision, pp. 1440–1448, 2015.

Girshick, R., Donahue, J., Darrell, T., and Malik, J. Rich feature hierarchies for accurate object detection and semantic segmentation. In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 580–587, 2014.

Gokberk Cinbis, R., Verbeek, J., and Schmid, C. Multi-fold mil training for weakly supervised object localization. In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 2409–2416, 2014.

Hoffman, J. Adaptive learning algorithms for transferable visual recognition. University of California, Berkeley, 2016.

Kolesnikov, A. and Lampert, C. H. Improving weakly-supervised object localization by micro-annotation. arXiv preprint arXiv:1605.05538, 2016.

Krasin, I., Duerig, T., Alldrin, N., Ferrari, V., Abu-El-Haija, S., Kuznetsova, A., Rom, H., Uijlings, J., Popov, S., Veit, A., et al. Openimages: A public dataset for large-scale multi-label and multi-class image classification. Dataset available from https://github.com/openimages, 2:3, 2017.

Krizhevsky, A., Hinton, G., et al. Learning multiple layers of features from tiny images. 2009.

Krizhevsky, A., Sutskever, I., and Hinton, G. E. Imagenet classification with deep convolutional neural networks. In Advances in neural information processing systems, pp. 1097–1105, 2012.

LeCun, Y., Cortes, C., and Burges, C. Mnist handwritten digit database. ATT Labs [Online]. Available: http://yann.lecun.com/exdb/mnist, 2, 2010.

Li, Y., Zhang, J., Huang, K., and Zhang, J. Mixed supervised object detection with robust objectness transfer. IEEE transactions on pattern analysis and machine intelligence, 41(3):639–653, 2018.

Li, Y., Zhu, H., Cheng, Y., Wang, W., Teo, C. S., Xiang, C., Vadakkepat, P., and Lee, T. H. Few-shot object detection via classification refinement and distractor retreatment. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 15395–15403, 2021.

Lin, T.-Y., Maire, M., Belongie, S., Hays, J., Perona, P., Ramanan, D., Dollár, P., and Zitnick, C. L. Microsoft coco: Common objects in context. In European conference on computer vision, pp. 740–755. Springer, 2014.

Lin, T.-Y., Goyal, P., Girshick, R., He, K., and Dollár, P. Focal loss for dense object detection. In Proceedings of the IEEE international conference on computer vision, pp. 2980–2988, 2017.

Liu, W., Anguelov, D., Erhan, D., Szegedy, C., Reed, S., Fu, C.-Y., and Berg, A. C. Ssd: Single shot multibox detector. In European conference on computer vision, pp. 21–37. Springer, 2016.

Oquab, M., Bottou, L., Laptev, I., and Sivic, J. Is object localization for free? weakly-supervised learning with convolutional neural networks. In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 685–694, 2015.

Pedersen, T., Patwardhan, S., and Michelizzi, J. Wordnet:: Similarity: measuring the relatedness of concepts. In Demonstration papers at HLT-NAACL 2004, pp. 38–41. Association for Computational Linguistics, 2004.
Redmon, J. and Farhadi, A. Yolov3: An incremental improvement. *arXiv preprint arXiv:1804.02767*, 2018.

Redmon, J., Divvala, S., Girshick, R., and Farhadi, A. You only look once: Unified, real-time object detection. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 779–788, 2016.

Ren, S., He, K., Girshick, R., and Sun, J. Faster r-cnn: Towards real-time object detection with region proposal networks. In *Advances in neural information processing systems*, pp. 91–99, 2015.

Russakovsky, O., Deng, J., Su, H., Krause, J., Satheesh, S., Ma, S., Huang, Z., Karpathy, A., Khosla, A., Bernstein, M., Berg, A. C., and Fei-Fei, L. ImageNet Large Scale Visual Recognition Challenge. *International Journal of Computer Vision (IJCV)*, 115(3):211–252, 2015. doi: 10.1007/s11263-015-0816-y.

Shi, Z., Siva, P., and Xiang, T. Transfer learning by ranking for weakly supervised object annotation. *arXiv preprint arXiv:1705.00873*, 2017.

Simonyan, K. and Zisserman, A. Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*, 2014.

Sun, B., Li, B., Cai, S., Yuan, Y., and Zhang, C. Fsce: Few-shot object detection via contrastive proposal encoding. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 7352–7362, 2021.

Tang, P., Wang, X., Bai, X., and Liu, W. Multiple instance detection network with online instance classifier refinement. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 2843–2851, 2017a.

Tang, P., Wang, X., Wang, A., Yan, Y., Liu, W., Huang, J., and Yuille, A. Weakly supervised region proposal network and object detection. In *Proceedings of the European conference on computer vision (ECCV)*, pp. 352–368, 2018.

Tang, Y., Wang, J., Gao, B., Dellandréa, E., Gaizauskas, R., and Chen, L. Large scale semi-supervised object detection using visual and semantic knowledge transfer. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 2119–2128, 2016.

Tang, Y., Wang, J., Wang, X., Gao, B., Dellandréa, E., Gaizauskas, R., and Chen, L. Visual and semantic knowledge transfer for large scale semi-supervised object detection. *IEEE transactions on pattern analysis and machine intelligence*, 40(12):3045–3058, 2017b.

Uijlings, J., Popov, S., and Ferrari, V. Revisiting knowledge transfer for training object class detectors. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 1101–1110, 2018.

Wang, C., Huang, K., Ren, W., Zhang, J., and Maybank, S. Large-scale weakly supervised object localization via latent category learning. *IEEE Transactions on Image Processing*, 24(4):1371–1385, 2015.

Wang, X., Huang, T. E., Darrell, T., Gonzalez, J. E., and Yu, F. Frustratingly simple few-shot object detection. *International Conference on Machine Learning (ICML)*, 2020.

Wang, Y.-X., Ramanan, D., and Hebert, M. Meta-learning to detect rare objects. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pp. 9925–9934, 2019.

Wu, J., Liu, S., Huang, D., and Wang, Y. Multi-scale positive sample refinement for few-shot object detection. In *European Conference on Computer Vision*, pp. 456–472. Springer, 2020.

Yan, X., Chen, Z., Xu, A., Wang, X., Liang, X., and Lin, L. Meta r-cnn: Towards general solver for instance-level low-shot learning. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pp. 9577–9586, 2019.

Zeng, Z., Liu, B., Fu, J., Chao, H., and Zhang, L. Wsod2: Learning bottom-up and top-down objectness distillation for weakly-supervised object detection. In *Proceedings of the IEEE International Conference on Computer Vision*, pp. 8292–8300, 2019.

Zheng, Y. and Cui, L. Zero-shot object detection with transformers. In *2021 IEEE International Conference on Image Processing (ICIP)*, pp. 444–448. IEEE, 2021.

Zhu, Y., Zhou, Y., Ye, Q., Qiu, Q., and Jiao, J. Soft proposal networks for weakly supervised object localization. In *Proceedings of the IEEE International Conference on Computer Vision*, pp. 1841–1850, 2017.