A Comparative Study on Effects of Original and Pseudo Labels for Weakly Supervised Learning for Car Localization Problem

Cenk Bircanoglu
Paris, France
cenk.bircanoglu@gmail.com

Abstract—In this study, the effects of different class labels created as a result of multiple conceptual meanings on localization using Weakly Supervised Learning presented on Car Dataset. In addition, the generated labels are included in the comparison, and the solution turned into Unsupervised Learning. This paper investigates multiple setups for car localization in the images with other approaches rather than Supervised Learning. To predict localization labels, Class Activation Mapping (CAM) is implemented and from the results, the bounding boxes are extracted by using morphological edge detection. Besides the original class labels, generated class labels also employed to train CAM on which turn to a solution to Unsupervised Learning example. In the experiments, we first analyze the effects of class labels in Weakly Supervised localization on CompCars dataset. We then show that the proposed Unsupervised approach outperforms the Weakly Supervised method in this particular dataset by approximately %6.

I. INTRODUCTION

Object localization is one of the most common tasks in Computer Vision literature and it has potential application areas such as robotics, e-commerce, automatization, and so on. The example implementations of the object localization solutions are applied in a wide range from simple cameras to self-driving cars in various businesses. In general, novel algorithms are quite powerful to achieve good results to provide products, however, they are hungry for data, and collecting or generating data became the costlier part rather than modeling. To fix this problem, researchers have been working on Weakly Supervised approaches that require labeled data but labeling is done for simpler attributes which takes less time than labeling complex attributes. As an example, using class labels which can be labeled by humans in less time than localization labels, became more popular and interesting for the researchers for localization problems as it requires less money, time, and effort. In the meantime, although it is also true the progress in Weakly Supervised is exciting, there is still a significant gap between the performances of Supervised and Weakly Supervised Learning approaches. Besides these approaches, there are Unsupervised approaches that do not require the labels in training. As there is no guide to achieve the results, Unsupervised approaches mostly give worse results yet on localization problems.

One of the most important aims of Weakly Supervised Learning algorithms on Computer Vision problems, reducing the cost and time of the labeling process, and achieving prediction of the more complex labels extracting information less complex ones. Various implementations of Weakly Supervised Learning approaches can be found in the literature and most common ones can be listed as,

- Object localization using class labels,
- Semantic segmentation using class labels,
- Semantic segmentation using localization labels.

This study contains two main parts, the first part strongly focuses WSL solutions using human-created labels which are tightly related to the first case listed above, the second part takes the WSL solution a bit further and turned it to an instance of Unsupervised Learning approaches.

The first part of this study is about the use of object class labels to achieve localization. We extend the available WSL method in [1] by applying some post-processing steps. Then we try to answer the question, What are the effects of the class labels in Weakly Supervised learning? What is unique in this study is to have different human-labels for each image as a class label. For instance, our car localization experiments we have Make, Model, and Year classes. All labels are targeting the same object in the image but have different meanings which are also relatively abstract. Also, there is a hierarchical relation between the two class labels, Make and Model. If the Model of the car is known, it means that Make labels are also known. These properties of the dataset make it so special for this study and enable the comparisons to look after to answer the question. To find out the answers, Class Activation Map (CAM), one of the most common algorithms in WSL, is employed for each class label. As CAM results are heatmaps over the objects, the bounding boxes are found with morphological edge detection algorithm.

In the second part of the study, the approach is extended to Unsupervised Learning. First, for each image, the embeddings are generated by using a pre-trained CNN model and clustering labels are generated from embeddings and they are used as pseudo labels in CAM training. So, without using any human-created class labels, there are class labels that enable the CAM and the subsequent steps. As a result, the question Can Weakly Supervised Learning be transformed to Unsupervised Learning? is answered at least for car localization.

The experimental results in the first part show the accuracy of localization increases as the number of classes increases.
In the second part, our proposed Unsupervised method outperforms the weakly supervised method on the same experimental setup with a significant difference, surprisingly. But it is also obvious there is still a gap between Unsupervised and Supervised approaches.

The paper is organized as follows: After giving a short overview of related works in section 2, the proposed architecture and the details of the dataset are explained in the subsequent sections. Section 5 describes the implementation details and experimental results. Finally, we conclude the paper with a discussion on the proposed approach.

II. RELATED WORK

Object localization problem is one of the most interesting and studied problems in the literature with various methods that can contain learning or not. These methods can be gathered in 3 main groups, Supervised Approaches, Weakly Supervised Approaches, and Unsupervised Approaches.

A. Supervised Approaches

Sliding Windows and variations of this method were used to localize the object in the images by searching the region that gives a maximum score which needs high computation power [2, 3]. Another method is called global and local context kernels which trains a single discriminative classifier on the combined features of multiple context models [4]. More recent approaches which are state-of-the-art models are implemented by using one or a combined version of Convolutional Neural Networks (CNN), Long-Short Term Memory (LSTM), Recurrent Neural Networks (RNN) [5, 6]. In these studies, the localization problem is handled as a regression problem and by using a specific equation called Non-Maximum Suppression which proposes the best possible regions from multiple proposals and confidence scores by adding threshold.

B. Weakly-Supervised Approaches

There are different techniques to do object localization with Weakly Supervised approaches. The first technique worth mentioning Exhaustive Search which tries to estimate the localization from local regions which are obtained using classifiers learned from weakly labeled data [7, 8, 9, 10].

There is another technique called Multiple-instance learning which tries to learn various object categories from the bag of positive and negative labeled images [11, 12, 13, 14, 15, 16]. And the object categories are used to improve the object localization results in these papers.

C. Unsupervised Approaches

[17] uses iterative spectral clustering to localize the objects. [18] They explained how to localize the same objects in the multiple images by using specific image-box formulation on object co-localization problem. In the study [19], they depend on a specific rule which exactly is each image contains the object which has the same labels to find localizations. [20] uses partial correspondences and clusters of local features as indicators to solve the co-localization problem. In [21], even the name of the paper contains unsupervised, it is not exactly an Unsupervised Learning from only images it also includes web tags which makes it a good example of Weakly Supervised Learning technique. [22] is also an example of the studies on object localization which uses Dilated Residual Network to generate saliency maps. [23] They implemented Object Location Mining to the features of the images obtained from pre-trained CNN. Also, Generative Adversarial Networks employed to achieve the location of the objects in the images [24].

Additionally, we need to mention about Class Activation Map (CAM) [1] algorithm as this study heavily depends on it. CAM is a relatively old algorithm and was used in multiple studies [25, 26] as it is or with some variations [27, 28] for multiple purposes such as obtaining saliency maps, object detection [29], instance, and semantic segmentation [30].

III. PROPOSED APPROACH

Principally, this study contains two different approaches, employing WSL training on given labels and applying WSL on generated labels. The first approach is obviously an instance of Weakly Supervised Learning proposed in [1], achieving object localization labels from object classes, the second approach is an extension of WSL for making the training stage unsupervised, i.e. no real label used in training or inference phase. The second approach inherited from the first one with an important update in labels that are used for training. It uses pseudo labels instead of human-generated labels in the training phase. In both approaches, Class Activation Map (CAM) algorithm and Morphological Edge Detection algorithms are employed for the same purpose, bounding boxes are reached by applying Morphological Edge Detection on heatmap results which are the output of CAM inference. The unsupervised approach contains a more complex pipeline which includes techniques such as Feature Extraction by using CNN and clustering by KMeans.

In summary, a common and well-known approach of WSL, CAM is extended for object localization, and additionally, a simple pipeline is built to generate new labels for the images by using output features of a pre-trained model and clustering labels of KMeans. In the next sections, all the details of the pipeline and algorithms are described.

A. Object Localization using Class Activation Map

In this method, Class Activation Map and Morphological Edge Detection algorithms are employed to locate the object using the image itself and class label of the object existing in the corresponding image. It is based on Class Activation Maps on Deep Learning architecture.

1) Class Activation Map: Class Activation Map (CAM) is one of the oldest and simplest methods which updates Convolutional Neural Network (CNN) architecture with some constraints, used in different purposes such as debugging the model to understand decision process, creating the saliency maps, reusing classification models as segmentation and localization models without nearly no effort and so on. In another
way, it is a technique for discriminating image regions used by a CNN to identify a specific class in the image, in another word, it is pointing out the regions in the image where the specific class relevant.

CAM algorithm has 2 specific constraints;
- There must be global average pooling layer after the final convolution layer
- There must be a linear layer after the pooling layer.

According to these two constraints, the network needs to be altered to do training or fine-tuning to keep the same behavior with the original CAM paper.

2) **Edge Detection:** As the CAM algorithm only gives the region as pixel-wise, this region is needed to be transformed to Bounding Boxes (BBox) purposefully. In this study, there are several steps applied to generate BBox from CAM results,
- Morphological closing performed on CAM results,
- After transformation, an algorithm that proposed in [31] is applied to retrieve contours from the binary image,
- The biggest area is selected if there are multiple contours,
- Calculate the bounding rectangle from the biggest contour area.

**Fig. 1. Weakly Supervised Learning Architecture**

Steps of the end-to-end methods are,
- Train a network which has pre-trained CNN as a backbone model with modifications mentioned III-A1 to reach CAM results,
- Do inference on test split by using the trained network,
- Generate gray-scaled images from CAM results
- Apply morphological edge detection algorithm on gray-scale images and create bounding boxes.

Visualization of the important steps of the method is visualized in Figure 1.

**B. Proposed Method**

The proposed method can be divided into two main parts as the first one is the generation of the labels and the second part is exactly operating the same steps as III-A1 on generated (pseudo) labels. Two well-known and common techniques are utilized to generate the pseudo labels to employ them, 1) Features Extraction using CNN, 2) Clustering on features.

1) **Feature Extraction:** Clustering on image datasets can be computationally costly and hard as the images in the dataset have high resolutions. And also as we are interested in the important points/regions of the images, so it is nice to have a summary of the image as a feature set. Using a pre-trained CNN is one of the possible choices and it is the chosen one here. Although there are various alternatives to create clusters from images, this study focused on feature extraction and clustering of the extracted features. As the main objective relies on achieving the more complex labels from less complex or in this case, without any label, employing pre-trained models just in the inference stage to create features is a meaningful approach as it does not require any training and there is nearly no cost to do that.

2) **Generating New Class Labels:** As the purpose of this study to understand the effects of the category labels on WSL, besides the categories of the dataset, more categories are generated with different methods. In the abstract, the target for the generation process is keeping it as simple as possible. The list below is the methods that are tested,
- Create new labels by merging predefined labels,
- Generate random labels,
- Use clustering to define labels.

**Fig. 2. Unsupervised Learning Architecture**

As it is shown in Figure 2 to generate labels for the images, inference done by using pre-trained CNN. But the network is not executed till the end, it cut off at the first linear layer and the inputs of the first linear layer taken as image embedding to use them as features for clustering in the next step. After applying clustering, cluster labels are appointed as pseudo-labels if the objects in the image. From this point to the end, the method described in Section III-A1 is employed as it is to reach the object localization labels.

**IV. DATASET**

In this section, general information about the dataset was given first. Afterward, specifically which features of this dataset are special and how they enable this study were explained. Finally, basic statistical information on the dataset was presented.

The dataset called The Comprehensive Cars (CompCars) [32] selected to investigate which have car images from different makes, models, and made years and gathered in 2015. The examples of the images are presented in Figure 3 with random selection. In the original paper, the dataset is split into two different groups, in one group it contains only images from the web, and in the other group, it has images from surveillance cameras. In this study, only the web-based images are used.

In general, the dataset can be described as it has clear images of the cars like there are no occlusions, no low-quality images, no bad lighting. If there are multiple cars in one image, the related car is the bigger and more focussed one. Also, the same car can be found in multiple images with different shooting angles which bring into more variations in
the perspective of dataset richness. The dataset has its own train and test splits and in this study, the same train and test splits are used as it is. The number of images in train and test dataset is given in Table I.

The dataset is selected due to its specific features

- Each image has multiple labels which point the same object in the image (Make, Model, Year) and these labels are the results of human effort
- Most of the images contain one car which is in the center of the image, in general (Although it is true there are multiple cars in some images, there is only one car which is focused)
- There can be multiple images for the same car with different viewpoints
- Cars also have localization labels which also labeled by manually (Bounding Boxes)

The listed features above are the enablers to this study as one of our targets is Analyse the effects of the different classification labels on Weakly Supervised Learning.

The first item makes it possible to analyze that if it makes differences to group the objects with multiple semantic meanings as make, model, and year. The differences between make, model, and year may be clear for people but it is really interesting as make and model is related in a hierarchical way and year and model may have many-to-many relation but it is obvious that make name is just a term about the manufacturer and model name is mostly about how manufacturer named them. Also, the year is more abstract value for images as even experts have some difficulties about guessing it and there are some other possibilities to make predicting year impossible like changing some parts of the car or painting car which creates a newer look.

As this is an initial study on this topic, having some constraints on the dataset like object are mostly centered and viewing the car nearly 360 degrees with multiple images can be helpful and make things possible like better and easier clustering.

The last item is the main point to choose this specific dataset as the study is all about finding the location of the car and it allows to analyze the results quantitatively. As it is mentioned before, there are 3 different category titles as Make, Model, and Year. The number of the categories is varied and as a result, the number of the items in train and test set per category relies on the category title. The numbers of the categories listed in Table I as 75, 431, and 16 for Make, Model, and Year respectively. It is obvious there is also a hierarchical relation between Make and Model categories as Model is the subset of Make class. It is not given but there is also many-to-many relation between Model and Year and as a result between Make and Year.

| Category Name | Make | Model | Year |
|---------------|------|-------|------|
| Number of Labels | 75   | 431   | 16   |

Also, it is possible to create new categories by using the existing labels as there are 3 different labels for the same object. For example, merging the labels are an easy and valid way to do that but not for Make and Model as they have one-to-many relation and there is no new category label by merging them. As a result, it can be double and valid to generate Make-Year and Model-Year labels by just concatenation of the labels.

| Number of Images | 36456 | 15627 |
|-------------------|-------|-------|
| Dataset Split     |       |       |

The number of new labels is 492, 1631 for Make-Year, and Year and Model-Year labels by just concatenation of the labels. As a result, it can be doable and valid to generate Make-Year and Model-Year respectively. In summary, the dataset is actually offering 5 different category sets to investigate.

V. IMPLEMENTATION DETAILS AND RESULTS

In this section, implementation details are explained, and also quantitative and visual outputs are presented.

A. Implementation Details

As it is mentioned, there are two different methods to do training in this study which one of them is the inherited another one. Every detail is the same for the common part in both methods and this enables us to make comparisons fairly.

In this study, ResNet 50 [33] which pre-trained on ImageNet [34] classification dataset is used as backbone model on CAM network architecture. Two different models and execution from one backbone model projected for training and evaluation phases. For the training phase, the first four residual blocks of ResNet 50 are kept unchanged and after the fourth block, the 2-dimensional Global Average Pooling (GAP) layer appended as it is one of the constraints. After the GAP, there is one dense layer like it is required for CAM implemented. The number of the output logits varies on the number of labels of the selected category. And also, in training, the weights of the first block are kept frozen and no changed done on these. In the evaluation phase, after the fourth block of ResNet, there is only the linear layer that contains the same weights as in the training network and after the linear layer, there is Rectified Linear Unit (ReLU) function as the activation function for ignoring negative activated neurons. The differences in training and inference phase enable that the network actually trained for classification problems but with the updates, it will support the creation of the heatmaps.
Additionally, training CAM contains the same mechanism with standard classification training with CNN, so it can be followed the training accuracy for class labels and the training can be tuned according to training accuracy and in this case, 10 epochs are enough to stop the training.

There is also one more specific change between the training and evaluation phase, training is done on the preprocessed images but the evaluation part uses the same image as two images, first as original second as a flipped image, and aggregate the results with a summation.

1) Preprocessing Images: There are mainly two different preprocessing applied to images, one for training one for evaluation. For training, images resized according to the longer side of the image, random cropping is applied with size 512, simple augmentation is done with horizontal flipping also normalization done on each image. In evaluation, there is only a normalization process and creating the second image from the same image as flipped and rescaled as 0.5.

After training and inference phase of CAM, Morphological closing performed on the results, Morphological closing performed with kernel size 3 and iteration count 8. With these steps, the first method is completed.

For the proposed model, there are more methods mentioned in [III-B] As it is chosen to use the intermediate features of one CNN as an embedding of the images, the network architecture needs to perform well enough on classification. So, in accordance with this opinion, inference by ResNet 152 which pre-trained on ImageNet was chosen to obtain the features as this model is one of the best classification models in the literature. The features which can be called embeddings own 2048 dimensions and this makes it possible to reduce the size of the image into 2048-d from much bigger size while keeping the important piece of information without effort.

Obtaining relatively low dimensional embeddings provides opportunities to apply various clustering algorithms. However, there are various possibilities to trials. KMeans algorithm is applied to achieve clustering labels as it is proven as working well on lots of studies.

From predefined labels, it is obvious that pairing Make and Model doesn’t change anything as they have hierarchical relations. So, there are only two options to construct new labels pairing Make with Year and Model with Year. As the dataset is not the hardest one for localization or segmentation, there is a feeling like it will be better to check with the random labels and see if it is working or not working with them. If some meaningful results are achievable, it means that doing any extra work is useless because the dataset is not appropriate for this comparison. To make all these clear, 3 different setup implemented, random labels with the size of 74, 431, 16 with the same size of the category labels Make, Model, and Year respectively.

In this study, label generation is attaining the same size of the dataset provided label sets as 16, 75, and 431. As a validation of the second approach, the label generated part replaced by the random generation phase and the following processes triggered. As a result of multiple trials, it is definitely obvious, random generation of the labels does not work to achieve meaningful results on the car localization problem.

The suggested method mentioned in Section [III-B] generating pseudo labels for images done by clustering. To make things proper and valid, a general feature extractor method is selected. With ResNet 152 that pre-trained on ImageNet, feature vectors are extracted for each image with the size of 2048. On these feature vector, KMeans clustering is applied with values of k 75, 431, and 16 separately. The statistical details about the clusters are reported in Table [III].

| k   | Split   | Mean  | Max   | Min   | Std   |
|-----|---------|-------|-------|-------|-------|
| 16  | All Data| 3255.19| 5049.00| 1499.00| 928.30|
|     | Training| 2278.50| 3528.00| 1061.00| 646.15|
|     | Test    | 976.49 | 1521.00| 438.00 | 283.02|
| 75  | All Data| 694.44 | 1157.00| 305.00 | 201.30|
|     | Training| 486.08 | 815.00  | 215.00 | 141.11|
|     | Test    | 208.36 | 342.00  | 90.00  | 61.88 |
| 431 | All Data| 120.84 | 445.00  | 1.00   | 96.96 |
|     | Training| 84.58  | 318.00  | 1.00   | 67.99 |
|     | Test    | 36.25  | 127.00  | 0.00   | 29.60 |

Deep Learning related to all algorithms, feature extractors, and CAM, in this study, is done by implemented in the PyTorch framework. And, all steps about Finding Bounding Boxes are implemented with OpenCV library. One AWS GPU instance that includes 8 NVIDIA® V100 Tensor Core GPUs, is used for training and inference phase as the algorithms require high computation power or time.

B. Results

The methods are analyzed from two different aspects, quantitative results, and visual results.

1) Quantitative Results: The first method is performed on 5 different setups by using different predefined or manually created labels from predefined ones which are Make, Model, Year, the combination of Make and Year as Make-Year, and also the combination of Model and Year as Model-Year. The results are reported in [IV].

As the problem is localization problem, it is meaningful to apply Intersection over Union (IoU) as an evaluation metric. It is a simple yet efficient metric calculated by dividing the area of the overlapping zone to the area of the union of the bounding boxes.

| Label       | Make      | Model     | Year      | Make-Year | Model-Year |
|-------------|-----------|-----------|-----------|-----------|------------|
| mIoU        | 0.4377    | 0.5422    | 0.4825    | 0.3600    | 0.3936     |

Table [V] shows the experimental results for the experiments with generated labels.
TABLE V
MEAN IOU VALUES (UNSUPERVISED LEARNING)

| Label          | kMeans (k=16) | kMeans (k=75) | kMeans (k=431) |
|----------------|---------------|---------------|---------------|
| mIoU           | 0.5132        | 0.6067        | 0.6078        |

TABLE VI
MEAN IOU VALUES (BEST OF)

| Label          | Weakly Supervised Model | Unsupervised kMeans (k=431) | Supervised YOLOv3 |
|----------------|-------------------------|----------------------------|------------------|
| mIoU           | 0.5422                  | 0.6078                    | 0.8909           |

As object localization is a widely studied problem in the literature, some pre-trained networks can be found online as YOLOv3 [35] which is trained as a Supervised Learning example on COCO dataset [36] which contains car images in training and test splits. The best version of the Weakly Supervised and Unsupervised implementation is reported in Table VI with the inference results of the pre-trained YOLOv3 model.

2) Visualization of the Results: One of the key approaches to analyzing the problems focused on images is the visualization of the results. In addition to that, the aimed task is also strongly suitable for analyzing manually by using images. Figure 4 contains the gray-scaled version of the CAM results and figure 5 the drawn version of the bounding boxes. The images in the two figures are not cherry-picked and selected randomly.

In Figure 4, each column contains the inference result of different CAM that trained on different labels, from left to right the labels are Make, Model, Year, Make-Year, Model-Year, KMeans (k=16), KMeans (k=75), KMeans (k=431).

![Fig. 4. Example CAM Results](image4.png)

The reviews can be done about the CAM results as,
- The results seem much better in the righter images,
- Mentioning the same object in an image differently, definitely has effects on CAM results.

Figure 5 contains the drawings of the bounding boxes which obtained with different setups and additionally it contains the bbox results of YOLOv3.

![Fig. 5. Example Bounding Box Results](image5.png)

VI. DISCUSSIONS AND CONCLUSION

This study contains 8 distinct experiments which have exactly the same training and inference pipeline. The only difference is the labels that are adopted as input with related images. For all experiments, the results are reported with the same metric mean Intersection over Union (mIoU) which is the most used metric in the literature in two different Tables, Table V and Table VI. The metrics are also supported by the visualization of the CAM outputs and also bounding boxes for each image.

In this study, the results of the experiments can be interpreted by using 3 outputs separately and also combined,
- mIoU metrics,
- Visualized CAM results,
- Visualized bounding boxes

All these 3 outputs are investigated in various point of views to obtain the answers
- results are compared within each approach,
- results are compared between the approaches

The gap between mIoU metrics of Weakly Supervised Learning experiments is significant and the best result is 0.5422 and the worst result is 0.3600 by using Model labels and Make-Year labels respectively.

Make labels are so specific and most of them have their own logo which stands on similar parts of the car. And people are mostly reaching Make information by checking the logo of the brand in the images, which can be the same for CNN architectures such as the CAM algorithm activates the neighborhood area of the logo. This hypothesis is verified with the CAM visualization and bounding box results. Most of the
CAM results are in the neighborhood of the logo if there is a logo in the image.

Model labels are the specialized form of the Make labels which includes more information about cars. For car professionals or people who have an interest in cars can understand more when they just learn the Model name. Learning Model of the car may also float more information about car if they have additional knowledge about the model like body shape, the number of doors, some more visual attributes which can be specific to this Model. So it is obvious to expect that employing Model labels in CAM training will result in better localization labels as the labels carry more information or point out the difference between cars in a better way. This hypothesis is also verified with numerical and visual results as mIoU value is way higher than mIoU value of Make and also others, and also bounding boxes cover more parts of the targeted cars.

When it comes to talking about the results of the experiments on Year, it is a bit hard to talk about as it is not related to any visual part of the car, it is an abstract way to point the car. Also, even professionals have some difficulties in predicting correctly the Year value of the car. In another way, in a more abstract way, it contains some specific pieces of information like there will be some relation between the shape of any part by the improvements in the technology or fashion change in the car industry. It is still surprising that the results of the Year labels are better than Make labels nevertheless it also makes sense Year value of the car can carry more information than the logo of the brand or it does not specifically target a specific part of the cars.

Although it gives rise to the thought that they can carry more information about a car in the first view, the combined labels Make-Year and Model-Year have not achieved better results than others. The main reason for that may be the number of the items for each category and the labels become too specific for the image and the CAM algorithm tried to distinguish between the cars and as a result, cannot learn the car as expecting.

The clustering labels are generated by KMeans by setting k values as the number of Make, Model, and Year labels, separately. The best result of the Unsupervised configuration has achieved when k value is set to 431. But there is no significant difference between the mIoU results of k values of 75 and 431. However, when k value is set to 16, the mIoU value is %9 lower than others. This means there may be a lower value above which the results are not significantly different. Even there are some differences between the mIoU metrics for configurations there is no pattern in the bounding box and CAM visualizations. Still, the bounding boxes cover the cars in a better way without specializing on any part of the cars. This makes sense as embeddings of the images may contain more attributes than any concrete label and clustering of the embeddings enables the grouping that CAM algorithm requires as it depends on classification while training process.

As it is not common to use Unsupervised Learning on object localization, obtaining %60 mIoU value is a good starting point as it is much better than the WSL approach. According to the results reported in Table VI YOLOv3 outperforms other results with a huge gap as %30 percent with the nearest one. Still, there are various improvement points in the Unsupervised method such as optimizing clustering, using a stronger algorithm rather than CAM, obtaining better features.

As a future study, the same approach can be used to obtain object segmentation labels. Furthermore, it is valuable to mention that the numeric and visual results also help to include the new investigation points as future research topics such as

- How and why the clustering labels results better than the results of the human-defined labels
- Can the clustering achieve better results by tuning the clustering?
- How does it affect if the labels are abstract or concrete in Computer Vision algorithms?
- How we can adopt this algorithm to use with multiple objects in the images?

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