Weakly Supervised Object Localization and Detection: A Survey

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Abstract—As an emerging and challenging problem in the computer vision community, weakly supervised object localization and detection plays an important role for developing new generation computer vision systems and has received significant attention in the past decade. As methods have been proposed, a comprehensive survey of these topics is of great importance. In this work, we review (1) classic models, (2) approaches with feature representations from off-the-shelf deep networks, (3) approaches solely based on deep learning, and (4) publicly available datasets and standard evaluation metrics that are widely used in this field. We also discuss the key challenges in this field, development history of this field, advantages/disadvantages of the methods in each category, the relationships between methods in different categories, applications of the weakly supervised object localization and detection methods, and potential future directions to further promote the development of this research field.

Index Terms—Weakly supervised learning, Object localization, Object detection.

INTRODUCTION

Weakly supervised learning (WSL) has recently received much attention in computer vision community. A plethora of methods on this topic have been proposed in the past decade to address the challenging computer vision tasks including semantic segmentation [16], object detection [111], and 3D reconstruction [38], to name a few. As shown in Fig. 1, a WSL problem is defined as the learning process when some partial information regarding the task (e.g., class label or object location) on a small subset of the data points is at our disposal. Compared to the conventional learning framework, e.g., fully supervised learning approaches, the WSL framework needs to operate on the small amount of weakly-labelled training data to learn the target model, which alleviates a huge amount of human labor to annotate training samples. It can also facilitate the learning process when the fine-grained annotation is extremely labor intensive and time consuming to even obtain the whole labeled data required by the fully-supervised approaches.

While a plethora of WSL-based vision methods have been developed, this survey mainly focuses on the task of weakly supervised object localization and detection, which is shown as the red dot in Fig. 1. It is well-known that object localization and detection is a fundamental research problem in computer vision. Learning object localization and detection models under weak supervision has attracted much attention in the past decades. While existing methods treat weakly supervised object localization and detection methods, and potential future directions to further promote the development of this research field.

1) Learning with inaccurate instance locations: This issue is mainly caused by the definition ambiguity in object parts and context. Without precise annotation or definition, it is difficult for a learner to decide whether an object category...
label associates with a discriminative object part, the whole object region, or the object with a certain context region. As a result, the bounding-box instance locations inferred by the learner may contain many inaccurate samples including the ones with local object parts or undesired contextual regions. These samples would negatively affect the performance of WSL-based detectors.

- **Learning with noisy samples**: Even when the bounding-box locations can be precisely labeled, the training examples enclosed by bounding-boxes may still be noisy as background pixels are usually included. As there is no additional information to separate foreground objects from the background, the learner may tag a “background” label to an object region when it fails to recognize the object category. In addition, the learner may mistakenly label a bounding-box that contains a bicycle as a motorcycle, as these two object categories share many similar features.

- **Learning with domain shifts**: For a certain object category, the image regions localized during the learning process may only contain samples with limited diversity in object shape, appearance, scale, and view angle. This makes the subsequent learning process biased to limited knowledge of the object category and does not generalize well for test samples. For instance, a learner can hardly localize or detect a flying swan when all the training samples contain the swimming ones on lakes. This issue happens frequently among the weakly supervised learning process when there is a large gap between the training and testing domains.

- **Learning with insufficient instance samples**: Similar to the issues in conventional learning methods, it is difficult to train effective object detectors under the weakly-supervised setting when the amount of training samples is limited. In addition, the number of positive samples is usually much smaller than that of negative samples for binary classes. Furthermore, the data distributions for a large number of categories is usually long-tailed. This issues are significantly exaggerated for the WSL-based methods using deep learning.

To address the above-mentioned issues in learning weakly supervised object detectors, existing methods are usually constructed based on two steps: initialization and refinement. The initialization stage is used to leverage certain prior knowledge to propagate image-level annotation into instance level, and thus can generate instance-level annotation (but with label noise, sample bias, and limited quality in location accuracy) for the learning process. The refinement stage is used to leverage new instance samples obtained from the first stage to mine truthful knowledge about the objects of interest gradually and finally obtain the desired object models for localization and detection. These two learning stages need to collaborate to address the aforementioned five-fold challenges. In initialization stage, efforts should be made to improve the annotation quality as much as possible to generate training instances with proper locations, accurate labels, high diversity, and high recall rate. As the annotation quality obtained in the learning stage cannot be perfect, in the refinement stage, further efforts should be made to improve the learner’s robustness to cope with the inaccurate instance location, noisy examples, biased instance sample, insufficient instance sample issues as well as the capacity to take advantage of the unlabelled instance samples. When properly addressing the problems in each learning stage, good weakly supervised object detectors can be learned.

In this work, we review the existing weakly supervised object localization and detection approaches, which are divided into three main categories and eight subcategories. These three main categories are based on classic approaches, feature representations from off-the-shelf deep models, and deep learning frameworks. The eight subcategories include approaches for initialization, refinement, initialization and refinement, pre-trained deep features, inherent cues in deep models, fine-tuned deep models, single-network training, and multi-network training. We further discuss the relationship between the approaches in different categories. In addition, we also discuss open problems and challenges of current studies and propose several promising research directions in the future for constructing more effective weakly supervised object localization and detection frameworks.

## 2 Taxonomy

In the last decade, a plethora of methods have been developed for weakly supervised object localization and detection. We can generally categorize existing methods based on classic formulations, feature representations from off-the-shelf deep models, and deep weakly supervised learning algorithms. While inside each main category, we further divide the approaches into two or three subcategories. Fig. 2 shows our taxonomy of the studies in the research field of weakly supervised object localization and detection.

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2. Some early methods, such as [24], [42], learn to localize category-wise key points under the weak supervision, while this survey mainly focuses on the methods for localizing instances with bounding-boxes.
Fig. 2. In the left block, taxonomy of the existing approaches for weakly supervised object localization and detection, which includes three main categories and eight subcategories. In the right block, the relationships between the approaches in different categories are shown.

Fig. 3. Developments of weakly supervised localization and detection methods. The yellow histogram shows the number of publications in this research field in each year, and the curves show the number of proposed methods each year for a particular category of approach.

In this section, we review the classic approaches that learn weakly supervised object localization or detector without using deep features. These methods typically consist of one initialization module followed by one refinement process as shown in Fig. 4. In [26], [27], [78], [128], [138], the detector is based on the deformable part model (DPM) [39]. In other approaches [13], [52], [167], [216], the detector is based on the support vector machine (SVM) classifier. The features used by these approaches are hand-crafted feature descriptors, such as HOG in [13], [150], [171], [216], SIFT in [134], [137], [138], [165], and Lab color in [129], [138], [165], which are sometimes used to build higher level representations such as bag-of-words (BOW) in [129], [134], [131], [137], [60], Fisher vector representation in [52], and subspace-based representation in [13]. In the following, we divide these approaches for initialization and refinement process.

3.1 Initialization
Numerous methods have been developed to mine reliable instance samples, using prior knowledge, as weak supervision for the following processes. A brief summary of these approaches are shown in Table 1.

Zhang et al. [216] leverage the prior-knowledge of object co-occurrence to identify translation and scale invariant high order features for weakly supervised object localization. In [130] Shi et al. propose a transfer learning paradigm to first use a RankSVM to learn the mapping relationship between the box overlap and appearance similarity from an auxiliary training data (with bounding-box level annotation) and then transfer the learned prior-knowledge for localizing objects of interest in the given weakly labeled images. A simple yet effective approach, named as negative mining, is developed by Siva et al. to explore the inter-class variance among the object regions in weakly labeled training images. The final object locations are obtained by using a linear combination of the inter-class variance and saliency prior. Similarly, Tang et al. [150] and Xie et al. [181] use the saliency prior and intra-class consistency to mine the initial object locations, respectively. In [128], [129], Shi et al. explore the appearance prior and geometry prior in their topic...
model to build a Bayesian joint modeling framework for weakly supervised object localization. On the other hand, Cao et al. [13] exploit the road map prior and density prior to mine the initial vehicle locations from the weakly labeled satellite images and then trained the vehicle detector under a modified multiple-instance learning (MIL) model.

### 3.2 Refinement

After potential object instances are obtained, these hypotheses are verified in the following refinement processes. The goals of these approaches are to design learning objective functions, optimization strategies, or learning mechanisms to gradually determine objects of interest from the extracted initial instance training samples. A brief summary of these approaches is shown in Table 2.

Hoai et al. [60], [106] propose an approach which localizes the instances of the positive class and learns a sub-window classifier to recognize the corresponding object class. Blaschko et al. [9] use a structured output SVM to learn a regressor from the weakly labeled training images to object locations that are parameterized by the coordinates of the bounding boxes. The object locations were treated as latent variables, while the image-level annotation was used to constrain the set of values the latent variable can take. Similarly, Pandey et al. [109] learn weakly supervised object detectors by using DPMs with latent SVM training. In [171], a soft-label boosting approach is developed to exploit the soft labels that are estimated during the MIL process to train object detectors based on Boosting algorithm. In [144], Tang et al. treat the weakly supervised object localization problem as an object co-localization task, and present a joint image-box formulation to mine reliable object locations via a Soft-label Boosting after MIL approach.
program. This approach can handle noisy labels in the image-level annotations. To address the property that the MIL process may converge to poor local optima after the initialization, Cinbis et al. [52] design a multi-fold MIL training paradigm. This method divides the whole weakly labelled training images into multiple folds and implements the detector training process and object re-localization process in different folds, thereby alleviating the issue with convergence of poor local optima.

### 3.3 Initialization and Refinement

A number of iterative approaches have been developed that take both initialization and refinement into account. In [139], Siva et al. propose an intra-class metric and an inter-class metric to present a conditional random field (CRF) model, which is used to learn generic prior knowledge of the objects from meta-training data firstly to localize the potential objects of interest in the feature representation and model complexity. The advantage of the classic weakly supervised learning methods is that the learning processes can be implemented on small-scale training data and the whole frameworks are quick in both the training phase and the testing phase. The disadvantage is that their performance is not satisfactory, which is due to the limitation in feature representation and model complexity.

### 4 Off-the-shelf Deep Models

In this section, we review the approaches that learn weakly supervised object localizer or detector based on classic formulations and feature representations based on the deep neural networks, either pre-trained from the ImageNet dataset [116] (with image tag annotation) or further fine-tuned on the weakly supervised training images in the target domain. The feature representations are based on the widely used deep models for image classification, such as AlexNet [85] and VGG [135]. The detectors are constructed based on classic formulations such as DPM and SVM [3], [57], [61], [112], [141], [149], [222], or recent models such as RCNN [50] and fast RCNN [49] [17], [75], [88], [126], [154]. We further divide these approaches into three subcategories using pre-trained deep features, inherent cues in deep models, and fine-tuned deep models as shown in Fig. 5.

#### 4.1 Pre-trained Deep Features

The methods of this category replace the hand-crafted feature representations with the pre-trained deep features typically from

**TABLE 4** Summary of the approaches using pre-trained feature representations, which is a subcategory in the weakly supervised object localization and detection approaches based on the off-the-shelf deep models. * indicates a certain variation of the corresponding model. An approach is considered for general object category when it is tested for detecting more than five object categories in the corresponding literature. The approaches with None detector indicate the weakly supervised object localization approaches.

| Methods | Detector | Descriptor | Prior knowledge | Extra training data | Learning model | Learning strategy | Object category |
|---------|----------|------------|-----------------|-------------------|----------------|----------------|----------------|
| Gonderkar & Vyas-2018 [56] | None | CNN | Supervised object score (Fast-RCNN+Filter) | ImageNet(tag label) | SVM | MIL | Object in art (watercolor, Eiffel tower) |
| Zadiga & Vulis-2018 [190] | None | VGG16 Conv5.2 | None | ImageNet(tag label) | Sparse model | None | Zebra crossings, traffic signs |
| Cindee & Tarnawa-2017 [11] | SVM | FC7 | Central prior | ImageNet(tag label) | SVM | Multi-Fold MIL | General objects |
| Wei & Ji-2017 [174] | None | CNN | None | ImageNet(tag label) | SVM | None | Deep descriptor transfering |
| Zhang & Li-2018 [209] | SVM | CNN | Salience prior | ImageNet(tag label) | SVM | Easy-to-hard MIL | General objects |
| Li & Ubc-2016 | None | FC7 | Strong detector prior (sparsity) | ImageNet(tag label) | SVM | Regularizing score distribution | General objects |
| Sun & Tanpa-2016 [122] | SVM | FC7 | None | ImageNet(tag label) | SVM | MIL | General objects |
| Wan & Cai-2016 [158] | SVM | FC7 | None | ImageNet(tag label) | SVM | MIL | General objects |
| Rock & Vuc-2016 [114] | None | Color histogram + CNN | Salience | ImageNet(tag label), Pascal VOC | SVM | None | General objects |
| Shi & Euc-2016 [127] | SVM | FC7(Satellite) | Size prior | ImageNet(tag label), Pascal VOC | SVM | Easy-to-hard curriculum | General objects |
| Wang & TP-2015 [141] | SVM | FC7 | None | ImageNet(tag label) | pLSA, SVM | Online latent category learning | General objects |
| Han & Tgrs-2015 [57] | SVM | DBM | Human fraction | ImageNet(tag label) | SVM | SVM-boost + SVM | General objects |
| Shi & Icpr-2016 [127] | SVM | FC7 | None | ImageNet(tag label) | SVM | SVM | SVM | General objects |
| Zhang & Ijcai-2016 [207] | SVM | CNN | Objectness score, word embedding prior | YouTube-Objects (for parameter validation), ... | SVM, Sparse reconstruction | Appearance transfer from test representation | General objects |
| Bilen & Cvpr-2015 [7] | SVM | FC7 | Spatial features | ImageNet(tag label) | SVM | Convex clustering | General objects |
| Wang & Cvc-2015 [173] | None | FC7 | None | ImageNet(tag label) | SVM | SVM | SVM | General objects |
| Zhou & ICMD-2015 [220] | SVM | FC7 | Salience prior | ImageNet(tag label) | SVM | SVM | SVM | General objects |
| Han & GRDS-2015 [157] | SVM | DBM | Salience, intra-class compactness, inter-class separability | ImageNet(tag label) | SVM | SVM | SVM | General objects |
| Mathieu & Arons-2014 [109] | Sequential detector | FC6 | Human fraction | ImageNet(tag label) | MIL+RL | MIL + MIL | General objects |
| Wang & Eccv-2014 [167] | SVM | FC6 | None | ImageNet(tag label) | MIL + Rl | MIL + MIL | General objects |
| Bilen & Hst-2014 [24] | SVM | DeCAF | None | ImageNet(tag label) | SVM | SVM | SVM | General objects |
| Song & Nips-2014 [141] | DPM | FC7 | Objectness score | ImageNet(tag label) | SVM | SVM | SVM | General objects |
| Song & Icmi-2014 [148] | SVM | DeCAF | None | ImageNet(tag label) | Graph model + LSTM | SVM | General objects |
Summary of the approaches using visual cues, which is a subcategory in the weakly supervised object localization and detection approaches based on the off-the-shelf deep models. * indicates a certain variation of the corresponding model. An approach is considered for general object category when it is tested for detecting more than five object categories in the corresponding literature. The approaches with None detector indicate the weakly supervised object localization approaches.

### Table 5

| Methods | Detector | Descriptor | Prior knowledge | Extra training data | Learning model | Learning strategy | Object category |
|---------|----------|------------|-----------------|---------------------|--------------|------------------|-----------------|
| Li-ECCV-2018 [85] | CAM* (VGG-F) | CNN | None | ImageNet(tag label) | VGG-F* | Learning training + CAM learning (patch, level) | Remote sensing objects |
| Wilhelms-DICTA-2017 [177] | None | CNN | None | ImageNet(tag label) | CAM | CAM+DS, refine | General objects |
| Tang-TNN-2017 [149] | DPM | CNN | None | ImageNet(tag label) | DPM+CNN | Region initializations-DPM and feature learning-boxing-bound modification | General objects |
| Kolenikov-MIVC-2016 [81] | None | CNN | Human feedback annotation | ImageNet(tag label) | CAM | Active learning for identifying object clusters | General objects |
| Bency-ECCV-2016 [8] | None | CNN | None | ImageNet(tag label) | VGG16 | Beam-search based on CNN classifier | General objects |
| Zhou-MISP-2014 [222] | SVM | FC7 | Salience prior | ImageNet(tag label), remote sensing dataset(unsupervised) | CNN (AlexNet), SVM | Deep feature transfer + MIL | General objects |
| Bergamo-WACV-2016 [5] | SVM | CNN | None | ImageNet(tag label) | CNN, SVM | Mask out initialization + SVM detector training | General objects |
| Hoffman-CVPR-2015 [61] | SVM | FC7 | Detector proposal representation prior | ImageNet(tag label), ILSVRC13 validation subsets(ann) | CNN, Latent SVM | Transferring detectors and representation from auxiliary data | General objects |

**TABLE 6**

| Methods | Detector | Descriptor | Prior knowledge | Extra training data | Learning model | Learning strategy | Object category |
|---------|----------|------------|-----------------|---------------------|--------------|------------------|-----------------|
| Zhang-ICCV-2019 [204] | Fast RCNN (VGG16) | Pre-trained FC7 | ImageNet(tag label) + mask out prior(AlexNet) | ImageNet(tag label) | SVM | Easy-ich谭 | General objects |
| Uijlings-CVPR-2015 [156] | None | CNN | Semantic objectness(SOD) | ImageNet(tag label), ILSVRC(full annotation) | SDP+VMM+Fast RCNN | MIL-kennowledge transfer | General objects |
| Jia-CVPR-2017 [79] | Fast RCNN (VGG16) | CNNV4 | Image-to-object transfer prior | ImageNet(tag label) | Fast RCNN (VGG36) | Initialization based on classification network and subgraph discovery + intensive Fast RCNN learning | General objects |
| Shi-CVPR-2017 [126] | Fast RCNN | CNNV4 | Things and stuff prior | ImageNet(tag label), PASCAL Context (full annotation) | FCN+Fast RCNN | Localizing objects based on things and stuff prior and training Fast RCNN iteratively | General objects |
| Singh-CVPR-2016 [88] | Fast RCNN | CNNV4 | Tracking prior | ImageNet(tag label), VGG, MDNet | Fast RCNN | Discriminative region minings-transferring object pattern + learn object detector | General objects |
| Li-CVPR-2016 [91] | CNNV4 | VGG* | Mask out prior(AlexNet) | ImageNet(tag label) | CNN, SVM | Progressive Domain Adaptation | General objects |
| Luang-IJCAI-2017 [97] | CNN | CNNV4 | Instance example, motion prior | ImageNet(tag label) | CNN+R-CNN | Seed selection based on instance example and instance tracking | General objects |
| Chun-CVPR-2015 [87] | RCNN | CNNV4 | Online data type | Web data (weak label) | RCNN net + E-LDA + RCNN | Simple image initialization + graph-based representation adaptation on hard image | General objects |
| Zhou-CVPR-2015 [220] | RCNN | FC7 | None | ImageNet(tag label) | SVM, R-CNN | Max-margin visual concept discovery + Domain-specific detector selection | General objects |

Fig. 5. Illustration of different usages of the off-the-shelf deep neural networks by the weakly supervised object localization and detection approaches based on the off-the-shelf deep models. as AlexNet and VGG. A brief summary of these approaches is shown in Table 4.

Song et al. [140, 141] determine discriminative feature configurations of an object class via graph modeling, and train object detectors within the multiple-instance learning paradigm. The deep features of this work are extracted based on the DeCAF scheme [30] and AlexNet [85]. By using the deep features and spatial features to represent each proposal region, Bilen et al. [7] propose a convex clustering process for learning the object models under the weak supervision. The learning objective is able to enforce the similarity among the selected proposal windows. In [127], Shi and Ferrari develop a curriculum learning strategy to feed training images into the MIL loop in a pre-defined order, where images containing larger objects are learned at the early stages while images containing smaller objects are learned at later stages. Ren et al. [112] present a bag-splitting-based MIL mechanism that iteratively generated new negative bags from the positive ones. This algorithm can gradually reduce the ambiguity in positive images and thus facilitate the learning of more reliable training instance samples. In [174], [175], Wei et al. leverage the pre-trained CNN model to implement a Deep Descriptor Transforming process, which can obtain the category-consistent image regions via evaluating the correlations of the descriptors in the convolutional activations of the CNN model.

### 4.2 Inherent Cues in Deep Models

Instead of using the pre-trained deep models as feature extractor, the methods of this category obtain useful information cues (such as the activations in the intermediate network layers and the semantic scores in the output network layer) from the pre-trained deep neural networks to facilitate the weakly supervised learning process. The focus of these approaches mainly lies in the initialization stage of the weakly supervised learning process. A brief summary of these approaches is shown in Table 5.
A brief summary of the approaches using single-network training scheme, which is a subcategory in the weakly supervised object localization and detection approaches with deep weakly supervised learning algorithms. * indicates a certain variation of the corresponding model. An approach is considered for general object category when it is tested for detecting more than five object categories in the corresponding literature. The approaches with None detector indicate the weakly supervised object localization approaches.

### 4.3 Fine-tuned Deep Models

The methods of this category fine-tune the off-the-shelf DNN models during the weakly supervised learning process to obtain strong object detectors [17], [126], [184]. A brief summary of these approaches is shown in Table 6.

Chen et al. [17] first train CNNs from the web image data via an easy-to-hard learning scheme. The learned deep features are used to mine object locations by using the exemplar-LDA detector [59]. The off-the-shelf RCNN detector is then adopted to learn object models based on their localization results. In [91], Li et al. first use the mask-out strategy based on the pre-trained classification network to obtain the class-specific object proposals. An SVM-based MIL process is used to localize object...
instances and the classification network is further fine-tuned on the localized object instances for better performance. Shi et al. [126] propose to transfer the prior knowledge of things and stuff to help the weakly supervised learning process. A semantic segmentation network is trained from the source set (with available bounding-box annotations) to generate the stuff map and thing map for the weakly labeled images in the target set. These maps are used to obtain potential object locations, and the fast RCNN model is adopted in a Deep MIL scheme to train the object detectors. Recently, [154] revisits knowledge transfer for training the weakly supervised object detector. In this method, a DNN-based proposal extractor is learned from the source data firstly. The DNN is designed based on the SSD [99] architecture and trained with a semantic hierarchy. The network is then used to propose proposals of other prior knowledge for the weakly labeled images in the target set. An MIL process is used to determine the proposals that cover the objects of interest based on which the fast RCNN model is adopted to learn the final object detectors. In [204], Zhang et al. first learn to localize the objects of interest via a collaborative self-paced curriculum learning mechanism based on pre-trained deep features. The fast RCNN model is applied to learn object detectors.

4.4 Discussion

Introducing the off-the-shelf deep models into the weakly supervised object localization or detection framework is the most straightforward approach to integrate deep learning and weakly supervised learning. The methods in this category show that 1) feature learning is an important factor to improve the weakly supervised learning process; 2) DCNN models can infer discriminative spatial locations when learned under the image-level supervision; 3) pre-training DNN models on large-scale auxiliary training data is a simple but effective way to encode useful cues for the weakly supervised learning process. Compared with the classic models, the methods of this category exploit large-scale auxiliary training data to learn powerful feature representations and top-down cues. By using DNN models as the object detector or localizer, a significant performance gain can be obtained. However, more effective feature learning models can be exploited in the weakly supervised learning process.

5 Deep Weakly Supervised Learning

In this section, we review the methods that learn weakly supervised object localizers or detectors by designing novel deep weakly supervised learning frameworks. Different from the approaches discussed in previous sections, both the feature representations and the object detectors of the approaches in this category are learned by newly-designed deep neural networks. The whole weakly supervised learning framework may be designed in a compact network model, such as in [47], [77], [103], [108], [119], [185], [187], [209], [224], [226], or contain several function-distinct DNN components, such as in [28], [100], [143], [164], [176], [198], [214]. We categorize these approaches into two groups using single-network training and multi-network training, respectively.

5.1 Single-Network Training

The methods of this category are designed with a single deep neural network using the training images (or together with the extracted object proposals) as inputs and the image-level classification labels as the outputs. These approaches do not usually rely on meticulously designed initialization processes to obtain the potential object regions. Instead, these methods discover the interested object regions solely based on the end-to-end learning process of the designed DNN models. The DNN models used in these approaches usually have similar feature learning layers as the conventional image classification network, e.g., AlexNet, VGG, GoogleNet, and ResNet, followed by the instance label inferring and image label propagation layers to inherently predict the labels of each proposal region and generate the final image labels from the predicted proposal labels, respectively. Some of the methods contain multiple network streams for online inferring multiple informative cues. A brief summary of these approaches are shown in Table 7.

In the DNN models proposed by Wu et al. [179] and Bilen et al. [8], the network inputs are the training images and extracted object proposal regions while the outputs are the image-level semantic scores. The first parts of these networks extract the features and infer the labels for each proposal region, and the second parts propagate the proposal scores to the image-level via the max pooling scheme [179] or the two-stream score regularization method [8]. Zhou et al. [221] present an end-to-end weakly supervised deep learning based on the class activation mapping (CAM). The weights of the feature maps in the intermediate layers are inferred based on the correspondence between the feature map and a certain object category. The feature maps are then combined to form the class activation maps based on the inferred weights, which highlight the locations of the objects of interest. Notably, this method is determined to be highly efficient in recent work [19]. Built on CAM [221], Durand et al. [33] introduce the multi-map transfer layer and the WILDCAT pooling layer to facilitate the more accurate deep MIL process.

Recently, a number of two-branch MIL models have been developed in which one is based on a typical deep network and the other one is introduced for weakly supervised learning. Based on the WSDDN [8], Tang et al. [147] integrate MIL branch and the instance classifier refinement branch into a unified deep learning framework such that more accurate online instance classifier learning is realized under the weak supervision. In [28], Diba et al. propose a weakly supervised cascaded convolutional network, which contains three branches. The first branch adopts the CAM module to generate the class activation maps. The second branch uses the generated class activation maps as the supervision signal to learn a segmentation module to generate the segmentation masks of the objects of interest. Using the candidate object proposals selected based on the obtained segmentation masks as supervision, the third network branch uses a MIL process to mine accurate object locations from the candidate object regions. In [211], Zhang et al. present a CAM-based network architecture which contains a classification branch and a counterpart classifier branch for object localization. Specifically, the classification branch is used to localize the discriminative object regions, which drives the counterpart classifier branch to discover new and complementary object regions by erasing its discovered regions from the feature maps. Wan et al. [159] propose a min-entropy latent model (MELM) for weakly supervised object detection based on the assumption that minimizing entropy results in minimum randomness of a system. The network architecture is similar to [147], but global
min-entropy and local min-entropy losses are introduced to train a DNN model to select the proposal cliques of largest object probability and mine truthful object locations from the selected proposal cliques. Zhang et al. [212] develop a self-generated guidance method for weakly supervised object localization. In this work, a self-generated guidance map is derived from a CAM layer to help learning features and object location masks from the previous network layers. More recently, Gao et al. [46] propose a token semantic coupled attention mapping for WSOL, which models the long-range visual dependency of the image regions and thus avoid partial activation. Ren et al. [113] introduce the instance-associative spatial diversification constraints and build the parametric spatial dropout block to address the instance ambiguity and incomplete localization problems. Besides, they additionally adopt a sequential batch back-propagation algorithm, which enables their model to use a large ResNet as the backbone\(^4\). Although there are other methods that use ResNet as the backbone \([2], [21], [193]\), there is a limited exploration of using more recent backbone architectures, e.g., DesNet [65] and Res2net [45], in both WSOL and WSOD frameworks.

### 5.2 Multi-Network Training

The methods in this school collaborate multiple networks, either in one training stage or in multiple training stages, to accomplish the weakly supervised object localization or detection task. The approaches of this category usually train a network to mine the initial object regions \([48], [94], [176]\) and another network for the detection task under the MIL framework \([94], [148], [163], [210]\). An additional object detection network, e.g., Fast RCNN, may also be used to train the final object detectors \([48], [200], [215]\). By integrating multiple networks, these methods tend to achieve better performance both in object localization and detection. A brief summary of these approaches is shown in Table 8.

| Methods | Detector | Descriptor | Prior knowledge | Extra training data | Learning model | Learning strategy | Object category |
|---------|----------|------------|-----------------|--------------------|----------------|-------------------|-----------------|
| Zhang-CVPR-2020 [197] | None | CNN | Common object co-localization | ImageNet tag label | VGG3, ResNet34(App/ResNet50) | Classification + pseudo supervised object localization | General objects |
| Zhong-ECCV-2020 [219] | Faster RCNN | CNN | Location prior | ImageNet tag label + COCO (box label) | One-class universal detector + MIL classifier (on ResNet50) | Progressive knowledge transfer | General objects |
| Konogi-ICCV-2019 [92] | Fast RCNN\* | CNN | Mask-out prior | ImageNet tag label | Mask-out + OICR (on ResNet50) | Mask-out prior-guided label refinement | General objects |
| Singh-CVPR-2019 [87] | Fast RCNN\* | CNN | Motion prior | ImageNet tag label, videos | RP + WSDDN + OICR (VGG16) | Training RP using weakly-labeled videos for WSOD | General objects |
| Anan-CVPR-2019 [1] | Fast RCNN | CNN | None | ImageNet tag label | Faster RCNN (VGG16) + OICR (VGG16) | Employed dissimilarity coefficient for modeling uncertainty | General objects |
| Li-TIPAMI-2019 [94] | Faster RCNN\* (VGG16), fast RCNN\* (VGG16), SSD | CNN | Objectness (classifier) prior | ImageNet tag label, ILSVRC2013 (box label for unseen categories) | Multi-view WSDDN + multi-view labeled | Two phase multi-view learning | General objects |
| Zhang-ECCV-2018 [214] | None | CNN | None | ImageNet tag label | Fast RCNN | Soft-Fast RCNN | General objects |
| Sun-CVPR-2016 [125] | None | CNN | None | ImageNet tag label | MIDN + Faster RCNN | MIDN + Faster RCNN | General objects |
| Zhang-CVPR-2018 [215] | None | CNN | None | ImageNet tag label | WSDN + Fast RCNN\* | MIDN + Faster RCNN\* | General objects |
| Zhang-CVPR-2018 [210] | None | CNN | None | ImageNet tag label | Fast RCNN\* (VGG16) | Fast RCNN\* (VGG16) | General objects |
| Tang-ECCV-2018 [148] | None | CNN | None | ImageNet tag label | Fast RCNN\* (VGG16) | Fast RCNN* (VGG16) | General objects |
| Tao-TMM-2018 [151] | None | CNN | None | ImageNet tag label | Faster RCNN* | Faster RCNN* + MIL \* | General objects |
| Wang-ICCV2019 [163] | Faster RCNN (VGG16) | CNN | Model consistency | ImageNet tag label | Faster RCNN* (VGG16) | Faster RCNN* + MIL \* | General objects |
| Wu-ECCV-2018 [176] | Faster RCNN (VGG16) | CNN | Shape prior + context prior | ImageNet tag label | Faster RCNN* (VGG16) | Faster RCNN* + MIL \* | General objects |
| Ge-CVPR-2018 [48] | Faster RCNN (VGG16) | CNN | Local objectness and global attention | ImageNet tag label | Multi-view WSDDN + multi-view labeled | Multi-view WSDDN + multi-view labeled | General objects |
| Dong-MM-2017 [51] | Faster RCNN\* (VGG16) | CNN | None | ImageNet tag label | Faster RCNN* + F-CN | Faster RCNN* + F-CN | General objects |
| Li-BMVC-2017 [93] | Faster RCNN\* (VGG16) | CNN | Local objectness | ImageNet tag label | Faster RCNN* + CAM-chopLab | Faster RCNN* + CAM-chopLab | General objects |
| Li-BMVC-2017 [114] | CNN | CNN | None | ImageNet tag label | CAM | CAM | General objects |
| Sun-CVPR-2016 [143] | None | CNN | None | ImageNet tag label | Multi-scale FCN + CNN (VGG16) | Multi-scale FCN + CNN (VGG16) | General objects |
| Zhang-IJCAI-2018 [218] | None | CNN | None | ImageNet tag label | Faster RCNN* (VGG16) | Faster RCNN* + MIL \* | General objects |

Li et al. [93] propose a multiple instance curriculum learning method, where a network based on the WSDDN [8] model is used to mine candidate object proposals and another one based on the CAM [221] algorithm to generate saliency maps from the selected proposals. A curriculum is designed to select confident training examples based on the consistency between the regions outputted by the two networks. The object detectors are then trained by using the confident training examples iteratively. Dong et al. [31] present a dual-network progressive approach for weakly supervised object detection, where a positive instance selection network and a region refinement network are adopted to minimize the classification error and object localization, respectively. These two networks are worked under a co-training paradigm. In [48], Ge et al. first obtain intermediate object localization and pixel labeling results using a classification network. A triplet-loss network and an instance classification network are then constructed to detect outlier and filter object instances. Finally, the filtered object instances are used as the supervision to train another Fast RCNN-based detection network. In order to overcome the limitations brought by the imprecise of the extracted object proposals, Wei et al. [176] propose to mine object proposals with tight boxes to learn weakly supervised object detector. The assumption is that the proposals with tight boxes are more likely to contain the objects of interest thus mining such kind of proposals would help screen the cluttered background regions. In their approach, a semantic segmentation network is first learned using the object localization map generated by CAM as the pseudo ground-truth. The predicted segmentation masks are used to mine object proposals with tight boxes, and fed into the instance classifier refinement (OICR) network to learn weakly supervised object detector. With the same motivation as [176], Tang et al. [148] propose to combine a two-stage region proposal network with an OICR network to learn the weakly supervised object detectors. Instead of mining proposals based
Datasets are divided into train, val, and test sets, where the 9,962, 21,738, and 22,531 images of 20 object classes. These three datasets are usually used for the WSOD task, while the common datasets for the WSOL task. #Categories indicates the number of object categories. #Images indicates the number of images. “GO” is short for Generic Objects.

### Table 9

| Dataset         | Content | #Categories | #Images | Metrics        |
|-----------------|---------|-------------|---------|----------------|
| PASCAL VOC 07   | GO      | 20          | 9,962   | mAP, CorLoc    |
| PASCAL VOC 10   | GO      | 20          | 21,738  |                |
| PASCAL VOC 12   | GO      | 20          | 22,531  |                |
| CUB-200-2011    | Birds   | 200         | 11,788  | Top-1/5 Loc    |
| ILSVRC 2016     | GO      | 1000        | 1.2 M   | GT Loc         |

Fig. 6. Illustration of examples from the PASCAL VOC (top block), CUB-200-2011 (bottom-left block), and ILSVRC 2016 (bottom-right block) datasets.

5.3 Discussion

Compared with the off-the-shelf deep model-based weakly supervised object detection and localization methods, the deep weakly supervised learning methods exploit the merits of deep learning and weakly supervised learning approaches. Without complex design in the learning initialization stage, the end-to-end deep weakly supervised learning methods have been shown to perform well by introducing the MIL mechanism into the network design of the DCNN models. While the multi-network training methods can further improve the learning performance by combining multiple function-specific networks. On the other hand, the performance of these methods is limited by whether the information extracted from the weakly-supervised module is effective or not. As such, prior knowledge may be useful to guide the deep learning process without solely relying on the weakly-supervised network.

6 Datasets and Evaluation Metrics

During the last decades, significant efforts have been made to develop various methods for learning weakly supervised object localization or detector. For fair performance evaluation, it is of great importance to introduce some publicly available benchmark datasets and evaluation metrics.

Existing weakly supervised object detection methods are usually evaluated on the PASCAL VOC datasets, including the PASCAL VOC 2007, 2010, and 2012 sets. The PASCAL VOC 2007 [36], PASCAL VOC 2010 [37] and PASCAL VOC 2012 [35] contain 9,962, 21,738, and 22,531 images of 20 object classes. These three datasets are divided into train, val, and test sets, where the trainval set (5,011 images for PASCAL VOC 2007, 10,869 images for PASCAL VOC 2010, and 11,540 images for PASCAL VOC 2012) are used to train the weakly supervised object detector, and the rest for evaluation. The mean of AP (mAP) metric is used to measure the performance where one object is successfully detected if the intersection over union (IoU) between the ground-truth and predicted boxes is more than 50 percentage.

The weakly supervised object localization performance is usually evaluated on the PASCAL VOC, ILSVRC, and CUB datasets. On the PASCAL VOC datasets [35], [36], [37], weakly supervised object localization methods only use the trainval sets, which are different from the setting in weakly supervised object detection. That is, both the weakly supervised learning process and localization process are implemented on the same image data. To evaluate the localization performance on the PASCAL VOC datasets, the correct localization metric (CorLoc) is adopted, where the bounding-box with the highest class-specific score from each image is examined to be whether correct (with more than 50% overlap with the ground-truth box) or not. In addition to the PASCAL VOC datasets, the ILSVRC 2016 dataset [116] (i.e., the ImageNet) and CUB-200-2011 dataset [155] are also widely used for performance evaluation. The ILSVRC 2016 dataset contains more than 1.2 million images of 1,000 classes for training, while the validation set, which contains 50,000 images, is used for testing. The CUB-200-2011 dataset contains 11,788 images of 200 categories with 5,994 images for training and 5,794 for testing. For these two datasets, The commonly-used evaluation metrics are GT-known localization accuracy (GT Loc), Top-1 localization accuracy (Top-1 Loc), and Top-5 localization accuracy (Top-5 Loc). Specifically, GT Loc judges the localization results as correct when the intersection over union (IoU) between the ground-truth bounding box and the estimated box is no less than 50%, while Top-1 Loc considers the localization results as correct when the class predicted with the highest score is equal to the ground-truth class and the estimated bounding box has no less than 50% IoU with the ground-truth bounding box [21]. Top-5 Loc differs from Top-1 Loc in that it checks if the target label is one of the top 5 predictions. As can be seen, the Top-1 Loc is a harder metric than the GT Loc as it needs to additionally...
predict the class label correctly. This will dramatically increase the task difficulty when performing under very large or fine-grained semantic spaces. The difficulty of Top-5 Loc is between Top-1 Loc and GT Loc as it requires the model to predict the class label but does not restrict the prediction to be perfectly correct.

We provide a brief summarization of the characteristics of the aforementioned datasets in Table 9. We additionally show some examples from each dataset to illustrate the bias of image content in different datasets. As displayed in Fig. 6, the PASCAL datasets contain relatively more complex image content, where multiple object instances and categories may appear in a single image and different images would contain objects with significant scale variations. Although it only contains 20 object categories, its category diversity is higher than the CUB-200-2011 dataset as all the 200 categories in the CUB-200-2011 dataset are related to birds. ILSVRC 2016 contains far more images and categories than the PASCAL datasets. However, the content of the images from the ILSVRC 2016 dataset tends to be simpler than that of the PASCAL datasets—each of the images from the ILSVRC 2016 dataset typically contains only one single object and the objects have more consistent sizes and are placed in clearer background context relative to those from the PASCAL datasets.

7 APPLICATIONS

In recent years, weakly supervised object localization and detection techniques have been used in numerous vision problems, especially when it is difficult to collect ground-truth labels.

7.1 Video Understanding

As it is time-consuming to obtain object-level annotations for each video frame, weakly supervised object localization and detection methods have also been applied in the field of video understanding [14], [68], [101], [118], [132], [191], [202] (see Fig. 7). For example, Chanda et al. [14] build a two-stream learning framework, which adapts the information from the labeled images (source domain) to the weakly labeled videos (target domain). In [202] Zhang et al. propose a self-paced fine-tuning network for learning two network heads to localize and segment the object of interest from the weakly labeled training videos. The network is equipped with the multi-task self-paced learning function which can integrate confident knowledge from each single task (localization or segmentation) and use it to build stronger deep feature representation for both tasks. On the other hand, [107], [132], [136], [166] develop methods to localize temporal actions in the given untrimmed videos, where the main goal is to predict the temporal boundary of each action instance contained in the weakly labeled training videos. Essentially, such a weakly supervised action localization (WSAL) task is an emerging, yet rapidly developing topic in recent years, and the methods for solving this task are highly related to the weakly supervised object detection and localization methods. The additional challenges are: (i) the duration of the interesting action has very large variation, i.e., from a few seconds to thousands of seconds; and (ii) the features extracted to represent the interesting action would be entangled with those of the complex scenes of the video frame. Notice that when applying to video understanding, there are strong correlations among adjacent video frames. So, additional informative constraints can be introduced to facilitate the weakly supervised object detection or localization under this scenario.

7.2 Art Image Analysis

One interesting application of the weakly supervised object localization and detection techniques is the analysis of art images (see Fig. 8). Inoue et al. [70] propose a cross-domain weakly-supervised object detection framework for learning the object detectors from weakly labeled watercolor images. A progressive domain adaptation method to transfer the style of the fully-labeled data from the source domain (the normal RGB domain) to the target domain (the watercolor domain) is developed. In [54] Gonthier et al. propose a weakly supervised learning algorithm for detecting objects in paintings. The IconArt database which contains object classes that are absent from the photographs in daily life is developed for performance evaluation. In addition, Crowley and Zisserman [25] adopt a weakly supervised object localization scheme for automatically annotating images of gods and animals in decorations on classical Greek vases. When applying to art image analysis, a key challenge arises due to the distinctiveness of the content domain—even the same semantics and image scenes would be presented differently to those in the natural environment. Under this scenario, models with stronger self-domain adaptation capacity would be required for the task.

7.3 Medical Imaging

As shown in Fig. 9, medical image analysis is one area where the weakly supervised object localization and detection methods are of critical importance as only few annotations of target objects by trained experts in bio-image (e.g., organ or tissues). To alleviate this problem, Hwang and Kim [69] develop a two-stream DNN model to localize the tuberculosis regions from the chest X-ray images. Considering that the medical image-based applications usually do not have the pre-trained networks, this work proposes a weakly supervised learning scheme without requiring any pre-trained network parameters. The proposed network contains a fully connected layer-based classification branch and a CAM-based localization branch with shared convolutional layers for feature extraction. Both of the two branches are supervised by image label annotation, where a weighting parameter is introduced to dynamically control the relative importance between them to gradually switch the focus of the learning process from the classification branch to the localization branch. The authors demonstrate that the features
Fig. 8. Examples of the application of weakly supervised object localization or detection approaches for the analysis of art images. The examples are from [25], [54], [70], where detection results in different colors in the painting images indicate different types of objects.

learned from the classification layer at the early stage can provide informative cues to learn the localization branch at the late stage. For detecting a general type of lesions, Wang et al. [168] model the normal image as the combination of background and noise, while modeling the abnormal images as the combination of background, blood vessels, and noise. With the assumption that the noise for the normal image and abnormal image is the unified distribution, the image data can then be decomposed by the low-rank subspace learning technique to obtain the vessel areas. In [33], Gondal et al. apply the weakly supervised object detection network on the retina images and achieve few false positives with high sensitivity on the lesion-level prediction. Li et al. [90] apply a sparse coding-based weakly supervised learning method for localizing actinophrys in microscopic images. Dubost et al. [32] propose weakly supervised regression neural networks for detecting brain lesions. Besides, some recent works also show great research interests in weakly supervised learning-based brain image analysis, such as brain disease prognosis [98], brain tumor or lesion segmentation [71], [180], brain structure estimation [10], etc. Notice that compared to common images, medical imaging data usually suffers from issues of low contrast and limited texture. Fortunately, some spatial priors could be obtained for different organs or lesions. These priors can be used to guide the weakly supervised learning process on medical imaging data.

7.4 Remote Sensing Imagery Analysis
Remote sensing imagery analysis is one of the most widely studied applications based on weakly supervised object localization and detection, where the input images are usually of large scale and the annotation process tends to be very time-consuming [18], [40], [41], [189][see Fig. 10]. Zhang et al. propose a coupled CNN method which combines a candidate region proposal network and a localization network to detect aircrafts in images. When applying to remote sensing imagery analysis, the target objects are usually very small in size, which would dramatically increase the localization and detection difficulty given only weak supervision.

Fig. 9. Examples of the application of weakly supervised object localization or detection approaches in medical image analysis. The examples are from [53], [69], [90].

Fig. 10. Examples of the application of weakly supervised object localization or detection approaches in remote sensing imagery analysis. The examples are from [57], [208].

Zhang et al. propose a coupled CNN method which combines a candidate region proposal network and a localization network to detect aircrafts in images. When applying to remote sensing imagery analysis, the target objects are usually very small in size, which would dramatically increase the localization and detection difficulty given only weak supervision.

8 Future Directions
We discuss the issues to be addressed in this field for future research.

8.1 Multiple Instance Learning
Weakly supervised object localization or detection methods can be easily formulated within the MIL framework. Early methods in this filed usually add prior knowledge [140] or post
regularization [6] on the classic MIL models, such as LSVM [190], while the current research obtains the breakthrough by building deep MIL models [172], [179], [221]. To further improve the weakly supervised learning performance, efforts should be made to introduce the most advanced ideas and techniques in the research filed of MIL, such as the set-level problem [182] the key instance shift issue [217] and the scalable issue [66] in MIL. Further research towards more advanced MIL techniques would also bring helpful insights for the WSOL and WSOD in the future.

8.2 Multi-Task Learning
Another future direction is to combine multiple weakly supervised learning tasks into a unified learning framework. These tasks may include object detection [49], semantic segmentation [16], instance segmentation [79], 3D shape reconstruction [38], and depth estimation [51]. Essentially, efforts for simultaneously accomplishing multiple aforementioned tasks have been made in the conventional fully supervised learning scenario [58], [79], [178], [218], [225], which have demonstrated that such learning mechanism can bring helpful information from one task to the other ones. The methods proposed by Zhang et al. [203] is an early attempt to implement such a weakly supervised multi-task learning mechanism and the experimental results show that training object segmentation and 3D shape reconstruction models jointly indeed benefits the both weakly supervised learning tasks. With similar spirits to [203], Zhang et al. [202] and Shen et al. [124] establish a self-paced fine-tuning network and a cyclic guidance network to jointly learn object localization and segmentation models under the weak supervision, respectively. Under the multi-task weakly supervised learning scenario, one key problem is that the learning ambiguity of each individual task might be aggregated and the imprecise prediction on one task might affect the learning on other tasks. To deal with this problem, one needs to disentangle the complex multi-task learning, separately learning each individual task first, and then leveraging the confidence knowledge from each task to provide informative priors to guide the learning processes of the other tasks.

8.3 Robust Learning Theory
To address the learning under uncertainty issue that is inherently existed in the weakly supervised learning process, robust learning strategy will become one of the key techniques in the future. The goal is to alleviate the influence of the noisy samples during the learning process. In implementation, such learning strategy is usually achieved by selecting easy and confident training samples in the early learning stages while using hard and more ambiguous training samples in the late learning stages. Essentially, a number of recent methods have already introduced the robust learning strategies into their learning frameworks. For example, Shi and Ferrari [127] propose a curriculum learning strategy to feed training images into the WSOL learning loop in order from images containing bigger objects down to smaller ones. The training order is determined by the size of the object, which is estimated based on a regression model. Similarly, Zhang et al. [210] design a zigzag learning strategy, where they first develop a criterion to automatically rank the localization difficulty of an image, and then learn the detector progressively by feeding examples with increasing difficulty. As can be seen, these methods are just intuitive ways to introduce robust learning strategy into the weakly supervised object localization and detection frameworks, while they have already achieved obvious performance gains when compared with the conventional learning strategy. Along this line, Zhang et al. [204] propose a self-paced curriculum learning framework for weakly supervised object detection. By integrating the curriculum learning [5] with the self-paced learning [86], the established learning framework provides a more theoretical-sounded way to improve the learning robustness. However, the solid robust learning theory is still lack in this research field.

8.4 Reinforcement and Adversarial Learning
Besides the conventional CNN models, it is also worth trying to apply some more advanced learning models into the learning process of the weakly supervised object detector. Here we give two examples. The first one is the deep reinforcement learning. According to [89], biological vision systems are believed to have a sequential process with changing retinal fixations that gradually accumulate evidence of certainty when searching or localizing objects. Several existing methods [11], [64], [74], [96], [192] have also demonstrated that designing deep reinforcement learning frameworks to model such a sequential searching process can indeed help to address the object localization, detection, and tracking problems in the computer vision community. Thus, it is highly desirable, both biologically and computationally, to explore deep reinforcement learning models that facilitate the weakly supervised object localization and detection systems in such a sequential searching process [205]. The second one is the generative adversary learning. As we know, generative adversary learning has been demonstrated to have advantages in unsupervised and semi-supervised learning scenarios [55], [133], [142], [153]. It can generate the desired data distribution based on very weak supervision, i.e., “real” or “fake”. Such capacity endows generative adversary learning very large potential in solving the weakly supervised object localization and detection problems. Although existing methods, such as [29], [125], [211], have already made efforts to introduce such a learning mechanism into the weakly supervised object localization and detection, there is still much room for improvement along this research direction.

8.5 Prior-guided Deep MIL
From Table 7 and Table 8, we can observe that most of the current deep weakly supervised object detection methods have not introduced any prior knowledge into their learning frameworks. However, from our review on classic models (see Sec. 3), prior knowledges actually play important roles in avoiding the weakly supervised learning process from drifting to trivial solutions. Considering this issue, some recent works utilize prior knowledges of saliency [92], objectness [110], [219], shape [93], count [44], [63], human action [188], human object interaction [80], mask-out scoring [183] in their frameworks. However, research towards building effective deep MIL frameworks (such as the one with prior knowledge distillation [15] or cross domain adaptation [62]) to embed helpful prior knowledge into the weakly supervised learning process needs to be further explored in the future. In addition, the co-occurring patterns mined in co-saliency detection [201], [206] and object co-localization [120], [179] approaches can also be used as informative priors to guide the deep multiple instance learning process in weakly supervised object localization and detection.

9 Conclusions
In this paper, we provide a comprehensive survey of existing literatures in the research field of weakly supervised object
localization and detection. We start with the introduction of the definition of the task and the key challenges that make the weakly supervised learning process hard to implement. Then, we introduce the development history of this field, the taxonomy of methods for weakly supervised object localization and detection, and the relationship between different categories. After reviewing existing literatures in each category of methodology, we introduce the benchmark datasets and evaluation metrics that are widely used in this field, which are followed by the reviewing of the applications of the existing weakly supervised object localization and detection algorithms. Finally, we point out several future directions that may further promote the development of this research field.

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