[Supplementary Material]
Object Discovery via Contrastive Learning for Weakly Supervised Object Detection

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https://github.com/jinhseo/OD-WSCL

In this supplementary material, we provide further results, both quantitative and qualitative, in the following order.

- Section A reports per-class Average Precision and Correct Localization results on PASCAL VOC datasets.
- Section B compares different proposal generation methods.
- Section C demonstrates the robustness of proposed method using similarity threshold guided by WSCL.
- Section D provides overall pipeline of Object Discovery.
- Section E provides additional qualitative results on PASCAL VOC and MS-COCO datasets.

\section{A Detailed Performance on PASCAL VOC}

In Tables 4 and 5, we provide additional performance of per-class average precision (AP) using Selective Search (SS) \textsuperscript{13} with VGG16 on VOC07 and VOC12 \textsuperscript{4}. Our method achieves the second-highest performance on VOC07 and the highest performance on VOC12. The proposed method successfully addresses the issue of missing objects with high performance for the classes with a large number of objects per image, such as \textit{cow}, \textit{person} and \textit{sheep} in Fig. 7.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{fig7.png}
\caption{Analysis of a number of objects per image on PASCAL VOC datasets.}
\end{figure}
In Tables [6] and [7] we report the results of per-class Correct Localization (CorLoc) scores using SS with VGG16 on VOC07 and VOC12. CorLoc is an additional evaluation metric commonly reported in WSOD literature to measure localization accuracy, equivalent to precision \(=\frac{\text{true positives}}{\text{true positives} + \text{false positives}}\). More specifically, it measures the percentage of correct localization predictions where a prediction is treated as “correct” if the IoU between the prediction and corresponding ground truth is greater than or equal to 0.5. Our method achieves the third-best result in CorLoc on both VOC07 and VOC12. Our slightly worse performance in CorLoc than in mAP is because, as a multiple instance labeling method, our approach captures more proposals than argmax-based methods: this significantly increases recall, but may slightly decrease precision (the only thing measured by CorLoc).

Table 4: Per-class AP results on VOC07

| Method      | Ave | Rec | Prec | Recall | Precision | mAP | mAP | mAP | mAP |
|-------------|-----|-----|------|--------|-----------|-----|-----|-----|-----|
| Ours        | 56.0| 62.4| 51.1 | 49.4   | 53.1      | 65.5| 55.5| 55.5| 55.5|
| C-WSL       | 56.1| 61.4| 50.5 | 49.4   | 53.1      | 65.5| 55.5| 55.5| 55.5|
| WSOD        | 56.0| 60.1| 51.0 | 52.0   | 51.0      | 65.5| 55.5| 55.5| 55.5|
| OICR        | 56.0| 59.8| 51.0 | 52.0   | 51.0      | 65.5| 55.5| 55.5| 55.5|

Table 5: Per-class AP results on VOC12

| Method      | Ave | Rec | Prec | Recall | Precision | mAP | mAP | mAP | mAP |
|-------------|-----|-----|------|--------|-----------|-----|-----|-----|-----|
| Ours        | 56.0| 62.4| 51.1 | 49.4   | 53.1      | 65.5| 55.5| 55.5| 55.5|
| C-WSL       | 56.1| 61.4| 50.5 | 49.4   | 53.1      | 65.5| 55.5| 55.5| 55.5|
| WSOD        | 56.0| 60.1| 51.0 | 52.0   | 51.0      | 65.5| 55.5| 55.5| 55.5|
| OICR        | 56.0| 59.8| 51.0 | 52.0   | 51.0      | 65.5| 55.5| 55.5| 55.5|

Table 6: Per-class CorLoc results on VOC07

| Method      | Ave | Rec | Prec | Recall | Precision | mAP | mAP | mAP | mAP |
|-------------|-----|-----|------|--------|-----------|-----|-----|-----|-----|
| Ours        | 56.0| 62.4| 51.1 | 49.4   | 53.1      | 65.5| 55.5| 55.5| 55.5|
| C-WSL       | 56.1| 61.4| 50.5 | 49.4   | 53.1      | 65.5| 55.5| 55.5| 55.5|
| WSOD        | 56.0| 60.1| 51.0 | 52.0   | 51.0      | 65.5| 55.5| 55.5| 55.5|
| OICR        | 56.0| 59.8| 51.0 | 52.0   | 51.0      | 65.5| 55.5| 55.5| 55.5|

Table 7: Per-class CorLoc results on VOC12

| Method      | Ave | Rec | Prec | Recall | Precision | mAP | mAP | mAP | mAP |
|-------------|-----|-----|------|--------|-----------|-----|-----|-----|-----|
| Ours        | 56.0| 62.4| 51.1 | 49.4   | 53.1      | 65.5| 55.5| 55.5| 55.5|
| C-WSL       | 56.1| 61.4| 50.5 | 49.4   | 53.1      | 65.5| 55.5| 55.5| 55.5|
| WSOD        | 56.0| 60.1| 51.0 | 52.0   | 51.0      | 65.5| 55.5| 55.5| 55.5|
| OICR        | 56.0| 59.8| 51.0 | 52.0   | 51.0      | 65.5| 55.5| 55.5| 55.5|
B Comparison of Proposal Generation Method

Current WSOD models rely on pre-computed proposal methods such as Selective Search (SS) [13] and Edge Boxes (EB) [16]. Although the choice of proposal generation methods has a significant impact on localization performance, most previous studies still exploit SS for PASCAL VOC and MCG for MS-COCO datasets. To better understand the effect of using different proposal methods, we compare our algorithm’s performance to that of several state-of-the-art algorithms with different proposal methods (SS [13], MCG [11], and COB [8]) on VOC07 (Table 8) and MS-COCO (Table 9) datasets. Note that COB generally captures the groundtruths the best among the three proposal generation methods whereas SS performs the worst.

In general, the better the proposals are, the higher the performance of detection is regardless of model. In Table 8 Ours performs the best with COB and then with MCG (COB: 61.8%, MCG: 58.7%, and SS: 56.1%), which is the same for CASD and MIST. Similarly, COB outperforms MCG with a large margin as observed on MS-COCO datasets as shown in Table 9. We chose to report only the performance of SS and MCG in the main paper because additional boundary information is required to train COB, which violates the definition of image-level supervision. Based on this experiment, we believe MCG should be the default proposal generation method for both PASCAL VOC and MS-COCO datasets unlike the previous convention in WSOD.

Table 8: Per-class AP results with different proposal generation methods on VOC07.

| Method | Backbone | Proposal Method | AP | AP50 | AP75 | AP50_90 | AP75_90 | AR | AR50 | AR75 | AR50_90 | AR75_90 |
|--------|----------|-----------------|----|------|------|---------|---------|-----|-------|-------|---------|---------|
| MIST   | VGG16    | SS              | 11.4 | 24.3 | 9.4  | 8.7     | 12.2    | 11.8 | 15.5  | 22.6  | 16.7    | 23.9    |
|        |          | MCG             | 12.8 | 20.4 | -    | -       | -       | -    | -     | -     | -       | -       |
|        |          | Ours COB        | 13.7 | 27.7 | 11.9 | 8.7     | 14.5    | 21.2 | 14.7  | 24.8  | 20.8    | 26.9    |
|        |          | Ours            | 15.1 | 29.3 | 13.8 | 4.5     | 15.9    | 23.4 | 16.0  | 26.5  | 22.2    | 28.2    |
| CASD   | VGG16    | SS              | 11.4 | 24.3 | 9.4  | 8.7     | 12.2    | 11.8 | 15.5  | 22.6  | 16.7    | 23.9    |
|        |          | MCG             | 12.8 | 20.4 | -    | -       | -       | -    | -     | -     | -       | -       |
|        |          | Ours COB        | 13.7 | 27.7 | 11.9 | 8.7     | 14.5    | 21.2 | 14.7  | 24.8  | 20.8    | 26.9    |
|        |          | Ours            | 15.1 | 29.3 | 13.8 | 4.5     | 15.9    | 23.4 | 16.0  | 26.5  | 22.2    | 28.2    |
| COB    | VGG16    | SS              | 11.4 | 24.3 | 9.4  | 8.7     | 12.2    | 11.8 | 15.5  | 22.6  | 16.7    | 23.9    |
|        |          | MCG             | 12.8 | 20.4 | -    | -       | -       | -    | -     | -     | -       | -       |
|        |          | Ours COB        | 13.7 | 27.7 | 11.9 | 8.7     | 14.5    | 21.2 | 14.7  | 24.8  | 20.8    | 26.9    |
|        |          | Ours            | 15.1 | 29.3 | 13.8 | 4.5     | 15.9    | 23.4 | 16.0  | 26.5  | 22.2    | 28.2    |

Table 9: Performance with different proposal generation methods on MS-COCO.

| Dataset | Backbone | Method | Proposal Method | AP | AP50 | AP75 | AR | AR50 | AR75 | AR50_90 | AR75_90 |
|---------|----------|--------|-----------------|----|------|------|-----|-------|-------|---------|---------|
| COCO14  | VGG16    | MIST   | MCG             | 11.4 | 24.3 | 9.4  | 15.5 | 22.6 | 16.7 | 23.9    | 28.2    |
|         |          | CASD   | MCG             | 12.8 | 20.4 | -    | -    | -    | -    | -       | -       |
|         |          | MCS    | MCG             | 13.7 | 27.7 | 11.9 | 14.4 | 21.2 | 21.4 | 24.8    | 26.9    |
|         |          | Ours   | COB             | 15.1 | 29.3 | 13.8 | 15.5 | 26.1 | 25.6 | 31.8    | 28.2    |
|         |          | Ours   | MCG             | 16.2 | 31.4 | 15.6 | 18.7 | 26.4 | 17.5 | 30.9    | 28.1/28.2 |
| COCO17  | VGG16    | MIST   | MCG             | 11.4 | 24.3 | 9.4  | 15.5 | 22.6 | 16.7 | 23.9    | 28.2    |
|         |          | CASD   | MCG             | 12.8 | 20.4 | -    | -    | -    | -    | -       | -       |
|         |          | MCS    | MCG             | 13.7 | 27.7 | 11.9 | 14.4 | 21.2 | 21.4 | 24.8    | 26.9    |
|         |          | Ours   | COB             | 15.1 | 29.3 | 13.8 | 15.5 | 26.1 | 25.6 | 31.8    | 28.2    |
|         |          | Ours   | MCG             | 16.2 | 31.4 | 15.6 | 18.7 | 26.4 | 17.5 | 30.9    | 28.1/28.2 |

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C Different Criterion for Object Discovery

In Section 4.3, we argued that the similarity of two proposals in the embedding space can be large even though they are not similar in classification score. To justify the necessity of using additional similarity scores for the object discovery module, Table 10 compares object discovery based on classification score, with various threshold values, to similarity score. Recall that the “adaptive” threshold we used for similarity score is determined by the average value of similarity between the argmax and its augmented samples: \( \tau_{n,k}^{c} = \frac{1}{|S_c|} \sum_{i=1}^{|S_c|} \text{sim}(z_n^{n,k}, S_{c,i}) \).

For object discovery based on classification score, we not only try fixed thresholds but also adaptive threshold defined as \( \tau_{n,k}^{c} = \frac{1}{|S_c'|} \sum_{i=1}^{|S_c'|} S_{c',i} \) where \( S' \) is the collection of classification scores that are calculated using the augmented features (same features for \( S \)).

In Table 10, the performance of the object discovery based on classification score is significantly worse than similarity score. Moreover, the best-performing threshold \( \tau_{n,k}^{c} = 0.4 \) (57.4%) is dramatically better than a similar threshold value \( \tau_{n,k}^{c} = 0.2 \). Thus, unlike similarity score (as shown in Section 5.3), performance is also very sensitive to the choice of threshold. Note that we train the model with the same hyperparameters \( (\tau_{nms} = 0.1, \lambda = 0.03) \) for fair comparison.

Table 10: The results of different criteria for object discovery

| Criterion       | Threshold \((\tau_{n,k}^{c})\) | mAP |
|-----------------|-------------------------------|-----|
| Classification  | 0.2                           | 50.3|
|                 | 0.3                           | 56.2|
|                 | 0.4                           | 57.4|
|                 | 0.5                           | 56.2|
|                 | 0.6                           | 56.1|
|                 | 0.7                           | 55.6|
|                 | 0.8                           | 54.4|
|                 | Adaptive                      | 58.7|

Fig. 8: Comparison of pseudo groundtruths generated by classification score vs. similarity score. The left and right images of each pair correspond to pseudo groundtruths based on classification and similarity scores, respectively.
D  Pseudo Code: Sampling and Object Discovery

Along with Fig.2 in the main paper, we provide the detailed procedure of sampling steps and object discovery. The main purpose of object discovery is to obtain more pseudo groundtruths in addition to the top-scoring proposals.

Algorithm 1 Sampling steps and object discovery

| Network: RoI feature extractor $\eta(\cdot)$, similarity head $\varphi(\cdot)$ |
| --- |
| **Input:** Proposal Scores: $x_{n,k}^{c,m}$, Embedding Vectors: $z_{n,m}^c$, Proposals: $R_n$, Image Labels: $Y_n$, Proposal Labels: $Y_{n,k}^{c,m}$ |
| **Output:** Updated $S_c$, $Y_{n,k}^{c,m}$ |

1. $S_c \leftarrow \emptyset$, $y_{n,k}^{c,m} = 0$, $y_{(c+1),m} = 1$
2. \textbf{for} $n = 1$ to $N$ \textbf{do}
3. \hspace{1em} \textbf{for} $k = 0$ to $K-1$ \textbf{do}
4. \hspace{2em} if $y_{n,k}^{c,m} = 1$ then
5. \hspace{3em} $m_{n,k}^c = \text{argmax}_m x_{n,k}^{c,(k-1)}$
6. \hspace{3em} if $\text{IoU}(r_m, r_{n,k}^m) > \tau_{\text{IoU}}, \forall m \in M^n$ then
7. \hspace{4em} $M_c^{n,k} \leftarrow m$
8. \hspace{3em} $Z_{\text{IoU}}^{n,c} = \{\varphi(\eta(f_m^n)) \mid m \in \bigcup_{k=0}^{K-1} M_c^{n,k}\}$
9. \hspace{3em} $D : D_{i,j} \sim U(0,1) \in \mathbb{R}^{H \times W}$
10. \hspace{3em} $D_{\text{drop}} = \begin{cases} 0 & \text{if } D < \tau_{\text{drop}} \\ 1 & \text{otherwise} \end{cases}$
11. \hspace{3em} $Z_{\text{mask}}^{n,c} = \{\varphi(\eta(f_m^n \odot D_{\text{drop}})) \mid m \in \bigcup_{k=0}^{K-1} M_c^{n,k}\}$
12. \hspace{3em} $D_{\text{noise}} : D_{i,j} \sim N(0,1) \in \mathbb{R}^{H \times W}$
13. \hspace{3em} $Z_{\text{noise}}^{n,c} = \{\varphi(\eta(f_m^n + f_m^n \odot D_{\text{noise}})) \mid m \in \bigcup_{k=0}^{K-1} M_c^{n,k}\}$
14. \hspace{2em} $S_c = \bigcup_{n=1}^{N} (Z_{\text{IoU}}^{n,c} \cup Z_{\text{mask}}^{n,c} \cup Z_{\text{noise}}^{n,c})$
15. \hspace{3em} \textbf{for} $n = 1$ to $N$ \textbf{do}
16. \hspace{4em} \textbf{for} $k = 0$ to $K-1$ \textbf{do}
17. \hspace{5em} if $y_{n,k}^{c,m} = 1$ then
18. \hspace{6em} $m_{n,k}^c = \text{argmax}_m x_{n,k}^{c,(k-1)}$
19. \hspace{6em} $\tau_n^c = \text{Avg}(\text{sim}(z_{m_{n,k}^c}^{n,k}, S_c))$
20. \hspace{6em} if $\text{sim}(z_{n,k}^{n,m}, z_{n,k}^{n}) > \tau_n^c, \forall m \in M^n$ then
21. \hspace{7em} $S_c \leftarrow z_{n,k}^{n}$
22. \hspace{6em} if $\text{IoU}(r_m, r_{n,k}^m) > 0.5, \forall m \in M^n$ then
23. \hspace{7em} $y_{n,k}^{c,m} = 1$
E More Qualitative Results

In Fig. 9, we provide more qualitative results for the three challenges of WSOD on VOC07. Columns on the left and right of each pair correspond to qualitative results from OICR [11] and our model, respectively.

In Fig. 10, we compare prediction results of OICR [11] on the left and Ours on the right. Our model shows much better results for COCO, which contains more instances per image. Although the issue of grouped instances is observed in some cases, our model correctly captures multiple objects and classifies them correctly, despite extremely complex backgrounds.

Fig. 11 shows failure cases of the proposed method. Our model misclassifies background objects that looks like a target class, for example human-like statues or dolls. In addition, the predicted boxes are separated in some cases, even though the object its full extent is captured.

Fig. 9: More qualitative results for the three challenges of WSOD on VOC07.
Fig. 10: Qualitative results on COCO14.
Fig. 11: Failure cases of the proposed method.

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