MOVE: Unsupervised Movable Object Segmentation and Detection

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Abstract

We introduce MOVE, a novel method to segment objects without any form of supervision. MOVE exploits the fact that foreground objects can be shifted locally relative to their initial position and result in realistic (undistorted) new images. This property allows us to train a segmentation model that achieves state of the art (SotA) performance on several evaluation datasets for unsupervised salient object detection and segmentation. In unsupervised single object discovery, MOVE gives an average CorLoc improvement of 4.5% over the SotA, and in unsupervised class-agnostic object detection it gives a relative AP improvement of 30% on average. Our approach is built on top of self-supervised features (from DINO), an inpainting network (based on the Masked AutoEncoder) and adversarial training with a projected discriminator.

1 Introduction

Image segmentation and object detection are today mature and essential components in vision-based systems with applications in a wide range of fields including automotive [1], agriculture [2], and medicine [3], just to name a few.

A major challenge in building and deploying such components at scale is that they require costly and time-consuming human annotation. This has motivated efforts in self-supervised learning (SSL) [4–6]. The aim of SSL is to learn general-purpose image representations from large unlabeled datasets that can be fine-tuned to different downstream tasks with small annotated datasets. While SSL methods have also been fine-tuned for image segmentation since their inception, it is only with the recent state of the art (SotA) methods, such as DINO [4] and Dense Contrastive Learning [6], that a clear and strong link to object segmentation has been observed. This has led to several methods for salient object detection built on top of SSL features [7–12].

Most prior work based on SSL features defines some form of clustering by either using attention maps [7–9] or similarity graphs [10–12]. In this work, we take a quite different direction. Rather than directly clustering the features, we train a network to map them to a segmentation mask. As supervision signal we use the *movability* of objects, *i.e.*, whether they can be locally shifted in a realistic manner. We call our method MOVE. This property holds for objects in the foreground, as they occlude all other objects in the scene. This basic idea has already been exploited in prior work with relative success [13–18]. Nonetheless, here we introduce a novel formulation based on movability that yields a significant performance boost across several datasets for salient object detection.

In our approach, it is not necessary to move objects to other images [13, 14] and thus we do not have to handle the context mismatch. It is also not necessary to employ generative models [15, 16], which can be challenging to train. Our working principle exploits observations also made by [17, 18].

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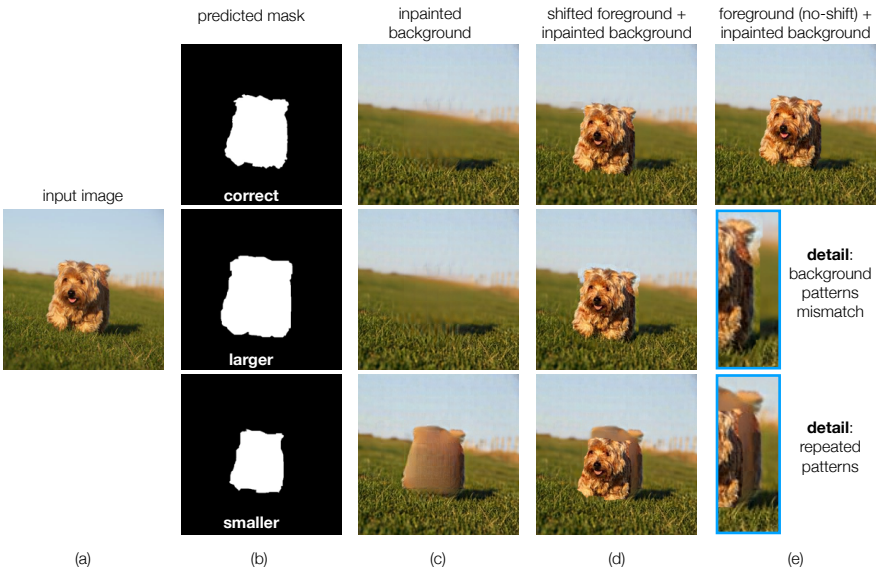

Figure 1: Exploiting inpainting and movability. (a) Input image. (b) Examples of predicted segmentation masks: correct (top), larger (middle) and smaller (bottom). (c) Inpainted backgrounds in the three corresponding cases. (d) Composite image obtained by shifting the foreground object in the three cases. (e) It can be observed that when the mask is incorrect (it includes parts of the background or it does not include all of the background), the background inpainting combined with shifting reveals repeated patterns and mismatching background texture, when compared to the original input image or composite images obtained without shifting.

They point out that the correct mask maximizes the inpainting error both for the background and the foreground. However, rather than using the reconstruction error as a supervision signal, we rely on the detection of artifacts generated through shifting, which we find to provide a stronger guidance.

We propose an adversarial training scheme, where we train a segmenter network against a discriminator. The segmenter predicts the segmentation mask of the foreground object (Figure 1 (b)) from a single image (Figure 1 (a)). Given the mask, we can separate the foreground from the background in the input image, locally shift it and then compose it with the background to synthesize a new image (see Figure 1 (d)). However, due to the shift, regions in the background that were previously occluded by the foreground object become exposed. Thus, to fill in the missing pixels, we also employ an inpainter network before adding the foreground (see Figure 1 (c)). Finally, the discriminator aims to distinguish these composite shifted images from real ones. In Figure 1, we consider several scenarios for the predicted mask. Suppose that the segmentation mask is correct (Figure 1 (b) top) and we feed the corresponding segmented background to the inpainter. Because the inpainter does not have any information about the foreground object, it can only complete the patterns from the background, *i.e.*, it can obtain a counterfactual image had the object not been there (Figure 1 (c) top). In this case, the discriminator should not be able to tell the difference between the composite shifted image (Figure 1 (d) top) and the real one (Figure 1 (a)). If the mask is instead incorrect (Figure 1 (b) middle and bottom), *i.e.*, it includes parts of the background or it does not include all of the foreground object, the composite shifted image will contain repeated and mismatching patterns (Figure 1 (d), (e) middle and bottom). In fact, in either case the inpainting model would complete the missing pixels in the background and predict foreground and/or background patterns that are in the incorrect foreground too (Figure 1 (e) middle and bottom). To encourage the discriminator to focus on detecting such repeated patterns, we also feed composite images without any shift (Figure 1 (e) top) as examples of "real" images.

As inpainter we use a publicly available Masked AutoEncoder (MAE) [19] trained with an adversarial loss.[1] Our segmenter uses a pre-trained DINO ViT as backbone [4]. We then train a neural network head based on an upsampling Convolutional Neural Network (CNN). Following [12], we also further

[1] `https://github.com/facebookresearch/mae/blob/main/demo/mae_visualize.ipynb`

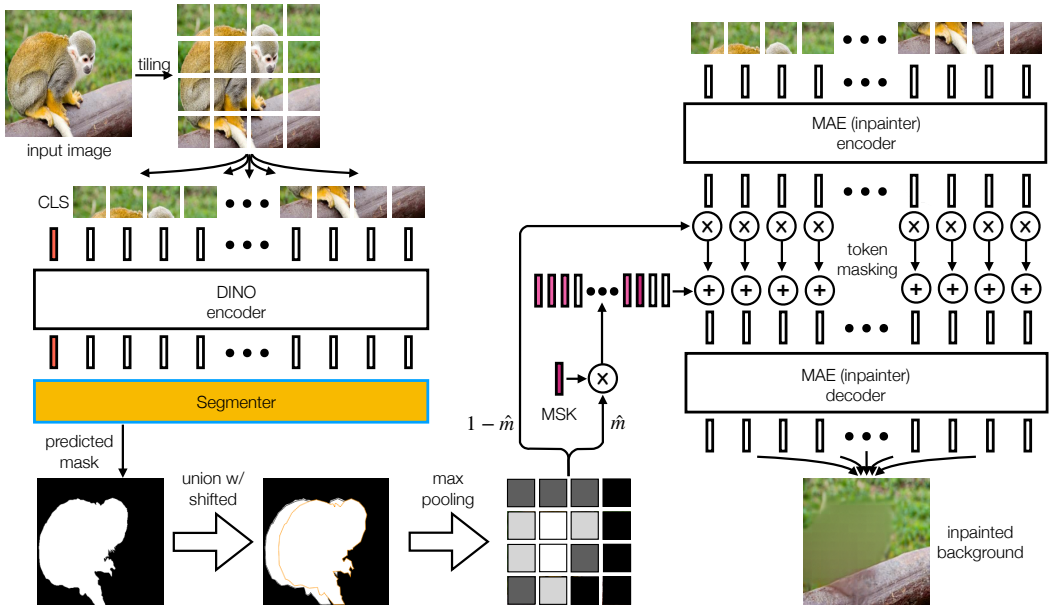

Figure 2: (Left) The segmenter is built on top of DINO features. To define the inpainting region for the background, the predicted mask is shifted and combined with the unshifted mask (bottom left). For better visualization purposes we highlight the edge of the shifted mask, but this does not appear in the actual union of the masks. This mask union is then downsampled to the size of the tile grid via max pooling and denoted $\hat{m}$. (Right) The inpainter is based on MAE. First, it takes all the tiles from the input image and feeds them to the MAE encoder. Second, it takes a convex combination between the encoder embeddings and the MSK learned embedding (but now frozen), where the convex combination coefficients are based on the downsampled mask $\hat{m}$. Finally, this combination is fed to the MAE decoder to generate the inpainted background.

refine the segmenter by training a second segmentation network (SelfMask [12]) with supervision from pseudo-masks generated by the trained segmenter.

Even without these further refinements MOVE shows a remarkable performance on a wide range of datasets and tasks. In particular, in unsupervised single object discovery on VOC07, VOC12 and COCO20K it improves the SotA CorLoc between 3.2% and 6%, and in unsupervised class agnostic object detection on COCOval2017 it improves the AP_{50} by 5% (a relative improvement of 41%), the AP_{75} by 1.2% (relative 29%) and the AP by 1.8% (relative 33%).

2 Method

Following the recent trend of methods for unsupervised object segmentation [7–12, 20], we build our method on top of SSL features, and, in particular, DINO features [4]. Thus, as a backbone, we adopt the Vision Transformer (ViT) architecture [21]. Following the notation in [10], we split an image $x \in \mathbb{R}^{H \times W \times 3}$ in tiles of size $P \times P$ pixels, for a total of $N = HW/P^2$ tiles (and we assume that H and W are such that H/P and W/P are integers). Each tile is then mapped through a trainable linear layer to an embedding of size d and an additional CLS token is included in the input set (see Figure 2 left).

The *segmenter* network is a CNN that takes DINO features as input, upsamples them and then outputs a mask for the original input image. The final output is generated by using a sigmoid to ensure that the mask values are always between 0 and 1. We also encourage the support of the predicted mask to lie between a minimum and a maximum size by using

$$\mathcal{L}_{\text{min}} = \frac{1}{n} \sum_{i=1}^{n} \max\left\{\theta_{\text{min}} - \sum_p \frac{m^{(i)}[p]}{HW}, 0\right\} \quad \text{and} \quad \mathcal{L}_{\text{max}} = \frac{1}{n} \sum_{i=1}^{n} \max\left\{\sum_p \frac{m^{(i)}[p]}{HW} - \theta_{\text{max}}, 0\right\}, \tag{1}$$

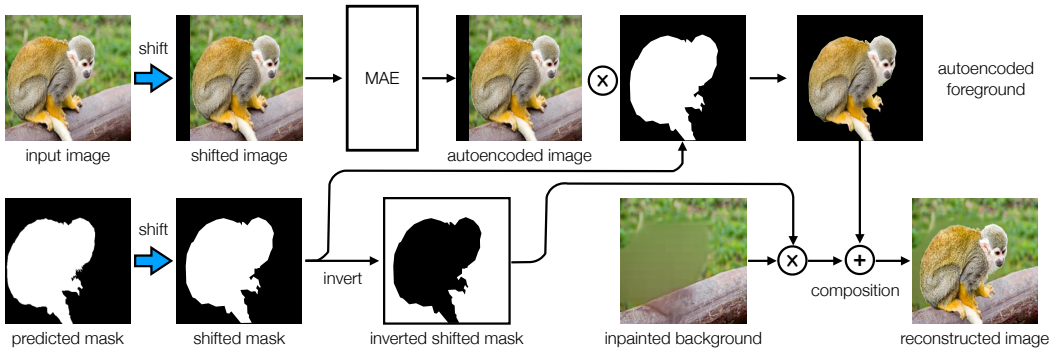

Figure 3: Synthetically shifted images. Since the MAE inpainter outputs artifacts in the inpainted background, we also autoencode the shifted foreground. In this way, the discriminator cannot easily distinguish the foreground from the background in the composite image. We shift both the input image and the predicted mask by the same amount. The composite image is obtained by pasting the shifted foreground on top of the inpainted background.

where n is the number of images in the training dataset, $m^{(i)}$ is the predicted mask from image $x^{(i)}$, p is a pixel location within the image domain, and θ_{min} and θ_{max} are thresholds for the minimum and maximum mask coverage percentage respectively (in the range $[0, 1]$, where 0 implies that the mask is empty and 1 implies that the mask covers the whole image). Since masks should only take binary values to clearly indicate a segment, we use a loss that encourages $m^{(i)}$ to take either 0 or 1 values

$$\mathcal{L}_{\text{bin}} = \frac{1}{n} \sum_{i=1}^{n} \frac{1}{HW} \sum_{p} \min \left\{ m^{(i)}[p], 1 - m^{(i)}[p] \right\} . \tag{2}$$

The main task of MOVE is to predict a segmentation mask that can be used to synthesize a realistic image, where the foreground object is shifted (see Figure 1 (e) top). Figure 3 shows the main steps used to synthesize a composite image where the foreground is shifted. The most challenging part is dealing with the background. When the shifted foreground is copied back onto the background, missing pixels remain exposed. To avoid this issue, we inpaint the background with a pre-trained network. As shown in Figure 2 on the right, we use a MAE [19], which is based on a ViT architecture and has been pre-trained in an adversarial fashion (as opposed to the standard training with an MSE loss) to output more realistic-looking details. Because MAE performs inpainting by masking or retaining entire tiles, it is necessary to also split the segmentation mask into a grid of tiles of $P \times P$ pixels and to map each tile to a single scalar between 0 and 1. We do that by using a max pooling operation within each tile and obtain a low-res mask $\hat{m}$. To avoid full masks $\hat{m}$ and to regularize the predicted mask m, all three losses $\mathcal{L}_{\text{min}}$, $\mathcal{L}_{\text{max}}$, $\mathcal{L}_{\text{bin}}$ are also computed on max pool downsampled masks (at scales 1/2, 1/4, 1/8, and 1/16 of the original image resolution; for more details see the supplementary material). Then, we feed the entire set of image tiles to the MAE encoder and obtain embeddings $\xi_1, \ldots, \xi_N$. Next, for $j = 1, \ldots, N$, we compute the convex combination between the embeddings ξ_j and the learned MSK (masked) token from MAE by using the low res mask $\hat{m}$ as $\hat{\xi}_j = \hat{m}[j] \cdot \xi_{\text{MSK}} + (1 - \hat{m}[j]) \cdot \xi_j$. Finally, we feed the new embeddings $\hat{\xi}_j$ in the MAE decoder and reassemble the output tiles back into the inpainted background image $\hat{b}$ (see Figure 2 bottom-right). Notice that we feed all the tiles as input to obtain a differentiable mapping that we can backpropagate on because we found that the embeddings ξ_j do not store significant information about their neighbors. This is in contrast to the typical use of MAE, where only the subset of "visible" tiles is fed as input to the encoder. However, such tile selection operation would make the inpainting not differentiable. The complete pipeline just described allows the synthesis of images, where the foreground is shifted relative to its original position. We obtain $\hat{x}_\delta[p] = m_\delta[p] x[p + \delta] + (1 - m_\delta[p]) \hat{b}[p]$, where $m_\delta[p] = m[p + \delta]$, $\delta \in [-\Delta W, \Delta W] \times [-\Delta H, \Delta H]$ is a 2D shift, with Δ the maximum shift range (relative to the image size). When the mask m corresponds to an object, for a limited range of shifts, the composite image $\hat{x}_\delta$ still looks realistic. Thus, it is possible to train the segmenter adversarially to a discriminator D that aims at distinguishing the composite image from a real one.

Despite the impressive performance of MAE, the inpainted backgrounds $\hat{b}$ have visible artifacts (typically blurriness) and, as a consequence, so do the composite images. This means that even when the predicted mask is correct, the discriminator could easily distinguish the original image from the

composite one due to its unavoidable artifacts. Thus, we also produce composite images with $\delta = 0$ (no-shift) and add them to the pool of real images. To make the inpainting artifacts in the no-shift composite image comparable to those in the shifted composite image, we define the background inpainting region as the union between the predicted mask and its shifted version (see Figure 2). Thus, $\hat{m} = \text{maxpool}_P(1 - (1 - m) \odot (1 - m_\delta))$. In this way, the discriminator will be forced to focus on differences between synthesized images other than the reconstruction and inpainting artifacts of MAE. Moreover, even when an empty mask is used in MAE, the reconstructed image will not be identical to the input image. Thus, to ensure that both the foreground and the background undergo the same processing, we also feed the shifted image to MAE before extracting the foreground and composing it (see Figure 3 top). The discriminator also needs a reference of what real images without inpainting artifacts are. To this aim we also use images $\check{x}$, which are real images x autoencoded through MAE. The adversarial loss for the discriminator can be written as

$$\mathcal{L}_{\text{advD}} = -\mathbb{E}_{x \in \mathcal{R}} \min\{0, D(x) - 1\} - \mathbb{E}_{\bar{x} \in \mathcal{S}} \min\{0, -D(\bar{x}) - 1\} \tag{3}$$

where $\mathbb{E}$ denotes the expectation, the "real" images set is $\mathcal{R} = \{\check{x}^{(i)}\}_{i=1,\dots,n} \bigcup \{\hat{x}^{(i)}_{\delta=0}\}_{i=1,\dots,n}$ and the synthetic images set is $\mathcal{S} = \{\hat{x}^{(i)}_{\delta}\}_{i=1,\dots,n}$, with uniform random samples $\delta \sim \mathcal{U}_2([-\Delta W, \Delta W] \times [-\Delta H, \Delta H])$. To speed up the convergence, we also use the projected discriminator method [22]. For the segmenter, we use instead the standard loss

$$\mathcal{L}_{\text{advS}} = -\mathbb{E}_{\bar{x} \in \mathcal{S}} D(\bar{x}). \tag{4}$$

Finally, with λ_{min}, λ_{max}, λ_{bin} nonnegative hyperparameters, our optimization is the adversarial minimization

$$S^* = \arg\min_S \mathcal{L}_{\text{advS}} + \lambda_{\text{min}}\mathcal{L}_{\text{min}} + \lambda_{\text{max}}\mathcal{L}_{\text{max}} + \lambda_{\text{bin}}\mathcal{L}_{\text{bin}} \tag{5}$$

$$\text{subject to } D^* = \arg\min_D \mathcal{L}_{\text{advD}}. \tag{6}$$

3 Implementation

We use a self-supervised DINO [4] ViT-S/8 transformer pre-trained on ImageNet [23] as a feature extractor in all our experiments. We take the output of the penultimate transformer block of DINO as the feature tokens with $P = 8$ and feed them to the segmenter. Our segmenter is a small upsampling convolutional neural network. It assembles the DINO features into a grid of size $H/P \times W/P$ and processes them with 3 upsampling blocks, so that the output matches the input image resolution. Each upsampling block first performs a 2×2 nearest upsampling, followed by a 3×3 convolutional layer with padding, batch normalization and a LeakyReLU activation function. We add an additional block without upsampling and a linear projection to 1 channel, representing the mask. Our inpainting network is a ViT-L/16 transformer pre-trained on ImageNet as a Masked Autoencoder (MAE) [19] with an adversarial loss to increase the details of the reconstructed images. For the discriminator we use the Projected Discriminator [22] in its standard setting, but we exclude CutOut differentiable augmentation. For the training we use random resized crops of size 224 with a scale in range $(0.9, 1)$ and aspect ratio $(3/4, 4/3)$. We set the minimum mask area $\theta_{\text{min}} = 0.05$ and maximum mask area $\theta_{\text{max}} = 0.8$. We set the minimum and maximum mask loss coefficients $\lambda_{\text{min}} = \lambda_{\text{max}} = 100$ and the binarization loss coefficient $\lambda_{\text{bin}} = 5$. We use the shift range $\Delta = 1/8$. We train the segmenter by alternatively minimizing the discriminator loss and the segmenter losses. Both are trained with a learning rate of 0.0002 and an Adam optimizer with betas $= (0, 0.99)$ for the discriminator and $(0.9, 0.95)$ for the segmenter. We implemented our experiments in PyTorch [24]. We train our model for 160 epochs with a batch size of 32 on a single NVIDIA GeForce 3090Ti GPU with 24GB of memory.

4 Experiments

4.1 Unsupervised saliency segmentation

Datasets. We train our main model using the train split of the DUTS dataset (DUTS-TR) [26], containing $10{,}553$ images of scenes and objects of varying sizes and appearances. We emphasize that we only use the images without the corresponding ground truth. For comparison, we evaluate our

Table 1: Comparison to the unsupervised saliency detection methods on 3 benchmarks.

Model	DUT-OMRON [25]			DUTS-TE [26]			ECSSD [27]		
	Acc	IoU	max F_β	Acc	IoU	max F_β	Acc	IoU	max F_β
HS [28]	.843	.433	.561	.826	.369	.504	.847	.508	.673
wCtr [29]	.838	.416	.541	.835	.392	.522	.862	.517	.684
WSC [30]	.865	.387	.523	.862	.384	.528	.852	.498	.683
DeepUSPS [31]	.779	.305	.414	.773	.305	.425	.795	.440	.584
SelfMask pseudo* [12]	.811	.403	-	.845	.466	-	.893	.646	-
BigBiGAN [32]	.856	.453	.549	.878	.498	.608	.899	.672	.782
E-BigBiGAN [32]	.860	.464	.563	.882	.511	.624	.906	.684	.797
Melas-Kyriazi et al. [33]	.883	.509	-	.893	.528	-	.915	.713	-
LOST [10]	.797	.410	.473	.871	.518	.611	.895	.654	.758
Deep Spectral [20]	-	.567	-	-	.514	-	-	.733	-
TokenCut [11]	.880	.533	.600	.903	.576	.672	.918	.712	.803
FreeSOLO [8]	.909	.560	.684	.924	.613	.750	.917	.703	.858
MOVE (Ours)	**.913**	**.585**	**.690**	**.944**	**.680**	**.789**	**.950**	**.809**	**.901**
LOST [10] + Bilateral	.818	.489	.578	.887	.572	.697	.916	.723	.837
TokenCut [11] + Bilateral	.897	.618	.697	.914	.624	.755	.934	.772	.874
MOVE (Ours) + Bilateral	**.925**	**.627**	**.720**	**.949**	**.692**	**.811**	**.952**	**.804**	**.906**
SelfMask on pseudo* [12]	.923	.609	.733	.938	.648	.789	.943	.779	.894
SelfMask on pseudo* [12] + Bilateral	**.939**	**.677**	**.774**	**.949**	.694	.819	.951	.803	.911
SelfMask on MOVE (Ours)	.916	.643	.739	.947	**.720**	**.824**	**.957**	**.839**	**.917**
SelfMask on MOVE (Ours) + Bilateral	.922	.657	.743	.948	.699	.817	.956	.819	.912

*We found that SelfMask's $\max F_\beta$ metric was computed with an optimal threshold for each image instead of the entire dataset as in other methods; we re-evaluated their model for a fair comparison

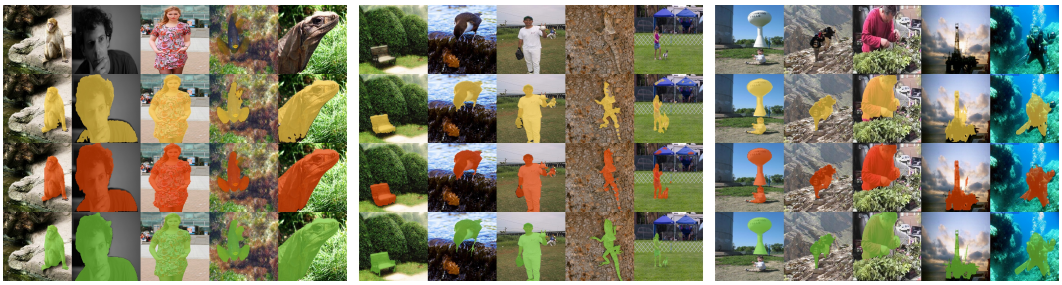

Figure 4: Qualitative evaluation of MOVE on ECSSD, DUTS-TE and DUT-OMRON. First row: input image; second row: MOVE; third row: SelfMask on MOVE; last row: ground truth. Best viewed in color. For more examples and a gray scale version see the supplementary material.

approach on three saliency detection datasets: the test set of DUTS (5,019 images), DUT-OMRON [25] (5,168 images) and ECSSD [27] (1,000 images). We report three standard metrics: pixel mask accuracy (Acc), intersection over union (IoU), $\max F_\beta$, where $F_\beta = \frac{(1+\beta^2)\text{Precision}\times\text{Recall}}{\beta^2\text{Precision}+\text{Recall}}$ for $\beta = 0.3$; the $\max F_\beta$ is the score for the single optimal threshold on a whole dataset.

Evaluation. We train our segmenter in an adversarial manner as specified in sections 2 and 3 and evaluate it on the test datasets. We compare with other methods in Table 1. Note that without any type of post-processing of our predicted masks, we surpass all other methods by a significant margin. We also follow [11, 12] and further refine our masks with a bilateral solver [34]. Since the bilateral solver only marginally improves or even decreases the quality of our segmentation, we conclude that our predicted masks are already very accurate. Using the bilateral solver might also inadvertently discard correct, but fragmented segmentations, as we show in the supplementary material. Next, we extract the predicted unsupervised masks from the DUTS-TR dataset and use them as pseudo ground-truth to train a class-agnostic segmenter. We use the same architecture (a MaskFormer [35]) and training scheme as SelfMask [12]. We then evaluate again on the saliency prediction datasets. Without additional pre-processing our method surpasses or is on par with the SotA across all metrics

Table 2: Comparisons for unsupervised single object discovery. We compare MOVE to SotA object discovery methods on VOC07 [36], VOC12 [37] and COCO20K [38, 39] datasets. Models are evaluated with the CorLoc metric. +CAD indicates training a second stage class-agnostic detector with unsupervised "pseudo-boxes" labels. (↑ **z**) indicates an improvement of z over prior sota

Method	VOC07 [36]	VOC12 [37]	COCO20K [38, 39]
Selective Search [10, 40]	18.8	20.9	16.0
EdgeBoxes [10, 41]	31.1	31.6	28.8
Kim et al. [10, 42]	43.9	46.4	35.1
Zhange et al. [10, 43]	46.2	50.5	34.8
DDT+ [10, 44]	50.2	53.1	38.2
rOSD [10, 39]	54.5	55.3	48.5
LOD [10, 45]	53.6	55.1	48.5
DINO-seg [4, 10]	45.8	46.2	42.1
FreeSOLO [8]	56.1	56.7	52.8
LOST [10]	61.9	64.0	50.7
Deep Spectral [20]	62.7	66.4	52.2
TokenCut [11]	68.8	72.1	58.8
MOVE (Ours)	**73.5** (↑ **4.7**)	**76.6** (↑ **4.5**)	**63.0** (↑ **4.2**)
LOD + CAD[10]	56.3	61.6	52.7
rOSD + CAD [10]	58.3	62.3	53.0
LOST + CAD [10]	65.7	70.4	57.5
TokenCut + CAD [11]	71.4	75.3	62.6
MOVE (Ours) + CAD	73.6	77.1	65.0
MOVE (Ours) Multi + CAD	**74.6** (↑ **3.2**)	**79.3** (↑ **4.0**)	**68.6** (↑ **6.0**)

Figure 5: Qualitative evaluation of object detection of MOVE on VOC07, VOC12 and COCO20k. Red is the ground truth, yellow is our prediction. For more examples see the supplementary material.

and datasets. While additional processing with the bilateral solver seems to benefit SelfMask [12], it mostly hurts the performance of our method. Figure 4 shows qualitative results of our method.

4.2 Single-object discovery

Datasets. We evaluate our trained model (see section 4.1) on 3 typical single-object discovery benchmarks: the train split of COCO20K [38, 39] and the trainval splits of VOC07 [36] and VOC12 [37]. Following [10, 11, 39, 45–49], we report the *Correct Localization* metric (CorLoc), *i.e.*, the percentage of images, where the IoU > 0.5 of a predicted single bounding box with at least one of the ground truth ones.

Evaluation. Since our method tends to produce a single segmentation mask for multiple objects in the scene, we separate the objects by detecting connected components via OpenCV [50]. We then convert the separate masks to bounding boxes and choose the biggest one as our prediction for the given image. In Table 2, we compare MOVE with other unsupervised methods and we show that just by using processed masks from our method we achieve SotA results on all three datasets, outperforming even methods that used their bounding boxes to train a Class Agnostic Detector (CAD). We show qualitative results for object detection in Figure 5. We also follow the practice of [10, 11] and use our predicted bounding boxes as pseudo-ground truth for training the CAD on each of the evaluation datasets. To train the detector, we use either the largest or all the bounding boxes that we obtained from the connected components analysis and after filtering those that have an area smaller than 1% of the image. For the evaluation we take the bounding box with the highest prediction confidence, as done in [10, 11]. We use the exact same architecture and training scheme as our competitors for a fair comparison. Training with a single bounding box slightly improves the performance of our method, while training with multiple ones gives it a significant additional boost.

Table 3: Unsupervised class-agnostic object detection on MS COCO `val2017`. Compared results are taken directly from FreeSOLO[8]

Method	AP_{50}	AP_{75}	AP	AR_1	AR_{10}	AR_{100}
Selective Search [40]	0.5	0.1	0.2	0.2	1.5	10.9
DETReg [51]	3.1	0.6	1.0	0.6	3.6	12.7
FreeSOLO [8]	12.2	4.2	5.5	4.6	11.4	**15.3**
MOVE (Ours)	**17.2**	**5.4**	**7.3**	**5.2**	**12.7**	**15.3**

Table 4: Ablation study. IoU of models trained on DUTS-TR and evaluated on HKU-IS-val

Base-line	no min. mask	no max. mask	no bin.	no pool loss	Δ 0	BA shift	Δ $1/16$	Δ $3/16$	Δ $4/16$	disc. real	disc. mae	disc. w/ shift	non-diff inp.	mse gan
0.782	.781	.781	0	0	.002	.769	.237	.749	0	.310	0	.110	.248	.756

Unsupervised class-agnostic object detection. We evaluate our unsupervised object detection model trained on COCO20K with CAD post-training and compare it with SotA on unsupervised class-agnostic object detection. We evaluate on COCOval2017 and report Average Precision (AP) and Average Recall (AR), as in [8]. MOVE yields a remarkable relative improvement over the AP SotA of 30% on average.

4.3 Ablation study

We perform ablation experiments on the validation split (500 images) of HKU-IS [52] to validate the relative importance of the components of our segmentation approach. For the ablation we train each model for 100 epochs on DUTS-TR. We report the IoU in Table 4. Our baseline model trained with 3 different seeds gives a mean IoU 0.782 with std $= 0.005$. Thus we only report results for a single run in all experiments.

Mask losses. We validate the importance of the mask losses: minimum mask area, maximum mask area, binarization and losses on downsampled max-pooled masks. We find that the minimum area or maximum area losses do not affect the performance much. The binarization loss is instead essential: Removing it results in mostly uniform small-valued masks, for which no inpainting is done. The same holds for the mask loss terms on the max-pooled downsampled versions of the masks.

Shift range. We evaluate different ranges of the random shift δ. A small range $\Delta = 1/16$ seems to be too challenging for the discriminator to detect inconsistencies. Larger shifts may cause objects to go out of the image boundaries ($\Delta = 3/16, 4/16$) and thus reduce the feedback at the object boundary to the segmenter. There is no incentive to produce any meaningful masks for $\Delta = 0$. We also try a boundary-aware (BA) shift, where we limit the shifts so that when the object is partly out of the image domain, we do not expose the clipped edge(s). In this case the segmenter sometimes outputs artifacts on the borders to limit the shift range and this hurts the performance.

Discriminator inputs. In our baseline model, we feed both composed images with no-shift and real images autoencoded with MAE as real samples for the discriminator training. We test the case *disc. real*, where we feed only real images without autoencoding. In this case, the discriminator can detect artifacts of MAE and has no incentive to look for image inconsistencies resulting from shifts. In *disc. mae* we only feed the autoencoded images as real. Here, the discriminator can focus on the mismatch from the inpainting artifacts and encourages the segmenter to output empty masks, where no inpainting is done. If we only feed the composite non-shifted images (*disc. w/ shift*), the artifacts resulting from an incorrect masks cannot be fixed because there is no reference of what the real images look like.

Non-differentiable inpainter. We evaluate the use of hard thresholded masks as input to the background inpainter. In this case the only feedback for the masks comes from the composition of the images. We find it to be insufficient for the segmenter to learn any meaningful masks.

Inpainter model. Finally, we substitute the MAE trained with a GAN loss with a MAE that was trained only to reconstruct missing patches with a Mean Squared Error (MSE) loss. In this case, both the inpainted regions and the autoencoded images are of poor quality. Even in this case the masks are accurate. It suggests that a realistic inpainter is important, but not crucial, to our approach, since we are feeding the autoencoded and composed no-shifted images as real samples to the discriminator.

5 Prior Work

In the past decade, research on object segmentation and detection has seen remarkable progress when full supervision is available [53–55]. To limit the cost of annotation several methods explored different forms of weak supervision [56, 57] or ways to avoid labeling altogether [13, 14, 58, 59]. MOVE falls in the latter category. Therefore, we focus our review of prior work on unsupervised methods for object segmentation and the related task of object detection.

Unsupervised Object Detection and Category Discovery. Unsupervised object detection and category discovery are extremely challenging tasks that have recently seen a surge of efforts [51, 60, 61] thanks to the capabilities of modern deep learning models. Recently, features based on deep learning have shown significant progress in object detection [51], even with just some noisy (unsupervised) guidance [40]. More in general, one limitation of unsupervised object detection is that it only provides a coarse localization of the objects. As we have shown with MOVE, it is possible to obtain much more information without supervision.

Unsupervised Object Segmentation. Object segmentation can be formulated as a pixel-wise image partitioning task [58, 59, 62, 63] or through the generation of layered models from which a segmenter is trained as a byproduct [8, 31, 64, 65]. The use of SSL features has spawned several methods with significant performance on real datasets, which we discuss in the following paragraphs.

SSL-Based Methods. Due to the success of SSL methods and the emergence of segmentation capabilities, several recent methods for unsupervised object segmentation have been built on top of SSL features. In particular, SelfMask [12] proposes a clustering approach that can use multiple SSL features and evaluates all possible combinations of DINO [4], SwAV [66] and MOCOV2 [67]. They find that combining features from all three SSL methods yields the best results for segmentation. FreeSOLO [8] instead finds that DenseCL features [6] work best. More in general, some methods use a weak (unsupervised) guidance and losses robust to the coarse pseudo-labels [8], but the majority is based on directly clustering SSL features [7, 9–11, 20, 68]. In contrast to these methods, we show that movability can provide a robust supervision signal.

Generative Methods. A wide range of methods also exploits generative models to create layered image representations [15, 17, 69–73]. A general scheme is to train a network to generate a background, a foreground and its mask. These components can then be combined to generate an image and then, in a second stage, one can train a segmenter that learns to map a synthetic image to its corresponding foreground mask. In alternative, the segmenter could be built during the training of the generative model as a byproduct. Some methods rely on the assumption that a dataset of only backgrounds is available [14, 74]. The use of shifts to define segments has also been used before [13, 15, 16]. However, MOVE does not require the training of a generative model, which can be a challenge on its own.

6 Limitations and Societal Impact

Limitations. As mentioned in the introduction, movability alone may not suffice in identifying an object unambiguously. In fact, the method can segment any combination of multiple objects. To address this we use a post-processing algorithm to find connected components, but there is no guarantee that all objects have been segmented. Another issue is that shifts would not expose artifacts when the background is uniform (*e.g.*, looking at the sky, underwater, with macrophotography).

Societal Impact. An important aspect that is relevant to unsupervised learning methods in general is the potential to become biased if the training datasets are unbalanced. This clearly has a potentially negative impact on the segmentation of categories that are underrepresented and thus this work should be integrated with mechanisms to take the dataset imbalance into account.

7 Conclusions

We have introduced MOVE, a novel self-supervised method for object segmentation that exploits the synthesis of images where objects are randomly shifted. MOVE improves the SotA in object saliency segmentation, unsupervised single object discovery, and unsupervised class agnostic object detection by significant margins. Our ablations show that movability is a strong supervision signal that can be robustly exploited as a pseudo-task for self-supervised object segmentation. We believe that our approach can be further scaled by exploring different architectures and larger datasets.

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Checklist

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes]
   (b) Did you describe the limitations of your work? [Yes]
   (c) Did you discuss any potential negative societal impacts of your work? [Yes]
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes]
2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? [N/A]
   (b) Did you include complete proofs of all theoretical results? [N/A]
3. If you ran experiments...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [No] We use publicly available datasets. We plan on sharing the code and the instructions at a later time.
   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes]
   (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [Yes] We trained our baseline model with 3 different seeds and reported mean and std IoU on the ablation dataset. We do not include it for all the experiments due to time and cost constraints.
   (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [Yes]
4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...
   (a) If your work uses existing assets, did you cite the creators? [Yes]
   (b) Did you mention the license of the assets? [No]

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(d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? [No] We use datasets publicly available for research

(e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [No]

5. If you used crowdsourcing or conducted research with human subjects...

(a) Did you include the full text of instructions given to participants and screenshots, if applicable? [N/A]

(b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [N/A]

(c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [N/A]