Wholly Unsupervised! Segmenting Objects by Contrast and Context

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Abstract

We study *unsupervised whole object segmentation* - identifying complete objects, including both distinctive and less salient parts, rather than only visually prominent fragments. Existing unsupervised methods often focus on salient regions (e.g., *head* but not *torso*), leading to incomplete object masks. Our insight is that whole objects emerge from the interplay of *part-level similarity* and *contrastive context*, both *within* and *across* images. This enables the grouping of heterogeneous regions into coherent object segments without any supervision or predefined templates.

We propose *Contrastive Contextual Grouping* (CCG) in a three-step algorithm: **1)** identify semantically similar yet visually diverse image pairs; **2)** perform co-segmentation via joint graph cuts with contrastive part-context affinity; and **3)** distill the results into a single-image segmentation model. CCG achieves state-of-the-art results across *unsupervised saliency detection, object discovery, video object segmentation*, and *nuclei segmentation*. Remarkably, it could even *surpass* SAM2, a supervised foundation model, at segmenting whole objects from box prompts.

1 Introduction

We consider segmenting *whole* objects from a collection of *unlabeled* images, without external supervision. Unlike prior approaches that often highlight visually distinctive parts, our goal is to recover whole objects, including less salient regions that are equally essential for coherent perception.

Despite progress, whole object segmentation is still challenging, even for supervised foundation models [17, 35, 36]. For example, SAM2 [35] is trained on massive collections of annotated, high-resolution images. Yet, even with *perfect, tight object bounding box* prompts, SAM2 often delineates only visually salient parts (e.g., *a dog's brown fur*, *a peacock's green train*) rather than the entire object (e.g., *the whole dog*, *the whole peacock*).

Unsupervised object segmentation in general has been widely explored, ranging from low-level salient cues to high-level statistical clustering. Key developments include objectness [2], category-independent object proposals [8], exemplar-based recognition through associations [26], multiscale combinatorial grouping [3, 33], object discovery via matching [37, 49], unsupervised feature learning [14, 16], slot attention [22, 38]. Some approaches leverage motion cues in unlabeled videos [63, 59, 21], assuming pre-trained optical flow detectors or piece-wise constant object motion models.

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Accepted to the NeurIPS 2025 workshop on Space in Vision, Language, and Embodied AI.

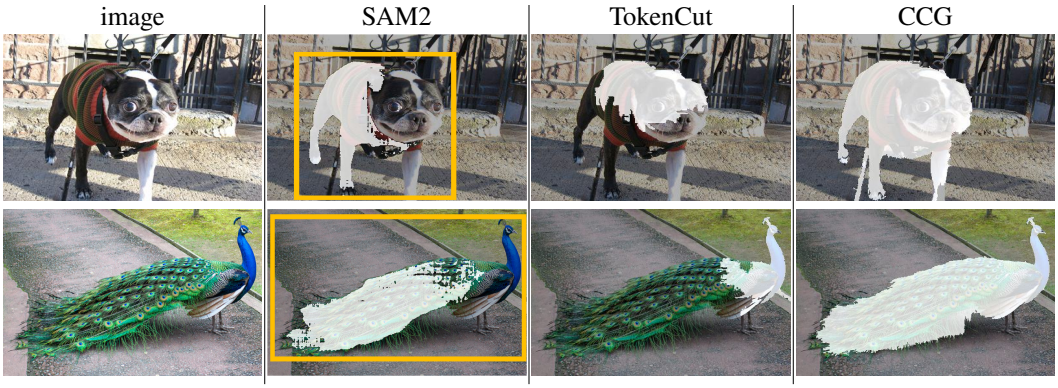


Figure 1: **Unsupervised whole object segmentation is extremely challenging and our CCG method excels. Col.1)** Can we discover and segment whole objects in object-centric images? **Col.2)** Even the latest, largest, extensively supervised model, SAM2 [35], with *the right bounding box prompt* can only delineate visually salient parts (*dog's brown fur, peacock's green train*). **Col.3)** Unsupervised methods such as TokenCut [55] rely on features unsupervisedly learned to optimize certain image-level criteria, discovering only statistically distinctive parts (*face/head*). **Col.4)** Our insight: Objects emerge as wholes through not only *intrinsic part similarity*, but also *extrinsic context contrast*; our CCG discovers *distinctive and unremarkable* parts in a whole without supervision.

Unsupervised *whole* object segmentation has been explored earlier using matting or boundary cues [45, 25] and, more recently, through feature similarity or attention maps [55, 28, 67, 44, 66] from self-supervised models like DINO [5]. However, because these features are optimized for image-level objectives, existing methods, e.g., TokenCut [55], tend to highlight only statistically distinctive parts, rather than capturing the object as a whole.

A largely underexplored challenge in object segmentation is discovering *whole* objects that include both distinctive and *unremarkable* parts. Existing methods primarily extract parts, whether visually salient, as in supervised SAM models [17, 35, 36], or statistically distinctive, as in unsupervised TokenCut [55]. While these approaches have advanced the field, they emphasize salient fragments over capturing the object in its entirety. This gap is critical, as real-world applications and cognitive processes require understanding objects as cohesive wholes, not merely collections of parts. Integrating both salient and unremarkable regions into unified segmentations is the central goal of our work.

Our novel approach to whole object discovery shifts the focus from *what the object is* to *how it contrasts with its context*. The key insight is that an object, even when composed of distinctive parts, can emerge as a cohesive whole through both *intrinsic similarity among its parts* and *extrinsic contrast with its surroundings*. This contextual relationship is crucial for binding diverse object parts into a unified entity in a bottom-up, data-driven manner [1]. In Fig. 1, while the green peacock train and blue peacock head have different textures, their colors starkly contrast with the gray background. Echoing the adage "*The enemy of my enemy is my friend*", the two distinctive parts become allies through their shared contrast with the background, allowing the peacock to emerge as a unified whole.

For richer grouping relationships, **we introduce a co-segmentation setting** using semantically similar yet visually different image pairs (Fig.2). These pairs can be derived from unlabeled data, such as images or videos of the same scene, or by clustering self-supervised ViT features [5, 31, 6] that capture semantic similarities. By leveraging co-segmentation, we gain additional contrastive and contextual grouping cues across image pairs, enabling more robust and accurate whole object segmentation.

We present **an unsupervised whole object segmentation algorithm** based on *Contrastive Contextual Grouping*. Our CCG operates in three steps: **1)** Identify semantically similar yet visually distinctive image pairs for co-segmentation. Identical images reduce the task to single-image segmentation, while unrelated pairs hinder co-segmentation. **2)** Perform co-segmentation via joint graph partitioning, where patches are nodes and edges encode two types of pairwise relationships: feature similarity and dissimilarity. The objective is not only to *discover friends through similarity*, but also to *discover allies through shared dissimilarity*, enabling robust whole object discovery. **3)** Distill co-segmentation results into a single-image segmentation model, with a ViT backbone and lightweight segmentation head, enabling efficient inference on individual images without requiring paired inputs. CCG achieves

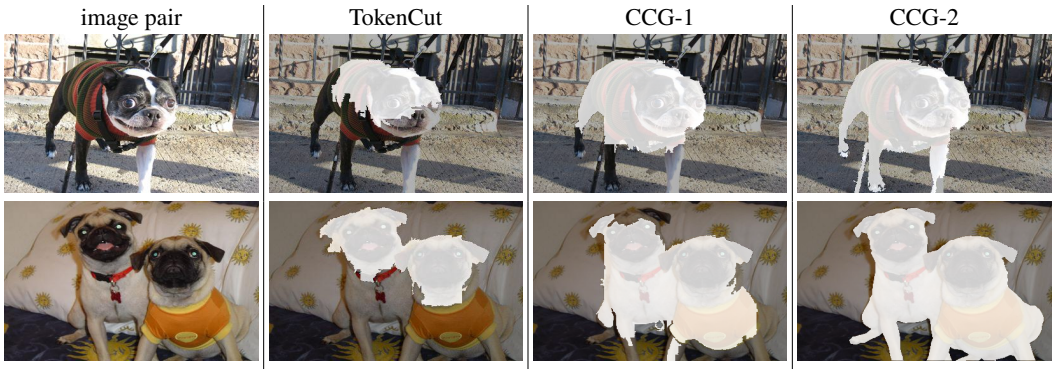


Figure 2: **Our CCG benefits from co-segmenting semantically similar yet visually distinct image pairs, identified without supervision.** CCG-1 (2) denotes single(two)-image (co-)segmentation results. Contexts and contrasts from paired images significantly enhance whole object discovery.

state-of-the-art performance on unsupervised saliency detection, object discovery, video object segmentation, and nuclei segmentation.

Our work makes three major contributions. **1)** We tackle the problem of *unsupervised whole object segmentation*, addressing the underexplored challenge of discovering both salient/characteristic and unremarkable parts in cohesive wholes. **2)** We propose a novel, fully unsupervised framework for bottom-up whole-object discovery, driven by data rather than labels. It operates via dual forces: *grouping by similarity* and *segregation by dissimilarity*, enhanced by co-segmentation, feature learning, and model distillation. **3)** We achieve consistent, significant gains over prior unsupervised methods across four benchmarks. CCG could even surpass the supervised foundation model SAM2 in segmenting whole objects given box prompts.

2 Related Work

Unsupervised Object Discovery. Most works leverage self-supervised features from visual transformers [5, 6, 4]. TokenCut [55] constructs a weighted graph using feature similarities (attraction) and performs graph cuts to separate objects from backgrounds. Unlike TokenCut, we introduce pairwise attraction and repulsion in a joint weighted graph for co-segmentation, enabling whole object localization and segmentation. SelfMask [42] clusters multiple self-supervised features to extract object masks, while LOST [43] localizes object seeds and expands them to similar patches. FreeSOLO [53] generates FreeMask predictions from feature similarities, and FOUND [44] uses heuristics to search for background seeds. HEAP [66] employs contrastive learning for clustered feature embeddings. PEEKABOO [67] localizes objects by hiding parts of images. However, these methods are limited to discovering descriptive parts of objects. In contrast, our CCG uses pairwise attraction and repulsion in co-segmentation to segment whole objects.

Unsupervised Video Object Segmentation. [62] proposes an adversarial-based method to predict object masks from images and optical flow maps. [23] adopts co-attention layers based on siamese networks for segmentation, requiring expensive training resources. [57] uses optical flow and contrastive motion clustering to segment moving objects in videos. However, these methods rely on externally supervised motion estimation networks [48, 46]. VideoCutLER [54] segments video objects via graph cuts on attractions and refines masks through training. While AMD [21] jointly learns segmentation and motion estimation end-to-end, its segment-wise constant motion assumption is too simplistic to yield fine segmentations with both details and complete parts. In contrast, our CCG , when trained on unlabeled videos, delivers more accurate whole-object segmentation.

Segmentation by Graph Cuts. Normalized cuts [40] frames segmentation as a graph partitioning problem, optimizing similarity within partitions. [29] derives partitions using stacked eigenvectors of the graph Laplacian matrix. [65] applies graph cuts to affinities of key, query, and value features of ViTs, revealing visual semantics and spatial locations of segments. Earlier work [64] introduces the role of repulsion for single-image segmentation based on fixed low-level features. [24] conduct segmentation using graph neural networks. In contrast, CCG is the first to address unsupervised whole object segmentation using data-driven learned features with co-segmentation and model distillation.

Co-Segmentation. [13] leverages color histogram similarities to segment common objects from similar image pairs. [20] employs a Siamese network to segment shared objects across image pairs. [15] introduces a unified ViT framework for joint co-segmentation and co-detection. However, these methods lack contextual relationship analysis and do not address whole object segmentation. In contrast, our approach incorporates attraction and repulsion across a related image pair, enabling whole object segmentation through contrastive contextual grouping.

3 Contrastive Contextual Grouping

We aim to discover and segment whole objects without supervision, based on *intrinsic similarity* between parts and *extrinsic contrast* with their surroundings.

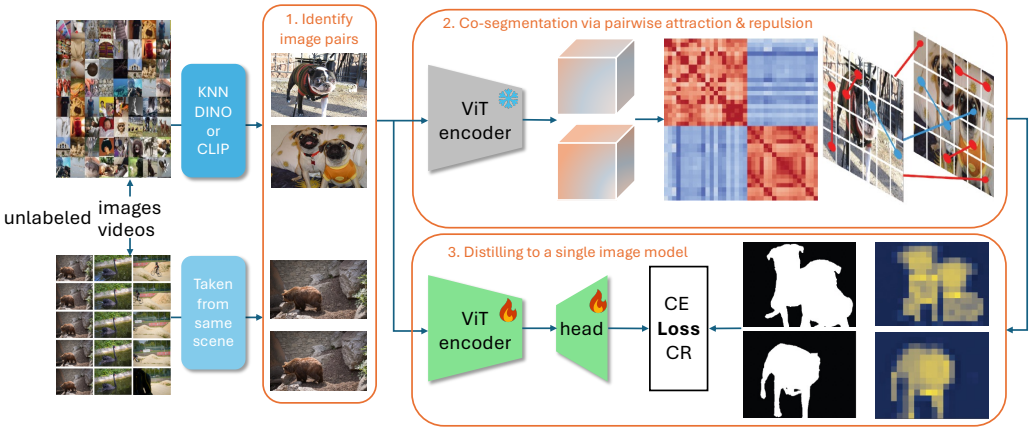


Figure 3: **Overview of our three-step CCG algorithm for unsupervised whole object discovery**. **Step 1)** Identify semantically similar yet visually different image pairs. For unlabeled videos, they are simply consecutive video frames, whereas for unlabeled images, they are k-nearest neighbors in some unsupervisedly learned feature space. **Step 2)** Co-segmentation based on pairwise similarity (attraction) and dissimilarity (repulsion) of image patch features extracted from a self-supervised ViT encoder. **Step 3)** Distill co-segmentation results to a single-image model with a ViT encoder and a segmentation head, trained with cross-entropy (CE) and contrastive (CR) losses.

Our CCG has three steps (Fig 3): **1)** identifying semantically similar yet visually different image pairs, **2)** performing co-segmentation through joint graph cuts with pairwise attraction and repulsion, and **3)** distilling the results into a single-image segmentation model.

Primer: Graph Cuts with Attraction and Repulsion. We apply prior work [64] to a ViT patch graph, where each node represents a square image patch used in ViT, and the edge between nodes i, j is attached with an attraction weight A_{ij} and a repulsion weight R_{ij}, both derived from the cosine similarity $\boldsymbol{S}_{ij}$ between their ViT patch features $\boldsymbol{F}_i$, $\boldsymbol{F}_j$:

$$\boldsymbol{S}_{ij} = \frac{< \boldsymbol{F}_i, \boldsymbol{F}_j >}{\|\boldsymbol{F}_i\| \|\boldsymbol{F}_j\|}. \tag{1}$$

The larger S_{ij}, the larger the attraction A_{ij} and the smaller the repulsion R_{ij}. $\boldsymbol{A}$ and $\boldsymbol{R}$ are defined as Gaussian functions of $\boldsymbol{S}$ (Fig.A1). Object segmentation is then formulated as a two-way node partitioning problem. Let $\mathbb{V}$ denote the set of all patch nodes, and $\mathbb{V}_1, \mathbb{V}_2$ two disjoint subsets: $\mathbb{V}_1 \cup \mathbb{V}_2 = \mathbb{V}, \mathbb{V}_1 \cap \mathbb{V}_2 = \varnothing$. We seek an optimal partitioning with dual forces: Group by similarity and segregate by dissimilarity. Given attraction $\boldsymbol{A}$ and repulsion $\boldsymbol{R}$, we maximize the following:

$$\xi_{AR} = \frac{\text{within-group } \boldsymbol{A}}{\text{total degrees of } \boldsymbol{A}, \boldsymbol{R}} + \omega \frac{\text{between-group } \boldsymbol{R}}{\text{total degree of } \boldsymbol{A}, \boldsymbol{R}}. \tag{2}$$

ω is a hyperparameter weighing the relative importance between attraction and repulsion. Let $\boldsymbol{p}_t$ be a binary partition indicator for $\mathbb{V}_t$. Let $\boldsymbol{D}_A$ ($\boldsymbol{D}_R$) be a diagonal degree matrix with each diagonal entry

indicating total A (R) weights a patch node has. The objective becomes [64]:

$$\max \xi_{AR}(\boldsymbol{p}) = \sum_{t=1}^{2} \frac{\boldsymbol{p}_t^T \boldsymbol{W} \boldsymbol{p}_t}{\boldsymbol{p}_t^T \boldsymbol{D} \boldsymbol{p}_t}, \tag{3}$$

$$\text{where } \boldsymbol{W} = \boldsymbol{A} - \boldsymbol{R} + \boldsymbol{D}_R, \quad \boldsymbol{D} = \boldsymbol{D}_A + \boldsymbol{D}_R. \tag{4}$$

The optimum in the relaxed continuous domain is the largest eigenvector $\hat{\boldsymbol{z}}$:

$$\boldsymbol{D}^{-1} \boldsymbol{W} \boldsymbol{z} = \lambda \boldsymbol{z}. \tag{5}$$

Please note that our CCG uses both A and R, whereas TokenCut [55] uses only A, a special case of ours when $\omega = 0$. See more details in the Appendix A.1.

Bipartitioning imposes an important bottleneck: Each region must commit to one of two camps, limiting grouping variability. **1)** Strict attraction-based bipartitioning precludes indirect grouping, which is essential for assembling whole objects composed of diverse parts. **2)** Repulsion enables such indirect grouping by aligning parts not because they are similar to each other, but because they are dissimilar to the same background, reflecting "*The enemy of my enemy is my friend*". Fig. 4 shows that attraction alone may isolate a single homogeneous region, but it is *repulsion* that allows visually distinct parts to emerge together as a coherent whole, without any preconception of object structure.

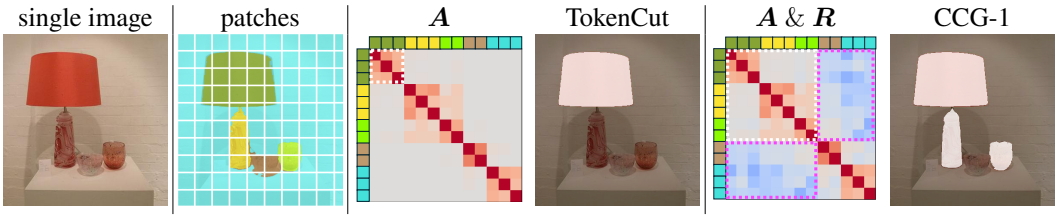


Figure 4: **Pop out whole objects by contrastive contextual grouping of patches within a single image. Left:** For visualization, we color code the patches of the image. **Center:** By attraction $\boldsymbol{A}$ alone (values shaded in red, outlined in white boxes), object parts are too weakly similar to be grouped as one; TokenCut [55] can thus only segment out the most distinctive part: *lamp shade*. **Right:** By repulsion $\boldsymbol{R}$ (values shaded in blue, outlined in magenta boxes) in addition to attraction $\boldsymbol{A}$, *lamp shade, lamp base* are both dissimilar to the background and need to be separated from it; our CCG can thus segment out the *whole lamp* and a similar item.

Now we detail the three steps of our algorithm.

Step 1. Identify Related Image Pairs. We adopt an image co-segmentation setting to facilitate whole object discovery. Ideally, image pairs should be semantically similar yet visually distinct to enhance within-group similarity and between-group dissimilarity, facilitating clearer figure-ground segregation (Fig.2). Such pairs can be found in unlabeled data, e.g., from videos of the same scene or by clustering self-supervised ViT features[5, 31, 6] that capture semantic similarity. Examples of k-nearest neighbors from DINO as well as pre-trained CLIP features are shown in Fig. A5.

Step 2. Co-Segmentation by Attraction and Repulsion. We construct a joint graph with patches from both images as nodes, compute attraction and repulsion as edge weights, and perform graph cuts accordingly. The joint partitioning finds not only two regions within each image, but also region correspondence across images. We follow TokenCut and select the foreground as the region with the maximum absolute value of the eigenvector components. Note that if the two images are identical, then the two-image co-segmentation based on attraction and repulsion within and across images is reduced to the single-image segmentation based on within-image attraction and repulsion only. For clarity, we denote the two-image and one-image cases as CCG-2 and CCG-1 respectively.

Fig. 5 shows that co-segmentation not only brings out two related whole objects, but also enhances the whole object segmentation within individual images. Compared to the partial lamp set discovered by CCG-1 in Fig. 4, the entire lamp set is now segmented out by CCG-2 .

Step 3. Distill to A Single-Image Segmentation Model. We distill co-segmentation results into a single-image segmentation model with a ViT encoder (shared with DINO) and a lightweight head composed of a 1×1 convolution followed by softmax. The model is trained using a combination of

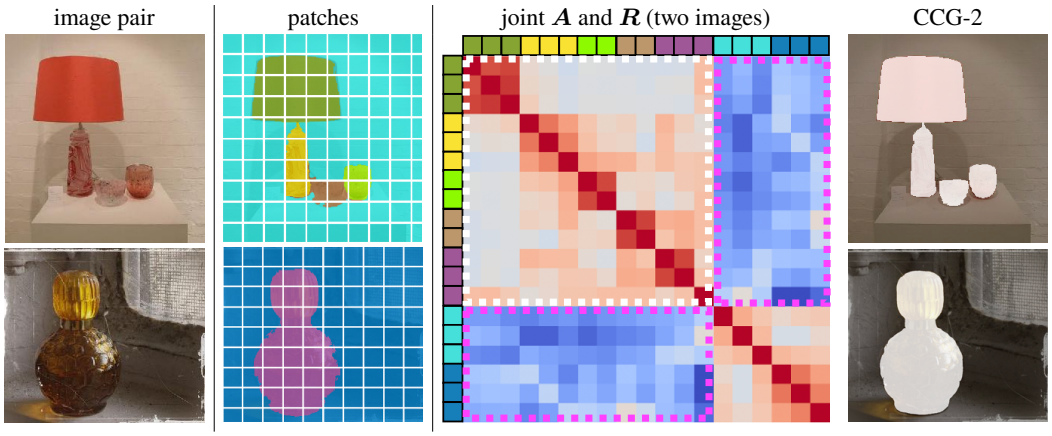


Figure 5: **Pop out whole objects more accurately with co-segmentation.** Image pairs are obtained by unsupervised clustering, or simply videos of the same scene. A joint graph is constructed using patches from both images. Patches are color-coded. To visualize the effects of attraction and repulsion, we sort patches by foreground then background. Strong foreground-background repulsion (values shaded in blue, outlined in magenta boxes) across these two images, strong attraction within foreground and background respectively, help our CCG discover the *whole lamp set* and the *whole vase* together.

cross-entropy (CE) loss and contrastive (CR) loss [58, 47, 39, 52]:

$$\mathcal{L}_{CE} = -\sum_{\text{pixel } i} y_i \log \hat{y}_i + (1 - y_i) \log(1 - \hat{y}_i) \tag{6}$$

$$\mathcal{L}_{CR} = -\frac{1}{|P|} \sum_{(i,j)\in P} \log \frac{\exp(\frac{f_i \cdot f_j}{\tau})}{\sum_{q\in Q(i)} \exp(\frac{f_i \cdot f_q}{\tau})}. \tag{7}$$

The **CE loss refines ViT features** using the whole object masks. It collects the total pixel-wise CE loss between the predicted probability map $\hat{y}$ and its binary mask y from co-segmentation. Given feature $\boldsymbol{f}$ extracted from the distillation ViT encoder, the **CR loss aims to sharpen the mask** by reducing the feature distance between pixels within the same region and increasing the feature distance between different regions. P is the set of positive (foreground-forground) pixel pairs, whereas $Q(i)$ is the set of negative (foreground-background) pixel pairs. τ is a temperature hyperparameter.

The three-step workflow (Fig. 3) can be made closed-loop by reusing the distilled ViT encoder as the initial encoder. Empirically, the model converges quickly, with minimal gain from further iterations.

4 Experiments

Our CCG aims to discover and segment whole objects without any supervision. In our framework, CCG-1 denotes the segmentation results from a single image, whereas CCG-2 represents the segmentation results from an image pair (the co-segmentation setting). We evaluate CCG performance and benefits in four tasks: 1) unsupervised saliency detection, 2) unsupervised object discovery, 3) unsupervised video object segmentation, and 4) unsupervised nuclei segmentation.

Implementation Details. Our ViT encoder follows the same architecture as DINO `ViT-S/8` during the distillation stage. The segmentation head consists of a single `conv` 1×1 layer. We train the ViT encoder using the AdamW optimizer with a learning rate of 0.001, while the segmentation head is optimized with AdamW at a learning rate of 0.05. Training is conducted over 300 epochs with a batch size of 16, on 4 A40 NVIDIA GPUs. ω is set to 0.2. For video frame pair selection, we use a frame interval of 10 to generate image pairs for co-segmentation See details in the Appendix A.2.

4.1 Unsupervised Saliency Detection

Benchmarks. We use three datasets: ECSSD [41] with 1000 images (train/val/test split: 700 / 150 / 150), DUT-OMRON [61] with 5186 images (train/val/test split: 3630 / 778 / 778), and DUTS [51]

Table 1: **CCG outperforms existing methods for unsupervised saliency detection task**. In the *w/o. training* setting, CCG outperforms the *SoTA* method TokenCut across all three datasets (performance gap in blue). In the *w/. training* setting, with initial object masks by attraction and repulsion, CCG surpasses the *SoTA* method HEAP (performance gap in green).

saliency	train?	ViT	ECSSD			DUTS			DUT-OMRON		
			maxF$_\beta$	IoU	Acc.	maxF$_\beta$	IoU	Acc.	maxF$_\beta$	IoU	Acc.
FUIS [27]	×		–	71.3	91.5	–	52.8	89.3	–	50.9	88.3
LOST [43]	×	S/16	75.8	65.4	89.5	61.1	51.8	87.1	47.3	41.0	79.7
DSS [28]	×	–	–	**73.3**	–	–	51.4	–	–	**56.7**	–
TokenCut [55]	×	S/16	80.3	71.2	91.8	67.2	57.6	90.3	60.0	53.3	88.0
CCG-1	×	S/16	82.7	72.8	93.1	**69.5**	60.2	92.8	62.6	55.3	**90.7**
			+2.4	+0.6	+1.3	+2.3	+2.6	+2.5	+2.6	+2.0	+2.7
CCG-2	×	S/16	**83.1**	73.2	**94.7**	69.3	**60.5**	**93.2**	**63.3**	56.4	90.6
			+2.8	+2.0	+2.9	+2.1	+2.9	+2.9	+3.3	+3.1	+2.6
SelfMask [42]	✓	S/8	–	78.1	94.4	–	62.6	92.3	–	58.2	90.1
FOUND [44]	✓	S/8	**95.5**	80.7	94.9	71.5	64.5	93.8	66.3	57.8	91.2
PEEKABOO [67]	✓	S/8	95.3	79.8	94.6	**86.0**	64.3	93.9	**80.4**	57.5	91.5
HEAP [66]	✓	S/8	93.0	81.1	94.5	75.7	64.4	94.0	69.0	59.6	92.0
CCG-1	✓	S/8	94.1	83.6	95.2	78.0	65.9	**94.6**	70.7	60.8	93.5
			+1.1	+2.5	+0.7	+2.3	+1.5	+0.6	+1.7	+1.2	+1.5
CCG-2	✓	S/8	94.5	**83.9**	**95.8**	78.2	**66.5**	94.4	71.2	**61.3**	**93.8**
			+1.5	+2.8	+1.3	+2.5	+2.1	+0.4	+2.2	+1.7	+1.8

with 1580 images (train/val/test split: 7373 / 1580 / 1580). We adopt three standard metrics: mean intersection-over-union (mIoU) with a threshold set at 0.5, pixel accuracy (Acc), and the maximal F_β score ($\max F_\beta$), where β^2 is set to 0.3, in accordance with [55], [44], and [66].

Baselines. We consider without and with feature training settings. Without training, we compare CCG-1 and CCG-2 directly against baselines such as FUIS [27], LOST [43], DSS [28], and TokenCut [55]. We also compare CCG-1 with SAM2 [35] on DUTS given bounding boxes as the prompts. With training, we apply distillation from both CCG-1 and CCG-2, and benchmark against methods that require network training: SelfMask [42], FOUND [44], PEEKABOO [67], and HEAP [66].

No-feature-training Results. Table 1 shows that both CCG-1 and CCG-2 **outperform TokenCut** with `ViT-S/16`. TokenCut uses graph cut with attraction and thus discovers only discriminative object parts, whereas CCG leverages both attraction and repulsion to discover whole objects. This contrast demonstrates the utility of repulsion in popping out whole objects from unlabeled images.

Feature-training Results. CCG with distillation into single image features **surpasses HEAP**, current state-of-the-art (SoTA), with `ViT-S/8`, confirming that distillation with initial object masks by attraction and repulsion greatly refines whole object segmentation, reaching new SoTA (Fig. A6).

In both settings, **CCG-2 outperforms CCG-1 overall, highlighting the benefits of co-segmentation**: Similar image pairs bring stronger contextual information for unsupervised whole object discovery.

Zero-Shot CCG-1 and SAM2 Results on DUTS. Since SAM2 [35] requires prompts for segmentation, we provide ground-truth bounding boxes as prompts. However, since using ground-truth boxes undermines the purpose of saliency detection, we gradually enlarge the box size until they cover the entire image. To eliminate the object size effect, we only evaluate images with medium-sized ground-truth boxes, where the length of the box diagonal is between 50-60% of the image diagonal. For each box prompt, we feed the corresponding region to CCG-1 for fair comparison.

Fig. 6 shows that, even with ground-truth boxes, SAM2 often fails to segment whole objects. As the box expands from tightly enclosing the object to covering the full image, SAM2 struggles to consistently identify the salient object. We attribute this to increasing heterogeneity within the prompted region. We measure heterogeneity as the standard deviation of the normalized L_2 distance between each patch feature and the mean feature within the box. The feature heterogeneity of the boxed region grows with the box size, indicating that more complex regions hinder SAM2's ability to segment whole objects. In contrast, our method remains robust by leveraging both patch similarity and contextual dissimilarity to discover complete objects even in heterogeneous regions.

bounding box ratio (%)	50-60	60-70	70-80	80-90	90-100
SAM2 (mIoU)	**84.0**	**76.0**	46.3	15.3	1.7
CCG-1 (mIoU)	59.3	64.3	**67.0**	**67.8**	**67.2**
feature heterogeneity	0.151	0.172	0.192	0.205	0.212

Figure 6: **CCG-1 outperforms SAM2 on DUTS segmentation on mid-size objects, especially when the bounding box prompt becomes larger. Top:** Sample results for three images (columns) comparing SAM2 and CCG-1 across different sizes of the bounding box (rows). Our results are stable and consistently closer to the ground-truth even when the box prompt covers the entire image, whereas SAM2 falters. **Bottom:** Segmentation accuracies and feature heterogeneity within the bounding box on DUTS images with mid-sized objects. When the box is tight, SAM2 is more accurate than CCG-1 (84% vs. 59.3%), but when it is loose, the performance drops quickly to the point of utter failure (1.7%), whereas our CCG-1 maintains stable at (67%). The larger the bounding box, the greater the feature variation, making repulsion essential for binding heterogeneous parts into a cohesive whole.

4.2 Unsupervised Object Discovery

Benchmarks. We use VOC07 [9] with 5011 images (train/val/test split: 3507 / 752 / 752), VOC12 [10] with 11,540 images (train/val/test split: 8078 / 1731 / 1731), and COCO20K [50] with 19817 images (train/val/test split: 13873 / 2972 / 2972). We follow [56, 7] and report the correct localization (*CorLoc*) metric, which measures the percentage of images where objects are correctly localized.

Baselines. In *w/o. learning*, both CCG-1 and CCG-2 are tested without distillation and compared against non-training approaches such as DINO-seg [5], DSS [28], LOST [43], and TokenCut [55]. In *w/. learning*, we access the results of distillation from CCG-1 and CCG-2 against the training-dependent methods SelfMask [42], FOUND [44], PEEKABOO [67], and HEAP [66].

Results. Table 2 shows that, in *w/o. training*, CCG-1 outperforms TokenCut by using repulsion. CCG-2 further gains over CCG-1 with co-segmentation. In *w/. training*, both CCG-1 and CCG-2 outperform SoTA HEAP. Fig. 7 shows that CCG-2 produces stable and complete object masks across scales, while TokenCut and FOUND yield partial or incorrect results that vary with object size.

4.3 Unsupervised Video Object Segmentation

Benchmarks. We use DAVIS [32] with 50 videos (train/val/test split: 30 / 10 / 10), FBMS [30] with 59 videos (train/val/test split: 25 / 9 / 30), and SegTV2 [19] with 14 videos (train/val/test split: 6 / 1 / 7). We follow [55, 60] and merge all moving objects into a single foreground mask for FBMS and SegTV2. Performance is measured by Jaccard index, the IoU between prediction and ground truth.

Table 2: **CCG-1 and CCG-2 outperform existing methods on unsupervised object discovery** in both *w/o. training* (performance gap in blue) and *w/. training* settings (performance gap in green).

unsupervised object discovery	train?	ViT	VOC07	VOC12	COCO20K
DINO-seg [5]	×	S/16	45.8	46.2	42.0
LOST [43]	×	S/16	61.9	64.0	50.7
DSS [28]	×	S/16	62.7	66.4	52.2
TokenCut [55]	×	S/16	68.8	72.1	58.8
CCG-1	×	S/16	71.4 (+2.6)	**73.8** (+1.7)	60.3 (+1.5)
CCG-2	×	S/16	**72.3** (+3.5)	73.7 (+1.6)	**61.7** (+2.9)
SelfMask [42]	✓	S/8	72.3	75.3	62.7
FOUND [44]	✓	S/8	72.5	76.1	62.9
PEEKABOO [67]	✓	S/8	72.7	75.9	64.0
HEAP [66]	✓	S/8	73.2	77.1	63.4
CCG-1	✓	S/8	76.4 (+3.2)	79.8 (+2.7)	65.6 (+2.2)
CCG-2	✓	S/8	**77.7** (+4.5)	**80.8** (+3.7)	**66.2** (+2.8)

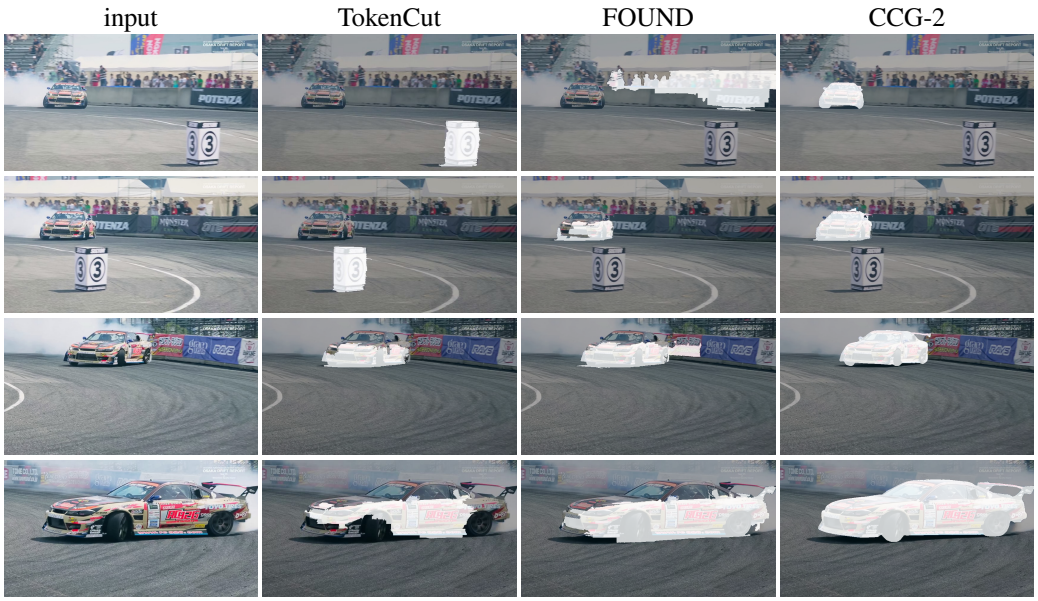


Figure 7: **CCG-2 achieves stable and complete object segmentation across large scale and viewpoint changes.** For video frames of a moving car from the Davis dataset, TokenCut and FOUND often drift toward background regions or capture only parts of the car, whereas CCG-2 consistently segments the *entire car* across frames, demonstrating the effectiveness of repulsion and co-segmentation in robustly separating objects from similar backgrounds across object sizes.

Table 3: **CCG is a strong unsupervised video object segmenter.** In *w/o. training* setting, CCG outperforms TokenCut (performance gap in blue). In *w/. training* setting, CCG-1 and CCG-2 surpass VideoCutLER which relies solely on attraction for object discovery (performance gap in green). They also achieve competitive results compared with models leveraging optical flows.

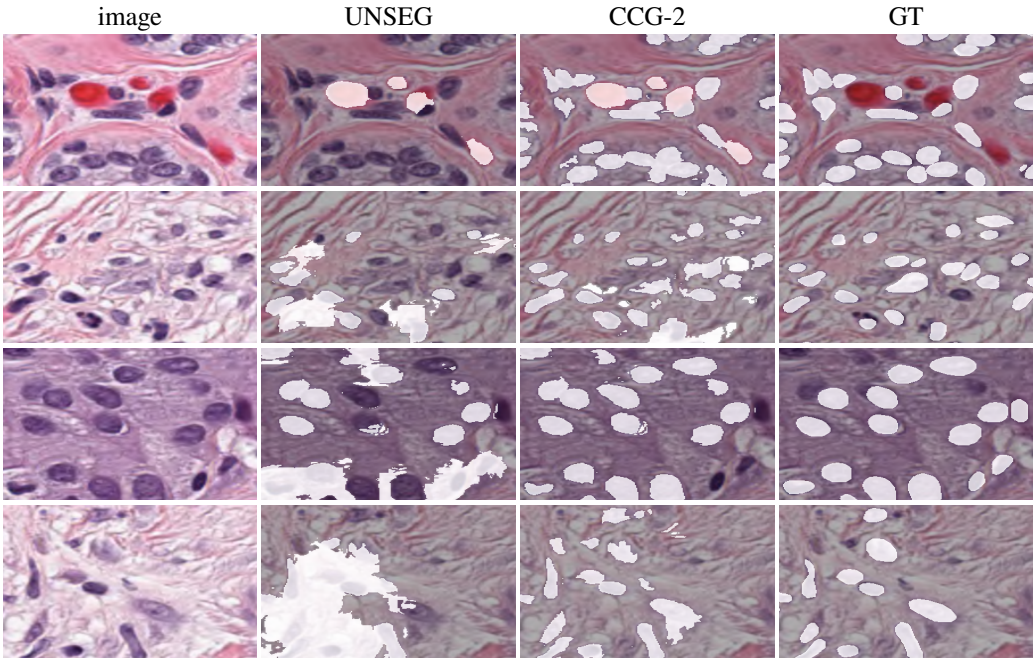
unsupervised video object segmenter	train?	use flow?	DAVIS	FBMS	SegTV2
TokenCut [55]	×	×	64.3	60.2	59.6
CCG-1	×	×	66.4 (+2.1)	62.5 (+2.3)	61.2 (+1.6)
CCG-2	×	×	**67.9** (+3.6)	**64.1** (+3.9)	**62.1** (+2.5)
CIS [62]	✓	✓	71.5	63.6	62.0
CMC [57]	✓	✓	**75.4**	66.8	62.6
AMD [21]	✓	×	45.7	28.7	42.9
VideoCutLER [54]	✓	×	68.4	64.6	62.5
CCG-1	✓	×	71.8 (+3.4)	66.4 (+1.8)	64.5 (+2.0)
CCG-2	✓	×	72.4 (+4.0)	**67.9** (+3.3)	**66.1** (+3.6)

Baselines. Unsupervised video object segmentation methods include AMD [21], CIS [62], CMC [57], and VideoCutLER [54]. Notably, VideoCutLER predicts object masks using only feature similarity (attraction). TokenCut, though training-free, still requires optical flow as inputs.

Results. Table 3 shows that, in *w/o learning*, CCG-1 with attraction and repulsion outperforms TokenCut. CCG-2 further boosts performance by cosegmenting adjacent frames, demonstrating CCG as an effective zero-shot segmenter from unlabeled video without relying on optical flow.

4.4 Unsupervised Nuclei Segmentation

We apply CCG to unsupervised nuclei segmentation on PanNuke [11] with 7,904 H&E-stained images (train/val/test split: 2,657 / 2,524 / 2,732). We compare against the SoTA UNSEG [18], which uses Bayesian inference to model nuclei priors for segmentation. Performance is evaluated using pixel accuracy, mIoU, and F_1 score. Even without distillation, both CCG-1 and CCG-2 outperform UNSEG by over 10%, demonstrating strong generalization from natural to medical images (Fig. 8).



unsupervised nuclei segmentation	accuracy	mIoU	F_1 score
UNSEG [18]	43.6	41.4	48.2
CCG-1	58.3 (+14.7)	54.5 (+13.1)	57.9 (+9.7)
CCG-2	61.1 (+17.5)	56.9 (+15.5)	58.6 (+10.4)

Figure 8: **Our CCG surpasses UNSEG by a large margin on unsupervised nuclei segmentation. Top:** Sample results. **Bottom:** Benchmark metrics. UNSEG [18] utilizes the prior distribution of nuclei, whereas ours has no training. With repulsion, it pops out nuclei cells all at once.

Summary. We formulate unsupervised whole-object segmentation as graph bi-partitioning driven by both attraction and repulsion. By maximizing within-group coherence and between-group contrast, co-segmenting related images to exploit richer contextual cues, and distilling co-segmentation into single-image segmentation via self-training, our method discovers entire objects (both distinctive and unremarkable parts) and outperforms prior approaches on object discovery, saliency detection, and video segmentation. It offers insights into how complex visual scenes can be parsed without any external supervision.

Limitation. Currently, our CCG performs binary co-segmentation on image pairs. It can be extended to multi-way segmentation across a large image collection.

Acknowledgements

This project was supported, in part, by NSF 2215542, NSF 2313151, and Bosch gift funds to S. Yu at UC Berkeley and the University of Michigan, with additional compute support provided by the NAIRR Pilot under CIS240431.

References

[1] Ralph Adolphs, Lauri Nummenmaa, Alexander Todorov, and James V Haxby. Data-driven approaches in the investigation of social perception. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 371(1693):20150367, 2016.

[2] Bogdan Alexe, Thomas Deselaers, and Vittorio Ferrari. Measuring the objectness of image windows. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 2928–2935, 2010.

[3] P. Arbeláez, J. Pont-Tuset, J. Barron, F. Marques, and J. Malik. Multiscale combinatorial grouping. In *Computer Vision and Pattern Recognition*, 2014.

[4] Mathilde Caron, Ishan Misra, Julien Mairal, Priya Goyal, Piotr Bojanowski, and Armand Joulin. Unsupervised learning of visual features by contrasting cluster assignments. *Advances in neural information processing systems*, 33:9912–9924, 2020.

[5] Mathilde Caron, Hugo Touvron, Ishan Misra, Hervé Jégou, Julien Mairal, Piotr Bojanowski, and Armand Joulin. Emerging properties in self-supervised vision transformers. In *Proceedings of the IEEE/CVF international conference on computer vision*, pages 9650–9660, 2021.

[6] Xinlei Chen, Haoqi Fan, Ross Girshick, and Kaiming He. Improved baselines with momentum contrastive learning. *arXiv preprint arXiv:2003.04297*, 2020.

[7] Minsu Cho, Suha Kwak, Cordelia Schmid, and Jean Ponce. Unsupervised object discovery and localization in the wild: Part-based matching with bottom-up region proposals. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 1201–1210, 2015.

[8] Ian Endres and Derek Hoiem. Category independent object proposals. In *Proceedings of the European Conference on Computer Vision (ECCV)*, pages 575–588, 2010.

[9] Mark Everingham, Luc Van Gool, Christopher KI Williams, John Winn, and Andrew Zisserman. The pascal visual object classes (voc) challenge. *International journal of computer vision*, 88:303–338, 2010.

[10] Mark Everingham and John Winn. The pascal visual object classes challenge 2012 (voc2012) development kit. *Pattern Anal. Stat. Model. Comput. Learn., Tech. Rep*, 2007(1-45):5, 2012.

[11] Jevgenij Gamper, Navid Alemi Koohbanani, Ksenija Benes, Simon Graham, Mostafa Jahanifar, Syed Ali Khurram, Ayesha Azam, Katherine Hewitt, and Nasir Rajpoot. Pannuke dataset extension, insights and baselines. *arXiv preprint arXiv:2003.10778*, 2020.

[12] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 770–778, 2016.

[13] Armand Joulin, Francis Bach, and Jean Ponce. Discriminative clustering for image co-segmentation. In *2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pages 1943–1950. IEEE, 2010.

[14] Tsung-Wei Ke, Jyh-Jing Hwang, Yunhui Guo, Xudong Wang, and Stella X. Yu. Unsupervised hierarchical semantic segmentation with multiview cosegmentation and clustering transformers. In *CVPR*, New Orleans, Louisiana, 19-24 June 2022.

[15] Tsung-Wei Ke, Jyh-Jing Hwang, Yunhui Guo, Xudong Wang, and Stella X Yu. Unsupervised hierarchical semantic segmentation with multiview cosegmentation and clustering transformers. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 2571–2581, 2022.

[16] Tsung-Wei Ke, Sangwoo Mo, and Stella X. Yu. Learning hierarchical image segmentation for recognition and by recognition. In *ICLR*, 2024.

[17] Alexander Kirillov, Eric Mintun, Nikhila Ravi, Hanzi Mao, Chloe Rolland, Laura Gustafson, Tete Xiao, Spencer Whitehead, Alexander C Berg, Wan-Yen Lo, et al. Segment anything. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 4015–4026, 2023.

[18] Bogdan Kochetov, Phoenix D Bell, Paulo S Garcia, Akram S Shalaby, Rebecca Raphael, Benjamin Raymond, Brian J Leibowitz, Karen Schoedel, Rhonda M Brand, Randall E Brand, et al. Unseg: unsupervised segmentation of cells and their nuclei in complex tissue samples. *Communications Biology*, 7(1):1062, 2024.

[19] Fuxin Li, Taeyoung Kim, Ahmad Humayun, David Tsai, and James M Rehg. Video segmentation by tracking many figure-ground segments. In *Proceedings of the IEEE international conference on computer vision*, pages 2192–2199, 2013.

[20] Weihao Li, Omid Hosseini Jafari, and Carsten Rother. Deep object co-segmentation. In *Computer Vision–ACCV 2018: 14th Asian Conference on Computer Vision, Perth, Australia, December 2–6, 2018, Revised Selected Papers, Part III 14*, pages 638–653. Springer, 2019.

[21] Runtao Liu, Zhirong Wu, Stella Yu, and Stephen Lin. The emergence of objectness: Learning zero-shot segmentation from videos. *Advances in neural information processing systems*, 34:13137–13152, 2021.

[22] Francesco Locatello, Dirk Weissenborn, Thomas Unterthiner, Aravindh Mahendran, Georg Heigold, Jakob Uszkoreit, Alexey Dosovitskiy, and Thomas Kipf. Object-centric learning with slot attention. In H. Larochelle, M. Ranzato, R. Hadsell, M.F. Balcan, and H. Lin, editors, *Advances in Neural Information Processing Systems*, volume 33, pages 11525–11538. Curran Associates, Inc., 2020.

[23] Xiankai Lu, Wenguan Wang, Jianbing Shen, David Crandall, and Jiebo Luo. Zero-shot video object segmentation with co-attention siamese networks. *IEEE transactions on pattern analysis and machine intelligence*, 44(4):2228–2242, 2020.

[24] Xiankai Lu, Wenguan Wang, Jianbing Shen, David J Crandall, and Luc Van Gool. Segmenting objects from relational visual data. *IEEE transactions on pattern analysis and machine intelligence*, 44(11):7885–7897, 2021.

[25] Aiyesha Ma, Nilesh Patel, Mingkun Li, and Ishwar K Sethi. Confidence based active learning for whole object image segmentation. In *Multimedia Content Representation, Classification and Security: International Workshop, MRCS 2006, Istanbul, Turkey, September 11-13, 2006. Proceedings*, pages 753–760. Springer, 2006.

[26] Tomasz Malisiewicz and Alexei A Efros. Recognition by association via learning per-exemplar distances. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 1–8, 2008.

[27] Luke Melas-Kyriazi, Christian Rupprecht, Iro Laina, and Andrea Vedaldi. Finding an unsupervised image segmenter in each of your deep generative models. *arXiv preprint arXiv:2105.08127*, 2021.

[28] Luke Melas-Kyriazi, Christian Rupprecht, Iro Laina, and Andrea Vedaldi. Deep spectral methods: A surprisingly strong baseline for unsupervised semantic segmentation and localization. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 8364–8375, 2022.

[29] Andrew Ng, Michael Jordan, and Yair Weiss. On spectral clustering: Analysis and an algorithm. *Advances in neural information processing systems*, 14, 2001.

[30] Peter Ochs, Jitendra Malik, and Thomas Brox. Segmentation of moving objects by long term video analysis. *IEEE transactions on pattern analysis and machine intelligence*, 36(6):1187–1200, 2013.

[31] Maxime Oquab, Timothée Darcet, Théo Moutakanni, Huy Vo, Marc Szafraniec, Vasil Khalidov, Pierre Fernandez, Daniel Haziza, Francisco Massa, Alaaeldin El-Nouby, et al. Dinov2: Learning robust visual features without supervision. *arXiv preprint arXiv:2304.07193*, 2023.

[32] Federico Perazzi, Jordi Pont-Tuset, Brian McWilliams, Luc Van Gool, Markus Gross, and Alexander Sorkine-Hornung. A benchmark dataset and evaluation methodology for video object segmentation. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 724–732, 2016.

[33] J. Pont-Tuset, P. Arbeláez, J. Barron, F. Marques, and J. Malik. Multiscale combinatorial grouping for image segmentation and object proposal generation. In *arXiv:1503.00848*, March 2015.

[34] Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, et al. Learning transferable visual models from natural language supervision. In *International conference on machine learning*, pages 8748–8763. PMLR, 2021.

[35] Nikhila Ravi, Valentin Gabeur, Yuan-Ting Hu, Ronghang Hu, Chaitanya Ryali, Tengyu Ma, Haitham Khedr, Roman Rädle, Chloe Rolland, Laura Gustafson, et al. Sam 2: Segment anything in images and videos. *arXiv preprint arXiv:2408.00714*, 2024.

[36] Tianhe Ren, Shilong Liu, Ailing Zeng, Jing Lin, Kunchang Li, He Cao, Jiayu Chen, Xinyu Huang, Yukang Chen, Feng Yan, et al. Grounded sam: Assembling open-world models for diverse visual tasks. *arXiv preprint arXiv:2401.14159*, 2024.

[37] Michael Rubinstein, Armand Joulin, Johannes Kopf, and Ce Liu. Unsupervised joint object discovery and segmentation in internet images. *IEEE Conf. on Computer Vision and Pattern Recognition (CVPR)*, June 2013.

[38] Maximilian Seitzer, Max Horn, Andrii Zadaianchuk, Dominik Zietlow, Tianjun Xiao, Carl-Johann Simon-Gabriel, Tong He, Zheng Zhang, Bernhard Schölkopf, Thomas Brox, and Francesco Locatello. Bridging the gap to real-world object-centric learning. In *The Eleventh International Conference on Learning Representations*, 2023.

[39] Jinhwan Seo, Wonho Bae, Danica J Sutherland, Junhyug Noh, and Daijin Kim. Object discovery via contrastive learning for weakly supervised object detection. In *European conference on computer vision*, pages 312–329. Springer, 2022.

[40] Jianbo Shi and Jitendra Malik. Normalized cuts and image segmentation. *IEEE Transactions on pattern analysis and machine intelligence*, 22(8):888–905, 2000.

[41] Jianping Shi, Qiong Yan, Li Xu, and Jiaya Jia. Hierarchical image saliency detection on extended cssd. *IEEE transactions on pattern analysis and machine intelligence*, 38(4):717–729, 2015.

[42] Gyungin Shin, Samuel Albanie, and Weidi Xie. Unsupervised salient object detection with spectral cluster voting. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 3971–3980, 2022.

[43] Oriane Siméoni, Gilles Puy, Huy V Vo, Simon Roburin, Spyros Gidaris, Andrei Bursuc, Patrick Pérez, Renaud Marlet, and Jean Ponce. Localizing objects with self-supervised transformers and no labels. *arXiv preprint arXiv:2109.14279*, 2021.

[44] Oriane Siméoni, Chloé Sekkat, Gilles Puy, Antonín Vobeckỳ, Éloi Zablocki, and Patrick Pérez. Unsupervised object localization: Observing the background to discover objects. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 3176–3186, 2023.

[45] Andrew N Stein, Thomas S Stepleton, and Martial Hebert. Towards unsupervised whole-object segmentation: Combining automated matting with boundary detection. In *2008 IEEE Conference on Computer Vision and Pattern Recognition*, pages 1–8. IEEE, 2008.

[46] Deqing Sun, Xiaodong Yang, Ming-Yu Liu, and Jan Kautz. Pwc-net: Cnns for optical flow using pyramid, warping, and cost volume. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 8934–8943, 2018.

[47] Guolei Sun, Wenguan Wang, Jifeng Dai, and Luc Van Gool. Mining cross-image semantics for weakly supervised semantic segmentation. In *Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part II 16*, pages 347–365. Springer, 2020.

[48] Zachary Teed and Jia Deng. Raft: Recurrent all-pairs field transforms for optical flow. In *Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part II 16*, pages 402–419. Springer, 2020.

[49] Huy V. Vo, Francis Bach, Minsu Cho, Kai Han, Yann LeCun, Patrick Pérez, and Jean Ponce. Unsupervised image matching and object discovery as optimization. In *CVPR*, 2019.

[50] Huy V Vo, Patrick Pérez, and Jean Ponce. Toward unsupervised, multi-object discovery in large-scale image collections. In *Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part XXIII 16*, pages 779–795. Springer, 2020.

[51] Lijun Wang, Huchuan Lu, Yifan Wang, Mengyang Feng, Dong Wang, Baocai Yin, and Xiang Ruan. Learning to detect salient objects with image-level supervision. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 136–145, 2017.

[52] Wenguan Wang, Tianfei Zhou, Fisher Yu, Jifeng Dai, Ender Konukoglu, and Luc Van Gool. Exploring cross-image pixel contrast for semantic segmentation. In *Proceedings of the IEEE/CVF international conference on computer vision*, pages 7303–7313, 2021.

[53] Xinlong Wang, Zhiding Yu, Shalini De Mello, Jan Kautz, Anima Anandkumar, Chunhua Shen, and Jose M Alvarez. Freesolo: Learning to segment objects without annotations. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 14176–14186, 2022.

[54] Xudong Wang, Ishan Misra, Ziyun Zeng, Rohit Girdhar, and Trevor Darrell. Videocutler: Surprisingly simple unsupervised video instance segmentation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 22755–22764, 2024.

[55] Yangtao Wang, Xi Shen, Yuan Yuan, Yuming Du, Maomao Li, Shell Xu Hu, James L Crowley, and Dominique Vaufreydaz. Tokencut: Segmenting objects in images and videos with self-supervised transformer and normalized cut. *IEEE transactions on pattern analysis and machine intelligence*, 2023.

[56] Xiu-Shen Wei, Chen-Lin Zhang, Jianxin Wu, Chunhua Shen, and Zhi-Hua Zhou. Unsupervised object discovery and co-localization by deep descriptor transformation. *Pattern Recognition*, 88:113–126, 2019.

[57] Lin Xi, Weihai Chen, Xingming Wu, Zhong Liu, and Zhengguo Li. Online unsupervised video object segmentation via contrastive motion clustering. *IEEE Transactions on Circuits and Systems for Video Technology*, 34(2):995–1006, 2023.

[58] Yunqiu Xu, Chunluan Zhou, Xin Yu, and Yi Yang. Cyclic self-training with proposal weight modulation for cross-supervised object detection. *IEEE Transactions on Image Processing*, 32:1992–2002, 2023.

[59] Charig Yang, Hala Lamdouar, Erika Lu, Andrew Zisserman, and Weidi Xie. Self-supervised video object segmentation by motion grouping. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 7177–7188, 2021.

[60] Charig Yang, Hala Lamdouar, Erika Lu, Andrew Zisserman, and Weidi Xie. Self-supervised video object segmentation by motion grouping. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 7177–7188, 2021.

[61] Chuan Yang, Lihe Zhang, Huchuan Lu, Xiang Ruan, and Ming-Hsuan Yang. Saliency detection via graph-based manifold ranking. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 3166–3173, 2013.

[62] Yanchao Yang, Antonio Loquercio, Davide Scaramuzza, and Stefano Soatto. Unsupervised moving object detection via contextual information separation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 879–888, 2019.

[63] Vickie Ye, Zhengqi Li, Richard Tucker, Angjoo Kanazawa, and Noah Snavely. Deformable sprites for unsupervised video decomposition. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 2657–2666, 2022.

[64] Stella X Yu and Jianbo Shi. Understanding popout through repulsion. In *Proceedings of the 2001 IEEE Computer Society Conference on Computer Vision and Pattern Recognition. CVPR 2001*, volume 2, pages II–II. IEEE, 2001.

[65] Xiao Zhang, David Yunis, and Michael Maire. Deciphering'what'and'where'visual pathways from spectral clustering of layer-distributed neural representations. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 4165–4175, 2024.

[66] Xin Zhang, Jinheng Xie, Yuan Yuan, Michael Bi Mi, and Robby T Tan. Heap: Unsupervised object discovery and localization with contrastive grouping. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 38, pages 7323–7331, 2024.

[67] Hasib Zunair and A Ben Hamza. Peekaboo: Hiding parts of an image for unsupervised object localization. *arXiv preprint arXiv:2407.17628*, 2024.

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A Technical Appendices

A.1 Unsupervised Whole Objectness by Contrastive Contextual Grouping

Attraction and Repulsion. Given the similarity matrix $\boldsymbol{S}$, attraction and repulsion matrices $\boldsymbol{A}$ and $\boldsymbol{R}$ are defined as Gaussian functions of $\boldsymbol{S}$ (Fig.A1). Here we heuristically take $\sigma_a = 0.4$. $\sigma_r = 0.3$.

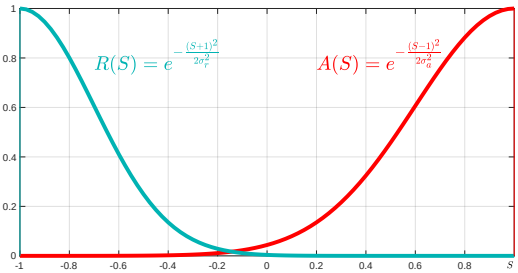

Figure A1: **We define attraction $\boldsymbol{A}$ and repulsion $\boldsymbol{R}$ as the Gaussian functions of pairwise feature similarity $\boldsymbol{S}$.** The larger (smaller) the similarity, the larger the attraction (repulsion).

Segmentation by Only Attraction. Previous methods [55, 28] formulate unsupervised object discovery as a graph partitioning problem and use normalized cut [40] to divide the graph into two parts. Let $C_A(\mathbb{V}_1, \mathbb{V}_2)$ as total connections of attraction from $\mathbb{V}_1$ to $\mathbb{V}_2$: $\sum_{i\in\mathbb{V}_1, j\in\mathbb{V}_2} \boldsymbol{A}(i,j)$. The normalized cut is equivalent to maximizing the attraction within partitioned groups by

$$\max \xi_A = \sum_{u=1}^{2} \frac{C_A(\mathbb{V}_u, \mathbb{V}_u)}{C_A(\mathbb{V}_u, \mathbb{V})} \tag{8}$$

The features from self-supervised Visual Transformers present strong feature attraction in discriminative parts of objects. TokenCut [55] utilizes attraction for graph cut which can only segments out characteristic local regions, not whole objects. An example of illustrating how TokenCut segment object parts is in Fig. 4.

Segmentation by Attraction and Repulsion. Instead of using normalized cut by using only attraction, we investigate whether attraction and repulsion can jointly contribute to pop out whole objects. Given attraction $\boldsymbol{A}$ and repulsion $\boldsymbol{R}$, we follow [64] and conduct a binary segmentation by using a unified grouping criterion

$$\begin{aligned} \max \xi_{AR} &= \frac{\text{within-group } \boldsymbol{A}}{\text{total degree of } \boldsymbol{A}\&\boldsymbol{R}} + \omega \frac{\text{between-group } \boldsymbol{R}}{\text{total degree of } \boldsymbol{A}\&\boldsymbol{R}} \\ &= \sum_{u=1}^{2} \frac{C_A(\mathbb{V}_u, \mathbb{V}_u)}{C_A(\mathbb{V}_u, \mathbb{V}) + C_R(\mathbb{V}_u, \mathbb{V})} + \\ &\quad \frac{C_R(\mathbb{V}_u, \mathbb{V}\backslash\mathbb{V}_u)}{C_A(\mathbb{V}_u, \mathbb{V}) + C_R(\mathbb{V}_u, \mathbb{V})}, \end{aligned} \tag{9}$$

where $C_R(\mathbb{V}_1, \mathbb{V}_2)$ represents total connections of repulsion from $\mathbb{V}_1$ to $\mathbb{V}_2$. It's easy to discover that ξ_{AR} is equivalent to ξ_A when the strength of repulsion $\boldsymbol{R}$ is not considered for grouping (we set up $\omega = 0$). Let $\boldsymbol{D}_A, \boldsymbol{D}_R$ represent the diagonal degree matrix of $\boldsymbol{A}, \boldsymbol{R}$:

$$\begin{aligned} \boldsymbol{D}_A &= \texttt{diag}(\texttt{sum}(\boldsymbol{A}, \texttt{dim} = 1)), \\ \boldsymbol{D}_R &= \texttt{diag}(\texttt{sum}(\boldsymbol{R}, \texttt{dim} = 1)). \end{aligned} \tag{10}$$

According to [64], the joint attraction and repulsion criterion is equivalent to

$$\begin{aligned} \max \xi_{AR}(\boldsymbol{p}) &= \sum_{u=1}^{2} \frac{\boldsymbol{p}_u^T \boldsymbol{W} \boldsymbol{p}_u}{\boldsymbol{p}_u^T \boldsymbol{D} \boldsymbol{p}_u}, \\ \boldsymbol{W} = \boldsymbol{A} - \boldsymbol{R} + \boldsymbol{D}_R,\ \boldsymbol{D} &= \boldsymbol{D}_A + \boldsymbol{D}_R, \end{aligned} \tag{11}$$

where $\boldsymbol{p}_u$ is a binary membership vector for $\mathbb{V}_u$. The real valued solution to this partition problem is finding the second largest eigenvector $\mathbf{z}^*$ of the eigensystem

$$\boldsymbol{D}^{-1}\boldsymbol{W}\boldsymbol{z} = \lambda \boldsymbol{z}. \tag{12}$$

A comparison between the solution eigenvectors of our method and TokenCut (which uses only attraction) is shown in Fig. A2.

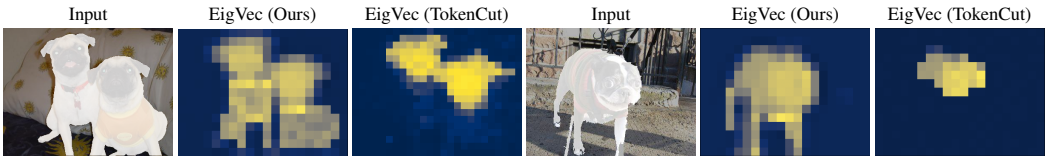

Figure A2: **Comparison of eigenvectors from CCG-2 and TokenCut.** We show a pair of input images (**left**) and eigenvectors from our CCG-2 (**middle**) and TokenCut (**right**). Eigenvector components are color coded where yellow represents larger values. We find the eigenvectors produced by CCG-2 leveraging both attraction and repulsion across reference images highlight the entire body of the dogs, whereas TokenCut using attraction isolates only the head regions.

Attraction and Repulsion within a Single Image. Given an unlabeled image x, we assume it contains at least one object, and segment the whole objects by attraction and repulsion from x.

Attraction and Repulsion across an Image Pair. So far we consider attraction and repulsion within a single image. It is straightforward to extend it to a co-segmentation setting, where two (or more) related images need to be jointly segmented.

A.2 Implementation Details

We choose `ViT-S/16` as the architecture for evaluation with the baselines in *w/o. training* setting and `ViT-S/8` to compare with the baselines in *w/. training* setting. To find semantically similar but visually distinct images as image pairs, we extract the features from DINO (`ViT-S/8`) and run k-nearest neighbors. It takes less than 1 hour to run k-nearest neighbors on 100,000 images as a preprocessing step. To find video frame pairs, we use a frame interval of 10 to create reference image pairs for co-segmentation: [(00.jpg, 10.jpg), (01.jpg, 11.jpg), (02.jpg, 12.jpg), $\cdots$]. Our ViT encoder at the distillation stage takes the same architecture as DINO `ViT-S/8`. The segmentation head contains a single `conv` 1×1 layer. During the distillation, our ViT encoder is trained using AdamW optimizer with a learning rate of 0.001, and our segmentation head trained using AdamW optimizer with a learning rate of 0.05. We set the batch size to 16 and have 300 training epochs. The repulsion weight ω is set to 0.2. The segmentation head contains a single `conv` 1×1 layer. During the distillation process, we set the batch size to 16 and have 300 training epochs. The training is run on 4 A40 NVIDIA GPUs. The repulsion weight ω is set to 0.2.

A.3 Ablation Study

Repulsion Weight. We analyze the effect of ω. Fig.A3 shows an ablation on unsupervised saliency detection (ECSSD). When $\omega = 0$ (red line), CCG reduces to TokenCut[55]. Optimal performance–measured by pixel accuracy, mean IoU, and maximal F_β–occurs near $\omega = 0.2$. We adopt this setting for all subsequent experiments, *removing the need for per-task tuning*.

Image Pair Discovery. We explore discovering similar image pairs from unlabeled data using k-nearest neighbors on DINO, CLIP and ResNet-50 (ImageNet pre-trained) features. The results evaluated on ECSSD, shown in Table A1, indicate that all three perform comparably. To minimize dependence on additional models, we use DINO features for all main experiments. CLIP achieves the best performance likely due to its supervised training on large-scale labeled data. Examples of retrieved image pairs can be found in Fig. A5.

Video Frame Pair Discovery. CCG employs a pair of frames taken from the same video clip, which may be captured at different timestamps. We examine how varying frame intervals affect unsupervised video object segmentation, as illustrated in Fig. A4. When the frame interval is set to 0, CCG-2 becomes equivalent to CCG-1 , as the two reference images are identical. The best results are obtained

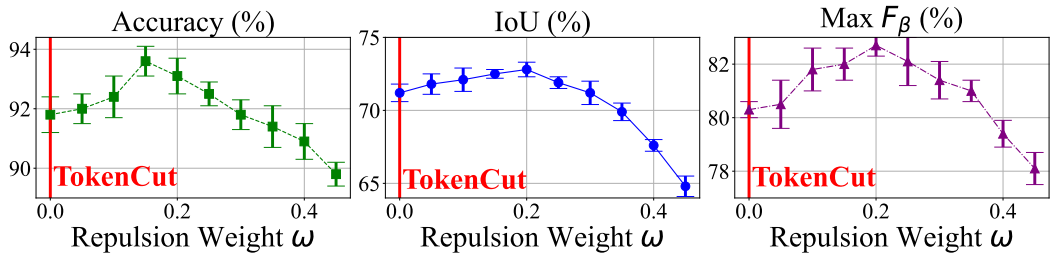

Figure A3: **The performance of CCG on unsupervised saliency detection on ECSSD dataset with different values of repulsion weight** ω. Overall, $\omega = 0.2$ yields the best performance.

Table A1: **Performance of CCG-2 using different features for pair discovery on ECSSD.** Overall, the results are comparable across feature types.

feature	maxF$_\beta$	IoU	Acc.
DINO [5]	83.1	73.2	94.7
ResNet-50 [12]	83.4	**74.2**	95.6
CLIP [34]	**83.8**	73.8	**95.8**

with video frame intervals ranging from 8 to 18. Therefore, we set the frame interval to 10 for all unsupervised video object segmentation experiments.

Table A2: **Ablation of the number of Conv layers in the segmentation head used for distillation.** Our implementation uses a single Conv layer in all tasks.

seg. head	maxF$_\beta$	IoU	Acc.
1 × Conv(1,1)	94.5	83.9	95.8
2 × Conv(1,1)	**95.2**	**84.4**	**96.3**
3 × Conv(1,1)	92.3	81.5	92.7

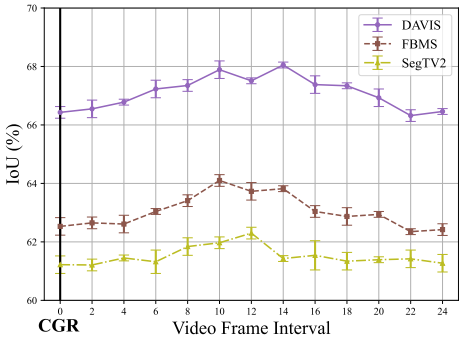

Figure A4: **Performance of CCG-2 on unsupervised video object segmentation with varying frame intervals**. Overall, the model performs best when the interval is between 8 and 18 frames.

Segmentation Head. We investigate the impact of distillation with different # of conv layers in the segmentation head. Table A2 presents the results of various head designs. Performance improves when using a 2×conv(1,1) configuration but degrades with a 3×conv(1,1) setup, suggesting a trade-off between model complexity and effectiveness.

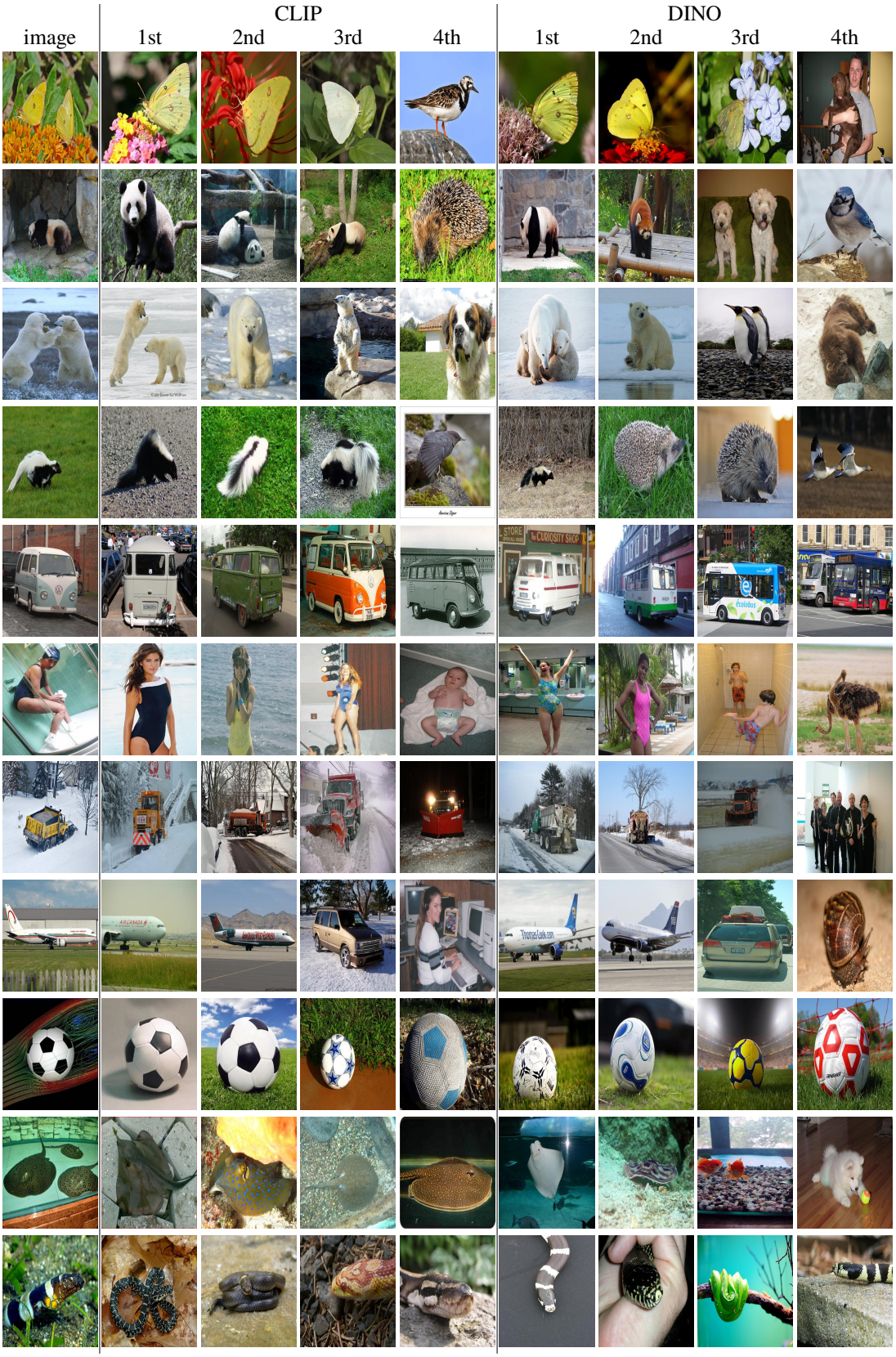

Figure A5: **Examples of nearest-neighbor images retrieved using CLIP and DINO feature distances.** The leftmost column shows the query images, and the top-4 nearest neighbors retrieved by each model are displayed to the right.

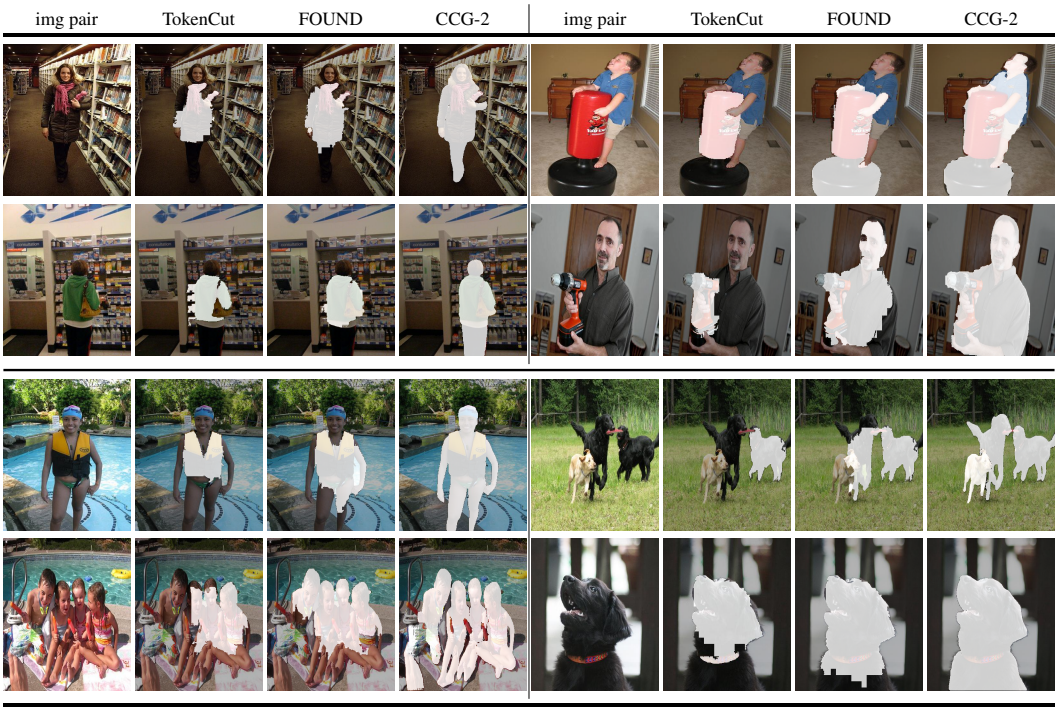

Figure A6: **CCG-2 outperforms both TokenCut and FOUND on unsupervised saliency detection.** Here we show four pairs of input images and their corresponding segmentation results. With the aid of repulsion, CCG-2 successfully segments whole foreground objects, whereas TokenCut and FOUND capture only statistically distinctive parts.