Perceptual Grouping in Contrastive Vision-Language Models

Kanchana Ranasinghe*, Brandon McKinzie, Sachin Ravi,
Yinfei Yang, Alexander Toshev, Jonathon Shlens†
Apple
kranasinghe@cs.stonybrook.edu

Abstract

Recent advances in zero-shot image recognition suggest that vision-language models learn generic visual representations with a high degree of semantic information that may be arbitrarily probed with natural language phrases. Understanding an image, however, is not just about understanding what content resides within an image, but importantly, where that content resides. In this work we examine how well vision-language models are able to understand where objects reside within an image and group together visually related parts of the imagery. We demonstrate how contemporary vision and language representation learning models based on contrastive losses and large web-based data capture limited object localization information. We propose a minimal set of modifications that results in models that uniquely learn both semantic and spatial information. We measure this performance in terms of zero-shot image recognition, unsupervised bottom-up and top-down semantic segmentations, as well as robustness analyses. We find that the resulting model achieves state-of-the-art results in terms of unsupervised segmentation, and demonstrate that the learned representations are uniquely robust to spurious correlations in datasets designed to probe the causal behavior of vision models.

1. Introduction

Recent vision-language models trained under weak supervision demonstrate a remarkable ability to learn generic and transferable visual representations [21, 43, 68, 95], but showcase a profound inability to associate visual content with individual objects (Fig. 1, bottom row). In other words, models trained on large weakly-supervised data have a limited ability to group together visually related content [31]. Because the representations have a poor understanding of *where* an object resides, they easily conflate background with foreground content. Hence, the learned representations are unable to learn the spatial layout of a scene [77, 80], and are susceptible to learning spurious correlations between a semantic label and extraneous content [55, 73].

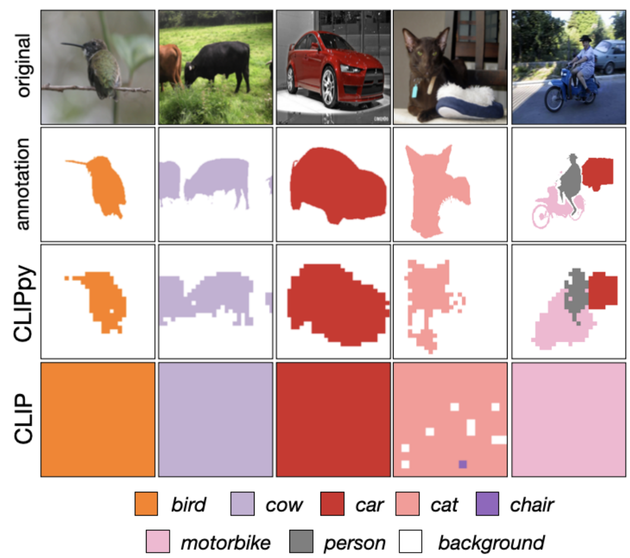

Figure 1. **Semantic localization in vision-language models.** We measure the ability of vision-language models to predict a label at each spatial position in a zero shot manner based on the similarity of location tokens to the corresponding language tokens on selected examples. CLIP / ALIGN [43, 68] have minimal understanding of the spatial location of individual objects (row 4). Our proposed CLIPpy (row 3) predicts the label at locations that correspond closely to human annotation for semantic segmentation (row 2). All predictions were performed with no access to any segmentation data during training or inference. More visualizations in App. B.

Recent work [91, 92] attempts to bridge this gap through grouping mechanisms under the same weakly supervised training paradigm, but focus more on foreground objects (neglecting background classes). Another direction is task specific unsupervised fine-tuning [23, 103] which loses the generic and transferable nature of these representations.

In this work, we explore vision-language models that learn from similar weakly labeled data, but a) retain the generic and transferable nature of features, and b) learns where all (background & foreground) visual content resides within an image. Unlike previous works using grouping specific architectures [91, 92] or dense human annota-

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†Work performed at Apple.

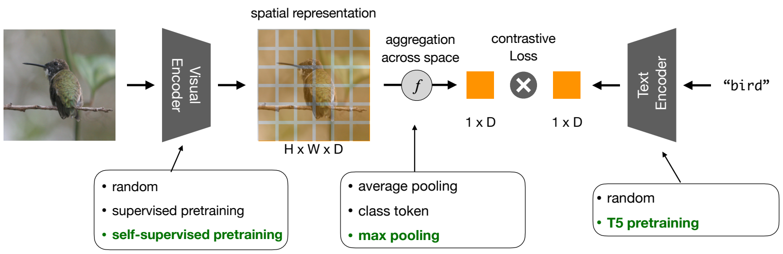


Figure 2. **Architecture diagram.** We demonstrate that two minimal design decisions (indicated in green) are of paramount importance for CLIP [68] models to perform perceptual grouping under image-level weak supervision.

Component	CLIP [68]	CLIP†	CLIPpy
Image Backbone	ViT-B/16	ViT-B/16	ViT-B/16
Text Backbone	T-B	T-5	T-5
Image Init	Random	Random	DINO
Text Init	Random	Random	Sent T-5
Image Pooling	CLS	CLS	Max
Text Pooling	Avg	Avg	Avg
Dataset	300M*	CC-12M	CC-12M
VOC mIoU (%)	16.4	17.5	**50.8** (+33.3)
VOC JS (%)	28.6	37.3	**47.5** (+10.2)

Figure 3. We highlight CLIPy differences from CLIP. CLIP† is our implementation following train settings identical to CLIPpy. *indicates OpenAI private data.

tions [31, 33, 48], we explore a minimal set of modifications to existing CLIP models [68] that leads to visual grouping while retaining their weakly supervised and scalable training procedure. We find that two small adjustments – employing specific pretraining strategies and adjusting spatial feature aggregation – results in models that are equally effective in zero-shot image recognition, but also retain spatial information regarding object locations (see Fig. 1, 3rd row).

The resulting model termed CLIPpy exhibits *perceptual grouping*: ability to select and combine related visual signals into semantically meaningful regions [60, 72, 89]. Endowing models with perceptual grouping – whether in a bottom up (based solely on visual content) or top down (guided by external information, language in this case) manner – in learned representations has been a long standing goal in computer vision [58, 59]. Further, this emergence of localization ability uniquely leads to robustness to counterfactual manipulations.

2. Methodology

Our work builds on CLIP [68], introducing two key modifications that emerge grouping behavior: alternate aggregation options and pre-training strategies (Fig. 2). Training uses the same contrastive objective under weak supervision.

2.1. Aggregation

The goal of aggregation is to collapse the image embedding from $[H, W, D]$ to D dimension. **Average pooling** across space is an established technique to obtain a final embedding independent of image resolution [57, 78]. Another approach for ViT is **class token (CLS)**, which learns an aggregated embedding from patch tokens. In this work we systematically explore these aggregation strategies to find that the application of **maximum pooling** across the spatial dimensions – while extremely simple – is also by far most effective (Tab. 4). We hypothesize that this may be due to gradient updates being focused solely on a single spatial location, and not spread across all spatial dimensions.

2.2. Pretraining

Language Model. For better sentence level representation, we utilize pre-training from Sentence-T5 [64], selected over auto-regressive models [6, 22] because their contrastive loss is aligned to our setup.

Image Model. We investigate using supervised and self-supervised ([10]) pre-training strategies. We focus on the latter direction due to impressive localization performance of those features [10, 36]. The visual encoder representation space can be viewed as containing per-image features (post-aggregation) vs per-spatial location features (pre-aggregation). We hypothesize that semantics tied boundaries of this representation space should operate at the latter granularity to induce perceptual grouping. Furthermore, we suggest that initializations facilitating the former will detriment grouping behaviour. In particular, visual pre-training strategies separating image-level representations by semantics (e.g. supervised ImageNet pre-training) will diminish perceptual grouping. Self-supervised pre-training strategies focused on more granular within image representations (e.g. [10]) will tend to enhance perceptual grouping. This hypothesis is empirically validated in ablations (see Table 4).

2.3. Visual Token Sub-Sampling

Motivated by vision transformers' ability to process sequences of length different to train time, we generate higher resolution segmentations during inference by sampling more image patches. In order to increase robustness to such varying resolution, we utilize up to $2\times$ higher resolution images during training but randomly drop 80% of visual tokens to minimize additional compute overhead (similar to [38, 52]). While improving inference quality, this also provides training stability possibly due to its regularization effect (see App. E for more details).

2.4. Inference

Classification and top-down grouping follows zero-shot analyses from [68] (see App. I) with latter doing at each patch similar to [30] . Bottom-up grouping follows analysis in DINO demos [10]. PCA on image features (from visual encoder pre-aggregation) gives top n (=8) principal components, used as cluster centers. Each same image feature is assigned to one of these n clusters based on proximity (cosine similarity) to the centers resulting in n clusters (groups).

	Dataset	IN	IN-v2
ALIGN [43]	ALIGN-1800M	76.4	70.1
CLIP [68]	CLIP-400M	65.5	60.8
CLIP †	CC-12M	46.0	40.3
GroupViT [91]	CC-12M+YFCC	42.9	-
GroupViT †	CC-12M	25.6	23.8
CLIPpy	CC-12M	45.3	40.0
ALIGN †	HQITP-134M	51.1	45.6
CLIP †	HQITP-134M	61.4	56.4
CLIPpy	HQITP-134M	60.3	54.8

Table 1. **CLIPpy achieves competitive zero-shot image recognition.** IN and IN-v2 denote ImageNet and ImageNet-v2 accuracy, respectively. † indicates our implementation. [43] evaluated at 640×640; others evaluated at 224×224. CLIPpy shows ±0.5 and ±0.9 IN acc. (5 runs) on CC-12M and HQITP-134M, respectively.

	Dataset	Train	VOC
MoCo [91]	ImageNet	self	28.2
DINO [10]		self	45.9
DSM [61]		self	37.2
COMUS [97]		self	47.3
DINO [91]	CC-12M & YFCC-100M	self	41.8
CLIP [91]		text	28.6
GroupViT [91]		text	51.8
CLIP †	CC-12M	text	37.3
GroupViT †		text	42.8 (+5.5)
CLIPpy		text	**47.5** (+10.2)
CLIP †	HQITP-134M	text	38.9
CLIPpy		text	**54.6** (+15.7)

Table 2. **CLIPpy effectively performs bottom-up grouping.** We report Jaccard Similarity, an instance average of the IoU between proposed and annotated segmentations, independent of the object label. † denotes our implementation.

	arch	dataset	ADE20K	COCO	VOC	COCO (obj)
GroupViT † [91]	ViT	CC-12M	6.2	12.7	40.1	17.5
MaskCLIP † [103]	ViT		6.8	8.1	22.1	13.8
OVS [92]	ViT		7.1	-	44.6	25.1
CLIP †	ViT		5.0	7.8	17.5	13.2
CLIPpy	ViT		**13.1** (+8.1)	**23.8** (+16.0)	**50.8** (+33.3)	**28.5** (+15.3)
ALIGN [30]	CNN	ALIGN-1800M	9.7	15.6	-	-
CLIP [68]	ViT	CLIP-400M	5.8	8.7	16.4	-
ALIGN †	CNN	HQITP-134M	7.5	14.4	29.7	-
CLIP †	ViT		5.1	8.0	18.1	-
CLIPpy	ViT		**13.5** (+8.4)	**25.5** (+17.5)	**52.2** (+34.1)	32.0

Table 3. **CLIPpy provides competitive top-down grouping (semantic segmentation) with no segmentation or location annotations.** All models trained without any segmentation annotations. Results grouped by training dataset (bold highlights best per dataset). Numbers are mean IoU. † indicates our implementation.

3. Experiments

Experimental Setup. We train our models on two datasets: Conceptual Captions 12M (CC-12M) [11] and High Quality Image Text Pairs (HQITP-134M) consisting of 12 million and 134 million image-text pairs, respectively (App. C for details). More training details in App. E.

We first measure performance of CLIP [68] and ALIGN [43] on zero-shot image classification on ImageNet and ImageNet-v2. Table 1 highlights these results. In the following experiments we attempt to address the following questions:

- Limitations of current vision-language models?
- Do we observe perceptual grouping in these models? (Tabs. 2 and 3).
- How resilient are they to counterfactual manipulations? (Fig. 5).

Finally, we report ablations on each component in Tab. 4.

3.1. Limitations of vision-language models

Visual representations learned in vision-language models exhibit an impressive ability to generalize across tasks [43,68]. However they also exhibit a profound shortcoming – learned visual representations maintain minimal information about *where* an object resides, failing to properly recognize what parts of an image constitute an object. Fig. 1 (bottom row) showcases failure of a CLIP model; namely, the model improperly conflates visual content not associated with an object with the actual object. One consistently observes the central object of interest being incorrectly predicted to reside at every spatial location. This failure of vision-language models to properly understand spatial organization of information is consistent with earlier observations [63,77,99].

In contrast, if we perform the same analysis on CLIPpy, we see that the model retains significant information about spatial information (Fig. 1, 3rd row). We take these visualizations as an impetus for further investigation.

3.2. Emergence of Bottom-Up Grouping

Unsupervised segmentation performance is a direct measure of bottom up perceptual grouping. We apply CLIPpy at test time to perform segmentation without prompting for any labels. Fig. 4 shows how image embeddings naturally group into spatially distinct clusters mirroring the image structure. We emphasize that this analysis does *not* rely on text prompts *nor* segmentation labels, but merely emerges from the image features alone. Hence the model has learned to *group* perceptually related pixels merely based on the pixel content and image-level captions during training. We quantify the accuracy of this bottom-up segmentation using Jaccard Index [10,91], and show results in Tab. 2. Our intu-

Figure 4. **Visualizations of bottom-up grouping by CLIPpy**. Each color represents one grouping learned on a given image.

ition is that CLS and average pooling breaks spatial structure of features and mixes image-level features across features at all spatial locations unlike in CLIPpy, leading to observed better bottom-up grouping.

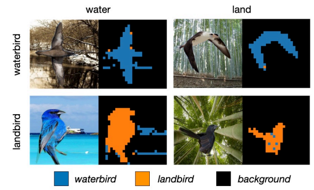
3.3. Emergence of Top-down Grouping

We next measure top-down grouping ability with zero-shot semantic segmentation. Fig. 1 visualizes predicted zero-shot segmentations and Tab. 3 quantifies these results using mean intersection over union (mIoU). CLIPpy outperforms all other approaches on semantic segmentation when trained on the same datasets, both for CC-12M and HQITP-134M. GroupViT [91] and OVS [92] containing grouping specific architectures and pre-training strategies provide important points of comparison. CLIPpy obtains clear performance improvements over these methods across all datasets.

3.4. Perceptual grouping may improve robustness

We next explore how observed perceptual grouping could improve robustness of image understanding. The synthetic benchmark is *Waterbirds* [73] places segmented birds over land or water background posing a two-way classification task of whether a bird belongs to the `waterbird` or `landbird` category. What makes this problem particularly challenging is when the background is not commensurate with the type of bird (e.i. landbird in water background).

We evaluate CLIPpy and a baseline CLIP model and report results in Fig. 5. Given the structured outputs from grouping, we perform a specialized inference procedure (App. H for details). For the CLIP baseline, model performance depends heavily on the background (δ column), indicating reliance on background features for prediction. Meanwhile, CLIPpy, while still susceptible to some spurious correlations, is far more robust than baseline CLIP. As points of comparison, all prior work train a supervised model on the training split. In contrast, our predictions are zero-shot, and we do not use the training set. That said, the best supervised training methods achieve a domain gap Δ of 4% to 8% [55], comparable to our results. We take these results to indicate that our zero-shot approach leveraging perceptual grouping provides another approach for addressing spurious correlations and learning robust image features.



CLIP	water	land	Δ
waterbird	80.2	48.1	**-32.1**
landbird	38.8	71.7	**-32.9**

CLIPpy	water	land	Δ
waterbird	76.9	74.9	**-2.0**
landbird	80.0	84.1	**-4.1**

Figure 5. **Perceptual grouping mitigates sensitivity to spurious correlations.** (left) Selected segmentation examples by CLIPpy of waterbirds and landbirds on each background. (right) Accuracy on the *test* split (5794 examples) of Waterbirds on CLIP and CLIPpy evaluated at 448×448 resolution. The domain gap Δ reports the drop in accuracy between on and off diagonal entries within a row.

I-P	I-F	T-F	IN	VOC
Cls	✓	✗	39.9	3.4
Max	✓	✗	24.2	10.4
Max	✗	✓	35.9	29.5
Max	✗	✗	**42.3**	**50.8**

Aggreg.	ImageNet	Pascal VOC	
	Accuracy	mIoU	Jaccard
Max	42.3	**50.8**	**47.5**
Avg	44.0	11.6	38.1
Cls	46.0	4.0	40.4

Table 4. **Ablation studies:** *(left)* Freezing pre-trained backbones. I-P for image backbone pooling, I-F for image backbone frozen, and T-F for text backbone frozen. Top-1 accuracy (%) for ImageNet (IN) and mean IoU for VOC reported. *(right)* Aggregation methods: max pooling (Max), average pooling (Avg), and class token (Cls). All models initialized with the same pre-trained features.

4. Discussion

In this work we demonstrate how contrastive vision-language models have a profound lack of understanding object location. We described a minimal set of changes to existing models - modifying the aggregation method and introducing optimal pre-training strategies - to endow the model with both bottom-up and top-down perceptual grouping. We emphasize that our changes are minimal but sufficient to match if not exceed the performance of custom-built architectures [91, 92] in achieving perceptual grouping.

We establish how our resulting model provides state-of-the-art results in terms of both bottom-up and top-down grouping – even though the model has been afforded *no* segmentation annotations whatsoever. Finally, we demonstrate the utility of these representations by demonstrating how perceptual grouping may be leveraged to learn visual features that are robust to spurious correlations.

We take these results to indicate that contrastive vision-language models may provide the emergence of perceptual grouping without supervision. We do see limitations in this approach as segmentation suffers with increasing visual clutter and label cardinality (e.g. ADE-20K). We suspect that recent advent of larger-scale open datasets [8, 74] and advanced in self-supervised learning [36, 61] may offer opportunities to demonstrate further benefits for endowing models with perceptual grouping. We also note the possibility of biases in our training data that may be reflected in our models. We highlight how all reported numbers contain an equivalent version on CC-12M only to enable reproducibility.

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