Unsupervised Part Discovery from Contrastive Reconstruction

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Motivation

Previous work
- Unsupervised scene decomposition
- Part discovery and segmentation
- Self-supervised and contrastive learning

Unsupervised part discovery
- Part criteria and losses
- Dataset details
- Architecture and Implementation details
- Evaluation metrics proposed
- Comparison with the state of the art

Experiments

Limitations

Conclusion
Motivation

• Major works: object or scene level segmentation

• Aim: Part segmentation of object

• Parts invariant to geometric and photometric changes

• Supervised learning requires manual annotations; infeasible. So unsupervised method.

• Unsupervised part discovery: Decompose an object into a collection of repeatable and informative parts without supervision.
1. **Unsupervised scene decomposition:**

- Spatially decompose scene into objects - object centric representation
- Representative and discriminative approach
- Performance well on simple, synthetic scenes
- Limitation: Decomposing a scene into object is different from decomposing object into parts.

*Fig: Introduction to Object Centric Learning by Michele De Vita (https://mik3dev.medium.com/)*
2. Part discovery and segmentation:

**Part based models**

- Various parts of the image are used separately
- Requires image labels for training
- Create attention maps to learn parts
- Intermediate step to discover important region to utilize for downstream task (fine-grained classification)

*Fig: Zixuan Huang and Yin Li. Interpretable and accurate fine-grained recognition via region grouping. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*
2. Part discovery and segmentation:

**DFF (Deep Feature Factorization)**
- Feature extraction from deep CNN
- Use NMF (non-negative matrix factorization) to get heat maps

![Diagram](image)

*Fig: Edo Collins, Radhakrishna Achanta, and Sabine Susstrunk. Deep feature factorization for concept discovery. In Proceedings of the European Conference on Computer Vision (ECCV)*

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2. Part discovery and segmentation:

ULD (Unsupervised Landmark Detection)

- Learn landmarks without supervision
- Rely on geometric constrains landmarks equivariance to transformations

Fig: James Thewlis, Hakan Bilen, and Andrea Vedaldi. Unsupervised learning of object landmarks by factorized spatial embeddings. In Proceedings of the IEEE international conference on computer vision
2. Part discovery and segmentation:

**SCOPS (Self-supervised Co-Part Segmentation)**
- Related to proposed paper – loss functions and backbone architecture
- Use features from convolutional layers for pretraining
- Losses – geometric concentration, equivariance, semantic consistency and objects as the union of parts

**Other**
- Generative adversarial methods – no supervision. Use motion in videos
- Probabilistic generative model

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Fig: Wei-Chih Hung, Varun Jampani, Sifei Liu, Pavlo Molchanov, Ming-Hsuan Yang, and Jan Kautz. Scops: Self-supervised co-part segmentation. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)
3. Self-supervised with contrastive learning (Related to current method):

- Pretext/Proxy using contrastive learning
- Key idea of contrastive learning: Encode two similar data points with similar embeddings; pushing the embeddings of dissimilar data apart
- No labels; Use data augmentations to create positive pair
- Learning utilized for downstream task

Fig: Advancing Self-Supervised and Semi-Supervised Learning with SimCLR by Ting Chen and Geoffrey Hinton
Defining Part: Two main ideas to define parts in unsupervised part segmentation

1. **Motion based approach:**
   “What moves together belongs together”

Learns to group pixels using motion as cue

Limitation: Segmentation not possible when all parts move together

Fig: Sara Sabour, Andrea Tagliasacchi, Soroosh Yazdani, Geoffrey Hinton, and David J Fleet. Unsupervised part representation by flow capsules. In International Conference on Machine Learning; “Unsupervised Discovery of Parts, Structure, and Dynamics” ICLR 2021
Defining Part:

2. Semantic correspondence based:
Learning based on semantic correspondence across collection of images

Challenge: Reidentify the same parts across different instances

Proposed method based on this approach

Fig: Wei-Chih Hung, Varun Jampani, Sifei Liu, Pavlo Molchanov, Ming-Hsuan Yang, and Jan Kautz. Scops: Self-supervised co-part segmentation. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR): “Unsupervised Part Discovery by Unsupervised Disentanglement”, CGPR 2020
Unsupervised part discovery

- Automatically learn a part detector.
- Assign each pixel to one of the $K$ semantic parts.
- No supervision, requires Proxy task.
- Part segmenter is a function $f : I \mapsto M$
- Predict mask $M \in \{0, 1\}^{K \times H \times W}$ on image $I \in \mathbb{R}^{3 \times H \times W}$ where $\sum_{k=1}^{K} M_u = 1$
Part: Criteria and its loss

• Parts should have uniform feature information – **Feature loss**

• Parts should be consistent across images and distinct from other parts – **Contrastive loss**

• Parts should be visually consistent – **Visual consistency loss**

• Part should be invariant to geometric and photometric transformations – **Equivariance loss**
Contrastive feature discovery

Feature belonging to same part type are similar. Parts should have uniform information

- Average part descriptor

\[ z_k(I) = \frac{1}{|M_k|} \sum_{u \in \Omega} M_{ku} \phi(I)_u, \quad |M_k| = \sum_{u \in \Omega} M_{ku} \]

- Feature Loss

\[ \mathcal{L}_f(M) = \sum_{k=1}^{K} \sum_{u \in \Omega} M_{ku} \| z_k(I) - \phi(I)_u \|^2_2. \]
Contrastive feature discovery

- Parts should be distinct across images and distinct from other parts
- Maximize the semantic similarity of same part across images
- Minimize the semantic similarity between all other parts in the same and other images

\[ L_c = - \sum_{n=1}^{N} \sum_{k=1}^{K} \log \frac{\exp(\hat{z}_k^n \cdot \hat{z}_k^n / \tau)}{\exp(\hat{z}_k^n \cdot \hat{z}_k^n / \tau) + \sum_{j \neq k} \sum_{i \neq n} \exp(\hat{z}_k^n \cdot \hat{z}_j^i / \tau)} \]

From Feature Encoder

Batch

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Parts should be visually consistent. They are roughly uniformly colored.

Visual Consistency Loss:

\[
\mathcal{L}_v(M) = \sum_{k=1}^{K} \sum_{u \in \Omega} M_{ku} \left\| I_u - \frac{1}{|M_k|} \sum_{v \in \Omega} M_{kv} I_v \right\|_2^2
\]
Transformation Equivariance

- Following transformations are applied: color jitter, brightness (±30%), contrast (±30%), saturation (±30%), hue (±30%), random rotations (±60°) and translations (±10%)

- Commutativity of the function: $T(f(I)) = f(T(I))$

- Equivariance Loss:

$$\mathcal{L}_e(I, T(I)) = \sum_{u \in \Omega} \mathcal{KL}(T_u(f(I)), f_u(T(I))) + \mathcal{KL}(f_u(T(I)), T_u(f(I)))$$

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Unsupervised part discovery

Objective:

Learn the function $f$, by minimizing the weighted sum of the prior losses

$$\lambda_f \mathcal{L}_f + \lambda_c \mathcal{L}_c + \lambda_v \mathcal{L}_v + \lambda_e \mathcal{L}_e$$
The Caltech-UCSD Birds-200 dataset (CUB-200-2011) - dataset for fine-grained recognition, comprising of 11,788 images of 200 bird species with annotations for 15 part locations.

Fig: https://www.researchgate.net/figure/Examples-of-images-in-the-Caltech-UCSD-Birds-200-2011-Dataset-Corresponding-categories_fig6_318204948

- winter wren
- downy woodpecker
- bohemian waxwing
- northern waterthrush
- yellow warbler
- warbling virco
- tree swallow
- black tern
- scarlet tanager
- hooded merganser
- green violetear
- florida jay
• **The large-scale fashion database (DeepFashion)** – fashion dataset containing 52,712 densely labelled images of people in different clothing items. The labels include 15 categories and a background class.

Fig: [https://mmlab.ie.cuhk.edu.hk/projects/DeepFashion.html](https://mmlab.ie.cuhk.edu.hk/projects/DeepFashion.html)
• **PASCAL-Part** - Extension of the PASCAL VOC 2010 dataset; contains 10,103 training and validation images and 9,637 testing images with part level annotations for the 20 categories.

• Current model is trained for following 10 categories – sheep, horse, cow, motorbike, plane, bus, car, bike, dog, cat.

Fig: http://host.robots.ox.ac.uk/pascal/VOC/voc2010/
Architecture and Implementation details

- Model $f$ as deep neural network - **DeepLab-v2 with ResNet-50**. Pretrained on ImageNet.

- Perceptual Network $\Phi$ – **VGG19**. For contrastive and feature objectives ($L_f$ and $L_c$). Pretrained on ImageNet. Frozen.

- CUB-200-2011 and DeepFashion: $\lambda_f = 5$, $\lambda_c = 2.3 \cdot 10^3$, $\lambda_v = 30$, $\lambda_e = 5.7 \cdot 10^3$

- PASCAL-Part: $\lambda_f = 5$, $\lambda_c = 2.3 \cdot 10^3$, $\lambda_v = 30$, $\lambda_e = 5.7 \cdot 10^4$, i.e. higher equivariance

- SGD using a learning rate of $10^{-5}$; Weight decay of $5 \cdot 10^{-4}$; Batch size of 6; Image size of $256 \times 256$

- Trained on foreground pixels only
Evaluation metrics proposed

Previous works’ evaluation metrics: Landmark/Keypoint regression error

➢ Convert part segmentation into Landmark (part center) and evaluate against ground truth
➢ Use Linear regressor to fit detected landmark against ground truth landmark for training
➢ If model predicts one single keypoint; then error is low. Does not correlate well with segmentation performance.

Fig: James Thewlis, Hakan Bilen, and Andrea Vedaldi. Unsupervised learning of object landmarks by factorized spatial embeddings. In Proceedings of the IEEE international conference on computer vision
Proposed: Adjusted Rand Index (ARI) to measure the information overlap between predicted and ground truth

\[
RI = \frac{\text{Number of Agreeing Pairs}}{\text{Number of Pairs}}
\]

\[
ARI = \frac{RI - \text{Expected RI}}{\text{Max}(RI) - \text{Expected RI}}
\]
Evaluation metrics proposed

Proposed: Normalized Mutual Information (NMI) to measure the information overlap between predicted and ground truth

\[ NMI(Y, C) = \frac{2 \times I(Y; C)}{H(Y) + H(C)} \]

Stricter NMI and ARI using only foreground information: FG-NMI, FG-ARI

Advantages of NMI and ARI: Comparing to Intersection-over-Union (IoU);
- Do not require the ground truth annotation to align exactly
- Do not impose a constraint in the value of number of parts (K)
Comparison with the state of the art

**CUB-200**

| Method                          | Keypoint Regression Error ↓ | FG-NMI↑ | FG-ARI↑ | NMI↑ | ARI↑ |
|--------------------------------|----------------------------|--------|--------|------|------|
|                                | CUB-001 | CUB-002 | CUB-003 | CUB-all |       |       |       |       |       |       |
| Image midpoint                 | 27.3    | 26.7    | 27.2    | 23.5    | 0.0   | 0.0   | 0.0   | 0.0   |       |       |
| GT keypoint avg                | 20.9    | 22.4    | 19.9    | 17.9    | 0.0   | 0.0   | 0.0   | 0.0   |       |       |
| “throat” kpt only              | 16.4    | 14.9    | 15.2    | 12.1    | 11.6  | -16.2 | 4.6   | -8.3  |       |       |
| ULD [68, 86]                   | 30.1    | 29.4    | 28.2    | -       | 32.4  | 14.3  | 25.9  | 12.4  |       |       |
| DFF [14]                       | 22.4    | 21.6    | 22.0    | -       | -     | -     | -     | -     |       |       |
| SCOPS [37] (paper)             | 18.5    | 18.8    | 21.1    | -       | -     | -     | -     | -     |       |       |
| SCOPS [37] (model)             | 18.3    | 17.7    | 17.0    | 12.6    | 39.1  | 17.9  | 24.4  | 7.1   |       |       |
| Huang and Li [36]              | 15.1    | 17.1    | 15.7    | 11.6    | -     | -     | 26.1  | 13.2  |       |       |
| Ours                           | **11.3** | **15.0** | **10.6** | **9.2** | **46.0** | **21.0** | **43.5** | **19.6** |       |       |

**Images**

- **Image**
- **SCOPS**
- **Ours**
Comparison with the state of the art

DeepFashion

|          | FG-NMI | FG-ARI | NMI  | ARI  |
|----------|--------|--------|------|------|
| SCOPS [37] | 30.7   | 27.6   | 56.6 | 81.4 |
| Ours     | 44.8   | 46.6   | 68.1 | 90.6 |
Comparison with the state of the art

PASCAL-Part

|          | sheep | horse | cow | mbike | plane | bus | car | bike | dog | cat | sheep | horse | cow | mbike | plane | bus | car | bike | dog | cat |
|----------|-------|-------|-----|-------|-------|-----|-----|------|-----|-----|-------|-------|-----|-------|-------|-----|-----|------|-----|-----|
| DFF [14] | 12.2  | 14.4  | 12.7| 19.1  | 16.4  | 13.5| 9.0 | 17.8 | 14.8| 18.0| 21.6  | 32.3  | 23.3| 37.2  | 38.3  | 28.5| 24.1 | 39.1 | 32.3| 37.5 |
| SCOPS [37]| 26.5  | 29.4  | 28.8| 35.4  | 35.1  | 35.7| 33.6| 28.9 | 30.1| 33.7| 46.3  | 55.7  | 51.2| 59.2  | 68.0  | 66.0| 67.1 | 52.4 | 52.2| 46.6 |
| K-means  | 34.5  | 33.3  | 33.0| 38.9  | 42.8  | 37.5| 38.4| 35.2 | 40.4| 44.2| 58.3  | 66.8  | 59.0| 63.1  | 76.8  | 66.4| 70.6 | 63.2 | 70.2| 71.9 |
| Ours     | 35.0  | 37.4  | 35.3| 40.5  | 45.1  | 38.8| 36.8| 34.8 | 46.6| 47.9| 59.8  | 68.9  | 59.7| 64.7  | 79.6  | 67.6| 72.7 | 64.7 | 73.6| 75.4 |

Image

SCOPS

Ours
Ablation experiment:

- Baseline: Clustering the perceptual features of concatenated layers relu5_2 and relu5_4 from VGG19 with K-means
- Remove various parts of the model and measure the decrease in performance.
- L2 instead of contrastive – Replace contrastive loss with simple L2 loss
- Lc w/ different views - use parts in differently augmented versions

| Variant                                | CUB-200-2011 (kp) | DeepFashion (fg) |
|----------------------------------------|-------------------|------------------|
|                                        | FG-NMI | FG-ARI | FG-NMI | FG-ARI |
| \(k\)-means cluster (VGG19)            |         |        |         |        |
| \([\text{relu5}_2, \text{relu5}_4]\)   | 34.9    | 14.7   | 30.3    | 21.4   |
| w/o consistency within parts           |         |        |         |        |
| \(\lambda_f = 0\)                     | 29.7    | 11.7   | 40.3    | 40.0   |
| w/o consistency across parts           |         |        |         |        |
| \(\lambda_c = 0\)                     | 41.3    | 19.0   | 39.0    | 40.1   |
| w/o visual consistency                 |         |        |         |        |
| \(\lambda_v = 0\)                     | 38.5    | 17.9   | 31.3    | 25.2   |
| w/o equivariance                       |         |        |         |        |
| \(\lambda_e = 0\)                     | 29.3    | 11.2   | 41.5    | 42.7   |
| \(L_2\) instead of contrastive         |         |        |         |        |
| \(L_c = \|\hat{z}_k^{(n)} - \hat{\hat{z}}_k^{(n)}\|_2^2\) | 34.0    | 13.4   | 36.7    | 32.0   |
| \(L_c\) w/ different views            |         |        |         |        |
|                                        | 44.4    | 20.2   | 36.4    | 33.4   |
| Ours (full model)                      | 46.0    | 21.0   | 44.8    | 46.6   |
Eliminating Supervision

- Method still rely on backbones pre-trained with ImageNet supervision (IN-1lk)
- Removing these supervised components and replace with unsupervised models
- Below results is determined on CUB-200-2011 dataset.

| Backbone of $f$                     | Perceptual Network $\phi$       | FG Mask | FG-NMI | FG-ARI |
|-------------------------------------|---------------------------------|---------|--------|--------|
| ResNet50 (IN-1k supervised)         | VGG19 (IN-1k supervised)        | GT      | 46.0   | 21.0   |
| ResNet50 (IN-1k supervised)         | VGG16 (IN-1k supervised)        | GT      | 39.7   | 19.1   |
| ResNet50 (SwAV[7])                  | VGG16 (IN-1k supervised)        | GT      | 35.4   | 16.4   |
| ResNet50 (SwAV[7])                  | VGG16 (DeepCluster-v1 [6])     | GT      | 32.3   | 14.0   |
| ResNet50 (SwAV[7])                  | VGG16 (DeepCluster-v1 [6])     | [56]    | 31.9   | 14.9   |
| ResNet50 (IN-1k supervised)         | ViT (DiNO[8])                  | GT      | 43.9   | 19.7   |
| ResNet50 (SwAV[7])                  | ViT (DINO [8])                 | [56]    | 42.7   | 20.0   |
Evaluation of different number of parts:

| Variant | CUB-200-2011 (kp) | DeepFashion (fg) |
|---------|-------------------|------------------|
|         | FG-NMI | FG-ARI | NMI   | ARI   | FG-NMI | FG-ARI | NMI   | ARI   |
| $K = 4$ | 46.0   | 21.0   | 43.5  | 19.6  | 44.8   | 46.6   | 68.1  | 90.6  |
| $K = 6$ | 47.2   | 23.0   | 44.4  | 20.7  | 43.5   | 42.2   | 66.2  | 91.0  |
| $K = 8$ | 58.2   | 34.0   | 51.5  | 28.3  | 39.2   | 30.7   | 62.4  | 90.6  |

Variability in results: Trained the model with $K = 4$ (with 5 different random seeds) and below are mean ± standard deviation of NMI and ARI

| Dataset      | FG-NMI  | FG-ARI  | NMI    | ARI    |
|--------------|---------|---------|--------|--------|
| CUB          | 45.3 ± 2.8 | 20.5 ± 1.5 | 42.8 ± 1.7 | 19.2 ± 0.5 |
| DeepFashion  | 44.6 ± 0.4 | 46.1 ± 0.6 | 68.2 ± 0.2 | 90.7 ± 0.1 |
Additional Results

- CUB-200 with $K=6$ and $K=8$
Additional Results

- DeepFashion with K=6 and K=8

(c) DeepFashion, K=6

(d) DeepFashion, K=8
Limitations

- Enforced visual consistency objective (e.g., the wheels of a car or a striped garment)

- Parts discovered in a self-supervised manner might not necessarily agree with human intuition (e.g., for humans one could segment arms, legs, torso, head or decompose arms into hands, fingers, etc)

- Failing to separate the foreground from the background
Proposed method expands on prior work by introducing constraints on contrastive formulation, equivariance and visual consistency in segmenting the object parts.

Few opinions for open discussion:

• Is using ‘supervised features’ reasonable for the model’s motivation of being unsupervised task?
• $K=4$ looks more visually better in part detection compared to other $K$ values.
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Thank you !!!
Discussion/Questions?