





Delving into Shape-aware Zero-shot Semantic Segmentation

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Introduction



Problems:



- In real-world, unknown objects may appear, hence there is a need to learn and achieve dense predictions for unknown object categories from limited samples.
- Dense prediction task requires not only accurate semantic understanding but also fine shape delineation.
- However, existing vision-language models are trained with image-level language descriptions.

Introduction



Solutions:



• Leverage the eigen vectors of Laplacian matrices constructed with self-supervised pixelwise features to promote shape-awareness.

• Propose to jointly optimizing a boundary segment constraint that aligns both the boundary of predicted semantic regions and the ground truth regions.

Method





Overall architecture



| | | | | | | | | | | | | <u></u> | | |
|-------------|------------|-----------|---------|-------------|-------------|--------------------|-------------|-------------|----------|-------------|-------------|-------------|------|-------------|
| Mada | Dealtheast | 0-44 | | | PASC | CAL-5 ⁱ | | | | | COC | $CO-20^{i}$ | | |
| Method | Backbone | Setting | 5^{0} | 5^1 | 5^2 | 5^3 | mIoU | FBIoU | 20^{0} | 20^{1} | 20^{2} | 20^3 | mIoU | FBIoU |
| FWB [38] | ResNet | 1-shot | 51.3 | 64.5 | 56.7 | 52.2 | 56.2 | _ | 17.0 | 18.0 | 21.0 | 28.9 | 21.2 | |
| DAN [52] | ResNet | 1-shot | 54.7 | 68.6 | 57.8 | 51.6 | 58.2 | 71.9 | - | _ | _ | _ | 24.4 | 62.3 |
| PFENet [51] | ResNet | 1-shot | 60.5 | 69.4 | 54.4 | 55.9 | 60.1 | 72.9 | 36.8 | 41.8 | 38.7 | 36.7 | 38.5 | 63.0 |
| HSNet [37] | ResNet | 1-shot | 67.3 | 72.3 | 62.0 | 63.1 | 66.2 | 77.6 | 37.2 | 44.1 | 42.4 | 41.3 | 41.2 | 69.1 |
| SPNet [54] | ResNet | zero-shot | 23.8 | 17.0 | 14.1 | 18.3 | 18.3 | 44.3 | _ | _ | _ | _ | _ | _ |
| ZS3Net [4] | ResNet | zero-shot | 40.8 | 39.4 | 39.3 | 33.6 | 38.3 | 57.7 | 18.8 | 20.1 | 24.8 | 20.5 | 21.1 | 55.1 |
| LSeg [25] | ResNet | zero-shot | 52.8 | 53.8 | 44.4 | 38.5 | 47.4 | 64.1 | 22.1 | 25.1 | 24.9 | 21.6 | 23.4 | 57.9 |
| Ours | DRN | zero-shot | 57.3 | 60.3 | 58.4 | 45.9 | 55.5 | 66.4 | 34.2 | 36.5 | 34.6 | 35.6 | 35.2 | 58.4 |
| LSeg [25] | ViT-L | zero-shot | 61.3 | 63.6 | 43.1 | 41.0 | 52.3 | 67.6 | 28.1 | 27.5 | 30.0 | 23.2 | 27.2 | 59.9 |
| Ours | ViT-L | zero-shot | 62.7 | 64.3 | 60.6 | 50.2 | 59.4 | 69.0 | 33.8 | 38.1 | 34.4 | 35.0 | 35.3 | 58.2 |

Our results on PASCAL-5^{*i*} and COCO-20^{*i*} datasets

The cross dataset results

| Model | Backbone | external dataset | target dataset | PASCAL-5 ⁱ |
|--------------|----------|------------------|------------------|-----------------------|
| LSeg | ViT-L | X | ✓ (seen classes) | 52.3 |
| SPNet | ResNet | × × | ✓ (seen classes) | 18.3 |
| ZS3Net | ResNet | × . | ✓ (seen classes) | 38.3 |
| LSeg | ResNet | × | ✓ (seen classes) | 47.4 |
| LSeg+ | ResNet | COCO | × × | 59.0 |
| OpenSeg [14] | ResNet | COCO | X | 60.0 |
| Ours | DRN | COCO | × | 62.7 |



Our results on COCO- 20^i dataset





Our results on PASCAL- 5^i dataset



Correlation of CO variance and mean language embedding locality on IoU



Our results on COCO- 20^i dataset



| Aeroplane | Image | Ours | GT | Image | Ours | GT | Diningtable |
|-----------|---------|------|----|---|------------|----|-------------|
| Bicycle | - | * | * | (and the second | Re | | Dog |
| Bird | | | | | A. | T. | Horse |
| Boat | 6 | 0 | | | 100 | 20 | Motorbike |
| Bottle | - (B) - | | | | 2 | 1 | Person |
| Bus | | | | The second | | 74 | Pottedplant |
| Car | | 1 | | Y | ø | Ø | Sheep |
| Cat | | | | | - | S. | sofa |
| Chair | | | - | | <u>B</u> Ş | | Train |
| Cow | | | | | | | Tymonitor |

Our results on PASCAL-5^{*i*} dataset



| Ablation study on COCO-20 ^{<i>i</i>} (ViT backbone) | | | | | | | | | | |
|--|---|--------------------------------|----------|----------|----------|--------|------|--|--|--|
| Model | Fusion | $\mathcal{L}_{\mathrm{shape}}$ | 20^{0} | 20^{1} | 20^{2} | 20^3 | mIoU | | | |
| SAZS | ✓ | ✓ | 34.2 | 36.5 | 34.6 | 35.6 | 35.2 | | | |
| SAZS | Image: A set of the set of the | | 33.7 | 38.2 | 33.4 | 35.5 | 35.2 | | | |
| SAZS | | ✓ | 28.4 | 27.6 | 25.4 | 25.1 | 26.6 | | | |
| SAZS | | | 24.2 | 28.5 | 24.4 | 23.3 | 25.1 | | | |
| LSeg [25] | | | 22.1 | 25.1 | 24.9 | 21.6 | 23.4 | | | |

Ablation study on COCO- 20^i (DRN backbone)

| Model | Fusion | $\mathcal{L}_{\mathrm{shape}}$ | $ 20^{0}$ | 20 ¹ | 20^{2} | 20^{3} | mIoU |
|-----------|--------|--------------------------------|------------|-----------------|----------|----------|------|
| SAZS | 1 | ~ | 33.8 | 38.1 | 34.4 | 35.0 | 35.3 |
| SAZS | 1 | | 33.3 | 39.0 | 33.9 | 32.7 | 34.7 |
| SAZS | | ~ | 30.0 | 30.4 | 27.5 | 28.5 | 29.1 |
| SAZS | | | 26.3 | 32.0 | 26.2 | 26.2 | 27.7 |
| LSeg [25] | | | 28.1 | 27.5 | 30.0 | 23.2 | 27.2 |

Ablation study on PASCAL-5ⁱ (ViT backbone)

| Model | Fusion | $\mathcal{L}_{\rm shape}$ | 50 | 5^1 | 5^2 | 5^3 | mIoU |
|-----------|--------------|---------------------------|------|-------|-------|-------------|------|
| SAZS | 1 | ✓ | 62.7 | 64.3 | 60.6 | 50.2 | 59.4 |
| SAZS | \checkmark | | 63.1 | 62.4 | 59.0 | 49.2 | 58.4 |
| SAZS | | ✓ | 59.7 | 63.4 | 44.3 | 42.2 | 52.4 |
| SAZS | | | 59.2 | 61.9 | 43.8 | 41.9 | 51.7 |
| LSeg [25] | | | 61.3 | 63.6 | 43.1 | 41.0 | 52.3 |

Impact of Z_{shape} and Z_{sem} of fusion module

| Model | external dataset | | $Z_{ m shape}$ | $Z_{ m sem}$ | PASCAL- 5^i |
|-------|------------------|--|----------------|--------------|---------------|
| SAZS | COCO | | | | 58.4 |
| SAZS | COCO | | \checkmark | | 58.6 |
| SAZS | COCO | | | ~ | 62.7 |

Conslusion



Our contributions:

- We propose a novel methodology for shape-aware zero-shot semantic segmentation models from language supervision, named SAZS, and set new state-of-the-art performance on PASCAL and COCO datasets.
- We propose to leverage the eigen vectors of Laplacian matrices constructed with self-supervised pixelwise features to promote shape-awareness.
- We propose to jointly optimizing a boundary segment constraint that aligns both the boundary of predicted semantic regions and the ground truth regions while narrowing the visual-language embedding space.
- We draw several interesting and conclusive observations: the benefits of promoting shape-awareness highly relates to objects' compactness and language embedding locality.