ECCV 2024

ClearCLIP: Decomposing CLIP Representations for Dense Vision-Language Inference

Mengcheng Lan[1], Chaofeng Chen[1], Yiping Ke[2], Xinjiang Wang[3], Litong Feng[3*], and Wayne Zhang[3]

[1] S-Lab, Nanyang Technological University
[2] CCDS, Nanyang Technological University [3] SenseTime Research
lanm0002@e.ntu.edu.sg {chaofeng.chen, ypke}@ntu.edu.sg
{wangxinjiang, fenglitong, wayne.zhang}@sensetime.com
https://github.com/mc-lan/ClearCLIP

- Problem / objective
  - CLIP 사용해서 Open-Vocabulary Semantic Segmentation
- Contribution / Key idea
  - Vision encoder의 마지막 layer에 3가지 수정을 함
    - 1. Residual connection 제거
    - 2. Self-self attention 적용
    - 3. Feed-forward network 제거

전유진

- **Semantic segmentation using CLIP**

  - ❑ Noisy 하다.
  - ❑ **이 noise는 어디서 왔으며, 어떻게 발생하였는가?**

$$\mathcal{M} = \arg\max_{c} \cos(X^{\text{visual}}_{\text{dense}}, X^{\text{text}}). \quad (4)$$

Image

CLIP

- **Noise가 어디서 왔는가?**
  - 실험 결과
    (1) 'X_attn의 크기': mIoU와 양의 상관관계.
    (2) 'X_res의 크기': CLIP-B/16에서 CLIP-L/14에서보다 훨씬 작은 값을 가진다.
    (3) Attention 수정: mIoU가 q-k baseline보다 CLIP-B/16에서는 일관되게 높지만, CLIP-L/14에서는 그렇지 않다.
  - 가설
    Attention 수정은 X_res의 영향(norm값)이 적을 때 효과적이다.

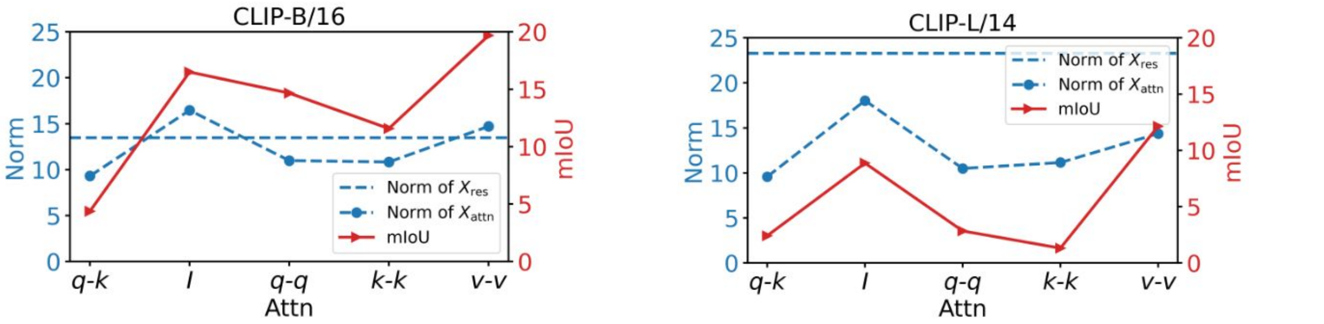
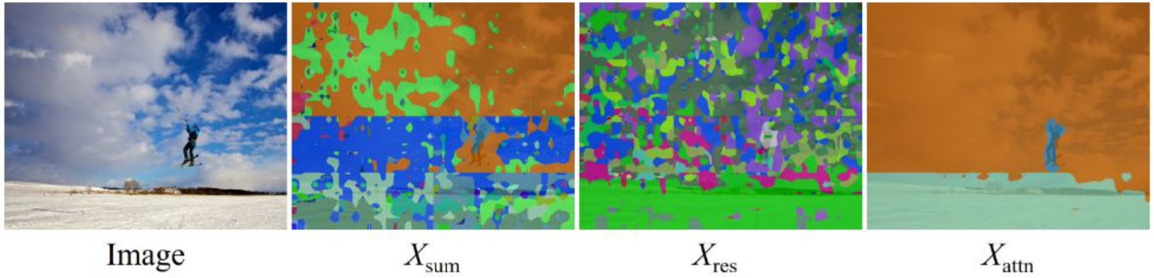


Fig. 2: Comparison of norms and mIoU of different attention mechanisms for CLIP-B/16 (left) and CLIP-L/14 (right). The norm curve of X_{attn} shows a positive correlation with the mIoU curve. A larger norm of X_{res} in CLIP-L/14 impedes the enhancement of performance through the revision of attention mechanisms.

LAN, Mengcheng, et al. Clearclip: Decomposing clip representations for dense vision-language inference. In: *European Conference on Computer Vision*. Cham: Springer Nature Switzerland, 2024. p. 143-160.

- **Noise가 어디서 왔는가?**
  - 가설 검증
    (1) X_res의 mIoU -> 0,
    (2) X_attn의 mIoU > X_sum의 mIoU 인 것을 보아,
    residual connection은 image segmentation에 도움이 전혀 안되고 있다.
  - 결론
    CLIP을 사용했을때 segmentation map의 noise는 residual connection에서 비롯되었다.

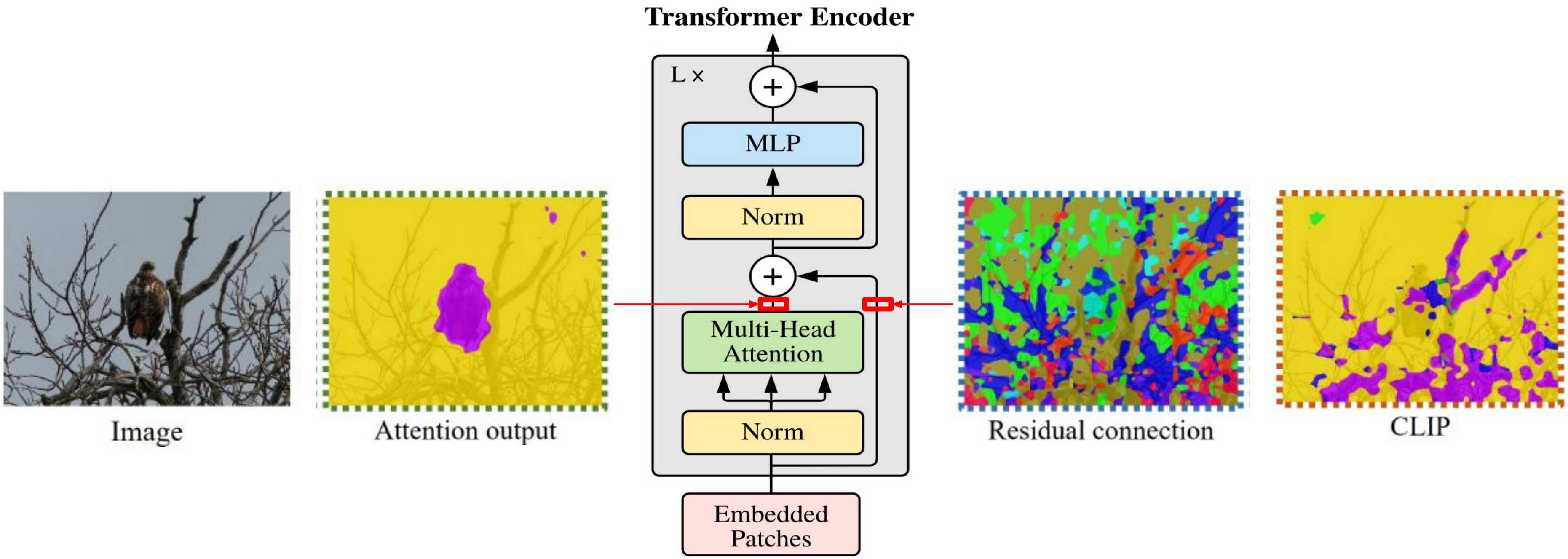


Features	mIoU
X_{sum}	4.4
X_{res}	0.01
X_{attn}	11.6

Fig. 3: Open-vocabulary semantic segmentation using different feature maps of CLIP-B/16 model on the COCOStuff dataset. A visualization of an example (left) and quantitative results (right).

LAN, Mengcheng, et al. Clearclip: Decomposing clip representations for dense vision-language inference. In: *European Conference on Computer Vision*. Cham: Springer Nature Switzerland, 2024. p. 143-160.

- **Noise가 어디서 왔는가?**



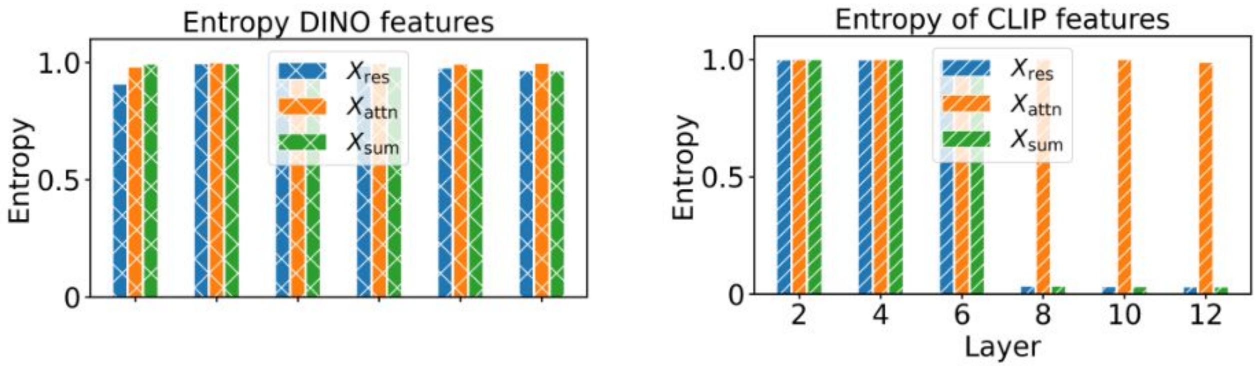
LAN, Mengcheng, et al. Clearclip: Decomposing clip representations for dense vision-language inference. In: *European Conference on Computer Vision*. Cham: Springer Nature Switzerland, 2024. p. 143-160.

- **Noise가 어떻게 발생하였는가 ?**

  ❑ 실험결과

  (1) DINO-B/16의 feature: 레이어 상관없이 엔트로피 값 일정하게 유지,
  CLIP-B/16의 feature: 레이어가 깊어짐에 따라 X_res와 X_sum의 엔트로피 값 급격히 (거의 0 수준까지) 감소.
  -> I.E., CLIP-B/16의 깊은 레이어의 X_res와 X_sum에 peak값들이 존재한다는 것.

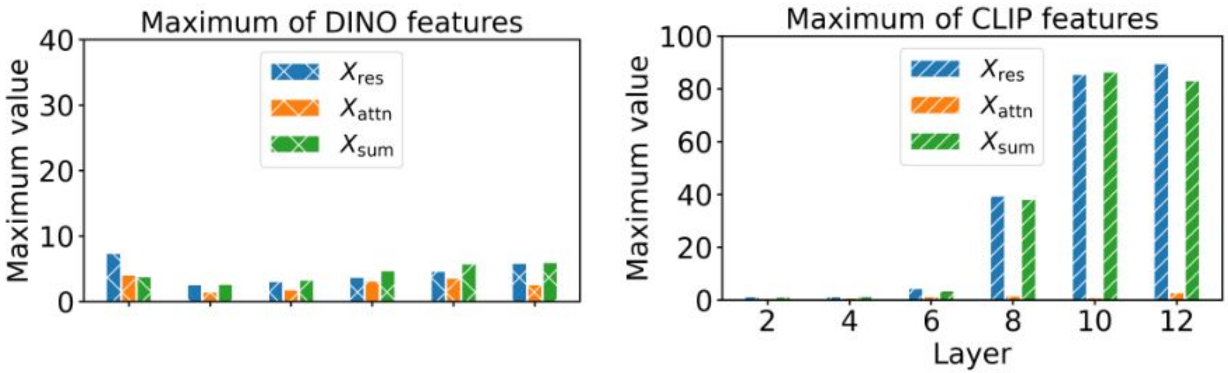
$$H(X^L) = -\frac{1}{\log(hw \times d)} \sum_{i,j} p(X^L_{i,j}) \log p(X^L_{i,j}), \quad p(X^L_{i,j}) = \frac{e^{X^L_{i,j}}}{\sum_{m,n} e^{X^L_{m,n}}}, \quad (5)$$



(a) Entropy

- **Noise가 어떻게 발생하였는가 ?**

  - 실험결과
    (2) DINO-B/16의 feature: 레이어 변함에 따라 최대값이 (10 이하로) 안정적으로 유지,
    CLIP-B/16의 feature: 레이어가 깊어짐에 따라 X_res와 X_sum의 최대값이 급격히 (초기보다 90배) 증가.
    -> 이것이 CLIP-B/16의 레이어가 깊어짐에 따라 X_res와 X_sum의 엔트로피 값 급격히 감소한 이유.
    -> I.E., X_res의 값 분포가 특정 채널/위치에 몰려있다.

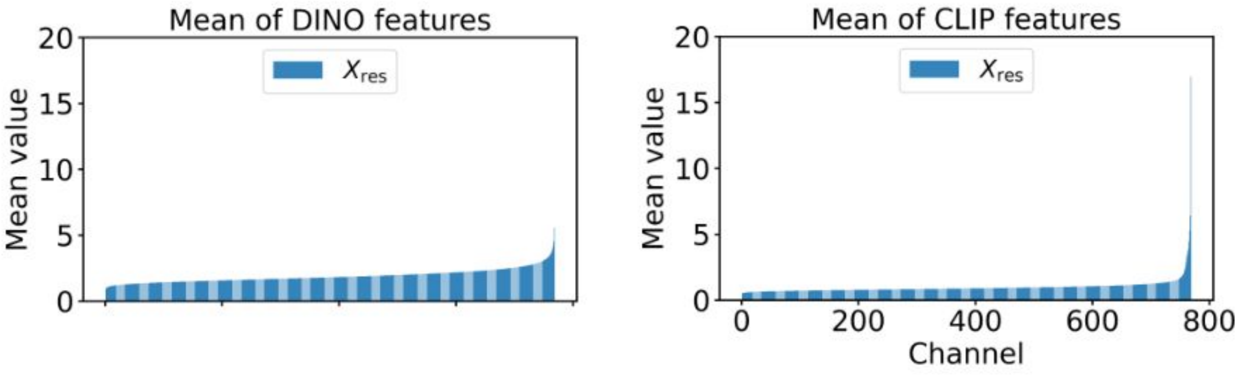


(b) Maximum

- **Noise가 어떻게 발생하였는가 ?**

  - 실험결과

    (3) DINO-B/16의 feature: 각 채널 별 X_res 평균값이 안정적으로 유지,
    CLIP-B/16의 feature: 소수의 특정 채널이 X_res 평균값의 peak들을 지배함.
    -> I.E., X_res의 값 분포가 특정 채널에 몰려있다.
    -> 각 feature들의 dominant channel이 같아, latent space에서 이 vector들의 방향이 유사하여, cosine similarity로 구분하기 어려움.
    -> 이는 global 정보를 중요시하는 image recognition task에서는 괜찮지만, local 정보를 중요시하는 dense prediction task에서는 부적합.



(c) Mean

LAN, Mengcheng, et al. Clearclip: Decomposing clip representations for dense vision-language inference. In: *European Conference on Computer Vision*. Cham: Springer Nature Switzerland, 2024. p. 143-160.

ECCV 2024

- **Noise가 어떻게 발생하였는가 ?**
  - ❑ 실험결과
    Residual connection의 영향을 줄일수록 성능 좋아진다.
  - ❑ 결론
    Residual connection 제거

$$X_{\mathrm{sum}} = X_{\mathrm{res}} + \alpha X_{\mathrm{attn}}$$

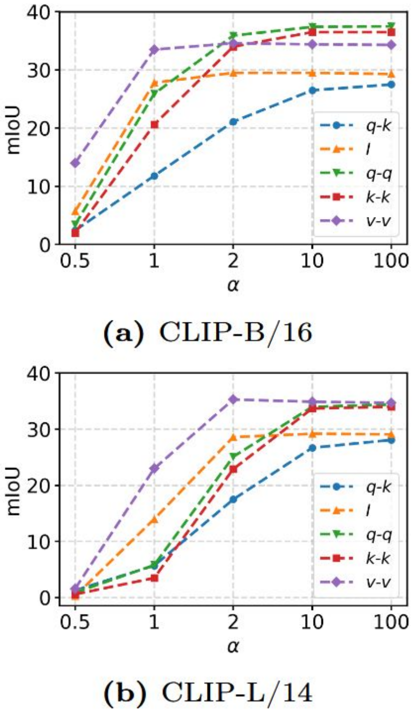


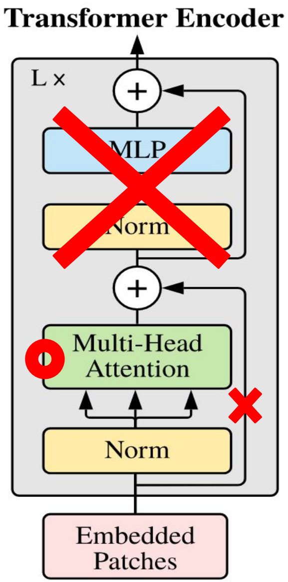
Fig. 6: Segmentation results w.r.t. the scaling factor α.

전유진

- **Conclusion**

1. Residual connection 제거
2. Feed-forward network 제거 (선행 연구 따라)
3. Query-query attention 적용 (선행 연구 따라)

$$X^{\text{visual}} = X_{\text{attn}} = \text{Proj}(\text{Attn}_{(\cdot)(\cdot)} \cdot v), \tag{6}$$



- **Experiments**

Table 1: Ablation results based on CLIP-B/16 architecture on five datasets *without* background class. RC denotes the residual connection.

Attn	RC	FFN	VOC20	Context59	Stuff	Cityscapes	ADE20k	Avg.
q-q	✓	✓	68.4	24.9	14.7	20.8	7.6	27.3
q-q	✓	✗	62.8	25.5	14.6	19.5	6.9	25.9
q-q	✗	✓	77.6	31.8	21.0	23.4	14.7	33.7
q-q	✗	✗	**80.9**	**35.9**	**23.9**	**30.0**	**16.7**	**37.5**

LAN, Mengcheng, et al. Clearclip: Decomposing clip representations for dense vision-language inference. In: *European Conference on Computer Vision*. Cham: Springer Nature Switzerland, 2024. p. 143-160.

- **Experiments**

Table 2: Open-vocabulary semantic segmentation quantitative comparison on datasets *without* a background class. † denotes results directly cited from TCL [6]. SCLIP* denotes our reproduced results under the standard setting without class re-name tricks.

Methods	Encoder	VOC20	Context59	Stuff	Cityscape	ADE20k	Avg.
GroupViT† [44]	ViT-S/16	79.7	23.4	15.3	11.1	9.2	27.7
CoCu [42]	ViT-S/16	-	-	13.6	15.0	11.1	-
TCL [6]	ViT-B/16	77.5	30.3	19.6	23.1	14.9	33.1
CLIP [35]	ViT-B/16	41.8	9.2	4.4	5.5	2.1	12.6
MaskCLIP† [56]	ViT-B/16	74.9	26.4	16.4	12.6	9.8	28.0
ReCo† [38]	ViT-B/16	57.7	22.3	14.8	21.1	11.2	25.4
CLIPSurgery [26]	ViT-B/16	-	-	21.9	**31.4**	-	-
SCLIP [40]	ViT-B/16	80.4	34.2	22.4	32.2	16.1	37.1
SCLIP* [40]	ViT-B/16	78.2	33.0	21.1	29.1	14.6	35.2
ClearCLIP	ViT-B/16	**80.9**	**35.9**	**23.9**	30.0	**16.7**	**37.5**
CLIP [35]	ViT-L/14	15.8	4.5	2.4	2.9	1.2	5.4
MaskCLIP [56]	ViT-L/14	30.1	12.6	8.9	10.1	6.9	13.7
SCLIP [40]	ViT-L/14	60.3	20.5	13.1	17.0	7.1	23.6
ClearCLIP	ViT-L/14	80.0	29.6	19.9	27.9	15.0	34.5

전유진

- **Experiments**

Table 3: Open-vocabulary semantic segmentation quantitative comparison on datasets *with* a background class. † denotes results directly cited from TCL [6]. SCLIP* denotes our reproduced results under the standard setting without class re-name tricks.

Methods	Encoder	VOC21	Context60	Object	Avg.
GroupViT† [44]	ViT-S/16	50.4	18.7	27.5	32.2
SegCLIP [30]	ViT-S/16	52.6	24.7	26.5	34.6
OVSegmentor [46]	ViT-B/16	**53.8**	20.4	25.1	33.1
PGSeg [54]	ViT-S/16	53.2	23.8	28.7	35.2
ViewCo [36]	ViT-S/16	52.4	23.0	23.5	33.0
CoCu [42]	ViT-S/16	40.9	21.2	20.3	27.5
TCL [6]	ViT-B/16	51.2	24.3	30.4	35.3
CLIP [35]	ViT-B/16	16.2	7.7	5.5	9.8
MaskCLIP† [56]	ViT-B/16	38.8	23.6	20.6	27.7
ReCo† [38]	ViT-B/16	25.1	19.9	15.7	20.2
CLIPSurgery [26]	ViT-B/16	-	29.3	-	-
GEM [3]	ViT-B/16	46.2	**32.6**	-	-
SCLIP [40]	ViT-B/16	59.1	30.4	30.5	40.0
SCLIP* [40]	ViT-B/16	51.4	30.5	30.0	37.3
ClearCLIP	ViT-B/16	51.8	**32.6**	**33.0**	**39.1**

- **Experiments**

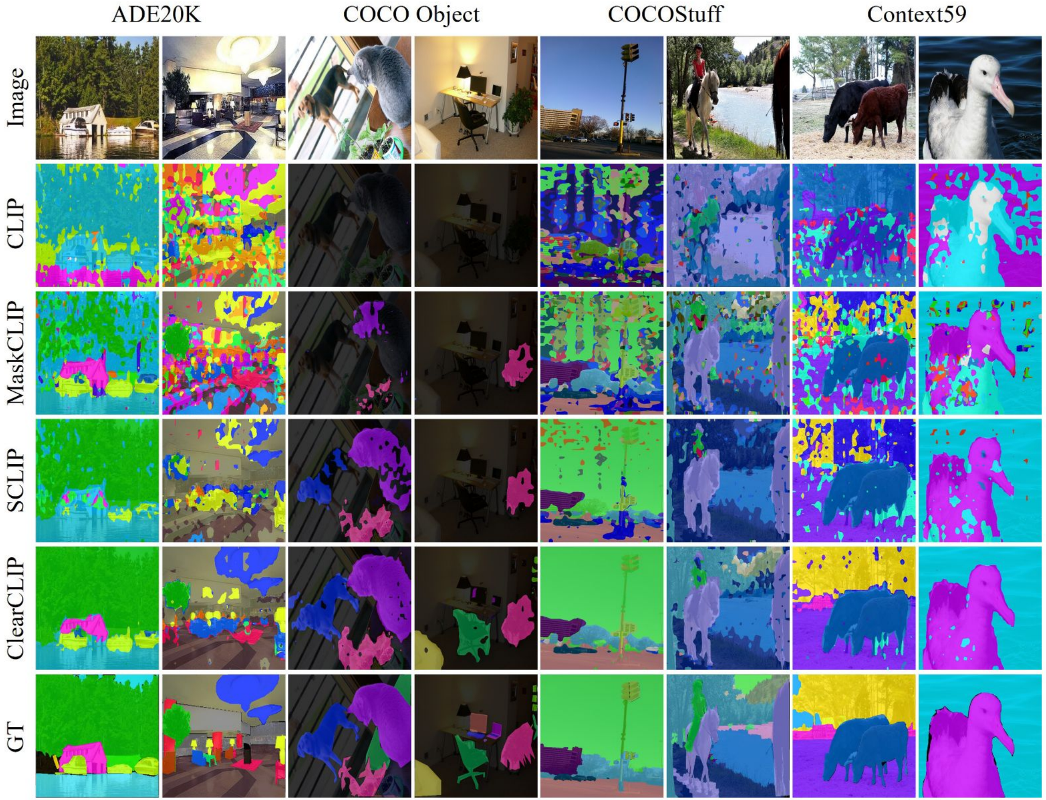


Fig. 7: Qualitative comparison between open-vocabulary segmentation methods.