Vision Transformers II

Rethinking Semantic Segmentation from a Sequence-to-Sequence Perspective with Transformers

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Outline

CNN Recap

- CNNs have long been the SOTA for performing computer vision tasks with deep learning
- CNNs learn to extract image features using stacked convolutional kernels and downsampling
  - This architecture makes CNNs translationally equivariant and locally shift invariant
  - It also introduces a strong inductive bias and assumed locality
- Problem: Learning long-range dependencies is fundamentally difficult because of limited receptive fields.
  - Recent developments towards solving this issue include the use of larger kernel sizes, dilated (atrous) convolutions, and feature pyramids

Enter the Vision Transformer (ViT)

- Dosovitskiy et al. [2020] introduced the idea of the Vision Transformer as a pure transformer architecture for image classification
- ViT processes images by reducing them to a sequence of patches which can be treated in the same way as tokens in a NLP setting, and used as inputs to a transformer decoder
  - Unlike CNNs, ViT has very little image-specific inductive bias. As a result, performance is worse than CNNs on smaller datasets, but with sufficient pre-training, ViT can out-perform CNNs
- Zheng et al. [2020] expand the use of ViT to semantic segmentation
  - This is pixel level rather than image level classification
  - Segmentation models are usually Fully Convolutional Networks (they only contain convolutional and sampling layers)

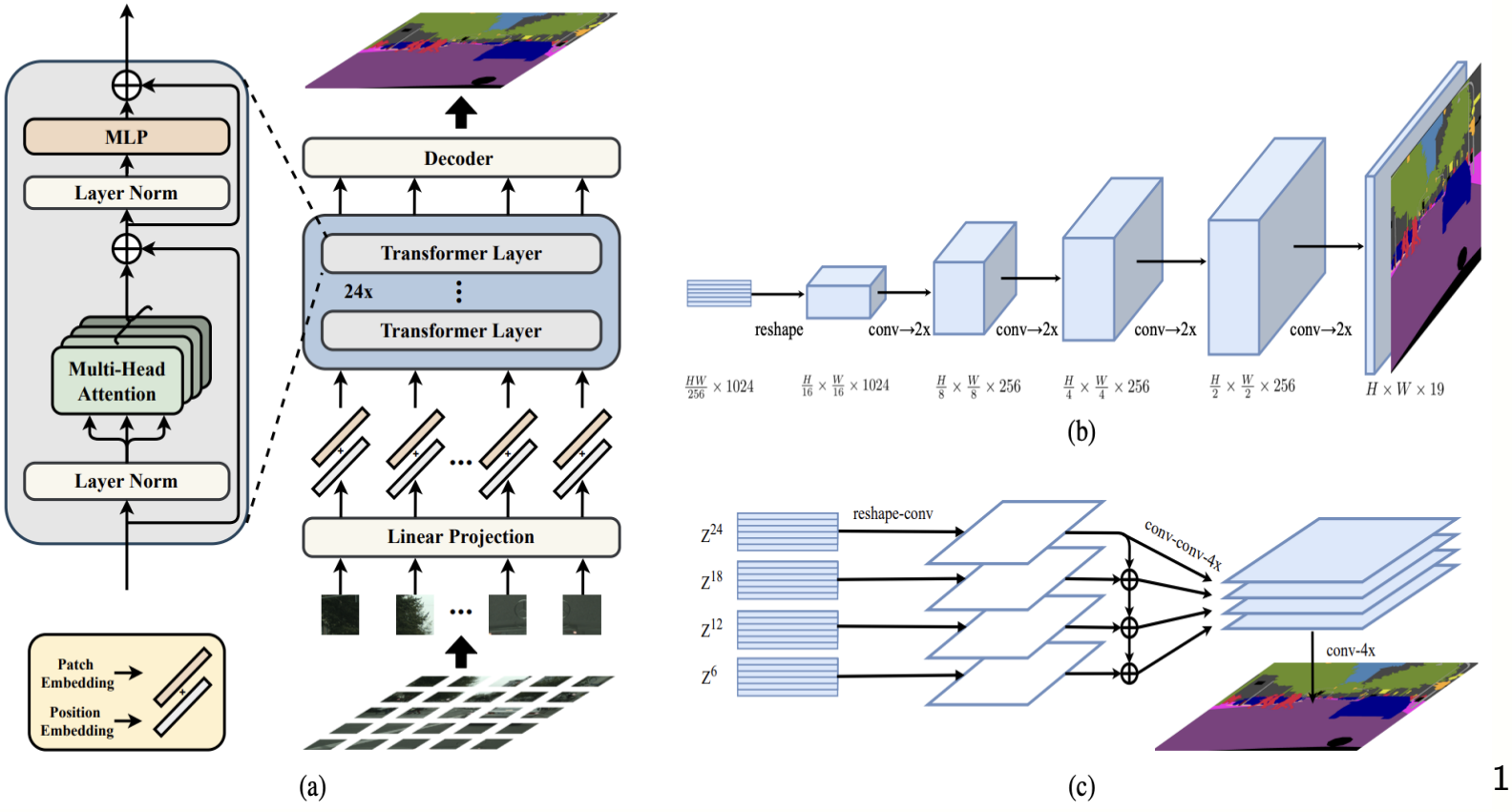
SETR

- Zheng et al. [2020] introduce the SEgmentation TRansformer (SETR)
  - Like ViT, SETR has a decoder arm consisting of transformer layers which accept a sequence of image patch representations
  - SETR replaces the ViT classification head with a decoder arm which generates a pixel-wise segmentation from the transformer features
- SETR was shown to give SOTA performance on two benchmark datasets, ADE20K and Pascal Context

Encoder recap

- Transformer accepts a 1D sequence of feature embeddings $Z \in \mathbb{R}^{L \times C}$ where L is the length of the sequence and C is the hidden channel size
  - Image sequentialization is needed to convert an image $x \in \mathbb{R}^{HxWx3}$ into Z (where 3 is the number of channels)
- A typical CNN encoder would downsample a 2D image into a feature map $x_f \in \mathbb{R}^{\frac{H}{16} x \frac{W}{16} x C}$
- Transformer sequence length L can therefore be set as $\frac{H}{16} x \frac{W}{16} = \frac{HW}{256}$
- To obtain the sequence of length $\frac{HW}{256}$, we divide the image $x \in \mathbb{R}^{HxWx3}$ into a uniform grid $\frac{H}{16} x \frac{W}{16}$, and then flatten this grid into a sequence
- Each vectorized patch p is further mapped into a latent C-dimensional embedding space using a linear projection function $f : p \rightarrow e \in \mathbb{R}^C$
- To encode spatial information, we learn a position encoding p_i for every location i which is added to e_i to form the final sequence input $E = \{e_1 + p_1, e_2 + p_2, ..., e_L + p_L\}$

Architecture



[1]

[1] Zheng et al. [2020]

Transformer

- Given the 1D embedding space E as input, a pure transformer-based encoder is employed to learn feature representations
  - The transformer encoder architecture consists of L_e layers of multi-head self-attention (MSA) and Multilayer Perceptron (MLP) blocks
- This means each transformer layer has a global receptive field
- Transformer features are denoted as $\{Z^1, Z^2, ..., Z^{L_e}\}$ where each feature vector Z has shape $\frac{HW}{256} xC$
- Note that Zheng et al. [2020] include two variants, T-Base where $C = 768$ and T-Large where $C = 1024$

Model	T-layers	Hidden size	Att head
T-Base	12	768	12
T-Large	24	1024	16

[2]

[2] Zheng et al. [2020]

SETR decoders

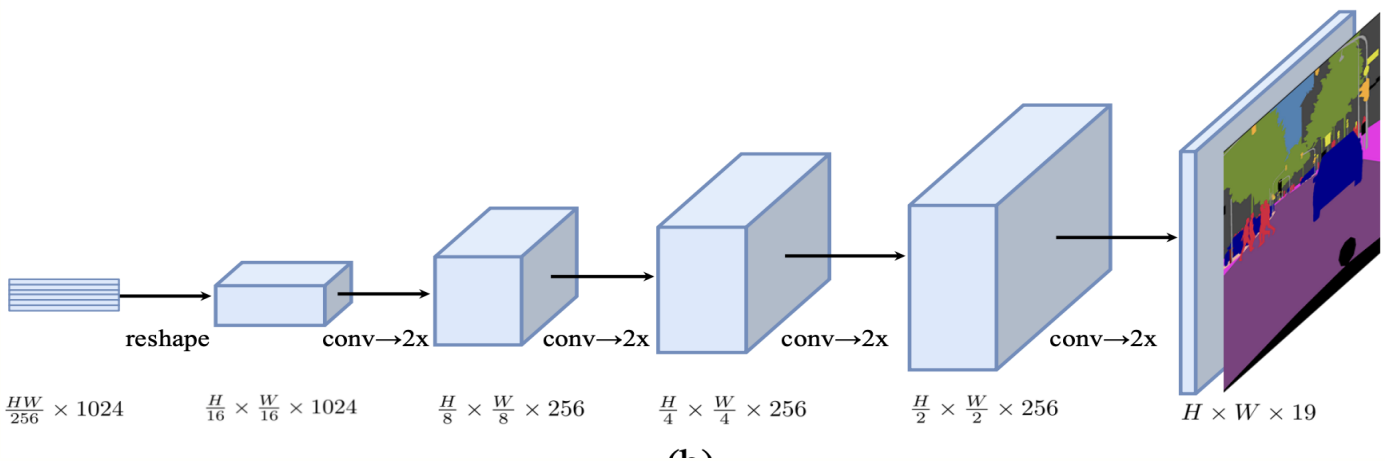
- The goal of the decoder is to generate the segmentation results in the original 2D image space *HxW*
  - To achieve this we need to reshape the encoder's features (Z) from a 2D shape of $\frac{HW}{256}xC$ to a standard 3D feature map $\frac{H}{16}x\frac{W}{16}xC$
  - The reshaped feature map is then fed into a decoder
- SETR compares three decoder designs:
  - Naive upsampling
  - Progressive upsampling (PUP)
  - Multi-Level feature Aggregation (MLA)

Naive upsampling

- First the transformer feature Z^{L_e} is projected into the dimension of the category number
  - e.g. ADE20K has 150 classes, so Z^{L_e} is projected from shape $\frac{H}{16}x\frac{W}{16}x1024$ to $\frac{H}{16}x\frac{W}{16}x150$ (for T-Large)
- This is done using a simple 2-layer architecture: 1x1 conv + (sync) batch norm + 1x1 conv
- Then bilinearly upsample the output to full image resolution, followed by a classification layer with pixel-wise cross-entropy loss

Progressive UPsampling (PUP)

- Instead of one-step upscaling, PUP uses a progressive upsampling strategy that alternates conv layers with upsampling operations
- Upsampling is restricted to 2x, so 4 operations are required to get back to the original image resolution



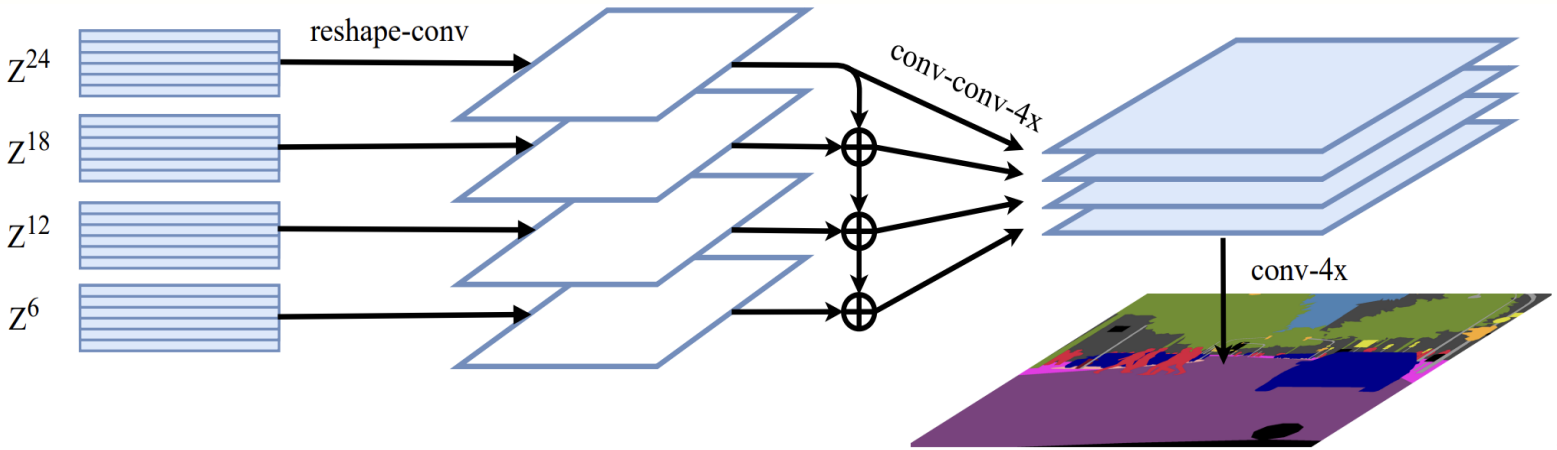
[3]

[3] Zheng et al. [2020]

Multi-Level feature Aggregation (MLA)

- Recall that each feature representation Z^l has the same shape $(\frac{HW}{256}xC)$
- Take as input the feature representations $\{Z^m\}(m \in \{\frac{L_e}{M}, 2\frac{L_e}{M}, ..., M\frac{L_e}{M}\}$ from M layers uniformly distributed across the layers with step $\frac{L_e}{M}$
- Then deploy M streams with each focusing on one specific layer
  - Within each stream we first reshape Z^l to $\frac{H}{16}x\frac{W}{16}xC$
  - A 3-layer (kernel size 1x1, 3x3, 3x3) network is applied with the feature channels halved at the first and third layer respectively
  - To enhance interaction across the streams, top-down aggregations via element-wise addition performed after the first layer
  - This is followed by 4x bilinear upscaling
- After the third convolutional layer, the feature maps are fused via channel-wise concatenation
- The fused feature map is then bilinearly upsampled 4x to obtain the original image resolution

SETR-MLA



[4]

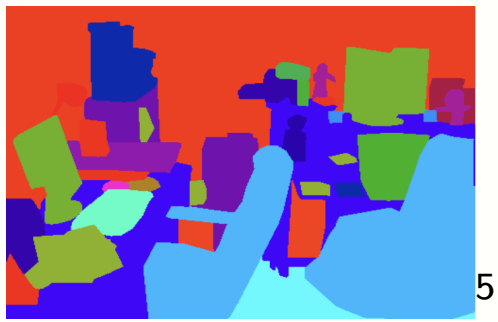
[4] Zheng et al. [2020]

Auxiliary loss

- All three decoder variants are trained using pixel-wise cross-entropy loss
- Zheng et al. [2020] also introduce auxiliary loss heads, using the outputs from different encoder layers
  - SETR-Naive: Layers 10,15,20
  - SETR-PUP: Layers 10,15,20,24
  - SETR-MLA: Layers 6,12,18,24
- Outputs are sent through a two layer Feed-Forward Network before bilinear interpolation
- $Loss = L_{CE} + \gamma \sum_i L_{Aux_i}$

Datasets

- Cityscapes [Cordts et al., 2016]
  - 19 object classes, 3K training images, 500 val images, 1500 test images
- ADE20K [Zhou et al., 2017]
  - 150 semantic classes, 20k training images, 2k val images, 3k test images
  - Challenging scene parsing benchmark
- Pascal Context [Mottaghi et al., 2014]
  - 60 most frequent classes, 5k training images, 5k val
  - Segments whole scene into "thing" and "stuff" classes

[5]

[5] Mottaghi et al. [2014]

Implementation details

- Augmentation pipeline applies random resizing, random horizontal flipping, random cropping
- Batch size 16 for ADE20K and Pascal Context, 8 for Cityscapes
- Polynomial learning rate decay schedule with SGD optimizer
  - Initial learning rate of 0.001 on ADE20K and Pascal, 0.01 on Cityscapes
- Patch size 16x16
- Pre-trained weights from ViT [Dosovitskiy et al., 2020] or DeiT [Touvron et al., 2021] to initialise transformer layers
- Evaluation using Mean Intersection Over Union (mIOU)

Comparing SETR variants

- Comparison of different pre-training strategies and backbones
  - "Pre" denotes the pre-training of transformer part. "R" means the transformer part is randomly initialized [Zheng et al., 2020]
  - Training dataset used is either ImageNet-1k or ImageNet-21k
  - Evaluated on Cityscapes validation set
  - R-101 = ResNet-101

Method	Pre	Backbone	#Params	40k	80k
FCN [39]	1K	R-101	68.59M	73.93	75.52
Semantic FPN [39]	1K	R-101	47.51M	-	75.80
Hybrid-Base	R	T-Base	112.59M	74.48	77.36
Hybrid-Base	21K	T-Base	112.59M	76.76	76.57
Hybrid-DeiT	21K	T-Base	112.59M	77.42	78.28
SETR-*Naïve*	21K	T-Large	305.67M	77.37	77.90
SETR-*MLA*	21K	T-Large	310.57M	76.65	77.24
SETR-*PUP*	21K	T-Large	318.31M	78.39	79.34
SETR-*PUP*	R	T-Large	318.31M	42.27	-
SETR-*Naïve-Base*	21K	T-Base	87.69M	75.54	76.25
SETR-*MLA-Base*	21K	T-Base	92.59M	75.60	76.87
SETR-*PUP-Base*	21K	T-Base	97.64M	76.71	78.02
SETR-*Naïve-DeiT*	1K	T-Base	87.69M	77.85	78.66
SETR-*MLA-DeiT*	1K	T-Base	92.59M	78.04	78.98
SETR-*PUP-DeiT*	1K	T-Base	97.64M	**78.79**	**79.45**

[6]

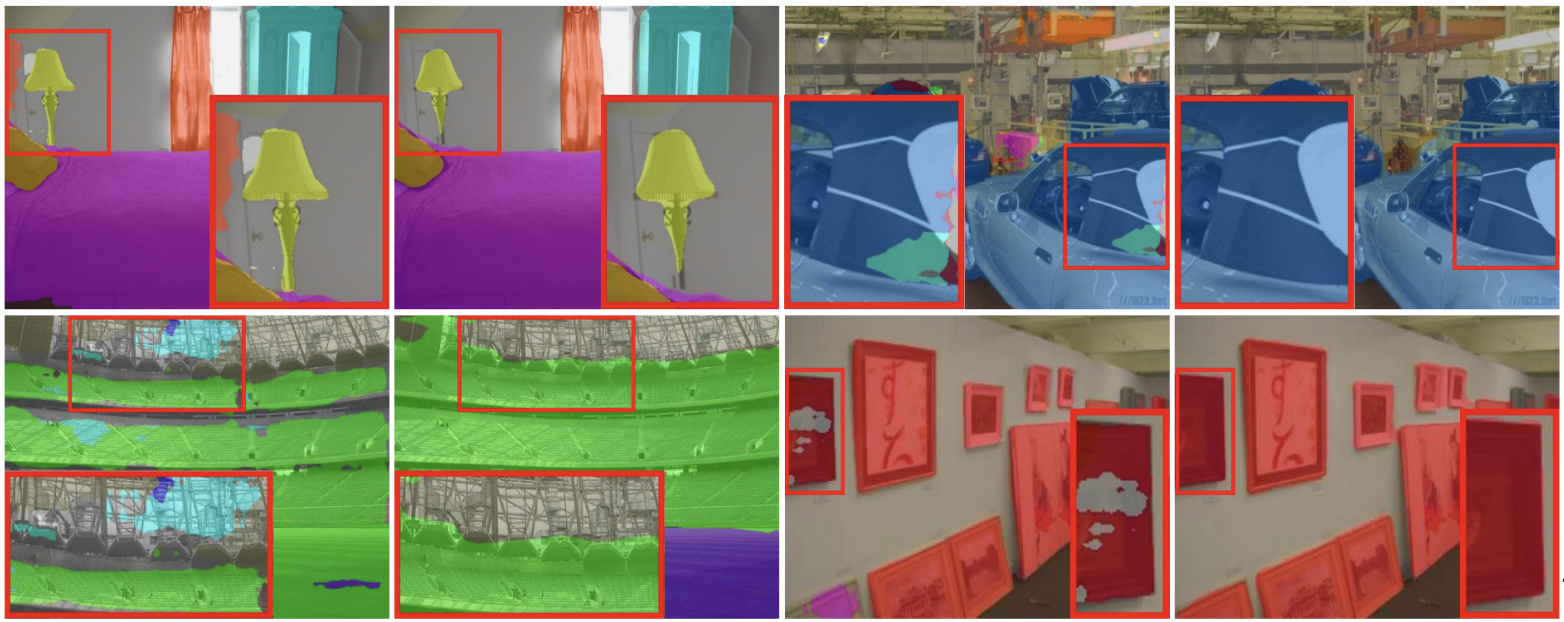
[6] Zheng et al. [2020]

Comparison to SOTA

- ADE20K
  - All SETR variants beat previous SOTA
  - SETR-MLA achieves superior mIOU of 52.8% compared to previous SOTA of 46.4%
- Pascal Context
  - SETR-MLA achieves mIOU of 55.83%, compared to previous SOTA of 54.7%
- Cityscapes
  - Performs well but slightly behind other methods, with SETR-PUP achieving 81.64% compared to SOTA at 81.9%

Qualitative results

ADE20K

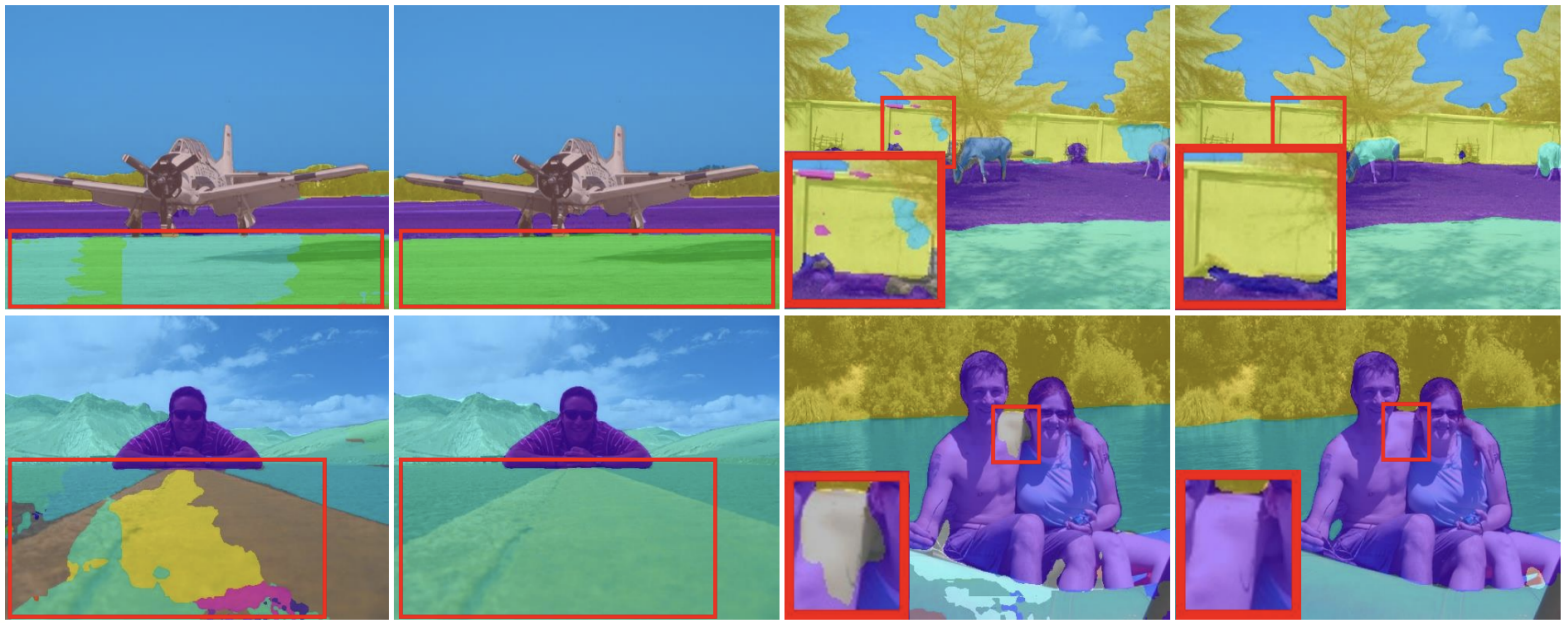


[7]

[7] Zheng et al. [2020]

Qualitative results

Pascal Context



[8]

[8] Zheng et al. [2020]

Qualitative results

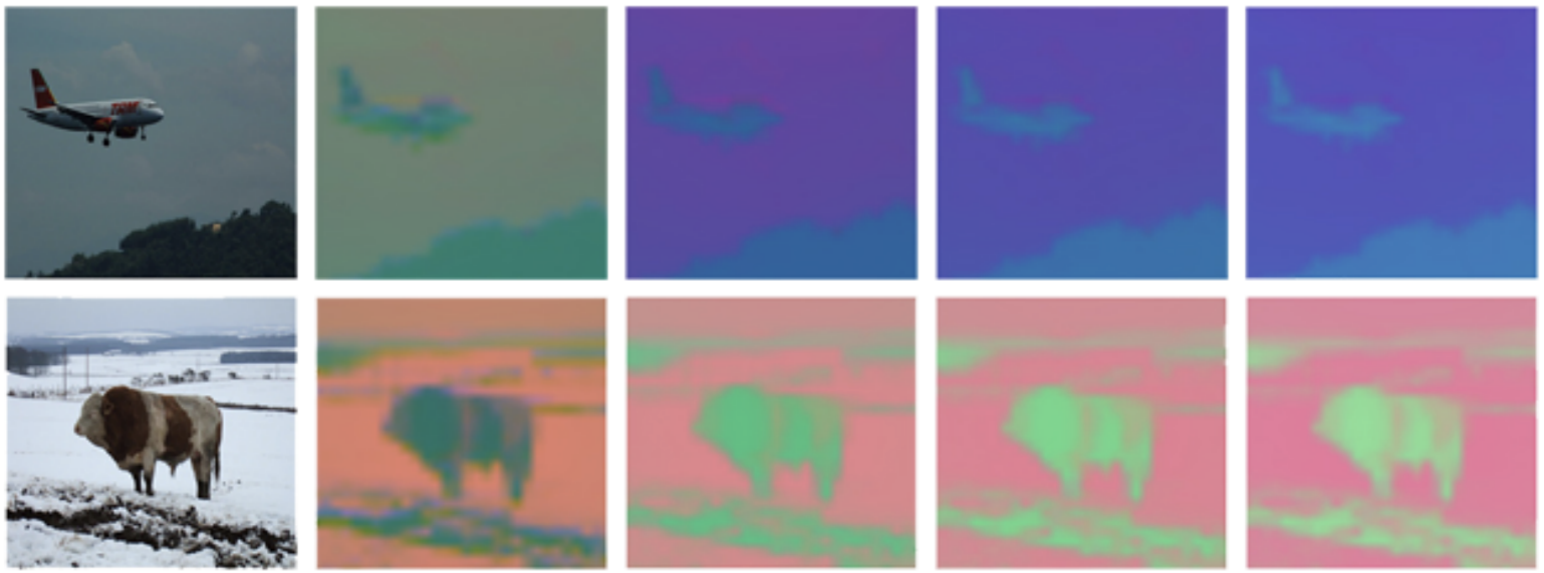
Cityscapes

[9]

[9] Zheng et al. [2020]

Qualitative results

Feature visualisations (layers 1, 9, 17, and 24)



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[10] Zheng et al. [2020]

Qualitative results

Attention maps

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[11] Zheng et al. [2020]

Conclusions

- Presented an alternative perspective for semantic segmentation by introducing a sequence-to-sequence prediction framework [Zheng et al., 2020]
- SETR performs well on three standard benchmarking datasets
- Removes reliance on FCN for image segmentation tasks
- Solves issue of limited receptive fields

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