Innía





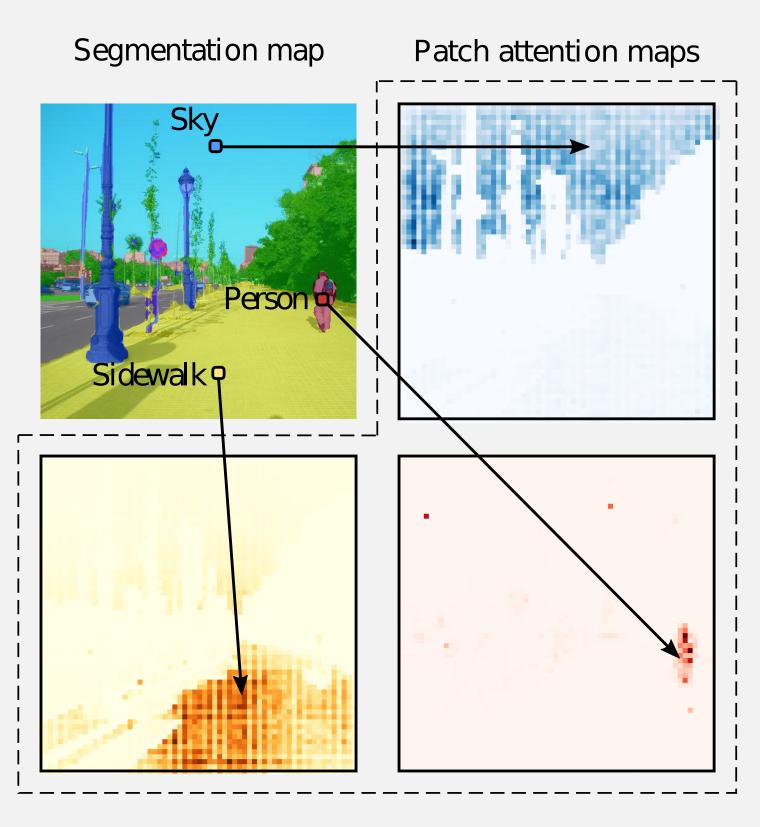
Motivation

State-of-the-art methods deploy Fully Convolutional Networks (FCN) to achieve excellent results on Semantic Segmentation.

- The local nature of convolutional filters, however, results in features capturing only local context coming from neighbouring pixels.

- Global information is key to perform accurate segmentation as pixel level labeling often depends on the global image context.

- Transformer architectures can be used to leverage contextual information at every layer of the model:



Contributions

1. Novel approach to semantic segmentation based on ViT, capturing contextual information by design

2. Transformer-based decoder generating class masks for general image segmentation tasks.

3. State-of-the-art performance on ADE20K and Pascal Context.



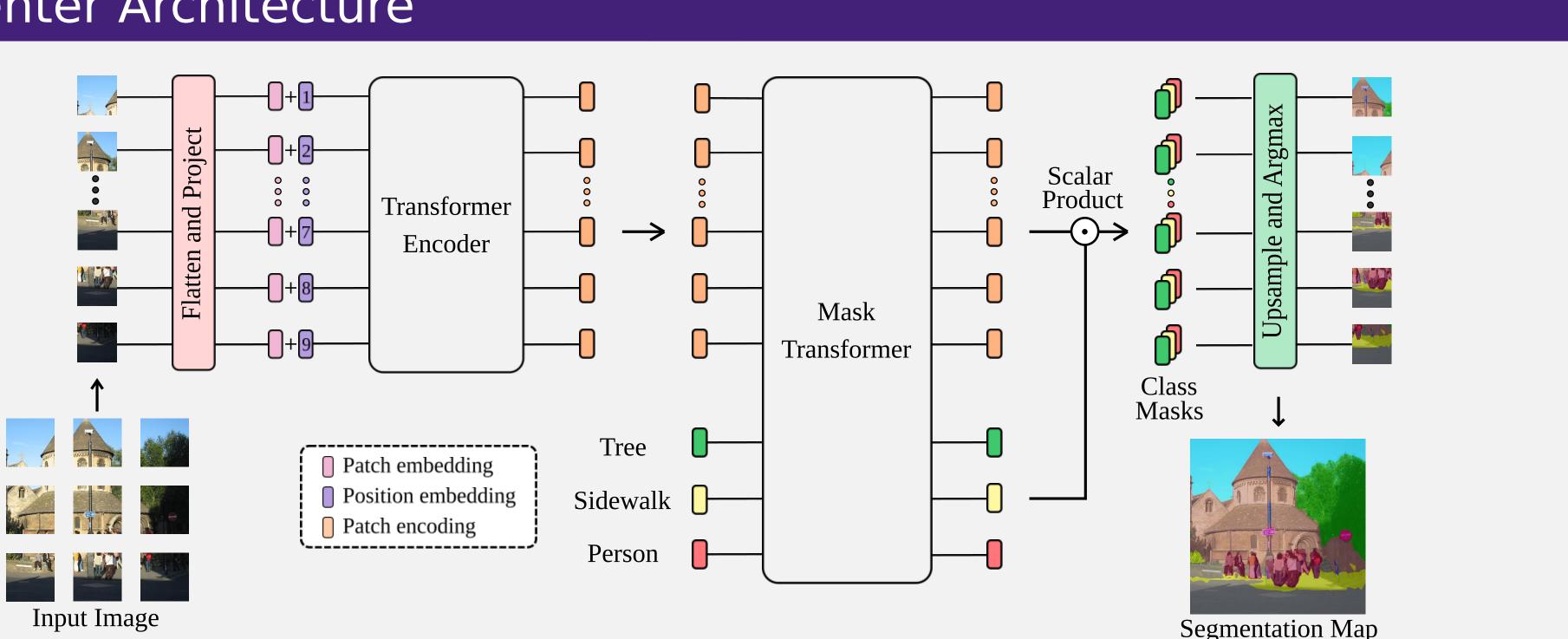
github.com/rstrudel/segmenter



Segmenter: Transformer for Semantic Segmentation

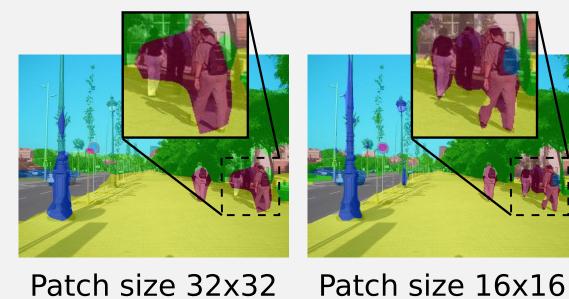
Robin Strudel^{* 1,2}, Ricardo Garcia^{* 1,2}, Ivan Laptev^{1,2}, Cordelia Schmid^{1,2} ²DI ENS, PSL ¹INRIA Paris

Segmenter Architecture

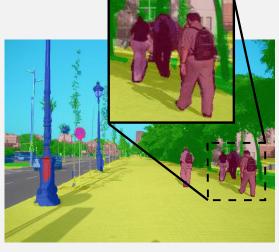


(Left) Encoder: The image patches are projected to a sequence of embeddings and then encoded with a transformer. (Right) Decoder: A mask transformer takes as input the output of the encoder and class embeddings to predict segmentation masks.

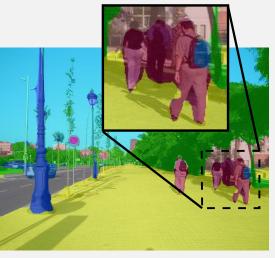
Impact of Patch Size

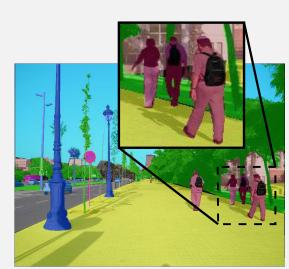


Patch size 32x32



Patch size 8x8





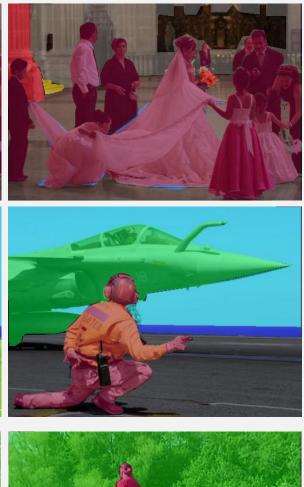
Ground Truth

Smaller patch size results in:

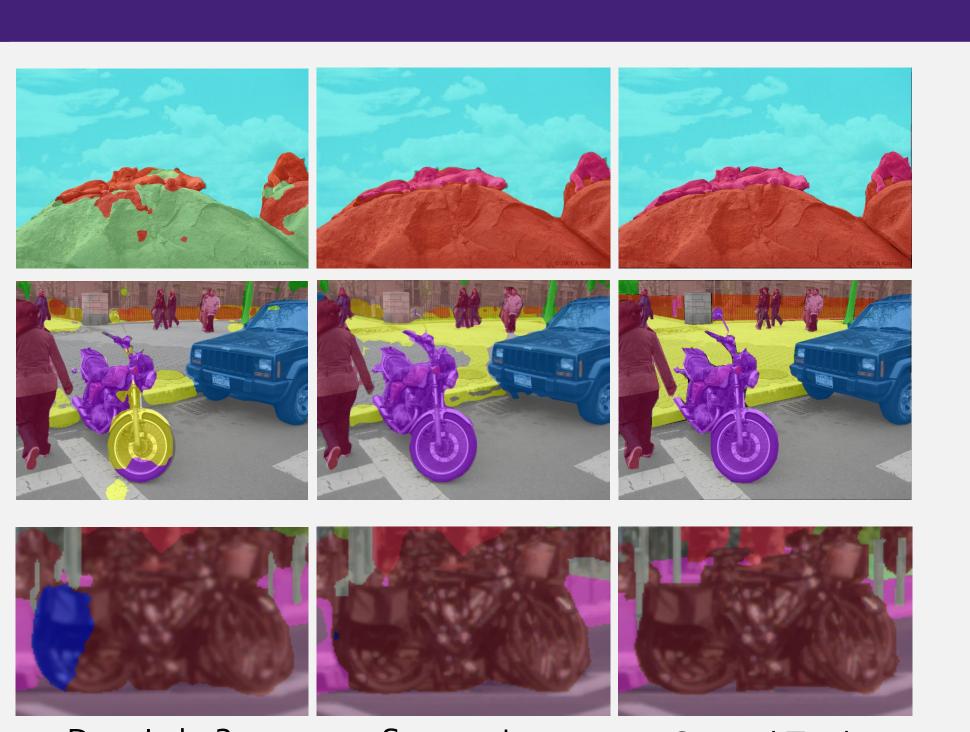
- Better boundaries in segmentation masks.

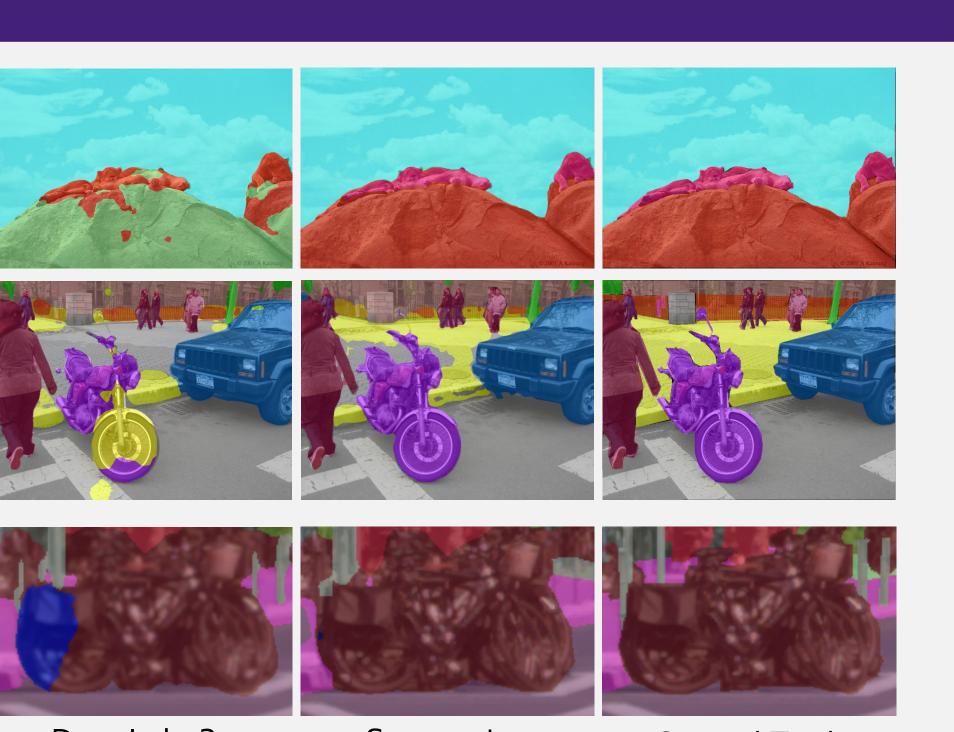
- Longer sequences, increasing the compute time and memory footprint.

Qualitative Results









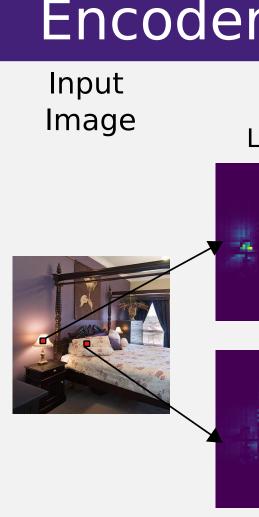
DeepLabv3+

Segmenter

Ground Truth

State-of-the-art ADE20K

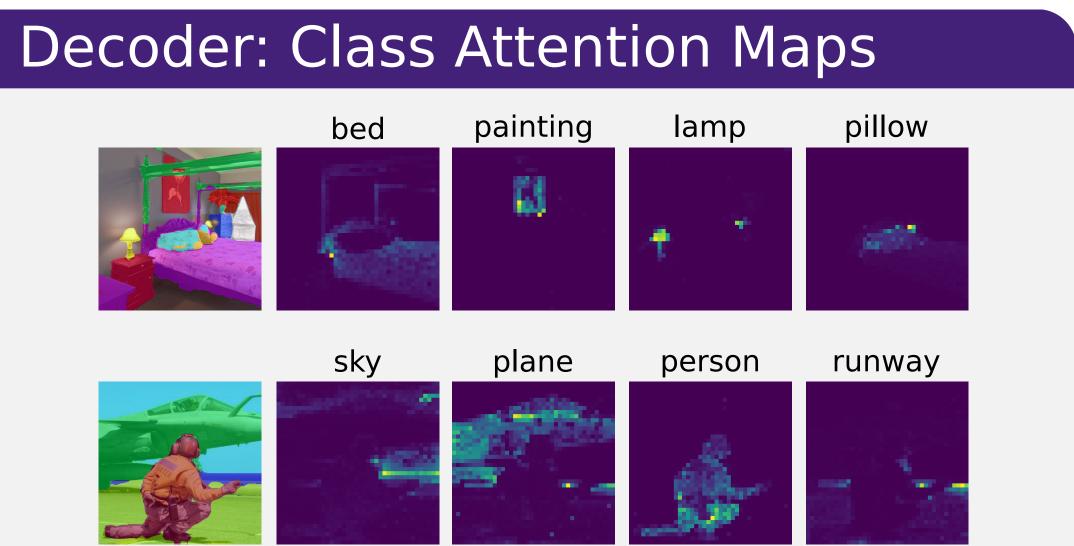
Method	Backbone	Im/sec	mIoU	+MS
	Duckeone	1114 500	inice	1110
OCR [60]	HRNetV2-W48	83	-	45.66
ACNet [24]	ResNet-101	-	-	45.90
DNL [57]	ResNet-101	-	-	45.97
DRANet [22]	ResNet-101	-	-	46.18
CPNet [58]	ResNet-101	-	-	46.27
DeepLabv3+ [10]	ResNet-101	76	45.47	46.35
DeepLabv3+ [10]	ResNeSt-101	15	46.47	47.27
DeepLabv3+ [10]	ResNeSt-200	-	-	48.36
SETR-L MLA [67]	ViT-L/16	34	48.64	50.28
Swin-L UperNet [35]	Swin-L/16	34	52.10	53.50
Seg-B [†] /16	DeiT-B/16	77	47.08	48.05
Seg-B [†] -Mask/16	DeiT-B/16	76	48.70	50.08
Seg-L/16	ViT-L/16	33	50.71	52.25
Seg-L-Mask/16	ViT-L/16	31	51.82	53.63

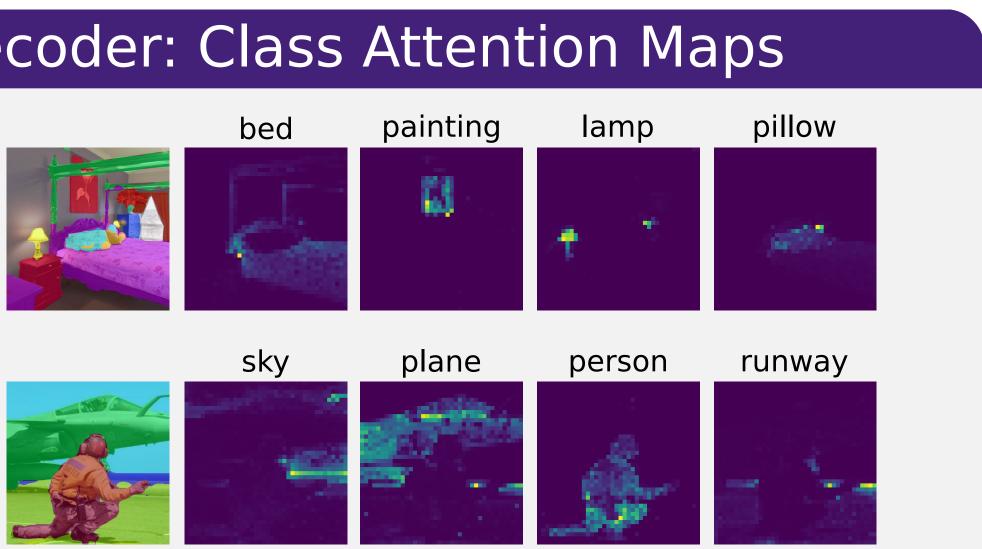


The attention map field-of-view adapts to the input image and instances size:

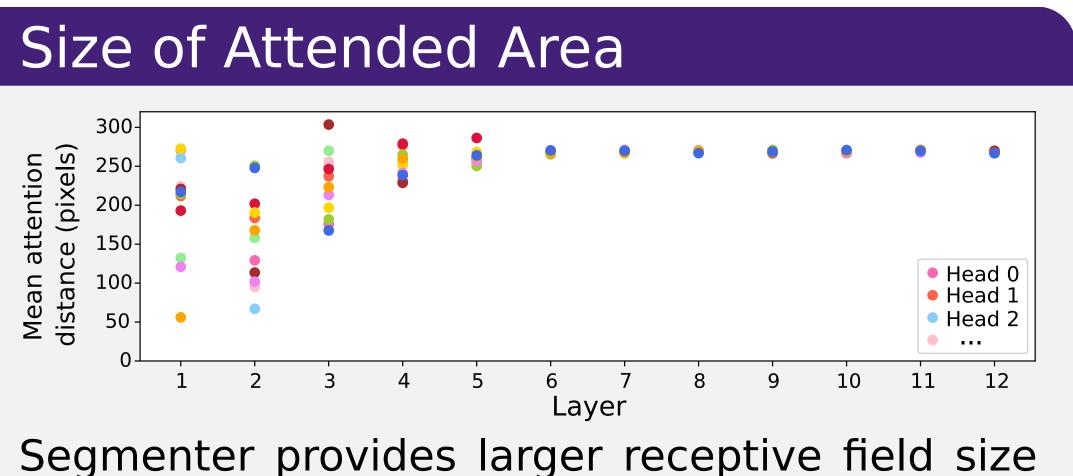
- Gathering global information on large instances, such as the bed.

- Focusing on local information on smaller instances, such as the lamp.





Class embeddings from the mask transformer attends to patch embeddings corresponding to its class in the input image.



than CNNs.

Already at the first layer, some heads attend to most of the image and distant patches which clearly lie outside the receptive field ResNet. initial layers.

DeepLabv3+

Segmenter

Ground Truth



CCV OCTOBER 11-17

Encoder: Patch Attention Maps

	Prediction			
Layer 1	Layer 4	Layer 8	Layer 11	Seg. Map
			-	