How Segmentation Model Learns?

Review: Per-Pixel Classification is Not All You Need for Semantic Segmentation

Bowen Cheng et al.

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Sungguk Cha

TL; DR

- We introduce **how segmentation models can learn.**
- We review Per-Pixel Classification is Not All You Need for Semantic Segmentation

  which **compares learning methods**.

Contents

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Introduction to Learning to Segment

- Image Classification to Segmentation
- Per-pixel Classification vs Mask Classification

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Image Classification to Segmentation

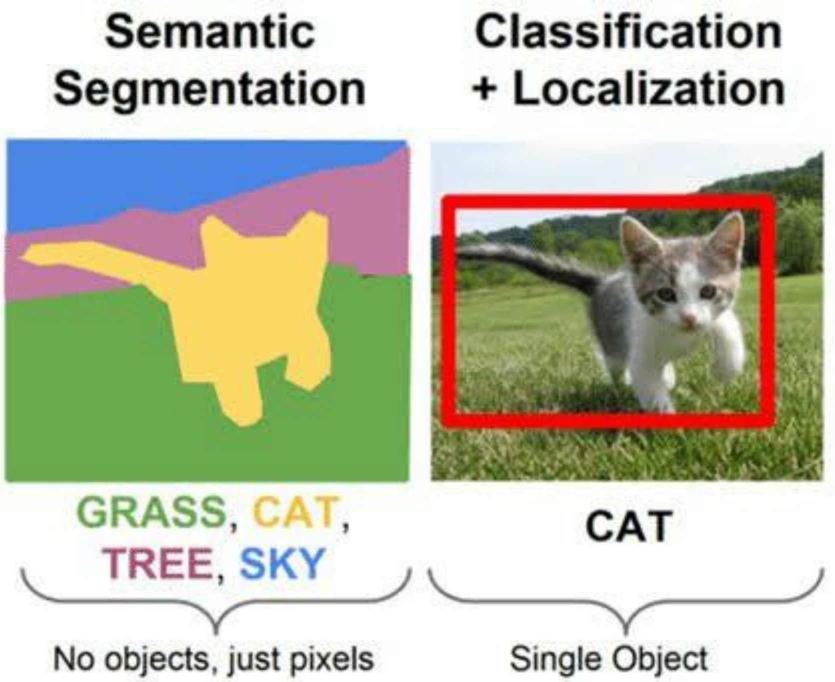

Image Source: https://www.quora.com/What-is-the-difference-between-segmentation-and-classification-in-image-processing

Image Classification to Segmentation

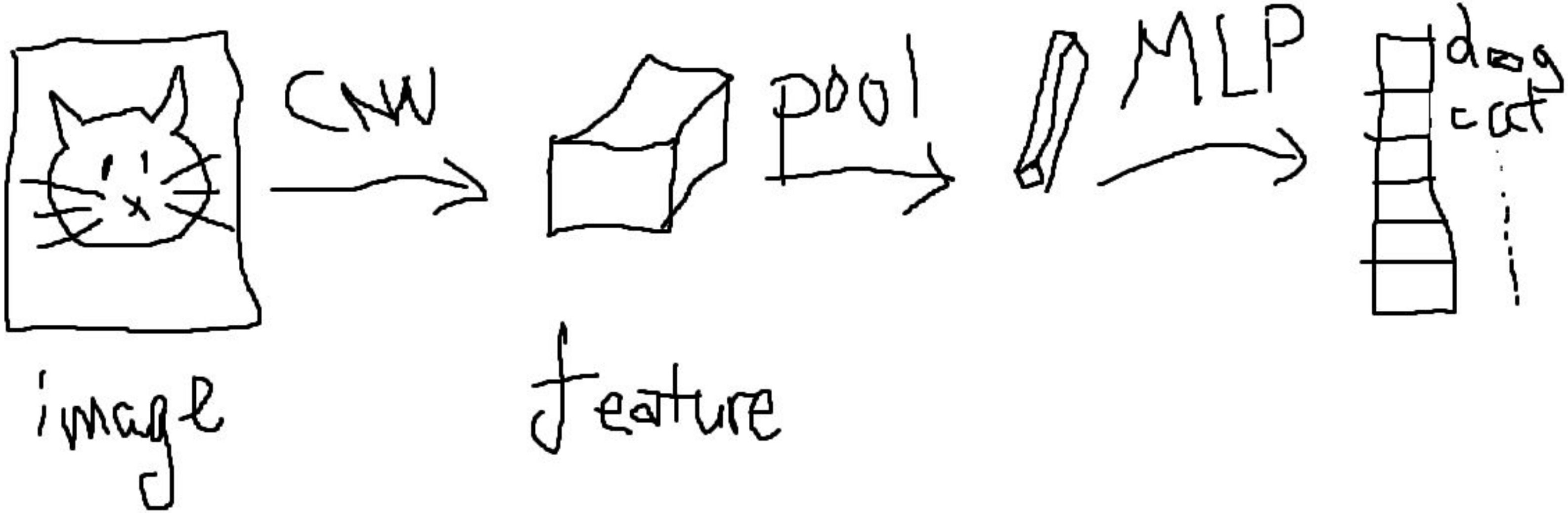

Fig. Image classification overview

Image Classification to Segmentation

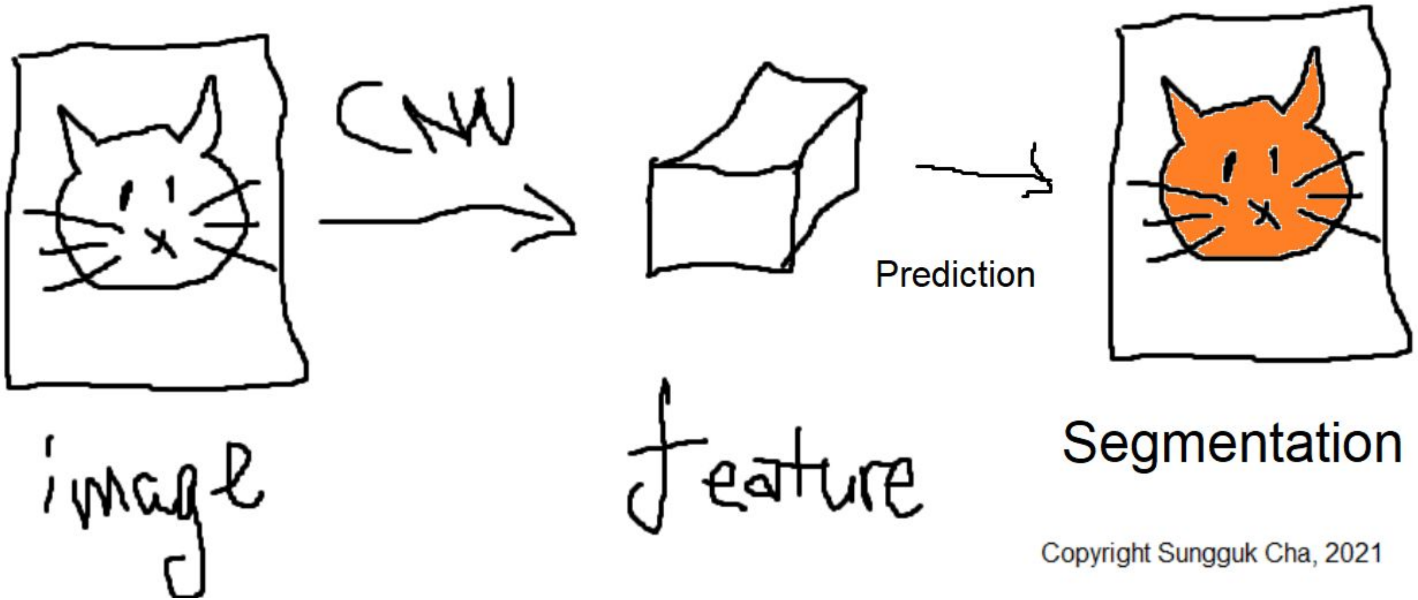

Fig. Image segmentation overview

Introduction to Learning to Segment

- Image Classification to Segmentation
- Per-pixel Classification vs Mask Classification

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Per-pixel Classification vs Mask Classification

Per-pixel Classification vs Mask Classification

- It can be seen as comparing

pixel-level supervision

vs

object-level supervision

Pixel-level Supervision

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Fully convolutional networks (FCN), U-Net, Deeplabs and SegFormer represent it.

Pixel-level Supervision

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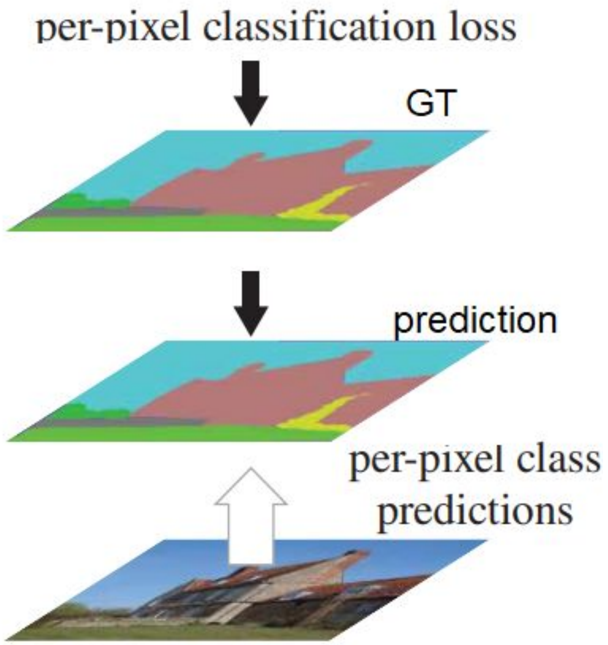


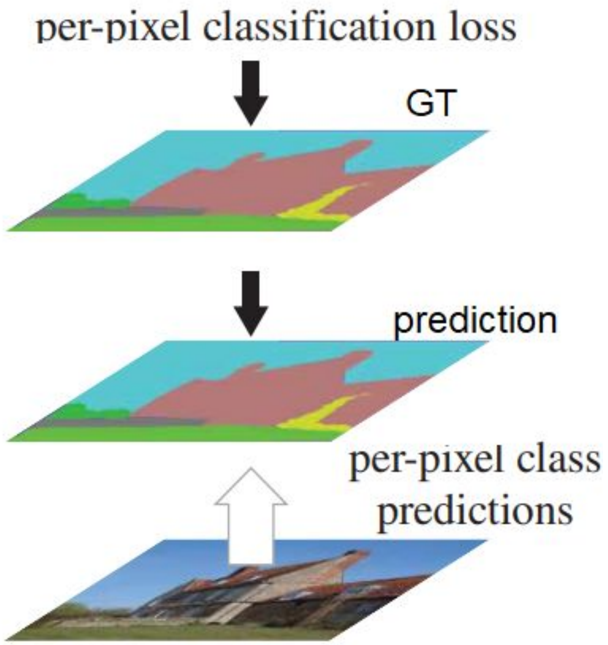
Original source: MaskFormer, Sungguk Cha edited

Pixel-level Supervision

Fully convolutional networks (FCN), U-Net, Deeplabs and SegFormer represent it.

It predicts the whole at once,

and supervises it at once.



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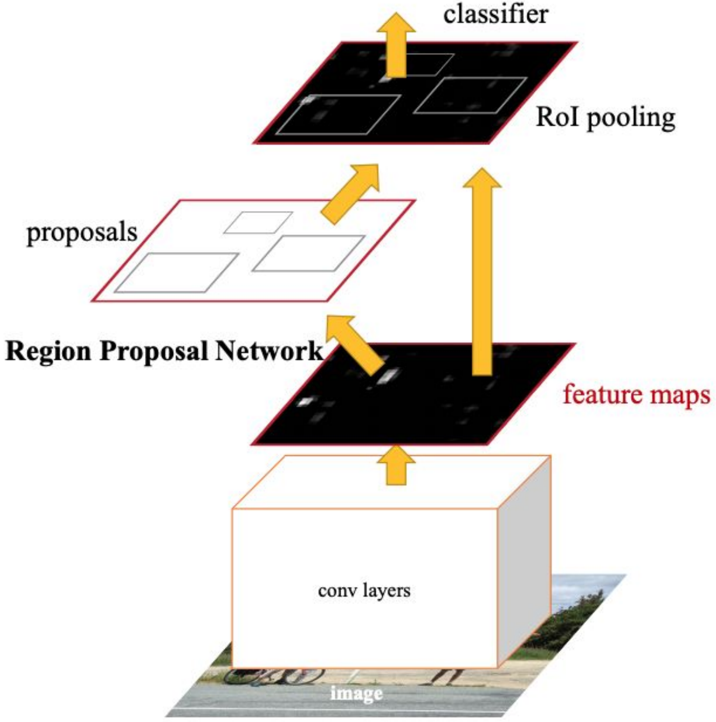


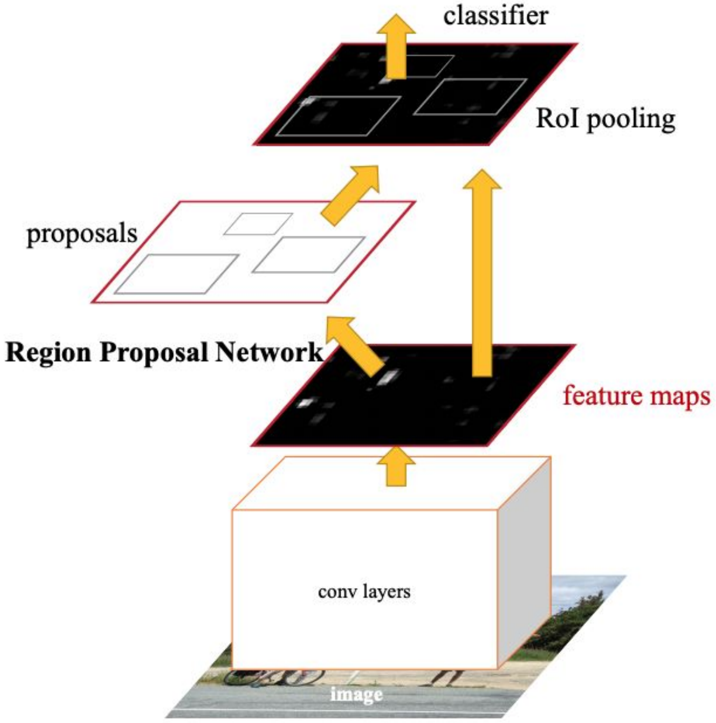
Original source: Faster R-CNN, He K. et al.

Object-level Supervision

Mask-RCNN and SETR represent it.

They **predict object regions** and learn by **object-level supervision**.

R-CNN is region proposal network that proposes target objects.



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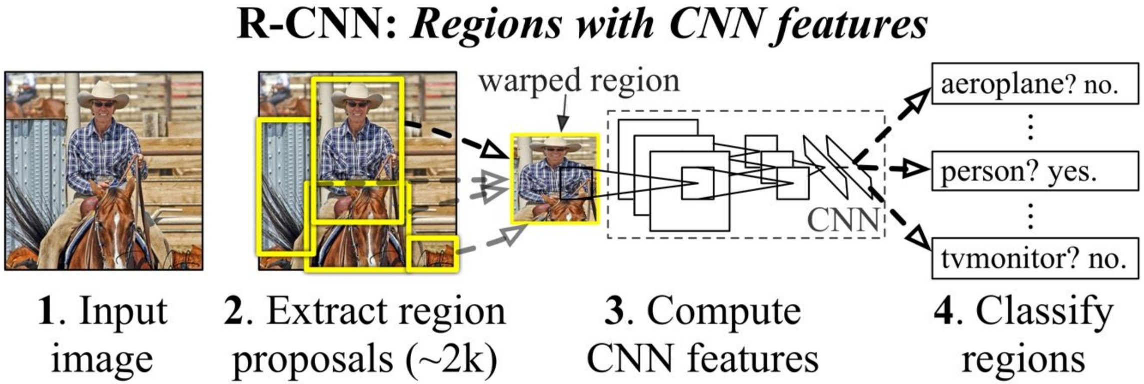

Original source: R-CNN, Ross Girshick et al.

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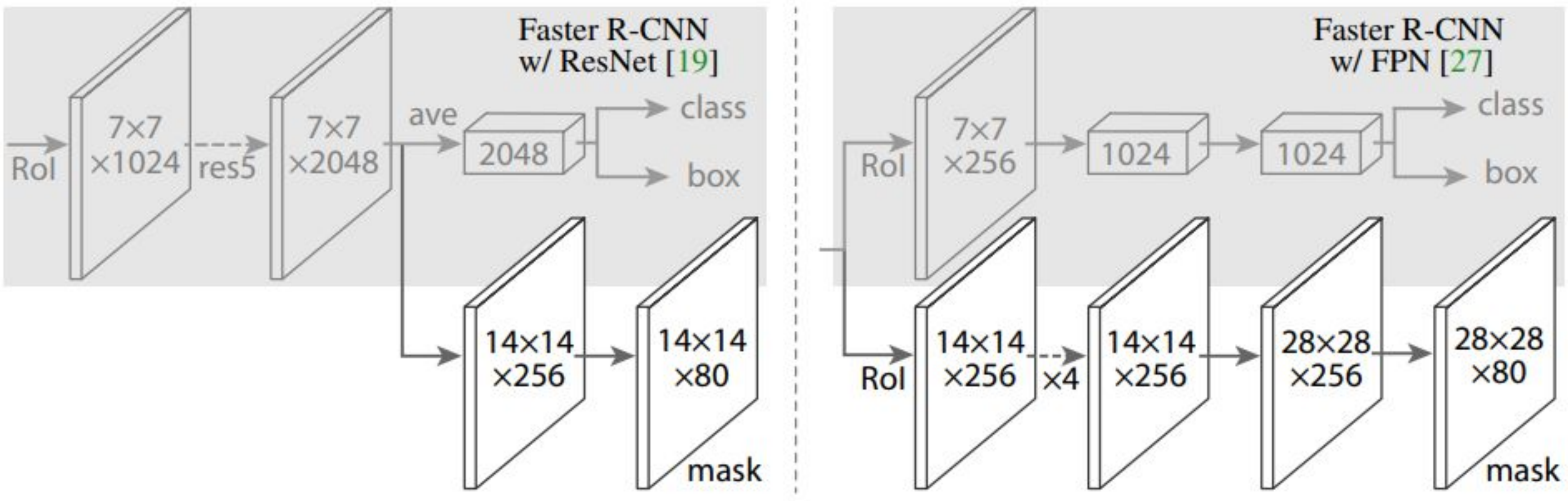
Object-level Supervision



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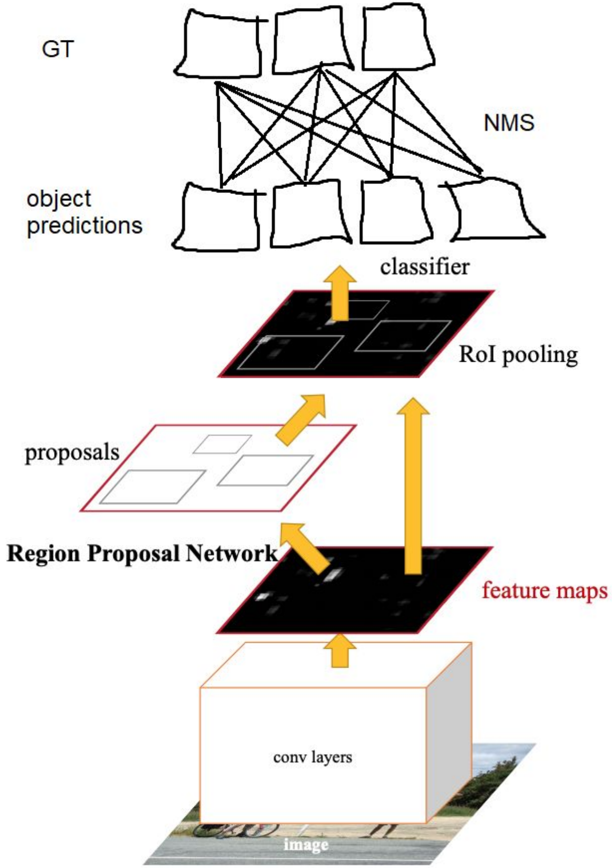

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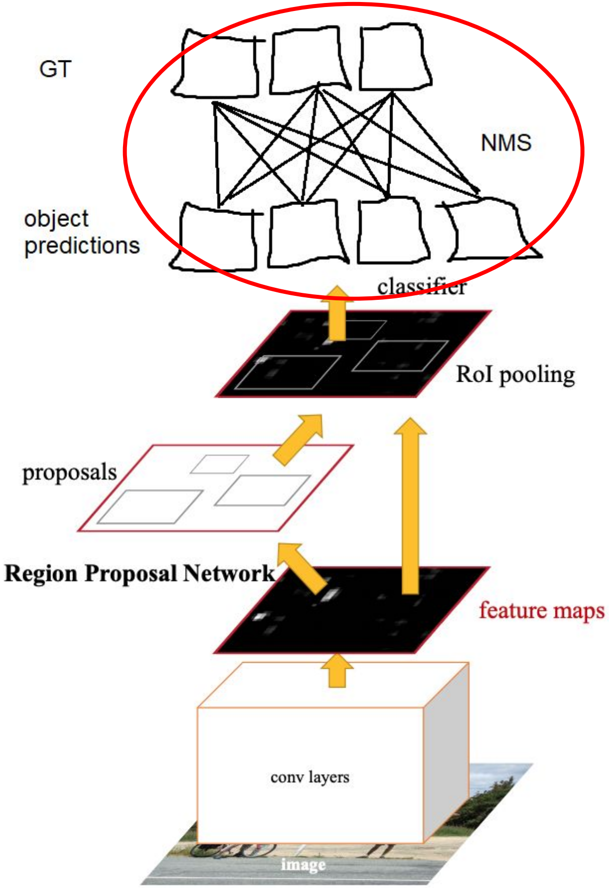

Original source: Faster R-CNN, He K. et al.
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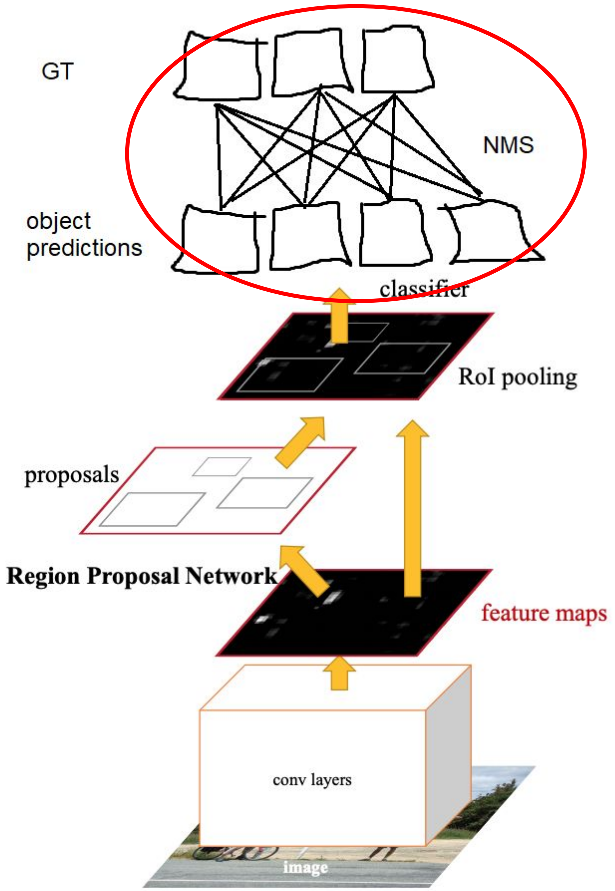
Object-level Supervision

These model learns by object-level supervision



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Per-pixel Classification vs Mask Classification Summary

	Pixel-level supervision	Object-level supervision
Model	U-Net, DeepLab	Mask R-CNN
Supervision	Pixel-level loss	Object-level loss

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Question now, is which one **superior**?

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This paper compares and contrasts the supervisions

and presents ***MaskFormer*** that takes advantages of mask-supervision

using the exact same model, loss, and training procedure.

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- MaskFormer
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MaskFormer

MaskFormer

They contrasted the two supervisions in a simple following manner.

MaskFormer

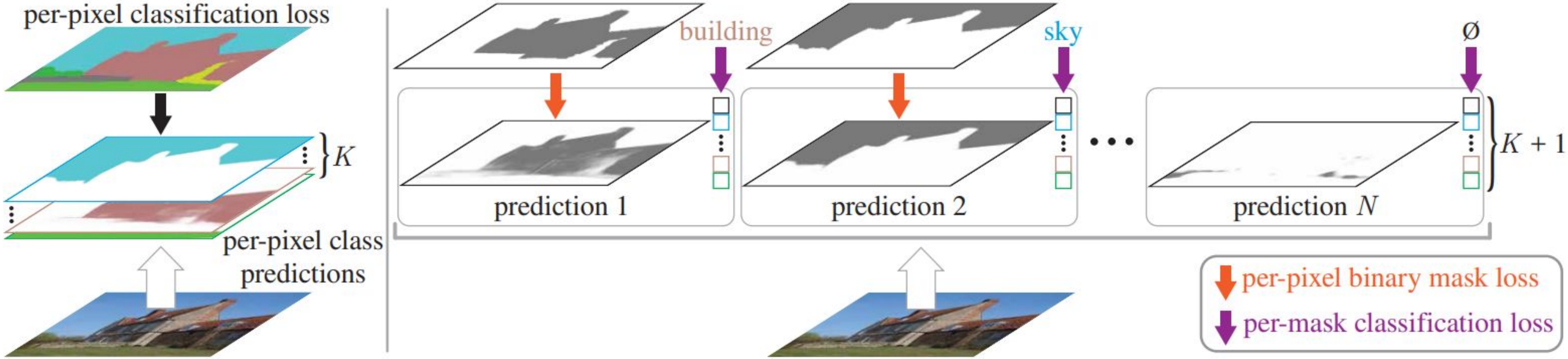


Figure: ***Per-pixel classification vs. mask classification***

MaskFormer

Instead of learning at once,
mask supervision teaches ***N*** categories independently.

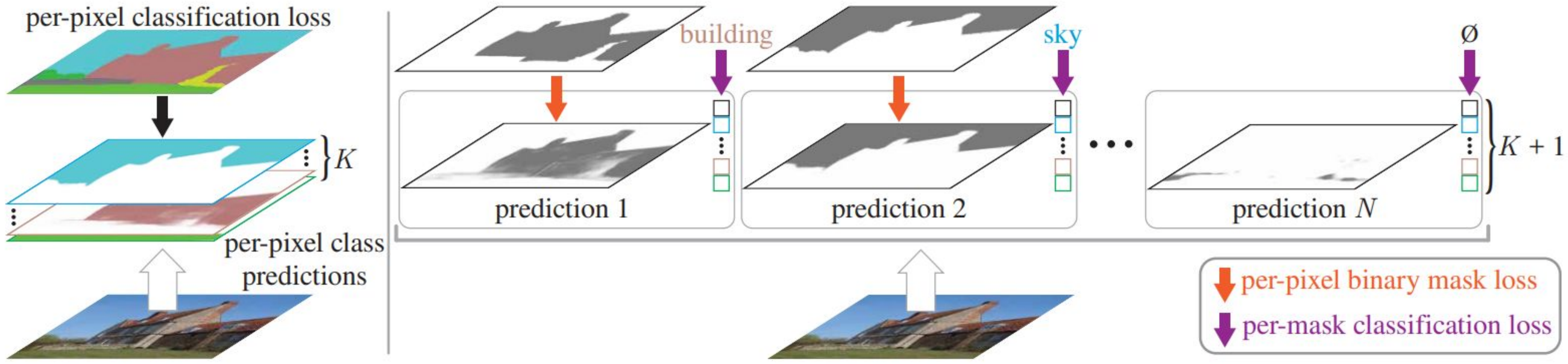
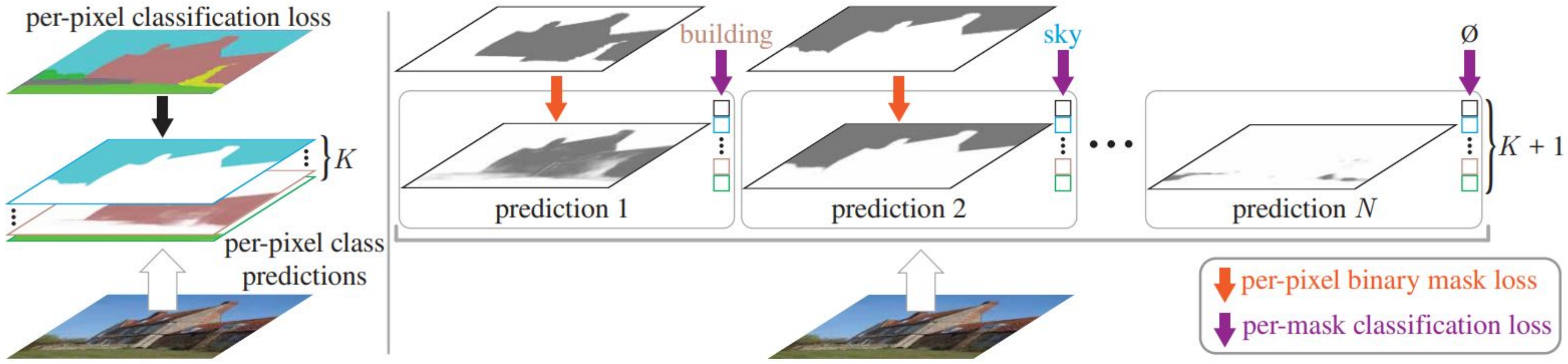


Figure: ***Per-pixel classification vs. mask classification***

MaskFormer

Instead of learning at once,
mask supervision teaches ***N*** categories independently.
I.e., mask classification has N category-predictors.



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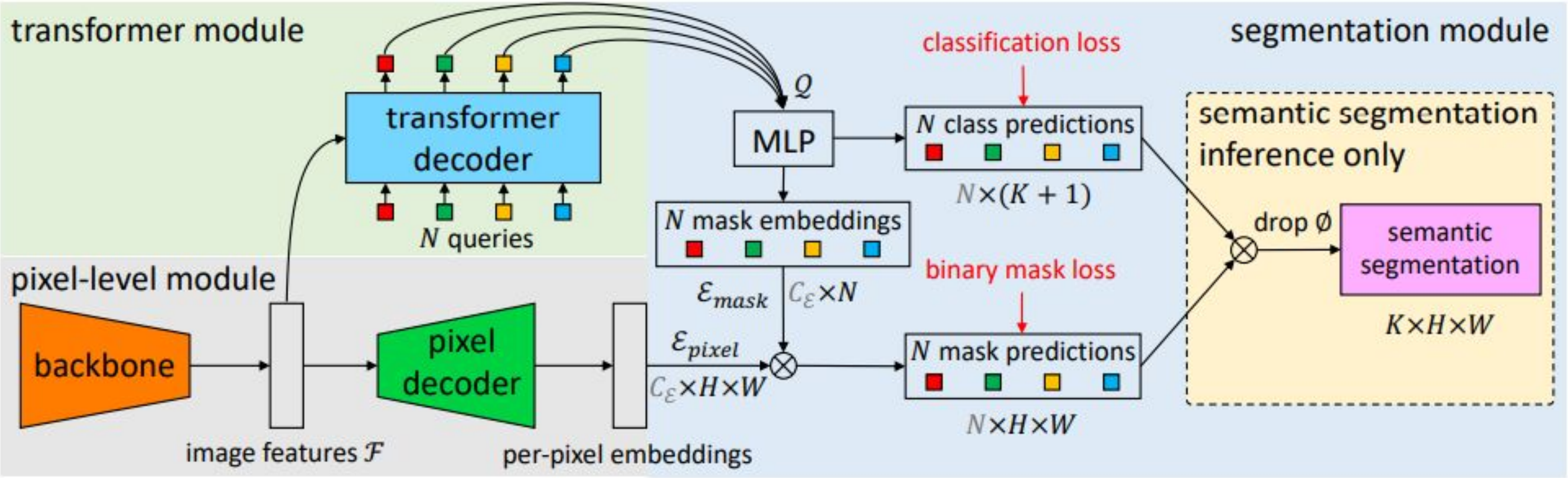
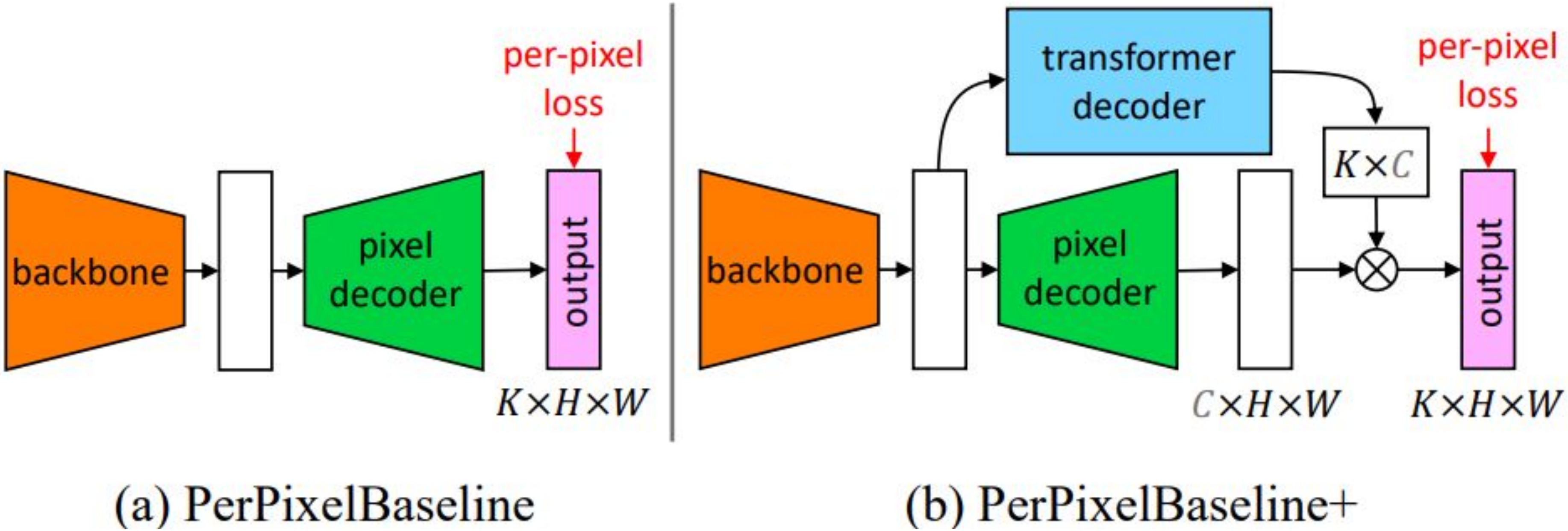


Figure: MaskFormer architecture

Baselines



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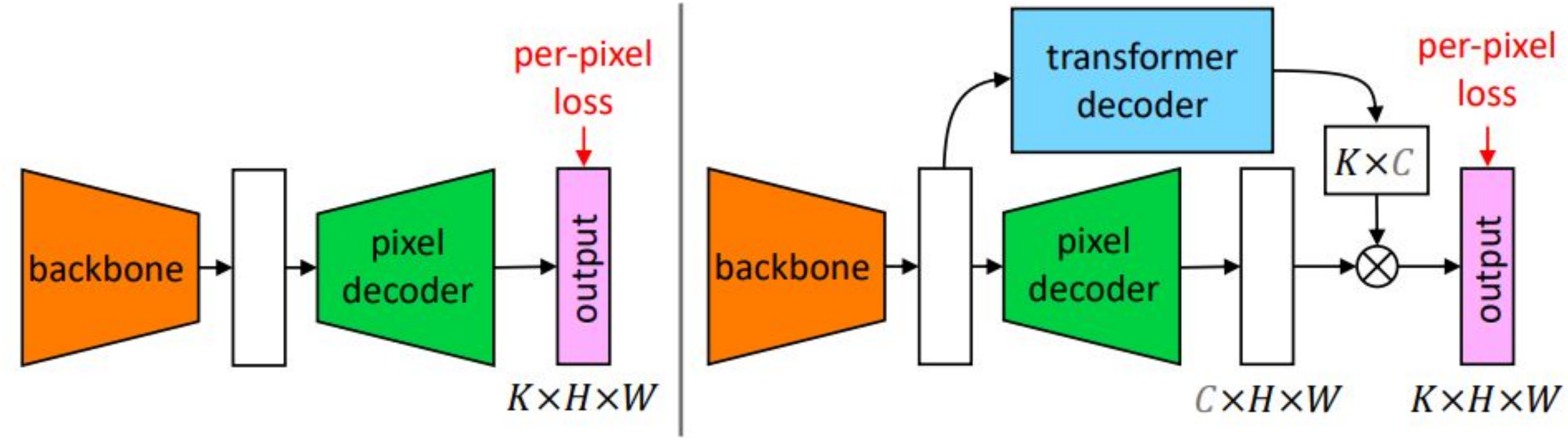
Baselines

For fair comparison w.r.t. #params,
they experimented PerPixelBaseline+ as well.



(a) PerPixelBaseline (b) PerPixelBaseline+

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Experiments

Experiments

It outperforms SOTAs

in semantic segmentation (ADE20K)

and in panoptic segmentation (COCO)

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Experiments on ADE20k

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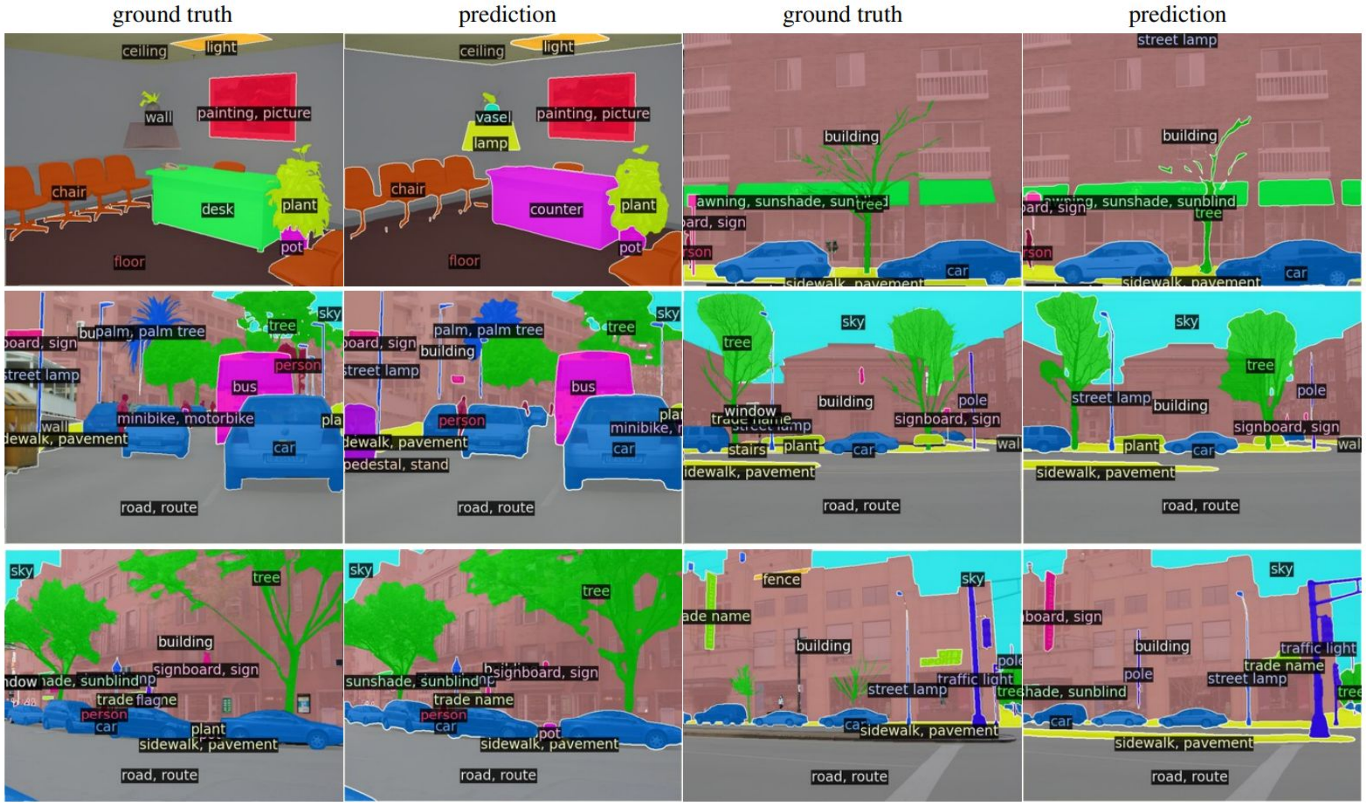
Experiments on ADE20k



Experiments on ADE20k

Table 1: **Semantic segmentation on ADE20K `val` with 150 categories.** Mask classification-based MaskFormer outperforms the best per-pixel classification approaches while using fewer parameters and less computation. We report both single-scale (s.s.) and multi-scale (m.s.) inference results with ±*std*. FLOPs are computed for the given crop size. Frames-per-second (fps) is measured on a V100 GPU with a batch size of 1.[3] Backbones pre-trained on ImageNet-22K are marked with †.

	method	backbone	crop size	mIoU (s.s.)	mIoU (m.s.)	#params.	FLOPs	fps
CNN backbones	OCRNet [50]	R101c	520 × 520	-	45.3	-	-	-
	DeepLabV3+ [9]	R50c	512 × 512	44.0	44.9	44M	177G	21.0
		R101c	512 × 512	45.5	46.4	63M	255G	14.2
	MaskFormer (ours)	R50	512 × 512	44.5 ±0.5	46.7 ±0.6	41M	53G	24.5
		R101	512 × 512	45.5 ±0.5	47.2 ±0.2	60M	73G	19.5
		R101c	512 × 512	**46.0** ±0.1	**48.1** ±0.2	60M	80G	19.0
Transformer backbones	SETR [53]	ViT-L†	512 × 512	-	50.3	308M	-	-
	Swin-UperNet [29, 49]	Swin-T	512 × 512	-	46.1	60M	236G	18.5
		Swin-S	512 × 512	-	49.3	81M	259G	15.2
		Swin-B†	640 × 640	-	51.6	121M	471G	8.7
		Swin-L†	640 × 640	-	53.5	234M	647G	6.2
	MaskFormer (ours)	Swin-T	512 × 512	46.7 ±0.7	48.8 ±0.6	42M	55G	22.1
		Swin-S	512 × 512	49.8 ±0.4	51.0 ±0.4	63M	79G	19.6
		Swin-B	640 × 640	51.1 ±0.2	52.3 ±0.4	102M	195G	12.6
		Swin-B†	640 × 640	52.7 ±0.4	53.9 ±0.2	102M	195G	12.6
		Swin-L†	640 × 640	**54.1** ±0.2	**55.6** ±0.1	212M	375G	7.9

Experiments on COCO panoptic

Table 3: **Panoptic segmentation on COCO panoptic `val` with 133 categories.** MaskFormer seamlessly unifies semantic- and instance-level segmentation without modifying the model architecture or loss. Our model, which achieves better results, can be regarded as a box-free simplification of DETR [4]. The major improvement comes from "stuff" classes (PQ^{St}) which are ambiguous to represent with bounding boxes. For MaskFormer (DETR) we use the exact same post-processing as DETR. Note, that in this setting MaskFormer performance is still better than DETR (+2.2 PQ). Our model also outperforms recently proposed Max-DeepLab [42] without the need of sophisticated auxiliary losses, while being more efficient. FLOPs are computed as the average FLOPs over 100 validation images (COCO images have varying sizes). Frames-per-second (fps) is measured on a V100 GPU with a batch size of 1 by taking the average runtime on the entire `val` set *including post-processing time*. Backbones pre-trained on ImageNet-22K are marked with †.

	method	backbone	PQ	PQ^{Th}	PQ^{St}	SQ	RQ	#params.	FLOPs	fps
CNN backbones	DETR [4]	R50 + 6 Enc	43.4	48.2	36.3	79.3	53.8	-	-	-
	MaskFormer (DETR)	R50 + 6 Enc	45.6	50.0 (+1.8)	39.0 (+2.7)	80.2	55.8	-	-	-
	MaskFormer (ours)	R50 + 6 Enc	**46.5**	**51.0** (+2.8)	**39.8** (+3.5)	**80.4**	**56.8**	45M	181G	17.6
	DETR [4]	R101 + 6 Enc	45.1	50.5	37.0	79.9	55.5	-	-	-
	MaskFormer (ours)	R101 + 6 Enc	**47.6**	**52.5** (+2.0)	**40.3** (+3.3)	**80.7**	**58.0**	64M	248G	14.0
Transformer backbones	Max-DeepLab [42]	Max-S	48.4	53.0	41.5	-	-	62M	324G	7.6
		Max-L	51.1	57.0	42.2	-	-	451M	3692G	-
	MaskFormer (ours)	Swin-T	47.7	51.7	41.7	80.4	58.3	42M	179G	17.0
		Swin-S	49.7	54.4	42.6	80.9	60.4	63M	259G	12.4
		Swin-B	51.1	56.3	43.2	81.4	61.8	102M	411G	8.4
		Swin-B†	51.8	56.9	**44.1**	81.4	62.6	102M	411G	8.4
		Swin-L†	**52.7**	**58.5**	**44.0**	**81.8**	**63.5**	212M	792G	5.2

Ablation: MaskFormer vs per-pixel

Table 2: **MaskFormer *vs*. per-pixel classification baselines on 4 semantic segmentation datasets.** MaskFormer improvement is larger when the number of classes is larger. We use a ResNet-50 backbone and report single scale mIoU and PQ^{St} for ADE20K, COCO-Stuff and ADE20K-Full, whereas for higher-resolution Cityscapes we use a deeper ResNet-101 backbone following [8, 9].

	Cityscapes (19 classes)		ADE20K (150 classes)		COCO-Stuff (171 classes)		ADE20K-Full (847 classes)	
	mIoU	PQ^{St}	mIoU	PQ^{St}	mIoU	PQ^{St}	mIoU	PQ^{St}
PerPixelBaseline	77.4	58.9	39.2	21.6	32.4	15.5	12.4	5.8
PerPixelBaseline+	**78.5**	60.2	41.9	28.3	34.2	24.6	13.9	9.0
MaskFormer (ours)	**78.5** (+0.0)	**63.1** (+2.9)	**44.5** (+2.6)	**33.4** (+5.1)	**37.1** (+2.9)	**28.9** (+4.3)	**17.4** (+3.5)	**11.9** (+2.9)

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PerPixelBaseline	77.4	58.9	39.2	21.6	32.4	15.5	12.4	5.8
PerPixelBaseline+	**78.5**	60.2	41.9	28.3	34.2	24.6	13.9	9.0
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It works better.