DE:TR: End-to-End Object Detection with Transformers

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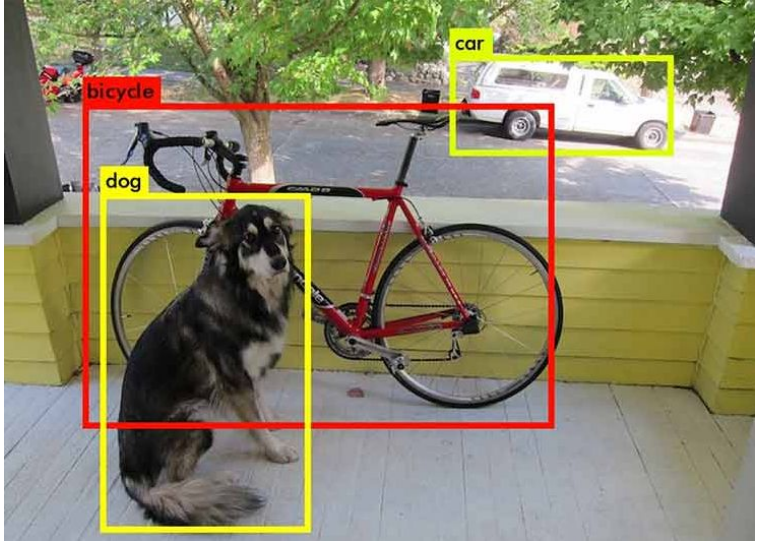
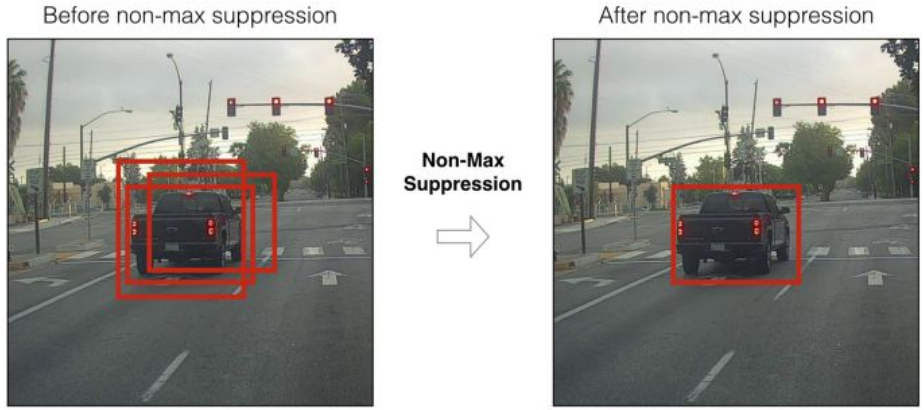
Motivation

Task: Predict a set of bounding boxes and category labels



Previous work:

- Often requires surrogate regressions and classification on a large set of proposals, anchors, window centers, etc.
- Influenced by post-processing steps
- End-to-end philosophy has not been applied to object detection successfully yet



DEtection TRansformer (DETR)

- Treat object detection as direct set prediction problem
- Predict in a single pass a set of objects and models their relation

Components: Backbone, encoder-decoder, and feed forward network

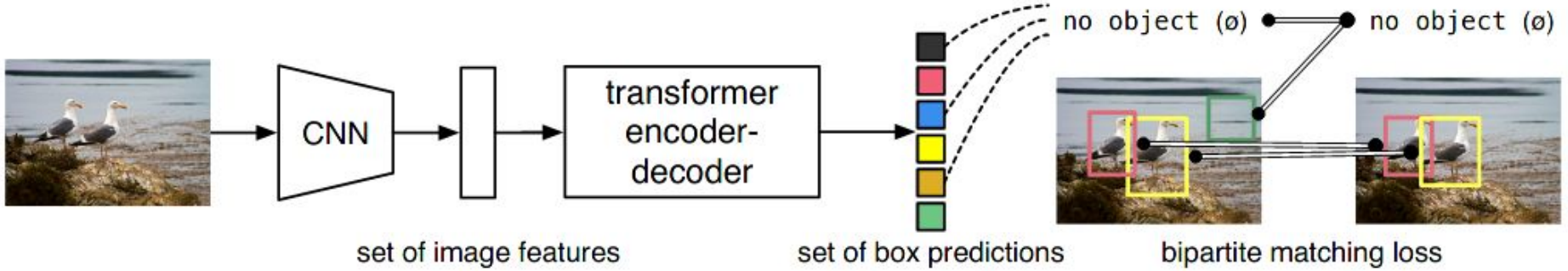


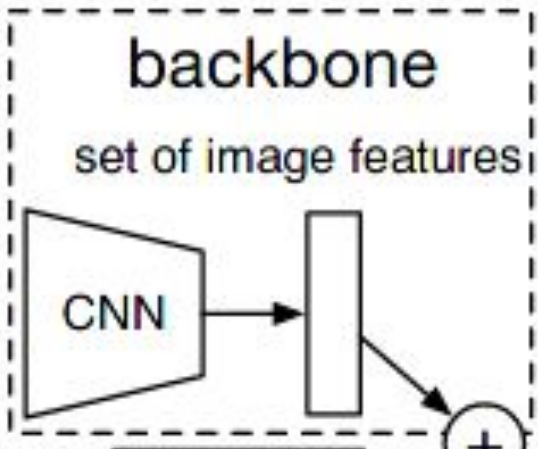
Fig. 1: DETR directly predicts (in parallel) the final set of detections by combining a common CNN with a transformer architecture. During training, bipartite matching uniquely assigns predictions with ground truth boxes. Prediction with no match should yield a "`no object`" ($\varnothing$) class prediction.

Architecture - Backbone and Preprocessing

Given an image of shape ($3xH_0xW_0$), CNN backbone generates a lower-resolution map of shape (CxHxW)

Typically, C=2048, H,W=$H_0/32$, $W_0/32$

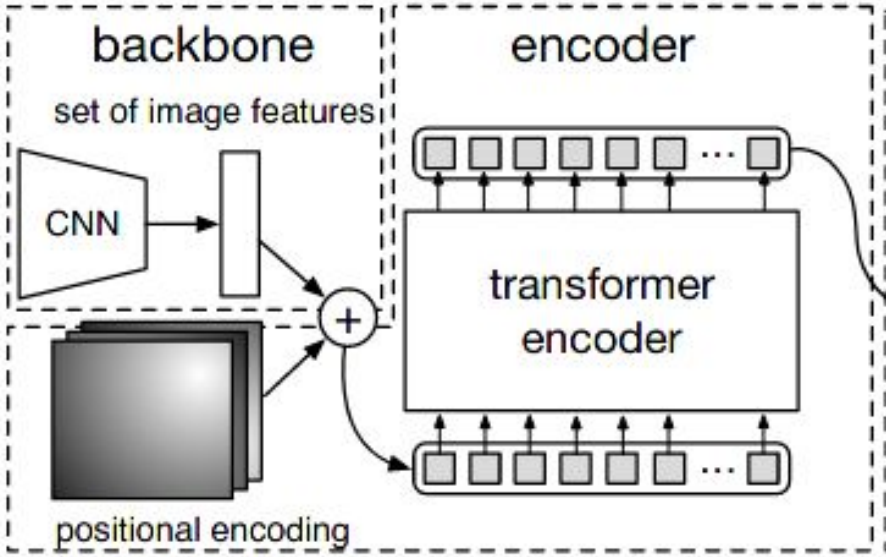
1x1 Convolution reduces channel dimension to shape (dxHxW)



Architecture - Encoder

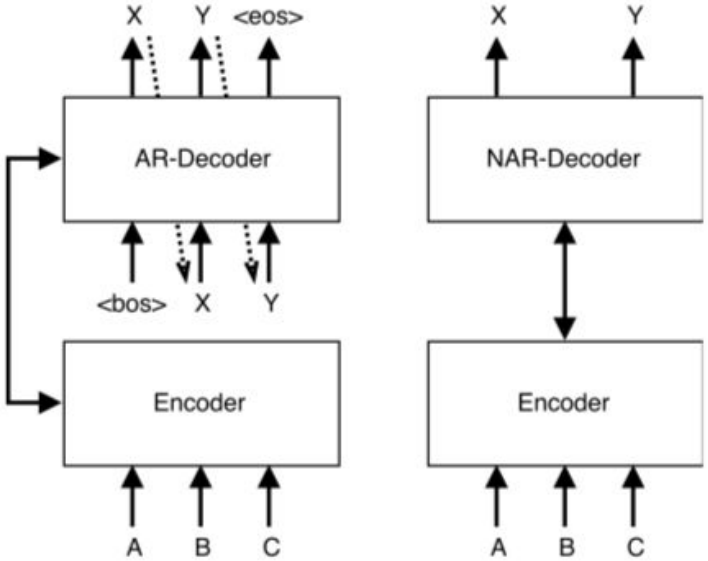
Encoder:

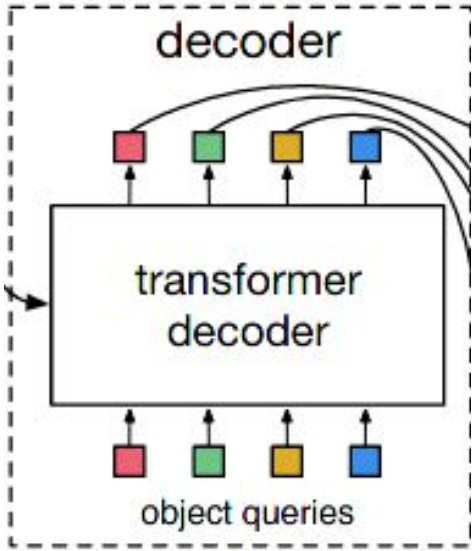
- Collapse the spatial dimensions into one dimension of of shape d x HW
- Add positional encoding before feeding to standard transformer encoder



Architecture - Decoder

- Non-autoregressive
- Input to the decoder are N learned positional encodings called object queries



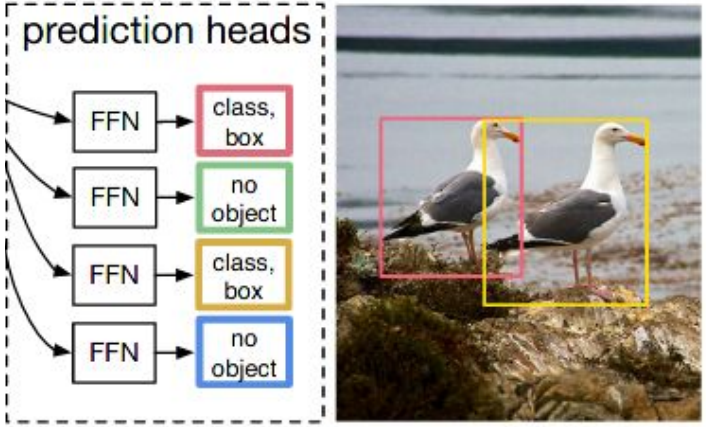


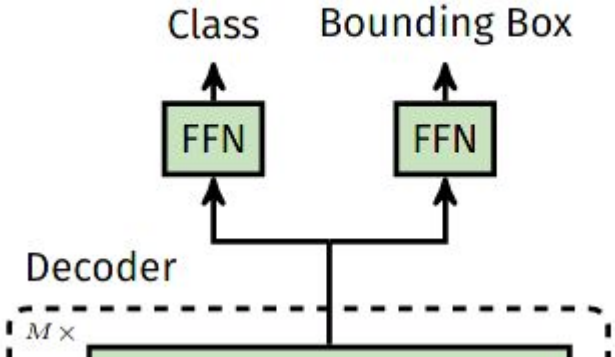
Architecture - Feed-forward networks

3-layer FFN with ReLu activation

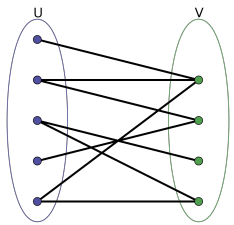
FFN predicts center coordinates, height and width of the box. Another linear layer predicts class label.

N is usually much larger than actual number of objects and thus include null class label (similar to “background”)





Loss - object detection set prediction loss



Find a bipartite matching by finding for a permutation of N with lowest cost

$$\hat{\sigma} = \arg\min_{\sigma \in \mathfrak{S}_N} \sum_{i}^{N} \mathcal{L}_{\text{match}}(y_i, \hat{y}_{\sigma(i)}),$$

L_{match} is the pair-wise matching cost of label c_i and the boxes $b_i \in [0,1]^4$):

$$-\mathbb{1}_{\{c_i \neq \varnothing\}} \hat{p}_{\sigma(i)}(c_i) + \mathbb{1}_{\{c_i \neq \varnothing\}} \mathcal{L}_{\text{box}}(b_i, \hat{b}_{\sigma(i)}).$$

L_{box} is the bounding box loss - linear combination of L1 loss and Generalized IoU Loss

$$\lambda_{\text{iou}} \mathcal{L}_{\text{iou}}(b_i, \hat{b}_{\sigma(i)}) + \lambda_{\text{L1}} ||b_i - \hat{b}_{\sigma(i)}||_1$$

Loss - object detection set prediction loss

Bipartite matching finds the optimal assignment $\hat{\sigma}$

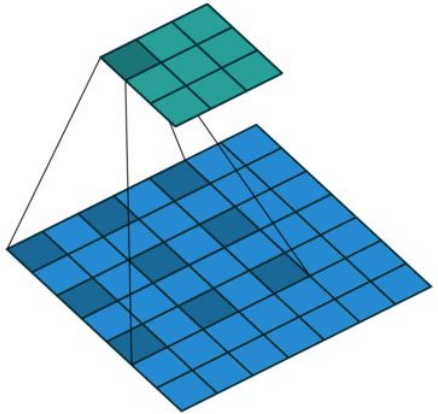
Hungarian Loss

- Linear combination of negative log-like and box loss
- Down-weight the log-probability of null label by a factor 10

$$\mathcal{L}_{\text{Hungarian}}(y, \hat{y}) = \sum_{i=1}^{N} \left[-\log \hat{p}_{\hat{\sigma}(i)}(c_i) + \mathbb{1}_{\{c_i \neq \varnothing\}} \mathcal{L}_{\text{box}}(b_i, \hat{b}_{\hat{\sigma}}(i)) \right]$$

Auxiliary Loss: Apply the loss after each decoder layer with shared FFNs

Experiments



Dataset: COCO 2017, 118k training images and 5k validation

Backbones:

- ResNet-50 and ResNet-101
- DC5: Add dilation and remove a stride front the first convolution to double resolution
- Scale augmentation to scale input images shortest side [480, 800] and longest side [800, 1333].
- Random crop augmentation

Faster R-CNN Baselines

Stronger faster R-CNN (typically trained with SGD and minimal data augmentation)

- Add generalized IoU to the box loss
- Same random crop augmentation
- Longer training (3x, 9x schedule)

Metric

Average Precision (AP): area under precision-recall curve evaluated at α IoU threshold

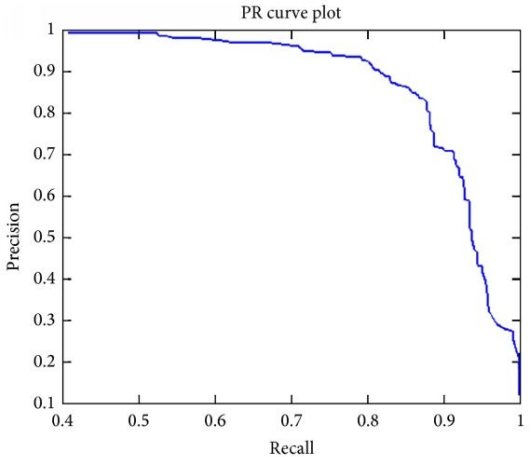
AP: average of AP ranging from IOU=50% to 95% at a 5% step size

AP_{α}: IOU=α

AP_S: AP for small objects: area< 32^2

AP_M: AP for medium objects: 32^2 < area < 96^2

AP_L: AP for large objects: area > 96^2



Result

Model	GFLOPS/FPS	#params	AP	AP_{50}	AP_{75}	AP_S	AP_M	AP_L
Faster RCNN-DC5	320/16	166M	39.0	60.5	42.3	21.4	43.5	52.5
Faster RCNN-FPN	180/26	42M	40.2	61.0	43.8	24.2	43.5	52.0
Faster RCNN-R101-FPN	246/20	60M	42.0	62.5	45.9	25.2	45.6	54.6
Faster RCNN-DC5+	320/16	166M	41.1	61.4	44.3	22.9	45.9	55.0
Faster RCNN-FPN+	180/26	42M	42.0	62.1	45.5	26.6	45.4	53.4
Faster RCNN-R101-FPN+	246/20	60M	44.0	63.9	**47.8**	**27.2**	48.1	56.0
DETR	86/28	41M	42.0	62.4	44.2	20.5	45.8	61.1
DETR-DC5	187/12	41M	43.3	63.1	45.9	22.5	47.3	61.1
DETR-R101	152/20	60M	43.5	63.8	46.4	21.9	48.0	61.8
DETR-DC5-R101	253/10	60M	**44.9**	**64.7**	47.7	23.7	**49.5**	**62.3**

Adding dilation improves smaller objects

Adding R101 improves overall performance

Result

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DETR is comparable to Faster R-CNN with similar size by improving AP_L by +7.8, but lag behind in AP_S by -5.5 (according to the paper).

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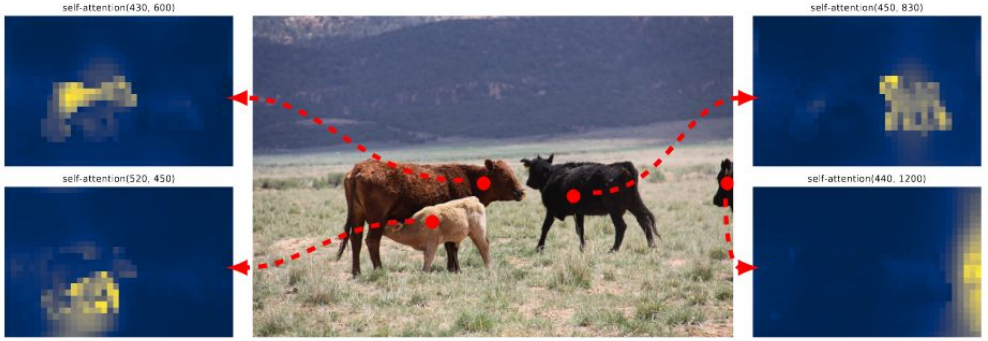
With dilation and thus similar FLOP counts, AP is better but still behind in AP_S.

Ablations - Encoder

Number of encoder layers

Overall AP drops by 3.9, 6.0 AP on larg
objects without encoder layers



Visualization shows that it already
separates instances

Table 2: Effect of encoder size. Each row corresponds to a model with varied number of encoder layers and fixed number of decoder layers. Performance gradually improves with more encoder layers.

#layers	GFLOPS/FPS	#params	AP	AP_{50}	AP_S	AP_M	AP_L
0	76/28	33.4M	36.7	57.4	16.8	39.6	54.2
3	81/25	37.4M	40.1	60.6	18.5	43.8	58.6
6	86/23	41.3M	40.6	61.6	19.9	44.3	60.2
12	95/20	49.2M	41.6	62.1	19.8	44.9	61.9

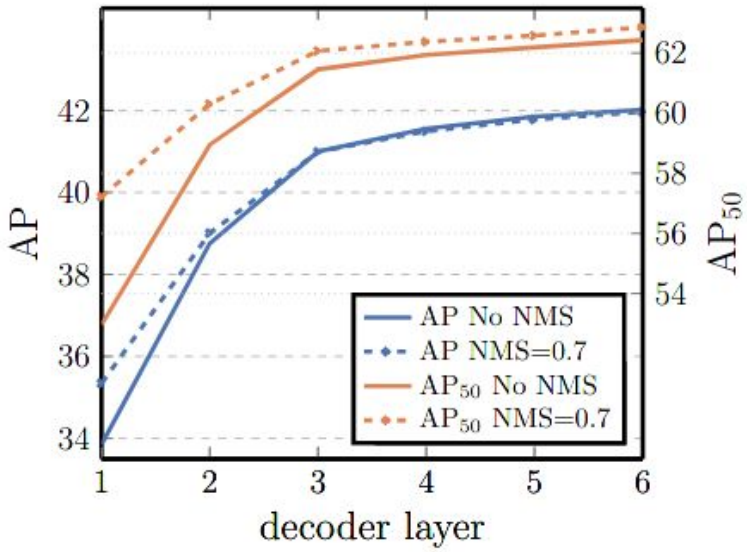
Ablations - Decoder

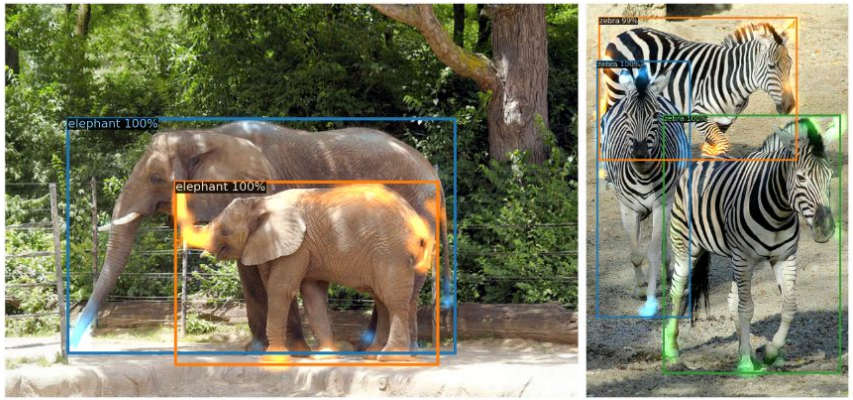
Auxiliary losses after each decoding layer and thus can predict output using every decoder layer

Every layer improves AP and AP_{50}

Non-max-suppression improves for early layers, but improvement diminishes

Decoder attention is local





Ablations - Positional Encodings

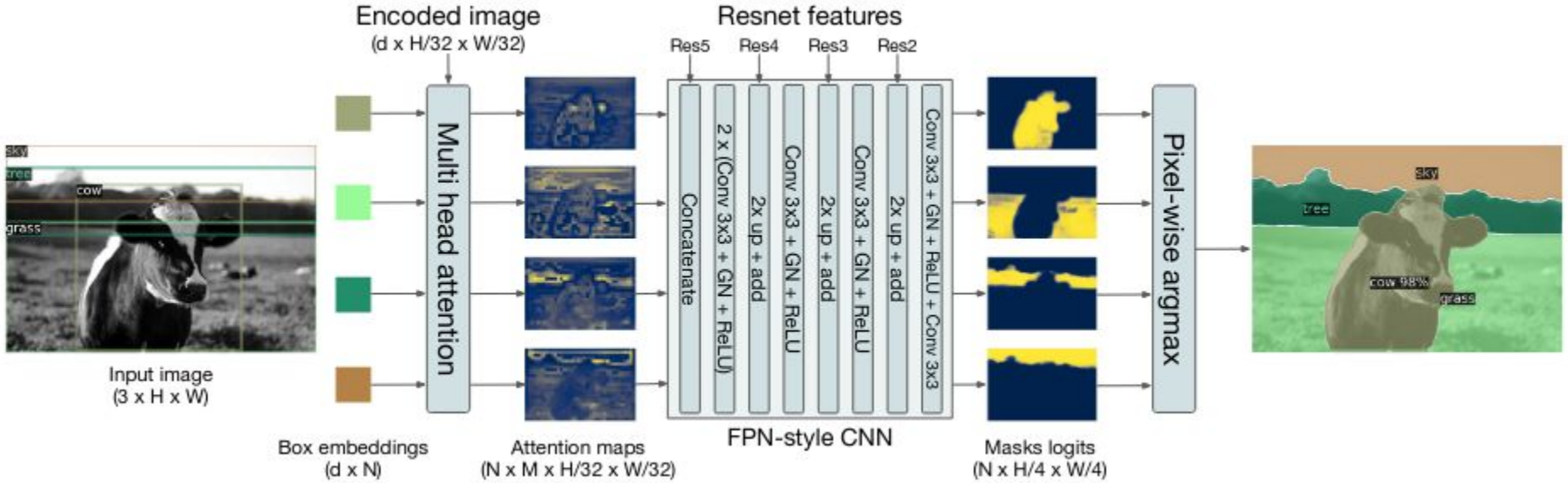
Surprising that removing spatial encoding in encoder only leads to AP drop of 1.3

spatial pos. enc. encoder	spatial pos. enc. decoder	output pos. enc. decoder	AP	Δ	AP_{50}	Δ
none	none	learned at input	32.8	-7.8	55.2	-6.5
sine at input	sine at input	learned at input	39.2	-1.4	60.0	-1.6
learned at attn.	learned at attn.	learned at attn.	39.6	-1.0	60.7	-0.9
none	sine at attn.	learned at attn.	39.3	-1.3	60.3	-1.4
sine at attn.	sine at attn.	learned at attn.	**40.6**	-	**61.6**	-

Extension - Panoptic Segmentation

Add a binary mask head on top of the decoder outputs

Computes multihead attention, the attention heatmap and then FPN



Result

- Outperform strong PanopticFPN baseline
- Dominant on “stuff” classes but lack behind in “things” classes

Table 5: Comparison with the state-of-the-art methods UPSNet [51] and Panoptic FPN [18] on the COCO `val` dataset We retrained PanopticFPN with the same data-augmentation as DETR, on a 18x schedule for fair comparison. UPSNet uses the `1x` schedule, UPSNet-M is the version with multiscale test-time augmentations.

Model	Backbone	PQ	SQ	RQ	PQ^{th}	SQ^{th}	RQ^{th}	PQ^{st}	SQ^{st}	RQ^{st}	AP
PanopticFPN++	R50	42.4	79.3	51.6	49.2	82.4	58.8	32.3	74.8	40.6	37.7
UPSnet	R50	42.5	78.0	52.5	48.6	79.4	59.6	33.4	75.9	41.7	34.3
UPSnet-M	R50	43.0	79.1	52.8	48.9	79.7	59.7	34.1	78.2	42.3	34.3
PanopticFPN++	R101	44.1	79.5	53.3	**51.0**	**83.2**	60.6	33.6	74.0	42.1	**39.7**
DETR	R50	43.4	79.3	53.8	48.2	79.8	59.5	36.3	78.5	45.3	31.1
DETR-DC5	R50	44.6	79.8	55.0	49.4	80.5	60.6	**37.3**	**78.7**	**46.5**	31.9
DETR-R101	R101	**45.1**	**79.9**	**55.5**	50.5	80.9	**61.7**	37.0	78.5	46.0	33.0

Discussions

Why does the model perform worse on smaller objects and better at larger objects?

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Why does the model perform worse on smaller objects and better at larger objects?

Cannot use multi-scale features (Feature Pyramid Network) commonly used to improve detection of small objects