

Sparse DETR:

Efficient End-to-End Object Detection with Learnable Sparsity

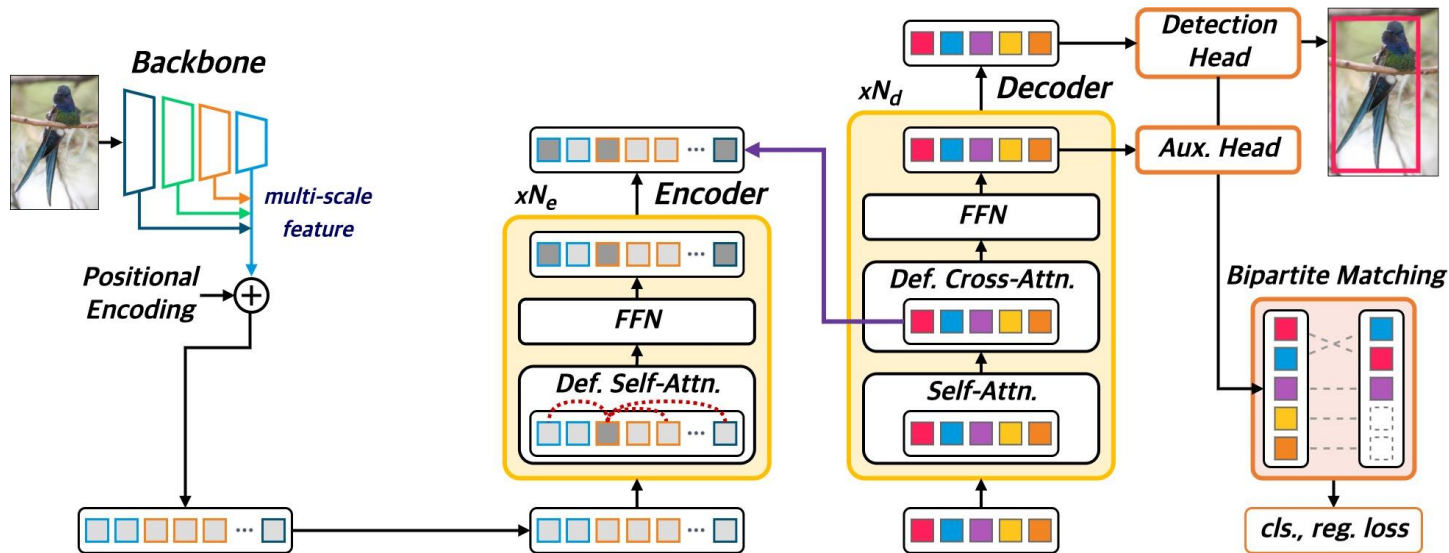
Byungseok Roh*, Jaewoong Shin*, Wuhyun Shin*, Saehoon Kim

Kakao Brain

*equal contribution

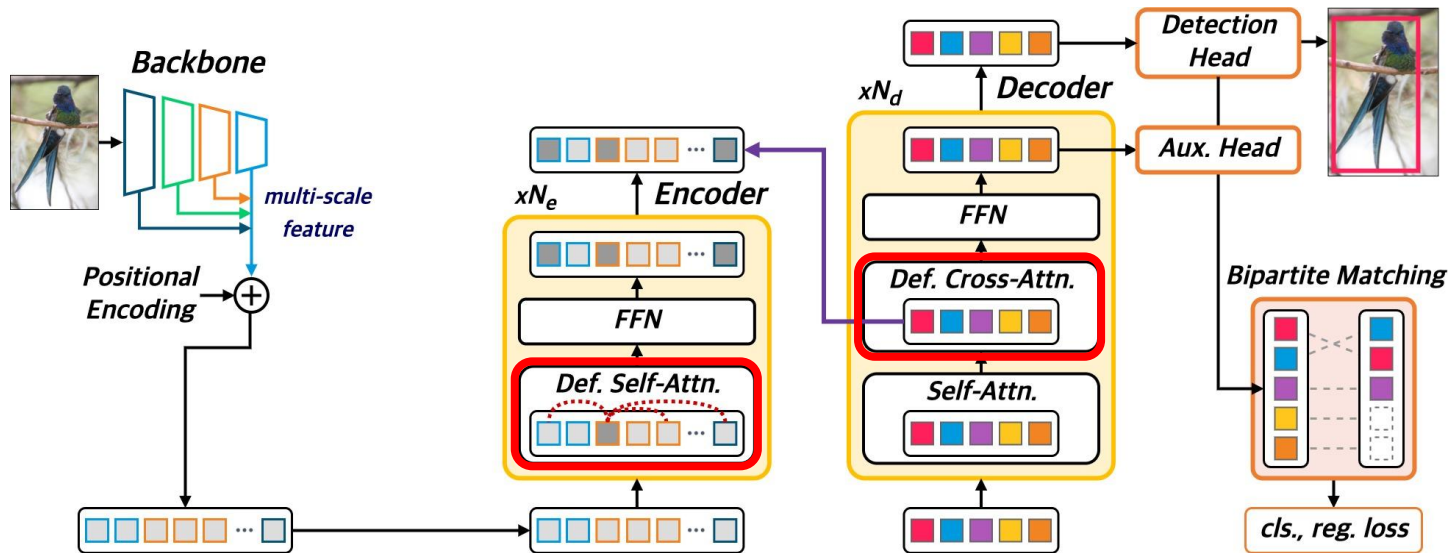
Motivation

- Deformable DETR introduces **deformable attention** which **reduces computation cost** from **quadratic to linear** complexity



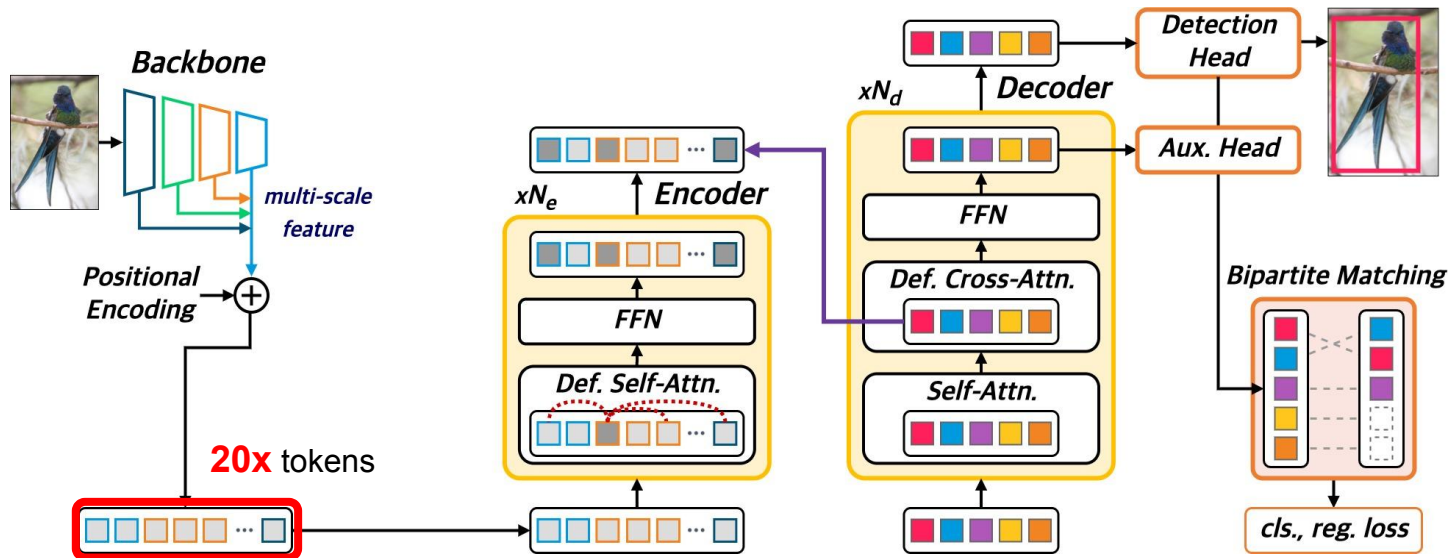
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- Using **the multi-scale features** as an encoder input **increases** the **number of tokens** to be processed by about **20 times**



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Method	AP	AP ₅₀	AP ₇₅	AP _S	AP _M	AP _L	params	FLOPs	FPS
DETR	42.0	62.4	44.2	20.5	45.8	61.1	41M	86G	28
Deformable DETR	43.8	62.6	47.7	26.4	47.1	58.0	40M	173G	19



Characteristic of Images for Object Detection

- On average, **only 30%** of the entire image is the foreground pixel.



MS COCO dataset

Characteristic of Images for Object Detection

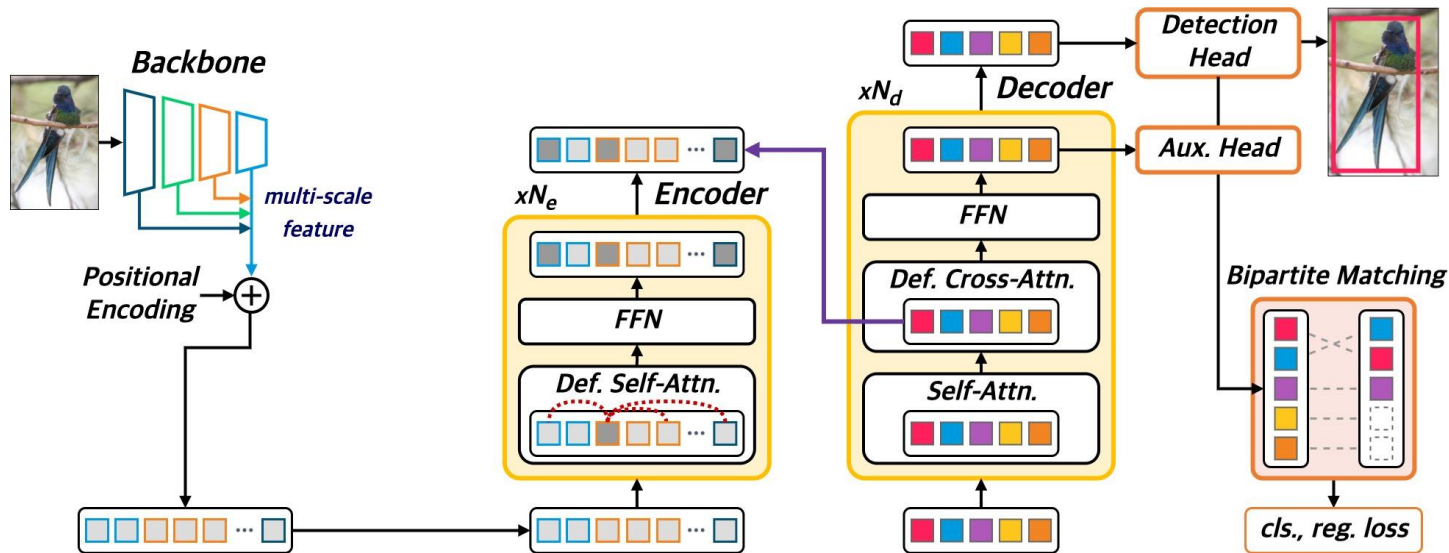
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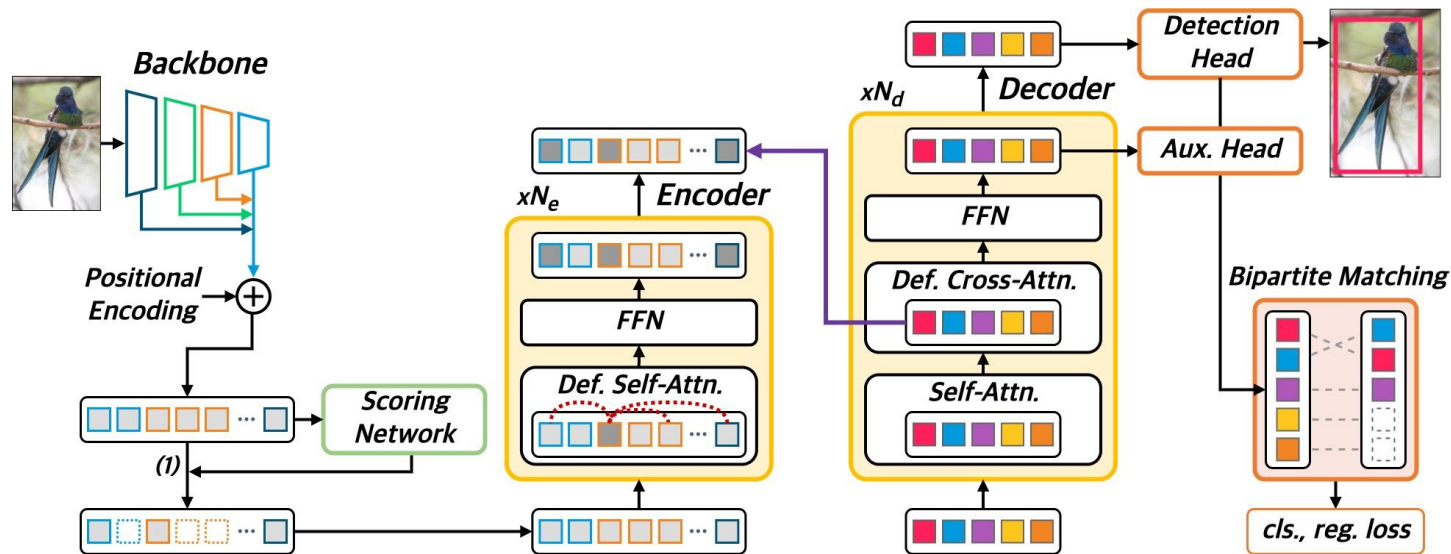
MS COCO dataset

- Do we need to compute **the entire token** in the encoder block?

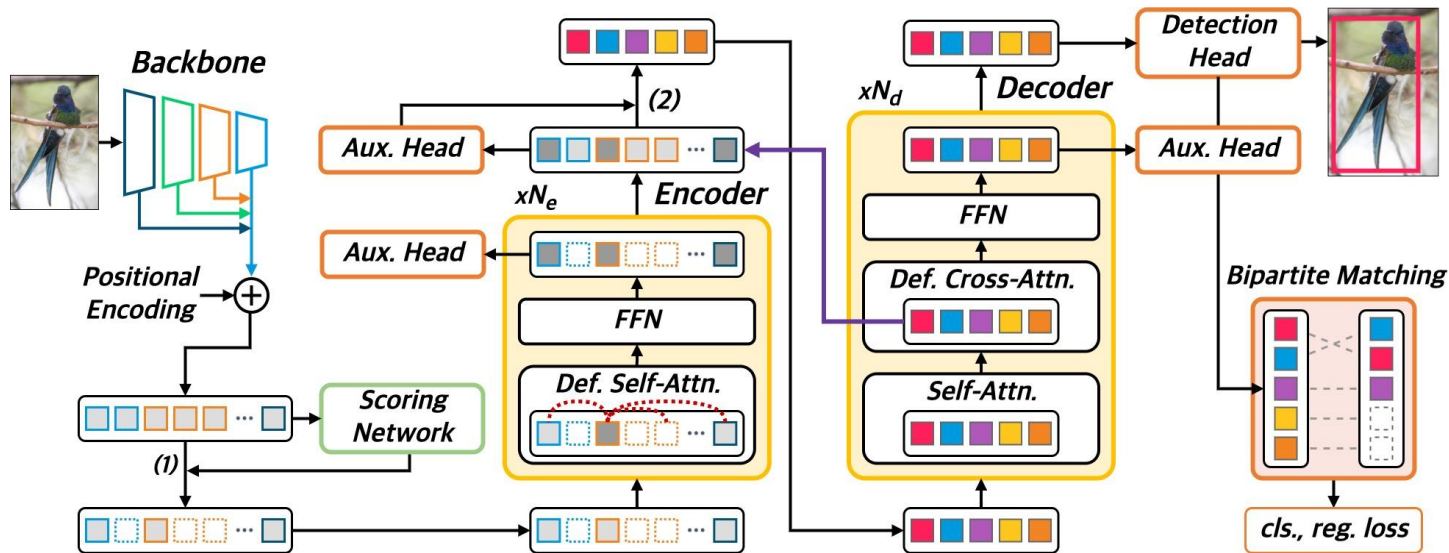
Architecture



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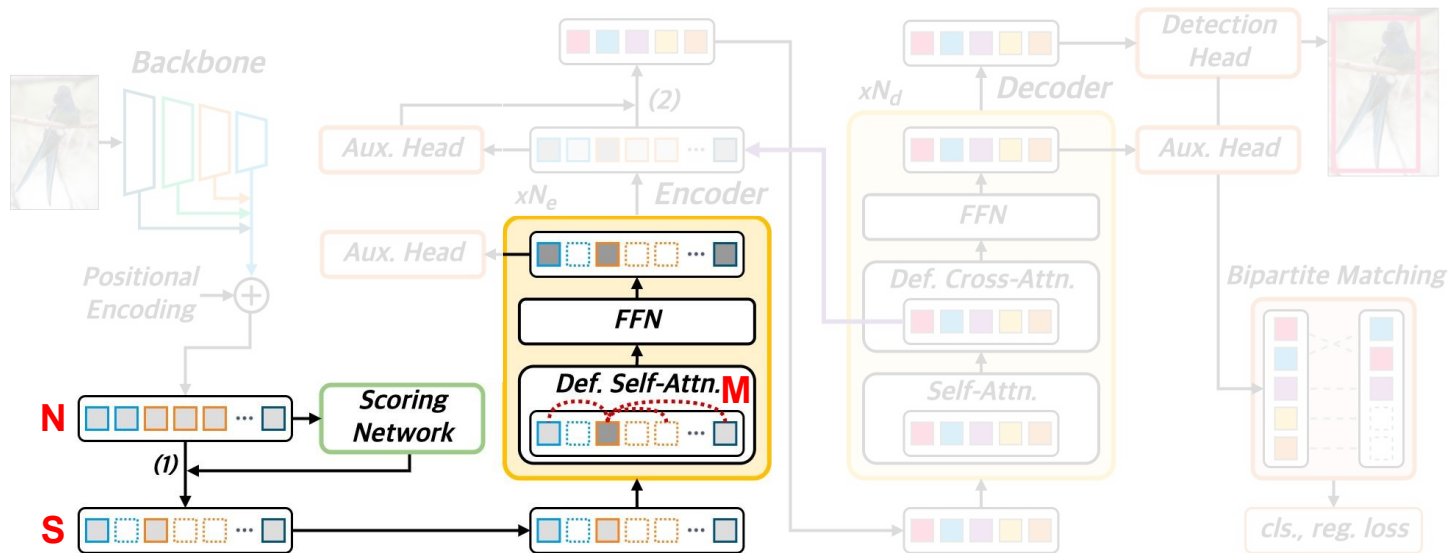
Architecture



Encoder Complexity

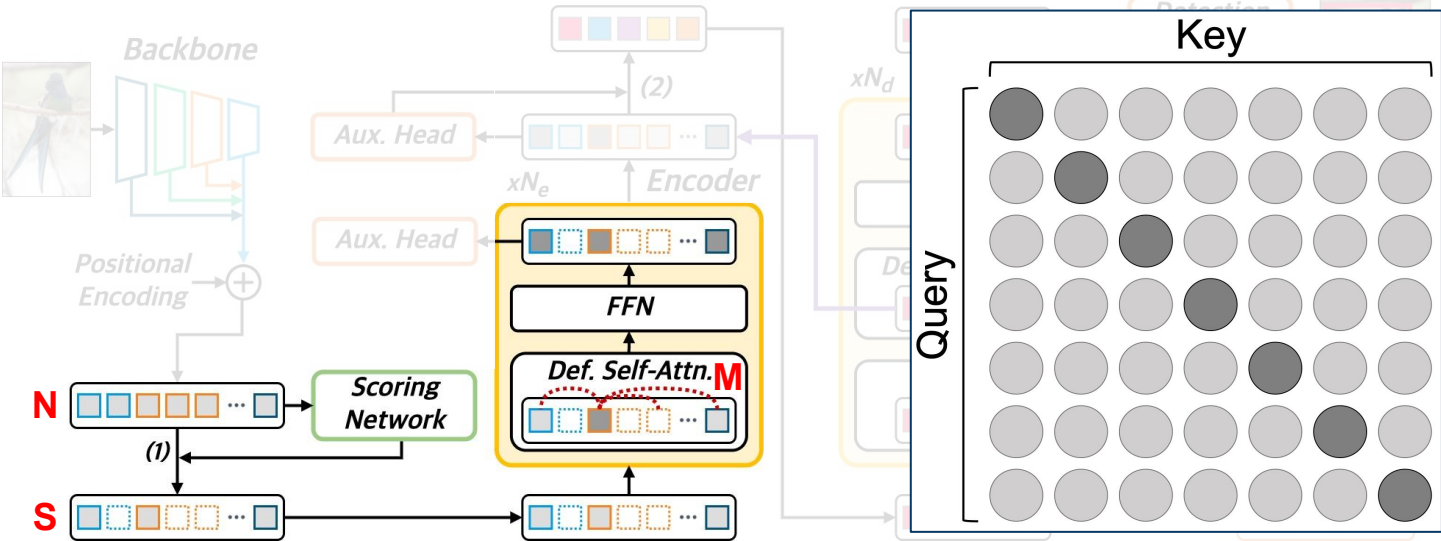
encoder complexity

N: # of tokens, **M**: # of sampling points (4)
S: # of sampled tokens in encoder ($0.1N$)



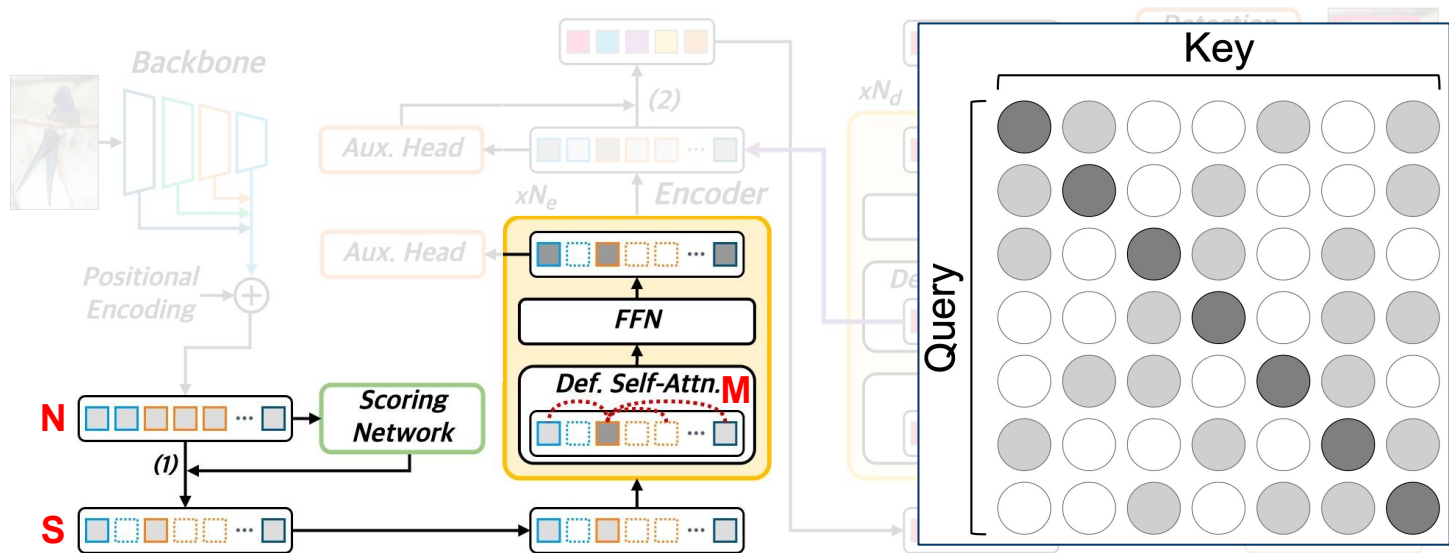
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DETR	
$N \times N$	



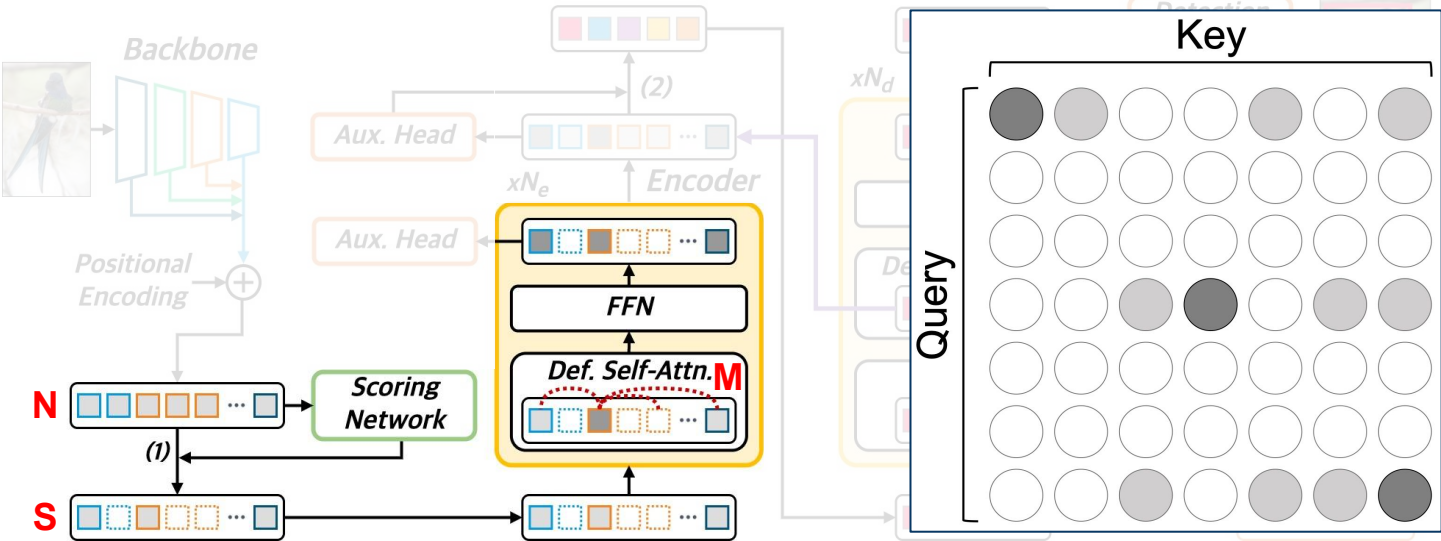
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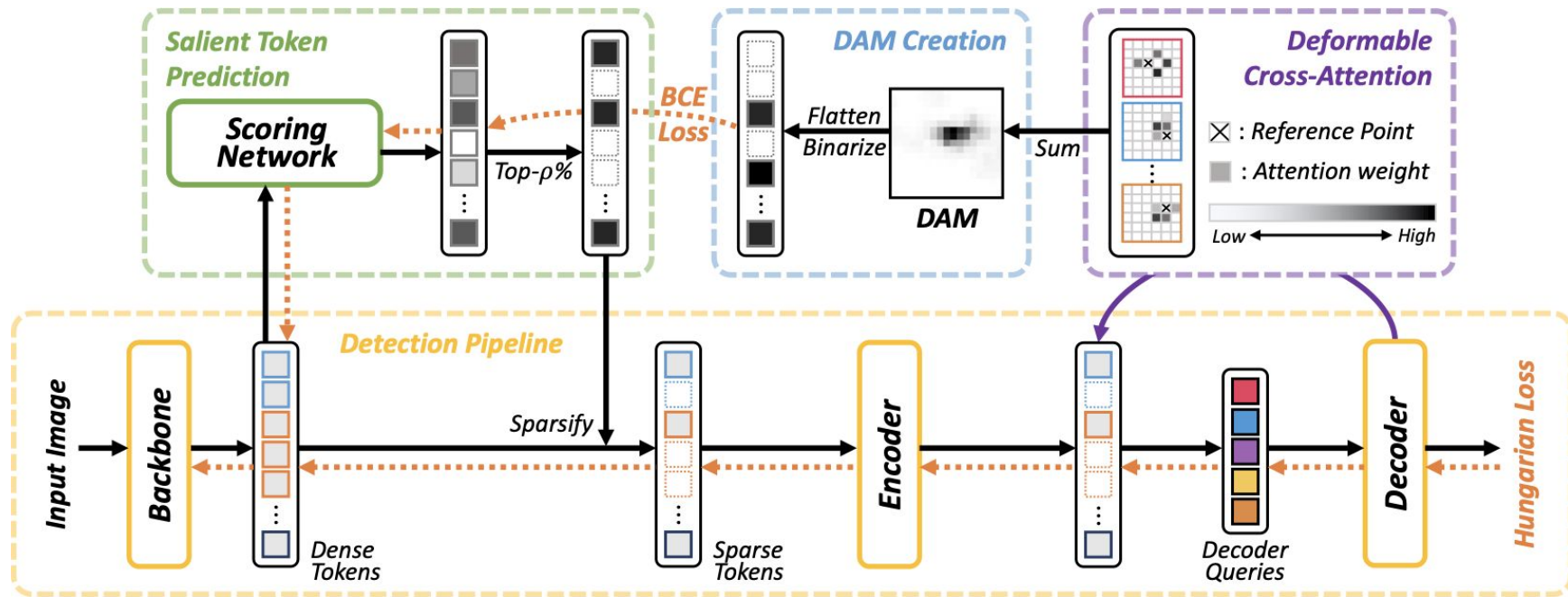


Encoder Complexity

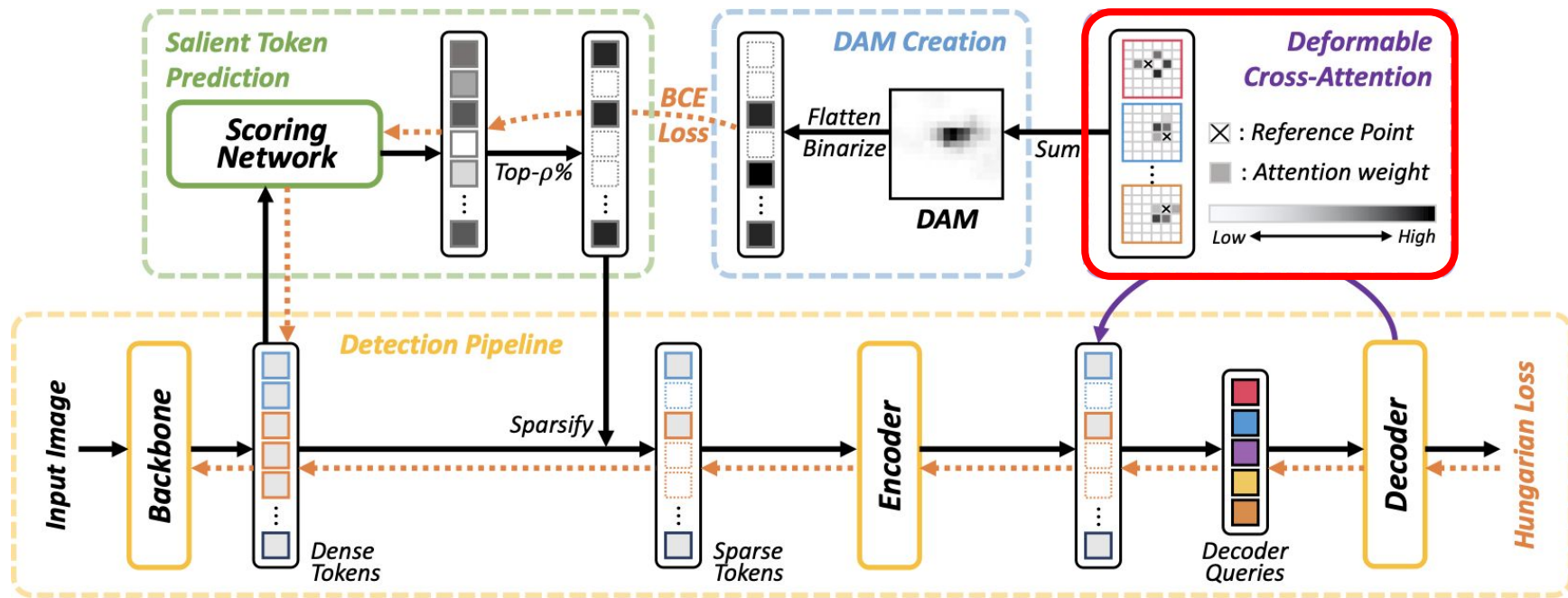
encoder complexity	N : # of tokens, M : # of sampling points (4) S : # of sampled tokens in encoder ($0.1N$)
DETR	$N \times N$
Deform. DETR	$N \times M$
Sparse DETR	$S \times M$



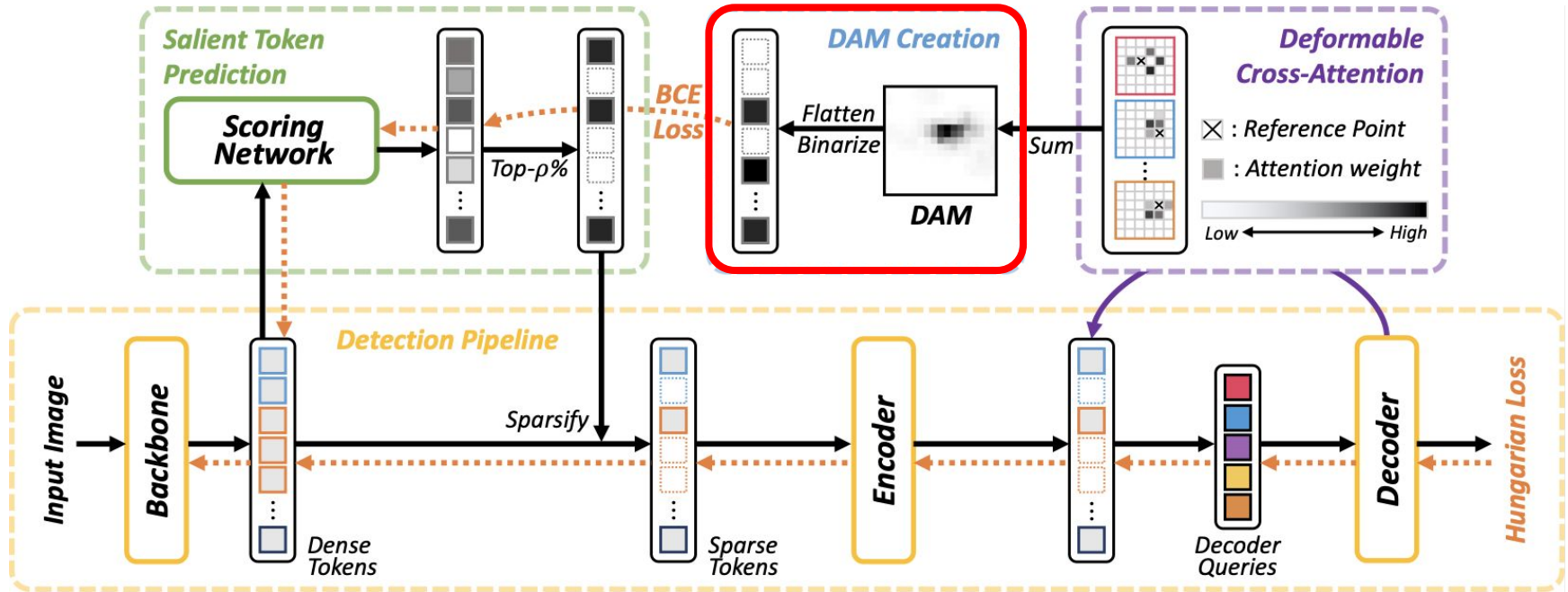
How to Train a Scoring Network



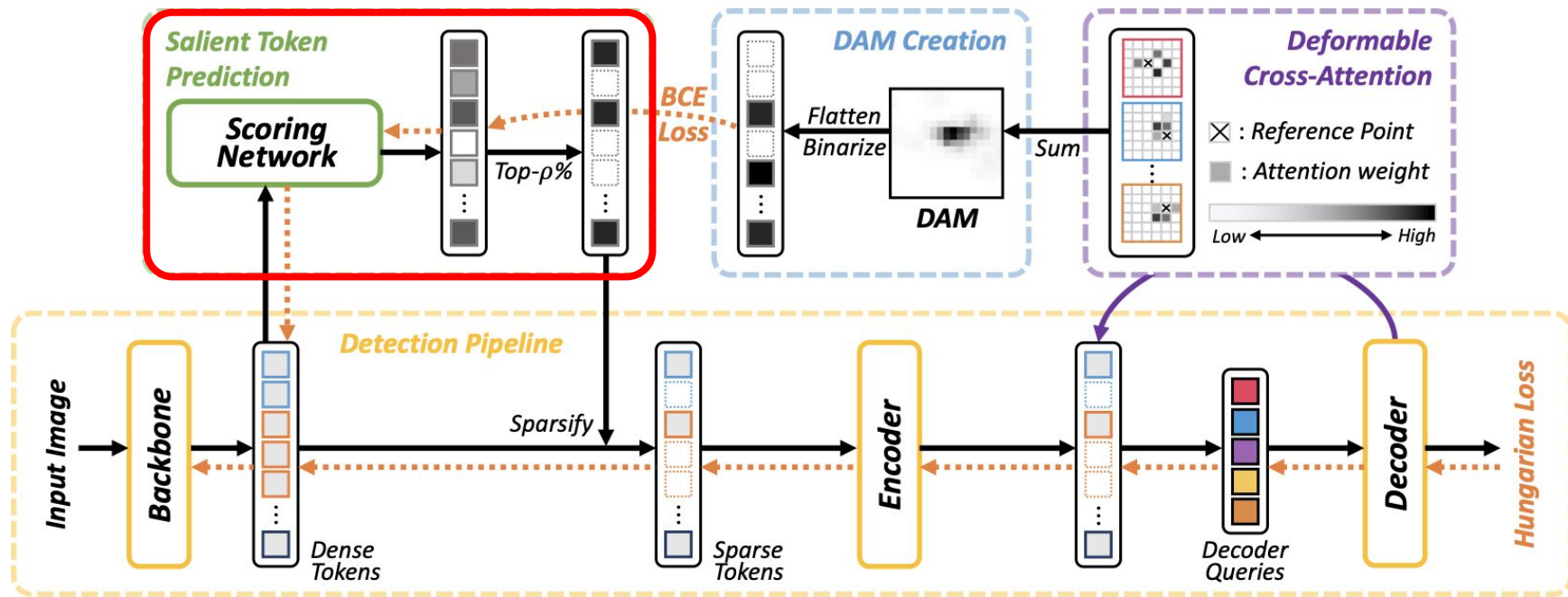
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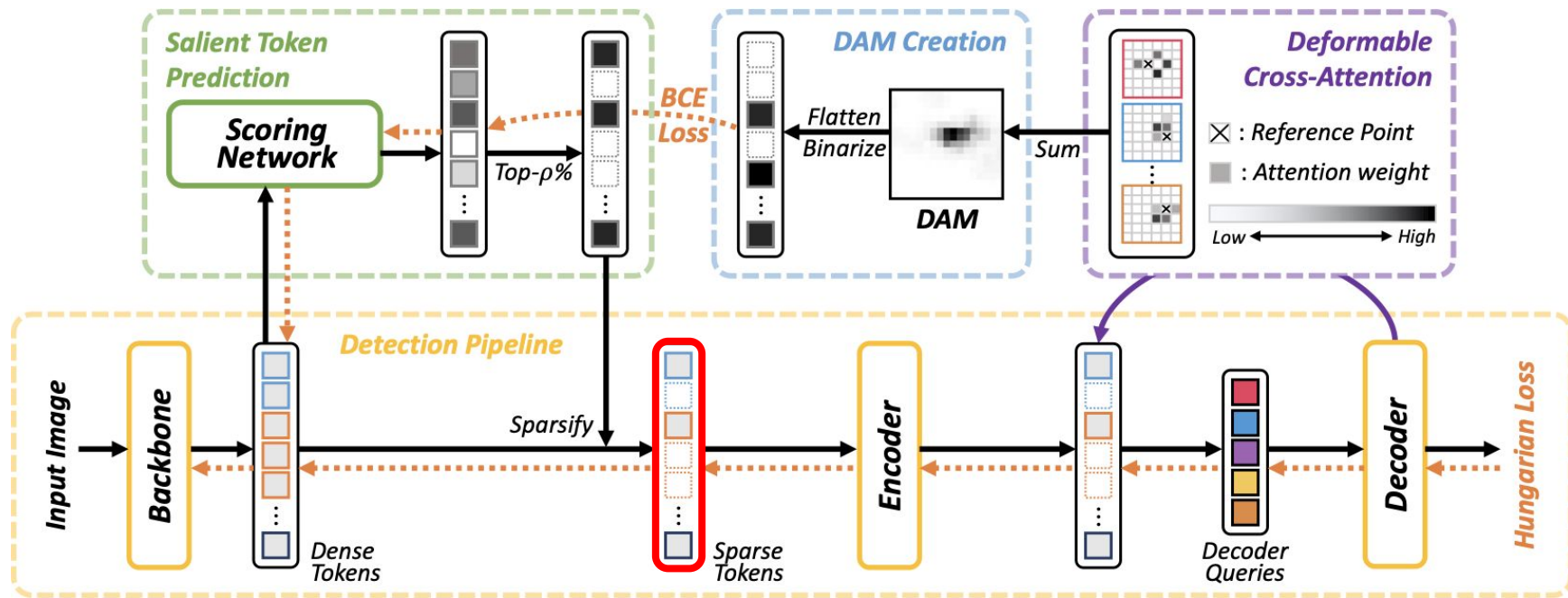
How to Train a Scoring Network



How to Train a Scoring Network



How to Train a Scoring Network



Experiments: ResNet-50

Method	Epochs	Keeping ratio (ρ)	Top- k & BBR	AP	AP ₅₀	AP ₇₅	AP _S	AP _M	AP _L	params	FLOPs	FPS
<i>ResNet-50 backbone:</i>												
F-RCNN-FPN [†]	109	N/A		42.0	62.1	45.5	26.6	45.4	53.4	42M	180G	26
DETR [†]	500	100%		42.0	62.4	44.2	20.5	45.8	61.1	41M	86G	28
DETR-DC5 [†]	500	100%		43.3	63.1	45.9	22.5	47.3	61.1	41M	187G	12

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PnP-DETR [‡]	500	33%		41.1	61.5	43.7	20.8	44.6	60.0	-	-	-
	500	50%		41.8	62.1	44.4	21.2	45.3	60.8	-	-	-
PnP-DETR-DC5 [‡]	500	33%		42.7	62.8	45.1	22.4	46.2	60	-	-	-
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Deformable-DETR	50	100%		43.9	62.8	47.8	26.1	47.4	58.0	40M	173G	19.1
	50	100%	✓	46.0	65.2	49.8	28.2	49.1	61.0	41M	177G	18.2

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Sparse-DETR	50	10%	✓	45.3	65.8	49.3	28.4	48.3	60.1	41M	105G	25.3
	50	20%	✓	45.6	65.8	49.6	28.5	48.6	60.4	41M	113G	24.8
	50	30%	✓	46.0	65.9	49.7	29.1	49.1	60.6	41M	121G	23.2

AP

0.0

GFLOPs

-56 (-32%)

FPS

+5.0 (22%)

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	500	50%		41.8	62.1	44.4	21.2	45.3	60.8	-	-	-
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	50	40%	✓	46.2	66.0	50.3	28.7	49.0	61.4	41M	128G	21.8
	50	50%	✓	46.3	66.0	50.1	29.0	49.5	60.8	41M	136G	20.5

AP

+0.3

GFLOPs

-41 (-23%)

FPS

+2.3 (13%)

Experiments: Swin-T

Method	Epochs	Keeping ratio (ρ)	Top- k & BBR	AP	AP ₅₀	AP ₇₅	AP _S	AP _M	AP _L	params	FLOPs	FPS
<i>Swin-T backbone:</i>												
DETR	500	100%		45.4	66.2	48.1	22.9	49.5	65.9	45M	92G	26.8
Deformable-DETR	50	100%		45.7	65.3	49.9	26.9	49.4	61.2	40M	180G	15.9
	50	100%	✓	48.0	68.0	52.0	30.3	51.4	63.7	41M	185G	15.4
Sparse-DETR	50	10%	✓	48.2	69.2	52.3	29.8	51.2	64.5	41M	113G	21.2
				<div style="border: 1px solid black; padding: 5px; text-align: center;"> AP +0.2 </div>				<div style="border: 1px solid black; padding: 5px; text-align: center;"> GFLOPs -72 (-39%) </div>			<div style="border: 1px solid black; padding: 5px; text-align: center;"> FPS +5.8 (38%) </div>	

Experiments: Swin-T

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DETR	500	100%		45.4	66.2	48.1	22.9	49.5	65.9	45M	92G	26.8
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	50	40%	✓	49.2	69.5	53.5	31.4	52.9	64.8	41M	136G	18.0
	50	50%	✓	49.3	69.5	53.3	32.0	52.7	64.9	41M	144G	17.2

AP

+1.3

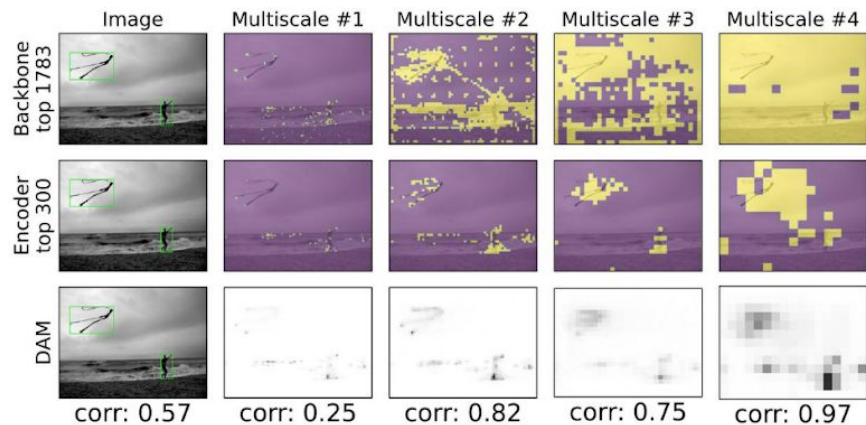
GFLOPs

-41 (-22%)

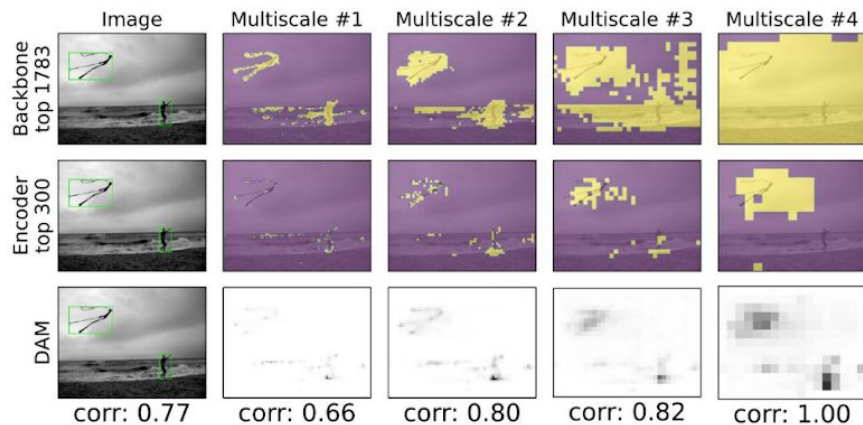
FPS

+1.8 (12%)

Visualization

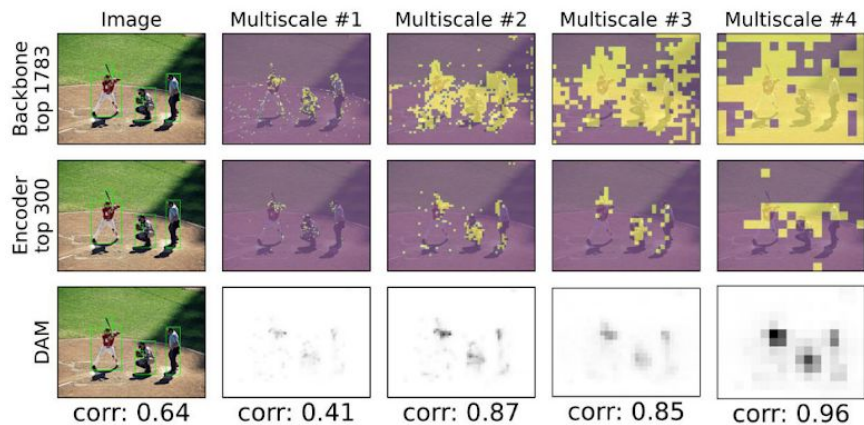


(a) OS-based model ($\rho = 0.1$)

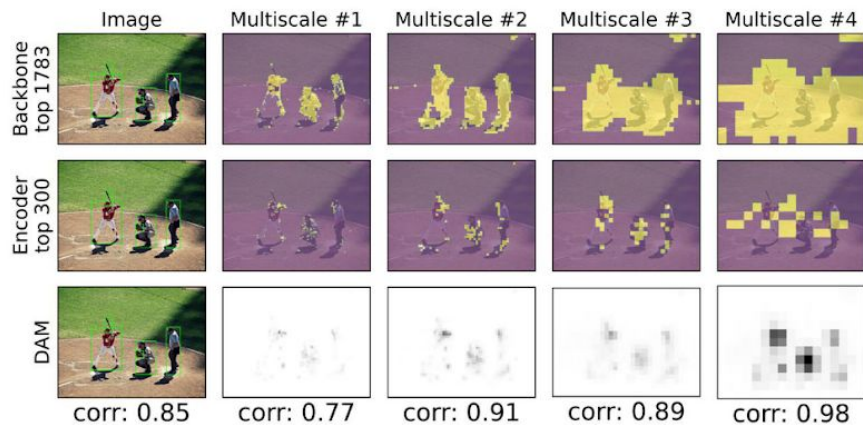


(b) DAM-based model ($\rho = 0.1$)

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- We propose **novel sparsification criteria to sample the informative subset** from the entire token set: *Decoder cross-Attention Map* (DAM)
- Sparse DETR **outperforms the Deformable DETR** even when **using only 10% of the encoder token**, and decreases the overall computation by 38%



Code & models are available now.

<https://github.com/kakaobrain/sparse-detr>

More experiments and ablation studies can be found in the paper