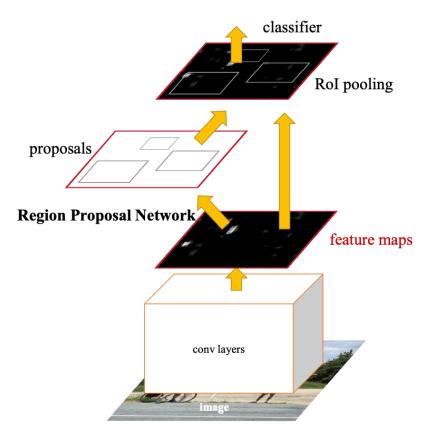
Real-time Instance Segmentation with the YOLACT Family

Yong Jae Lee
UC Davis / Cruise Al

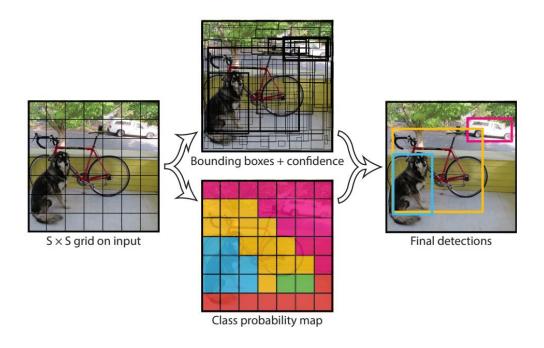


Back in 2018 ...



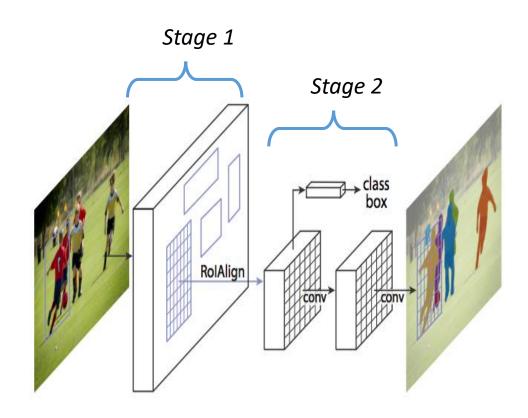
2-stage object detection:

Faster-RCNN



1-stage object detection: YOLO, SSD

Back in 2018 ...



2-stage instance segmentation:
Mask-RCNN

"Boxes are stupid anyway though, I'm probably a true believer in masks except I can't get YOLO to learn them." - Joseph Redmon, YOLOv3



1-stage instance segmentation:

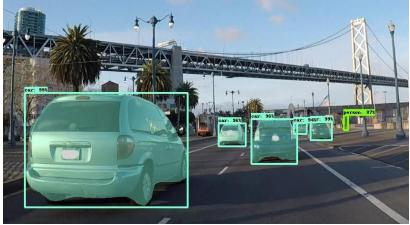
FCIS ... but no real-time method

Real-time instance segmentation applications

Robotics



Self-driving



Drones

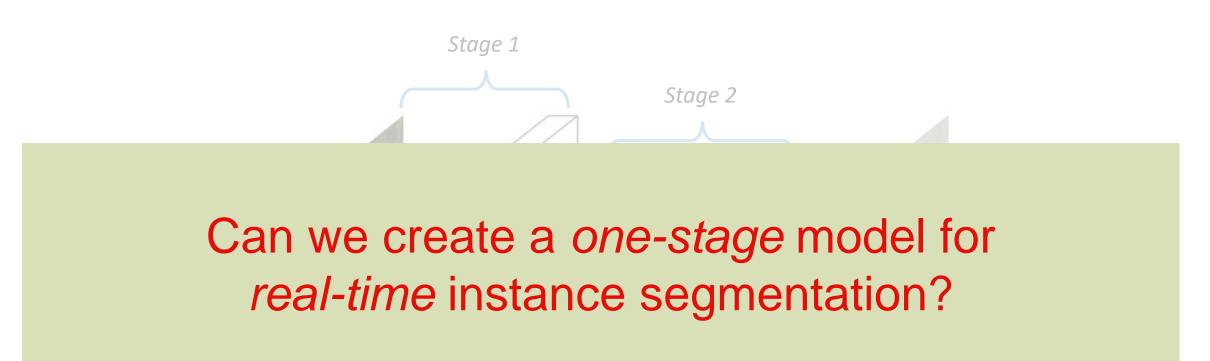


Instance segmentation is challenging



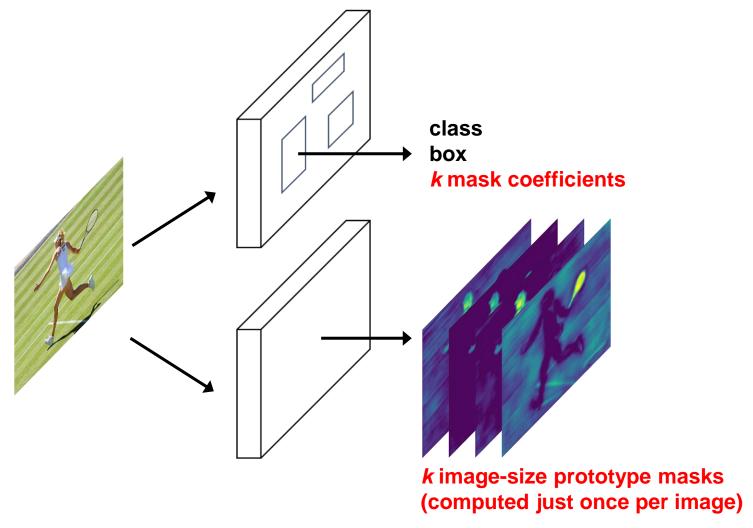
• Requires different outputs for same class instances in different locations (i.e. translation variance)

2-stage instance segmentation (e.g. Mask-RCNN)



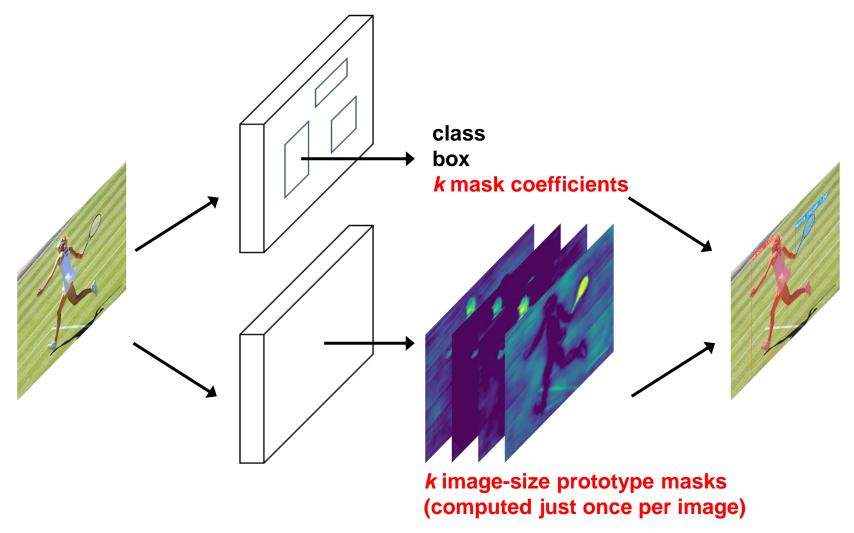
- Stage 1: use Region Proposal Network to generate region proposals
- Stage 2: pool features for each proposal (via ROI-align) and classify

YOLACT Main Idea: Predict masks via two parallel tasks

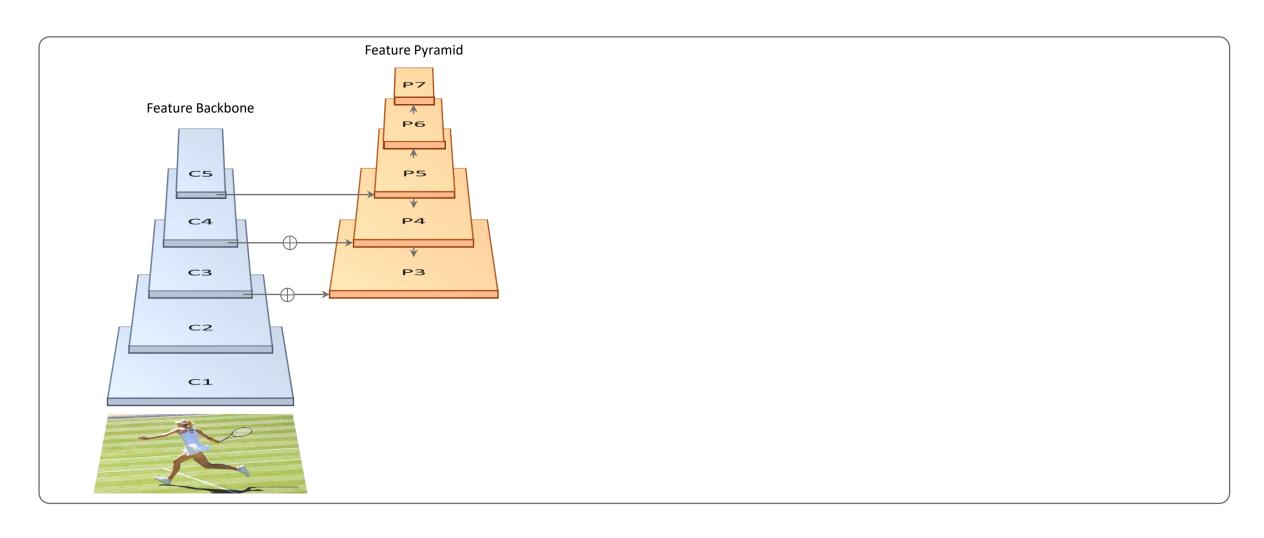


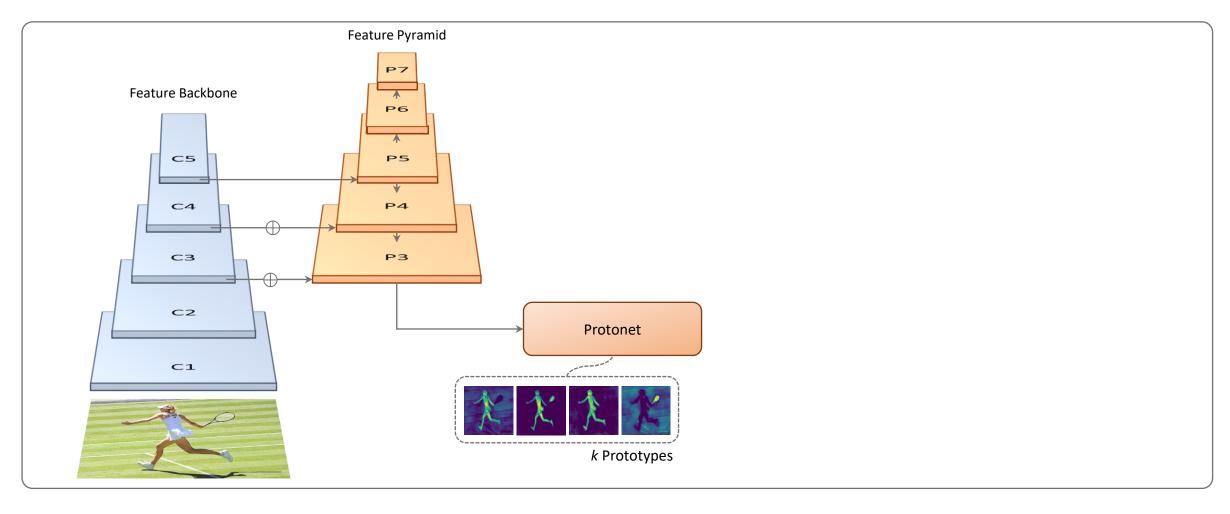
• Linearly combine image-size prototype masks with mask coefficients

YOLACT Main Idea: Predict masks via two parallel tasks

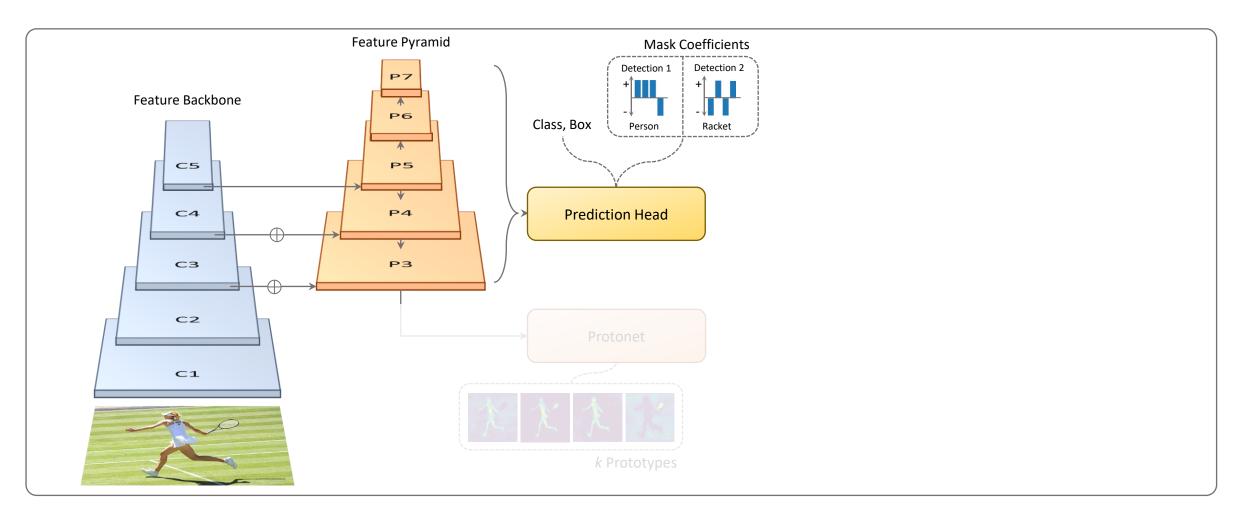


• Linearly combine image-size prototype masks with mask coefficients

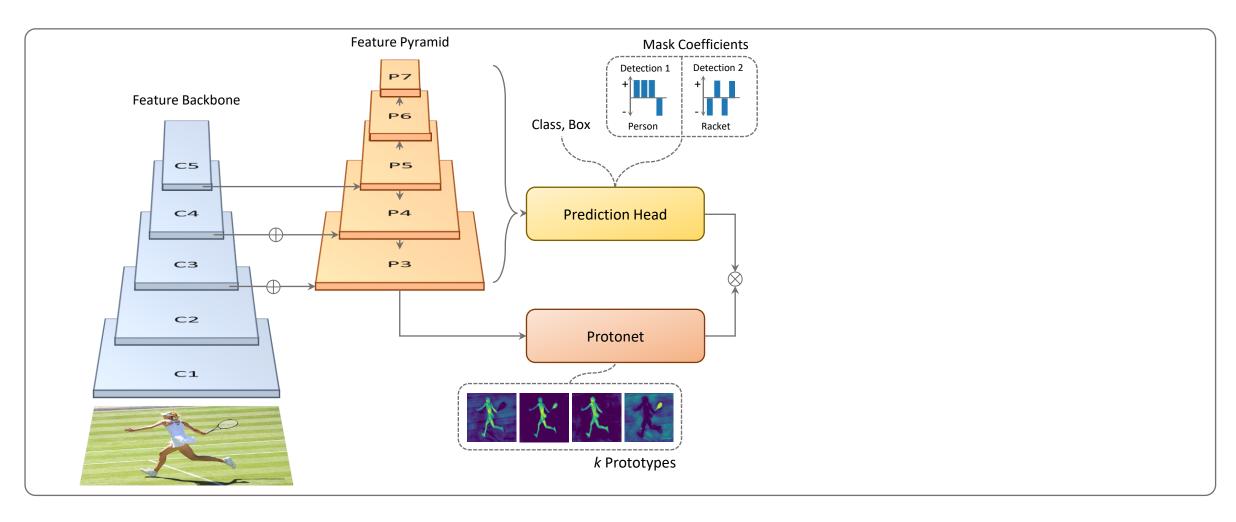




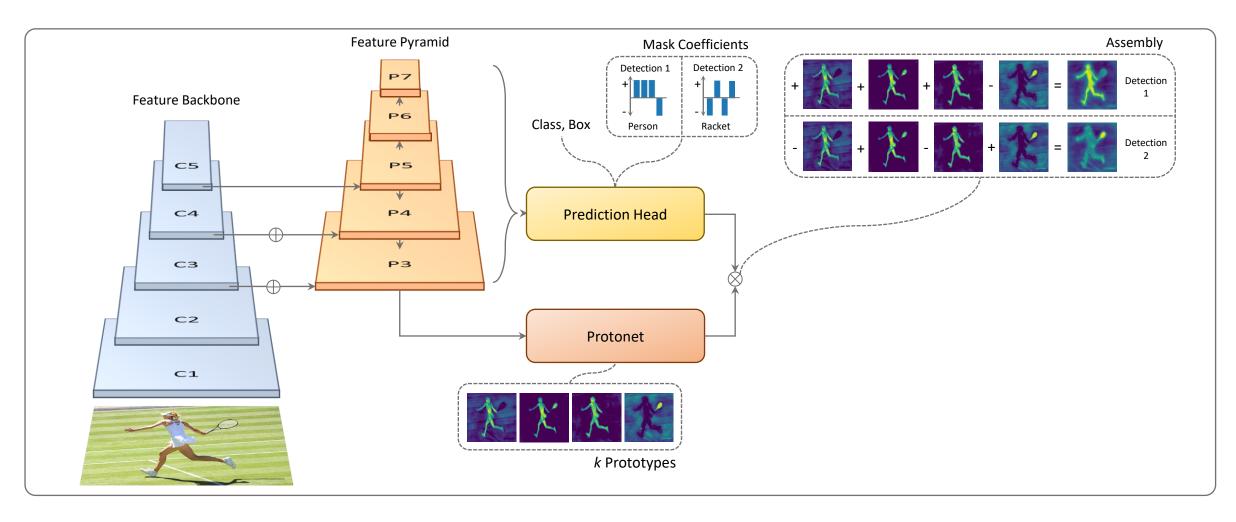
 Attach an FCN ("ProtoNet") to the largest feature layer (P3) to produce k image-resolution prototype masks



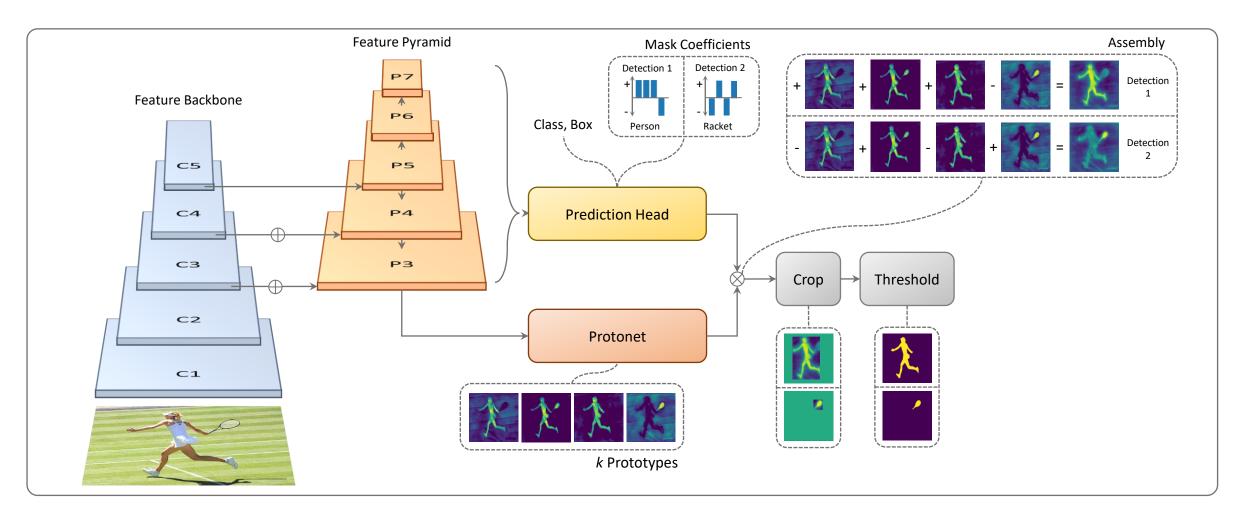
• In parallel, predict *k* mask coefficients for each anchor box (in addition to class confidences and box coefficients)



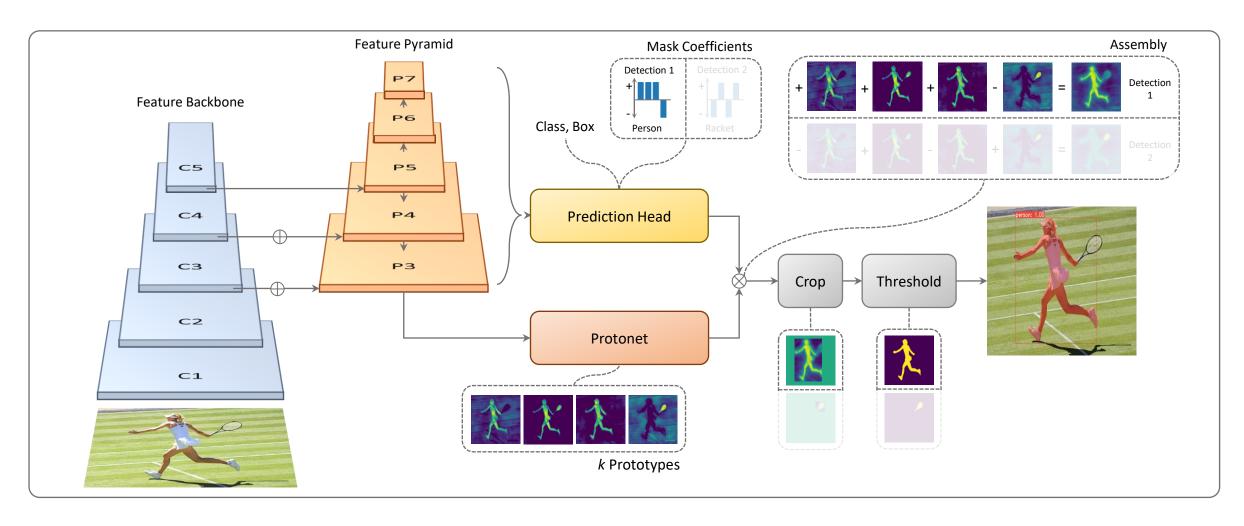
• For each instance, linearly combine prototypes using corresponding predicted coefficients



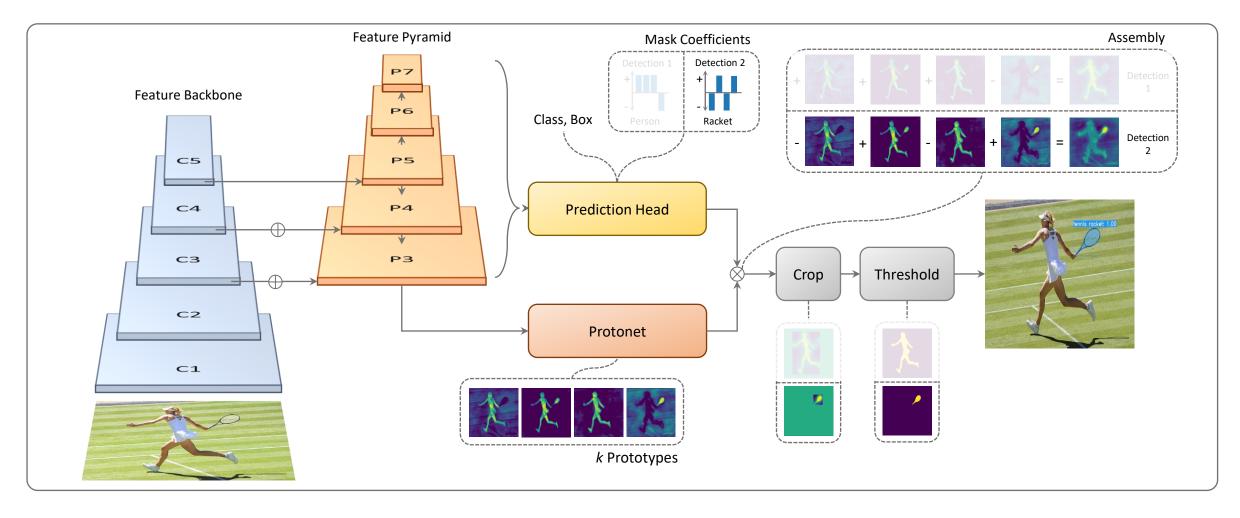
• For each instance, linearly combine prototypes using corresponding predicted coefficients



• Finally, crop with the predicted bounding box and threshold

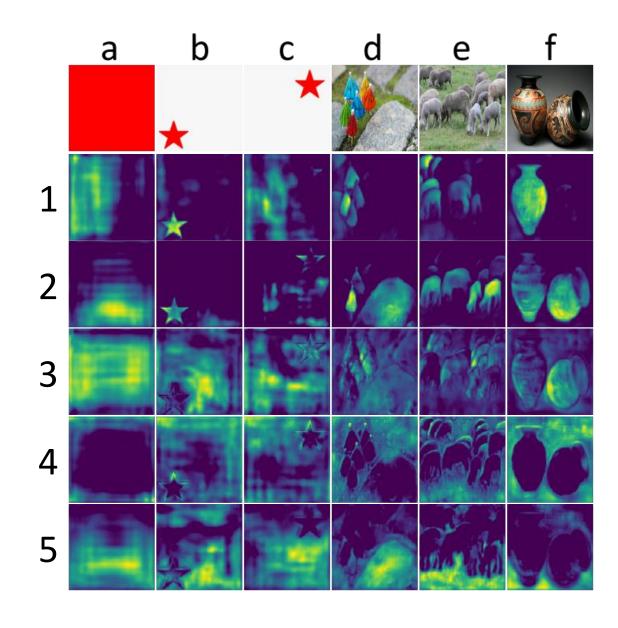


Example 1: Person

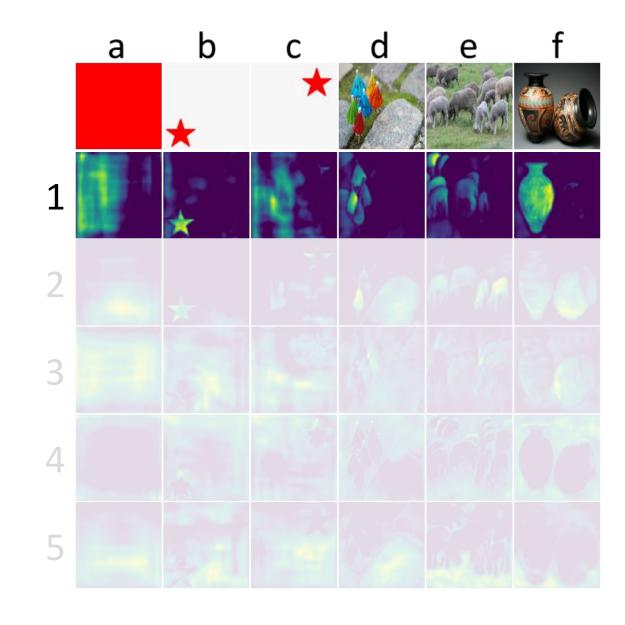


Example 2: Tennis Racket

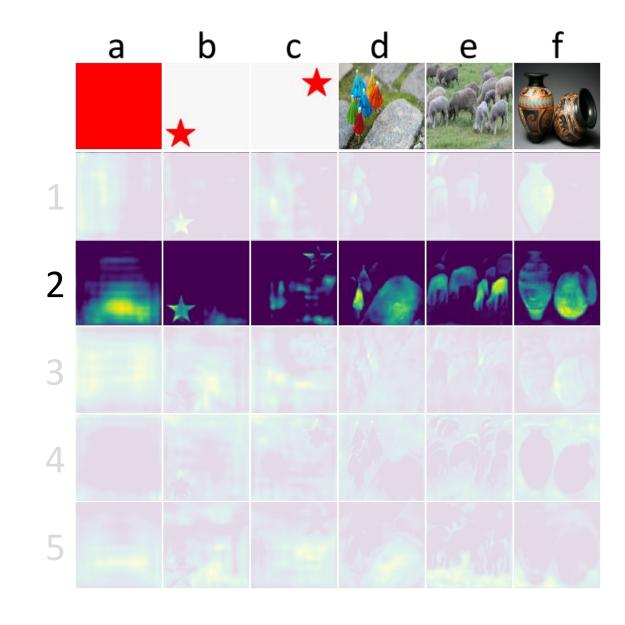
- Supervision only comes from final mask loss
- Spatially partition the image
- Segment background
- Detect instance contours
- Encode position-sensitive directional maps
- Most do a combination



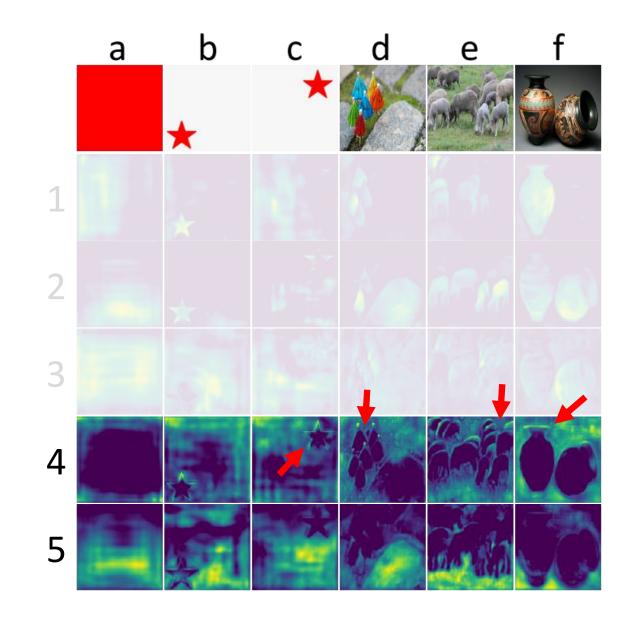
- Supervision only comes from final mask loss
- Spatially partition the image
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- Detect instance contours
- Encode position-sensitive directional maps
- Most do a combination



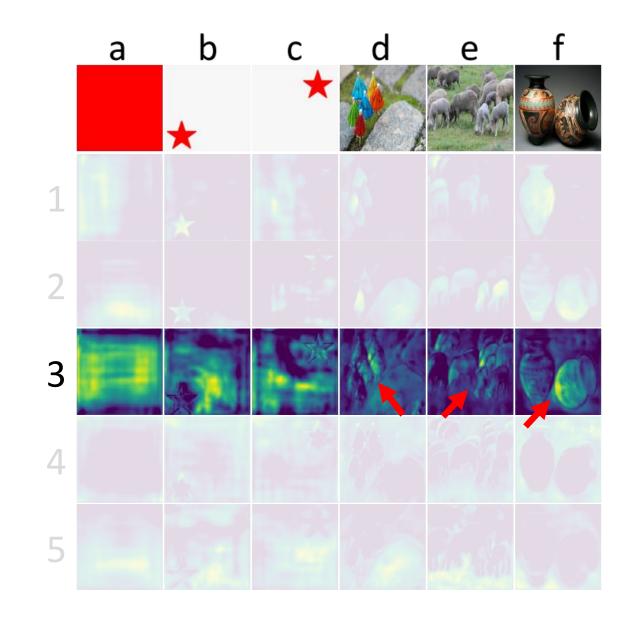
- Supervision only comes from final mask loss
- Spatially partition the image
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- Most do a combination



- Supervision only comes from final mask loss
- Spatially partition the image
- Segment background
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- Encode position-sensitive directional maps
- Most do a combination

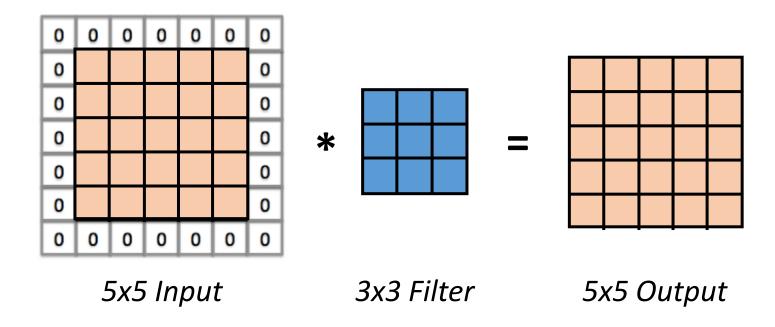


- Supervision only comes from final mask loss
- Spatially partition the image
- Segment background
- Detect instance contours
- Encode position-sensitive directional maps
- Most do a combination

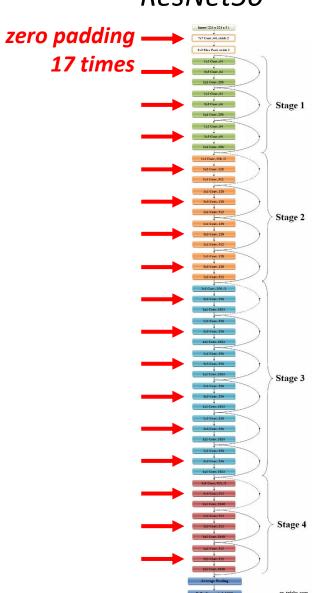


Zero-padding in ResNets

Needed to keep input and output spatial resolution same



ResNet50



^{*}Same finding in How Much Position Information Do Convolutional Neural Networks Encode? Islam et al. ICLR 2020

YOLACT++

- 1) Fast Mask-Rescoring (inspired by "Mask Scoring R-CNN")
- 2) Deformable conv in backbone
- 3) Optimized prediction heads

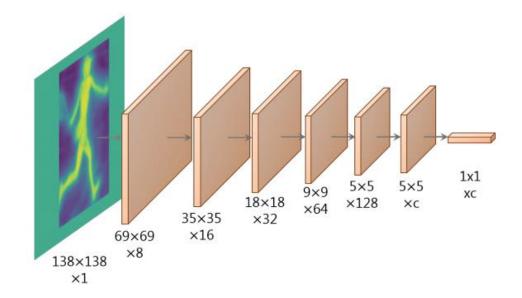


Fig. 6: Fast Mask Re-scoring Network Architecture Our mask scoring branch consists of 6 conv layers with ReLU non-linearity and 1 global pooling layer. Since there is no feature concatenation nor any fc layers, the speed overhead is only ~ 1 ms.

Results

First real-time (> 30 fps)
 instance segmentation
 algorithm with competitive
 results on the challenging
 MS COCO dataset

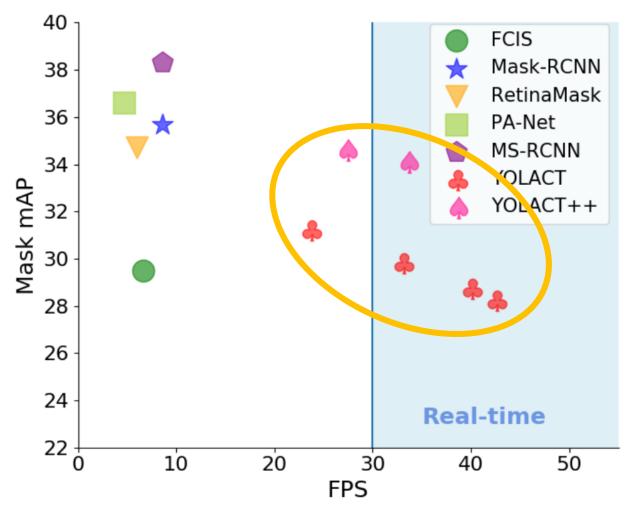


Figure 1: Speed-performance trade-off for various instance segmentation methods on COCO.



One-stage instance segmentation is an active area

BlendMask: Top-down meets bottom-up for instance segmentation, Chen et al., CVPR 2020

Centermask: Real-time anchor-free instance segmentation, Lee & Park, CVPR 2020

SOLO: Segmenting Objects by Locations, Wang et al., ECCV 2020

Conditional Convolutions for Instance Segmentation, Tian et al., ECCV 2020

SOLOv2: Dynamic and fast instance segmentation, Wang et al., NeurIPS 2020

• • •

Real-time instance segmentation on Edge devices

• YOLACT not fast enough for real-time inference on *edge devices* (Jetson Xavier AGX: ~6 FPS)



YolactEdge Main Idea: Exploit temporal redundancy in video



• Compute features on *keyframes* and re-use on *non-keyframes*

YolactEdge Main Idea: Exploit temporal redundancy in video



zoom-in

- Compute features on *keyframes* and re-use on *non-keyframes*
- Need both warped features and computed features
- Inspired by [Zhu CVPR'17; CVPR'18] but our focus is real-time instance segmentation on edge devices

Where is the computational bottleneck?

	C_1	C_2	C_3	C_4	C_5
# of convs	1	9	12	69	9
TFLOPS	0.1	0.7	1.0	5.2	0.8
%	1.5	8.7	13.2	66.2	10.3

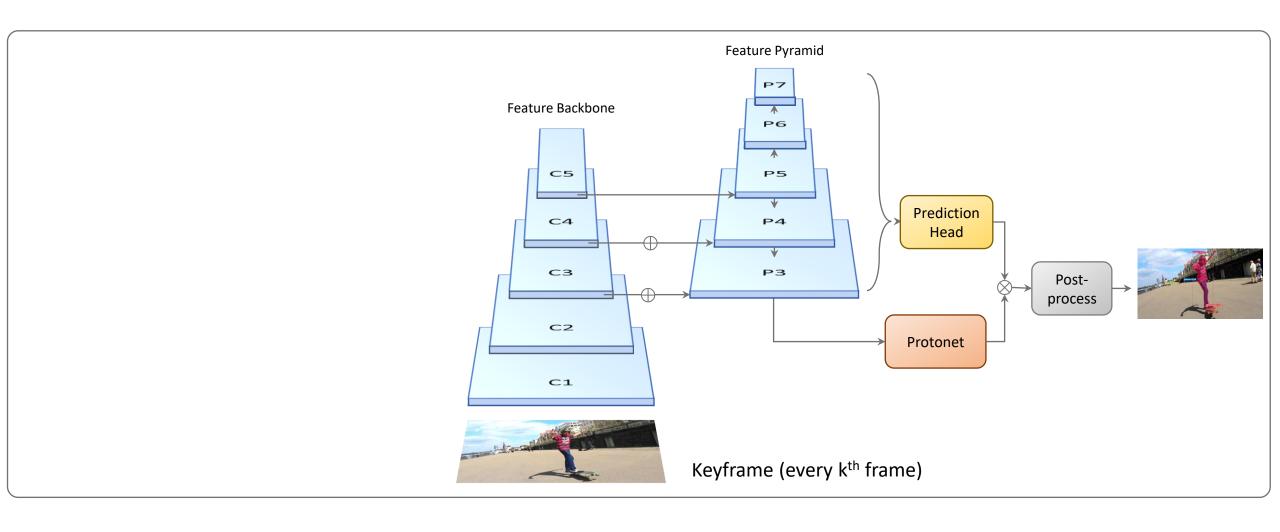
Stage	%	Stage	%
Backbone	54.7	FPN	6.4
ProtoNet	7.8	Pred	10.6
Detect	6.6	Other	13.1

(a) ResNet-101 Backbone

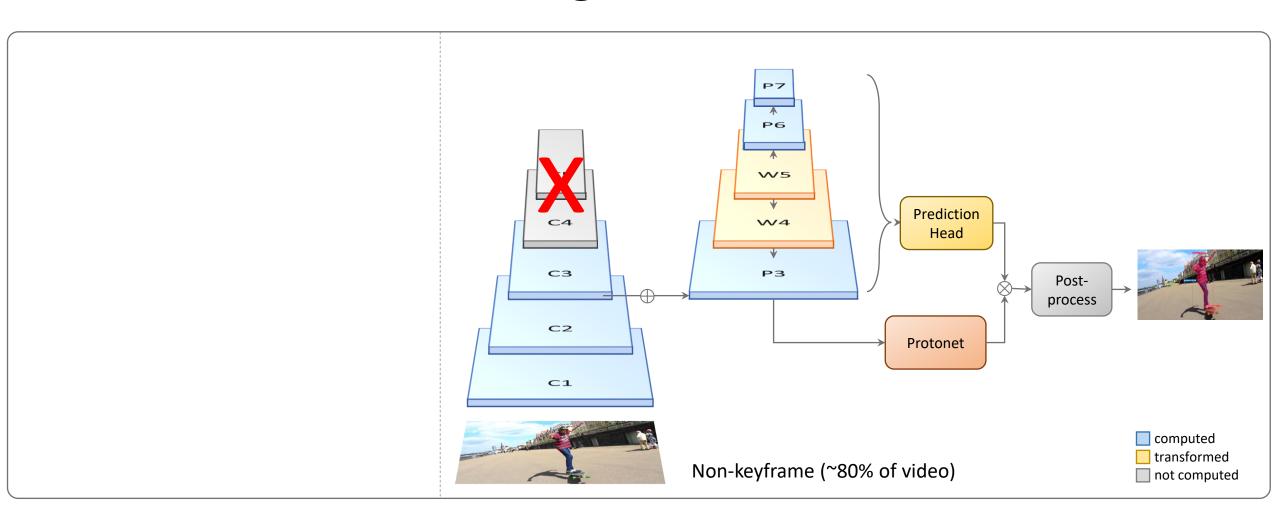
(b) **YOLACT**

- Compute C1-C3 features on all frames
- Only compute C4 features on keyframes, warp to non-keyframes

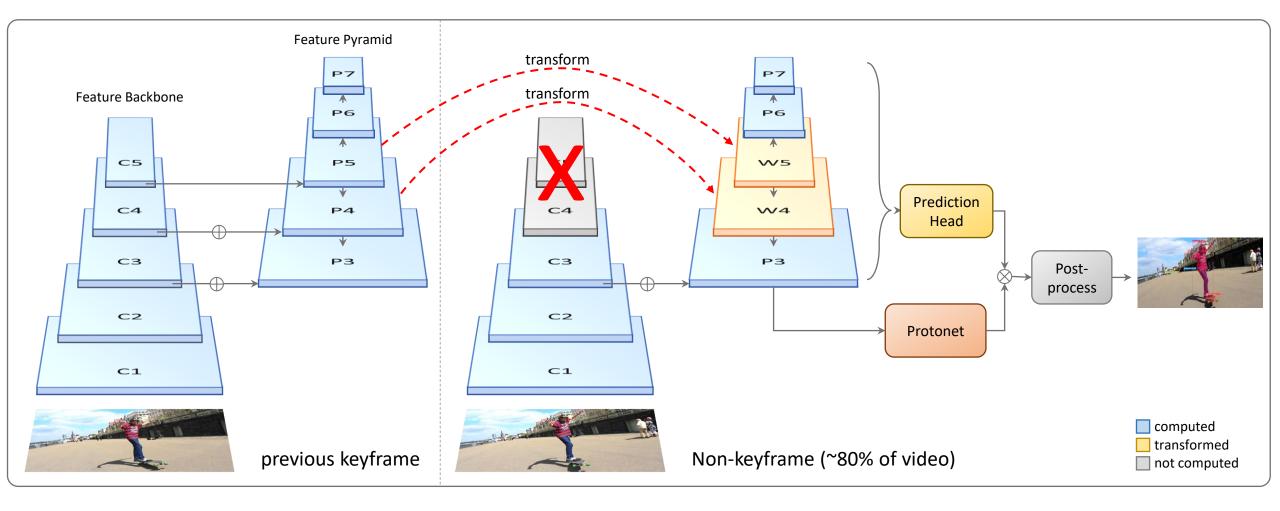
YolactEdge architecture



YolactEdge architecture

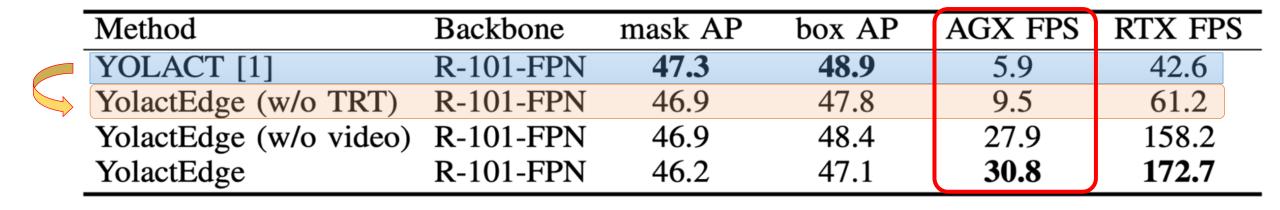


YolactEdge architecture



• Partial feature transform to preserve high-res details in the prototype masks

Real-time on NVIDIA Jetson Xavier AGX



Exploiting temporal redundancy leads to ~1.6x speedup

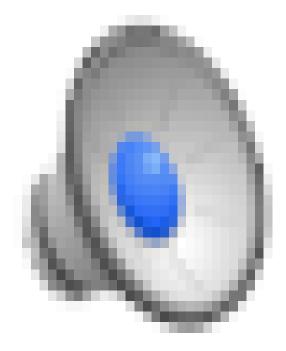
Real-time on NVIDIA Jetson Xavier AGX

	Method	Backbone	mask AP	box AP	AGX FPS	RTX FPS
	YOLACT [1]	R-101-FPN	47.3	48.9	5.9	42.6
	YolactEdge (w/o TRT)	R-101-FPN	46.9	47.8	9.5	61.2
	YolactEdge (w/o video)	R-101-FPN	46.9	48.4	27.9	158.2
W.	YolactEdge	R-101-FPN	46.2	47.1	30.8	172.7

- Exploiting temporal redundancy leads to ~1.6x speedup
- TensorRT optimization enables real-time (30 fps) speeds on Xavier AGX

YolactEdge webcam demo



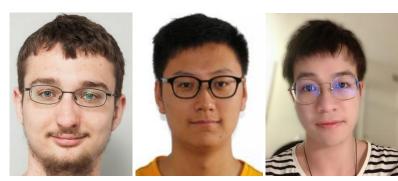


Conclusions

- YOLACT: First competitive real-time instance segmentation algorithm
- Limitations: small objects, crowds
- Future work: on-device learning







Daniel Bolya

Chong Zhou

Haotian Liu





Rafael A. Rivera Soto

Fanyi Xiao

github.com/dbolya/yolact
github.com/haotian-liu/yolact_edge