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Instance Segmentation of Urban Street Scenes

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Vision and Cognitive Systems – Prof. Lamberto Ballan

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DIPARTIMENTO MATEMATICA

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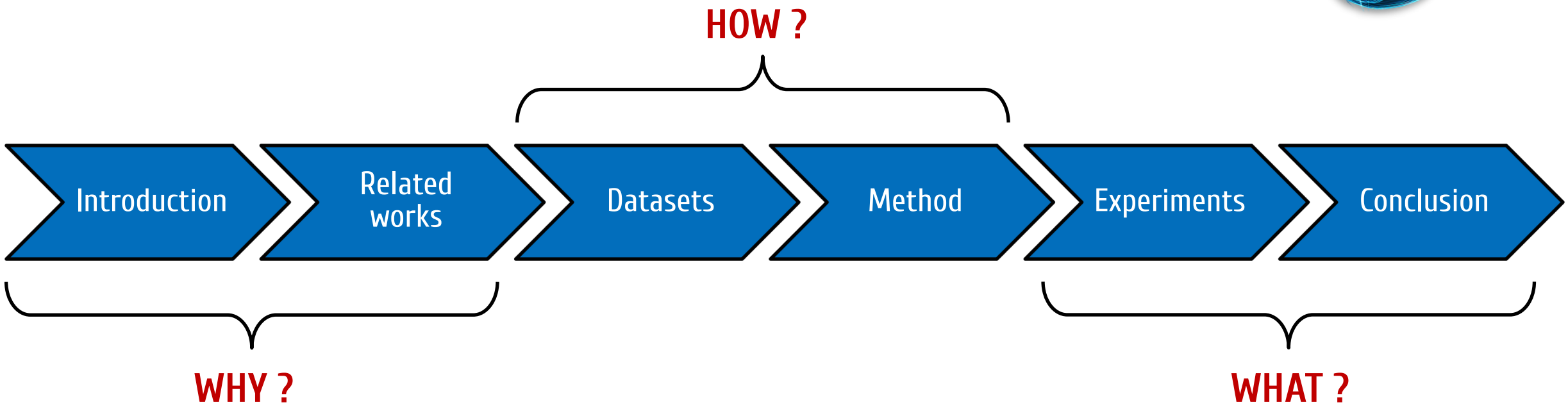
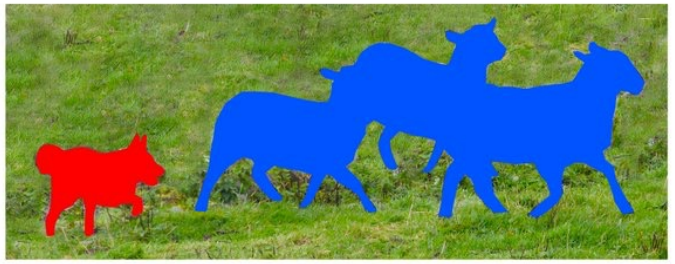
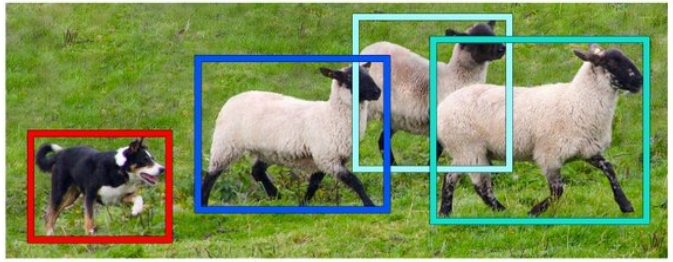


➢ Goal: ⟶ Instance Segmentation of Urban Street Scenes

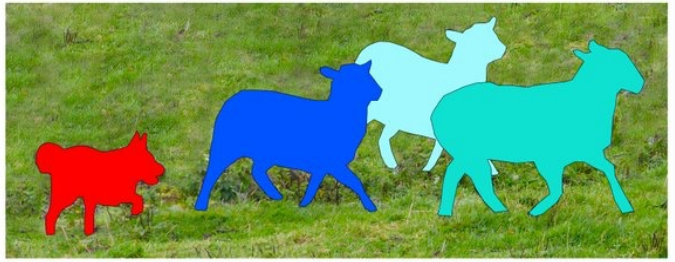
Image Recognition



Semantic Segmentation



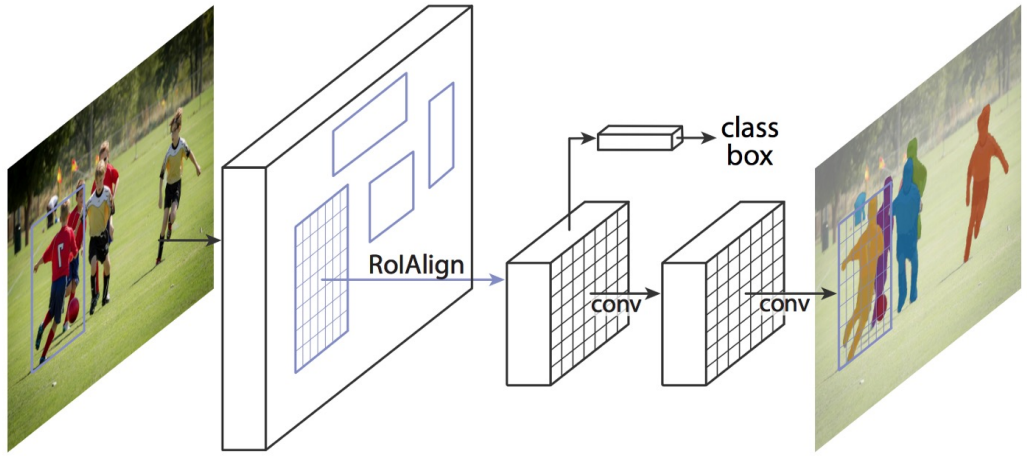
Object Detection

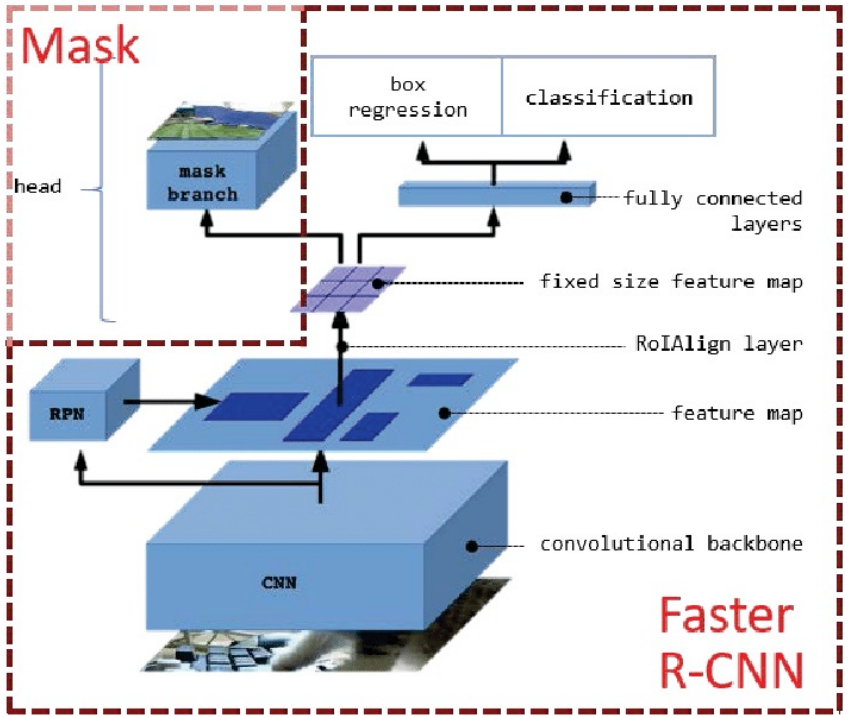


Instance Segmentation

➢ Mask R-CNN: Box-based two stage approch

- Generates a segmentation mask for each instance
- Region Proposal Network
- Class label, bounding box offset and object mask
- Backbone and head
- RoIAlign

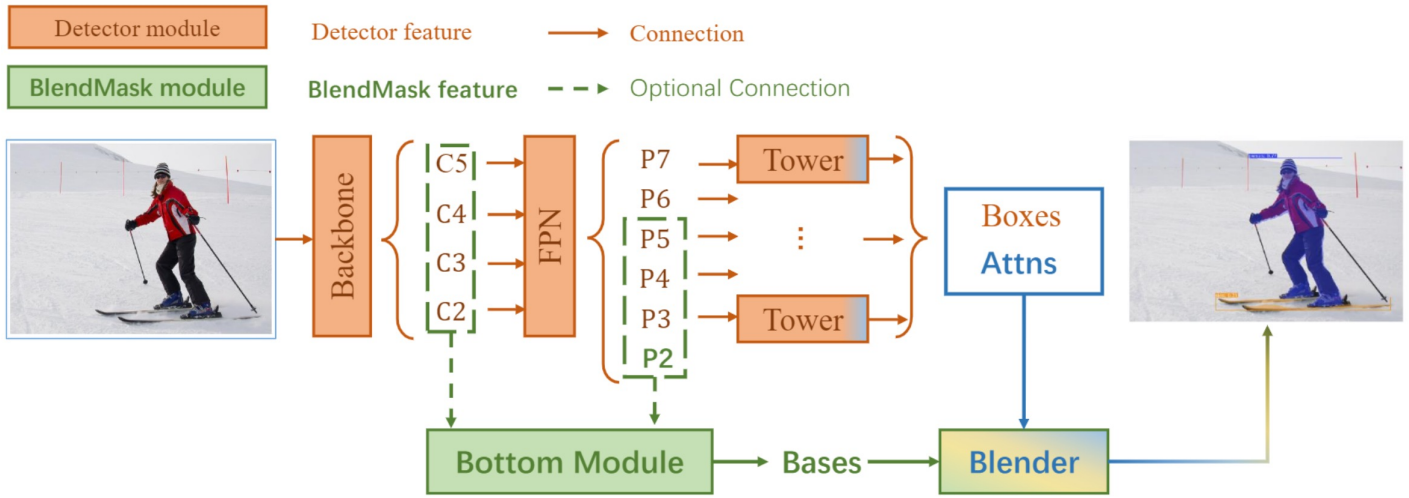




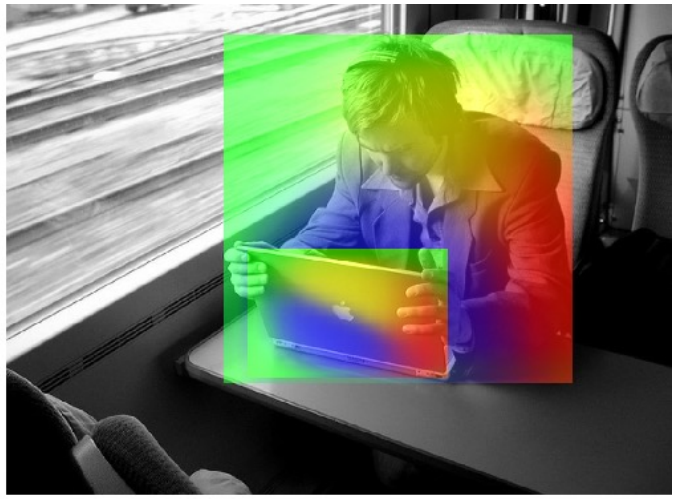
❌ COMPLICATED SCENARIOS

❌ MULTI-TASK NETWORK

➢ BlendMask: Anchor box-free one-stage approach



(a) Bottom-Level Bases



(b) Top-Level attentions

- **Bottom module:** deals with the production of the bases

- **Top layer:** a single convolution layer, one for each tower. Predictions attention instances

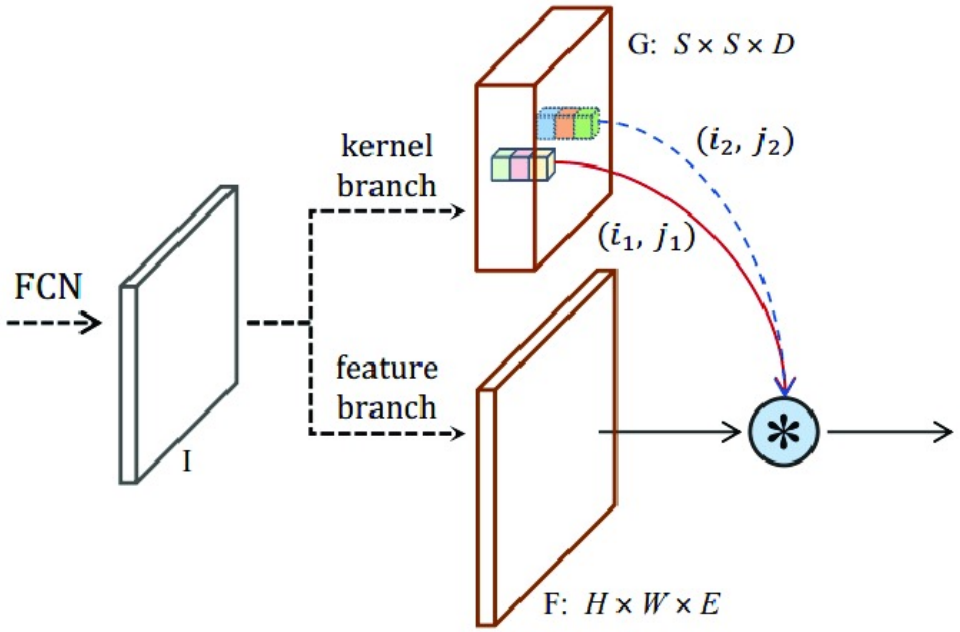
- **Blender module:** combines bases with attentions

✓ BETTER IN TIME AND PRECISION

SOLOv2

➢ Box-free one-stage approach

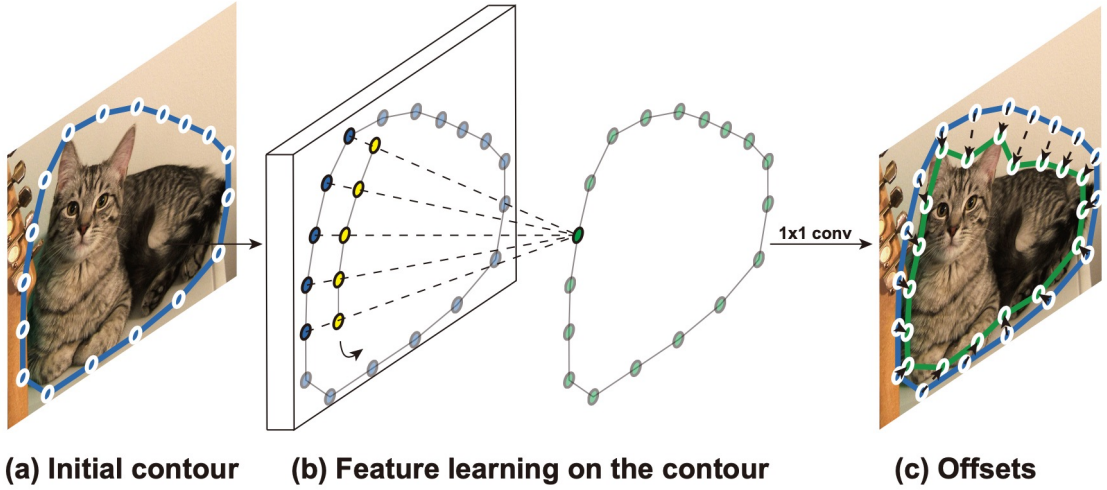
- Mask kernel prediction and mask feature learning
- Matrix non-maximum suppression (NMS)



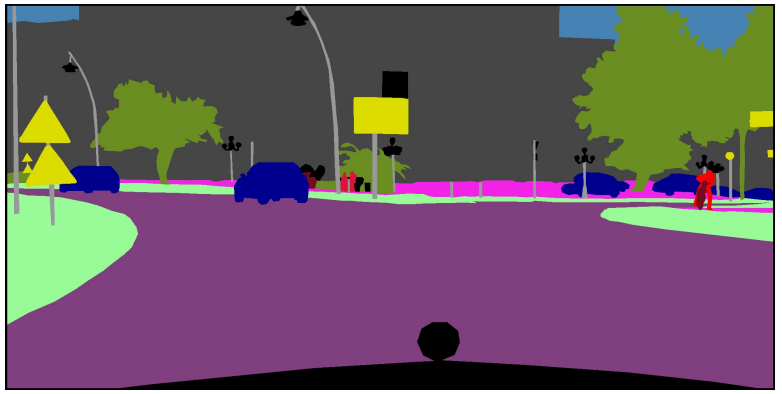
DEEP SNAKE

➢ Contour-based approach

- Initial contour proposal iteratively deforms
- Circular Convolution



➢ Cityscapes



- Benchmarks and large-scale datasets for semantic urban scene understanding
- Video sequences, recorded in 50 different cities
- High-quality annotations or/and coarse annotation
- gtFine & leftImg8

category	#instances	category	#instances	category	#instances
person	17918	rider	1781	car	26963
truck	484	bus	380	train	168
motorcycle	737	bicycle	3675		
total	52106				

- **3475** train/val images
- **1525** test images
- **5000** total images
- **8** classes

❗ **PROBLEM : always images in good weather conditions**

➢ WildDash

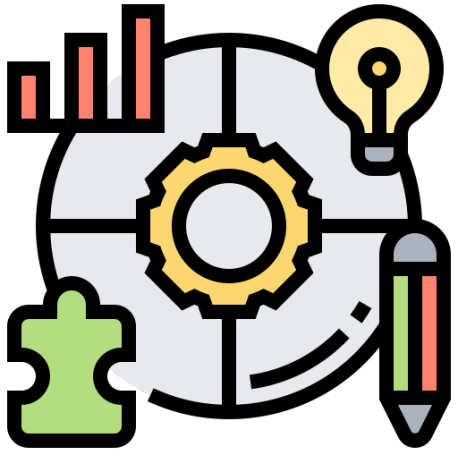
- Benchmark suite and dataset for semantic and instance segmentation for the automotive domain
- Scenarios such as rain, darkness and road cover
- public gt package

category	#instances	category	#instances	category	#instances
ego vehicle	504	person	1479	rider	589
car	4045	truck	439	bus	128
caravan	16	trailer	20	train	6
motorcycle	536	bicycle	74	pickup	266
van	201				
total	8303				

- **3405** train images
- **851** test images
- **4256** total images
- **13** classes

CHALLENGES

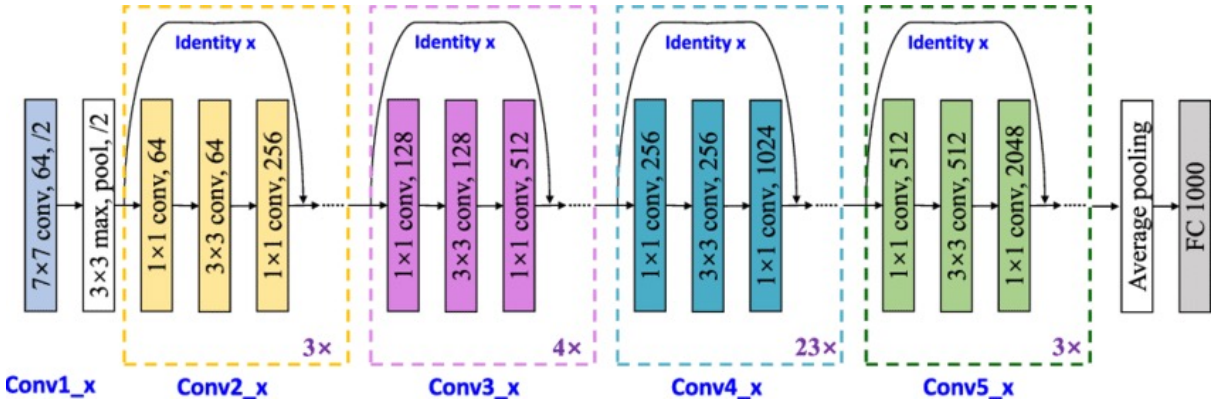
➢ Method

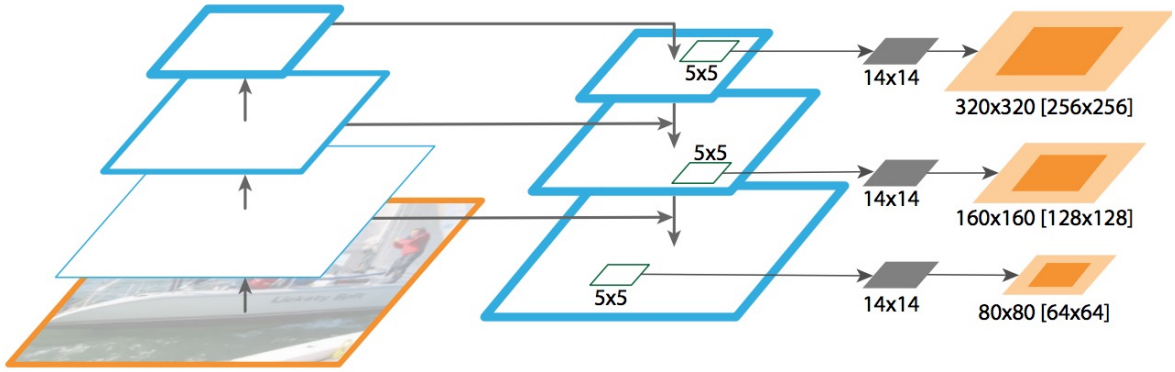


- Detectron2
- AdelaiDet
- Ideal models found during the experiments
- Metrics for concretise the concept of comparison

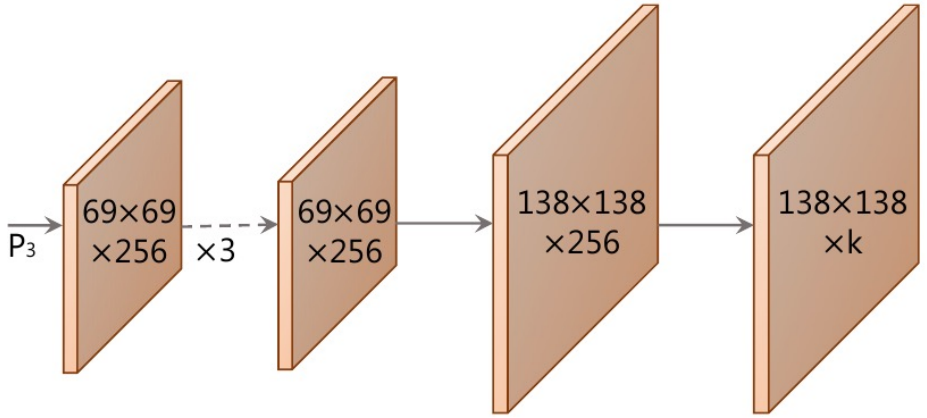
➢ Architecture

- We decided to use **ResNet-101-FPN** as a backbone





- In addition, as the bottom module of **BlendMask**, we have instantiated **ProtoNet**



➢ Hyperparameters

- We tried to keep the same parameters defined in the papers (Mask R-CNN & BlendMask)
- We modified those that did not allow us to run on Colab:

- **Number of iterations:** 4.000 for Mask R-CNN (default 40.000)
- **Number of iterations:** 2.000 for BlendMask (default 40.000)
- **Batch size per image:** 128 (default 512)
- **Images per batch across all machines:** 1 (we use only 1 GPU)

(Number of RoI per image = 128 · 1)

Loss functions

Mask R-CNN

$$L = L_{cls} + L_{box} + L_{mask}$$

(Multi-task loss on each RoI)

- L_{cls} : classification loss
- L_{box} : bounding-box loss
- L_{mask} : average binary cross-entropy loss

BlendMask

Simulate the same Loss

(optional – no big difference)

$$L^s(\alpha, p) \propto -log \sum_{x \models \alpha} \prod_{i:x \models X_i} p_i \prod_{i:x \models \neg X_i} (1 - p_i)$$

- α : sentence in propositional logic defined on variables $X_1, \dots, X_n$
- p : probability vector for each variable X_i
- $L^s(\alpha, p)$: semantic loss between α and p

Evaluation

- We use Average Precision (AP): $\int_0^1 p(r)dr$
- $p(r)$: the area under the curve of maximum intersection between:

- Recall

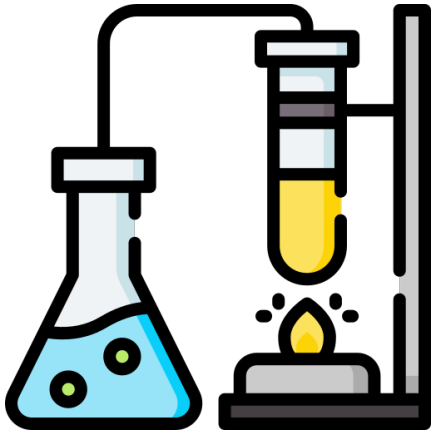
$$\frac{\text{true positive}}{\text{true positive + false negative}}$$

- Precision

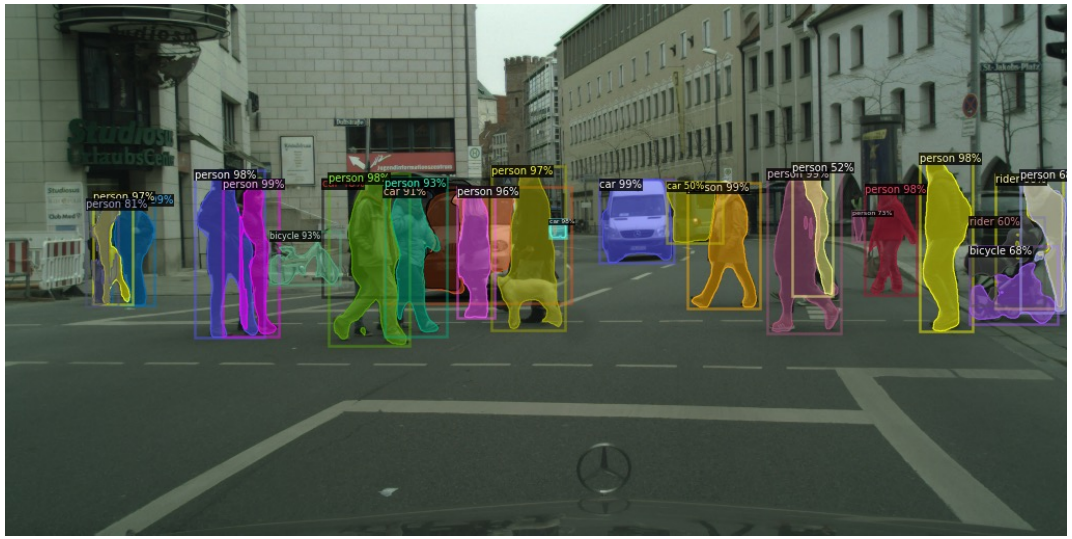
$$\frac{\text{true positive}}{\text{true positive + false positive}}$$

- 10 IoU thresholds from the range .50:.05:.95
- AP is averaged over Intersection over Union (IoU) values (standard COCO metrics)
- For each metric are extracted the 100 detections with the highest score (1000 proposal)

➢ Experiments



- Define "Ideal Models" via experiments:
    - Backbones
    - Frozen Layer
    - (Parameters to run on Colab and Semantic loss)



Backbones

Architecture	*Cityscapes*	*WildDash*
Mask R-CNN: ResNet-50-C4	box AP: 25.935 mask AP: 20.005	box AP: 18.730 mask AP: 17.589
Mask R-CNN: ResNet-50-DC5	box AP: 25.591 mask AP: 20.285	box AP: 17.871 mask AP: 16.543
Mask R-CNN: ResNet-50-FPN	box AP: 24.437 mask AP: 20.327	box AP: 16.865 mask AP: 16.017
Mask R-CNN: ResNet-101-C4	box AP: 30.888 mask AP: 24.562	box AP: 20.459 mask AP: 19.331
Mask R-CNN: ResNet-101-DC5	box AP: 29.125 mask AP: 24.062	box AP: 19.391 mask AP: 18.529
Mask R-CNN: ResNet-101-FPN	**box AP: 28.563 mask AP: 24.676**	**box AP: 19.024 mask AP: 17.994**

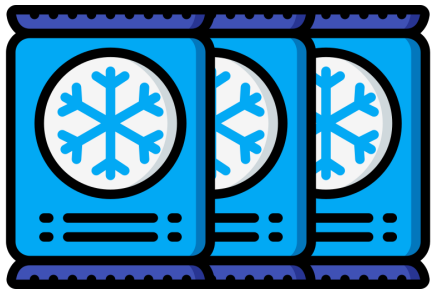
Table 1. Experiments on *backbone* Mask R-CNN.

Architecture	*Cityscapes*	*WildDash*
BlendMask: ResNet-50-FPN	box AP: 30.129 mask AP: 25.325	box AP: 20.225 mask AP: 19.810
BlendMask: ResNet-101-FPN	**box AP: 31.017 mask AP: 26.411**	**box AP: 20.347 mask AP: 20.162**
BlendMask: ResNet-101-FPN + dcni	box AP: 32.196 mask AP: 27.212	box AP: 20.497 mask AP: 20.236

Table 2. Experiments on *backbone* BlendMask.

→ ResNet-101-FPN

➢ Frozen Layers



Architecture	*Cityscapes*	*WildDash*
Mask R-CNN: ResNet-101-FPN + freeze at 2nd	**box AP: 28.563 mask AP: 24.676**	**box AP: 19.024 mask AP: 17.994**
Mask R-CNN: ResNet-101-FPN + freeze at 3rd	box AP: 26.297 mask AP: 22.179	box AP: 19.132 mask AP: 18.224
Mask R-CNN: ResNet-101-FPN + freeze at 4th	box AP: 25.053 mask AP: 21.349	box AP: 19.824 mask AP: 18.448

Table 3. Experiments on *frozen layers* Mask R-CNN.

Architecture	*Cityscapes*	*WildDash*
BlendMask: ResNet-101-FPN + freeze at 2nd	**box AP: 31.017 mask AP: 26.411**	**box AP: 20.347 mask AP: 20.162**
BlendMask: ResNet-101-FPN + freeze at 3rd	box AP: 28.596 mask AP: 23.649	box AP: 18.993 mask AP: 17.802
BlendMask: ResNet-101-FPN + freeze at 4th	box AP: 31.379 mask AP: 26.936	box AP: 21.597 mask AP: 20.537

Table 4. Experiments on *frozen layers* BlendMask.

→ Freeze at 2nd

➢ Ideal Models

Method	*Cityscapes*	*WildDash*
Mask R-CNN:	box AP: 28.563 mask AP: 24.676	box AP: 19.024 mask AP: 17.994
BlendMask:	box AP: 31.017 (+2.45 AP) mask AP: 26.411 (+1.74 AP)	box AP: 20.347 (+1.32 AP) mask AP: 20.162 (+2.17 AP)

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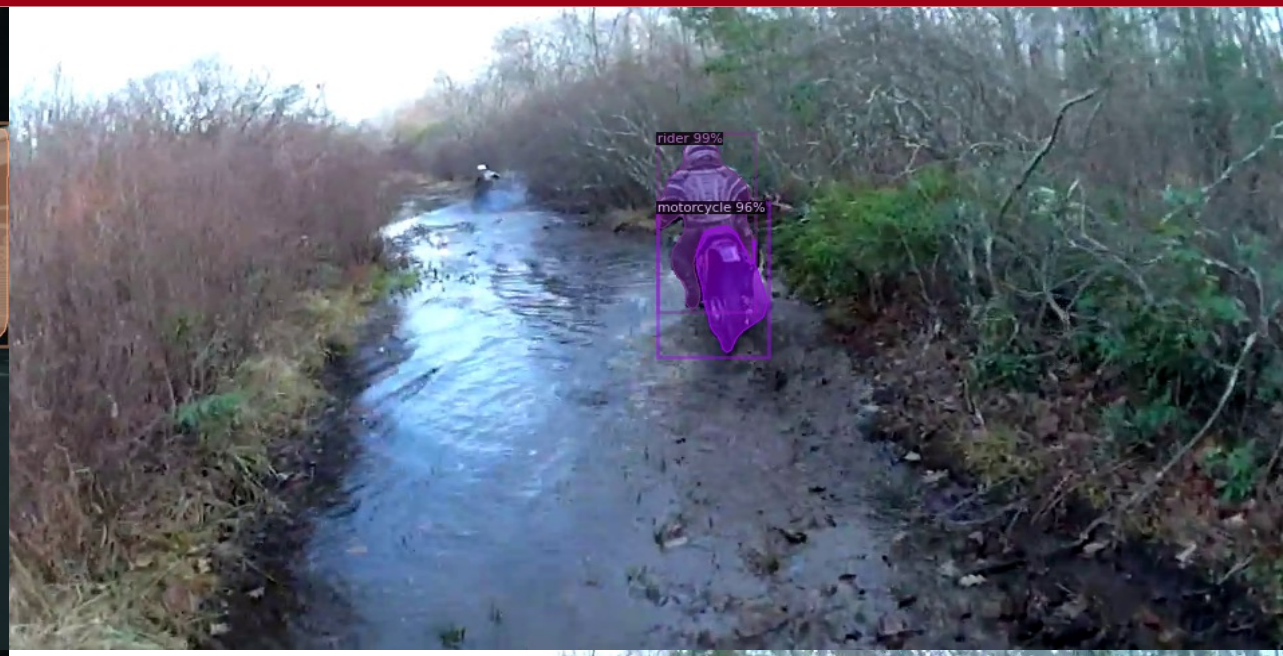
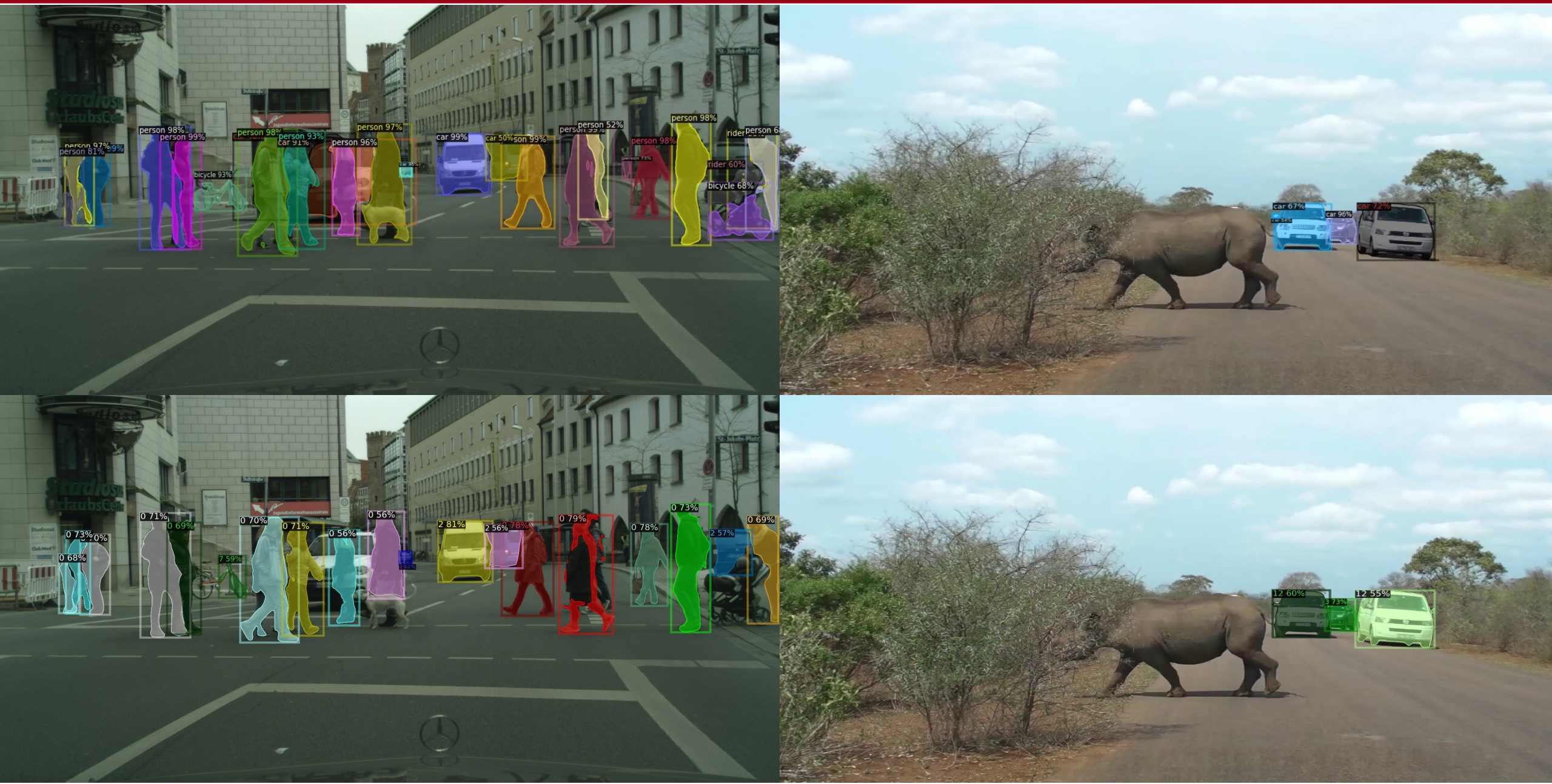



person 98%
person 99%
person 81%
bicycle 93%
person 98%
person 93%
car 91%
person 96%
person 97%
car 99%
car 50%
son 99%
person 52%
person 98%
person 98%
rider 60%
bicycle 68%
car 67%
car 96%
car 72%
0 71%
0 69%
0 73%
0 68%
0 70%
0 71%
0 56%
0 56%
2 81%
2 56%
78%
0 79%
0 78%
0 73%
2 57%
0 69%
12 60%
12 55%

Conclusion

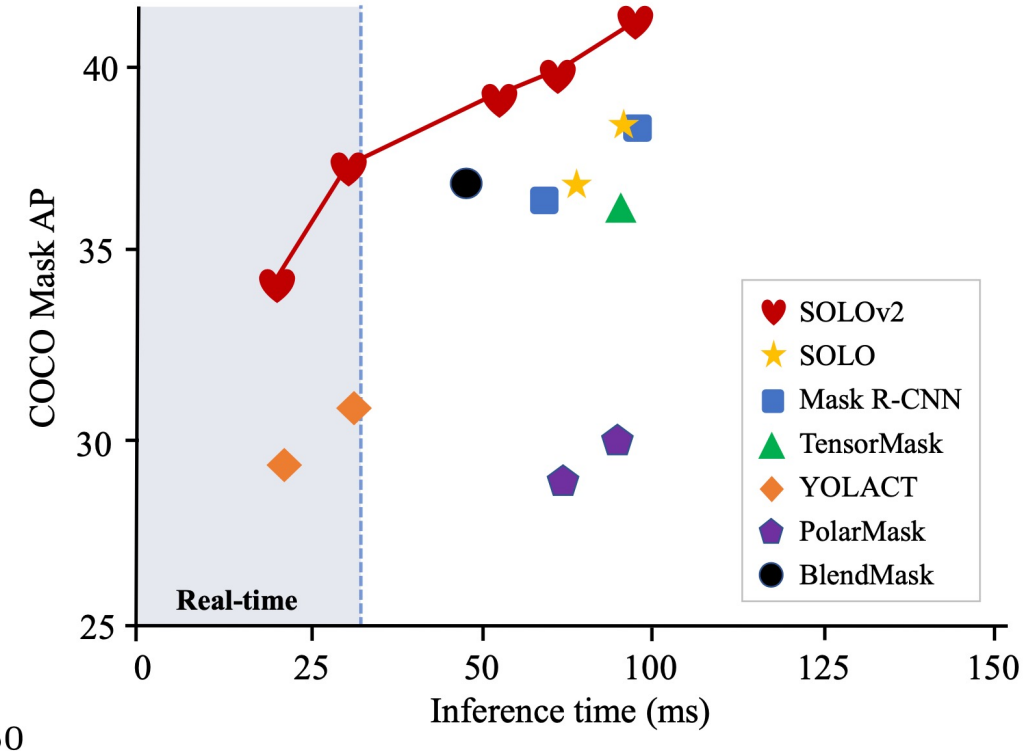
- **One-stage and anchor box-free techniques**, suitably modified, perform better than box-based two-stage methods

- Caused by the hybridisation of top-down and bottom-up methods and the detection of unanchored objects

BLENDMASK wins in Average Precision and Time against Mask R-CNN

Is it possible to do better ?

- A box-free stage approach combined with matrix NMS, such as **SOLOv2**, is demonstrated to be very competitive against BlendMask

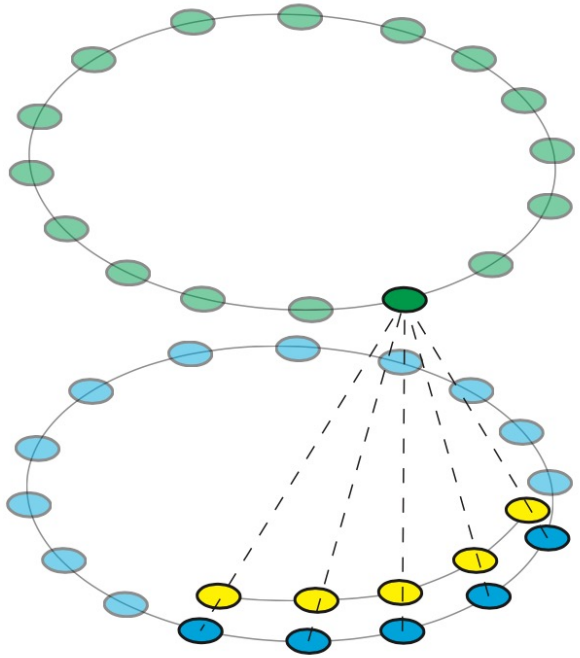


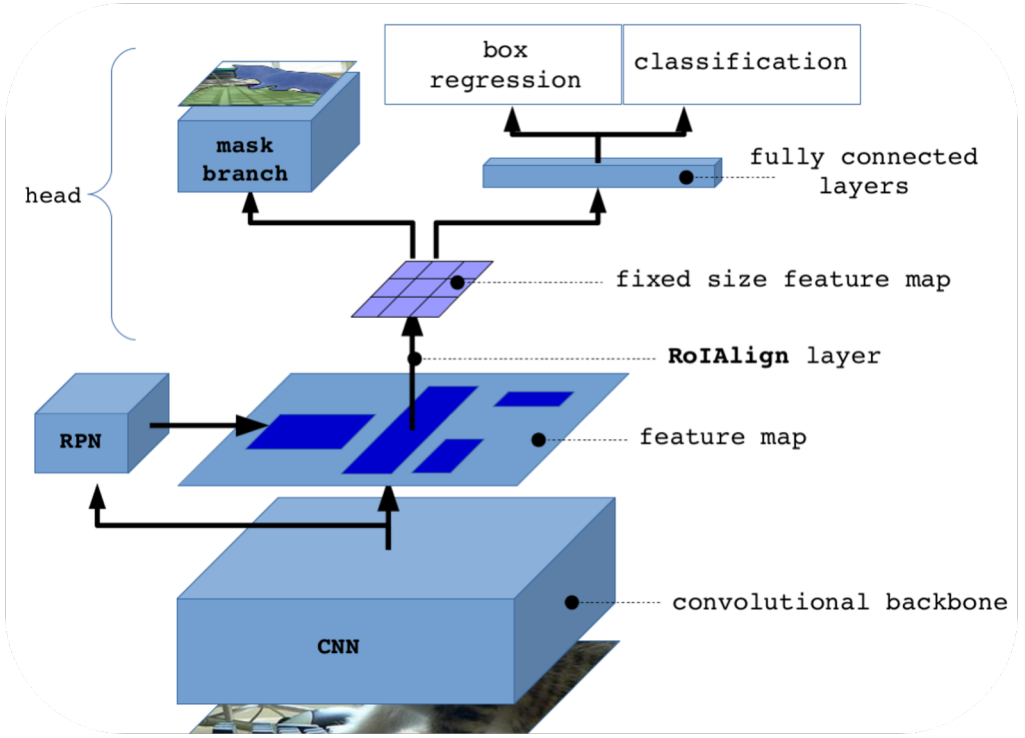
- **Deep Snake** outperforms Mask R-CNN in inference speed and AP

	training data	fps	AP [val]	AP	AP_{50}
SGN [26]	fine + coarse	0.6	29.2	25.0	44.9
PolygonRNN++ [1]	fine	-	-	25.5	45.5
Mask R-CNN [18]	fine	2.2	31.5	26.2	49.9
GMIS [28]	fine + coarse	-	-	27.6	49.6
Spatial [31]	fine	11	-	27.6	50.9
PANet [27]	fine	<1	36.5	**31.8**	57.1
Deep snake	fine	4.6	**37.4**	31.7	**58.4**

➢ Possible extensions

- Improve the performance of BlendMask by trying to use Deep Snake **contour-based approach for detecting object bounding boxes** of an image





That's all folks!

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