

Madrid Rooftops Image Segmentation

Implementación Mask R-CNN para la segmentación de tejados residenciales, piscinas y canchas deportivas en la Comunidad de Madrid

Ana Blanco Delgado
Septiembre 2021

idealista/energy

Calle Prim, 11:

<https://www.idealista.com/energy/calcula-dora-de-ahorro-solar/#ref=1350216VK4715A0001FW&lat=40.422026&lng=-3.6937241>



293 € ahorro anual en la factura de la luz por vecino

23.009 € coste de la instalación de 61 paneles solares (15,6 KWp de potencia)

5 años tardaría la instalación en amortizarse.

190.746 € ahorro total durante 25 años de vida útil de la instalación

[Ver detalles del cálculo de ahorro y financiación](#)

Instalación solar óptima para el tejado de Calle Prim 11, Madrid

🏠 164 m² disponibles

☀️ 3.043 horas de sol al año

⚡ 38% de inclinación

🔌 61 paneles solares

⚡ 15,6 KWp de potencia

🌳 6 tn de CO2 menos al año

El ahorro total contempla la pérdida de rendimiento de los paneles. Los cálculos están basados en un comportamiento regular de la instalación y son siempre orientativos y no vinculantes.

Madrid Rooftop Image Segmentation project

Segmentación



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Mask R-CNN

Mask Region Convolutional Neural Network

Mask R-CNN paper oficial

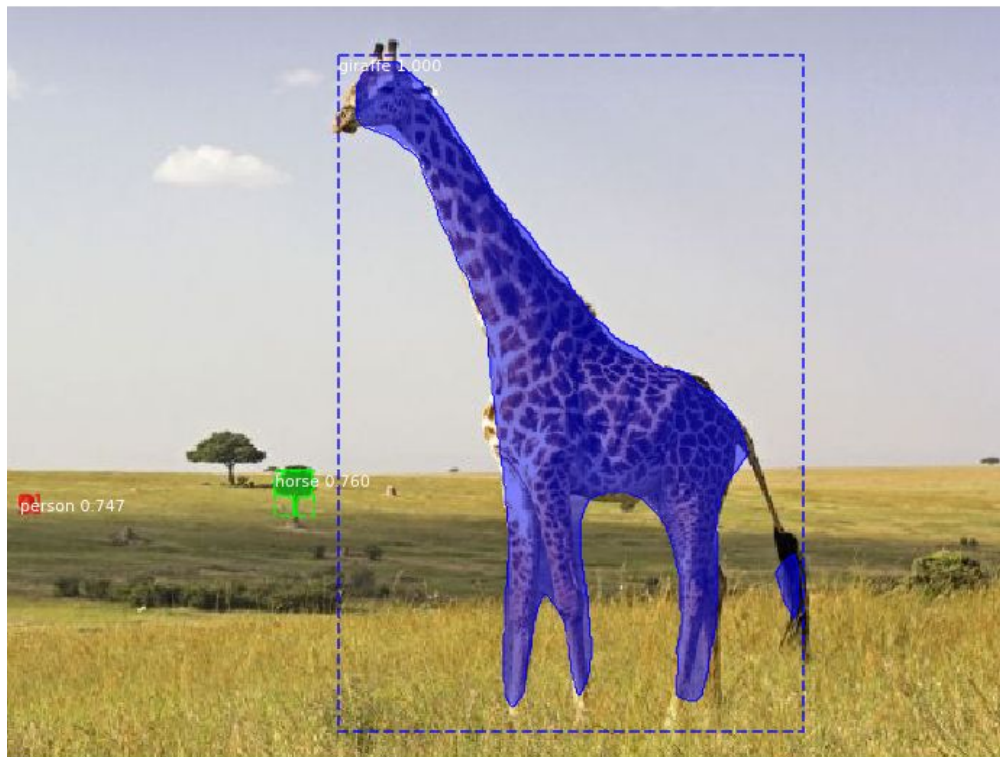
<https://arxiv.org/abs/1703.06870>

Mask R-CNN for Object Detection and Segmentation
(repositorio open-source de Matterplot)

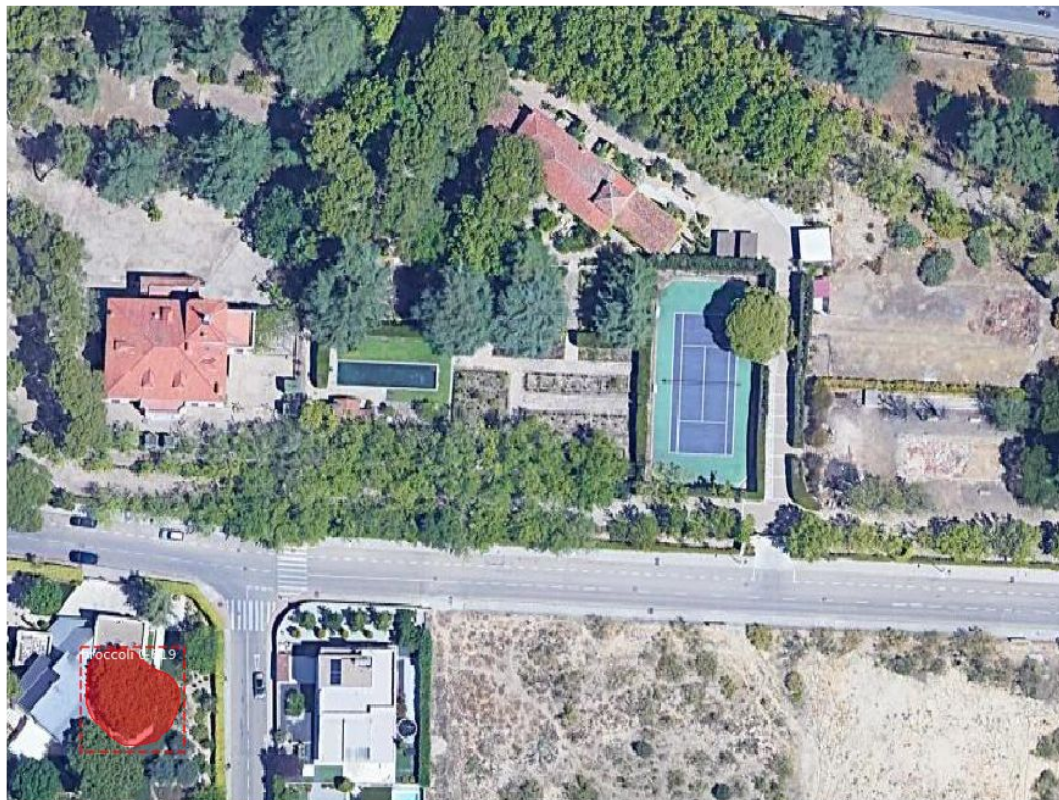
https://github.com/matterport/Mask_RCNN

Mask R-CNN

COCO Dataset Classes: ['BG', 'person', 'bicycle', 'car', 'motorcycle', 'airplane', 'bus', 'train', 'truck', 'boat', 'traffic light', 'fire hydrant', 'stop sign', 'parking meter', 'bench', 'bird', 'cat', 'dog', 'horse', 'sheep', 'cow', 'elephant', 'bear', 'zebra', 'giraffe', 'backpack', 'umbrella', 'handbag', 'tie', 'suitcase', 'frisbee', 'skis', 'snowboard', 'sports ball', 'kite', 'baseball bat', 'baseball glove', 'skateboard', 'surfboard', 'tennis racket', 'bottle', 'wine glass', 'cup', 'fork', 'knife', 'spoon', 'bowl', 'banana', 'apple', 'sandwich', 'orange', 'broccoli', 'carrot', 'hot dog', 'pizza', 'donut', 'cake', 'chair', 'couch', 'potted plant', 'bed', 'dining table', 'toilet', 'tv', 'laptop', 'mouse', 'remote', 'keyboard', 'cell phone', 'microwave', 'oven', 'toaster', 'sink', 'refrigerator', 'book', 'clock', 'vase', 'scissors', 'teddy bear', 'hair drier', 'toothbrush']



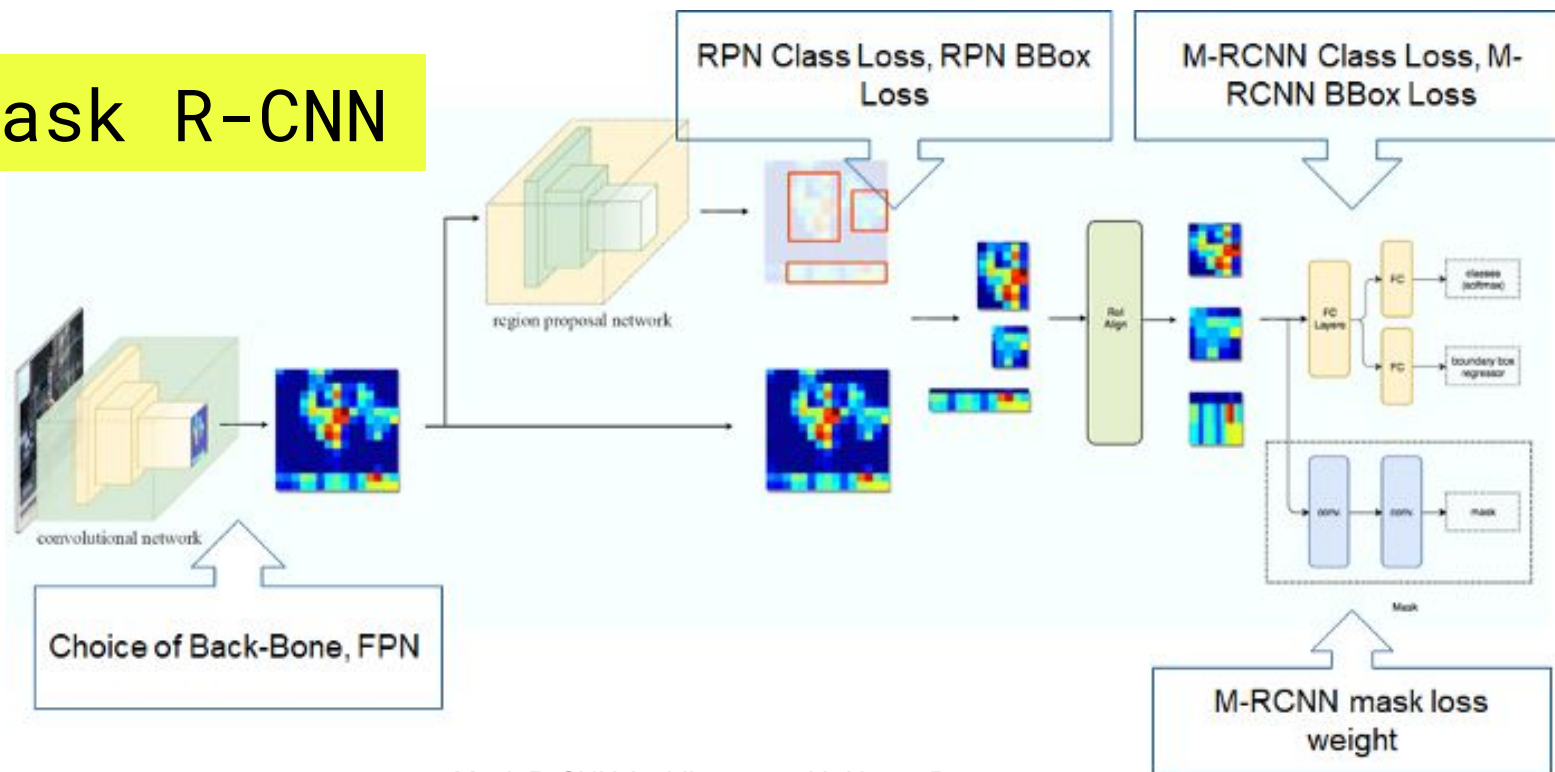
Mask R-CNN



Mask R-CNN



Mask R-CNN



Mask R-CNN Architecture with Hyper-Parameters

1. Backbone

2. RPN

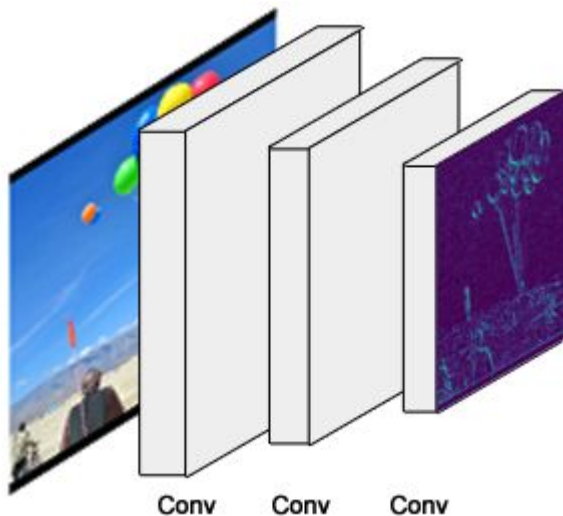
3. ROI-Clf/BB-Regr

4. Segmentation

CNN ResNet101

`model.resnet_graph()`

Input image
1024 x 1024 x 3



Features
32 x 32 x 2048



1. Backbone

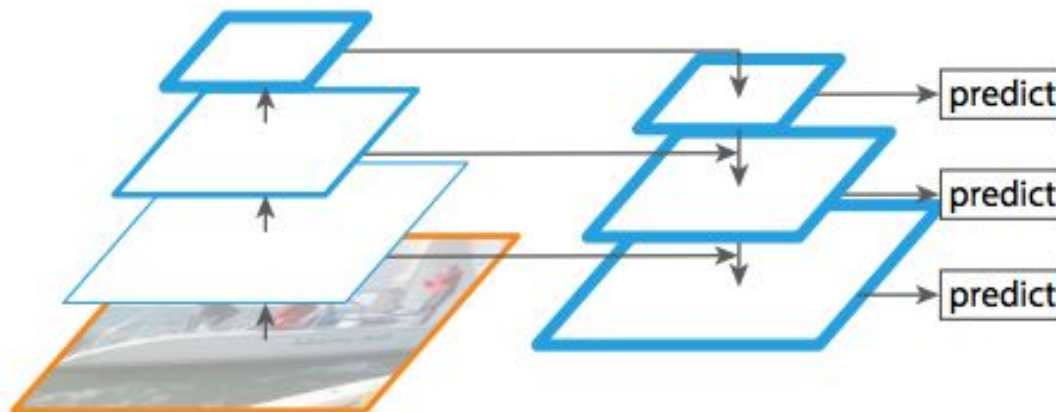
2. RPN

3. ROI-Clf/BB-Regr

4. Segmentation

Feature Pyramid Networks (FPN)

```
model.build()
```



1.Backbone

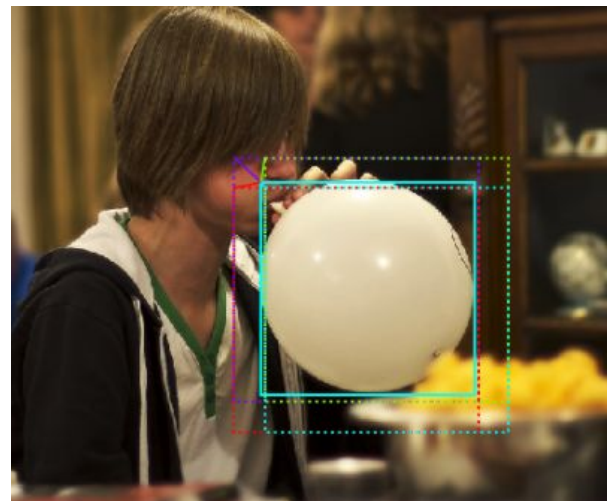
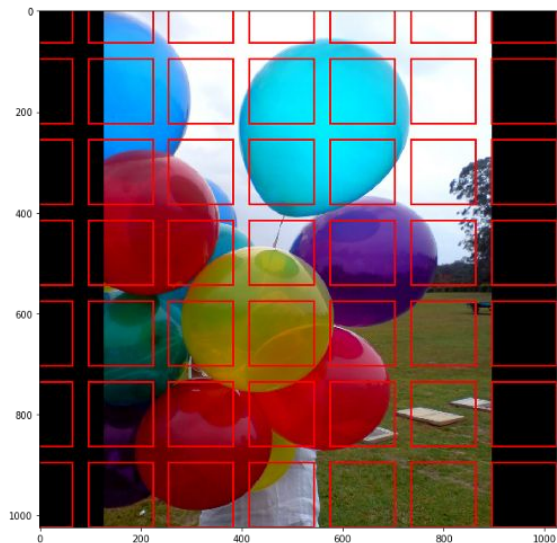
2.RPN

3.ROI-Clf/BB-Regr

4.Segmentation

Region Proposal Network (RPN)

`model.rpn_graph()`



1.Backbone

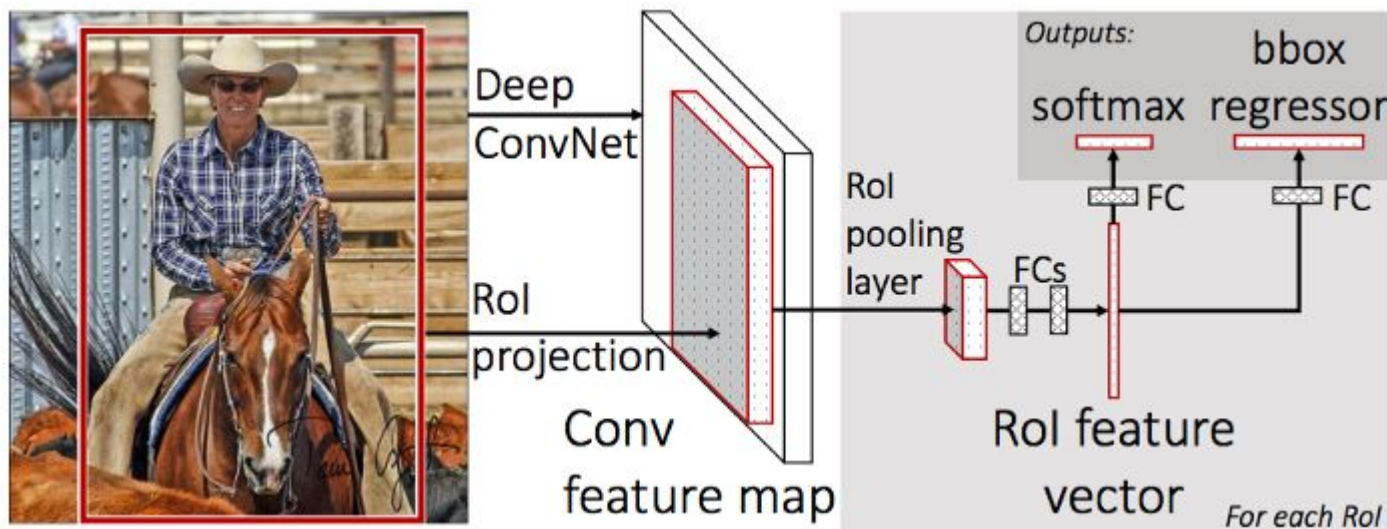
2.RPN

3.ROI-Clf/BB-Regr

4.Segmentation

ROI Classifier & Bounding Box Regressor

```
model.fpn_classifier_graph()
```



1.Backbone

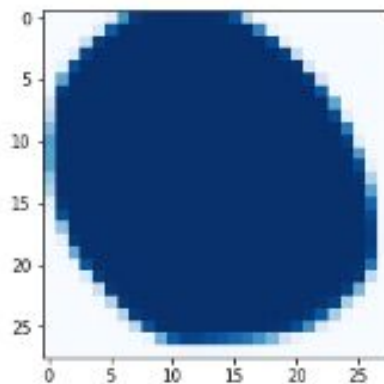
2.RPN

3.ROI-Clf/BB-Regr

4.Segmentation

Segmentation Masks

```
model.build_fpn_mask_graph()
```



28x28 Soft Mask



Resized Binary Mask

train_set

Image Count: 69
Polygon Count: 1488

Class Count: 4

- 0. BG
- 1. roof
- 2. pool
- 3. sports

val_set

Image Count: 22
Polygon Count: 545

Class Count: 4

- 0. BG
- 1. roof
- 2. pool
- 3. sports

Image Count: 91
Polygon Count: 2033

Aravaca, Cercedilla, Fuenfría, Navacerrada, Nuevo
Baztán, Pozuelo, Somosaguas y Soto del Real

1. Imágenes

2. Annotations

Map Puzzle

The screenshot shows the 'Map Puzzle v1.6.7' application window. It has three tabs: 'Map Settings' (active), 'Bulk Download', and 'General Application Settings'.

Map Settings

GPS Coordinate

Latitude: Decimal (Required) < Degrees, Minutes, and Seconds N

Longitude: > W

Address:

Base (Required)

Alternative Base (Optional)

Overlay (Optional)

Image Settings

Zoom: ☐ Landscape

Width:

Height:

Addons

☐ Image Addons:

☐ Save Each Tile In Separate File

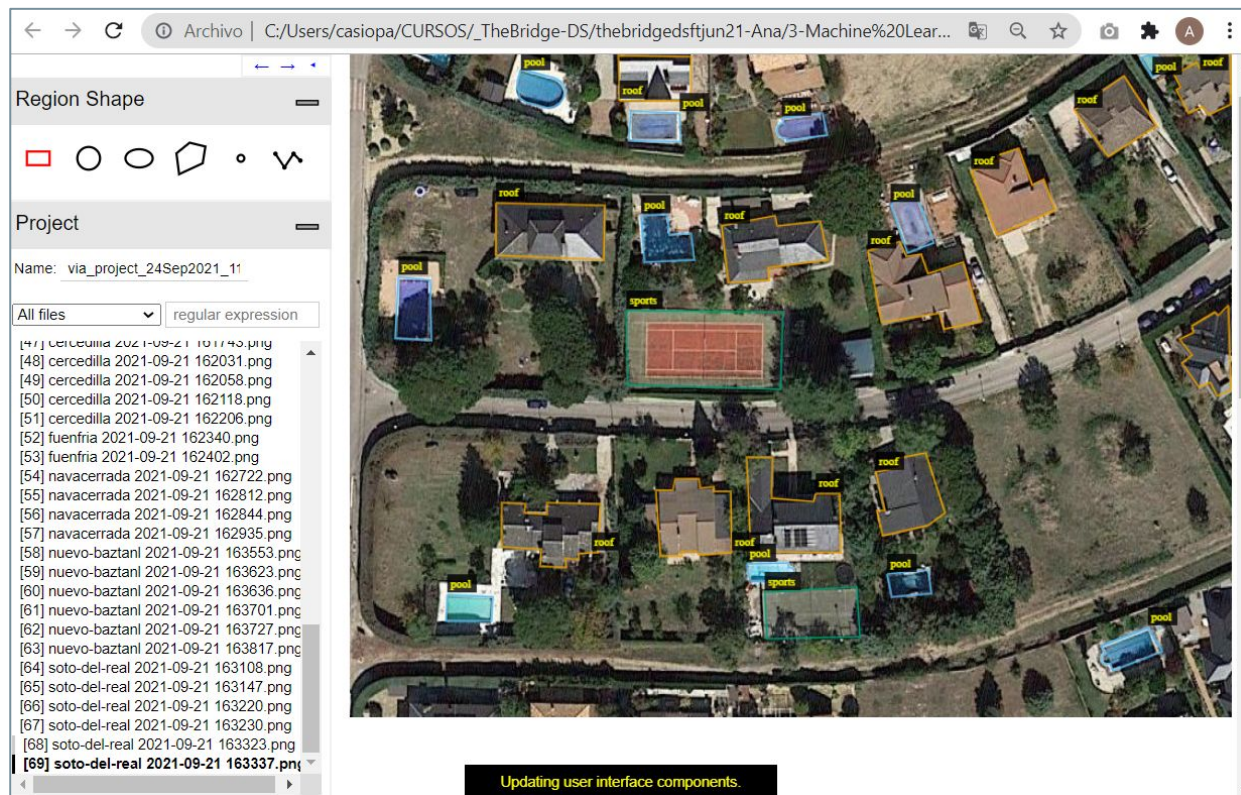
☐ Generate world file

☒ UTM

1. Imágenes

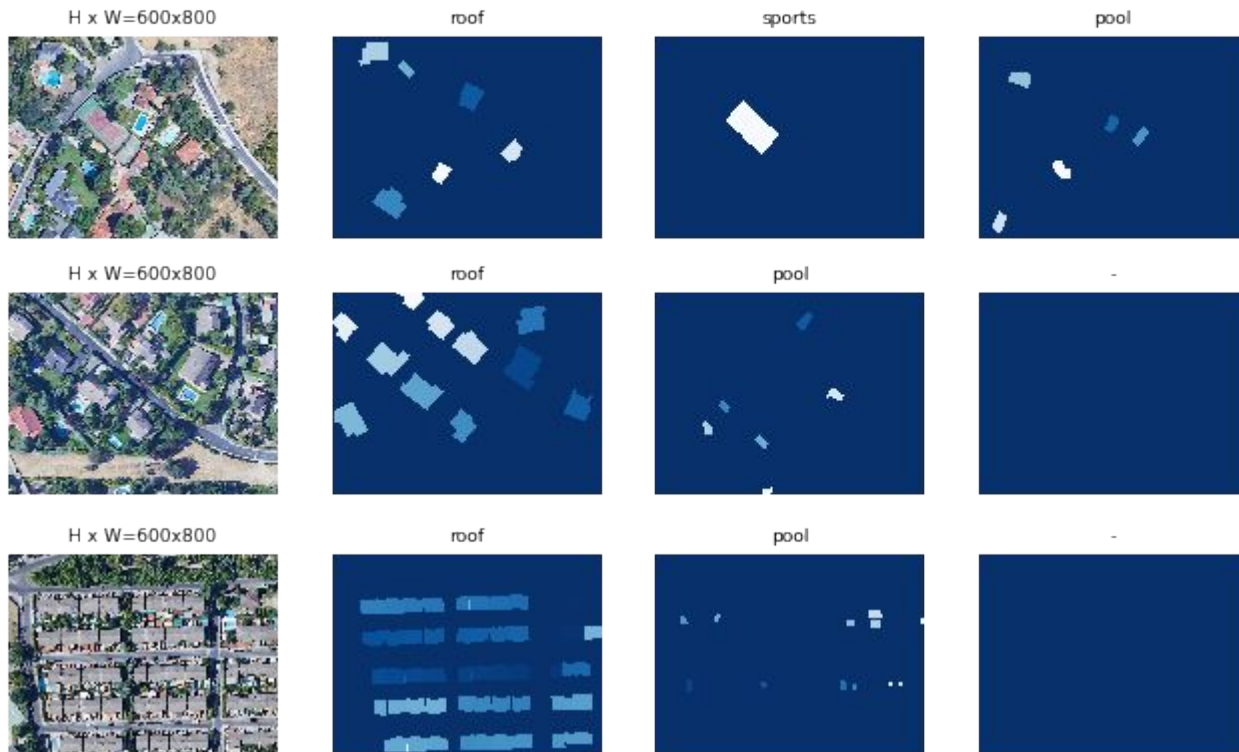
2. Annotations

VGG Image Annotator (VIA)



1. Imágenes

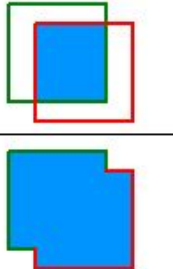
2. Annotations

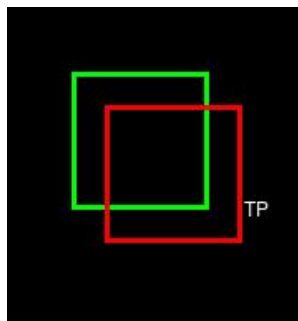


1.AP

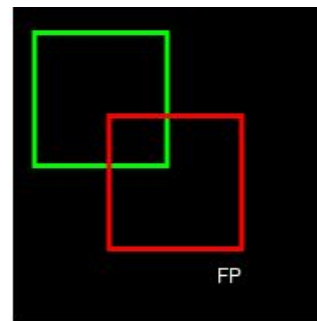
2.mAP

Intersect over Union (IoU)

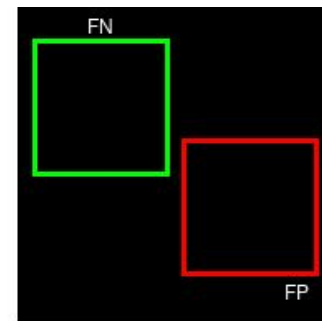
$$IOU = \frac{\text{area of overlap}}{\text{area of union}} = \frac{\text{area of intersection}}{\text{area of union}}$$




IoU = 0.86



IoU = 0.24



IoU = 0

1.AP

2.mAP

Precision/Recall

		Predicted		
		P	N	
Actual	P	TP	FN	Recall
	N	FP	TN	
		Precision		

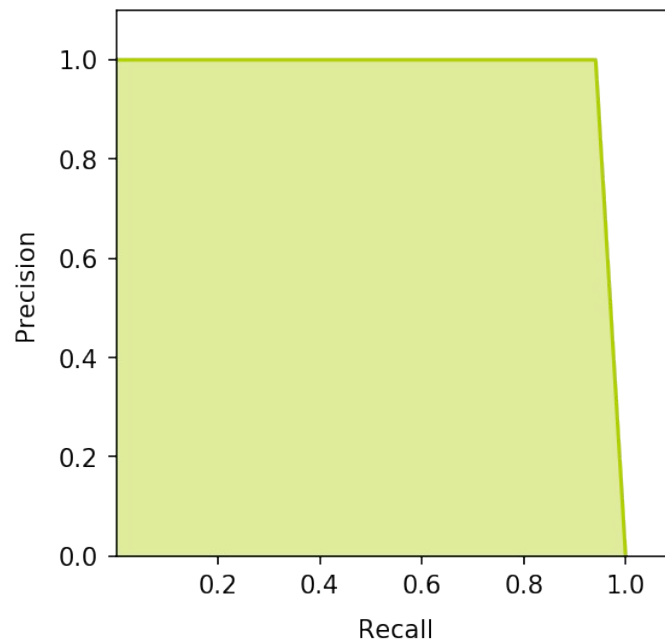
1.AP

2.mAP

Área bajo la curva
Precision/Recall
AUC-PR

Average Precision
AP

Precision-Recall Curve. AP@50 = 0.941



1.AP

2.mAP

Mean Average Precision
Formula

$$\text{mAP}@{\alpha} = \frac{1}{n} \sum_{i=1}^n \text{AP}_i$$

1. Baseline model

Learning Rate: 60 epochs: 0.001

Loss Weights: 'rpn_class_loss': 1.0
'rpn_bbox_loss': 1.0
'mrcnn_class_loss': 1.0
'mrcnn_bbox_loss': 1.0
'mrcnn_mask_loss': 1.0

Train mAP@50: 0.720

Val mAP@50: 0.527

2. Hyperparameter tuning

Learning Rate: 10 epochs: 0.001
+10 epochs: 0.0005

Loss Weights: 'rpn_class_loss': 1.0
'rpn_bbox_loss': 0.8
'mrcnn_class_loss': 6.0
'mrcnn_bbox_loss': 6.0
'mrcnn_mask_loss': 6.0

Augmentation 50%: Flip1r(0.5)
Blur [1, 5]

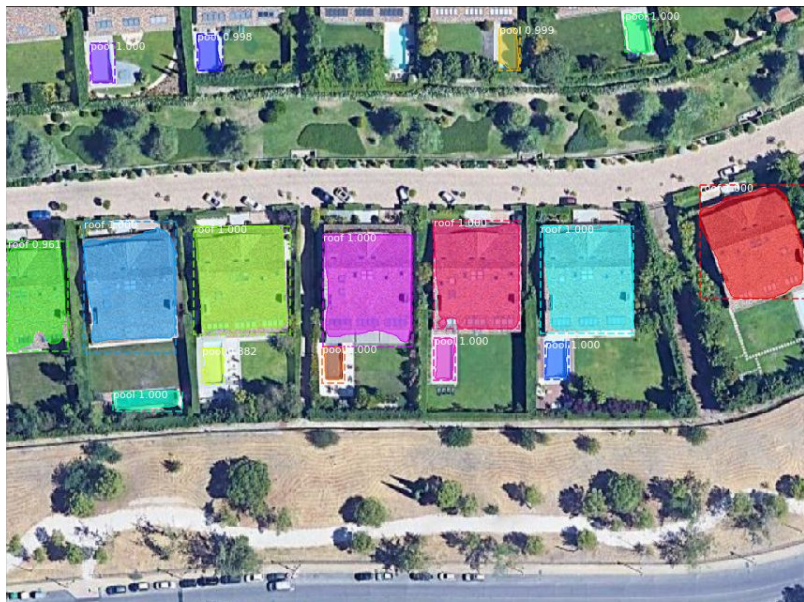
Train mAP@50: 0.562

Val mAP@50: 0.469

Test_set prediction image

1.Casas

2.Edificios

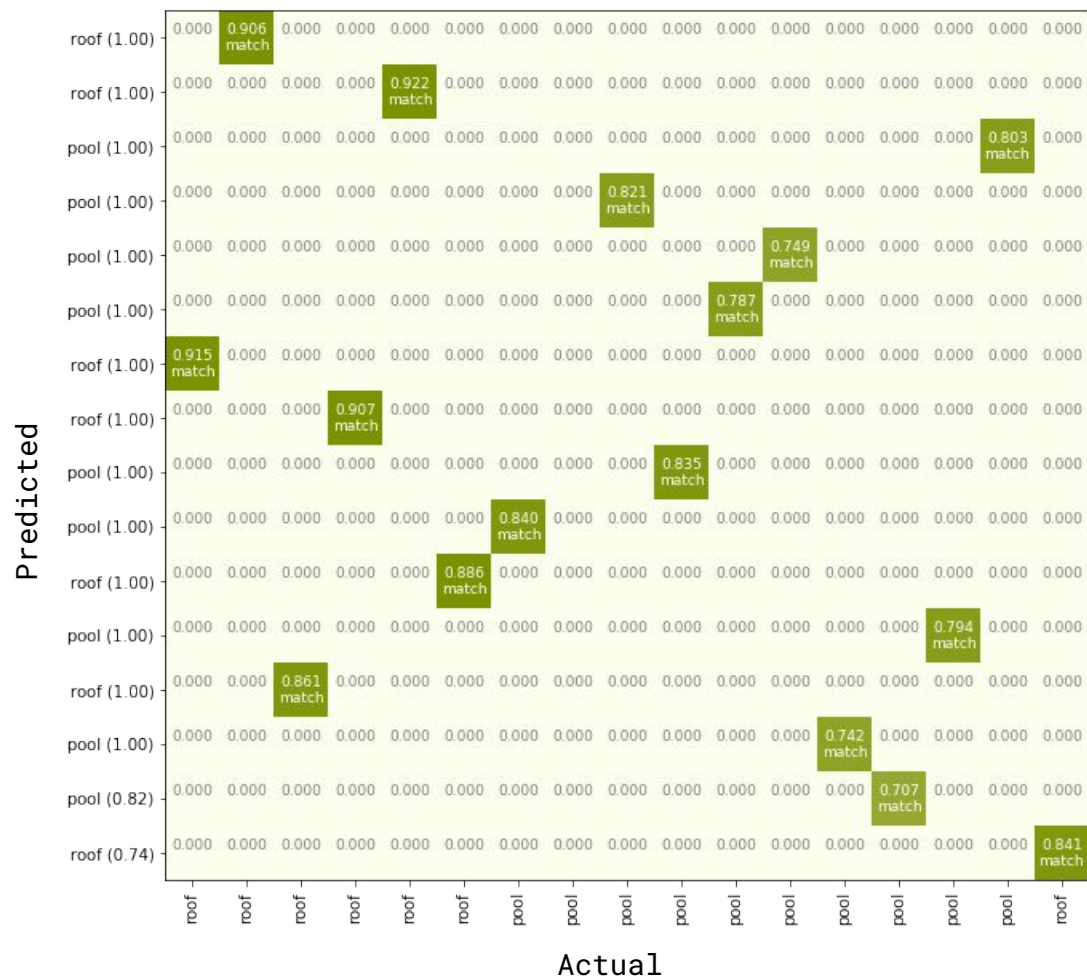


somosaguas 2021-09-13 194952.png

Predicted

roof (1.00)	0.000	0.906 match	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
roof (1.00)	0.000	0.000	0.000	0.000	0.922 match	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
pool (1.00)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.803 match	0.000
pool (1.00)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.821 match	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
pool (1.00)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.749 match	0.000	0.000	0.000	0.000	0.000	0.000	0.000
pool (1.00)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.787 match	0.000	0.000	0.000	0.000	0.000	0.000	0.000
roof (1.00)	0.915 match	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
roof (1.00)	0.000	0.000	0.000	0.000	0.907 match	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
pool (1.00)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.835 match	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
pool (1.00)	0.000	0.000	0.000	0.000	0.000	0.000	0.840 match	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
roof (1.00)	0.000	0.000	0.000	0.000	0.000	0.886 match	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
pool (1.00)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.794 match	0.000	0.000
roof (1.00)	0.000	0.000	0.881 match	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
pool (1.00)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.742 match	0.000	0.000	0.000	0.000	0.000	0.000
pool (0.82)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.707 match	0.000	0.000	0.000
roof (0.74)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.841 match	0.000
roof	roof	roof	roof	roof	roof	pool	pool	pool	pool	pool	pool	pool	pool	pool	pool	pool	pool	pool	roof

Actual



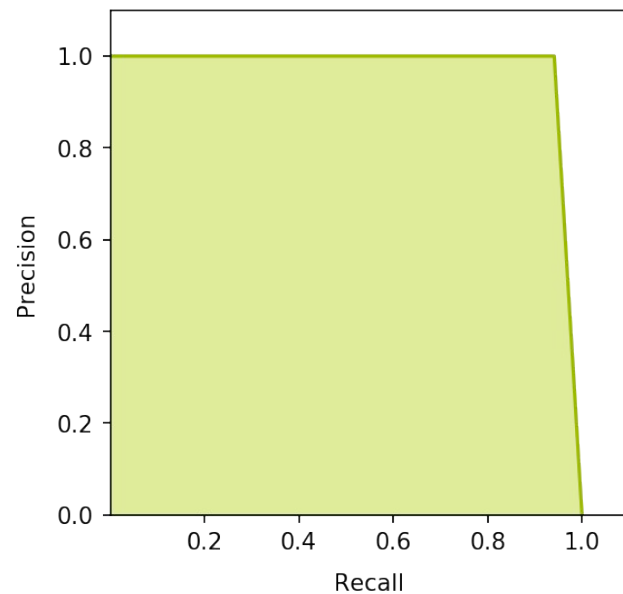
1.Casas

2.Edificios



somosaguas 2021-09-13 194952.png

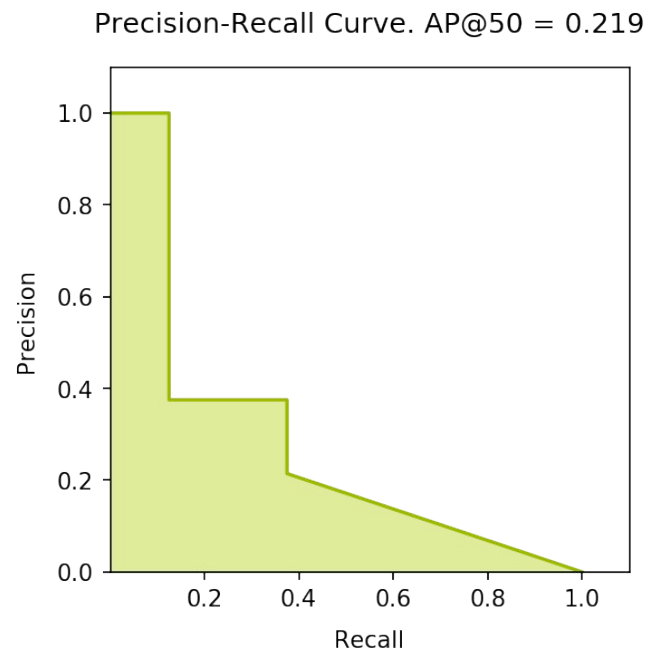
Precision-Recall Curve. $AP@50 = 0.941$



2.Edificios



2.Edificios



Modelo orientado para segmentar:

- Viviendas residenciales aisladas (casas, chalets)
- Instancias por imagen < 20
- Imágenes con buena resolución

Madrid Rooftops Image Segmentation project

Septiembre 2021



https://github.com/casiopa/Madrid_Rooftops