Madrid Rooftops Image Segmentation

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

idealista/energy

Calle Prim, 11:

https://www.idealista.com/energy/calcula dora-de-ahorro-solar/#ref=1350216VK4715A 0001FW&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

61 paneles solares

→ 3.043 horas de sol al año

∮ 15,6 KWp de potencia

/\ 38% de inclinación

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.

Clasificación

Detección

Segmentación





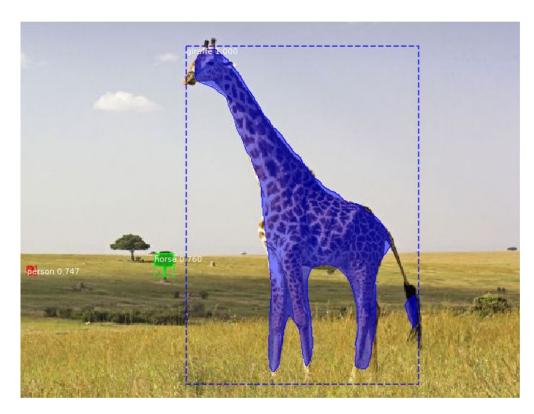


Mask Region Convolutional Neural Network

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

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']

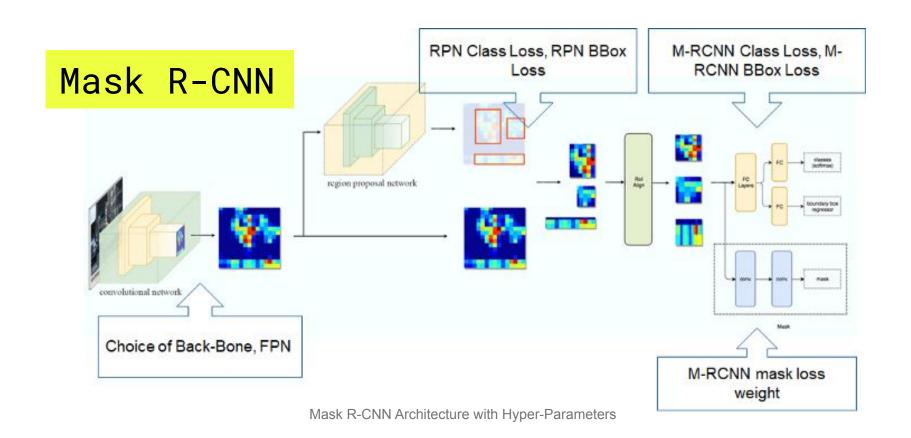


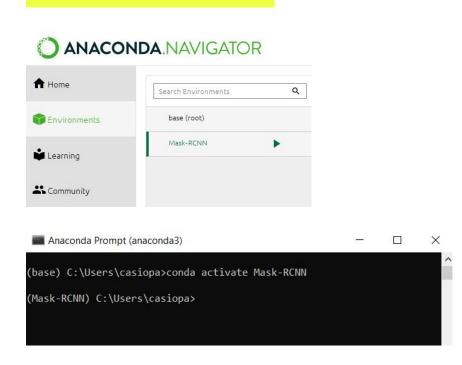


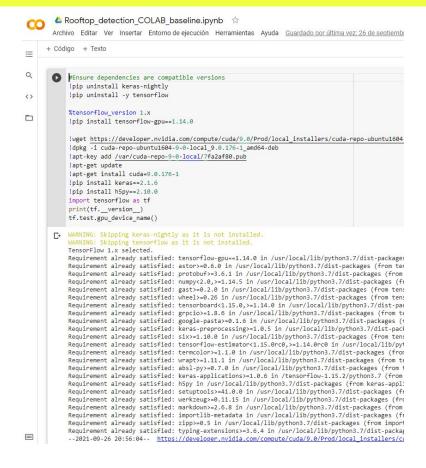












2.RPN

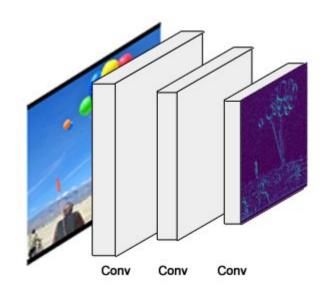
3.ROI-Clf/BB-Regr

4.Segmentation

CNN ResNet101

model.resnet_graph()

Input image 1024 x 1024 x 3



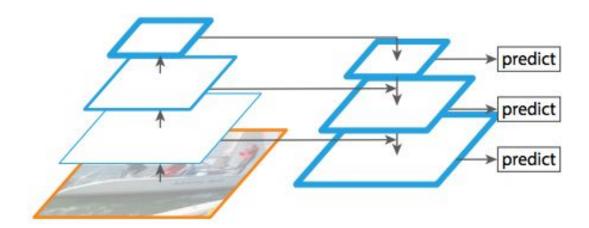
Features 32 x 32 x 2048

2.RPN

3.ROI-Clf/BB-Regr

4.Segmentation

Feature Pyramid Networks (FPN) model.build()



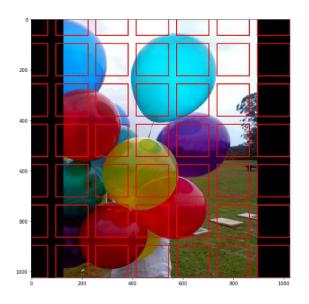
2.RPN

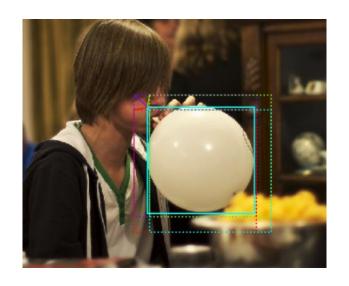
3.ROI-Clf/BB-Regr

4.Segmentation

Region Proposal Network (RPN)

model.rpn_graph()





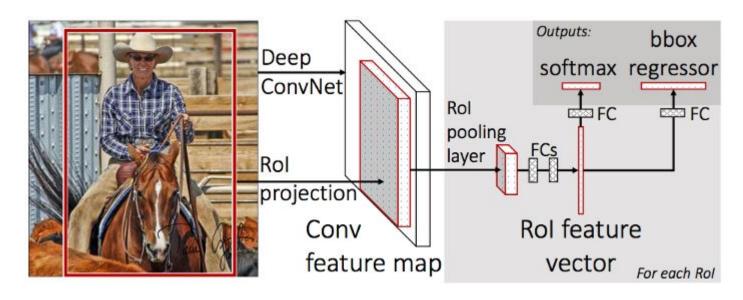
2.RPN

3.ROI-Clf/BB-Regr

4.Segmentation

ROI Classifier & Bounding Box Regressor

model.fpn_classifier_graph()



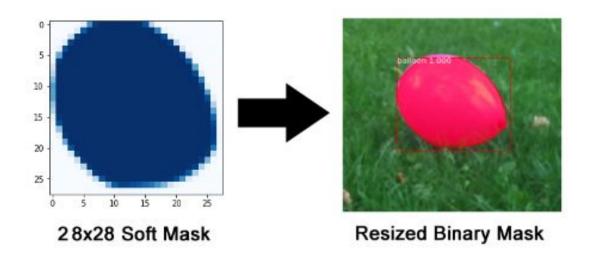
2.RPN

3.ROI-Clf/BB-Regr

4.Segmentation

Segmentation Masks

model.build_fpn_mask_graph()



train_set	val_set	test_set
<pre>Image Count: 69 Polygon Count: 1488</pre>	<pre>Image Count: 22 Polygon Count: 545</pre>	<pre>Image Count: 11 Polygon Count: 258</pre>
Class Count: 4 0. BG 1. roof 2. pool 3. sports	Class Count: 4 0. BG 1. roof 2. pool 3. sports	Class Count: 4 0. BG 1. roof 2. pool 3. sports

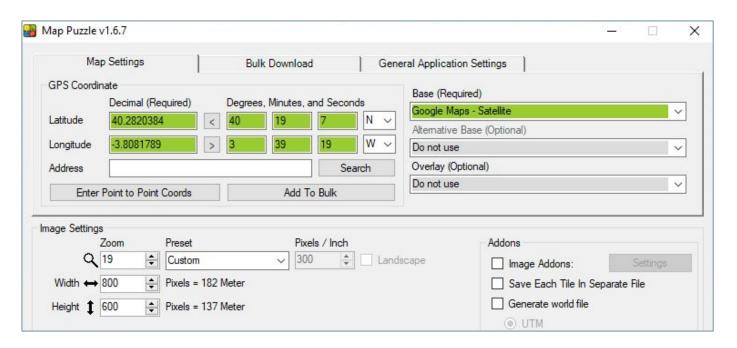
Image Count: 102
Polygon Count: 2291

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

1. Imágenes

2. Annotations

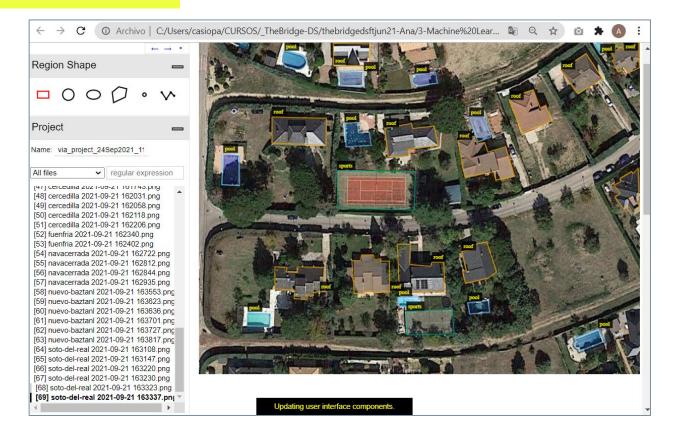
Map Puzzle



1. Imágenes

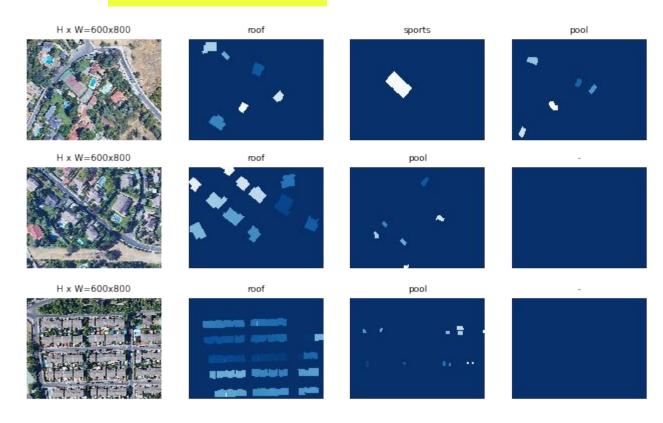
2. Annotations

VGG Image Annotator (VIA)



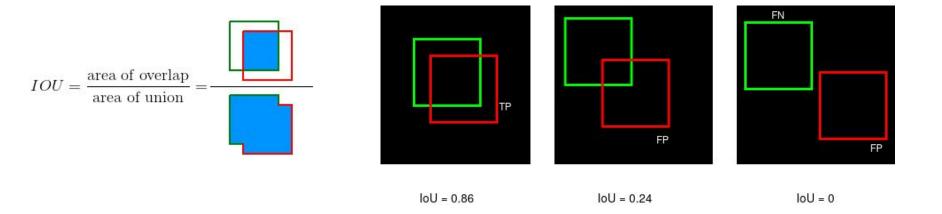
1.Imágenes

2. Annotations



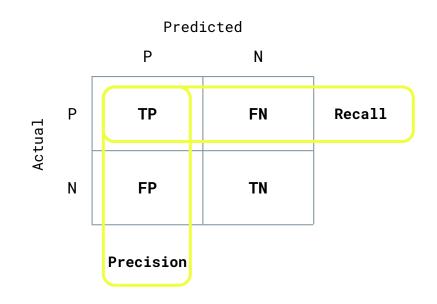
2.mAP

Intersect over Union (IoU)



2.mAP

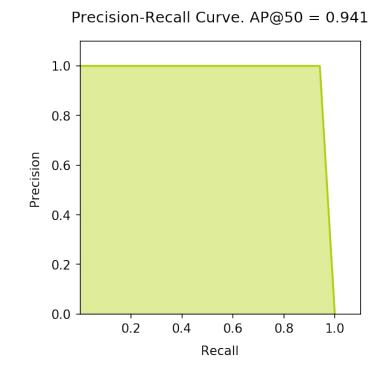
Precision/Recall



2.mAP

Área bajo la curva Precision/Recall **AUC-PR**

Average Precision AP



2.mAP

Mean Average Precision Formula

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

1.Baseline model

Learning Rate: 80 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

Best model 60 epochs: Train mAP@50: 0.720

Test mAP@50: 0.624

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%: Fliplr(0.5)

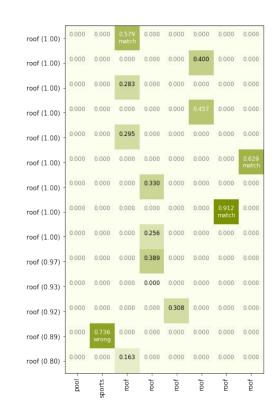
Blur [1, 5]

Train mAP@50: 0.562 Val mAP@50: 0.469 1. Edificios

2.Casas



pozuelo 2021-09-13 200628.png



Predicted

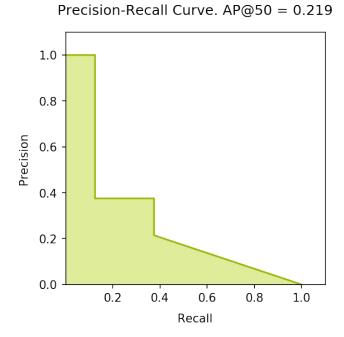
Actual

1. Edificios

2.Casas



pozuelo 2021-09-13 200628.png



Test_set prediction image

1.Edificios

2.Casas



somosaguas 2021-09-13 194952.png



Actual



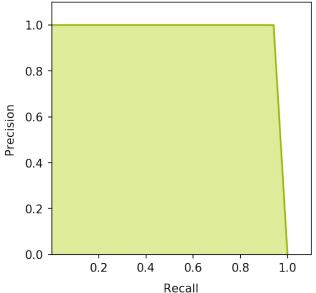
Actual

1.Edificios

2.Casas



Precision-Recall Curve. AP@50 = 0.941



somosaguas 2021-09-13 194952.png

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