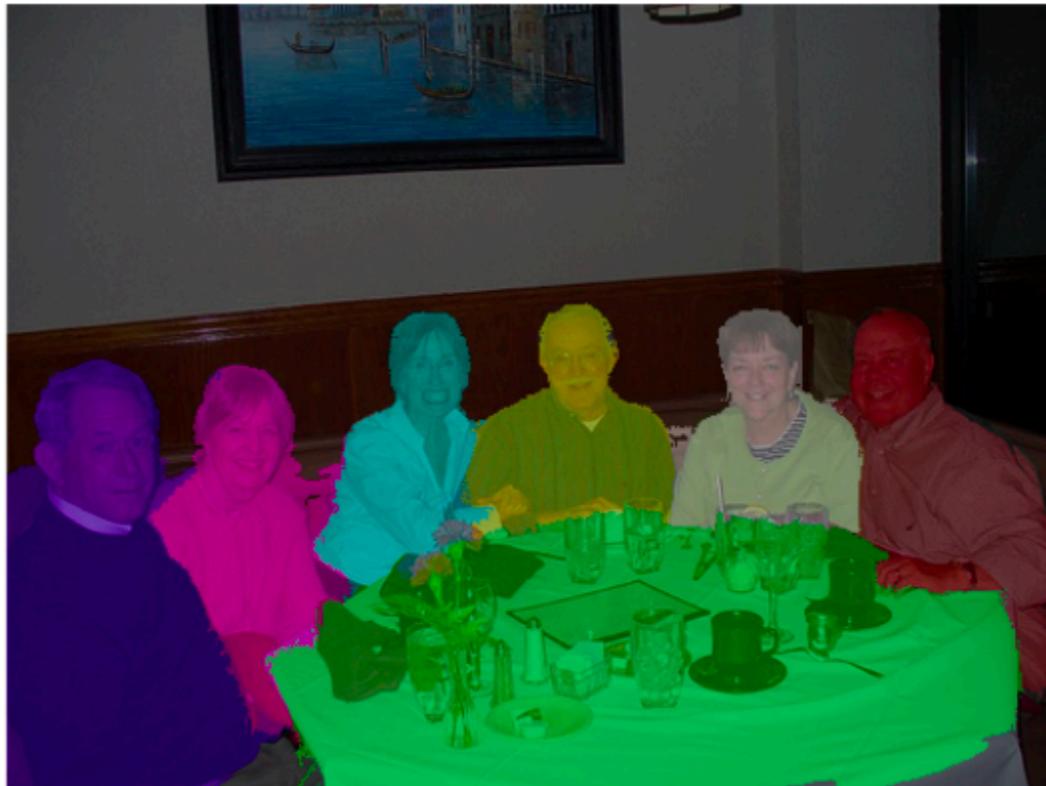


Segmentación



Segmentación semántica



Segmentación de instancias

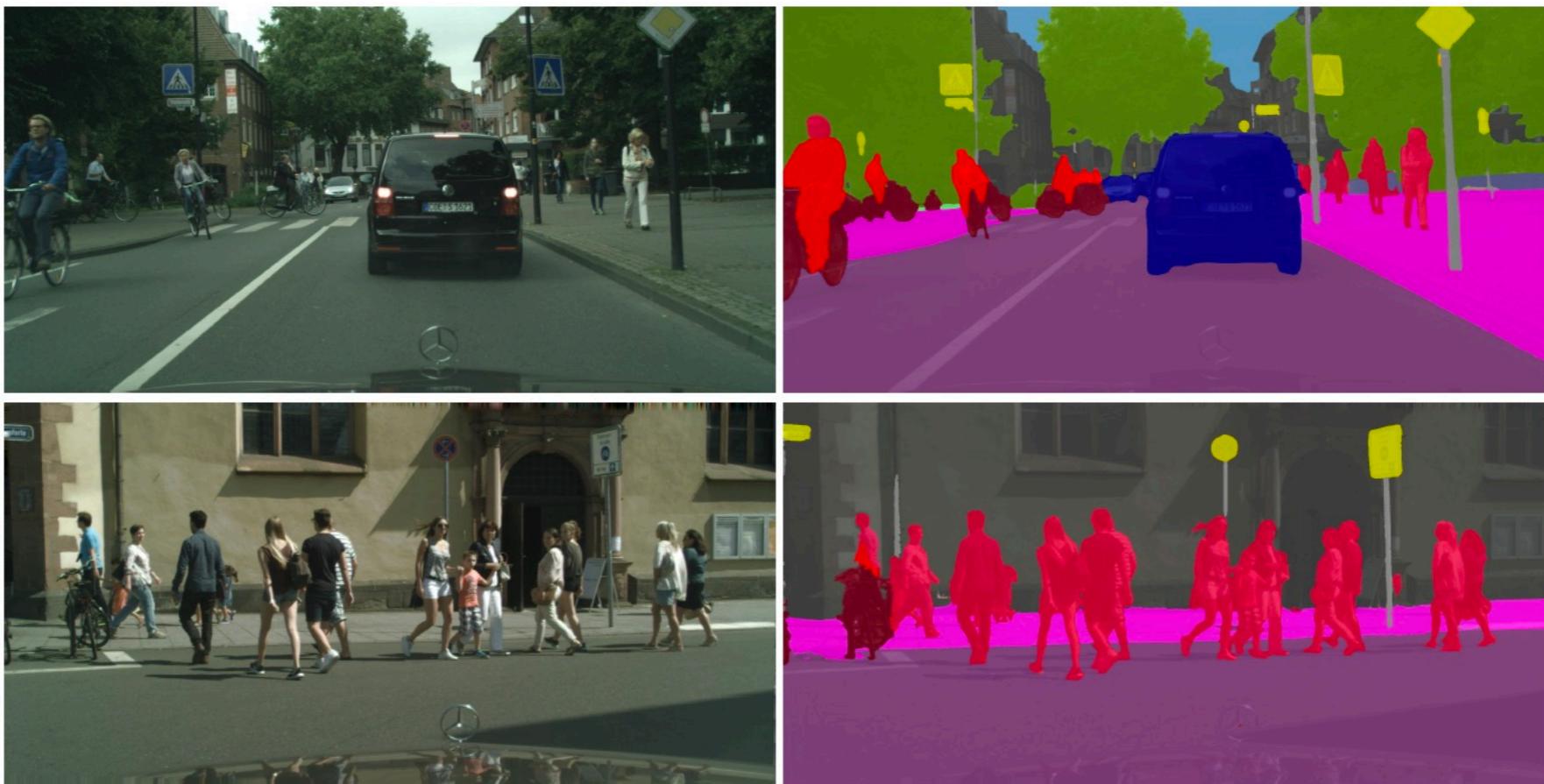
Segmentación semántica

+

detección de objetos

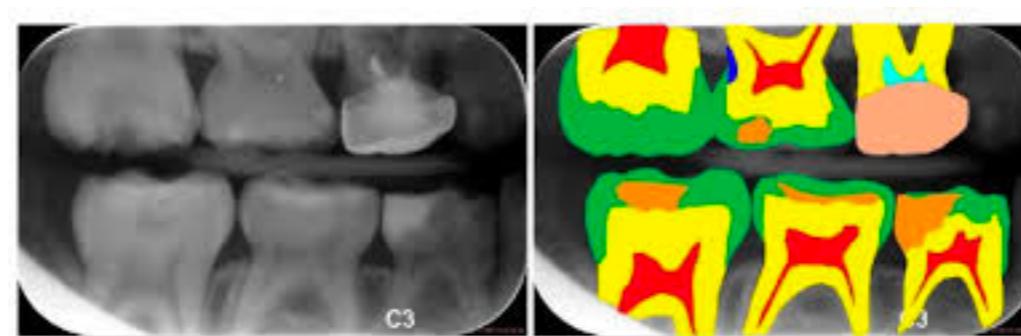
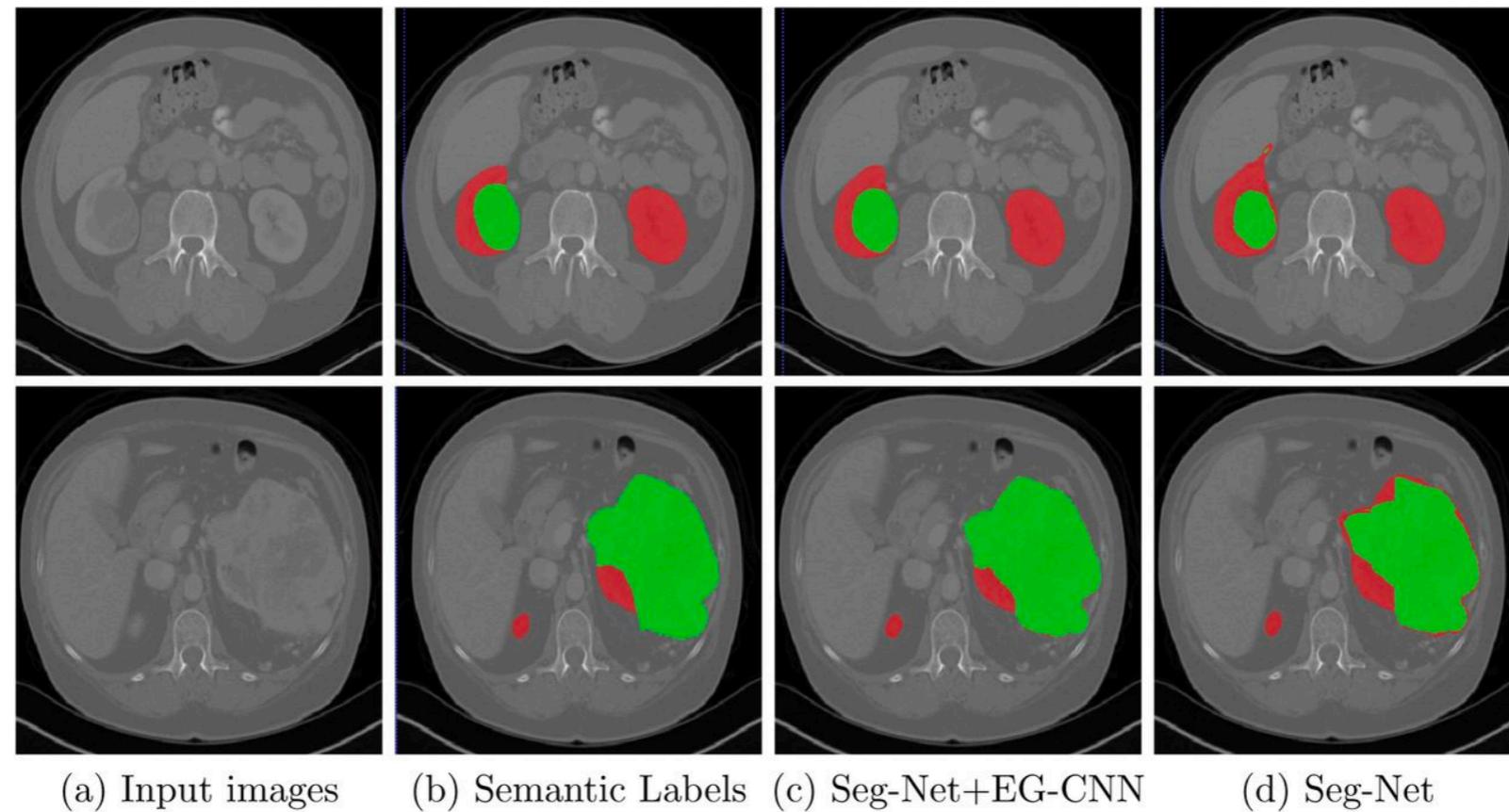
Usos

Conducción autónoma



Usos

Medicina



Detección de texto y OCR

TO ALL APPLICANTS: Please do not photocopy or scan this page. If you do, all your application information will be rejected.

Part 14. Interpreter's Contact Information, Certification, and Signature

wide the following information about the interpreter.

Interpreter's Full Name

Interpreter's Family Name (Last Name) Interpreter's Given Name (First Name) Ishaqmuhammed ravid

Interpreter's Business or Organization Name (if any)

Interpreter's Mailing Address

Street Name Av. Ste. # 195042

City or Town United States of America, Toronto State Washington Zip 650

Province

(a)

TO ALL APPLICANTS: Please do not photocopy or scan this page. If you do, all your application information will be rejected.

Part 14. Interpreter's Contact Information, Certification, and Signature

wide the following information about the interpreter.

Interpreter's Full Name

Interpreter's Family Name (Last Name) Interpreter's Given Name (First Name) Ishaqmuhammed ravid

Interpreter's Business or Organization Name (if any)

Interpreter's Mailing Address

Street Name Av. Ste. # 195042

City or Town United States of America, Toronto State Washington Zip 650

Province

(c)

deviations. Per-pixel displacements are then computed using bicubic interpolation. Drop-out layers at the end of the contracting path perform further implicit data augmentation.

4 Experiments

We demonstrate the application of the u-net to three different segmentation tasks. The first task is the segmentation of neuronal structures in electron microscopic recordings. An example of the data set and our obtained segmentation is displayed in Figure 2. We provide the full result as Supplementary Material. The data set is provided by the EM segmentation challenge [14] that was started at ISBI 2012 and is still open for new contributions. The training data is a set of 30 images (512x512 pixels) from serial section transmission electron microscopy of the *Drosophila* first-instar larva ventral nerve cord (VNC). Each image comes with a corresponding fully annotated ground truth segmentation map for cells (white) and membranes (black). The test set is publicly available, but its segmentation maps are kept secret. An evaluation can be obtained by sending the predicted membrane probability map to the organizers. The evaluation is done by thresholding the map at 10 different levels and computation of the “warping error”, the “Rand error” and the “pixel error” [14].

The u-net (averaged over 7 rotated versions of the input data) achieves without any further pre- or postprocessing a warping error of 0.0003529 (the new best score, see Table 1) and a rand error of 0.0382.

This is significantly better than the sliding-window convolutional network result by Ciregan et al. [1], whose best submission had a warping error of 0.000420 and a rand error of 0.0504. In terms of rand error the only better performing

(b)

deviations. Per-pixel displacements are then computed using bicubic interpolation. Drop-out layers at the end of the contracting path perform further implicit data augmentation.

4 Experiments

We demonstrate the application of the u-net to three different segmentation tasks. The first task is the segmentation of neuronal structures in electron microscopic recordings. An example of the data set and our obtained segmentation is displayed in Figure 2. We provide the full result as Supplementary Material. The data set is provided by the EM segmentation challenge [14] that was started at ISBI 2012 and is still open for new contributions. The training data is a set of 30 images (512x512 pixels) from serial section transmission electron microscopy of the *Drosophila* first-instar larva ventral nerve cord (VNC). Each image comes with a corresponding fully annotated ground truth segmentation map for cells (white) and membranes (black). The test set is publicly available, but its segmentation maps are kept secret. An evaluation can be obtained by sending the predicted membrane probability map to the organizers. The evaluation is done by thresholding the map at 10 different levels and computation of the “warping error”, the “Rand error” and the “pixel error” [14].

The u-net (averaged over 7 rotated versions of the input data) achieves without any further pre- or postprocessing a warping error of 0.0003529 (the new best score, see Table 1) and a rand error of 0.0382.

This is significantly better than the sliding-window convolutional network result by Ciregan et al. [1], whose best submission had a warping error of 0.000420 and a rand error of 0.0504. In terms of rand error the only better performing

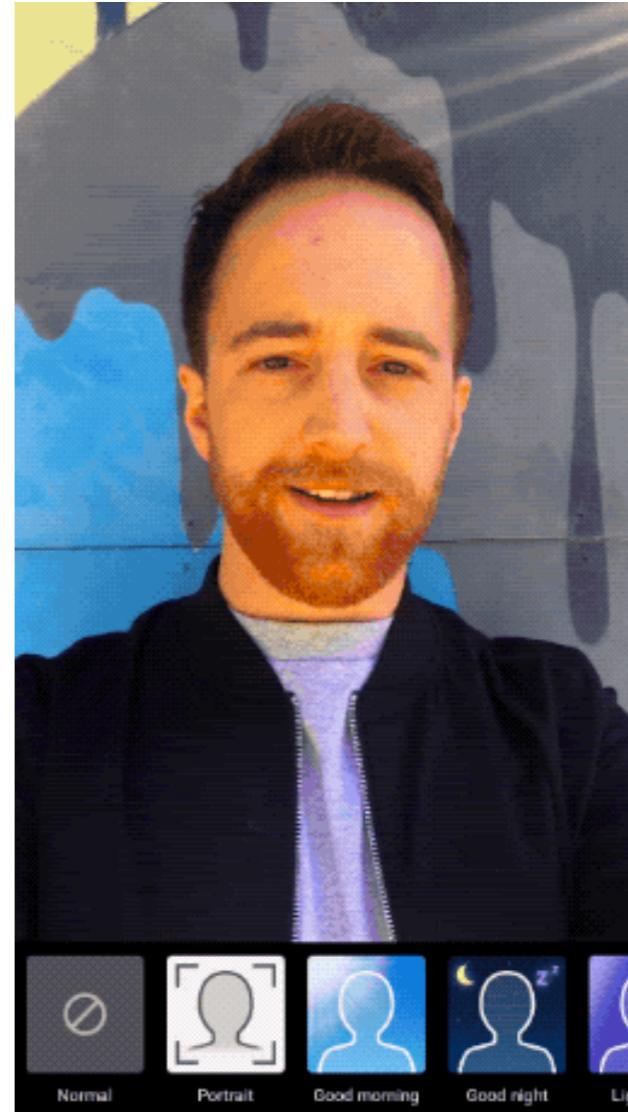
(d)

Modo retrato



Usos

Cambios de Fondo



Usos

Detección de texto y OCR

NOTE TO ALL APPLICANTS: If you do not completely fill out your application or fail to submit required documents listed in the instructions, USCIS may deny your application.

Part 14. Interpreter's Contact Information, Certification, and Signature

Provide the following information about the interpreter.

Interpreter's Full Name

Interpreter's Family Name (Last Name) Interpreter's Given Name (First Name)

Interpreter's Business or Organization Name (if any)

Interpreter's Mailing Address

Street Number Apt. Ste. Fl

City or Town State Zip Code

Province Postcode County

(a)

NOTE TO ALL APPLICANTS: If you do not completely fill out your application or fail to submit required documents listed in the instructions, USCIS may deny your application.

Part 14. Interpreter's Contact Information, Certification, and Signature

Provide the following information about the interpreter.

Interpreter's Full Name

Interpreter's Family Name (Last Name) Interpreter's Given Name (First Name)

Interpreter's Business or Organization Name (if any)

Interpreter's Mailing Address

Street Number Apt. Ste. Fl

City or Town State Zip Code

Province Postcode County

(c)

deviation. Per-pixel displacements are then computed using bicubic interpolation. Drop-out layers at the end of the contracting path perform further implicit data augmentation.

$$P(\bar{x}|\bar{y}) = \prod_{i=1}^n P(x_i|y_i)$$

$$= \prod_{i=1}^n P(x_i|y_i, z_i) = P(\bar{x}|\bar{y}, \bar{z})$$

4 Experiments

We demonstrate the application of the u-net to three different segmentation tasks. The first task is the segmentation of neuronal structures in electron microscopic recordings. An example of the data set and our obtained segmentation is displayed in Figure 2. We provide the full result as Supplementary Material. The data set is provided by the EM segmentation challenge [14] that was started at ISBI 2012 and is still open for new contributions. The training data is a set of 30 images (512x512 pixels) from serial section transmission electron microscopy of the Drosophila first-instar larva ventral nerve cord (VNC). Each image comes with a corresponding fully annotated ground truth segmentation map for cells (white) and membranes (black). The test set is publicly available, but its segmentation maps are kept secret. An evaluation can be obtained by sending the predicted membrane probability map to the organizers. The evaluation is done by thresholding the map at 10 different levels and computation of the “warping error”, the “Rand error” and the “pixel error” [14].

The u-net (averaged over 7 rotated versions of the input data) achieves without any further pre- or postprocessing a warping error of 0.0003529 (the new best score, see Table 1) and a rand-error of 0.0382. This is significantly better than the sliding-window convolutional network result by Ciresan et al. [1], whose best submission had a warping error of 0.000420 and a rand error of 0.0504. In terms of rand error the only better performing

(b)

deviation. Per-pixel displacements are then computed using bicubic interpolation. Drop-out layers at the end of the contracting path perform further implicit data augmentation.

$$P(\bar{x}|\bar{y}) = \prod_{i=1}^n P(x_i|y_i)$$

$$= \prod_{i=1}^n P(x_i|y_i, z_i) = P(\bar{x}|\bar{y}, \bar{z})$$

4 Experiments

We demonstrate the application of the u-net to three different segmentation tasks. The first task is the segmentation of neuronal structures in electron microscopic recordings. An example of the data set and our obtained segmentation is displayed in Figure 2. We provide the full result as Supplementary Material. The data set is provided by the EM segmentation challenge [14] that was started at ISBI 2012 and is still open for new contributions. The training data is a set of 30 images (512x512 pixels) from serial section transmission electron microscopy of the Drosophila first-instar larva ventral nerve cord (VNC). Each image comes with a corresponding fully annotated ground truth segmentation map for cells (white) and membranes (black). The test set is publicly available, but its segmentation maps are kept secret. An evaluation can be obtained by sending the predicted membrane probability map to the organizers. The evaluation is done by thresholding the map at 10 different levels and computation of the “warping error”, the “Rand error” and the “pixel error” [14].

The u-net (averaged over 7 rotated versions of the input data) achieves without any further pre- or postprocessing a warping error of 0.0003529 (the new best score, see Table 1) and a rand-error of 0.0382. This is significantly better than the sliding-window convolutional network result by Ciresan et al. [1], whose best submission had a warping error of 0.000420 and a rand error of 0.0504. In terms of rand error the only better performing

(d)

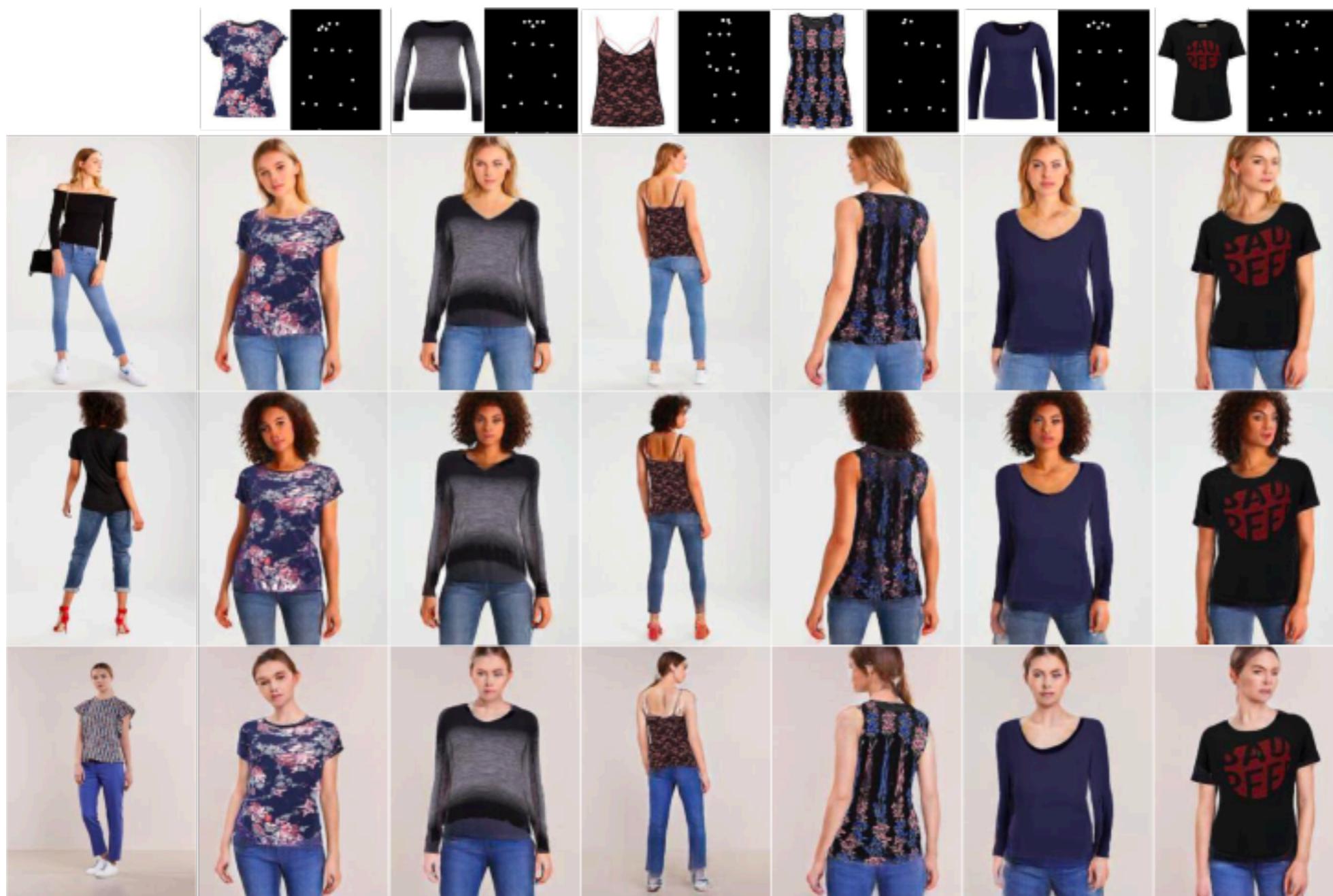
Usos

Maquillaje virtual



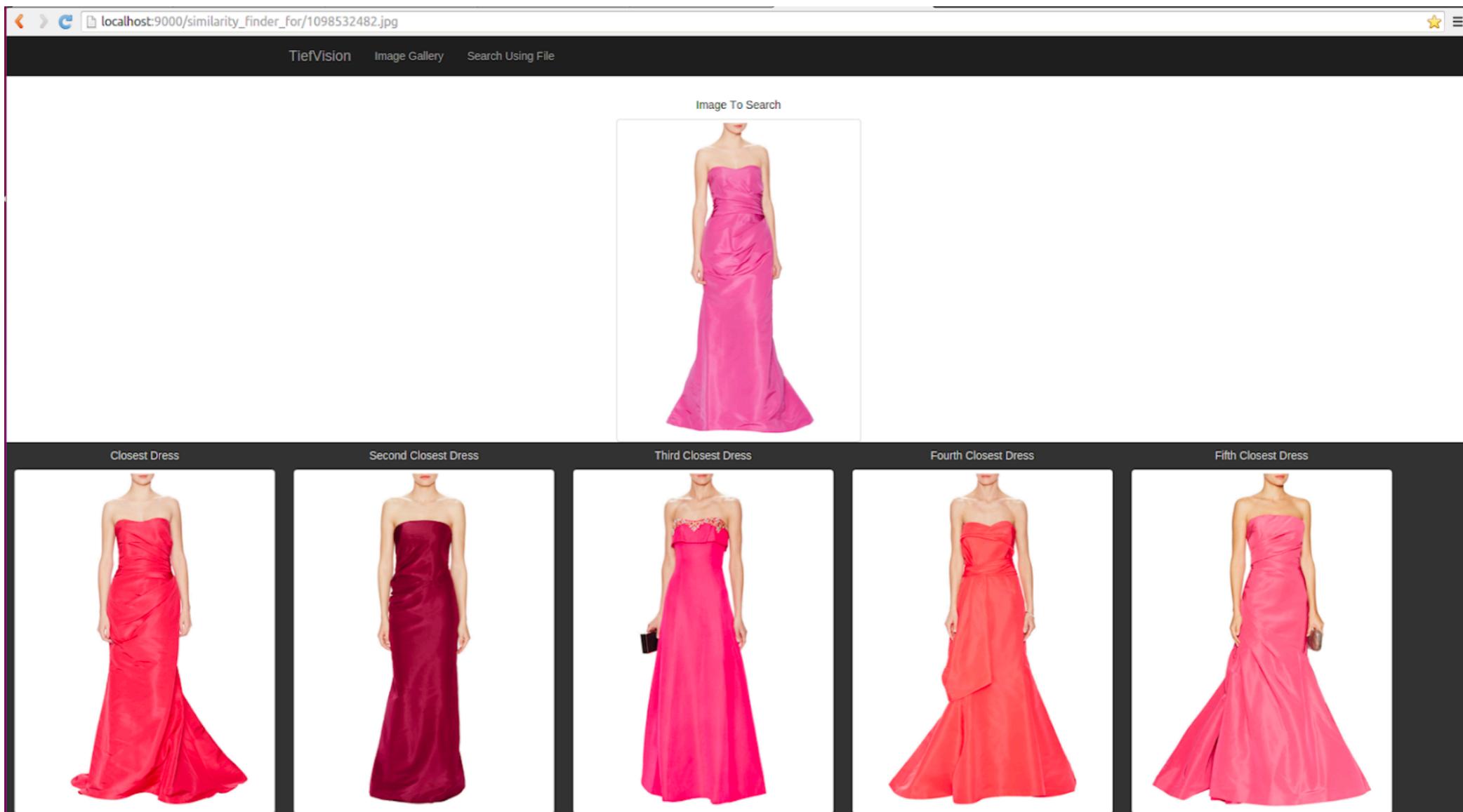
Usos

Probador virtual



Usos

Buscador de imágenes inteligente



Usos

Discriminación de objetos en cámaras seguridad



Usos

Webcams con auto tracking

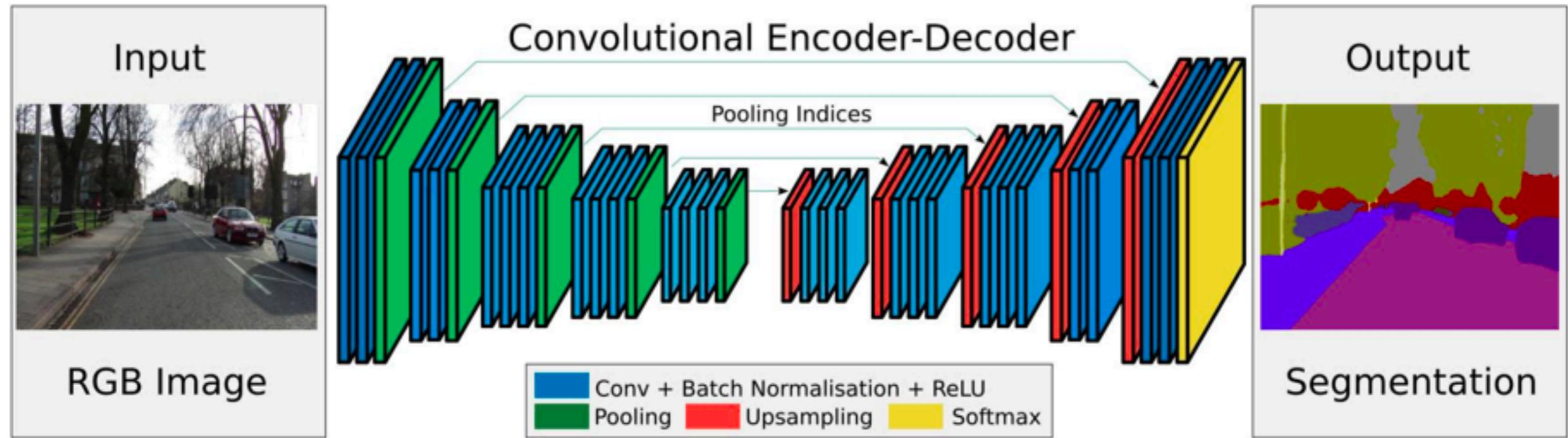


Plug and Play
As charging adapter for
phone long -time Live
streaming

 Face tracking  High speed tracking motor

 Horizontal and Vertical  No APP required

Segmentación



En segmentación, la mayoría de las arquitecturas constan de un codificador y un decodificador. Normalmente el decodificador genera una máscara que contiene la forma del objeto y objetos.

U-Net

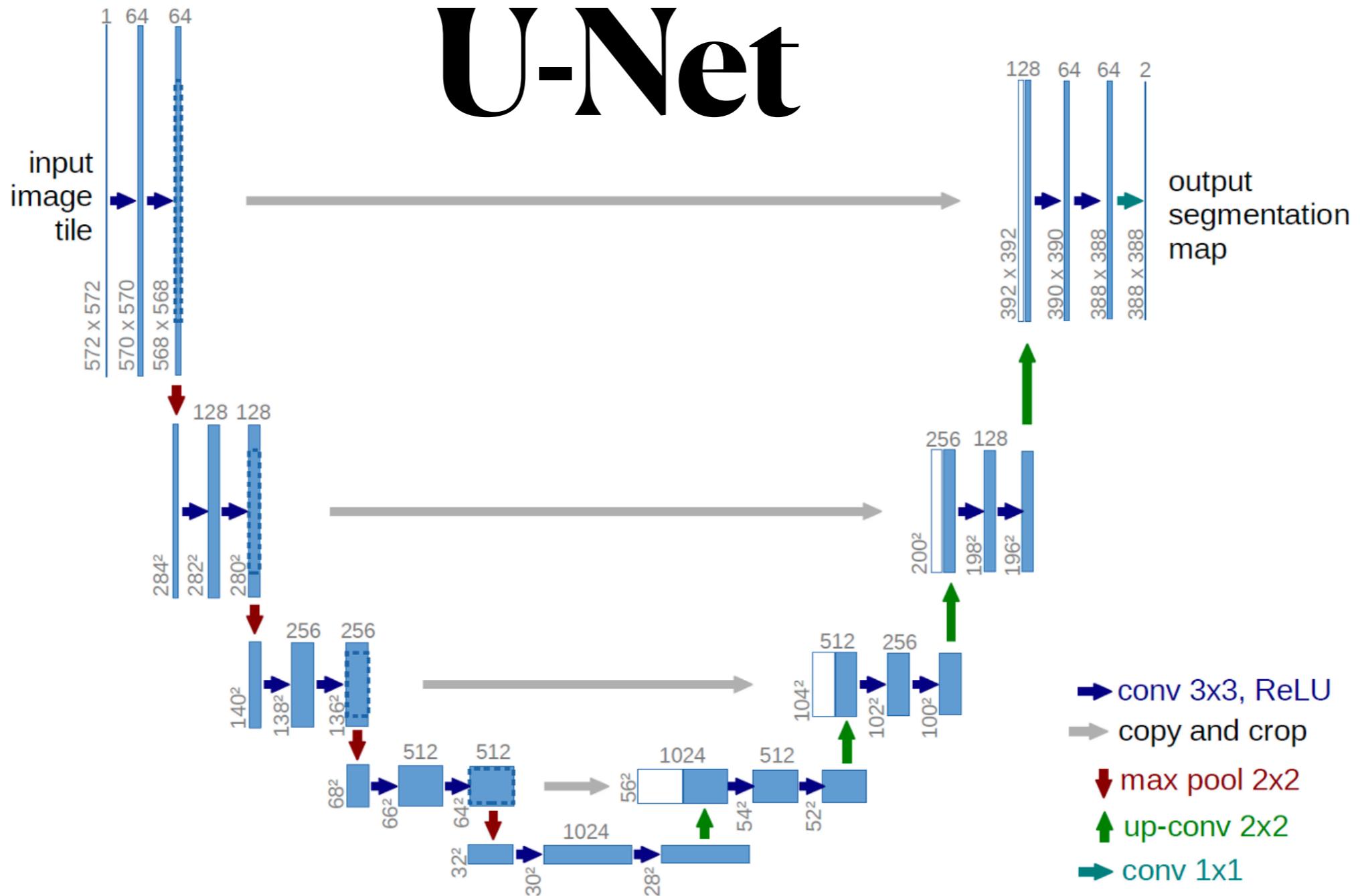


Fig. 1. U-net architecture (example for 32x32 pixels in the lowest resolution). Each blue box corresponds to a multi-channel feature map. The number of channels is denoted on top of the box. The x-y-size is provided at the lower left edge of the box. White boxes represent copied feature maps. The arrows denote the different operations.

FastFCN – Fast Fully Convolutional Network

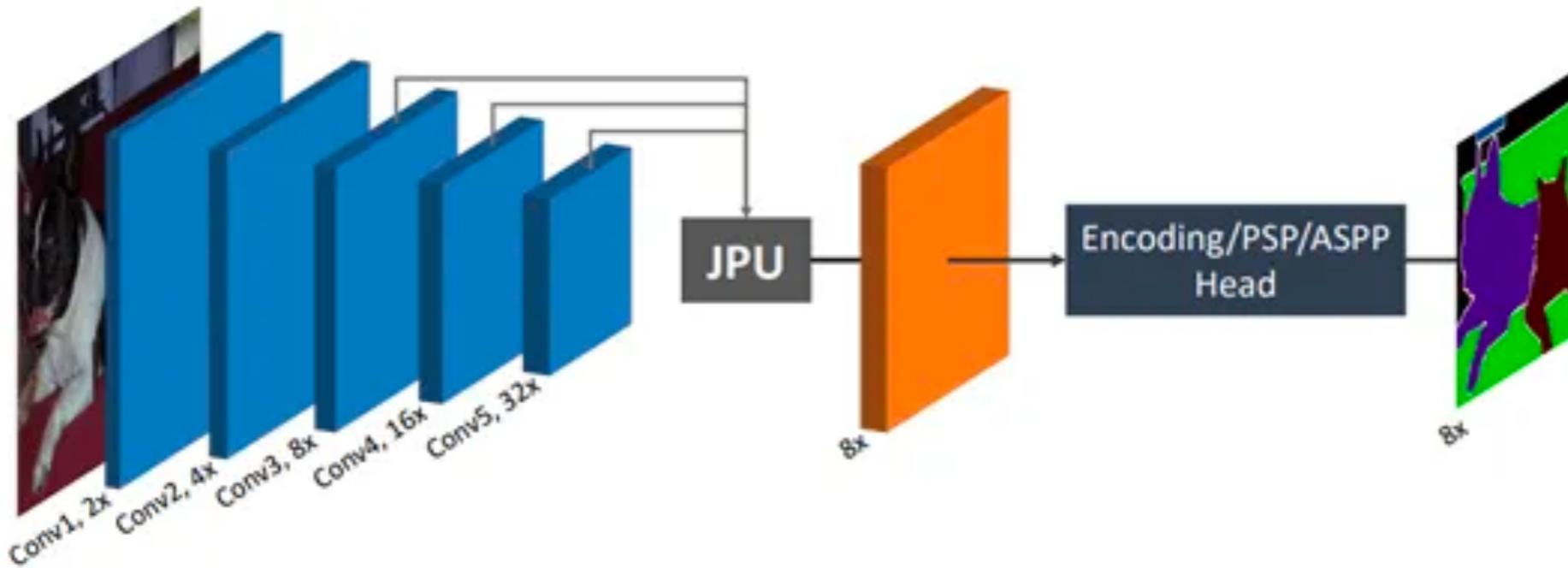


Figure 2: **Framework Overview of Our Method.** Our method employs the same backbone as the original FCN. After the backbone, a novel upsampling module named Joint Pyramid Upsampling (JPU) is proposed, which takes the last three feature maps as the inputs and generates a high-resolution feature map. A multi-scale/global context module is then employed to produce the final label map. Best viewed in color.

Gated-SCNN

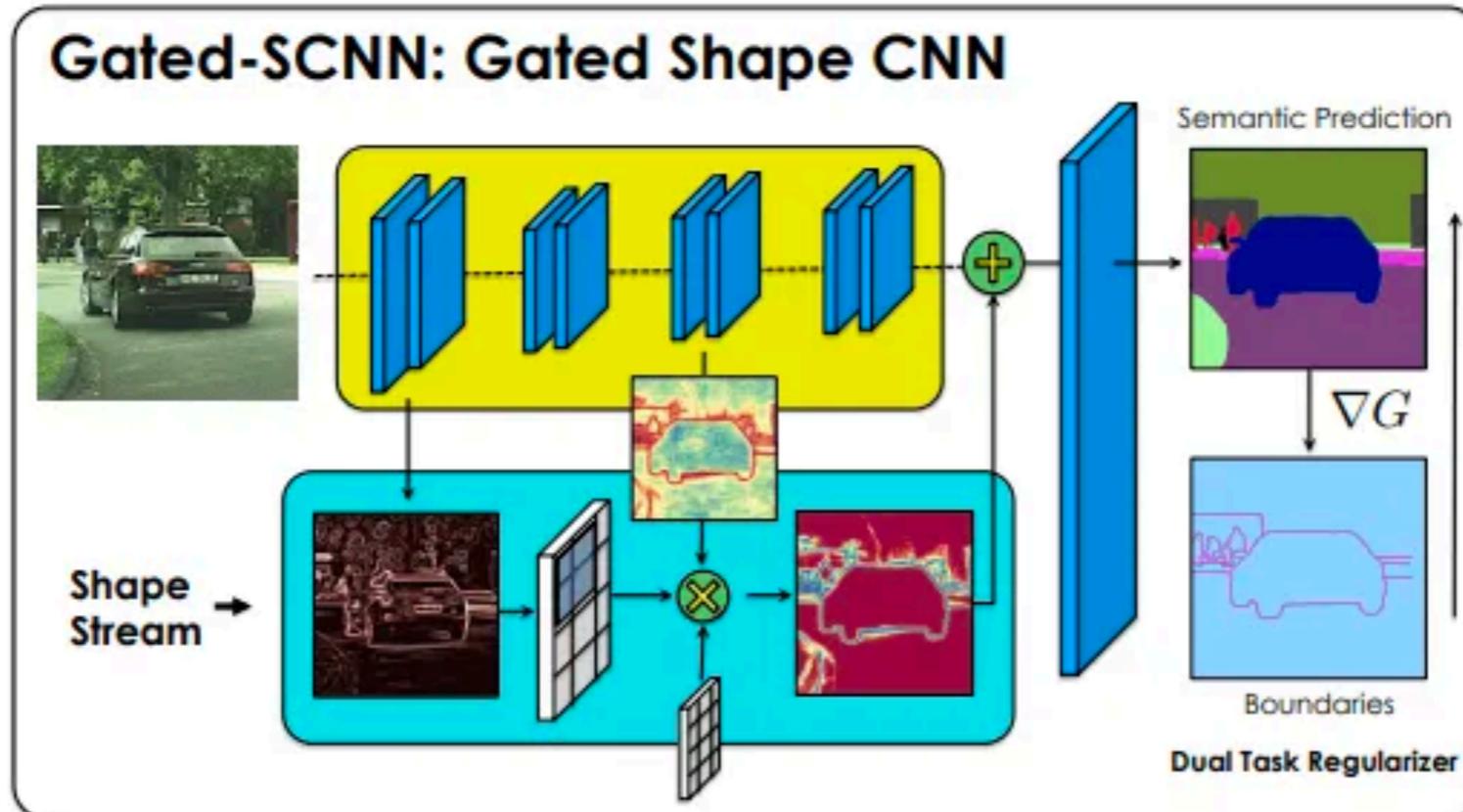


Figure 1: We introduce *Gated-SCNN* (GSCNN), a new two-stream CNN architecture for semantic segmentation that explicitly wires shape information as a separate processing stream. GSCNN uses a new gating mechanism to connect the intermediate layers. Fusion of information between streams is done at the very end through a fusion module. To predict high-quality boundaries, we exploit a new loss function that encourages the predicted semantic segmentation masks to align with ground-truth boundaries.

DeepLab

3

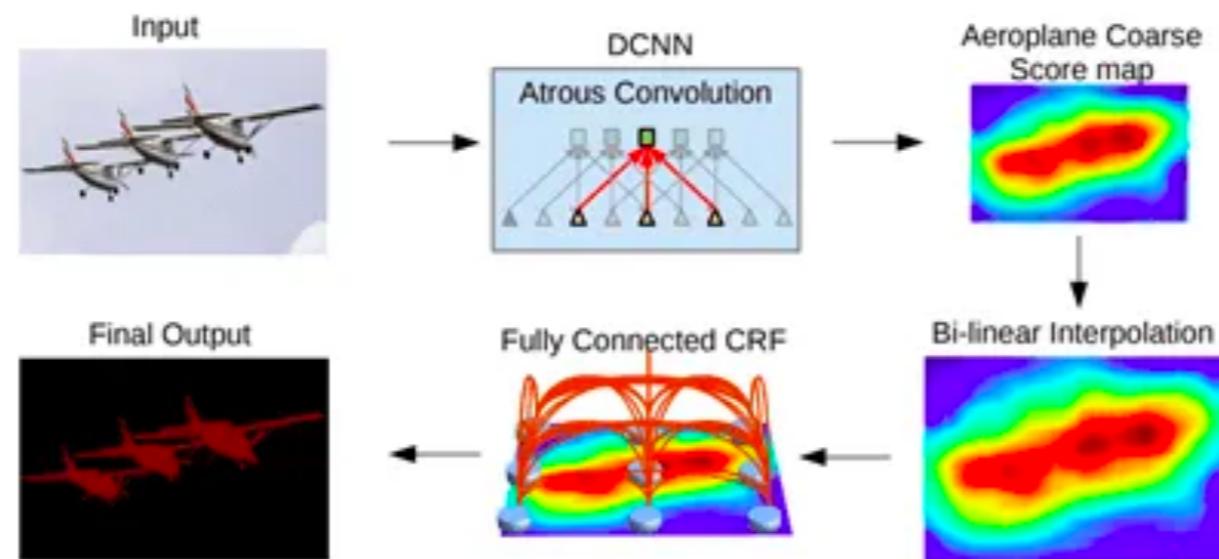


Fig. 1: Model Illustration. A Deep Convolutional Neural Network such as VGG-16 or ResNet-101 is employed in a fully convolutional fashion, using atrous convolution to reduce the degree of signal downampling (from 32x down 8x). A bilinear interpolation stage enlarges the feature maps to the original image resolution. A fully connected CRF is then applied to refine the segmentation result and better capture the object boundaries.

Mask R-CNN

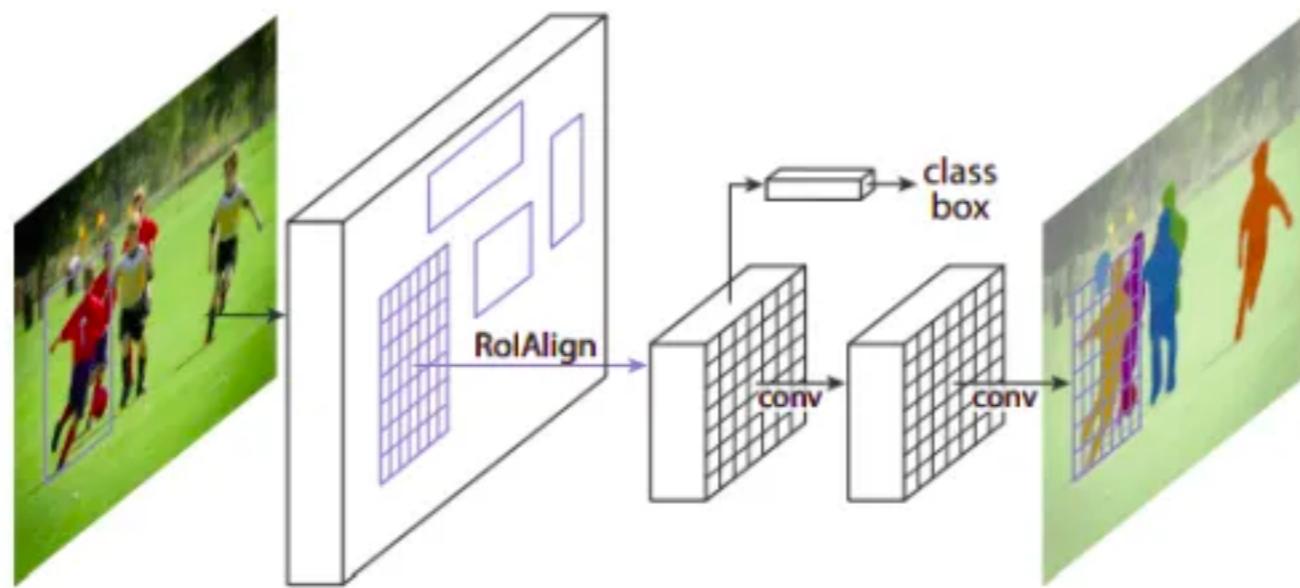
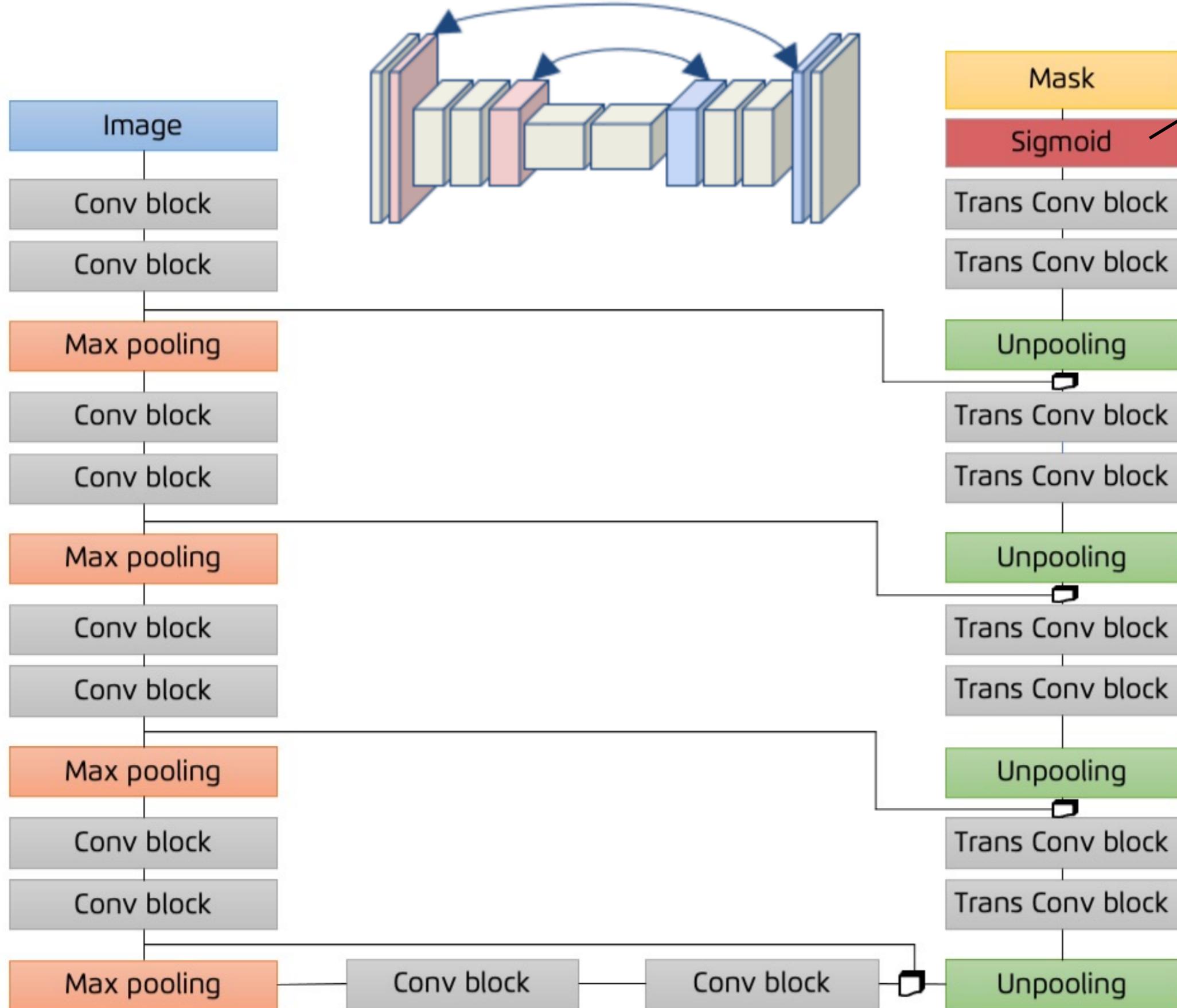
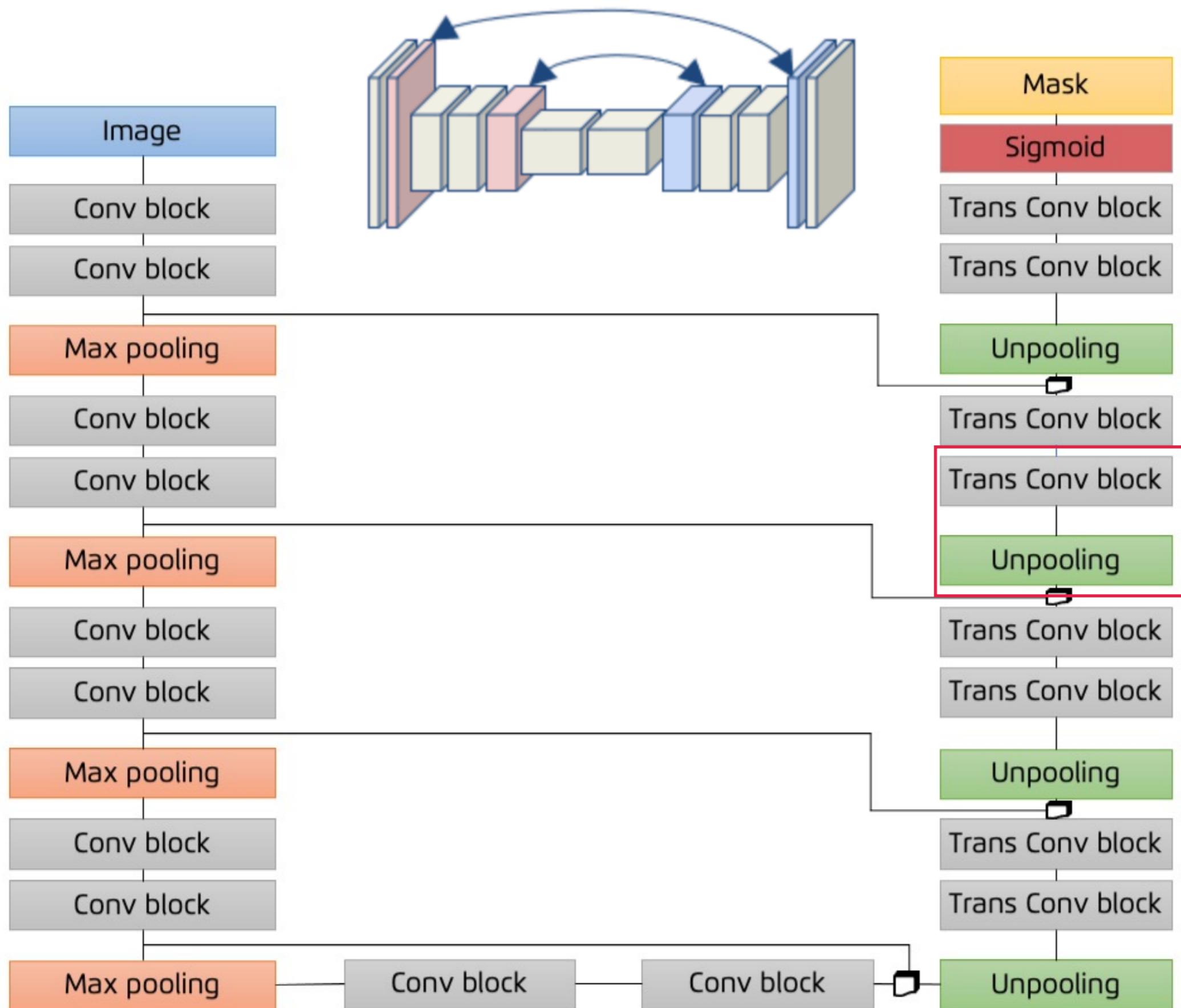


Figure 1. The **Mask R-CNN** framework for instance segmentation.

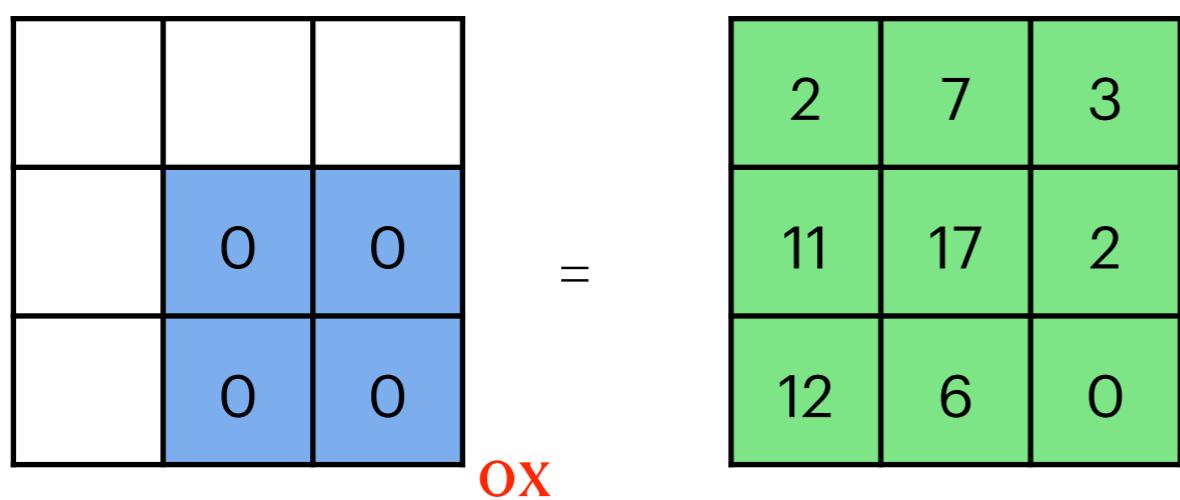
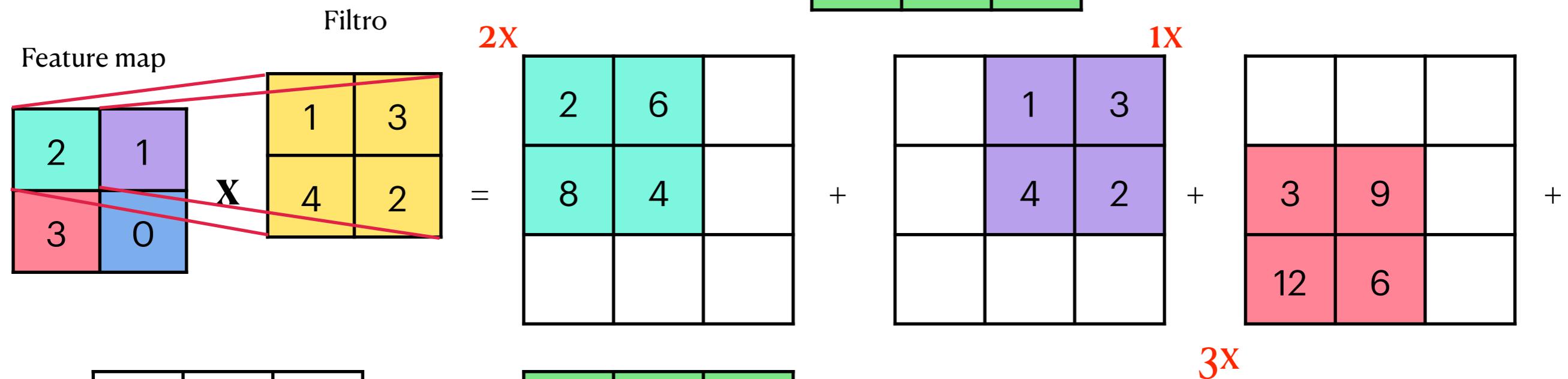
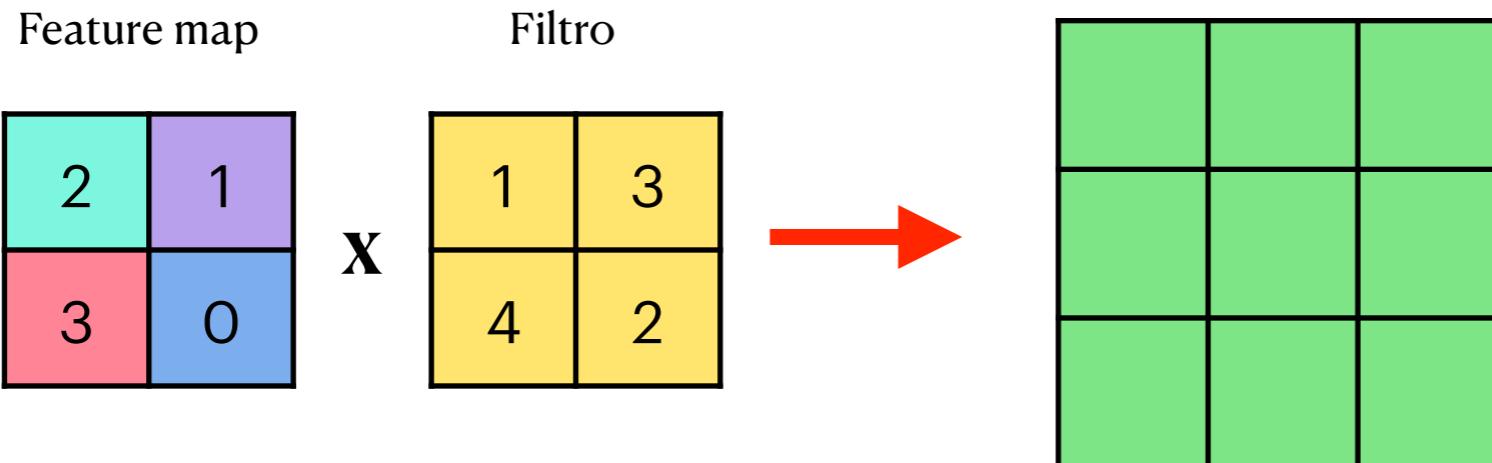


Función de activación de la capa de salida (sigmoid o softmax)



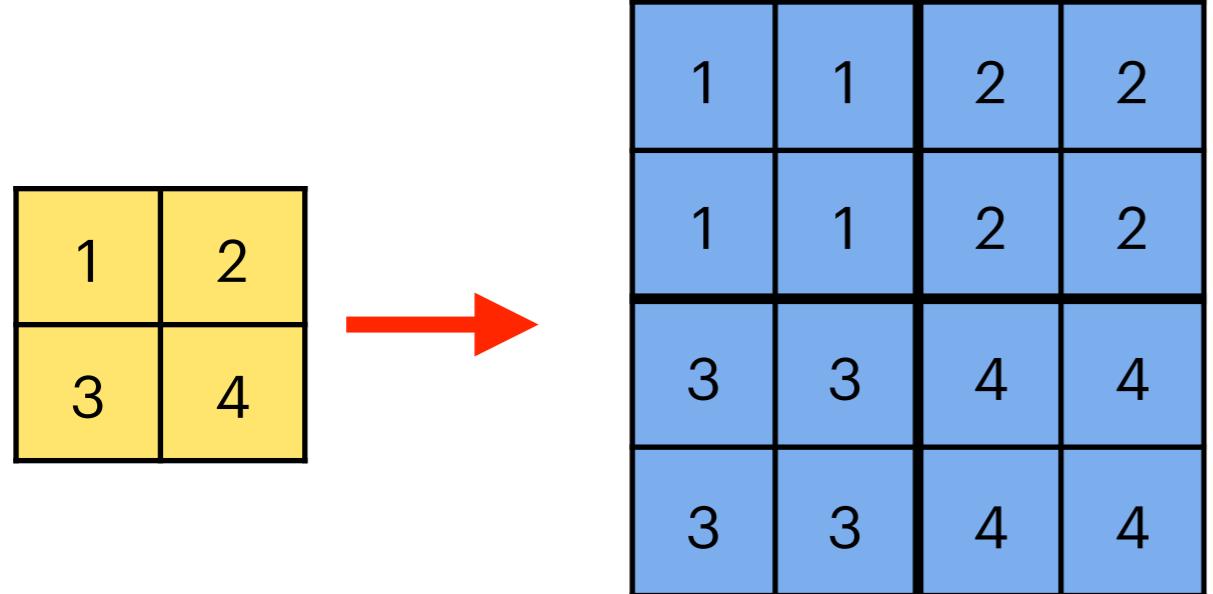
Capa de convolución transpuesta

Ejemplo: filtro de 2×2 , stride 1 y cero padding

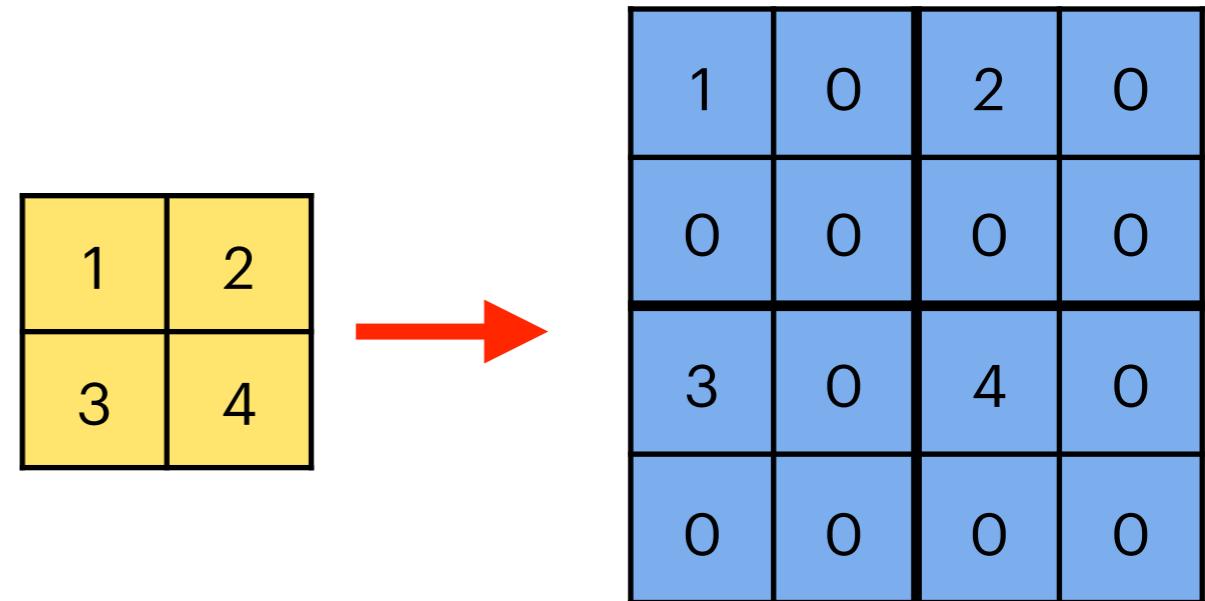


Capa de upsampling o unpooling

Nearest neighbour



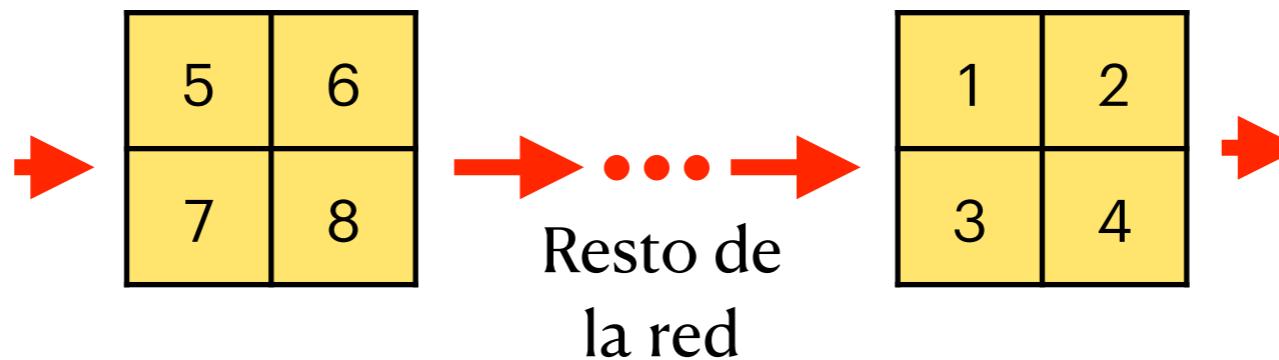
Bed of nails



Max Pooling

1	2	6	3
3	5	2	1
1	2	2	1
7	3	4	8

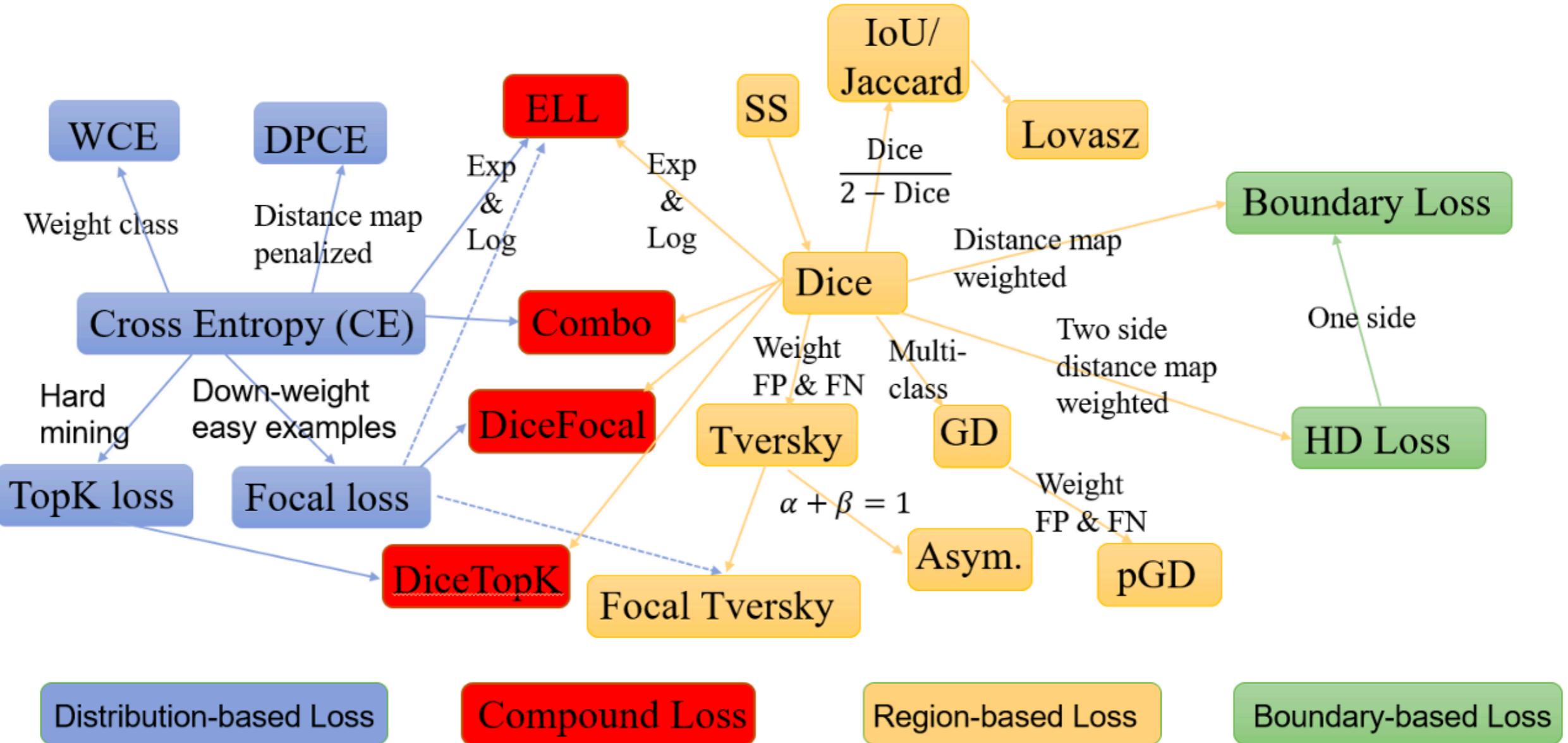
Se conservan las posiciones de los valores máximos de Max Pooling



Max Unpooling

0	0	2	0
0	1	0	0
0	0	0	0
3	0	0	4

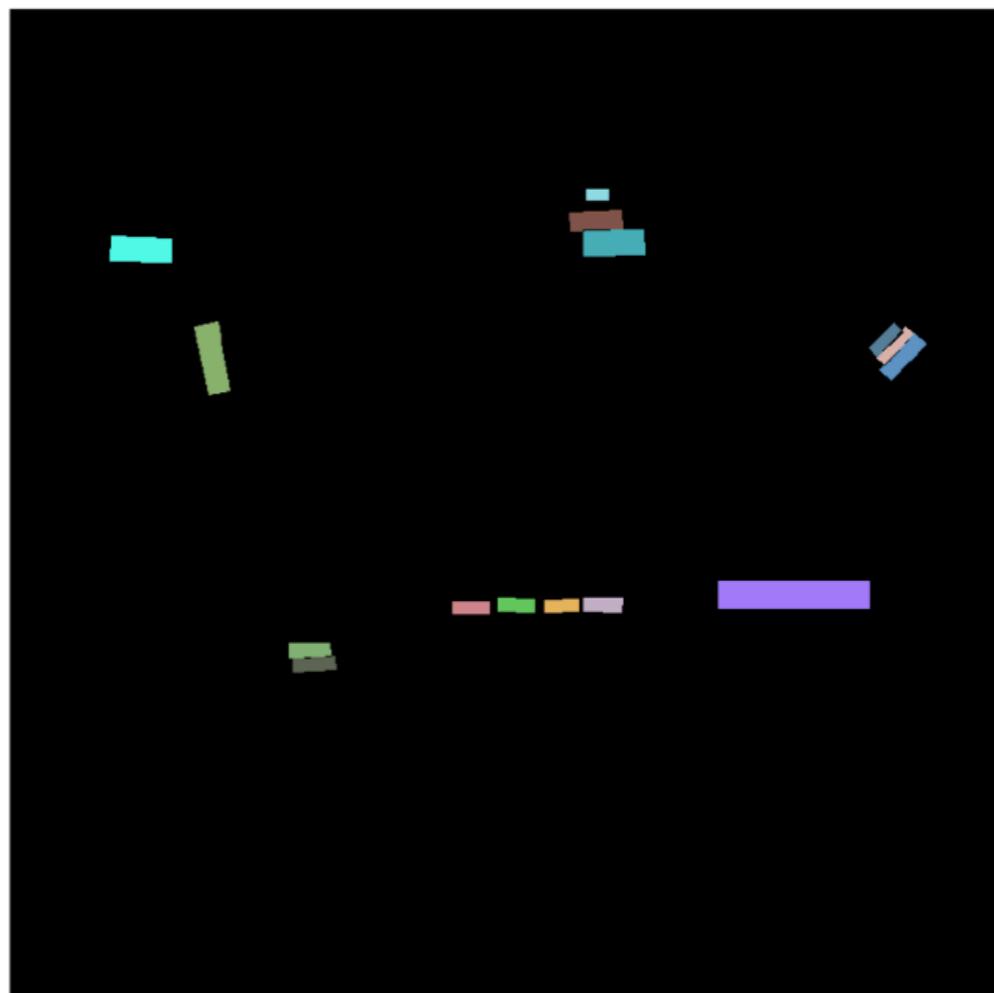
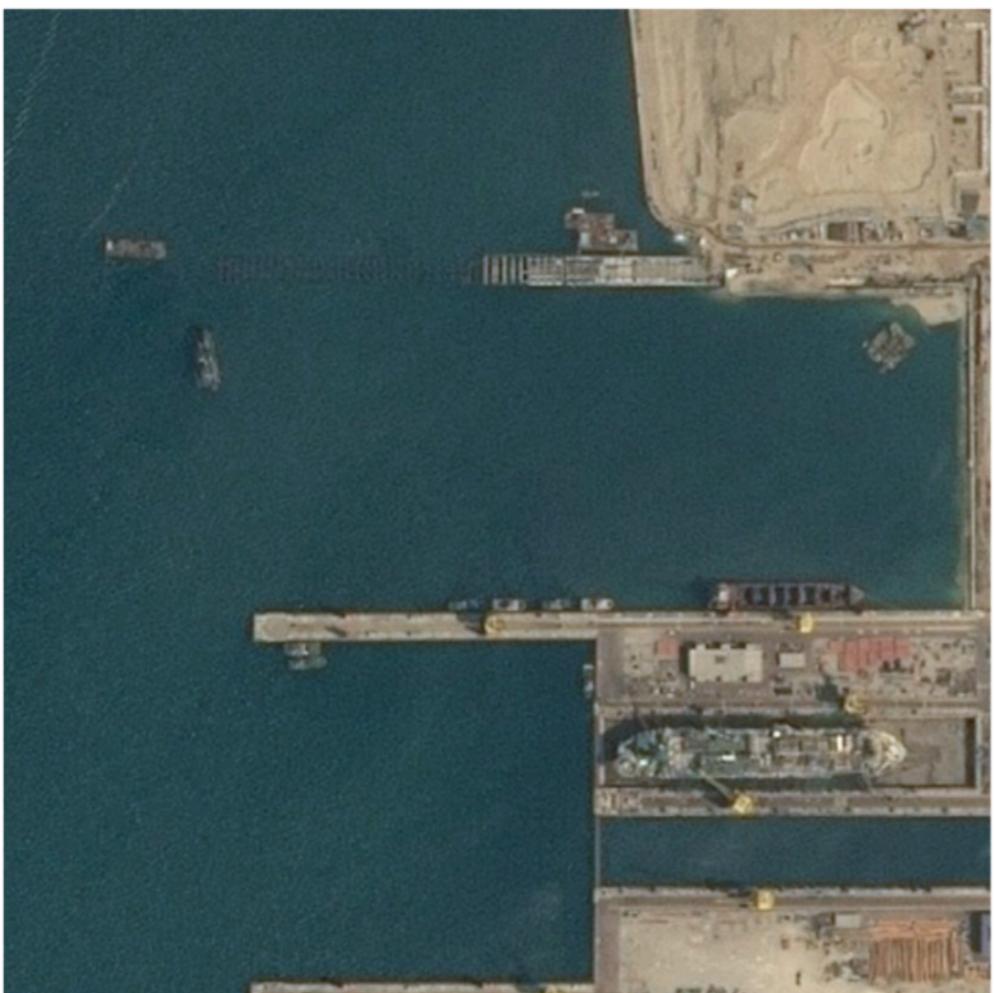
Función de pérdida (loss function)



Las más usadas son **Dice**, o **Tversky** para clases poco balanceadas

Métricas

- Pixel Accuracy
- Intersection-Over-Union (Jaccard Index)
- Dice Coefficient (F1 Score)

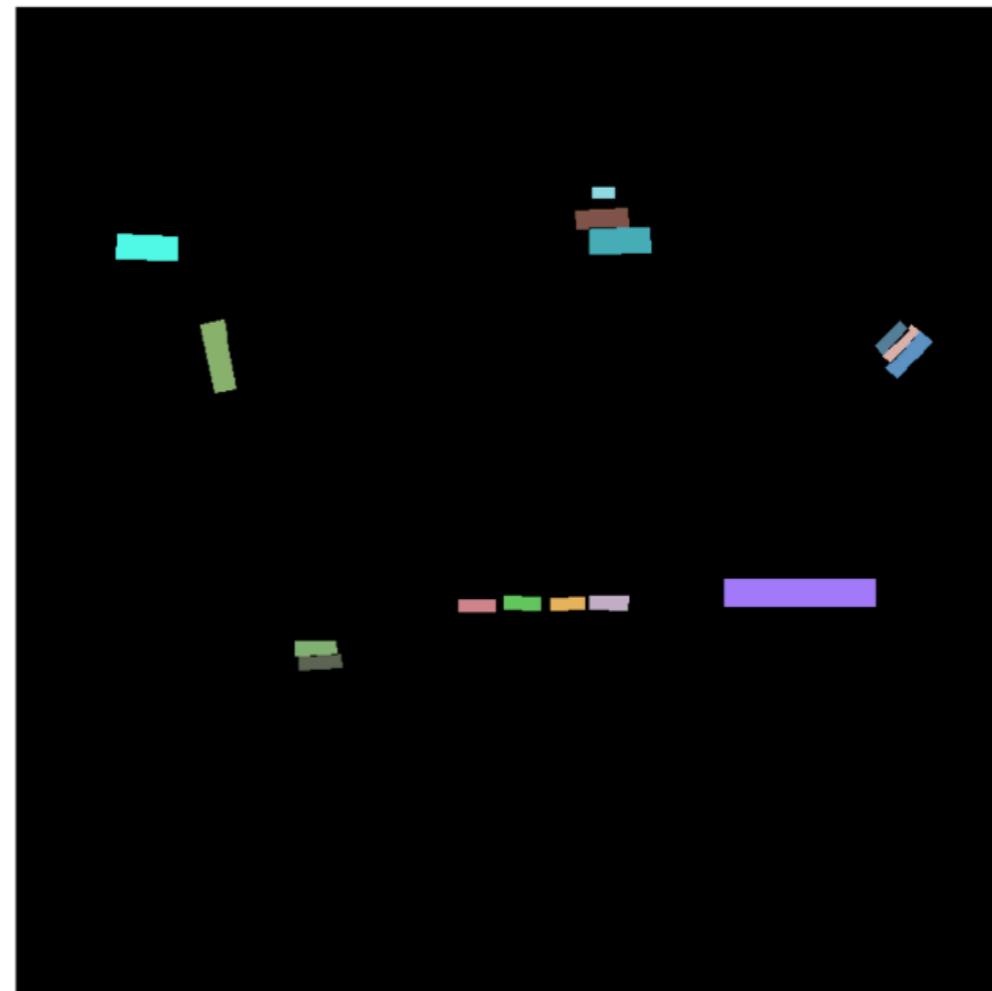
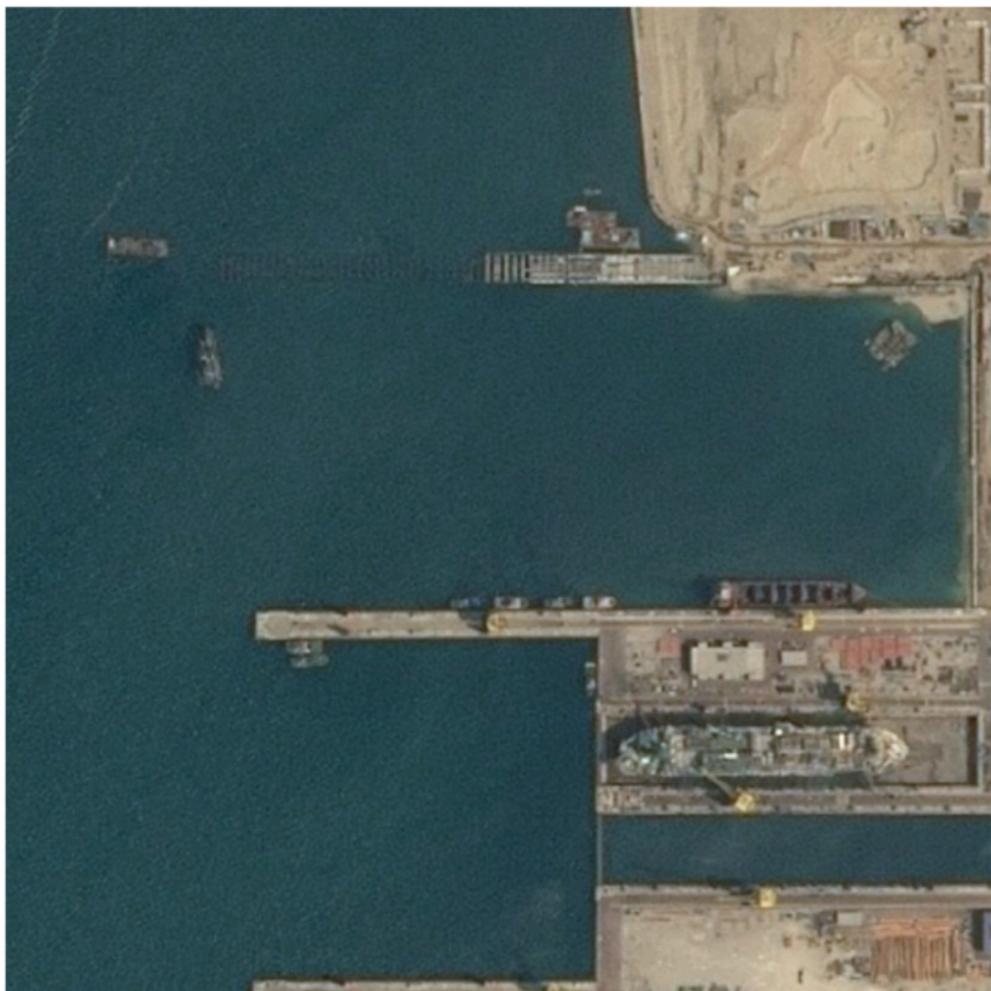


Métricas

- Pixel Accuracy

Es el porcentaje de píxeles correctamente clasificado

Es la masa sencilla de entender pero no la mejor

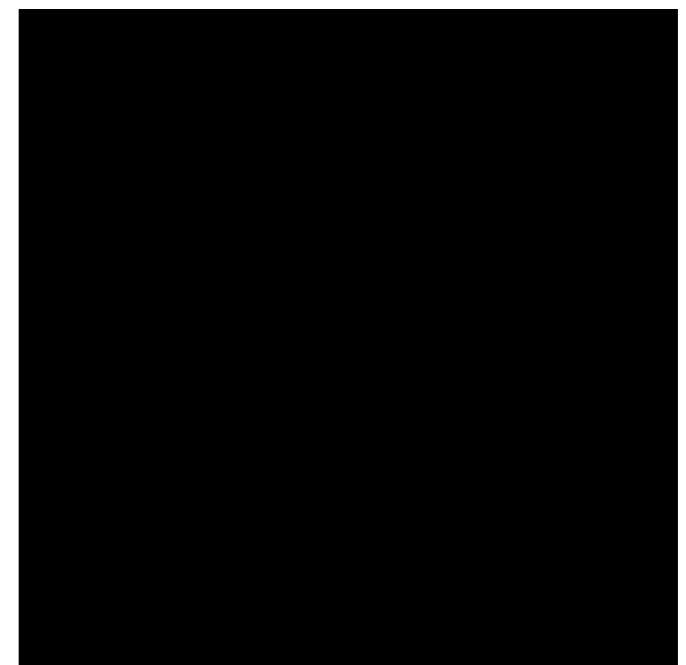
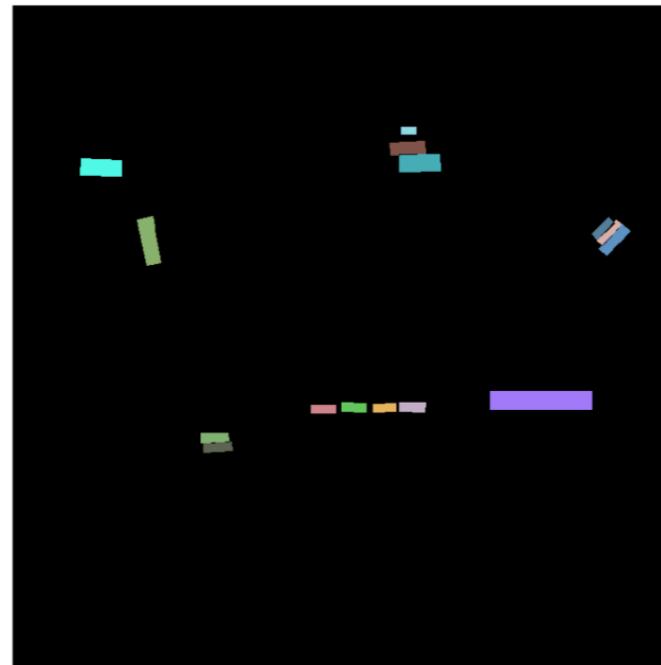
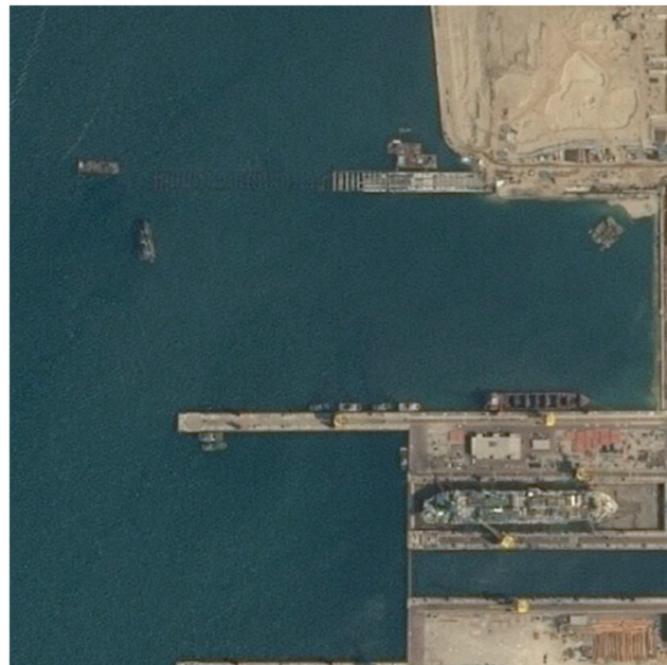


Métricas

- Pixel Accuracy

Es el porcentaje de píxeles correctamente clasificados

Es la más sencilla de entender pero no la mejor

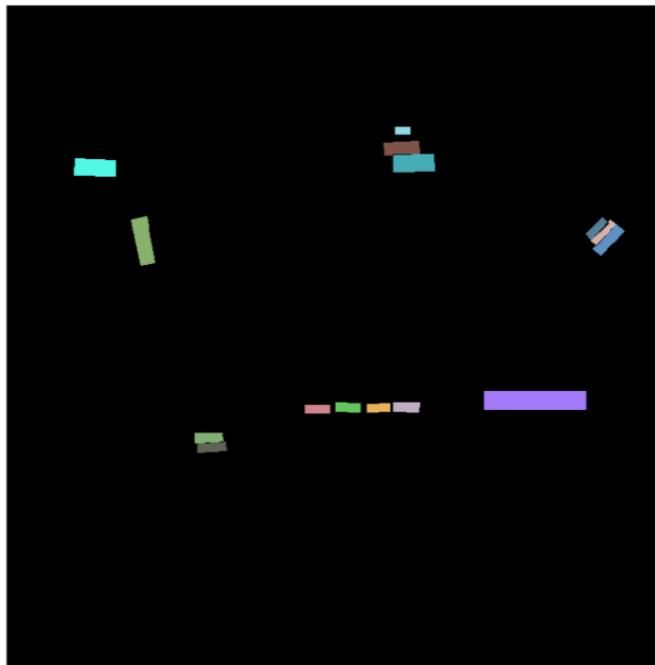
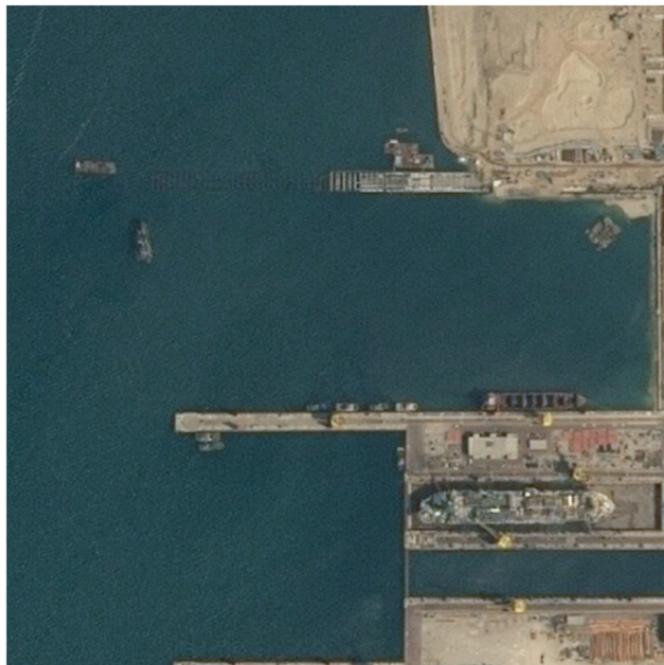


Esta máscara conseguiría el 95% de exactitud.
El culpable es el desbalanceo de clases

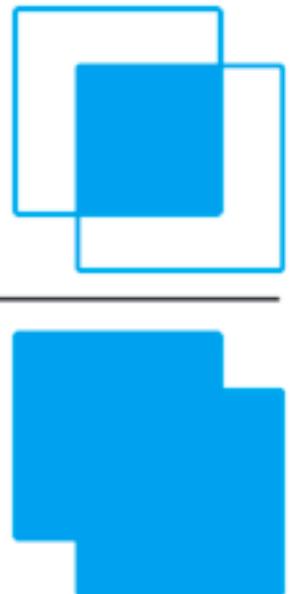
Métricas

- Intersection-Over-Union (Jaccard Index)

Es el área de superposición entre la segmentación predicha y la real dividida por el área de la unión entre la segmentación predicha y la real



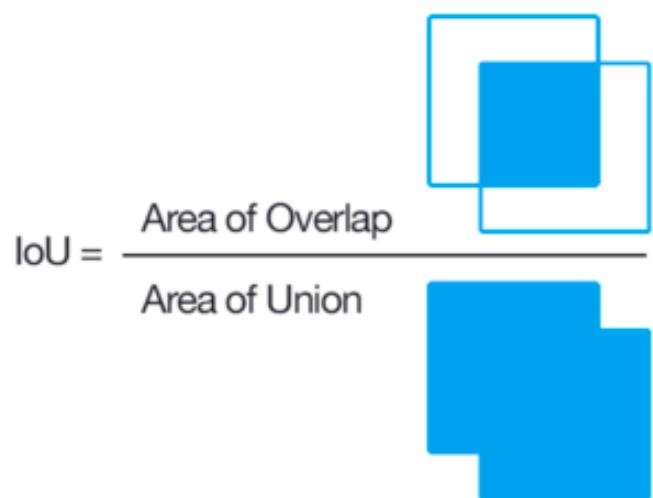
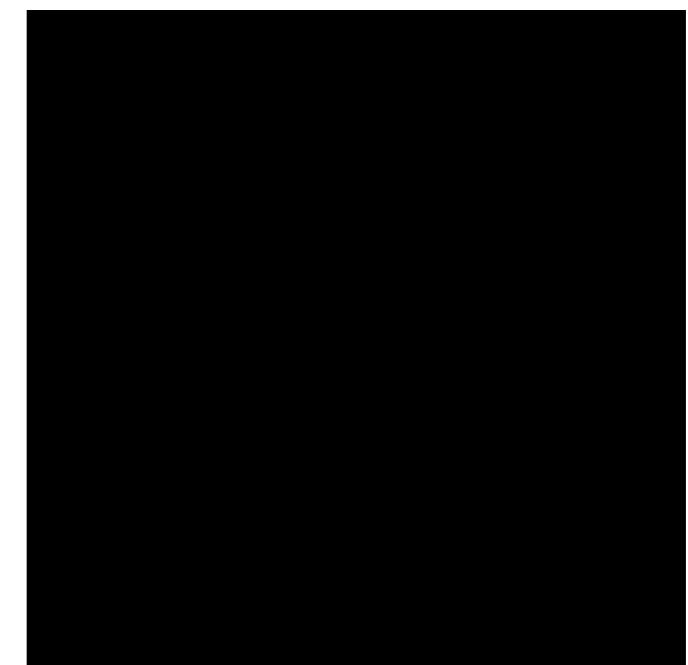
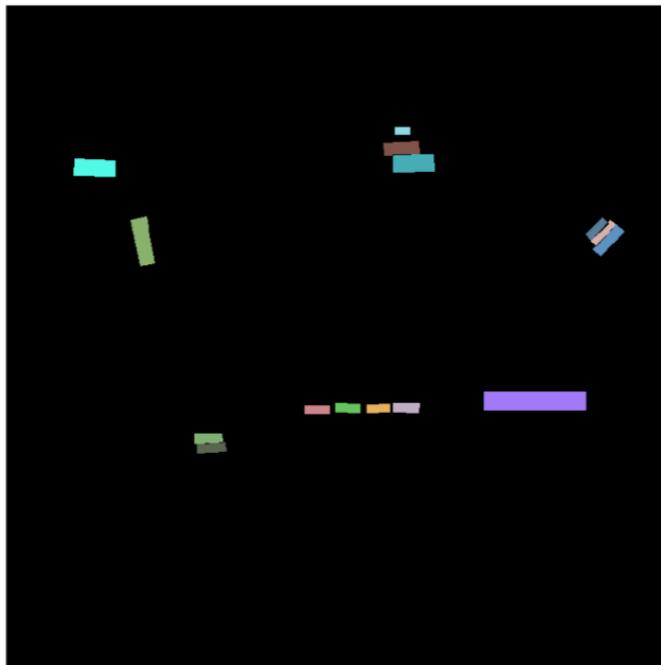
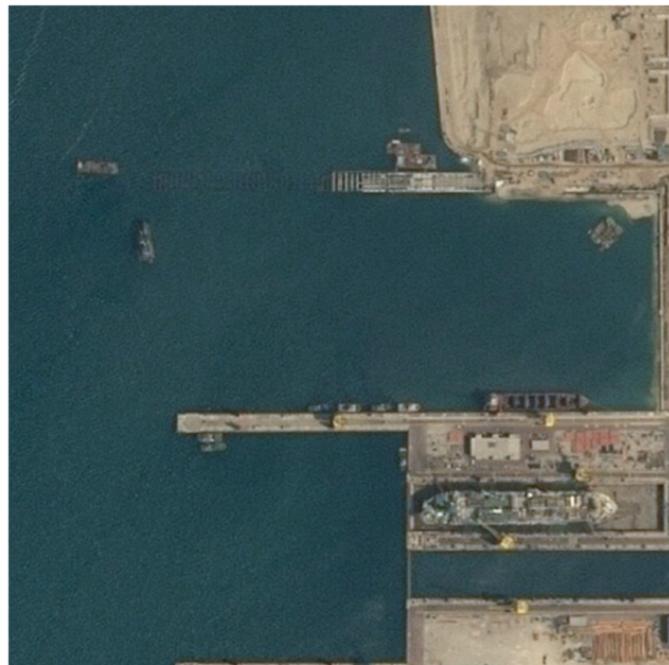
$$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}}$$



Métricas

- Intersection-Over-Union (Jaccard Index)

Es el área de superposición entre la segmentación predicha dividida por el área de la unión entre la segmentación predicha y el realidad



Supongamos área total de la imagen = 100

Area superpuesta para barcos = 0

Area unión para barcos = 5

$$\text{IoU} = 0 / 5 = 0\%$$

Area superpuesta para fondo = 95

Area unión para fondo = 100

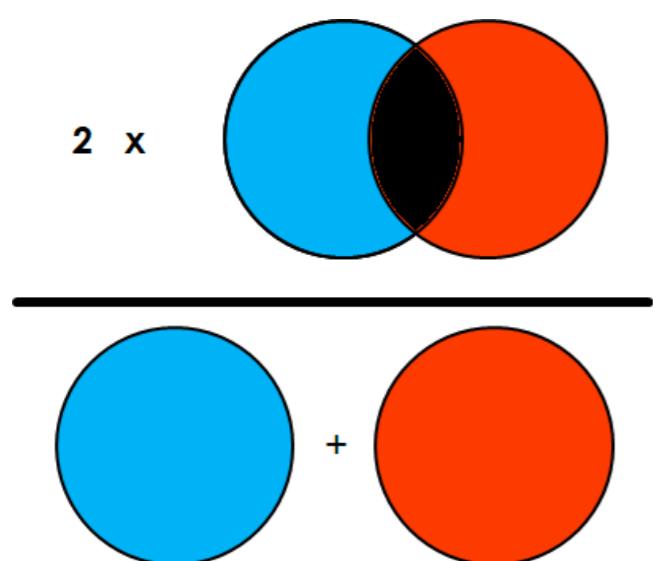
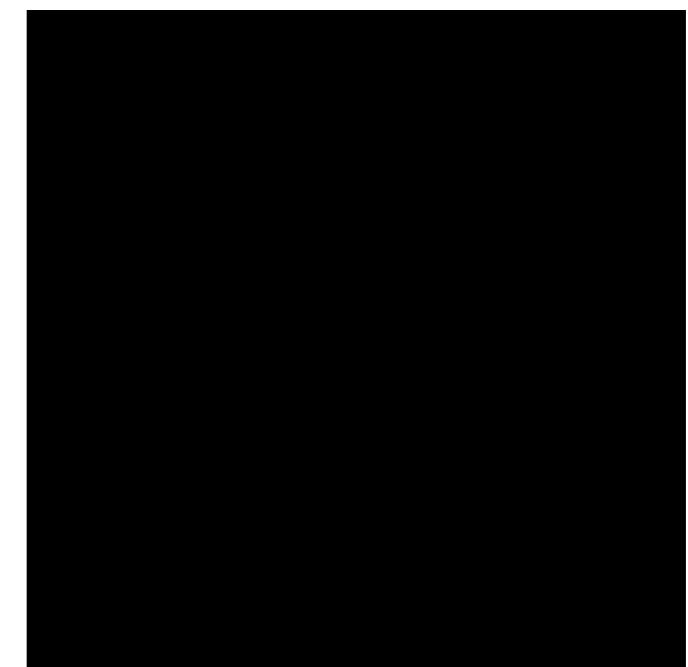
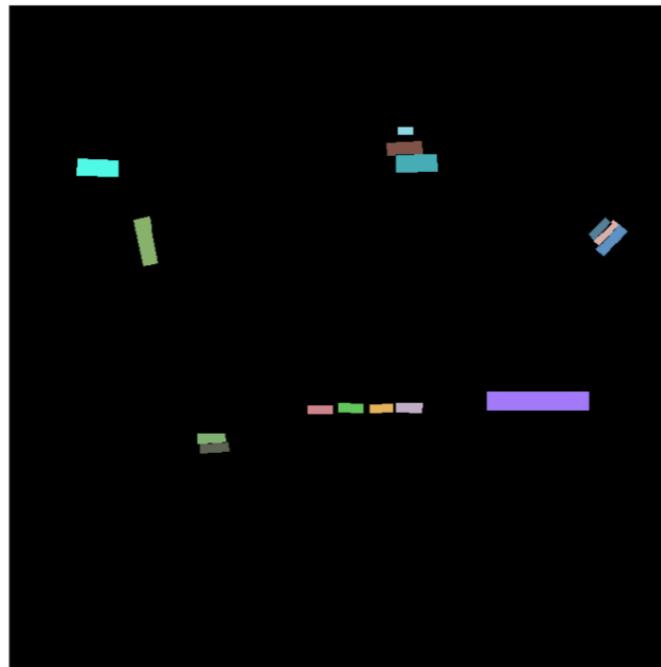
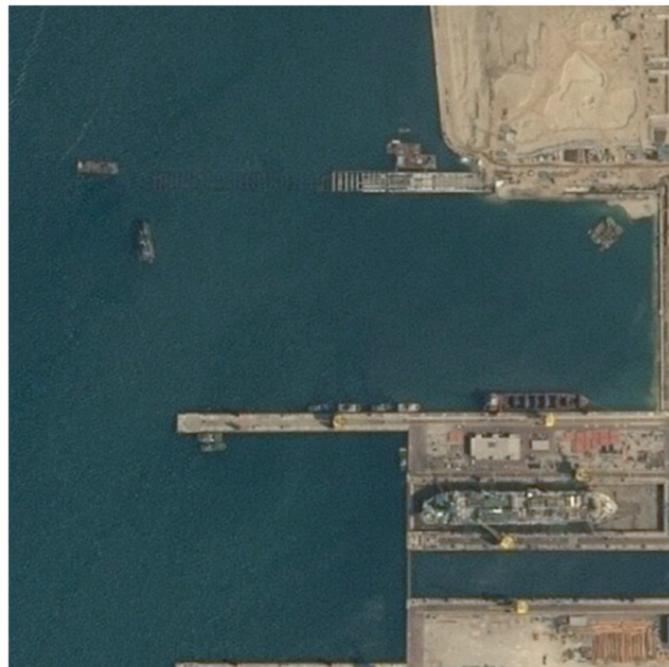
$$\text{IoU} = 95 / 100 = 95\%$$

$$\text{IoU media} = (0 + 95) / 2 = 47.5\%$$

Métricas

- Dice Coefficient (F1 Score)

Es $2 * \text{el área superpuesta dividido por el número total de píxeles en ambas imágenes}$



$$\text{Nº total de píxeles en ambas imágenes} = 200$$

$$\text{Área de superposición para barcos} = 0$$

$$2 * 0 / 200 = 0$$

$$\text{Área de superposición para fondo} = 95$$

$$2 * 95 / 200 = 0.95$$

$$\text{Dice} = (\text{barcos} + \text{fondo}) / 2 = (0 + 0.95) / 2 = 47.5\%$$

Mismo valor que IoU, pero no siempre será así