

# 1º RASCore

## Visão Computacional e Deep Learning

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# Introdução

- O que é uma imagem?
- Resolução.
- Canais de cor.



x →

	0	1	2	3	4
y 0	0	1	2	3	4
1	5	6	7	8	9
2	10	11	12	13	14
3	15	16	17	18	19
4	20	21	22	23	24

← width = 5 →

```
cv2.imread() cv2.imshow()  
cv2.VideoCapture()  
cv2.waitKey()
```

# Operações Básicas

- Dimensões de uma imagem. `img.shape`
- Acessando valor de um pixel. `img[y, x]`
- Separando e juntando canais. `cv2.split` `cv2.merge`
- ROI (Region of Interest). `img[y0:y1, x0:x1]`

# Operações Básicas

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- Separando e juntando canais. `cv2.split` `cv2.merge`
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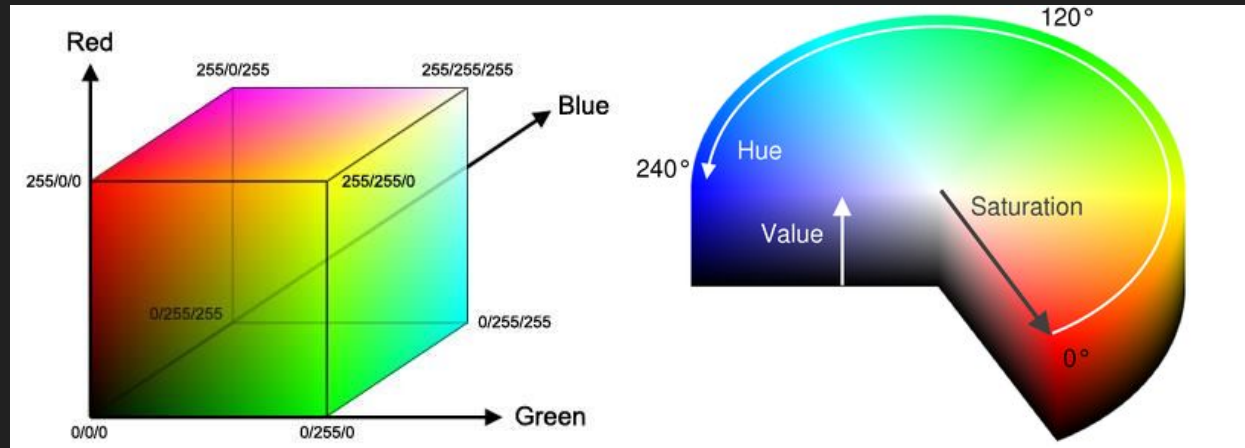
Exercício: Aumentar o brilho de um dos canais de uma imagem RGB.

Exercício: Aumentar o brilho de apenas uma região da imagem.

# Espaços de Cor

- RGB.
- GRAY.
- HSV.

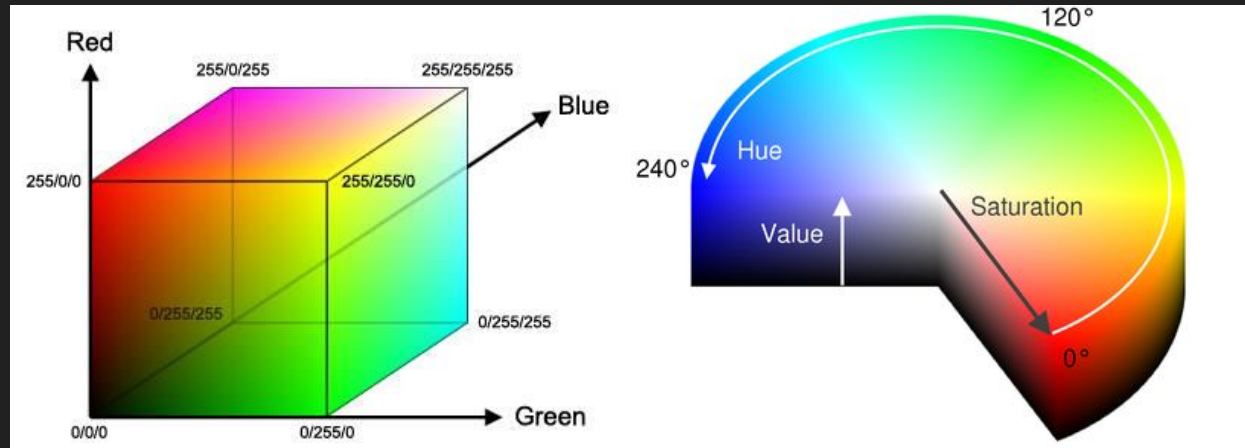
`cv2.cvtColor(imagem, flag_de_conversao)`



# Espaços de Cor

- RGB.
- GRAY.
- HSV.

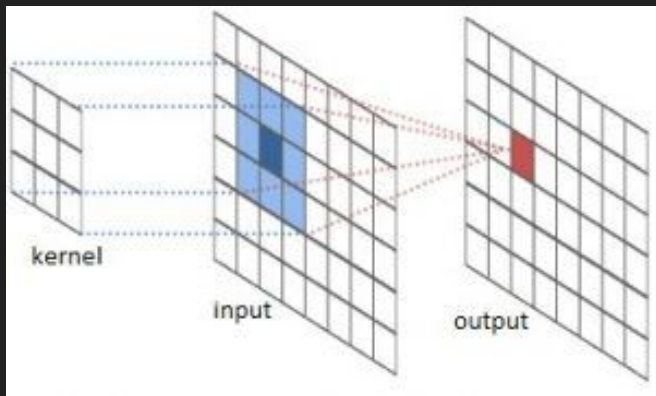
`cv2.cvtColor(imagem, flag_de_conversao)`



Exercício: Fazer uma conversão de RGB (BGR) para Gray na “mão”.

# Convolução e Filtros

- Convolução 2D.



Original      Averaged

The image shows two side-by-side grayscale photographs of a woman wearing a hat. The left image is labeled 'Original' and the right image is labeled 'Averaged'. The 'Averaged' image is a blurred version of the 'Original' image, where the details are smoothed out.

1	1	1	1	1
1	0	0	0	1
1	0	0	0	1
1	0	0	0	1
1	1	1	1	1

*Blur*

1	1	1	1	1
1	5	5	5	1
1	5	44	5	1
1	5	5	5	1
1	1	1	1	1

*Smooth*

1	1	2	1	1
1	2	4	2	1
2	4	8	4	2
1	2	4	2	1
1	1	2	1	1

*Gaussian*

# Convolução e Filtros

- Convolução 2D. `cv2.filter2D(img, -1, kernel)`
- Filtro Box. `cv2.blur(img, kernel_size)`
- Filtro Gaussiano. `cv2.GaussianBlur(img, kernel_size, sigmaX)`



# Convolução e Filtros

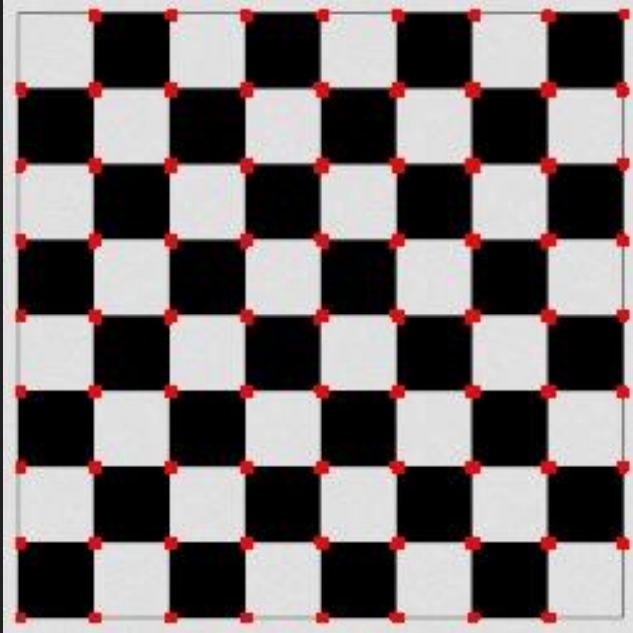
- Convolução 2D. `cv2.filter2D(img, -1, kernel)`
- Filtro Box. `cv2.blur(img, kernel_size)`
- Filtro Gaussiano. `cv2.GaussianBlur(img, kernel_size, sigmaX)`

Exercício: Experimente utilizar kernels diferentes com a operação Filter2D.

# Processamento de Imagem x Visão Computacional

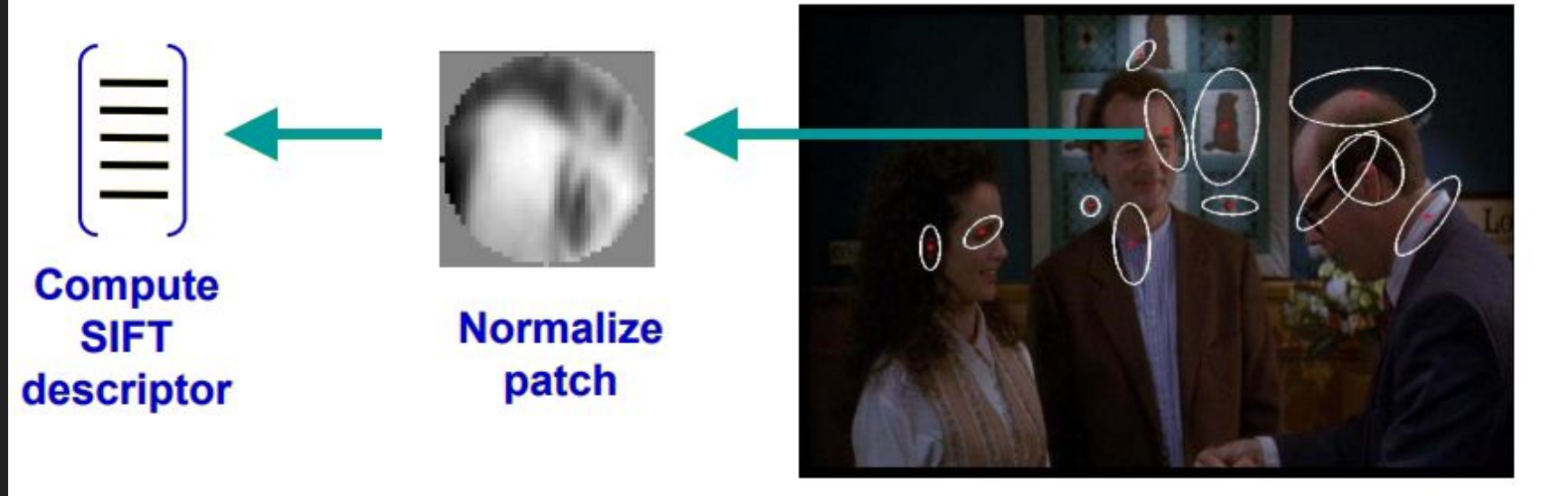


# Algoritmos “Clássicos” - Detecção de Features

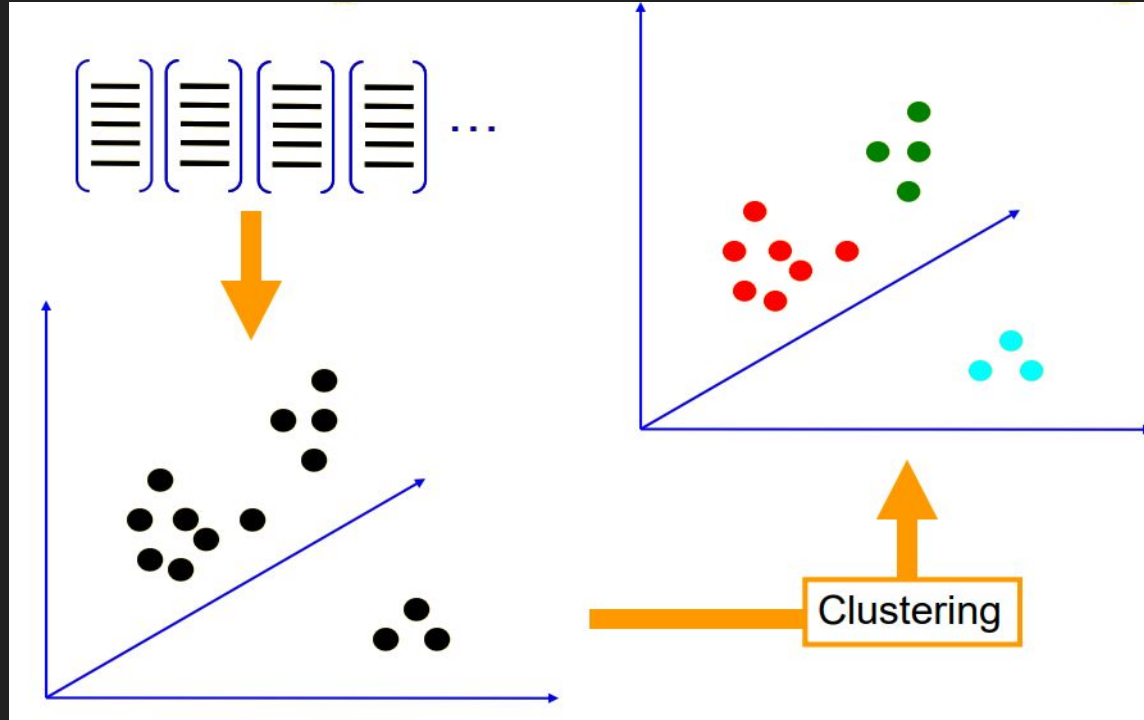


- Harris-Corner
- Shi-Tomasi
- SIFT (Scale Invariant Feature Transform)
- Detecção de Objetos - Homografia

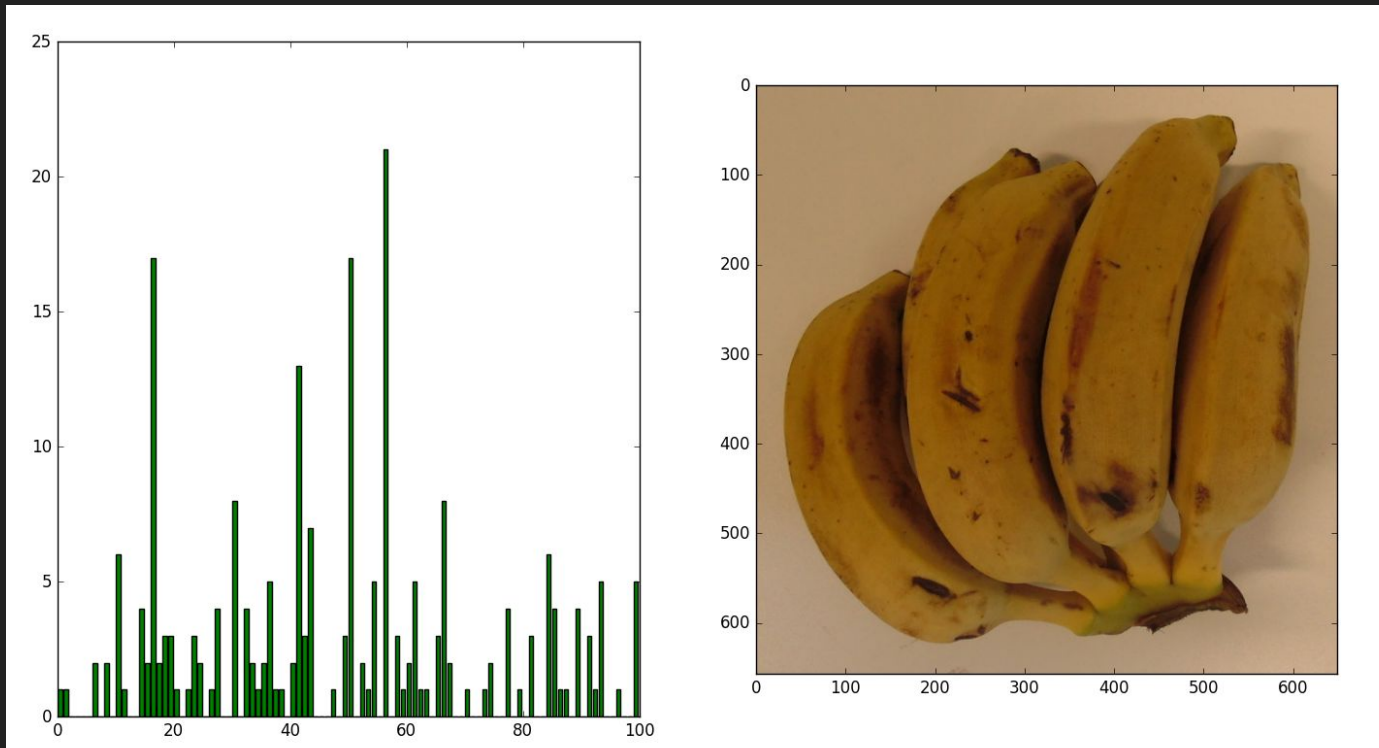
# Classificação por Bag of Features - Extração



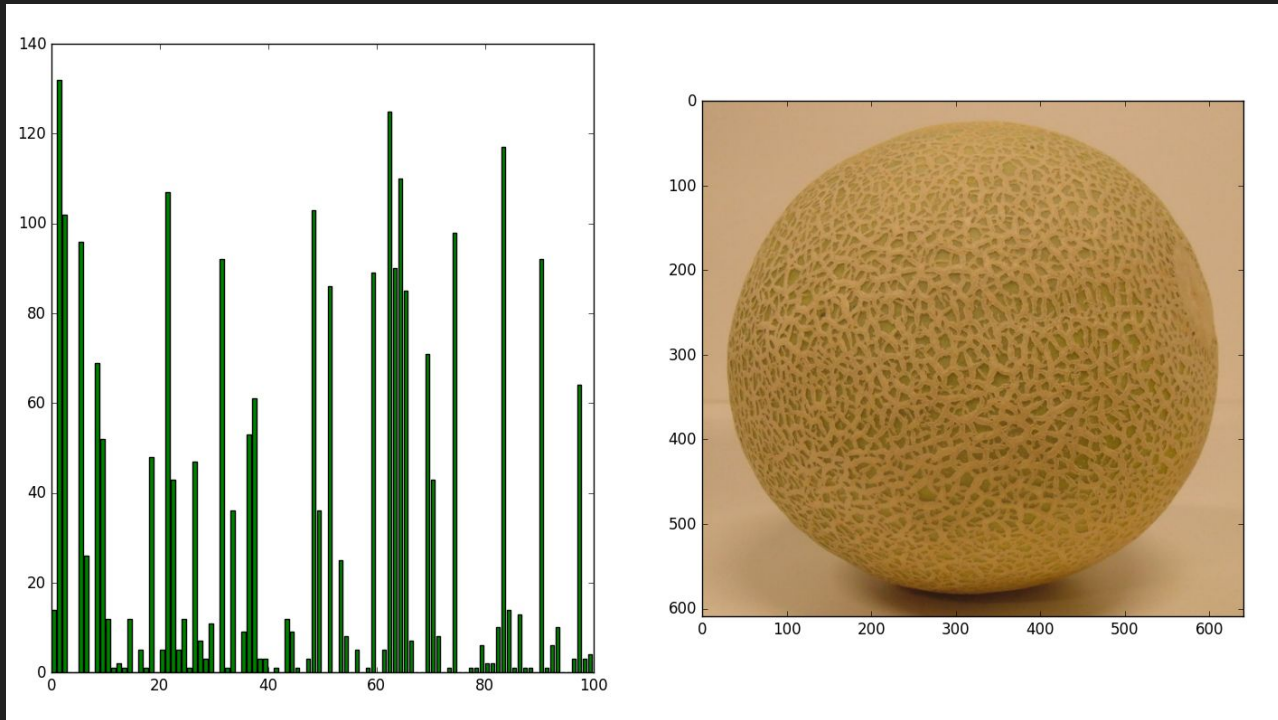
# Classificação por Bag of Features - Clustering



# Bag of Features - Histograma

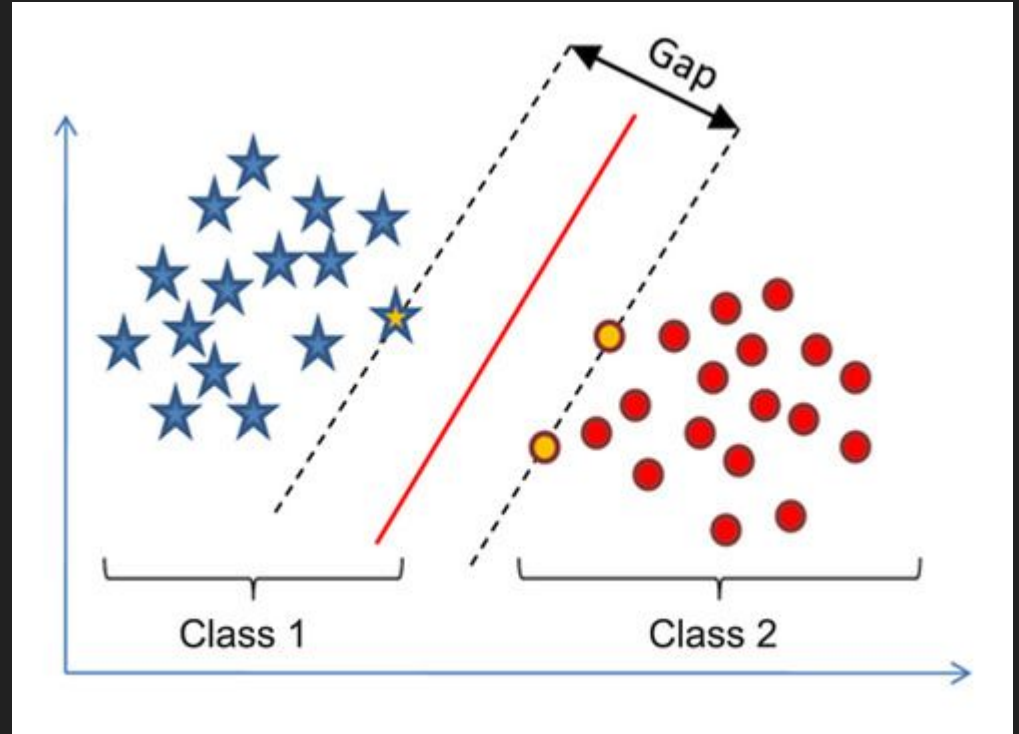


# Bag of Features - Histograma



# Classificação a partir dos Histogramas

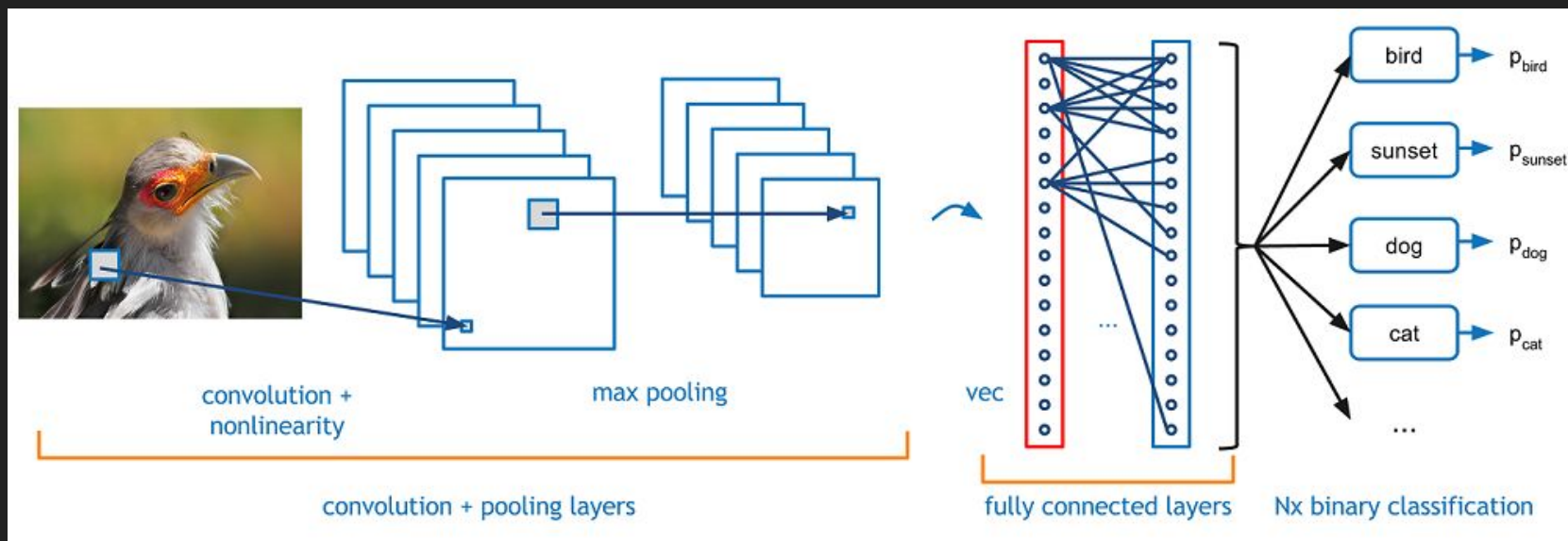
- Regressão Linear
- SVMs
- Redes Neurais



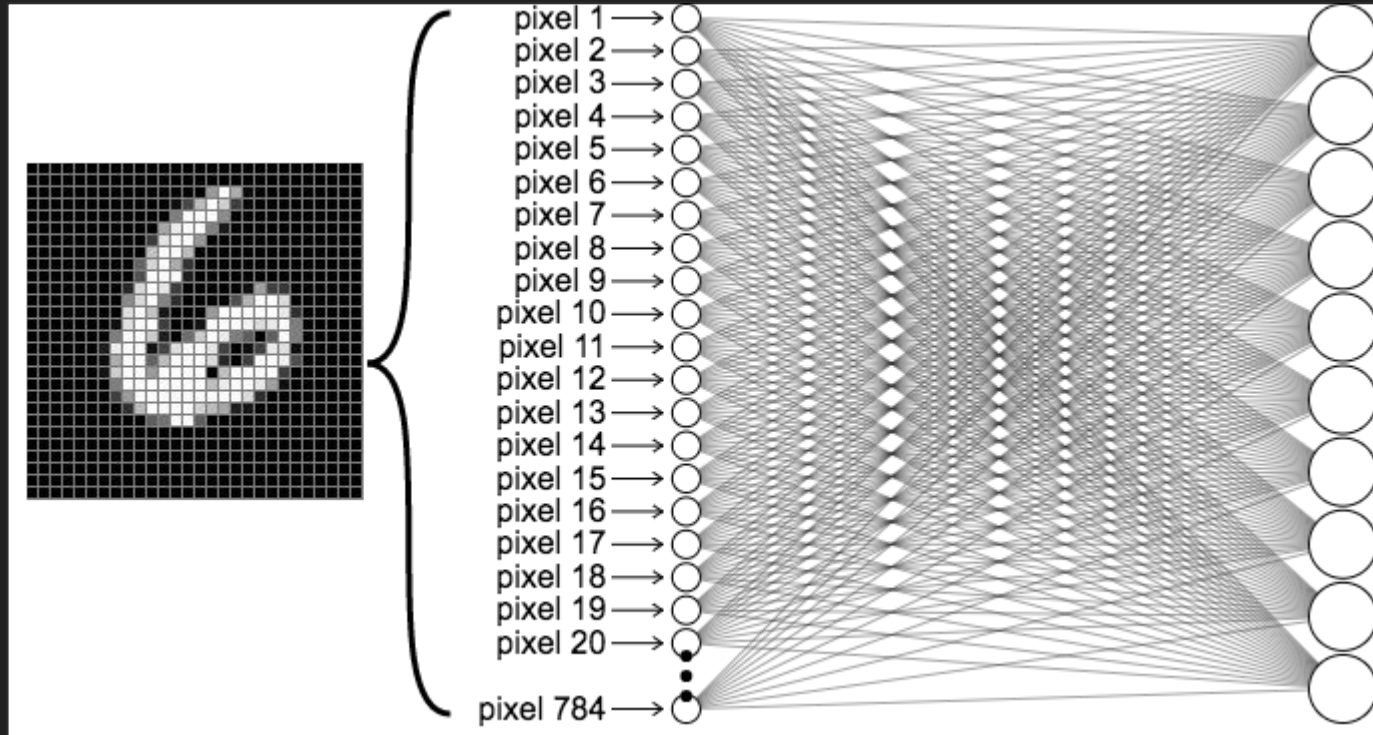


# Deep Learning para Visão Computacional

- Classificação End-To-End



# Camadas Fully-Connected (Dense)



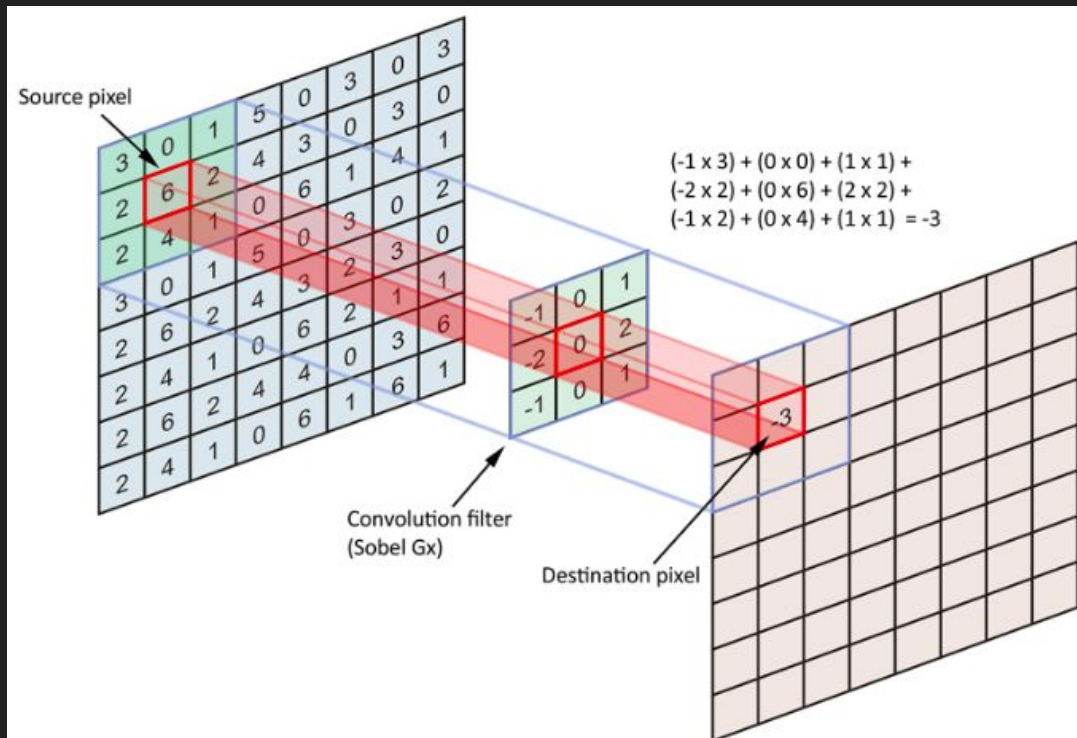
# Camadas Fully-Connected (Dense)

- Número de parâmetros

$$\text{Nº Parâmetros FC} = \text{DIM\_INPUT} * \text{N\_NEURONIOS} + \text{N\_NEURONIOS}$$

# Camadas de Convolução

- Filtros
- Tamanho de Kernel
- Strides
- Padding



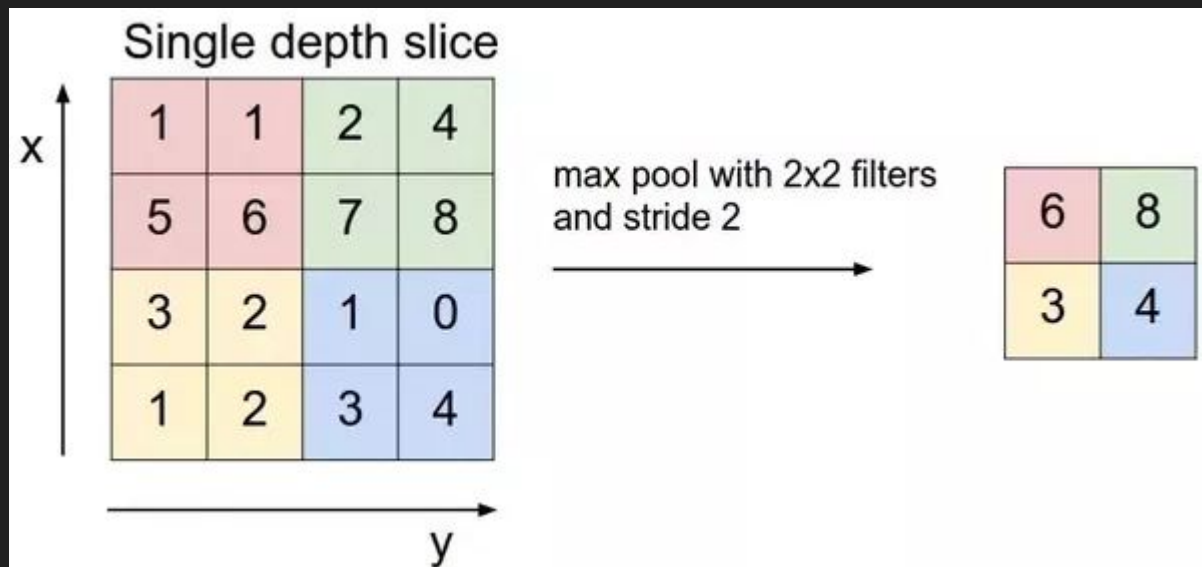
# Camadas de Convolução

- Número de parâmetros

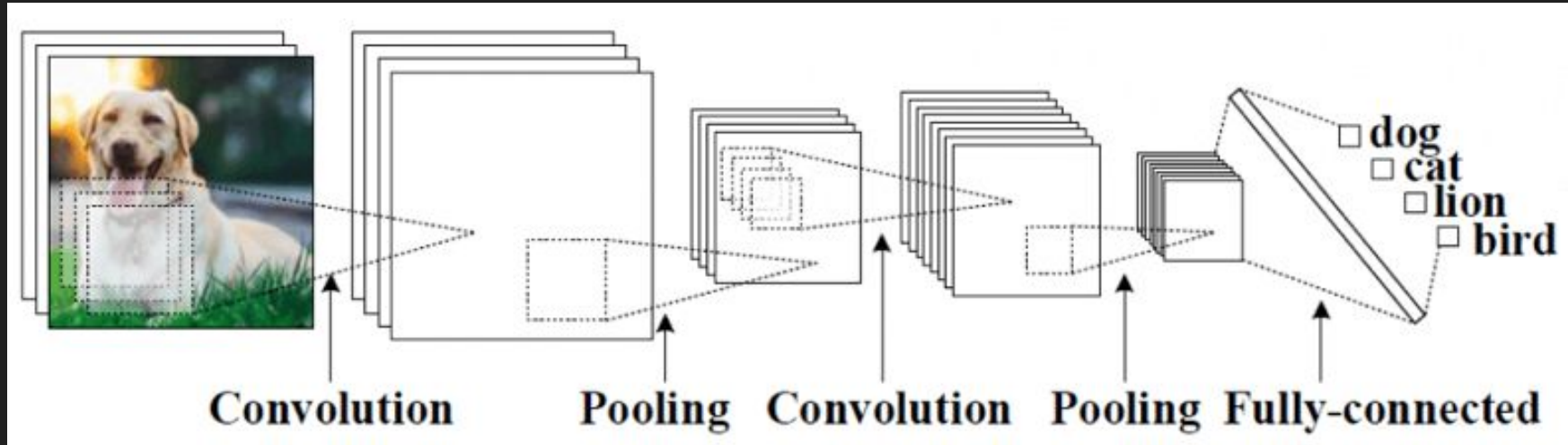
$$\text{N}^\circ \text{ Parâmetros CNN} = (\text{INPUT\_CHANNELS} * \text{KERNEL\_SIZE} * \text{OUT\_CHANNELS} + \text{OUT\_CHANNELS})$$

# Camada de Pooling

- Pool Size
- Max Pooling
- Average Pooling



# Topologia CNN -> Pooling -> FC



- Exemplo com MNIST

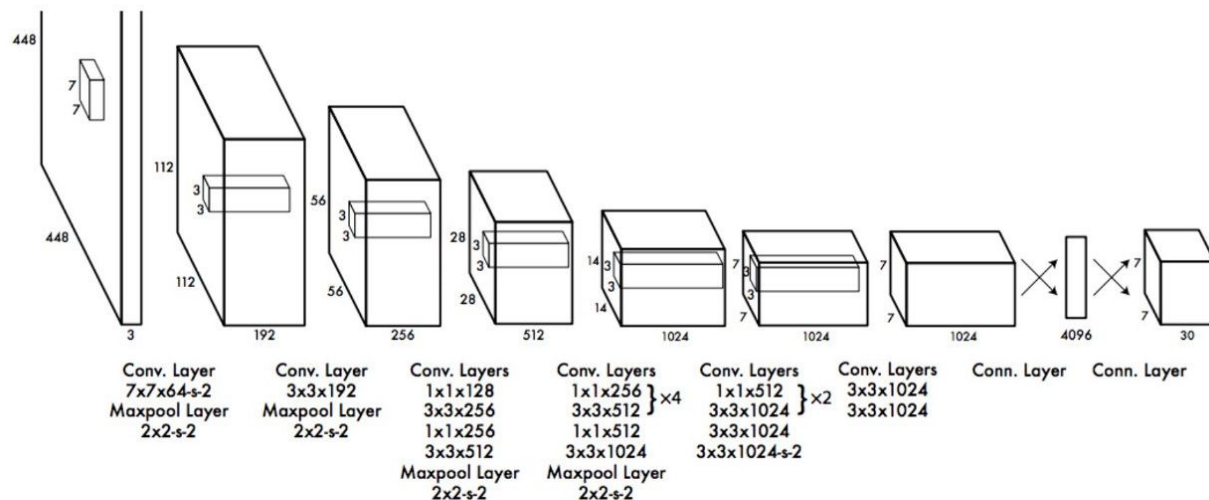
# Exercício

Treinar uma rede com camadas de convolução seguidas de max pooling e classificação a partir de camada Fully-Connected.



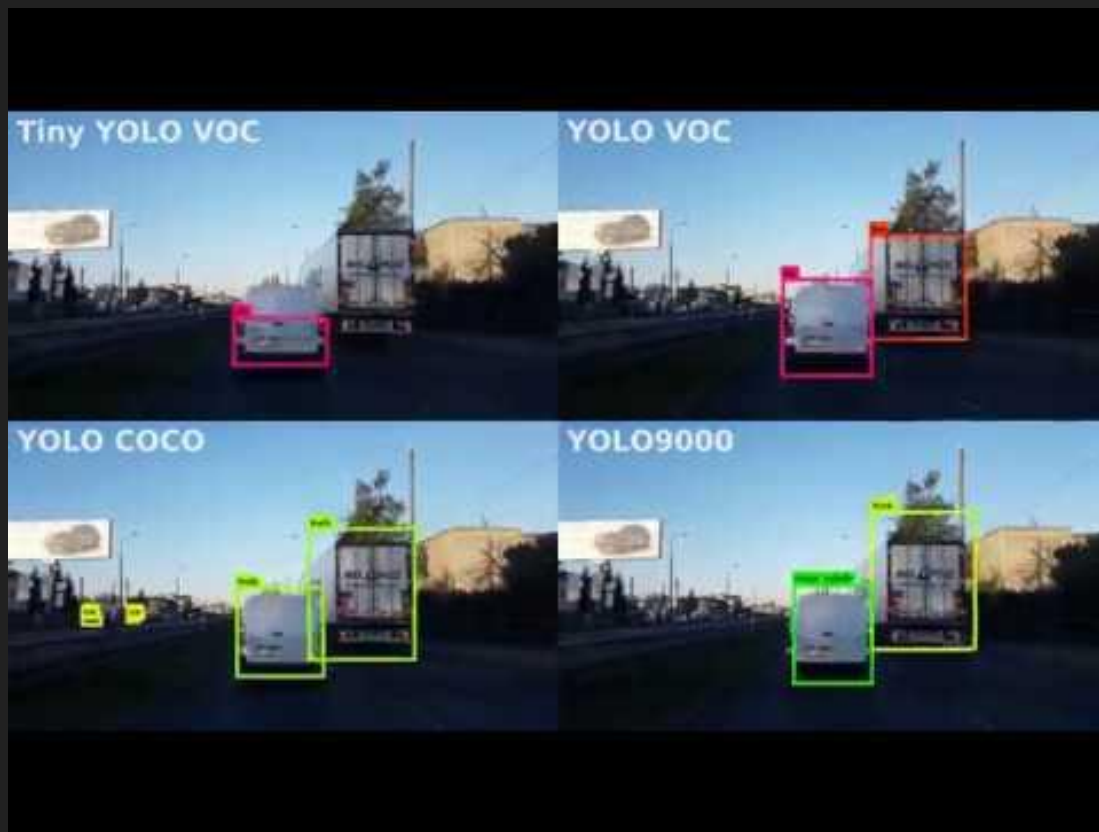


# YOLO V2



**Figure 3: The Architecture.** Our detection network has 24 convolutional layers followed by 2 fully connected layers. Alternating  $1 \times 1$  convolutional layers reduce the features space from preceding layers. We pretrain the convolutional layers on the ImageNet classification task at half the resolution ( $224 \times 224$  input image) and then double the resolution for detection.

# YOLO (You Only Look Once)



# Retina Net

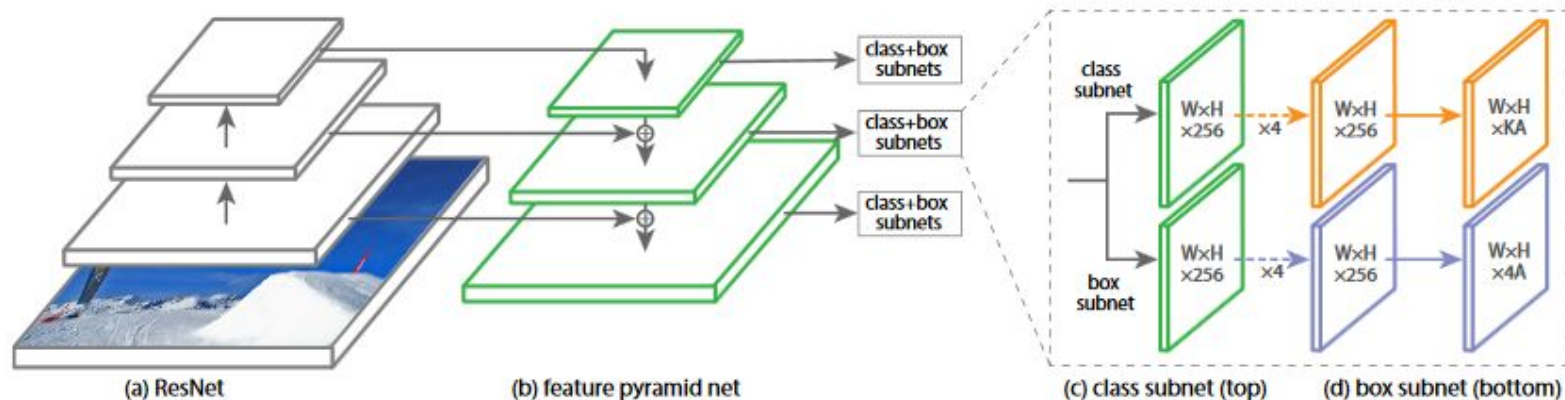
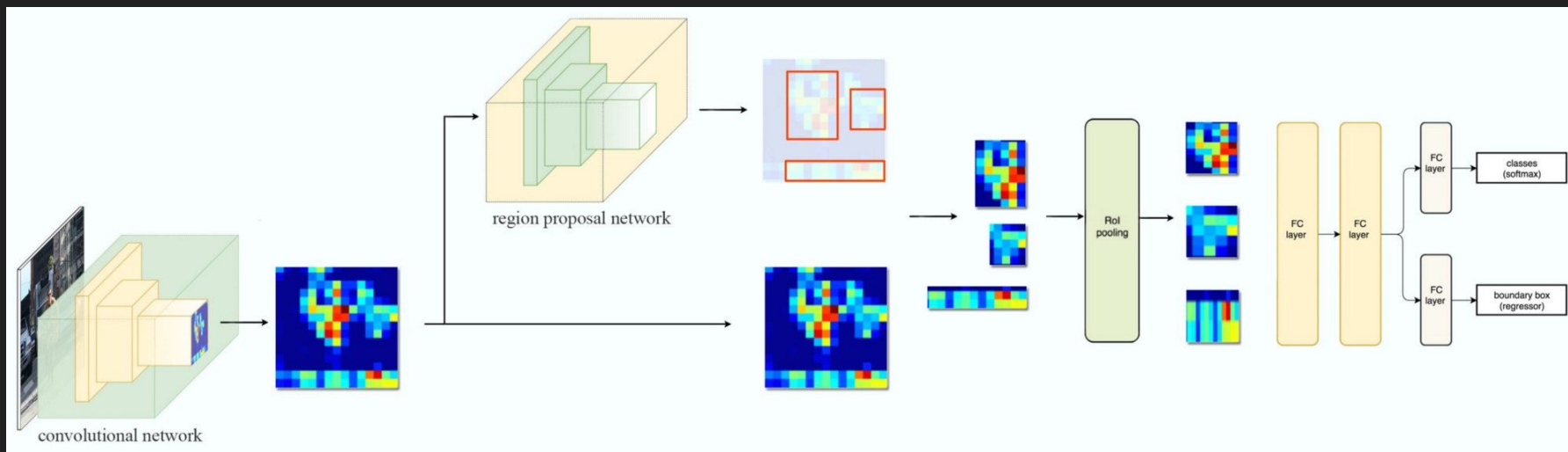


Figure 3. The one-stage **RetinaNet** network architecture uses a Feature Pyramid Network (FPN) [19] backbone on top of a feedforward ResNet architecture [15] (a) to generate a rich, multi-scale convolutional feature pyramid (b). To this backbone RetinaNet attaches two subnetworks, one for classifying anchor boxes (c) and one for regressing from anchor boxes to ground-truth object boxes (d). The network design is intentionally simple, which enables this work to focus on a novel focal loss function that eliminates the accuracy gap between our one-stage detector and state-of-the-art two-stage detectors like Faster R-CNN with FPN [19] while running at faster speeds.

# Retina Net



# Mask R-CNN



# Mask R-CNN

Mask R-CNN

- Object Detection
- Segmentation

