

Aprendizaje Automático Profundo (Deep Learning)







Visualización de Filtros

Visualización de Filtros

from keras.applications.vgg16 import VGG16
model = VGG16()

print(model.summary())

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	(None, 224, 224, 3)	0
block1_conv1 (Conv2D)	(None, 224, 224, 64)	1792
block1_conv2 (Conv2D)	(None, 224, 224, 64)	36928
block1_pool (MaxPooling2D)	(None, 112, 112, 64)	Θ
block2_conv1 (Conv2D)	(None, 112, 112, 128)	73856
block2_conv2 (Conv2D)	(None, 112, 112, 128)	147584
block2_pool (MaxPooling2D)	(None, 56, 56, 128)	0
block3_conv1 (Conv2D)	(None, 56, 56, 256)	295168
block3_conv2 (Conv2D)	(None, 56, 56, 256)	590080
block3_conv3 (Conv2D)	(None, 56, 56, 256)	590080
block3_pool (MaxPooling2D)	(None, 28, 28, 256)	

block4_conv1 (Conv2D)	(None, 28, 28, 512)	1180160
block4_conv2 (Conv2D)	(None, 28, 28, 512)	2359808
block4_conv3 (Conv2D)	(None, 28, 28, 512)	2359808
block4_pool (MaxPooling2D)	(None, 14, 14, 512)	Θ
block5_conv1 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv2 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv3 (Conv2D)	(None, 14, 14, 512)	2359808
block5_pool (MaxPooling2D)	(None, 7, 7, 512)	0
flatten (Flatten)	(None, 25088)	Θ
fc1 (Dense)	(None, 4096)	102764544
fc2 (Dense)	(None, 4096)	16781312
predictions (Dense)	(None, 1000)	4097000
Total params: 138,357,544	=======================================	=======

Trainable params: 138,357,544

Non-trainable params: 0

Acceso a los filtros. Verificación de su tamaño

```
or layer in model.layers:
   if 'conv' not in layer.name:
      continue
   filters, biases = layer.get_weights()
   print(layer.name,filters.shape)
```

- 64 filtros de 3x3x3
- 64 filtros de 3x3x64
- 128 filtros de 3x3x64
- 128 filtros de 3x3x128
- ..
- 512 filtros de 3x3x512

```
Filter (h,w,cin,cout)
block1_conv1 (3, 3, 3, 64)
block1_conv2 (3, 3, 64, 64)
block2_conv1 (3, 3, 64, 128)
block2_conv2 (3, 3, 128, 128)
block3_conv1 (3, 3, 128, 256)
block3_conv2 (3, 3, 256, 256)
block3_conv3 (3, 3, 256, 256)
```

```
Filter (h,w,cin,cout)
block4_conv1 (3, 3, 256, 512)
block4_conv2 (3, 3, 512, 512)
block4_conv3 (3, 3, 512, 512)
block5_conv1 (3, 3, 512, 512)
block5_conv2 (3, 3, 512, 512)
block5_conv3 (3, 3, 512, 512)
```

Selección de la capa en base al nombre

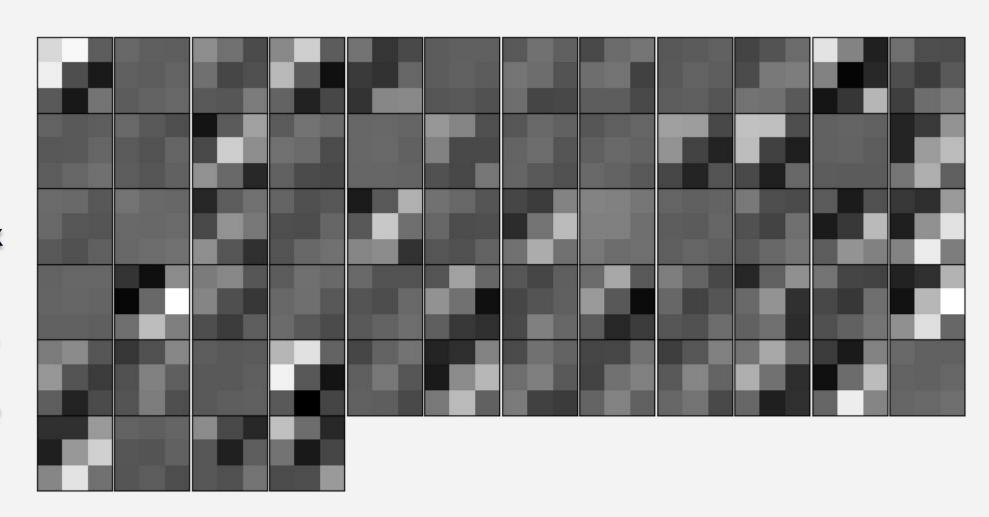
```
def layer_by_name(model,layer name):
 for layer in model.layers:
   if layer.name==layer name:
     return layer
 raise ValueError(f"Invalid layer name {layer name}")
#Elegir capa convolucional y nro de filtro
layer name="block1 conv2"
filter index=0
#dibujar filtro
layer = layer_by_name(model,layer_name)
filters, biases = layer.get_weights()
plot conv weight(layer.name,filters[:,:,:,filter index])
```

Visualización de Filtros

```
def plot_conv_weight(layer_name,filters,cols=32):
h,w,c=filters.shape
 rows=(c//cols) + int((c/w cols)>0)
 gs = gridspec.GridSpec(rows, cols,wspace=0.1,hspace=0.1)
# maximo y minimo para dibujar todos en la misma escala
mi,ma=filters.min(),filters.max()
for i in range(c):
     ax = plt.subplot(gs[i])
     ax.imshow(filters[:,:,i],cmap="gray",vmin=mi,vmax=ma)
     ax.set xticks([])
     ax.set yticks([])
# poner en blanco los ax que sobran
for i in range(c,cols*rows):
   ax = plt.subplot(gs[i])
                                             Ejemplo Completo
   ax.axis("off")
```

Verificación de aprendizaje correcto

- Capablock1_conv2
- block1_conv2 (3, 3, 64, 64)
- Primer filtro (filter_index =0)
- shape = (3,3,64)
- 64 cuadrados de 3x3
- c/u: pesos sobre el Feature Map anterior



Importante: No son todos 0 (filtros muertos)